MODELING COMPLEX SYSTEMS FOR PUBLIC POLICIES

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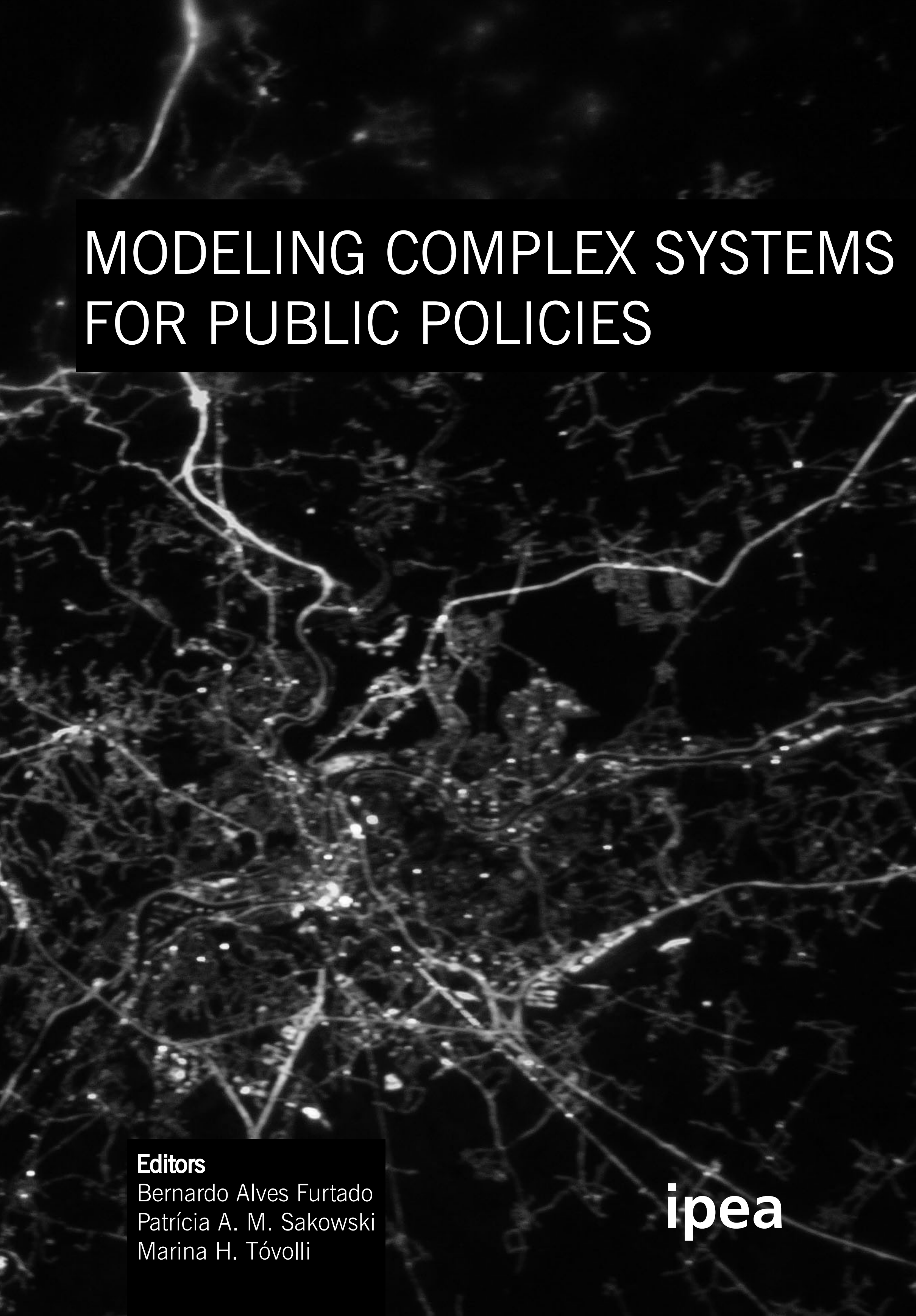

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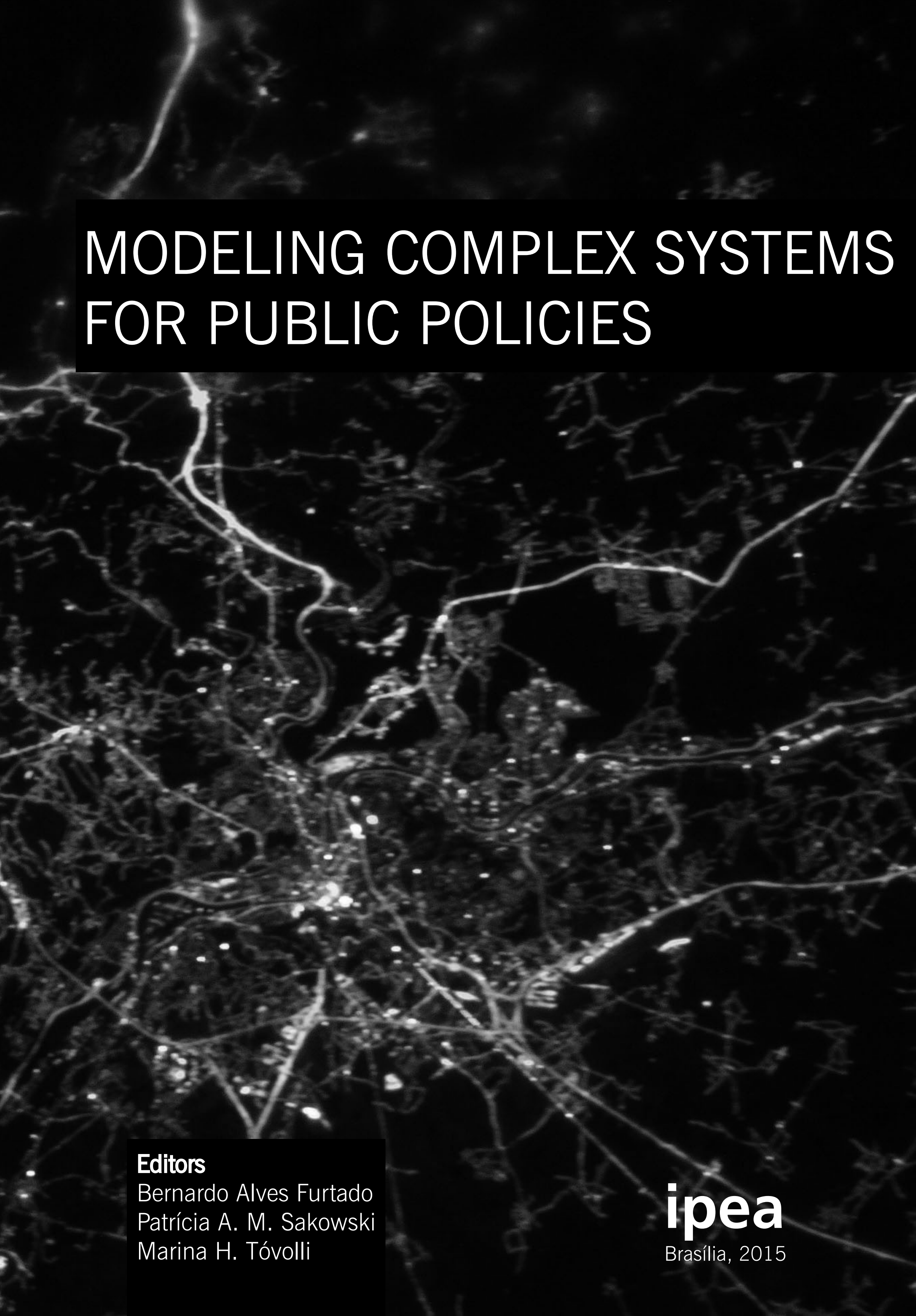

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Brasília, 2015

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FOREWORD

Policy is the means and end of the Institute for Applied Economic Research. Policy evaluation, policy design and monitoring along with advising the State using the best scientific knowledge are at the core of the Institute. Thus, tools that enable policy-makers and academia alike to foster a deeper understanding of policy mechanisms and their intertwined, asynchronous, and spatially-bound effects are at the forefront of our interests.

Complexity is a relatively new approach to science, which has integrated knowledge from different fields, trying to understand collective behavior in living systems and complex phenomena such as emergence. It has brought important insights for science, but little has been done trying to explore the policy aspects of this new approach both in Brazil and worldwide.

This book tries to help building this bridge between complexity and public policies, by bringing together an international group of prominent researchers, stemming from the very Santa Fe Institute, University of Maryland, University of Tokyo, University of Sidney, ETH Zurich, Bielefeld University, Utrecht University, New England Complex Systems Institute, Polytechnic Institute of Lisbon, MITRE Corporation, University of Brasilia, University of São Paulo and EMBRAPA and Ipea researchers. By introducing the major concepts, methods and state-of-the-art research in the area, the book is intended to be a seminal contribution to the application of the complexity approach to public policies, and a gateway for the world of complexity.

As an Institute whose middle name is policy, I think it is high time for us to look more and more at the policy aspects of this new approach and to explore the insights and applications they can bring into policy making and analysis. You are invited to join us in this journey.

Jessé Souza
President of the Institute for Applied Economic Research

PREFACE

Scott E. Page[1]

In Norman Juster's classic *The Phantom Toolbooth,* the protagonist Milo and his companion, a large dog named Tock, cannot figure out how to get their wagon to move forward. A Duke arrives and tells them that if the wagon to go, they must sit quietly, that it (the wagon) goes without saying. The same might be thought about the relevance of complexity theory to public policy – that it too goes without saying.

Given the complexity of the political and bureaucratic processes that generate policies and the complexity of the systems within which most policies are applied, it would seem that complexity's relevance should go without saying. Yet, that's not the case. The patchwork of models, concepts, and ideas that comprise the field of complexity studies rarely enter into policy discussions and when they do, they primarily engage at the fringes.[2]

Therefore, unlike Tock and Milo, complexity scholars cannot sit quietly. If complexity scholars want their ideas to advance and improve public policy, they must speak clearly and loudly. In this volume, many leading scholars choose to do just that. Their impact should be substantial.

What follows includes contributions from many of the leading scholars in the field of complex social systems. It should then come as no surprise that the volume achieves multiple, ambitious goals: it introduces the concepts and tools of complex systems, it demonstrates complexity theory's relevance to public policy, it contrasts the complexity approach to public policy to traditional methods, and, finally, it presents case studies and examples that demonstrate proof of concept by focusing on specific policy domains in Brazil and elsewhere.

So what are complex systems? Complex systems consist of diverse, adaptive actors who interact with their neighbors and over networks. These interactions produce both additive outcomes – aggregate oil consumption or the average price of #2 red wheat – as well as emergent phenomena such as traveling waves in traffic patterns, stock market crashes, and even Spanish culture. These aggregate

1. University of Michigan, Santa Fe Institute.

2. Climate change models, which might be seen as a counterexample, can be seen as a type of complex system model, but they tend to be mash ups of standard economic models with geophysical models, lacking many of the core components of complex systems models.

phenomena become part of the world and induce adaptations at the micro level. These in turn create new macro level phenomena.

The resulting dynamics can take many forms. They can converge to equilibria. They can produce cycles or simple patterns, such as the near linear trend in the global output of oil over the past hundred years. They can produce complex time series, as is the case with oil prices. Finally, they can produce data that appears random, a property nearly satisfied by detrended stock prices. In brief, complex systems can produce anything. And because they can, they can help us understand almost anything.

The pitch then, the two-minute elevator speech for why we need to bring complexity research to policy domains, partly relies on this resonance: if we want to understand a policy domain produces complex outcomes such as constantly changing stock and housing prices, traffic patterns, or divergent paths of school success, then we should use models capable of producing similar types of complexity.

Cast in a comparative frame, this logic challenges the predominant equilibrium paradigm: why would someone base policy in a complex domain on a model that assumes equilibrium? The argument extends what William Rand in this volume relates as the "standing under the streetlight" criticism of neoclassical economic models: they shine light, but not where we should be looking. Complex systems' models represent flashlights to guide us to new locations in modeling space.

The pitch also relies on the interconnectedness of policy actions. Education policy, environmental policy, zoning policy, infrastructure decisions, and energy policies all bump into one another. Put metaphorically, policies do not operate in silos. Put mathematically, nonzero cross partials abound. Efforts to reduce wealth inequality by extending home loans induce residential sorting which influences school quality, traffic density, crime rates, and so on. As described by Furtado et al. in this volume, complex systems' approaches, "enable public policies to be considered comprehensively and simulated explicitly in all their multiplicity of sectors and scales, of cause and effect." An observation echoed in and elaborated on in the excellent chapter by Claudio Tessone.

Advocacy notwithstanding, the volume takes a measured stance. No one denies that standard approaches to evaluating policies – equilibrium models and, when possible, natural experiments – are useful and often powerful tools. Complex systems do not represent a silver bullet, but another arrow in the policy maker's quiver. More accurately, all of these tools put together can be thought of as multiple imperfect arrows that provide insight into what is likely to happen, what could happen, and how what happens might spill into other domains.

Consider, for example, a gold standard natural experiment that reveals a policy to be a success. Complex systems models might suggest that the policy could create multiple types of outcomes. The success of the policy might well have been good luck – like picking up a die and rolling a six. Rather than roll out the policy nationwide, a prudent policy maker might run a few more experiments to see if in fact, the outcome was a lucky roll.

Alternatively, complex systems models might show that the policy, though successful, produces long-term negative feedbacks. An analysis of these feedbacks, as William Rand demonstrates in his chapter, provides us with a deeper understanding of the full effects of a policy.

Notice that these feedbacks produce a type of nonlinear effect which along with heterogeneity can make a model may intractable using game theoretic or mathematical optimization techniques. For decades, these tractability constraints limited the dimensionality and realism of models. Policy makers had to rely on models they could solve. Those models were not complex.

Owing to increases in computing power and the introduction of a new methodology, agent based models (ABM), tractability has become less of a constraint. Any model that can be coded can be explored. Yet, we should be skeptical, dubious (dare I say dismissive) when someone claims "I have a simulation that shows (fill in the blank)." A vast continent of poorly constructed, spaghetti coded, invalidated, unverifiable, non-calibrated models surrounds a much smaller region of useful models. As Gentile, Glazner and Koehler's chapter makes clear, ABMs have enormous potential as a tool for policy comparisons, but ABMs must be constructed by people well versed in the methodology.

The resulting models can include agents who use sophisticated learning algorithms (see Jaime Sichman's chapter) or they can rely on relatively simple rules. No one ABM model will tell us with one hundred percent certainty the full effects of policy, but many models with multiple levels of granularity and domains of interaction will give us a better understanding of the set of the possible and ensure more robust policies. And, isn't avoiding surprise an important aim of policy makers?

Economic policy is one domain where surprise events can have dramatic consequences. More than two decades ago, several leading economists advanced the notion that the economy would be more accurately thought of as a complex adaptive than as an equilibrium system. Though equilibrium models still predominate, those models include networks, learning, and heterogeneous agents who do not always make optimal decisions. Furthermore, state of the art equilibrium monetary models (dynamic stochastic general equilibrium models – DSGE) spend almost all of their time out of equilibrium.

At their core though, the DSGE models rely on equilibria to characterize the dynamics. The economy is always headed toward an equilibrium. In other words, the modeler and the actors in the model know where they economy is headed. In contrast, ABM models of the economy make assumptions and then, echoing ideas from Orlando Gomes' and Rand's chapters, the economy emerges from the bottom up.

Two chapters in this volume clarify this complexity approach to modeling the economy. Gomes both makes the intellectual case for a complexity approach and presents a (relatively) simple complex systems model. In contrast, Herbert Dawid shows how one can embrace complexity in full. He provides an introduction to the elaborate Eurace@Unibi model of the economy. This intendedly realistic model includes spatially situated consumers with budgets and firms with suppliers and inventories has produced meaningful policy insights, among them: policy can be relevant away from equilibrium, individual responses may differ from aggregate effects,[3] outcomes can be path dependent, and institutional details can matter. These are not empty claims. Evidence suggests that in some domains ABMs can make better predictions than standard models.

But ABMs can also make worse predictions. And while it's tempting to stage a horse race between complexity models and equilibrium models of the economy, doing so misses the earlier point about multiple arrows in the policy maker's quiver. Economic models consider the economy. Complexity models have the potential to see the economy within a broader system in which people engage in social movements, confront political regime changes, respond to threats of epidemics, natural disasters, and climactic change. All of this can be seen as operating within one system. We can try to peel off the economy and study it in isolation, just as we could study only the circulatory system, the nervous system, the immune system, or the digestive system, but if we do, we miss the real show.

The real show occurs at multiple scales: from family, to city, to nation, to world. Cities offer one useful scale as, Luis Bettencourt shows in his chapter summarizing years of scholarship. Cities, as many have noted, are the engines of the economy. As Paul Krugman once quipped, almost anyone can identify cities from an airplane on a clear night, but almost no one could draw country boundaries. Cities, therefore, might be a important level of activity to analyze. Bettencourt shows this to be true, highlighting provocative findings of scaling laws – productivity scales superlinearly and infrastructure scales sublinearly – and juxtaposing implications from the complexity paradigm with historical views of the city that

3. This would be the case when an outcome is emergent as opposed to additive. When feedbacks and nonlinearities are present, agent heterogeneity can produce aggregate results that differ from what would be produced by an economy composed of identical agents.

take an engineering approach. He embraces the roles of information and learning in thinking through policy effects and identifies criteria when local adaptation should outperform top down implementation.

Yaneer Bar-Yam takes on a multiple scales – from single markets to the world writ large. Deregulation of a commodity (a national scale economic policy) results in global scale price changes. These in turn can depress firm scale revenues, which could under certain conditions, result in regional scale uprisings. Quoting Bar-Yam: "One nation's energy subsidies can cause global food prices to spike, setting off political unrest halfway around the world." The general phenomena to which he speaks is captured in the famous lyrics of Disney's Richard and Robert Sherman, it is in fact "a small world after all."

Within that small world, policy makers must make choices. Inevitably, there will be successes and failures. The *raison d'être* of the volume is to increase the former and decrease the latter. Perhaps the single most powerful statement in the book appears in the chapter by Bernardo Mueller describing two case studies. Writing of the Brazilian policy apparatus, he writes: "I have not found any example of an explicit use of complex thinking in any policy in this country."

In Brazil, the complexity wagon does not go without saying despite the fact that legislative institutions within Brazil appear to be quite complex, as proven by Acir Almeida, who shows the relative contributions of a complexity perspective on legislative activity. Using models from political science and complex systems, he shows how ideas from complexity theory add to our understanding of emergent patterns of law-making in the Brazilian Congress.

That law making occurs within a Brazilian system in which, according to Mueller, the Executive wields enormous power. Of course, a structure of checks and balances, reigns in that power, but what's most relevant is how the policies are formulated. Mueller finds fault with what he calls a reductionist, i.e. non-complex, approach. The policy domains in question: land use, public health, the environment, and transportation, these are all complex domains. Policies are developed and evaluated as if they were not. In his opinion, that's a mistake.

The subsequent chapter by Dick Ettema unpacks this line of criticism in even greater detail. He describes the engineering approach to transportation policy with its focus on meeting individual level criteria of success or utility such as avoidance of congestion and pollution. These models level out the effects on housing markets, equity, and social exclusion.

Most people accept that transportation systems and stock markets are complex. People experience congestion and traffic jams. They watch stock prices rise for weeks with only small changes and then drop five to ten percent in a few hours.

Other systems, such as educational systems, are less obviously complex. Time unfolds more slowly. Phenomenological changes are more abstract and less easily measured. Yet, as Michael Jacobson demonstrates, schools can be usefully seen as complex systems.

Policies can try to improve them by pulling levers – reducing class size or increasing teacher quality. Policies can also try to improve mechanisms. Both types of policies have a linear orientation and are presented as such leading to claims that an decrease of *X* percent in pupil teacher ratios will lead to an increase of *Y* percent in student test scores. This is yet another example of a misplaced focus on a single partial derivative within a complex system, a point reinforced by Sakowski and Tóvolli in their analysis of Brazilian education policy.

Policies have interactions in other domains. In constructing an effective policy, one cannot proceed dimension by dimension. Step 1: minimize average commute time. Step 2: maximize student test scores. Step 3: reduce inflation. Step 4: produce sustainable forest management plan. Policies occur within systems and those systems interact. In particular, the social and the physical interact, as made abundantly clear in Marcos Aurélio Santos da Silva's chapter on socioterritorial systems.

In sum, whether we focus our lens on the forests or students of Brazil or the world writ large, we cannot help but see the inherent complexity. We see diverse, purposeful connecting people constructing lives, interacting within institutions, and responding to rules constraints, and incentives created by policies. These activities occur within complex systems and when the activities aggregate they produce feedbacks and create emergent patterns and functionalities. By definition, complex systems are difficult to describe, explain, and predict, so we cannot expect ideal policies. But we can hope to improve, to do better. Having more tools, especially the evolving and maturing tools of complexity science, can only make us better. Complex scholars can move the needle. But they can no longer sit quietly.

PART I
Complexity: theory, methods and modeling

CHAPTER 1

A COMPLEXITY APPROACH FOR PUBLIC POLICIES

Bernardo Alves Furtado[1]
Patrícia Alessandra Morita Sakowski[2]
Marina Haddad Tóvolli[3]

1 INTRODUCTION

Complex Systems can be defined in a broad manner and embrace concepts from different fields of science, from physics to biology, to computing and social sciences. Mainly, the definition includes nonlinear dynamical systems that contain large number of interactions among the parts. These systems learn, evolve, and adapt, generating emergent non-deterministic behavior.[4] Public policies are to be applied upon a vast range of issues that involve the public, the broad community of citizens and communities, firms and institutions. Public policies are also to be employed on a number of sectorial issues which are intertwined, asynchronous, and spatially superposed. This coupled understanding of complex systems and public policies suggests that most objects of public policies – be them of economic or urban nature, be them of environmental or political consequences – can be viewed as complex systems. Thus, if public policies' objects can be seen as complex systems, their understanding may benefit from the use of associated methodologies, such as network analysis, agent-based modeling, numerical simulation, game theory, pattern formation and many others within the realm of complex systems. These methodologies have been applied to different aspects of science, but less frequently to public policy analysis.[5] We hypothesize that the use of these concepts and methodologies together improves the way policies of complex objects are viewed, adjusted, and operated upon from a public point of view.

Given these broad definitions of complex systems and public policies, this chapter further describes the concepts, methodologies and computing implementation of complex systems. Then, it demonstrates the adherence of those concepts and

1. Researcher at Diset/Ipea, Productivity researcher at CNPq.

2. Reseacher and Chief of the Planning and Institutional Articulation Advisory Board (Aspla/Ipea).

3. Research Assistant at Dirur/Ipea.

4. A didactically complete discussion of Complexity is available at Mitchell (2011). The initial concepts that compose the complexity sciences can be found in Furtado and Sakowski (2014).

5. Initially, one could look at Colander and Kupers (2014) who provide a review focused on economics. Edmonds and Meyer (2013) give a detailed background. An earlier report can be found at OECD (2009).

methodologies to social policies, economic, urban and environment analysis; and highlights some applications on transport planning, in education, on the study of the legislative and on territorial analysis. After having described the concepts and methods and why public policies' objects can be easily viewed as complex systems, the chapter lists the advantages of using complex systems' approach specifically to public policies. Thus, this chapter introduces and summarizes the contents of the book (and project) of the same name.

In short, it is the objective of this chapter to define complex systems and its more prominent attributes; list the more common methodologies associated with complex systems; present a varied scope of applications of complex systems modeling to public policies and discuss yet briefly the advantages of applying these approaches to a public policy context.

2 DEFINITIONS OF COMPLEX SYSTEMS AND PUBLIC POLICIES

Complex systems definition is usually attached to a specific context; however, it usually incorporates the following set of features.

Firstly, the idea of interaction among parts from and across scales, space and time is relevant. These interactions, in turn, lead to a system that is not reducible; a system that cannot be described by the attributes of the parts alone. Basically, to quote Anderson's classic "More is different" paper (1972, p. 395, our emphasis): "In this case we can see how the whole becomes not only *more than but very different from the sum of its parts.*"

Secondly, the interaction among parts can lead to self-organization of the system without the need of central control. This implies that local interactions can generate bottom-up emergent behavior. This powerful concept can be illustrated for the novice reader with the example of a bird flocking. No actual bird controls the direction and position of all birds in a given flock flight. Each one bird only observes those near it and synchronizes with their immediate neighbors. As a result, coordinated flight emerges.

A third attribute to highlight is that complex systems can experiment feedback. In complex systems, interactions have effects in time: actions in a given moment reflect on possibilities and constraints in the following moments. That is why complex systems are said to be adaptive and evolutionary.

All these briefly mentioned characteristics of complex systems seem to be useful to the study of public policies. As stated below most objects of public policies contain similar features and can be easily labeled complex systems. The relevance of viewing objects of public policies as complex systems is that the associated methods and methodologies available for the study of such systems could be applied to public policies, helping improve their analysis.

Essentially that means that modeling and simulation can be used to investigate public policies. This is especially relevant in areas of public policies where experiments are usually not simple, cheap or even viable.

> To simulate means to model the action and the interaction among citizens, firms, institutions, and the environment constrained by legislation and regulation, the budget, politics and spatial boundaries (…) working with complex systems applied to public policy means to create computational experimental environments in which the essence of the systems is present and from which one can withdraw elements of improvement of public policies in a relatively simple and cheap way, besides increasing the understanding of the effects (spatially and temporally) of the policies (Furtado and Sakowski, 2014).

Thus, complex systems methods have the potential to inform public policies and help tackle their effects, effectiveness, direct and indirect costs.

Throughout the book, similar definitions of both complex systems and public policies are presented. However, each one emphasizes different perspectives which add up to a more complete definition as the book progresses. Fuentes recovers the definition of Murray Gell-Mann and Seth Lloyd of “effective complexity” as “the length of a highly compressed description of its regularities” (p. 68). Sichman in chapter 5 – focuses on interactions as “information processing.” Tessone delves into the concept of heterogeneity distinguishing idiosyncratic heterogeneity, such as cultural heritage; from endogenous heterogeneity that surfaces as a complex system unfolds. Dawid and Orlando Gomes discuss economics and remind the reader of the relevance of non-equilibrium states. Bettencourt states that the problem of interacting citizens inhabiting urban spaces comes down to “how to create a set of processes in space that makes such interactions possible at a cost that is commensurate with their benefits” (Bettencourt, in this volume, p. 227). Mueller picks up from Sichman’s information processing idea advocating that

> policy is information-intensive when information is scarce; it tries to centralize a policy that is inherently local; it assumes the ability to control the process when in reality it can only act reactively; it requires measurement and evaluation along a series of diverse and subtle margins, while in reality a single and imprecise metric is used (the number of settled families); it deals myopically with a policy area that unfolds over the long-term (Mueller, in this volume, p. 268).

Consistently, the chapters refer to the dynamics of influence between objects and subjects in time; the dynamics of crossed-effect causalities in which “effects and outcomes are, at the same time, causes and inputs of what had produced them” (Morin 2011, p. 74, *apud* Sakowski and Tóvolli, p. 321). Thus, methodologies have to be able to explicitly “account [for] endogenous change” (Almeida, in this volume, p. 345) or “explicitly capture the underlying causal hypotheses of policy proposals in a way that allows us to experiment” (Gentile et al., in this volume, p. 78).

This discussion of dynamics also leads to a debate over the timing of the analysis and the timing of policy. Bettencourt argues that there are problems that can be managed in "its simpler, shorter-term technical management", but also phenomena that yearn for "longer-term complex challenges" (Ettema, in this volume, p. 222). For Ettema, transportation may fall into both categories: a performance metric-based engineer-like problem, such as the frequency of a single bus line; but transportation would also fall well into a city-mobility long-term intricate issue. Still on the dynamics of processes, Jacobson says that cognitive learning takes place in a varied number of places, moments and experiences through minutes, hours, semesters and years.

Finally, Mueller also mentions that typical evaluation of public policy is implicitly based on a definition of a system that can be easily tracked and measured upon metrics that are known a priori. This assumption leaves no room for systems that adapt, evolve and learn which are exactly what objects of public policies, such as the economy, the environment, the society and the cities (chapters 6-9) are.

3 METHODS

The methods and methodologies[6] used in complex systems approach come from already existing disciplines and are not new themselves. However, they reflect the principles and concepts discussed above.

Thus, a first thing to point out is explicitly considering the nonlinearity of systems. Put simply, nonlinear systems are those in which the outputs are not proportional to the inputs. Nonlinearity is attached to the idea that interaction among elements may generate emergent behavior. Also, the system's outcome cannot be entirely deductible *ex ante*. Approaches that include nonlinearity have been used in applications of physics (laser, superconductors, fluid dynamics, and engineering), biology (biological rhythms, insect outbreaks, genetic studies), chemistry and cryptography (Strogatz, 2014).

Network analysis studies interactions (edges) among parts (nodes). How strong, how lengthy and how relevant are the links among people or institutions? How connected is a given network so that a change in a specific node would affect the connections significantly? Those are some of the questions that network analysis may help answering.[7]

Strictly connected to the analysis of networks is information theory or, according to Shannon (1948), theory of communication. Information theory was proposed before network science and it is related to the definition of what infor-

6. A detailed description of methods and methodologies is found in chapter 3.

7. See Newman (2003), Newman et al. (2006) and William and Martinez (2000).

mation is; to the quantification and definition of the elements involved in any information exchange, and its storage and compression. It is from this theory (and probability theory[8]) that quantities such as entropy and mutual information come into play. These quantitative measures are applied to different areas of science from telecommunications to biology to probability theory to statistical physics, computer science and medicine. A central aspect of information theory and its associated measures is the quantification of uncertainty. Given past information, how uncertain is the next bit? This is related to the notion of a measure of complexity and also to the definition of entropy (Crutchfield and Feldman, 2001; Gell-Mann and Lloyd, 2004; Szilard, 1964; Turing, 1952).

Two other very commonly used methodologies within complex systems are cellular automata (CA) and agent-based models (ABM).[9] They are similar in the sense that both use agents – of free and ample design – that follow rules. The usage of ABMs and CA is a way to simulate the interactions in the system and the ensuing emergent properties. The difference between CAs and ABMs is that the former is fixed in space and the latter may be mobile. CAs are more relevant to study spatial analysis where local interactions, physically bounded, are relevant to the problem at hand. ABMs, in turn, can be modeled to be fixed or mobile and they can be in such a framework that space is completely irrelevant. They can even be thought so that the agents are connected through links, thus resembling network analysis.

Finally, it is worth mentioning efforts arising from computing science and contemporary availability of detailed, micro, spatially-precise data. This abundance of data is fertile land for the use of methodologies such as data mining, machine learning and artificial intelligence, which are collections of techniques that can be put together to help simulate complex systems and which are likely to improve insightfulness.

3.1 Methodologies' tools

Most methodologies are implemented using computational methods. Actually, it is the availability of computing power along with databases that are temporally-spatially-individually detailed that helped fuel complex systems in recent years.[10] There is a number of customized software developed to run specific proprietary and open-source models.[11]

8. Such as in clustering and decision tree procedures.

9. A thoroughly review of the application of ABMs in social sciences is found in chapter 5.

10. Journals dedicated to complex systems include: Journal on Policy and Complex Systems, Complex Systems, The Journal of Artificial Societies and Social Simulation, Complex Adaptive Systems Modeling, Ecological Modelling, Advances in Complex Systems, Computers, environment and urban systems, Complexity, Computational Economics. A list of 41 complexity centers can be found at http://en.wikipedia.org/wiki/Complex_systems.

11. Examples include, not exhaustively: MASON, Swarm, RePast, NetLogo, Flame, MASS, and at least 78 others <http://en.wikipedia.org/wiki/Comparison_of_agent-based_modeling_software>.

Models can also be simulated in typical program language such as C++, Java, or statistical and modeling programs (Matlab or Mathematica). As a high-level, flexible language, Python has been used quite a lot for simulation and modeling (Downey, 2012; McKinney, 2012; North, Collier and Vos, 2006) – for example using the SimPy[12] library – or associated to spatial software, such as QGIS. Specifically for network analysis, Python's library NetworkX[13] is very useful for both creating and analyzing networks.

A software program that has been around for some time now is NetLogo.[14] Based on Java, it contains a user-friendly set of commands that quickly takes the beginner programmer to an operational modeler. It allows for cellular automata spatially-bounded modeling as well as for full agent-based models. More recently it has incorporated network-like link capabilities and it is easily coupled with other languages and analysis programs such as Python, R or QGIS.

4 PUBLIC POLICIES AS COMPLEX OBJECTS

This section discusses the complex nature of objects of public policies, such as social, economic, urban and environmental systems. The hypothesis is that all these objects can be easily defined as complex systems. Chapters 6 to 9 of the book deepen the arguments.

4.1 Social

Social systems can be described as a collection of heterogeneous agents (individuals, banks, countries etc.), whose state (opinion, liquidity, wealth, etc.) influences and is influenced by the state of others, and whose interactions give rise to global properties of the system that are more than the sum of individual behavior. These features characterize social systems as complex. Understanding how these systems respond to external influences is of particular interest for the analysis of public policy. For example, how does a social system respond to an external signal such as a change in policy? Simulating the effects of policy change is particularly useful to steering policy measures.

4.2 Economy

An economic system is composed of heterogeneous actors, with different characteristics, expectations and behavioral rules that interact with each other and with the environment. Besides, the actors are in constant adaptive learning, generating evolutionary systems. The traditional or classic view, based on the assumptions of

12. Full documentation is available at: <https://simpy.readthedocs.org/en/latest/>.
13. Full documentation is available at: <https://networkx.github.io/>.
14. Full documentation is available at: <https://ccl.northwestern.edu/netlogo/>.

market clearing, perfect foresight, and equilibrium behavior, does not focus on the aforementioned elements, producing a more abstract analysis, which makes it difficult to comprehend the system as a whole.

In this context, alternative models that incorporate such elements are recommended in order to increase the availability of alternate understanding of economic processes. The heterogeneity of agents and the features of institutional setups that drive economic interactions should not be ignored. Many methodologies, already presented in section 2, have been used in order to capture such elements. One of the most used methodologies in economic modeling has been the agent-based simulation approach. This method is the basis of the Eurace@unibi model,[15] a closed agent-based macroeconomic model that has been used as a unified framework for policy analysis in different economic policy areas, such as fiscal policy, labor market, and issues related to income inequality. Besides, not only Agent-based Computational Economics models (Farmer and Foley, 2009; Le Baron and Tesfatsion, 2008), but also network analysis (Jackson, 2010; Newman, 2010), and analytical approaches for the analysis of agent models (Alfarano, Lux and Wagner, 2008; Dawid, 1996; Delli Gatti et al., 2012), are useful for a clearer picture of the dynamics of economic systems.

4.3 Cities

Cities in particular or urban spaces in general are *par excellence* places where people and institutions entangle themselves, usually, in productive and innovative ways (Glaeser, 2012; Jacobs, 1970). However, to reach the most out of their potential, people and institutions need to cover some basic functions within their shared space: dwell, commute, work and play.[16] On top of it all, cities are politically managed, which reinforces the fact that even those four basic actions cannot be accomplished individually. All activities share a common space. Moreover, cities are thought out to thrive, to harvest the best (and sometimes the worst) of societies. Thus, using sectorial policies, such as housing policies, sanitation policies or transport policies with no theoretical and methodological background to firmly go through the interactions – as mentioned above – makes applying policies to cities very hard work.

Even the approach to cities as an object of science may differ significantly. Are cities to be viewed as machines to be “fixed”, as markets to be regulated (or freed), as organisms in a jungle ecosystem, or as a social exercise in which political or religious values prevail above all?

Mainly, the message of relevance is that attempts to change the city – and occasionally even inaction and omission on policies on the city – have to be made

15. See chapter 9 and Dawid et al. (2012, 2014) for details of the Eurace@unibi model.
16. Those are the four principles of the functional city proposed by architect Le Corbusier in *Charte d’Athènes* in 1943.

with clear view of its consequences across all aspects and layers of the city. In short, city planning calls for integrated, connected, nonlinear, dynamic approaches. As those attributes are typical of complex systems, it may be of interest to apply them to the study and policy applications of cities.

4.4 Environment

Sustainable development is one of the major challenges for society today. How to manage natural resources in a world that is more and more complex, and where everything is interconnected? How to deal with sustainability problems, such as climate change or biodiversity conservation that are too complex to be tackled by a single discipline?

Complex systems views and methodologies can provide tools to help analyze these social-ecological systems and to inform environmental and sustainability policy making. Actually, many of the insights and concepts from complexity theory come from the field of biology.

Emergent behavior and information processing is often exemplified by the way ants forage for food, or how neurons interconnect to produce global cognitive behavior. The immune system is another example of self-organization, through which the interaction of simple cells leads to complex behavior without the presence of a central controller. Food webs and trophic dynamics are used to understand biodiversity and to analyze the implications of different types of disruptions to the ecosystem.

Modeling can be a valuable approach to understanding the dynamics of environmental systems. Through modeling, one aims to identify the key factors and rules governing a system, allowing the simulation of different scenarios and the performance of sensitivity analysis. This approach has been used to study climate change, the spread of diseases and the change in land use over time.

Modeling can also help identifying dangerous tipping points[17] in the social ecosystem. This can be useful, for instance, for the management of water resources, which might have a turning point, after which water pollution becomes costly and difficult to reverse.

Similarly, conservation policy can benefit from the analysis of food webs and the resilience of ecosystems to external shocks, such as an increase in deforestation or in carbon emissions.

17. Mitchell (2011, p. 253) defines tipping point as "points at which some process (...) starts increasing dramatically in a positive-feedback cycle." See also Gladwell (2006).

These and other methodologies from complex systems can help figure out how to manage natural resources, how to build sustainable cities, and how to promote more effective environmental and sustainable policies.

5 OTHER SYSTEMS AND APPLICATIONS

5.1 Education

A considerable amount of research has been done exploring the complex nature of educational systems, learning and teaching. A report from Organisation for Economic Co-operation and Development – OECD (Snyder, 2013) investigates how to operationalize a complexity approach to educational reforms, and provides examples of educational reforms that have used complexity principles in different countries. Other studies (Lemke et al. 1999; Morrison 2003, Batista and Salvi 2006; Santos 2008) focus on the complex nature of learning, with a focus on curriculum development, calling attention to transdisciplinarity. One academic journal[18] is dedicated exclusively to the study of education and complexity (Davis, Phelps and Wells, 2004).

5.2 Transport

Transport is a typical example of a system composed by a large number of interacting, independent agents, who follow some rules, and who react to their local environment; a system from which emergent, collective behavior can be observed. If a number of commuters have to travel a specific route across the city and they have some window interval to do that, they might probabilistically just decide to go at the same time. That (unlikely) decision is definitely suboptimal as it decreases the total capacity of flow of the system. Also, if a central traffic controller established a specific, precise time of departure for all travelers, one small disturbance might once again settle total congestion. On average, neither will occur. Anyway, the example shows that transport systems are complex, within the concepts described above.

Planners and transport engineers have used simulation models in order to derive scenarios or possibilities that are not able to pinpoint exact flows of traffic, but that can predict the size of the demand on the system, specifying at times, how the system has to be dimensioned.

A more recent usage of modeling in transport attempts to simulate both the dynamics of the city – considered as density and land-use type – coupled with the dynamics of commuters. UrbanSim (Waddell et al., 2007) is a pioneer example. More sophisticated modeling also tries to compute location and change of the job

18. Complicity: an international journal of complexity and education.

market and the behavior of housing markets. Together, the models try to anticipate the "movement" the city is taking – along with its possibilities or "vocation" – and attach the planning of the transport system accordingly.

All in all, as most other modeling experience, modeling in transport may help policy-makers envision scenarios in which key adjusting parameters are visible and their consequences measured.

5.3 The legislative process

The process of law-making entails heterogeneous individuals (legislators), usually under no centralized control, who strategically interact with each other in order to produce collective decisions.[19] When this interaction occurs under a majority rule institution, collective choice problems may arise. In this sense, complexity theory might help explain why outcomes vary within the context in which they are embodied, and how legislative institutions emerge and change.

6 COMPLEX SYSTEMS AND PUBLIC POLICIES

This section summarizes the main insights regarding the use of complexity concepts, methods and methodologies to public policy.

First, complexity concepts can prevent an oversimplified view of the objects of public policy. Complexity points out that, when thinking of public policy, one has to consider that agents are heterogeneous.

6.1 Agents are heterogeneous

Assuming a representative agent, such as an average consumer or firm, can be highly inaccurate and produce misleading insights for public policy. This is specially the case in countries like Brazil, where inequalities of different types are prevalent.

As Claudio Tessone summarizes it, "heterogeneity can crucially affect the observed properties of the system, and also be the source of *a priori* unexpected phenomena in socio-economic systems."

6.2 Everything is interconnected

This is another way of saying that "the whole is more than the sum of the parts"; that non-trivial complex behavior emerges from the interaction among agents; or that systems are nonlinear. In public policy, this brings awareness to the fact that many traditional linear type analyses might be inadequate or insufficient. This feature also points out that the connections among agents, sectors, and scales should not be neglected, suggesting an interdisciplinary and systemic view of policy objects.

19. This section is based on the contributions of Acir Almeida to the Project "Modeling Complex Systems for Public Policies."

The analysis when viewed by a multiplicity of sectors warrant that externalities, interests and perspectives are properly weighted among each other. The multiplicity of scales links the microanalysis – at the level of individuals, firms or the household – to the macro analysis of communities and parties, large sectors of the economy, neighborhoods, and cities and metropolis.

The multiplicity of scales seems central given that the emergence of patterns or, similarly, the effectiveness of public policies tends to be specific to one scale and not automatically valid over other scales. There are continuous interaction and idiosyncrasies in interaction across scales. This is especially true when considering public policies objects, especially across federative levels. Macroeconomic policy, such as interest rate setting, generates results that vary by regions, sectors, and firm size. It may impact suppliers and buyers differently. Further, actions of multiple agents with multiple interests, means and views may generate results that can also differ in scope, speed of occurrence, qualitative characteristics and permanence of effects.

6.3 Policy does not work with clear, linear or immediate cause and effects

The hope for action-reaction policies might be somehow naïve, as complex systems do not work in a mechanical way, but change, evolve, and adapt. They are dynamic. Policy should thus take into consideration multiple causalities and indirect effects that arise as a consequence of the interaction among different agents.

Romanian philosopher Basarab Nicolescu (1999) lists three fundamental principles of the hard sciences that are not easily applicable to human sciences. They are: *i*) the existence of general, fundamental laws; *ii*) the use of experiments to decode such laws; and *iii*) the possibility that given the same conditions (*coeteris paribus*), independently, it would be possible to replicate the experiments and thus the laws that they attest.

The difficulties to apply the fundamental laws, their experimentation and replicability is clear in social phenomena and public policies by realizing the *i*) discontinuities, jumps and ruptures; *ii*) unique, discrete events, that do not follow a clear universal pattern which could be decoded into mathematics in any immediate way; and *iii*) uncertainties which together with subjectivity of actors and lack of coherent and strict rationality leads to a non-deterministic social environment.

Therefore, policy might be more effective if geared towards *i*) improving the resilience of the system and decreasing its vulnerabilities; *ii*) avoiding (promoting) dangerous (positive) tipping points, and *iii*) identifying the key actors in a network that can promote changes in the system.

In other words, an OECD document states: "(…) it is not uncommon for small changes to have big effect; big changes to have surprisingly small effects; and for effects to come from unanticipated causes" (OECD, 2009, p. 2). This means that policy-making should try to understand the underlying mechanisms of the system under analysis in order to identify how to best steer it towards the desired path.

Second, complexity methods and methodologies can help take into account the complex features of the systems under analysis.

1. Modeling is a good strategy to obtain better understanding of how a system works, and one which allows incorporating the complex features of the system. Modeling can help identify the important players in the system under analysis (agents), their different characteristics (heterogeneity), their interrelations (interconnectedness), and how these components together give rise to complex and sometimes unexpected behavior. Examples of such modeling techniques are cellular automata and agent-based modeling. Heemskerk and colleagues collect a clarifying sequence of modeling definitions:

> A model is an abstraction or simplification of reality. Scientists often use models to explore systems and processes they cannot directly manipulate (Jackson et al. 2000). Models can be more or less quantitative, deterministic, abstract, and empirical. They help define questions and concepts more precisely, generate hypotheses, assist in testing these hypotheses, and generate predictions (Turner et al. 2001). Model building consists of determining system parts, choosing the relationships of interest between these parts, specifying the mechanisms by which the parts interact, identifying missing information, and exploring the behavior of the model. The model building process can be as enlightening as the model itself, because it reveals what we know and what we don't know about the connections and causalities in the systems under study (Levins 1966; Jackson et al. 2000; Taylor 2000). Thus modeling can both suggest what might be fruitful paths of study and help pursue those paths (Heemskerk; Wilson; Pavao-Zuckerman, 2003).

2. Modeling permits simulating scenarios as a decision-support tool to inform policy making. Models work as platforms for so-called *in silico* experiments, by means of which different policy options can be computationally simulated and "cheaply" tested.

3. Modeling stimulates a forward-looking, prospective view of policy, by allowing scenario building and testing. Models can enable prognosis that are less based solely on probabilities but that include essential interactions at various scales and with various agents' interests considered. Policy-makers can thus work with spaces of scenarios and realms of probabilities that occur given known rupture points.

4. Models can be continuously improved, as more knowledge is gained about the system. Models can also be simple and provide general insights, or specific to help tackle a particular problem.

5. Models are a means of communicating one's ideas and theories and can work as a "meeting point" for collaborative work among interdisciplinary teams. "Models not only help formulate questions, clarify system boundaries, and identify gaps in existing data, but also reveal the thoughts and assumptions of fellow scientists" (Heemskerk, Wilson and Pavao-Zuckerman, 2003).

6. The notion of multiple models contributes to the understanding of social phenomena in particular and of public policies in general because it is based on the richness of diversity, difference and dissimilarities (Page, 2007). As Page (2007) argues, no single model can independently cover comprehensively the intricacies of some phenomena, especially those of subjective nature, complex ones. He also states that models section the analysis with specific parameters, be it from the theoretical, methodological or procedural point of view. Thus, the diversity of models implies a larger coverage of possible scenarios that are more keen to envelope unexpected sequences, unlikely important events, unique tipping points.

Third, data are a valuable resource for policy making and complexity methods give insights into how to use them to the best extent.

1. Data can help visualize, describe and identify features of the system to be better explored. Social network analysis, for instance, relies on the visual representation of networks to convey complex information.

2. Data mining, machine learning, network analysis and other association studies can provide insights into the functioning of the system.

3. Data can help validate and improve models.

Finally, knowledge can be viewed as a feedback process, "an endless cycle of proud proposing and disdainful doubting" (Mitchell, 2011, p. 295). Modeling provides a way to structure this process and to improve the understanding of the system one wants to impact. The cycle of data analysis, modeling, validation, simulation, implementation, data analysis, remodeling and so on might be the "strange loop" that can provide decision support for tackling complex problems through public policy. If not a certain, determined path to be tread on, complex systems may illuminate the key pathways to policy-makers, clarifying what is likely to happen given choices of sets of paths, after so much has been traveled on.

7 MAPPING THE BOOK

The book is organized in three parts. *Part I – Complexity: theory and methods* discusses the main concepts of complex systems, its methods and methodologies and brings two chapters specifically on the computational modeling needed to implement such an approach.

This is the introductory chapter. The second chapter *Complex systems: concepts, literature, possibilities and limitations* written by William Rand presents the main concepts of complex systems, and briefly describes some complex systems´ methods. Besides, it discusses possibilities and limitations of complex systems analysis, in contrast with traditional methods, indicating the advantages of complex systems´ applications to public policy.

The third chapter *Methods and methodologies of complex systems* by Miguel Fuentes presents more technical details and a guided reading of the literature on the methods that are commonly used in the complex systems approach. The chapter provides a discussion at the conceptual level and references for further reading, aiming to reach readers from different fields.

The fourth chapter, *Simulation Models for Public Policy*, is authored by computer scientists James E. Gentile, Chris Glazner and Matthew Koehler. The chapter presents an overview of modeling and simulation, with clear statements for stakeholders and concerned audience. It argues that computational modeling can be an interesting tool for policy analysts to compare policy options. It focuses on ABM, and gives an overview of its benefits for policy analysis. Besides, the chapter discusses each step of model construction – implementation, verification, validation, and refinement –, pointing out the main challenges in each of them.

Chapter 5, *Operationalizing complex systems*, by Jaime Sichman presents some concepts and tools of computational simulation, and provides a detailed panorama of the main tools used in the complex systems approach. The chapter aims to help the reader interested in implementing the methods and techniques of complex systems computationally. The chapter focuses on the concepts and implementation tools of Multi-Agent-Based Systems (MABS), but also discusses the implementation of other methods, such as social networks and machine learning.

Part II contains four chapters that together qualify grand objects of public policies as complex systems.

Chapter 6 *Understanding the environment as a complex, dynamic natural-social system*, by Masaru Yarime and Ali Kharrazi discusses the coupling-uncoupling of social natural systems and the implications of viewing sustainability from a system's perspective. Their approach views both the quantitative and the qualitative dimensions of concepts such as resilience, efficiency and redundancy. After developing their conceptual framework, they move on to address actual governance cases of networked systems and their public policies effects.

The complex nature of social systems, by Claudio Tessone, is the theme of chapter 7. The chapter discusses why society should be viewed as a complex system, and presents the challenges involved in modeling the complex behavior found in social systems. Besides, the chapter discusses what the policy implications of this view are. It also describes the characteristics of social systems that are most relevant to the analysis of public policy, such as the heterogeneity of agents, the dynamic evolution of society by means of interaction and feedback, the systemic nature of society that renders its decomposition or break down in different aspects inadequate, and the finiteness of such systems.

Economics is discussed in two chapters. Chapter 8 *The economy as a complex object* by Orlando Gomes presents a more general defense of economics as a complex object. It reviews the contemporaneous literature on complexity economics, and discusses why the macro economy should be analyzed as a complex system. The chapter also provides an illustrative example of a complex economic environment simulated with a network model. Chapter 9 *Modeling the economy as a complex system* by Herbert Dawid continues the line of thinking, focusing on how to model the economy under a complex systems framework. The chapter emphasizes agent-based modeling, and discusses the advantages and disadvantages of this modeling approach for economic analysis. The chapter is particularly strong in discussing issues related to modeling the economy for policy analysis and provides insightful illustrations of applications to public policy, such as the Eurace@Unibi model.

Chapter 9, *Cities as complex systems* authored by Luis Bettencourt discusses why cities should be viewed and analyzed as complex systems. It presents a brief historical overview of the concepts of city, and how they have been perceived in urban planning and policy. Then it describes the main properties of cities as complex systems, and discusses how this new understanding of cities reveals that urban areas of different sizes pose different challenges to the planner. The chapter discusses the implications of the complex systems approach for urban planning and policy, and counterbalances it with problems of engineering solutions.

Part III presents applications in the world and in Brazil, besides a number of applications in transport, education, the legislative process and a territorial approach.

The first chapter of the applications, *Complexity theory in applied policy worldwide,* by Yaneer Bar-Yam emphasizes the importance of analysis of the potential effects of policy changes in one part of the world into another part, considering the increasingly interdependent world. The chapter highlights some methodologies of complex systems, such as multiscale analysis, networks, and patterns of behavior. It also presents the applications of such methodologies in the analyses of financial and commodities markets, disease spread, and violence, and argues that complex systems have been proven to explain and predict global phenomena.

Bernardo Mueller, in *Complex system modeling in Brazilian public policies* presents two case studies of policy in Brazil, one success and one failure, and builds on these examples to explain why a complex systems approach may be more adequate to evaluate public policies of complex systems rather than usual metrics widely disseminated. Further, the chapter presents a panorama of studies related to public policies' issues that have used the complex systems approach in Brazil. The mapping of such studies indicates the potential use complex systems' methodologies in relevant areas for the country, and also allows the reader to identify researches on his/her topic of interest

Chapter 13, *Complexity methods applied to transport planning* by Dick Ettema, looks into a specific area of public policies: transport planning. It discusses why transport should be viewed as a complex system, and reviews the main characteristics of existing complex methods in transport planning, the implementation issues related to these methods, and the main implications for the transport system, for cities and society. In general, the chapter provides an overview of traffic and transport simulation models, highlighting the innovations and challenges for complex transport models.

Two chapters focus on education. The first one, *Education as a complex system: implications for educational research and policy*, by Michael Jacobson, discusses why education should be considered a complex system, and which are the methodological implications of this view for researchers and policy makers. Besides, the chapter provides an overview of applications of complexity methods in educational policy and research. The second chapter, *Complex approaches for education in Brazil*, by Patrícia Sakowski and Marina H. Tóvolli, contributes to the discussion on education made on the previous chapter, adding to the conceptual discussion and looking specifically to Brazil. The chapter presents what has been done in the complexity area in Brazil, and discusses how this approach may contribute to education in the country.

Chapter 16, *Overcoming chaos: legislatures as complex adaptive systems*, by Acir Almeida, describes the complex nature of legislatures and discusses why they should be seen as complex adaptive systems. It presents two main models of legislative organization and discusses the limitations of these traditional approaches in explaining the evolution of legislative institutions. The chapter highlights the potential contribution of the complex systems approach for the analysis of the emergence and change of institutions. Looking specifically to the Brazilian case, the chapter points out how the complex systems approach may explain the recent evolution of law-making patterns in the Brazilian Congress.

Finally, chapter 17, *The territory as a complex social system*, by Marcos Aurélio Santos da Silva, focuses on the study of socioterritorial systems, and the need of interdisciplinary methods for the analyses of such systems. The chapter presents the Sociology of Organized Action (SOA) theory to rethink the analyses of power and dependence relations in socioterritorial systems. The chapter then presents the Soclab method, which is a formalization of the SOA theory. The chapter highlights how the Soclab method may contribute to the analysis of social relations in social-territorial systems through computational simulation.

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CHAPTER 2

COMPLEX SYSTEMS: CONCEPTS, LITERATURE, POSSIBILITIES AND LIMITATIONS

William Rand[1]

1 INTRODUCTION

The goal of public policy is often to alter, or maintain the behavior of a large group of individuals or organizations to achieve some societally desirable outcome. The challenge with evaluating public policy is that every individual in a population does not react the same way to the introduction of a new policy or a set of incentives. Moreover, the overall result of a public policy is not simply the sum of the individual reactions; instead, those reactions interact and feed off of each other. As a result, the outcome of the implementation of any public policy is an emergent product of many individual decisions, and the way that those decisions interact with each other and the policy.

For example, a governmental organization or entity may put into practice a policy such as a tax policy, a speed limit, or an urban renewal incentive. Different individuals that are affected by that policy may react in different ways. Since individuals are not always perfectly rational, or necessarily law abiding, sometimes they will react in ways that the governmental organization never intended. For instance, some organizations may evade taxes, some drivers may speed, and some residents may move away from urban areas; while other individuals act in exactly the way intended by the policy. Moreover, individuals do not just react to the policy they also react to each other and may modify their behavior based on what they see in others. The effect of public policy is not just a one-time, static event, but rather it is the result of a series of actions taken by both government and citizens to achieve a desired outcome. For instance, new policies may be enacted to attempt to corral some of the unintended behavior, or citizen action groups may form to attempt to alter policy. The aggregation of all these different actions results in an emergent, complex pattern of behavior, which will affect future policy making, and will also feedback to affect individual level decisions. Thus, the effect of public policy is not just a product of government control, and it is not just a product of market forces, and it is not just a product of citizen action, but rather it is a combined product of the interaction of all actors (Colander and Kupers, 2014).

1. Center for Complexity in Business, Robert H. Smith School of Business, University of Maryland, Van Munching Hall, College Park, MD USA 20742. E-mail: <wrand@umd.edu>.

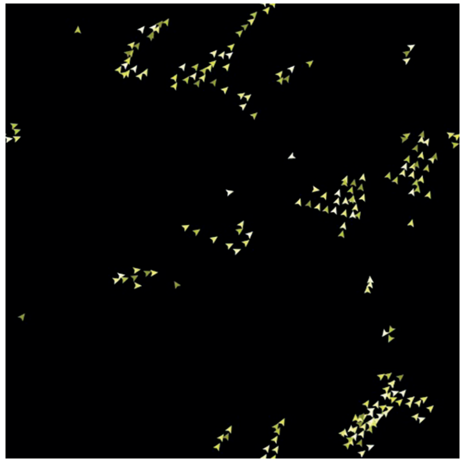
Studies of the kinds of complex interactions that are readily apparent in public policy are at the core of the study of complex systems. *Complex systems* are systems of interacting, autonomous components, where the outcome of the system is not simply the sum of the underlying parts (Mitchell, 2009; Waldrop, 1993; Casti, 1994). This makes complex systems a natural lens through which to study public policy.

One classic example of complex systems was described in chapter 1 when the process of bird flocking was described. Craig Reynolds illustrated in his "boids" model that birds can flock without any central leader dictating how the birds should flock (Reynolds, 1987). In the boids model, the agents (birds/boids) follow three simple rules: *i*) avoid other birds; *ii*) head toward the center of mass of nearby birds; and *iii*) align your heading with other birds nearby. This model is robust and will generate emergent patterns of behavior that resemble flocks under a wide variety of situations. However, none of the birds contains the notion of a "flock" and the flock as an entity does not exist, instead it is entirely composed of individual birds.

Another classic example of complex systems within public policy is something that has been explored using a variety of methods over the years, the traffic jam (Resnick, 1994). Highway traffic is composed of many individual actors, i.e., the drivers of cars, trucks, and other types of moving vehicles. None of these individual actors defines a traffic jam. Instead a traffic jam is the emergent product of many different individual decisions. However, the overall emergent pattern of stuck traffic, feeds back to affect individual decisions. Drivers slow down, they change their routes, and they may even alter their decision to drive in the first place. This system, which seems simple at first, already contains the basic components of a complex system, specifically emergent patterns of behavior that feedback to affect individual decisions.

Because of the complex interactions of these systems and the nonlinear way in which the elements of a complex system give rise to overall patterns of behavior, complex systems can be very difficult to predict, control and manage. Therefore the best use of complex systems analysis methods for public policy evaluation is not in the context of perfect prediction, but rather as a "flight simulator" (Holland, 1996; Sterman, 2000; 1994). A regular flight simulator is not the same as flying a plane, but nonetheless provides the potential pilot with an education about how a plane might react in different conditions, and different environments. In the same way, complex systems can give an analyst or manager the ability to understand how a policy might play out, and even develop contingency plans as to what actions to take in different contexts. Some systems cannot be easily manipulated or changed. A policy flight simulator can identify these places where no matter what policies are implemented the system still winds up in a pre-determined outcome. The incentive structure or the forces at work may be such that it is very difficult if not impossible to alter the process of the system. Though this may be frustrating, it tells the user of the policy flight simulator to look for alternative solutions, or to consider reprioritizing their goals and objectives.

FIGURE 1
An Agent-Based Model of Flocking Behavior implemented in NetLogo



Source: Wilensky (1998; 1999).

FIGURE 2
An Agent-Based Model of Traffic implemented in NetLogo

Source: Wilensky (1997; 1999).

The goal then of a complex systems analysis of public policy is to provide insight and understanding of how the complex system of society may be affected by the application of a policy. Moreover, by examining a suite of policies, it is possible to identify the policies that will have the greatest benefit for the least cost. Additionally, robustness and sensitivity analysis can be carried out, and supplementary policies can be examined to help adapt to unforeseen circumstances.

In this chapter, we will present the basic concepts and ideas of complex systems, including a brief description of the tools that complex systems employs.[2] We will then discuss the possibilities and the limitations of complex systems analysis. Finally we will end with a brief discussion of the future of the complex systems approach to public policy evaluation.

2. A longer description of the tools of complex systems is available in chapter 3, and a detailed discussion of the application of complex system tools to a wider variety of application areas is available in chapters 6 through 17.

2 CONCEPTS AND TOOLS

The basic conceit of complex systems is that many systems that we observe and want to understand around us, are best described through methods that enable the modeling and examination of the interactions of different parts of the system. To this extent a number of different concepts and tools that are employed by complex systems science focus on the interactions and properties of a large number of interacting parts. To explain this in more detail, we will begin this section by exploring some basic concepts in this space, and then move on to examine tools that are used to examine complex systems. We will then finish this section by describing some areas where these concepts and tools have been applied in the realm of public policy.

2.1 Concepts

There are several standard features that complex systems regularly exhibit that are useful to understand from a public policy perspective. These features help policy analysts and researchers describe and comprehend the properties of these systems that often make them difficult to manage and predict. As highlighted in the introduction, there are two main concepts that are important in every complex system. They are *emergence* and *feedbacks*.

Emergence is the idea that "the action of the whole is more than the sum of the parts" (Holland, 2014). Complex systems are inevitably composed of many different entities or individuals. These individuals have their own properties and actions, but an emergent property is something that cannot be discovered by inspecting any of the individual agents. Instead it is a product of the interactions of the different agents and can only be observed at the population level (Holland, 1999; Miller and Page, 2009). For instance, in the traffic jam example none of the agents defines a traffic jam or contains the property of a "traffic jam" within it, however the emergent result of all the actions of many individuals is a traffic jam. Similarly, no single individual can be responsible for the development of a city. Instead, the development pattern of a city is an emergent result of developers, residents, employers, politicians, the environmental landscape and many other factors. No single entity within this system contains the property of "city development"; instead, that property is the emergent result of many actors acting together. Moreover, these emergent properties *feedback* to affect individual decisions. For instance, within the context of city development the evolution of the city will eventually affect where developers build new buildings, where residents decide to live, what kinds of business will move into the city, how politicians will position their campaign platforms, and it will even transform the physical environment of the city. In turn these decisions will result in new emergent patterns of behavior, which will in turn result in new feedbacks.

So how is a public policy analyst supposed to understand these systems? One of the best ways is to create a model of the underlying system. As discussed in the introduction of this chapter, the results of these models should not be used as perfect predictions or complete understandings, but rather as flight simulators. In fact, one of the best uses of complex systems analysis for public policy evaluation is in the identification of leverage points within the overall societal system (Holland, 1996). *Leverage points* are places in a complex system where the system can be altered or changed. Modeling gives analytics the ability to identify these leverage points by trying out many different scenarios and interventions and seeing what policies have the largest positive effect on the goal that they are hoping to reach. By identifying leverage points, it is possible to explore a policy (Bankes, 1993; Lempert, 2002) and to figure out when a policy and at what magnitude a policy will be most effective.

Leverage points are also related to another important concept in complex systems, known as *tipping points*. Tipping points are when a system suddenly changes state based on a small change in a parameter of the system (Lamberson and Page, 2012; Mitchell, 2009; Schelling, 1972). In some fields, this is also called a *phase transition* (Lamberson and Page, 2012) or *bifurcation* (Drake and Griffen, 2010). Systems with tipping points can sometimes seem like they are not responding at all to public policy that is attempting to alter them, and then suddenly with just a few small changes the system will change dramatically (Shiell, Hawe and Gold, 2008).

However, other systems may be stuck in a state they cannot escape from due to choices made early on in the evolution of the state. This is a concept known as *path dependence* (Brown et al., 2005a). Path dependence means that the current possibilities of the system are in some sense constrained by the past choices that were made. For instance, urban development often features path dependent effects, since residents tend to move toward where services are available in cities, and then cities and businesses tend to place services where there are lots of residents, meaning that early on when a few residents or services make a few choices they can dramatically alter the future development of the city (Brown et al., 2004).

A special case of path dependence is *sensitivity to initial conditions* (Mitchell, 2009). This property, which is also a hallmark of chaotic systems, states that every starting point of the system is very close to another starting point with a vastly different future.

This is sometimes referred to as the "butterfly effect", i.e., as Edward Lorenz put it, "does the flap of a butterfly's wings in Brazil set off a tornado in Texas?" (Lorenz, 1972). In other words, the exact conditions of a system must be known in order to understand how that system will develop in the future, and, unfortunately, from a predictability standpoint, knowing close to the exact conditions does not help you very much in predicting the future. This is a very strong claim about a system, and in general many complex systems do feature some sensitivity to initial conditions, but do not have exactly this property. However, a weak version of this property might just state that where you start matters significantly, which does seem to affect most complex systems. In other words, many complex systems may be greatly affected by their starting conditions even though the resulting states of the systems may not be completely divergent from similar starting conditions. However, there can easily be regions of starting conditions and it may be possible that altering one parameter of the system can move a system from one region into another. This is again similar to the concept of tipping points, but now stated in terms of the initial conditions of the system rather than the ongoing state of the system.

Sensitivity to initial conditions and tipping points are some of the many properties that arise in complex systems that are *nonlinear.* Nonlinearity was also discussed in the first chapter, but a nonlinear system is one where the inputs do not necessarily affect outputs in a linear manner. In other words, it may be the case that changing one input to a system in a gradual manner, gradually alters the output until a certain point, but suddenly it may no longer affect the resultant output, or it could be the case that interactions between various inputs mean the you cannot just solve problems by breaking the problem down into its components assessing each component and then reassembling the parts. Nonlinearity means that complex systems often have to be considered as holistic systems and it is not possible to simply assess the impact of each of the individual components separately from each other.

In fact, in some cases you may be able to remove whole subcomponents of the system without the system breaking down at all, or significantly altering the out- come of the system. This is what is known as the property of *robustness* (Lempert, 2002; Bankes, 2002b). Robustness means that a system maintains its characteristic behavior even after a perturbation of the system (Bankes, 2002a). Robustness is a property that we often strive for in public policy, since it is important that policies are robust to individual actions and to changes in systems. Ideally policies are useful and maintain their legitimacy of long timeframes, which would make them truly robust. However, it is quite possible that robustness in complex systems can be a bad thing. For instance, Ross Hammond and Robert Axelrod (Hammond and Axelrod, 2006) showed using an agent-based model that even under a wide range of parameter values there are many cases of societal evolution that lead to the primacy of ethnocentric behavior, i.e., individuals helping others like themselves and hurting others who are different than themselves. This system can be said to be robust even under large perturbations, but this is not something that is usually considered societally desirable.

One of the hallmarks of complex systems analysis is embracing the modeling of *diversity and heterogeneity* (Page, 2010; Hong and Page, 2004; Sondahl and Rand, 2007). As both the first and seven chapter in this book indicate understanding the heterogeneity of a system can be crucial to understanding the system itself. Traditionally, modeling approaches have focused on assuming away as much heterogeneity as possible, since heterogeneity often makes systems difficult to model. However, complex systems understands the value of heterogeneity, and a good complex systems model will represent heterogeneity appropriately within the model. A fundamental assumption of many forms of complex system analysis is that diversity can greatly alter the outcome of a system (Sharara, Rand and Getoor, 2011). Many traditional approaches to system analysis have failed to account for sufficient underlying diversity and this can lead to incorrect or at least misleading understandings of the system.

One of the reasons that modern society is increasingly diverse is because it is also features a high level of *interconnectedness and interactions* between individuals (Barabási, 2014). The use of networks, which was also discussed in the first chapter, to examine complex systems is a powerful tool. We can now reach people halfway around the world for a phone call in a matter of seconds, and we can teleconference with individuals that we have never met before. These complex interactions which effect are decisions in interesting ways are the very essence of what gives rise to the emergent patterns of behavior that are observed in complex systems. As society becomes increasingly connected and these patterns of communication increase, complex systems analysis becomes increasingly more important.

Now that we have a basic vocabulary to discuss the concepts of complex systems in public policy, it is time to look at the tools that enable the study of complex systems.

2.2 Tools

The next chapter (chapter 3) in this book by Miguel Fuentes will discuss tools of complex systems in more detail, but in this chapter we will briefly look at some of the tools of complex systems, because they are indelibly linked to the concepts and help us to talk about basic notions, such as agents and networks, which we will need as we continue to discuss the use of complex systems in public policy. It is worth noting that one of the goals of complex systems is to develop theories and understandings that are *generalizable* – sometimes called *universal* (Boccara, 2004; Holland, 2012). These theories can be applied to a wide variety of situations and application domains. As such, it is often the case that the same tools are used in many different contexts within complex systems, and one of the hallmarks of a good complex systems analysis is that the findings can easily be translated to other systems.

One tool that many people associate with complex systems is *agent-based modeling* (ABM) (Wilensky and Rand, 2015; North and Macal, 2007; Epstein and Axtell, 1996; Bankes, 2002a; Bonabeau, 2002; Gilbert, 2007), where computational entities are created that have a mapping to the real-world components of the system. This enables the modeling of each and every individual in a complex system, along with their interactions. ABM, which was also discussed in the first chapter, is a description of the process of how agents interact with each other and with the environment around them. In the public policy context, ABM has been employed in a number of different contexts, because it enables researchers to see what effect policies would have on the basic rules of agent behavior. ABM is more generally a framework for simulation; several of the other complex systems tools fall under the purview of simulation (Gilbert and Troitzsch, 2005; Casti, 1997), which enables the analysis of hypothetical scenarios. The tools of simulation are helpful for public policy analysis since they allow analysts to play out many different scenarios and to understand the ramifications of those scenarios on society.

Another tool often used by complex systems researchers, is *social network analysis* (SNA) (Wasserman and Faust, 1994) and the related tools of *network science* (Newman, 2003). The goal of SNA and network science it to understand complex systems by describing the system of interactions that occur within the system. Many public policies either directly affect social network ties (e.g., a policy that changes school boundaries and thus effects who makes friends with whom), or alternatively, information about the policies is diffused over social network (e.g., citizens find out about speed cameras from talking to their co-workers). As a result, understanding the effect of social networks on public policy is important in order to properly evaluate how those public policies will play out.

Geographic Information Systems (GIS) is often used in complex systems research for public policy evaluation, because it provides a unified way of describing complex spatial data (Heppenstall, Crooks and See, 2012). Since many times a full understanding of complex systems requires a number of different data sets, a unifying theme for these datasets must be identified. This enables a wide variety of data to be tied in to one unifying database. One example of a way to unify disparate data is to attach spatial coordinates to it, when appropriate. The pattern of this data can then be described using spatial statistics and methods. As a result, GIS is a good description of the patterning of complex systems. Coupled with ABM, which describes process, GIS, which describes patterns, can make for a powerful tool for complex systems analysis of public policies (Brow et al., 2005b).

Another tool of complex systems, *System dynamics modeling*, describes high-level interactions between populations and resources (Sterman, 2000). System dynamics is built around the notion of stocks and flows, and can be used to model a complex system since it enables descriptions of concepts, such as positive and negative feedback. In the context of public policy evaluation within system dynamics, policies are often evaluated by examining how changing some of the flows of the system effects the output of the system.

Machine learning extracts patterns of behavior from large-scale sets of data, and attempts to learn an overall model that can predict what data is likely to be observed given current inputs based on previous data (Holland, 1975; Mitchell, 1997). Machine learning allows complex systems researchers to infer individual-level models from large datasets, which can then be used to evaluate how a new policy will affect the decisions of those individuals.

Of course, in addition to these more novel methods, complex systems research with regards to public policy evaluation, also employs many standard methods for understanding systems, such as *statistical analysis*, *psychology experiments*, *surveys*, *game theory*, *dynamical systems analysis* and other more traditional methods. The true value of complex systems analysis is not in any particular method or tool, but rather the combination of tools and methods that help to best answer the questions on hand. There will be several chapters in this book examining how to apply these various tools to a wide range of applications, and so we will not go in to depth at this point about the application of these tools, but complex systems has been applied to a wide range of areas including: *social systems* (Gilbert and

Troitzsch, 2005; Casti, 1995; Epstein, 2006), *finance and the economy* (Tesfatsion, 2003; LeBaron, 2001; Holland and Miller, 1991; May, Levin and Sugihara, 2008; Arthur and Durlauf, 1997), *cities* (Batty, 2005; Zellner et al., 2009; Benenson and Torrens, 2004), *ecology* (Schmitz and Booth, 1997; Grimm, 1999; Pascual and Dunne, 2006; Williams and Martinez, 2000; Grimm et al., 2005), *transportation systems* (Lu, Kawamura and Zellner, 2008; Bazzan and Klugl, 2004; Balmer et al., 2004; Zhang and Levinson, 2004; Balmer, Axhausen, and Nagel, 2006), *education* (Maroulis et al., 2010; Klopfer, 2003), *legislative analysis* (Rand and Liepelt, 2009), *business* (Rand and Rust, 2011; North and Macal, 2007), and *land-use and land-change* (Parker et al., 2003; Brown et al., 2008).

3 ADVANTAGES AND POSSIBILITIES

Complex system methods and tools provide several unique possibilities and benefits that traditional methods either do not provide, or that are difficult to obtain within traditional methods. For instance, many complex systems methods can model a level of *heterogeneity* (Rand et al., 2003) and *diversity* (Page, 2010) in the underlying individual components that is not easily modeled using traditional methods (Goldenberg, Libai and Muller, 2001). Moreover, complex systems methods can incorporate models at multiple scale levels (North et al., 2010), which enables a modeling framework that is not constrained to simply looking at the policy results for one scale level.

Many complex systems methods also enable *adaptive* and *evolutionary* behavior (Holland and Miller, 1991; Mitchell, 2009). This allows the individuals being modeled to not only change their behavior once as a result of a new policy, but to adapt and evolve their behavior over time. One benefit of this approach is that it has the potential to help overcome the Lucas critique of policy (Lucas, 1976). The Lucas critique is that since models constructed to understand the policy effects on macro-level patterns of behavior are built under the current micro-level rules of behavior, the predictions that they make will inevitably be wrong, because the low-level behavior of individuals will change in the face of a new policy. Complex systems methods give analysts a way to model how individuals learn and adapt to new policies at the micro-level. This means that if the model of adaptation is valid (and assuming the policy does not affect the actual process of adaptation, but only the behavior an individual exhibits) that the model will be able to take into account changes to micro-level behavior in the face of the new policy, and, thus, still make accurate predictions. This by its nature means that public policy analysts may be able to more easily avoid the curse of “unforeseen consequences” when using complex systems methods.

Finally, complex systems analysis has more benefits than traditional methods as a communications device for stakeholders and decision makers. Complex Systems methods provide a number of advantages. Most complex systems methods can generate a large amount of data. This data is useful in constructing and creating powerful visualizations for the story that the researcher is trying to explore (Bankes, 2002b; Kornhauser, Wilensky and Rand, 2009). Moreover, many complex systems methods have an ontology (i.e., theory of things that exist in the model) that is closer to real-world systems. In other words, if the researcher is trying to describe an educational system using ABM and SNA, then they can actually describe the agents interactions with their peers in the school, and explain that interaction model to a stakeholder. As opposed to a traditional equation-based model (Rahmandad and Sterman, 2008; Parunak, Savit and Riolo, 1998) where the researcher often has complex mathematical terms that describe these interaction properties. This makes complex system analysis easier for many stakeholders to understand than traditional methods.

All in all, complex systems methods provide a powerful set of tools for understanding public policy.

4 RESISTANCE AND LIMITATIONS

There has been resistance to the widespread adoption of complex systems methods within public policy. This resistance comes from a number of different areas. First of all, complex systems is a fairly young field (Waldrop, 1993) and as such there is a lack of education in complex systems methods and how to apply them. As a result, researchers are resistant to use methods that they do not fully feel they understand. The solution to this is to continue efforts to educate public policy analysts and stakeholders about public policy. Increasing education about how to interpret and understand complex systems analysis may not only lead to greater acceptance of the methods, in terms of influencing public policy, but previous research (Cockcroft et al., 2014) has also shown that educating policymakers about how to interpret evidence for policy increases the effectiveness of that policy.

Another factor in the resistance to complex systems methods has been that traditional methods, such as equation-based modeling and classic statistics, have been very successful at doing what they do, and they have been able to provide researchers and stakeholders with a number of interesting findings and solution to public policy problems. As a result there is a predilection to continue using these methods to solve problems and examine solutions, even when these tools may not be well-fitted for the job. To understand why there would be an emphasis on methods that may not be applicable to the problem at hand, it is sometimes useful to examine the story of the drunk, the keys and the streetlight (Colander and Kupers, 2014). The story goes that a sober man is walking down the street when he finds a drunk man holding on to a streetlight and looking for something under the streetlight. When the sober man asks the drunk man what he is looking for, the drunk man replies that he is looking for his house keys. After helping him search for a while the sober man asks why the drunk man is only looking under the streetlight, and inquires whether the keys could be under the hedge where it is dark. The drunk man replies that there is no use looking in the dark for his keys because he would not be able to find them there anyway, so he might as well stick to the streetlight. In the same way, researchers and analyst often continue to use the methods they know well, to try to solve problems, even when those problems are not actually applicable to the problem at hand (Colander and Kupers, 2014).

The solution to this resistance is to show that complex systems approaches can indeed solve problems that traditional methods do not address appropriately. The chapters in this book on the applications of complex systems methods to public policy are offered partially as a first step in this direction.

Moreover, there is also a deep-seated psychological resistance to complex systems approaches. In the 1990s, Mitchel Resnick and Uri Wilensky carried out a number of psychological studies to show that from a young age people tend to develop what they termed *the deterministic and centralized (DC) mindset* (Resnick and Wilensky, 1993a; 1993b; Resnick, 1994). The DC mindset basically is that people expect that all systems have deterministic rules that govern their behavior and that there is a central controller in most systems. It is this mindset that leads some policy experts to believe that just enacting a policy with sufficient penalties will encourage the behavior they seek, and thus lead to the outcome they desire. However, complex systems shows that in many systems, there is no true deterministic pattern of behavior, instead chance and opportunity play a large role. Moreover, not all systems require a centralized controller. For instance, the traffic example that we mentioned in the beginning features nondeterministic actions (e.g., users speed up and slow down in irrational and at times unpredictable ways), and distributed (not centralized) causes (i.e., there is no centralized cause of the traffic jam in many cases) (Resnick, 1994). These features of complex systems mean that some individuals face cognitive dissonance when trying to understand complex systems analyses.

Though complex systems provides us benefits to understanding public policy, there are also some legitimate limitations to complex systems analysis as compared to traditional approaches: *i*) *high computational cost*; *ii*) *many free parameters*; *iii*) the *individual-level knowledge* requirement; *iv*) *lack of education*; and *v*) *literacy*. Three of these restrictions (high computational cost, many free parameters, and individual-level knowledge) apply to the current practitioner of complex systems research, and two of them (lack of education and literacy) apply to the future application of complex systems research for public policy.

A high computational cost results from the fact that most complex systems approaches employ simulations and large-scale data analysis. However, the high computational cost comes with a benefit, because it provides a lot more detail and models interactions at a finer detailed level than traditional methods. Many complex systems method do employ a large number of free parameters, and it is important to make sure that model results are robust to changes in these parameters when appropriate, and finding appropriate settings for these parameters. However, this limitation is also a benefit because it provides the researcher or analyst with more control over the method. Complex systems methods often require knowledge or at least theories about individual-level knowledge and how individual components will behave when confronted with new policies. Sometimes there is no strong knowledge and few theories describing how individuals will behave in such a system making complex systems methods difficult to apply at times.

However, it is this very limitation that enables a finer grained analysis and gives complex systems the ability to model detailed individual heterogeneity and adaptation rules for individuals. It is important to note that it is not necessary to have exact individual-level data, but having a theory (or two) about how individuals behave at the micro-level is important.

Currently, there are not many educational programs that teach students or re- searchers how to apply complex systems methods to public policy, and so there is a lack of knowledge about the practice of complex systems with respect to public policy analysis. As a result, it can be difficult to build up a research group or create a functional organization within a government that builds complex systems models. However, this can be rectified by increasing the emphasis on complex systems education in the future. This education needs to happen not only at the level of students, but also at the level of stakeholders and decision makers, who need to understand the analyses in order to make appropriate decisions. In some cases, they do not currently have the complex systems literacy necessary to understand the results. Education will help this, but so will increased efforts in visualization, since visualization can make results and models easier to understand. Moreover, though complex systems methods may be new and require learning different terminology, often complex systems methods employ ontologies that are closer to real world ontologies than traditional methods are. Meaning that it will probably be easier to increase complex systems literacy among policymakers than it has been to increase literacy around other technical ideas.

5 CONCLUSION

In conclusion, for a wide variety of public policy applications, complex systems provides a useful lens to understand the impact and policy ramifications of policies. There are many areas of public policy that do not currently employ complex systems, and so there is a large range of possibilities and advantages that have yet to be explored. If we return to the goals of public policy, complex systems does provide the ability to gather insight into how we can maintain or alter the behavior of large groups of individuals or organizations, and thus can provide a unique view into understanding the application of public policy.

The future for the use of complex systems for public policy is promising. We finally have some of the tools that are truly necessary to understand how the complex system of society evolves in direct response to public policy. We can not only describe how citizens will take different actions in response to policy, but also how their behavioral model will adapt; this gives researchers and analysts the ability to incorporate adaptation and learning in to their models. Moreover, we can account for the social interaction between individuals which is becoming increasingly important as the cost of communication drops to near zero even over very long distances. Of course, there are still many challenges ahead since these models of learning and communication must be validated and verified if they are to be used to actually make policy decisions. However, the ability to actually account for these features at all makes the goal worth pursuing.

In fact in some ways, the future of this application may have been foreseen by one of the greatest science fiction writers. Isaac Asimov in his *Foundation* books wrote about a character named Hari Seldon who used a fictional science called *psychohistory* (Asimov, 1951). In these books, psychohistory represents a combination of history, sociology, and mathematics, which are fields that have also influenced complex systems analysis. Psychohistory was used to make approximate predictions about the future behavior of large groups of individuals. Similarly, complex systems has the potential to help us understand how large groups of individuals and organizations will react to new public policy, potentially paving the way for a real psychohistory (Turchin, 2007). However, much like Asimov's Seldon, the goal should not be to make specific predictions but rather to embrace the uncertainty of the future and to create policies that are robust and can be altered in response to changing circumstances.

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CHAPTER 3

METHODS AND METHODOLOGIES OF COMPLEX SYSTEMS[1]

Miguel Angel Fuentes[2]

1 INTRODUCTION

Complexity Science has become a major branch in the scientific landscape. It is highly likely that its success is based fundamentally on the root of the activity that a complexity scientist pursues in her/his daily agenda. Complexity Science is not a disciplinary branch of science; it is an inter/transdisciplinary exploration of nature, in almost all scales and environments. It covers fields apparently so far away as plasma physics at one edge, to the evolution of human languages on the other.

In the past, the frontier of science has been defined mainly by two fascinating extremes: the very small (an example is the great success of quantum physics from its tender appearance after Max Planck's work circa 1900), and the very large (we can mention here another enormous paradigmatic change, after the relativity theory, an incredible contribution made by the twenty six year old Albert Einstein during his Annus Mirabilis in 1905). However, nowadays an important part of the scientific community is making great efforts to understand, in a quantitative scientific manner, the phenomena that involve collective behavior in living systems. We can say the shore of the frontier of science has moved: we are trying to understand human behavior (among other types of similar systems). In this sense, the present book *Modeling complex system for public policies* focuses on a very important and difficult task: the intersection of science and policy.

In the following sections of this chapter I present some of the methods used in complex system science. I describe methodologies coming from: nonlinear science, bifurcation theory, pattern formation, network theory, game theory, information

1. In this chapter I present methods used in complex system science. This introductory chapter is addressed to colleagues that come from fields beyond the usual scope of this branch of science. I discuss the following subjects: introduction to complexity science and its importance in public policy, non-linear science, bifurcation theory, pattern formation, network theory, game theory, information theory, super-statistics, complexity measures, cellular automata, agent-based modeling and data mining. In each section, I provide several references, hoping to motivate the reader to continue to search for more introductory and/or formal texts. The author thanks the support of CONICYT Project: Anillo en Complejidad Social SOC-1101 and FONDECYT 1140278.

2. Instituto Santa Fe, 1399 Hyde Park Road, Santa Fe, NM 87501, Estados Unidos; Instituto de Investigaciones Filosóficias, Sadaf, Conicet, Bulnes 642, Buenos Aires 1428, Argentina; Instituto de Sistemas Complejos de Valparaıso, Subida Artillerıa 470, Valparaıso 2340000, Chile.

theory, super statistics, measures of complexity, cellular automata, agent-based modeling and data mining.

It is worth noticing that some of the methods discussed here have a long tradition in physics and mathematics, while others (like Network Theory in its present form, without taking into account its connection to Graph Theory) are relatively new. Only the complex system approach gives a new sense to all these traditional methodologies, a new way to explore nature in a quantitative manner, always approaching the question with a deep interdisciplinary view.

Even though there is no precise, and therefore unique, definition of complex systems, most researchers agree on some of the essential properties a system has to possess to be called complex (Boccara, 2004; Erdi, 2008; Mitchell, 2009). A complex system: *i*) consists of a large number of agents interacting usually via simple rules; *ii*) exhibits emergence: a hard-to-predict collective behavior (does not result from the existence of a central controller, i.e. it is self-organized) (Miller and Page, 2007). A good discussion on these characteristics (that any complex system exhibits) and the mathematical models that could be used as an approximation for them can be found in Nicolis and Nicolis (2007). The basic idea exposed there is that non linear-behavior is a necessary condition for complex behavior and its signature is the multiplicity of different states that the system can achieve.

2 NON-LINEAR SCIENCE

Scholars from a few decades ago had an established idea: for a given system (phenomena) subject to a set of conditions – say temperature, pressure, etc, for physical systems, or population size and mean education degree in case of human societies – slight changes on these conditions produce also small (or similarly unimportant) changes in the final behavior of the system. When studying the superposition of effects on the system, the expected final effect of two or more actions on the system will be the simple superposition of each effect taking into account each action separately (Nicolis, 1995).

The properties mentioned before are the laws of a linear world. Unfortunately linear systems are in general very rare, even though some important dynamical equations are linear (e.g. the Schrodinger equation, in quantum physics). Many body systems, such as complex and human societies, are highly non-linear. This basically means that in this type of systems abrupt transitions can be observed, i.e. the state of the system changes dramatically upon small perturbations. For instance, it can collapse, go extinct or thrive. In some cases, multiple possible stable solutions can arise; and also, unpredictability in both, space and time, which in deterministic systems, is known as classical chaos (Strogatz, 2001).

Another topic, sometimes related with thermodynamics, is scaling. An important attribute of power laws is scale invariance. That is, given a relation of a mathematical function, when scaling the argument by a constant factor, it causes only a proportionate scaling of the function itself. It is easy to see that when logarithms are taken on the function and the argument, this behavior is what produces a linear relationship. The importance of this simple relation is that the equivalence of power laws with a particular scaling exponent sometimes can have a deeper origin in the dynamical processes that generate this behavior at a microscopical level. The critical exponent, as it is usually referred to in physics, is associated with phase transitions in thermodynamical systems. In complex systems science, it is very usual to find this particular characteristic. Scaling laws appear in: biological systems (for example the relation between metabolic rate and the size of an organism) (West, Brown and Enquist, 1997); fractals; social interactions; cities (an example can be the total road length as a function of population size) etc.

For all these reasons nonlinear science is a corner stone in complexity studies. The variety – and unpredictability – of solutions sometimes is referred to as emergent behavior (Bedau and Humphreys, 2008), something that is usual in social and biological systems.

3 BIFURCATION THEORY

As I mentioned before, non-linear behavior is the usual type of dynamics observed in social systems. In those systems, the final stable solutions (equilibrium points or final states) can change drastically when some of the parameters (i.e. control parameters) that drive the evolution of the system reach some particular value. To understand this property, common to almost all non-linear systems, we will study a few classical bifurcations (Hale and Kocak, 1996; Guckenheimer and Holmes, 2002). An interesting recent application to social science, particularly to economic geography, can be found in Ikeda and Murota (2013). As the reader can anticipate, a bifurcation is the structural change in the solution of a differential equation. I mention in this section only a few local bifurcations. In this case the dynamics of the complete system is reduced to what happens in the neighborhood of the bifurcation point. The reduced form of the evolution equation is called: the normal form.

3.1 The saddle-node bifurcation

This bifurcation appears when two equilibrium points collide and – immediately after this point – they disappear. The name refers, as in all typical bifurcations, to the characteristics of the bifurcation. As mentioned before, in the saddle-node bifurcations there are two fixed points that collide. One is stable (the node) and the other unstable (the saddle). The equation in normal form that defines a saddle-node bifurcation is:

$$\dot{x} = -\alpha + x^2 \,. \tag{1}$$

We have then: for $\alpha > 0$ that there are two equilibrium points, a stable equilibrium at: x=-$sqrt(\alpha)$ and an unstable one at x=$sqrt(\alpha)$. At $\alpha = 0$ the two stationary solutions collapse to the saddle-node fixed point $x = 0$; finally, when $\alpha < 0$ there are no stationary points for the system.

3.2 Transcritical bifurcation

This is a typical bifurcation that occurs when two stationary solutions change their stationary properties at a critical value for the control parameter α. To understand what happens, let's write down the normal form of this bifurcation:

$$\dot{x} = x(\alpha - x). \tag{2}$$

The stationary points are $x = 0$ and $x = \alpha$. It is easy to see that there will be a change of the stability behavior on these stationary points depending on the sign of α. If it is less than zero, the stable point is $x = 0$, while $x = \alpha$ is unstable. When α is greater than zero, the stability properties of these points change, i.e. $x = 0$ is unstable and $x = \alpha$ is stable. The bifurcation point in this case is also $\alpha = 0$.

3.3 Pitchfork bifurcation

The case of the pitchfork bifurcation is very interesting. It can be associated to some symmetry properties of the involved system. It is worth to remember that in physical systems, for every continuous mathematical symmetry, there is a corresponding conserved quantity, which is indeed a very important property. The evolution equation for this bifurcation can be written as

$$\dot{x} = \alpha x \pm x^3. \tag{3}$$

When the sign in the cubic term is negative, the bifurcation is called supercritical. In this case, for α less than zero there is only one equilibrium at $x = 0$. While for α greater than zero there are three solutions, one unstable, at $x = 0$, and two stables at $x = \pm$ $sqrt(\alpha)$. The subcritical case is when the sign of the cubic term, in the evolution equation, is positive. There is an inversion of the stable solutions and its stability properties. For the subcritical case: for α less than zero there are three stationary solutions, $x = 0$ stable and x = $\pm$ $sqrt(\alpha)$ unstable. For α greater than zero the only (unstable) solution is $x = 0$. Clearly, the bifurcation point happens at $\alpha = 0$.

4 PATTERN FORMATION

In line with the topic previously discussed, there is a very important phenomenon, mathematically formulated for the first time in the context of morphogenesis. It is also a type of bifurcation, known as the Turing instability.

Patterns appear everywhere in nature. Spatio-temporal patterns can be observed in chemical reactions or in living systems such as bacteria cultures (Murray, 2007).

It is very important to notice that, as in almost all quantitative studies, the usual treatment of pattern formation is done by tracking macroscopic interactions (Hoyle, 2006; Cross and Greenside, 2009), since in general the scale – or length – of the observed pattern is orders of magnitude the size of the microscopic interaction that generates it (I will come back to this point later, explaining agent-based models). After discussing the typical mathematical formulation of the Turing mechanism, we will give an important example of the application of this model in social sciences.

4.1 The Turing mechanism

The word diffusion comes from the Latin: *diffudere*, to spread out. Until the work of Turing in 1952, diffusion was usually thought of as a mechanism that homogenizes the system where it is acting. The important insight of Turing's work was to demonstrate how a diffusion mechanism can concentrate elements from a system in a particular region, creating spatio-temporal patterns.

Let's write down a classical reaction-diffusion equation for the Turing instability:

$$\partial t\, u(x, t) = f(u, v) + Du\, \partial xx\, u. \tag{4}$$

$$\partial t\, v(x, t) = g(u, v) + Dv\, \partial xx\, v. \tag{5}$$

I keep the discussion simple, and guide the curious readers to a more formal and complete discussion on the subject in the references below. In these equations, we have the reaction parts: the functions f and g; and the diffusion terms, characterized by two diffusion parameters Du and Dv. A necessary condition for the Turing instability is a difference in these diffusion coefficients. In particular the diffusion of the so called inhibitor, v, must be greater that the activator u. With the right conditions, there is a bifurcation point where the solution of this equation changes from a uniform solution to a patterned one.

In a recent work, by Lim, Metzler and Bar-Yam, the authors have studied *Global Pattern Formation and Ethnic/Cultural Violence* (Lim, Metzler and Bar-Yam, 2007). Using a more sophisticated model than the previously discussed, they predict zones of conflict – the patterns – in Eastern Europe with astonishing accuracy. This type of studies shows the power and universality of these concepts.

5 NETWORK THEORY

Until now I have dealt with continuous models. The case of a network is different. A network is a set of nodes (also called vertices) that are connected by edges (Newman, Barabasi and Watts, 2006). Network theory can be traced back to the celebrated Konigsberg Bridge problem and its solution by Euler in 1735, which has been treated as the formal beginning of graph theory, a mathematical theory that preceded network theory. It is very important to realize that there are many instances where approaches of the continuous type, like the Turing mechanism (see equations above), are not a good approximation for the problem in hands and only a network view will describe the phenomena in an accurate way. Among this type of systems are: social networks, with connections between individuals; transport networks in cities or between cities, as for example airplane networks; the World Wide Web; food webs; neural networks; collaboration networks: scientific, organizations or business communities etc. “There are a few important concepts to grasp when dealing with networks, some of them are” (Costa et al., 2007; Newman, 2010):

Degree: the number of vertices connected to a node. One can easily see the importance of this, but after some recent works we now know that in the case of many systems this is not the most important concept since, for example, nodes that are poorly connected act only as the intermediaries between parts of a big network.

Directed or undirected: If an edge runs only in one direction, it is called directed, think for example in a one way road. In contrast if the edge goes in both directions, it is called undirected.

Geodesic Path: Is the shortest path, following the connecting edges, between two nodes. This quantity is important when addressing questions such as propagation of information, spread of infectious diseases, or alike.

6 GAME THEORY

Game theory, or the theory of social dilemmas, focuses on how a group of elements interact using strategic decision making. Even though the history of game theory can be traced back to early 1700, the modern version of it appears after the work of John von Neumann, in 1928 (von Neumann and Morgenstern, 2007). Several works follow von Newmann’s efforts. For instance, I can mention the important work made by Nash in 1950, which introduced the idea of Nash Equilibrium, a mutual consistency of strategies. Nowadays this theory is also applied in different fields such as: political science, biology, economics (Kahneman and Tversky, 2000), computer science etc. An interesting example of a branch of this discipline is evolutionary theory, which focuses in the dynamics of the strategy change. In this context, games are called evolutionary games.

In the classical set up of game theory, the players have movement choices (decisions they can make with different payoffs), and the game can be in a single round or repetitive ones. The rules or choices the players can make are usually arranged in decision trees or matrixes.

Let's show a very simple example to see how the theory works. I will discuss a well known example in game theory: the prisoner dilemma. Two players are partners in a crime and after been captured, on suspicion of its commission, they are confined in different cells. The police offer them the opportunity to confess the crime. We can then represent the players in a two by two matrix with the different pay-offs of the four possible choices depending on the criminal confessions (figure 1): *i*) Prisoner A stays silent, Prisoner B stays silent: Each serves 1 year; *ii*) Prisoner A stays silent, Prisoner B betrays: Prisoner A: 3 years, Prisoner B: is released; *iii*) Prisoner A betrays, Prisoner B stays silent: Prisoner A: is released, Prisoner B: 3 years; *iv*) Prisoner A betrays, Prisoner B betrays: Each serves 2 years.

The best possible outcome for the two prisoners is to not confess. If only one confesses, she/he gains a lot of utility while the other loses. The alternative is the confession of the two prisoners. What would then be the most probable final outcome in this scenario?

As the reader can guess, game theory can be applied also in complex networks, taking into account the topology where the individual interacts: the social network. There are many types of games, we can mention: cooperative, non-cooperative; discrete and continuous games; simultaneous, sequential; evolutionary games; perfect or imperfect information; many players, population games, etc.

It is important to realize that in all the situations, for the particular case of rational behavior, the players (which can be a person, a firm etc.) must anticipate what to do, taking into account what the other agent will infer from the other's actions (Camerer, 2003).

FIGURE 1
Matrix for the game "the prisoner dilemma" discussed in the text

Prisoner B \ Prisoner A	stays silent	betrays
stays silent	Prisoner A: serves 1 year Prisoner B: serves 1 year	Prisoner A: is freed Prisoner B: serves 3 years
betrays	Prisoner A: serves 3 years Prisoner B: is freed	Prisoner A: serves 2 years Prisoner B: serves 2 years

Elaborated by the author.

7 INFORMATION THEORY

Claude Shannon developed a theory to find the limits of signal processing; his work "A Mathematical Theory of Communication" was published in the Bell System Technical Journal in July and October 1948. This is the landmark for what now is called Information Theory (Shannon, 1948). Since Shannon's work, Information Theory has been successfully applied to different fields (Pierce, 1980; Cover and Thomas, 2006): molecular genetics, cryptography, statistical inference, physics, biology, and in general to data analysis. In complex systems, information theory has been used in connection with a theory that was developed by E.T. Jaynes. In a series of papers *circa* 1952 he discussed the correspondence between statistical mechanics and information theory (Rosenkrantz, 1989).

This giant step tells us that statistical mechanics (and all the applications/predictions of this very successful body of knowledge) must be seen as a particular case of a more general theory: Information Theory. Jaynes's work paid attention to a general principle: the Maximum Entropy Principle (or MaxEnt). Nowadays MaxEnt is used to understand several distributions appearing in biology and ecology (from a complex system approach) as for example: size distribution, range distribution, energy distribution, etc. In a very recent effort I applied MaxEnt theory to understand social and urban systems, but this work is still unpublished and in progress.

8 SUPER-STATISTICS

I have emphasized the importance of the contribution of statistical mechanics and MaxEnt theory to the study of complex systems and natural phenomena in general. In a recent work, Cohen et al. introduced a natural generalization of statistical mechanics (Beck and Cohen, 2003; Cohen, 2004). The idea is very simple, but also very powerful. When dealing with complex non-equilibrium systems with long-term stationary states subject to spatio-temporal fluctuations of an intensive quantity, the probability distribution, which has very peculiar characteristics, can be obtained by calculating the average over these fluctuations. An example of these characteristics can be a long tail behavior.

To be more explicit, suppose we have a system composed by many subsystems. Each subsystem has particles diffusing with different diffusion parameters. In consequence, each subsystem will be characterized by a Gaussian distribution characterized by the particular diffusion parameter that it has. But if we consider the complete system (the aggregation of all subsystems) we must average using all these Gaussian distributions. To understand how this can be achieved, let's take a look at a simple example.

Imagine we have a brownian particle described by the following stochastic differential equation

$$\frac{dr}{dt} = \sigma\xi(t), \tag{6}$$

where $\xi(t)$ is a white gaussian noise of unit variance, i.e.,

$$\langle \xi(t) \rangle = 0, \tag{7}$$

$$\langle \xi(t)\, \xi(t') \rangle = \delta\,(t - t'), \tag{8}$$

t is the time, and σ is the strength of the noise. Under Ito's calculus, this stochastic dynamic leads immediately to a probability evolution equation, or the Fokker-Planck equation, this is

$$\frac{\partial P(r,t)}{\partial t} = \frac{\sigma^2}{2}\frac{\partial^2 P(r,t)}{\partial r^2}. \tag{9}$$

This equation has an analytical solution, which is the same that L. Bachelier found for non log-transformed prices in 1900 (Bachelier, Davis and Etheridge, 2006), and which, five years after him, Einstein suggested as the distribution for Brownian particles: the normal distribution (Einstein, 1905). "The problem, which corresponds to the diffusion from a single point (ignoring the interactions between diffusing particles) is now mathematically completely defined, its solution is:"

$$P(r,t) = \sqrt{\frac{1}{2\pi\sigma^2 t}}\exp\left(-\frac{r^2}{2\sigma^2 t}\right). \tag{10}$$

"Therefore, the distribution of the resulting displacements in a given time t is the same as random error", from (Einstein, 1905, our translation).

Now, imagine the quantity $\beta = 1/\sigma$, fluctuate according to a Gamma-distribution, a straight forward calculation will give a final distribution for the system

$$P(r,\tau) = \frac{\Gamma[(n+1)/2]}{\Gamma[n/2]}\sqrt{\frac{\beta_0}{2\pi\tau}}\left(1 + \frac{\beta_0 r^2}{n\tau}\right)^{-(n+1)/2}, \tag{11}$$

which is a variant of the Student's t-distribution. The non-Gaussian shape of the distribution results from collecting r's from time periods separated by long intervals where β is different.

It is easy to realize the power of this concept and the generalization that can be made following these methods (Hanel, Thurner and Gell-Mann, 2011). When considering a compound of elements, it is necessary to first check if their interaction can be decomposed into subsystems. There is no formal method to do this, the only tool to know what is the proper subdivision of the system is the information in hand of the problem. For example, in a recent paper, financial time series data was divided in days, i.e. a trading-day was the temporal division for the complete system, which was many years of trading-days (Gerig, Vicente and Fuentes, 2009). If this sort of subdivisions can be made, these subsystems will follow the same underlying dynamics (as the brownian particle in the example above), and the only difference will be some fluctuation in an intensive variable. Then, the behavior of the aggregated system will simply be an average of the subsystems.

9 COMPLEXITY MEASURES

Much has been written trying to define (or measure) the complexity of a system. The importance of this can be understood when thinking that systems with the same level of complexity (defined in some way) may share universal properties.

The history of the study of probabilistic regularities in physical systems can be traced back to 1857 with the very idea of entropy proposed by Rudolf Clausius. Claude Shannon derived the same functional form used almost one century before to introduce the concept of information entropy. Even though the intuitive idea of complexity and information in a physical system share some similarities, it was necessary to introduce several measures in order to understand various types of complexities, and in order to quantify properties of the system closely related with both of them (Lloyd, 2001): Kolmogorov complexity, logical depth, effective complexity, etc.

Some of these measures have been proposed to study different systems (e.g. strings of symbols, the data that the system produces, etc.). From all of these measures, I think the one that captures in a more accurate way the notion of the complexity of a given system is Effective Complexity, introduced by Murray Gell-Mann and Seth Lloyd (Gell-Mann, 1995; Gell-Mann and Lloyd, 1996). In short, the effective complexity of an entity corresponds to "the length of a highly compressed description of its regularities". The idea is simple, elegant, and profound: if we split the algorithmic information content of some data string into two components: one with its regularities (related to the Kolmogorov Complexity) and the other with its random features (related to its entropy), the Effective Complexity of the data will only be the algorithmic information content of its regularities.

A perceptive reader will notice a very important aspect of the theory developed by Gell-Mann and Lloyd, that the effective complexity of an entity is context dependent (Gell-Mann, 1994). We will give a naive example to motivate the analysis of this aspect of the theory. Imagine we are studying a particular system: a living organism, then, what is its complexity? There is no doubt that we must be more specific mentioning exactly which characteristic or feature we want to study using this concept, and what set of data we have in order to do so. Not only that, but to be more precise, we must have a theory that explains the data.

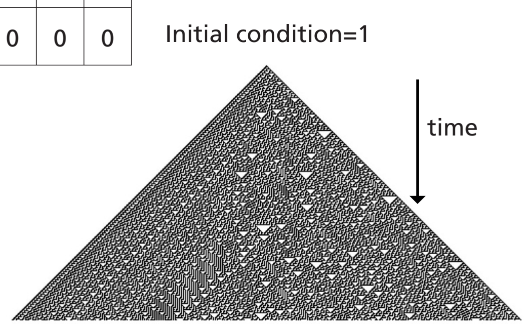
10 CELLULAR AUTOMATA

Circa 1950 Stanislav Ulam and John von Neumann created a model to understand the behavior of discrete units as a function of the behavior of its neighboring ones. It was the beginning of Cellular Automaton models. Cellular Automaton is a discrete model based on cells, each one having a set of states: on-off or alike. The cell positions are usually on a regular grid (but again they can be arranged in complex networks as the one mentioned before). Then, given an initial condition for the cellular automata, the next state will be an update of each grid according to local rules (Toffoli and Margolus, 1987; Schif, 2008).

To explain the essential ideas, let us take a look at a simple example: the one dimensional cellular automata. In a one dimensional cellular automaton each cell can be in two states: zero and one (or on and off, etc.). Given the state of a cell at time *t*, its configuration at time *t* +1 will depend on: its own state at time *t* and the state of the two neighbors also at time *t*. It is clear then that the possible values for a neighborhood is two to the power of three, i.e. 2^3=8, and then given the on or off option, there will be a total of 2^8=256 rules for a one dimensional cellular automata. In figure 2 we show the so-called rule 30. At the left we can see the evolution rule, to the right is the evolution of an initial condition with only the center cell with a state 1, all the rest of the cells are in a 0 state.

FIGURE 2
An explicit view of rule 30 of a one dimensional cellular automaton

State at time: ***t***	111	110	101	100	011	010	001	000
State at time: ***t+1***	0	0	0	1	1	0	0	0



Elaborated by the author.
Obs.: The figure shows the evolution rule (left) and the result in time for an initial condition which has only one cell with the 1 state at the center (right).

Depending on their behavior, S. Wolfram, in his book A New Kind of Science, defined four categories into which cellular automata can be classified. In class one nearly all-initial patterns evolve quickly into a stable, homogeneous state, and any randomness in the initial pattern disappears. In class two nearly all-initial patterns evolve quickly into stable or oscillating structures, and some of the randomness in the initial pattern may filter out, but some remain. Local changes to the initial pattern tend to remain local. Class three has nearly all initial patterns evolving in a pseudo-random or chaotic manner. Any stable structure that appears is quickly destroyed by the surrounding noise. Local changes to the initial pattern tend to spread indefinitely. Finally in class four nearly all initial patterns evolve into structures that interact in complex and interesting ways, with the formation of local structures that are able to survive for long periods of time.

Applications of Cellular Automata can be found in different fields such as computer processors used to understand pattern formation in biology, epidemiology, and models to simulate urban dynamics through the local actions of cellular automata (Batty, 2007), etc.

11 AGENT-BASED MODELING

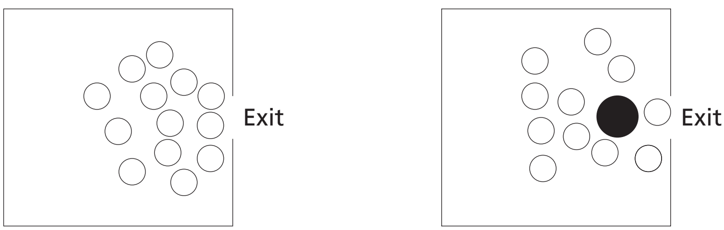
With the arrival of new technologies and the increasing computational power, it is straightforward to consider computational models to study the evolution of many agents, at different scales and scenarios. Agent-based modeling can be thought of as the evolution of cellular automata models. This can be considered as a bottom-up approach due to the fact that the properties observed in the system as a whole (i.e. emergent properties) are the result of the interactions of the microscopic components of the system. Such view differs from the others discussed in this chapter, as for example the Turing mechanism, where the diffusion of particles is modeled through a spatial operator that acts on a macroscopic scale.

There is no specific recipe to apply agent-based modeling, since it can be used in many different scenarios and systems in general. Usually they can be studied at various levels, such as individuals (Axelrod, 1997), population (Gustafsson and Sternad, 2010), organizations etc; models for decision making (notice that game theory can be applied as well); the topology of interactions, regular or irregular lattices, complex networks; the environment where the interaction happens and learning rules (or adaptive processes).

It has been argued that the main benefits of agent-based modeling are the following (Bonabeau, 2002): *i*) it captures emergent phenomena. This is because in principle emergent phenomena come from microscopic interactions (or individual entities), and when using agent-based models any macroscopic characteristic will be by definition a result of microscopic rules acting on a great number of agents. These emergent phenomena can appear when: individual behavior is nonlinear, agent interactions are heterogeneous and can generate network effects, agent-based models can amplify fluctuations (something that is difficult to achieve aggregating differential equations) and when individual behavior exhibits path dependence and/or memory (like in the case of a traffic jam); *ii*) In many cases agent-based modelling provides the most natural way to describe the dynamics and rules of the system, focusing on the individual rules of the agents.

Some of the areas where agent-based modeling is being applied are: diffusion of innovation and adoption, operational risk, organization design, stock market, flows (as for example traffic or evacuation, see figure 3 for an example), etc.

FIGURE 3
Agent-based simulation of a fire escape



Source: Helbing, Farkas and Vicsek (2000).
Obs.: People are represented by open circles. On the right the room has a column represented by a black circle. The simulation shows that the flow of people leaving the room with a column in the exit is more efficient, this means that the flow that the column generates allows more people to exit per unit of time.

12 DATA MINING

There are many systems where the underlying dynamics are unknown. These are in some way very different forms of the classical type of dynamical systems, where first-principle models can be proposed to describe them. In these systems, Newton's equation of motion, for classical systems; Maxwell equations, for electromagnetic systems; quantum or relativistic equations, can be the starting point to build models that will describe the phenomenon using a bottom-up approach. For other systems, this type of reduction is impossible due to: the complexity of the problem, which sometimes makes it almost impossible to create a mathematical model; the lack of information since sometimes the data or output of the system is available only at a very high and macroscopic level, etc.

Nowadays there is much data available: from scientific institutions, governments, different type of businesses, the worldwide web, etc. All these available data can be stored and studied, but as the reader can guess for some of them the first-principle approach is far from being achieved.

The term data mining does not refer to the extraction and collection of a huge amount of data, as usually is believed. Data mining refers to the extraction and recognition of patterns in large data sets. In this sense, data mining has two primary goals (Kantardzic, 2003): prediction and description. To achieve them, data mining uses the following task: classification, regression, clustering, summarization, modeling and deviation detection.

Even though the recognition of patterns and sometimes the detection of signs of causality in some interactions has been a research topic using old methods (e.g. correlation and regression analysis); data mining explores a huge amount of data available thanks to the increment of computer power and storage. Data mining identifies unknown (patterns) properties present in the data, by using (among others) artificial intelligence and machine learning techniques (Hastie, Tibshirani and Friedman, 2009). Due to the variety of data available nowadays, thanks to the internet, cellphones communications, etc., data mining is becoming a powerful tool to study social patterns in urban systems. Common applications of this branch of computer science can be seen in astronomy, genetics, social behavior, transport, financial systems, telecommunication, etc.

13 CONCLUSIONS

As we can see every day, the world around us and the society where we live are full of very complex networks of relationships at many scales. There is an entangled interaction between people, companies, cities, ecological systems, etc., and in order to understand them and make good predictions, and specifically public policy, it is hard to imagine solving a problem in complete isolation. To do this it is necessary to have a good representation of the system, taking into account its constituents and the interactions between them.

The methods shown in this chapter are some of the ones used in complexity science, which, at the same time, is probably the best scientific methodological way to deal with the kind of problems concerning public policy.

It is very important to realize that none of the methods included in this chapter define complexity science, neither the agglomeration of them. Beyond the concepts, tools and methods presented, complexity science offers a new way to think about policy making. It focuses attention on dynamic connections, evolution and interdisciplinary thinking.

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CHAPTER 4

SIMULATION MODELS FOR PUBLIC POLICY

James E. Gentile[1]
Chris Glazner[2]
Matthew Koehler[3]

1 APPLICATIONS OF COMPUTATIONAL MODELING TO POLICY ANALYSIS

Public policy analysis wrestles with the challenge of identifying and implementing a desired change in our social and governmental systems. Defined by (Weimer and Vining, 1996), it is the "systematic comparison and evaluation of alternatives available to public actors for solving social problems". We often turn to policy analysis to help us understand which available options lead to the most "desirable" outcomes. To be able to compare policies or outcomes, however, we must be able to understand how an action will result in a change, and we must be able to agree on what is desirable.

Given the complexity of even the smallest of social systems, this analysis is not trivial. Social systems are comprised of autonomous people who do not behave in perfectly rational ways, and they have different explanatory mental models for how society works. Social systems do not behave in deterministic ways that lend themselves to a simple spreadsheet analysis or a closed form mathematical formulation at the causal level. The behavior of social systems cannot be neatly constructed, as a watchmaker would build a watch to keep time. Given these challenges, how can the policy analyst compare among policy options, with unclear relationship between cause and effect?

The relationship between a cause and its effect can be understood through models. At its most basic form, a model can simply be a mental concept, a description of a belief for how a system will respond to a change. A mental model can be shared on a simple napkin or via an elaborate slide presentation, but does not have the ability to provide defensible comparisons of how effectively policies will result in desired outcomes. Quantitative analytical models, from simple spreadsheet models through more advanced mathematical representations as used in classical economics, usually contain rigid assumptions about behavior, as exemplified by

1. Ph.D. E-mail: <jgentile@mitre.org>.
2. Ph.D. E-mail: <cglazner@mitre.org>.
3. Ph.D. E-mail: <mkoehler@mitre.org>.

the perfectly rational actor model frequently used in classical economics. While we know that deterministic, quantitative models are not valid (people are not fully rational, nor do they have perfect information, nor are they homogeneous), they have served the basis for much of policy analysis of our time. Furthermore, they implicitly assume that the system can be known and controlled.

Policy operates in a highly complex space, beyond what can be controlled or observed in a deterministic way. In forming policy, we must consider beyond what we can control and closely examine what we can influence. We must be able to explicitly capture the underlying causal hypotheses of policy proposals in a way that allows us to experiment, and provides a way for stakeholders to share and test their own hypothesis and ideas with others in an analytically defensible way.

Simulation modeling has the potential to provide this capability. Some of the earliest simulation models that captured the complex relationships in policy were created using the System Dynamics methodology, developed by Jay Forrester at MIT in the 1950s and 1960s. System Dynamics models systems using differential equations, paired with an easy to learn diagramming technique (Causal Loop Diagramming) that makes it feasible for subject matter experts to participate in the modeling process, rather than relegate it to mathematicians or computer scientists alone. The approach is particularly well suited to policy modeling in that it visualizes causal relationships, and explicitly gives the policy maker access to “levers”, such as funding to a program or production rate. This control creates a clear linkage between policy and behavior in the model output. The models are simulated using computers, and critical metrics are graphed over time, in contrast with the often static cost benefit calculations prevalent in policy analysis. The models themselves run quickly, encouraging policy makers to build an intuitive understanding of cause and effect via experimentation.

Forrester became very interested in urban policy after discussions with the mayor of Boston, John Collins. He authored the book Urban Dynamics in 1969 (Forrester 1969), which examined the long-term impact of housing policies in urban areas stemming from policy modeling done for Boston. His model gave policy makers the tools to share mental models and discover counter-intuitive policy effects that had not been popularly addressed. It invited criticism, and provided policy analysts with a framework for quantified comparison.

Forrester’s students, lead by Donella Meadows, created one of the most controversial policy models built to date, World3, documented in the book Limits to Growth in 1974 (Meadows et al., 1974). This model examined the relationship between population growth and our planet, and predicted dire consequences given the resource policies of the day. It was met with vehement critique, stemming from both the available data as well as assumptions made about how individuals and technology will be able to adapt to future change (Nordhaus, 1973). It presents a "top down" perspective of policy, driven by the structure of the system with direct, deterministic causal relationships. While this may be true of some policy systems, it is not true of many: societal behavior does not emerge from a top down edict. While System Dynamics still has a community of practitioners and still has great utility to policy modelers, it never became a primary tool of policy makers in the wake of the controversy surrounding Limits to Growth.

A way forward emerged from the thought experiment of Thomas Schelling, a future Nobel laureate in Economics who, like Forrester, was very interested in urban policy in the late 1960s. As opposed to Forrester, Schelling looked at the problem not from the perspective of the policy maker, but from the perspective of a citizen. Using a simple model of "agents" arrayed on a piece of graph paper using coins, he was able to demonstrate that it took only a very slight preference among populations to live among similar races to produce a dramatic segregation in the population over time. Schelling later published this work in the book Micromotives and Macrobehavior in 1978 (Schelling, 1978). While Schelling's models are not prescriptive for policy makers, nor do they give specific policy levers to encourage experimentation by policymakers, they highlight the emergence of macrobehaviors driven by motivations at the individual level that may seem contradictory. This is a powerful lesson for policy makers to understand.

Since Schelling's first explorations using coins and paper, a class of computational models known as Agent-Based Models have become popular. This class of models examine the emergence of macrobehaviors from interacting software agents. Once in software, agents can take on a range of behaviors, such as geographical location, path dependence, communication with social networks, and even artificial intelligence. This greatly opens up the doors to what can be done with models, and over the past 20 years it has found wider acceptance as the workhorse tool in the study of complex adaptive systems (Holland, 1992) and more recently, in the field of behavioral economics (Arthur, 1994; Tesfatsion, 2006) and social science (Epstein and Axtell, 1996; Miller and Page, 2007).

Agent-Based Modeling is a paradigm, rather than a tightly knit toolkit with an associated policy engagement tools as found in System Dynamics. The flexibility of agent-based models has made them extremely powerful, but the learning curve associated with creating simulations, and the lack of tools for sharing results, have inhibited their use as a common tool for policy analysis. To truly understand the complex adaptive relationships so often associated with policy, we must further develop the tools and methods needed to support agent-based modeling as a practical tool for policy analysis.

2 REASONING CAUSAL BEHAVIORS

Understanding generating mechanisms is important for two reasons (at least). First, if you can uncover the potential generating mechanisms of a dynamic, then you can begin to determine how to affect the system to cause a particular change (the ultimate goal of policy analysis). Without an understanding of the generating mechanisms it would be very difficult to know which policy lever would produce the desired impact. Second, generative methods will allow one to understand, or at least characterize, the temporal dynamics over time. This, in turn, will help you to design a monitoring regime that is sensitive to the changes you are interested in making.

Now we will add a bit more formality to the discussion and define abductive reasoning. Fundamentally, agent-based models (ABMs) are a type of simulation, no better, no worse. What differentiates it as a tool for policy analysis is that it focuses on the individuals and their interactions. It explicitly represents each individual within the system and how they all interact (Axtell, 2000), (Epstein, 2006). In this way ABMs can handle adaptive, boundedly rational humans and outliers that may have a disproportionate impact on the evolution of the system. Given the enormous potential expressiveness of ABMs, this tool must be applied in a principled way especially when used to impact public policy. Moreover, this allows the policy analyst to embrace outliers and other low base-rate events that may drive the system rather than, often, ignoring them with statistical methods.

Typical closed form optimization analysis of a system is a mathematical deduction. One starts with a set of statements about a system and then deduces an optimal solution. Unfortunately, given the open and stochastic nature of the systems typically studied with ABMs a single deductive solution may not be not useful. Rather, many runs of the ABM must be performed each mapping to a particular outcome. At this point, one might be tempted to argue that "big data" are the solution. One could simply analyze enough data from a system to understand all of its potential dynamics to include outliers. However, from a policy perspective this analytic approach is of limited utility. What a big data analysis can provide is the correlative structures present within a dataset. This is quite different than the causal structure. Moreover, policy analysis is typically undertaken to inform a desired change to the system. This being the case, the potential new system would be "out of sample" from the big data analysis and how the old and new systems relate may not be clear.

ABMs, on the other hand, allow one to investigate potential generating mechanisms and experiment with causal structures. As Epstein has termed it: "If we did not generate *x*, we did not explain *x*" (Epstein, 2006). As pointed out by Axtell, growing a particular outcome only demonstrates sufficiency

(Axtell, 2000). One can demonstrate what will cause an outcome but, likely, will not be able to prove that is the actual mechanism being used by the system under study. This observation does call into question the utility of the ABM method. A mathematical deduction leads to one and only one outcome that can then be used to support decision-making. Use of ABM requires a more nuanced logical structure making use of deduction, indication, and often abduction.

As stated above, and ABM is a type of simulation. Therefore, when one properly controls for any stochasticity within the model, each execution of the model is a strict deduction and leads to one and only one outcome (Epstein, 2006). As one changes various settings or random numbers contained within the ABM one can build up a set of mappings (sufficiency theorems) from ABM inputs to outputs.

As deductions accumulate, they can then be used to inductively produce hypotheses about the causal relationships that may exist in the system under study, a statistical and data mining exercise. As with most induction one can only fail to reject a causal hypothesis, you are never guaranteed to uncover the actual causal structure of the real system with these methods. One must run the model many times to explore and define the mapping between model inputs and model outputs. As the ABM's dynamics are better understood the outputs can be categorized into three basic bins: expected valid, expected invalid (known input values that cause degenerate behavior), and unexpected results. These unexpected results are what create insight into the system (Koehler, 2006). However, in order to know how much faith one should have in them as much of the parameter space as possible should be explored to provide a full understanding of the behavior of the model.

Often the results generated from multiple runs of an ABM are used as part of an abductive investigation of a phenomena, such as the well known study about segregation completed by Thomas Schelling (1978), discussed supra. Abduction is simply a method to discover a missing component of our model of the behavior of a system (Aliseda, 2006). An abductive investigation is typically preceded by observing surprising or seemingly mutually exclusive behaviors from the system. For example, in the Schelling study the two system signals were: *i*) segregated settlement patterns; *ii*) population self-reporting a desire to live in integrated neighborhoods. The amount of information used to define the initial system, and the specificity of the surprising dynamic, will constrain the potential new components, and also dictate the needed data.

If the system is reasonably abstract and the surprising dynamic is a general macroscopic observation of the system; then, too, the new sufficient feature will be abstract. Using Axtell's Levels of Empirical Relevance (Axtell, 2005) what would be produced under these conditions is, likely, an agent-based model of Level 1 (macro-level qualitative correspondence to the referent) Empirical Relevance. As the specificity of the system and the surprising dynamic increase, it is likely that the specificity of the new feature will need to increase, as well. Now, the ABM is likely trying to achieve Level 2 Empirical Relevance (macro-level quantitative correspondence). There are two additional Levels in Axtell's framework: Level 0 (micro-level qualitative correspondence-agents that behave plausibly for a given system), and Level 3 (micro-level quantitative correspondence-agents that behave identically to their "real-world counterparts"). Level 0 ABMs are, essentially, thought experiments and are unlikely to be used for policy making. Level 3 ABMs, on the other hand, would be ideal for supporting policy making as they are a near perfect representation of the system in question. However, given the data needs to create a Level 3 ABM, it is unlikely to be possible to create such a model. This implies particular standards for the ABM based upon its intended use. Thought experiments and initial investigations are well served by Levels 0 and 1. Whereas ABMs used for helping to define policies to be implemented should achieve Level 2 at least. This is discussed further in the next section.

As implied above, understanding how well an ABM represents the system under study is extremely important as this will help to inform a decision maker on how to use the results of the ABM as part of their decision's support. In addition to the level of detail and amount of data used to create the ABM, the model can, and likely should, be compared to a referent (the real world or another model). The correspondence with the referent system can be characterized using the Docking Framework created in (Axtell et al., 1996). In their Docking Framework there are three levels of correspondence: *identity* (where the simulation produces identical results to the referent data from the real system or another simulation), *distributional* (where the simulation produces results that are statistically indistinguishable from the referent), and *relational* (where the simulation produces results that are statistically distinguishable from the referent but are qualitatively similar). As discussed above, ABMs used for thought experiments may be thought of as adequate if they have relational equivalence to the human system being studies. ABMs used for informing decisions that will impact human systems should relate to said system at least at the distributional level (additional details of the use of docking and the empirical relevance framework for ABM evaluation can be found in (Egeth et al., 2014; Koehler, 2006; Barry et al., 2009).

3 MODELING AND SIMULATION

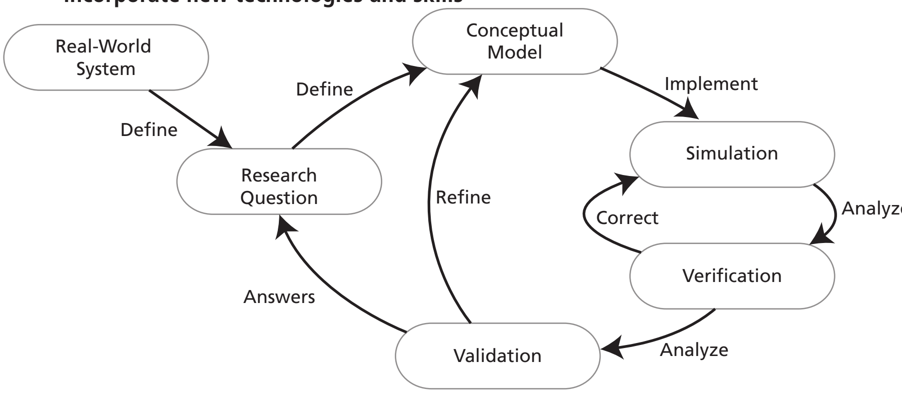
Modeling and simulation (M&S) provides scientists with a toolset to solve problems without analytical, numeric solutions. However, this approach has its own set of challenges where relevance is likely principal. The relevance of an M&S effort hinges on stakeholder buy-in and often determines the project's longevity and impact. Stakeholder engagement is often dependent on how they consider the conceptual model. Many academic models may fail in this regard and can be quickly dismissed as too assumptive.

The simulation scientist must balance the tradeoff between constructing a very simple, toy model and generating a model that is too cumbersome to explain and understand. A very large, very inclusive model can quickly lead researchers to make many simplifying assumptions out of their domain of expertise (such as guessing how persons would react in various situations). A good model for policy is likely somewhere between these two extremes, a model that is built to include many of the key characteristics of the systems while not capturing lesser dynamics. The modeling and simulation process helps the researcher know what should be included.

Modeling and simulation is an iterative process where simulation scientists often work closely with domain experts. At each round of the cycle, the results of a model are verified, validated and refined (seen in figure 1). Models should begin with a research question that is directly relevant to a real world problem, then a conceptual model is constructed. Normally, this conceptual model is a natural-language description of the dynamics of the model. The conceptual model is implemented, generally in computer code, and the results are analyzed. The simulation output should first be compared to the conceptual model to check that the code is properly implemented, this is known as verification. Here, scientists should scrutinize the simulation's output until they believe the implementation correctly describes the conceptual model. Then the simulation output is validated to external data sources, this can include analytical forms of validation and fitting as well as face validity among the domain experts. If the implementation fails to answer the initial research question, the conceptual model should be refined, this often requires capturing more dynamics.

The M&S process can give us great insights but its methods require us to focus on the engineering processes behind model construction since our results will only be reproducible with clear and concise structures and documentation. Modeling complex systems can require researchers to characterize very complicated behaviors and interactions in programmatic logic but these implementations can be non-trivial.

FIGURE 1
Modeling and simulation is an iterative process that has many cycles – each step can incorporate new technologies and skills



The modeling and simulation team must ensure that their implementation represents the conceptual model and this can be a cumbersome process when we consider that many agent-based models are used to study emergence and emergence is not always known a priori. Here the verification challenge is compounded because the simulation model's results cannot be compared to a known, conceptual outcome. In cases like this, the model can be disassembled into components and each component can be independently verified. This process is often known as unit testing where a component's operation is compared to a formal functional specification. As the components are reassembled, portions of the system can be validated by bringing the system to known steady-state phases (Gentile et al., 2012).

The process can be further complicated by a series of pitfalls that often beset projects (Barth et al., 2012) from stakeholder engagement to overly detailed simulation models. To avoid some of these, teams can be encouraged to frequently revisit the task's research question, engage and communicate with stakeholders, always look for ways to simplify the model, and follow the best practices of software and systems design.

Axelrod (1997) mandates that the programming of a simulation model should be verified (referred to as internal validity), useful and extendible. None of these requirements are easy to achieve with any model, especially not as simulations scientists iterate in the simulation process and incorporate more and more dynamics in their conceptual model. Each new dynamic often carries a new set of assumptions and a limited interface to the whole model. For usability and extensibility, the user must be able to easily interact with existing dynamics and add new ones.

It is best practice to maintain a log of the simulation's model, complete with a list of assumptions. A standard process for documentation logs a model elements' overview, design concepts and details (Grimm et al., 2010). This template is extremely useful in maintaining many design decisions behind modeling and often gives the simulation team a better understanding of how the elements and sub models work, which can decrease the time required for verification.

4 CONCLUSIONS

Modeling and simulation techniques have a long history with policy analysis, most of these methods involve System Dynamics models and closed-form mathematical equations. These methods do not expose underlying micro-level behaviors that cause the observed macro-level dynamics. Many policy options can efficiently affect these micro-level choices which can lead to very different systemic outcomes. In order to change the system at the micro-level, we need to understand which individual behaviors cause different emergent properties of the system.

Agent-based modeling (ABM) provides a toolset for analysts to test which underlying behaviors could cause macro-level dynamics. This is performed through abductive reasoning exercises where plausible explanations are tested *in silico*, over many repetitions. ABM's goal is not predicting an outcome but, rather, explaining how an outcome can be achieved through the choices and interactions of many actors.

This experimentation method is unique because we build the system we observe. Generally, this is all done through computer simulation models where a conceptual model is expressed is computer code and executed. Modeling and simulation is an iterative process where simulation scientists add complexity into their models until the output seems valid. This rapid iteration can challenge development and cause software bugs to creep into the simulation. These errors are of large concern because the goal of a system is to study emergence which is not known a priori. Therefore, we must check and recheck our implementations, always looking for ways to simplify our model, verify the simulation's operation and validate the simulation model's output to the real-world system. Researchers need to understand the potential of complexity tools for public policy but we must also accurately convey the proper use and limitations of these methods.

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CHAPTER 5

OPERATIONALIZING COMPLEX SYSTEMS[1]

Jaime Simão Sichman[2]

1 COMPLEX SYSTEMS AS MULTI-AGENT SYSTEMS

In this introductory section, we characterize social and complex systems, and show how multi-agent systems (MAS), a theoretical and applied branch of artificial intelligence (AI), are considered as the ideal computing realization for these kind of systems. We then introduce a simulation technique based on MAS, called multi-agent-based simulation (MABS), presenting its goals, advantages, and limitations.

1.1 Social systems as complex systems

As seen in the previous chapters of this book, complex systems present as a major characteristic the fact of being composed of a collection of a great number of *individuals* that *interact* with each other, following different rules and taking into account different contexts. The main characteristics of such systems are the following:

1) *nonlinearity*: interaction patterns among different individuals rarely follow linear rules;

2) *multiple abstraction levels*: one can view and analyze such systems by adopting the perspective of different abstraction levels, ranging from individuals to collective entities;

3) *emergence*: the behavior of the overall system can hardly be predicted a priori, since local interactions may result in some dynamic emergent phenomena;

4) *open systems*: in real complex systems, it is quite often the case that individuals can enter and leave dynamically the system, without a global governance.

Thus, certain physical, biological and social phenomena may be characterized as complex phenomena. If we consider specifically human social systems, these

1. The application examples shown in this chapter and the SimCog survey were developed within a cooperative research with Prof. Helder Coelho, from Universidade de Lisboa, Portugal, and were carried on by some previous students, Diana Francisca Adamatti, Nuno David, Maria das Graças Bruno Marietto, Júlio de Lima do Rego Monteiro and Luis Gustavo Nardin, to whom the author is very grateful.

2. Laboratório de Técnicas Inteligentes (LTI) Escola Politécnica (EP) Universidade de São Paulo (USP). E-mail: <jaime.sichman@poli.usp.br>. Jaime Simão Sichman is partially funded by CNPq, Brazil, grant 303950/2013.

present at least two further dimensions, *2nd order emergence* and *social constructs*. By the term 2nd order emergence, we denote the following process:

1) interactions at the individual level create patterns at the global level;
2) however, unlike other complex systems, some of such global patterns may continue to exist even when the individuals that originated them leave the system;
3) such patterns are then recognized by other individuals, who name and represent them as part of the social reality, and respond to them adequately;
4) in this way, there is a feedback from the global level to the individual level, generating what is called 2nd. order emergence.

Moreover, since people exchange their subjective representations of reality by using natural language, we can consider that these global patterns are socially constructed by the individuals.

As an example, a public land occupation policy that deforests a certain area for constructing a new highway generates a unique global phenomenon. A GPS system can detect a clearing in the woods, a significant area without green coverage. However, the social constructs created by the individuals involved can be very different: probably, local residents interested in a faster displacement will consider these phenomena as positive ("they are performing well the task of the highway construction"), whereas the inhabitants of the region concerned with sustainability will adopt a negative bias ("they are destroying the forest"). Such social constructs are taken into account in the next decision cycles of these agents ("I will/I will not vote for this candidate because of this fact").

Such characteristics make it difficult the use of conventional computing techniques for the development of such systems. No predefined algorithm can predict the emergence of collective phenomena, neither the feedback occurrence between individual and collective levels. Thus, more specific modeling and implementation techniques should be used, as explained next.

1.2 Multi-Agent Systems (MAS)

Multi-agent systems (MAS) is a well-established branch of theoretical and applied research, whose origin comes from artificial intelligence (AI), and which tries to solve problems encountered when one decides to resolve a set of interacting tasks in a distributed computational environment. Named in the early days as distributed artificial intelligence (DAI), a comprehensive synthesis of the MAS domain is out of scope of this chapter, please refer to Ferber (1995) and Wooldridge (2002) for more details.

DAI soon revealed the need for a certain degree of *autonomy* to its components: the more autonomous the local units of the system are, the more efficient the distribution of tasks and operation is, and consequently the lower the computational load of the global system is as well. This discovery stimulated AI researchers and designers to focus their attention to certain intriguing and seemingly philosophical issues, such as how to conceive, design and develop an *autonomous* system. Moreover, the development of autonomous systems raised a second question, maybe even more complicated than the first one: how to get *coordination* and *cooperation* between autonomous systems that perform a common task? In other words, how to *orchestrate* cooperative behaviors in societies of self-interested agents? Interestingly, these issues are also fundamental for policy makers, as illustrated in the latter examples of this chapter.

Thus, the MAS domain is characterized by the study, design and implementation of artificial agents societies. These agents can be very different, ranging from very simple ones, called *reactive* agents, to more complex ones, endowed with some cognitive skills, called *deliberative* agents.

In particular, DAI and MAS provided architectures and platforms to design and implement autonomous agents. This fact contributed significantly to establishing a simulation technique called multi-agent-based simulation (MABS), an approach that has produced a large body of simulation results of social and complex phenomena; in particular, the reconstruction of the more traditional approach of cellular automata, thanks to new MABS technical and theoretical instruments. For a review of simulation studies based on cellular automata, see Hegselmann, (1997), and for a comprehensive view of MABS, please refer to Sichman (2008).

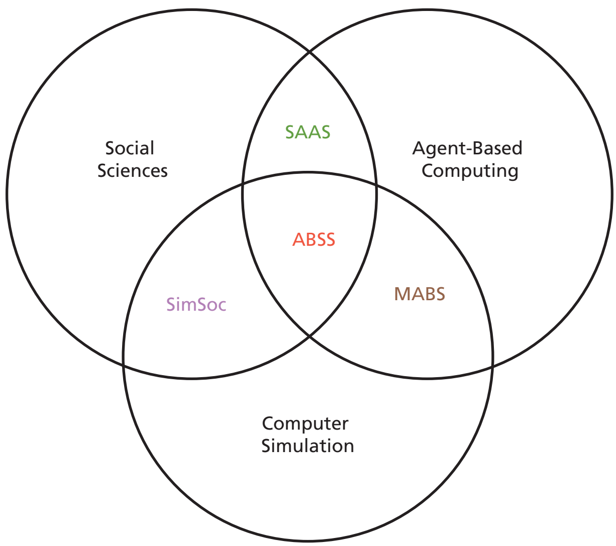
The multi-agent-based simulation approach strengthened the potential of computer simulation as a tool to theorize about scientific issues in complex and social systems. In particular, the notion of a computational agent, implementing cognitive capabilities (Doran, 1998), is encouraging the construction and operation of *artificial societies* (Nigel and Conte, 1995; Epstein and Axtell, 1996).

1.3 Multi-Agent-Based Simulation (MABS)

In Davidsson (2002), Paul Davidsson defines the *Agent-Based Social Simulation* (ABSS) domain research as “the use of agent technology for simulating social phenomena on a computer”, and characterises it by the intersection of three scientific domains: *agent-based computing*, *social sciences*, and *computer simulation*, as shown in figure 1.

Agent-based computing is considered to be a computer science subdomain, whose goal is to model, design and implement artificial agents. On the other hand, social sciences aim to study interactions among social entities, like social psychology, management, policy, and some areas of biology. Finally, computer simulation proposes different techniques for simulating any phenomena on a computer, as discrete event, object-oriented, and equation-based simulation. It provides a more detailed understanding of the phenomena, allowing experiments that cannot be made in the real world, or whose cost and time involved would be prohibited.

FIGURE 1
The intersections of the three areas defining ABSS



Source: Davidsson (2002).

Any combination of two of these domains presents interesting challenges and has some interesting work being currently carried on:

- *Social Aspects of Agent Systems (SAAS)*: intersection between social sciences and agent-based computing, it is mainly concerned with the study of social constructs of both human and biological societies, that can serve as inspiration to develop computational models for implementing social-based techniques, such as norms, institutions, organizations, cooperation, competition etc.
- *Multi Agent Based Simulation (MABS)*: intersection between computer simulation and agent-based computing, it aims to use agent technology for simulating any phenomena on a computer.
- *Social Simulation (SocSim)*: intersection between the social sciences and computer simulation, it is interested in simulating social phenomena on a computer, using any simulation technique; typically, it uses simple

models of the simulated social entities, like cellular automata and objects, resulting in interactions that are not too much complex.

Hence, ABSS could be seen as a particular specialization of SocSim, by aggregating software agents, with more powerful cognitive models and richer communications and interaction mechanisms.

Quoting Davidsson (2002), the MABS approach, as well as other micro simulation techniques, present some advantages to simulate complex phenomena:

> The contribution from agent based computing to the field of computer simulation mediated by ABSS is a new paradigm for the simulation of complex systems with much interaction between the entities of the system. As ABSS, and other micro simulation techniques, explicitly attempts to model specific behaviors of specific individuals, it may be contrasted to macro simulation techniques that are typically based on mathematical models where the characteristics of a population are averaged together and the model attempts to simulate changes in these averaged characteristics for the whole population. Thus, in macro simulations, the set of individuals is viewed as a structure that can be characterized by a number of variables, whereas in micro simulations the structure is viewed as emergent from the interactions between the individuals. Parunak, Savit and Riolo (1998) compared these approaches and pointed out their relative strengths and weaknesses. They concluded that (...) agent-based modeling is most appropriate for domains characterized by a high degree of localization and distribution and dominated by discrete decision. Equation-based modeling is most naturally applied to systems that can be modeled centrally, and in which the dynamics are dominated by physical laws rather than information processing.

Hence, we think that the same conclusions derived by Davidsson for the advantage of using MABS techniques to address social phenomena hold if we consider other complex, but not necessarily social, phenomena. In other words, if we substitute in figure 1 the social science domain by other one related to the complex phenomena we want to study, like Physics, Environmental Sciences, or Traffic Engineering, we would possibly have the same advantages of using agent-based techniques to analyze this phenomena.

Thus, we believe that MABS techniques may be seen as a major substrate for simulating any complex phenomena.

1.3.1 MABS Advantages and Limitations

The main advantages of a MABS approach are the following ones (Nigel and Troitzsch, 2005):

1) The experimental hypotheses are expressed at the individual level, and thus easier to model, implement and visualize;
2) By specifying the interaction rules between the agents, in a simple way, one can model complex dynamics patterns in the societal level;

3) The models themselves are the experimental objects, i.e., they are simulated, which increases the understanding of their positive and negative aspects.

One the other hand, their major drawbacks are the following ones (Nigel and Troitzsch, 2005):

1) The exact reproduction of the complexity of the real system, including 2nd. order emergence (micro/macro link) is very difficult to obtain;
2) Due to the great number of local interactions, possibly distributed in several abstraction levels, it is very difficult in some cases to understand how the results are produced;
3) Validation is a hard task, as discussed in section 2.2.

1.3.2 MABS Goals

An exploratory survey of the structure of interdisciplinary research in Agent-Based Social Simulation is presented in David et al. (2004). One hundred and ninety six researchers participated in a survey, called SimCog survey, completing an on-line questionnaire. The questionnaire had three distinct sections: a classification of research domains, a classification of models, and an inquiry into software requirements for designing simulation platforms.

The survey results allowed to disambiguate the variety of scientific goals and modus operandi of researchers with a reasonable level of detail, and to identify a classification of agent-based models used in simulation.

In particular, researchers were motivated to use MABS for different reasons;

- *Artificial social models*: to model and simulate artificial societies that do not necessarily reference a concrete target or specific theory about the real world, but only some theory or proposed idea of abstract nature;
- *Social-scientific models*: in this trend, researchers use the theoretic framework of social and/or environmental sciences to model social and environmental phenomena. The target systems are directly observable, or those for which there is some meaningful evidence about their existence. Two main directions can be detected:
    - *Socio-cognitive models*: to model socio-cognitive or sociological theories and implement computational animation of logical formalisms, in order to refine/extend social theories and check its consistency;
    - *Socio-concrete models*: to model and simulate concrete social systems based on direct observation and statistical data, in order to understand social and institutional processes and phenomena;

- *Prototyping for resolution*: to model and simulate multiagent systems to explore multiagent system requirements and intended behaviours, for use in real environments and general-purpose engineering.

On the other hand, Amblard (2010) classifies the possible goals of MABS in three distinct groups:

- *Comprehension:* the goal is to have a better undertanding of a social/complex phenomena. This goal can be achieved by the test/elaboration of hypotheses, which can be considered as a kind of prospective simulation, and by the formalization/verification of complex systems theories;
- *Decision:* the goal is to use MABS as a tool to help stakeholders to makedecisions in complex settings. This can be achieved by doing predictive simulation for decision-making in order to test different scenarios through simulation, and/or by constructing artifacts for helping negotiation and/or coordinated management;
- *Participatory Simulation:* the goal is to use MABS as a tool for enhance stakeholders and/or students to interact in a common complex environment, aiming training or teaching purposes. This feature is also known in the management domain as Serious Games.

2 MABS DEVELOPMENT METHODOLOGY

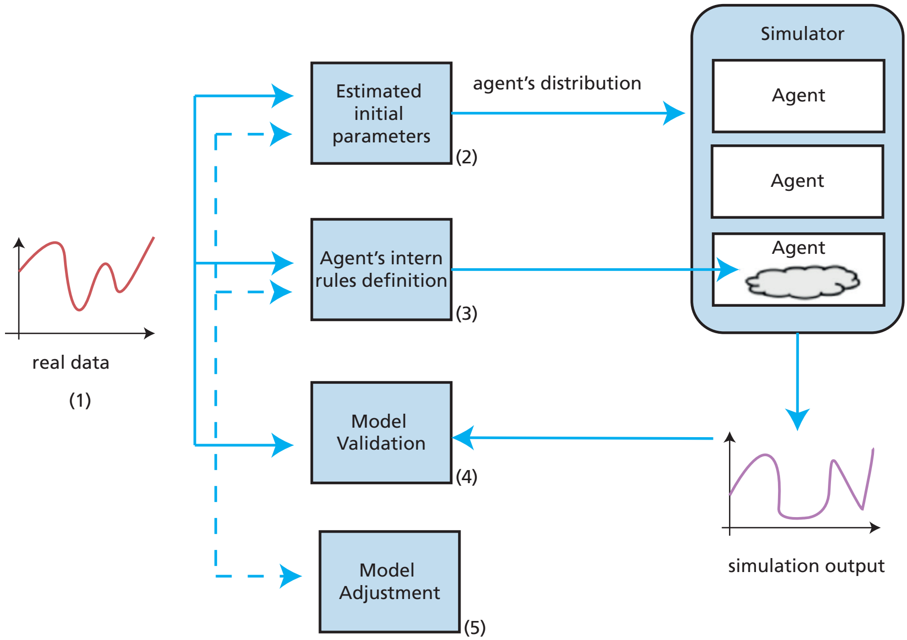
In this section, we show the several steps that one must face to design, implement and test a MABS experiment. We also briefly discuss some fundamental issues, like verification, validation and calibration. In the sequence, we indicate how one can enhance the experiment's readability and repeatability.

2.1 Development steps

Considering the class of socio-concrete models introduced in section 1.3, the classic steps to develop a MABS of a complex phenomenon are the following (Hassan, Pavon and Nigel, 2008):

1) real-world data collection;
2) development of an agent model and a simulation model driven by an underlying theory and by empirical data collected;
3) definition of initial parameters, based on surveys and censuses;
4) implementation of simulation and generation results;
5) validation of the simulation model by comparing the results with the data collected, which must necessarily be different from those used to construct the model.

FIGURE 2
MABS development steps



Elaborated by the author.

Figure 2 illustrates these sequence of steps. In step 1, we collect real world data. Traditionally, this has been an ad hoc process, and basically collected data remained static. As it became common the spread of new forms of human interaction heavily based on the Internet and providing thousands of individuals opinions and relations, it has then become possible to capture dynamic data flows, which reflect the change in the behavior of individuals over periods of time. Such a scenario seems more suitable for social simulations, since society is essentially a complex system as a result of dynamic processes, implying that the simulation should consider that people have the ability to identify and respond to emerging phenomena. This means that it is necessary that the input data should reflect changes in the communication structure and its impact on human behavior. However, currently there are no well established techniques that allows to incorporate flows of data restricted to specific periods, i.e. time windows in social simulation models are still in the border of the state of art.

Step 2 consists on defining the agents behavior. At this step, the rules and external conditions that guide the behavior of agents are defined on the basis of those aspects that are considered relevant in the context of the simulation. The huge number of previously developed theories then gains a considerable importance, since these theories indicate the relevant factors in the human decision making process.

However, this modeling process becomes almost a craft process when deciding on which aspects are discarded and which are incorporated into the agent decision making process. Furthermore, in situations where MABS is used to test possible scenarios, one needs to ensure a homomorphism between the simulation model and the real world, i.e., there must be a mapping between simulated and real data. When analyzing data collected from the real world, there must be a judgment on which factors in the process of the agents' internal decision making are crucial for determining the behavior of the system as a whole. Being a complex phenomenon, and given the nonlinearities of the system, such a task is far from being trivial. In the state of art, there is no formal method yet to help defining these factors.

In step 3, data obtained from surveys and censuses are used as MABS inputs. This usually requires some definition of the simulation parameters, such as initial conditions values and exogenous factors. In general, parameters such as the percentage of the society's agent profiles distribution are defined in two ways (Hassan, Pavon and Nigel, 2008):

- randomly, based on a uniform distribution, which may not represent the real world. Typically, the simulation final result is considered as the aggregation of partial simulation results generated from several rounds, each of them initialized with a different random value. In this approach, it is considered that the real world probably has similar values to those obtained in several simulation rounds, which is not necessarily true;
- based on empirical data collected through research. In this case, micro-simulations techniques, such as Gupta and Kapur (2000) may be used to guide the choice of simulation parameters. This approach was quite successful in traffic simulations, but it seems inappropriate to social simulations, since parts of the system captures constituents *i*) individually, i.e. without considering the social interaction and interference of communication structures on the behavior of agents; and *ii*) statically, thus reflecting a momentary picture of the system at a given point in time.

After running the simulation, the results must be validated with the data collected in the real world to establish its reliability. This activity, represented in step 4, is extremely important, although still very controversial.

Step 5 shows the simulation correction module, that attempts to calibrate the system whenever a predefined error threshold is exceeded. By applying some techniques, it is possible to identify whether the divergence of data is systemic, i.e. the agent decision rules should be changed, or it is merely a normal discrepancy caused by different initial random conditions. In figure 2, the output dashed line of this module indicates that this improvement is optional, and does not need to be performed necessarily if the deviation in the simulation results is within acceptable limits.

These two last steps are discussed in detail in the sequence.

2.2 Verification, validation and calibration

As mentioned by David, Sichman and Coelho (2005), the first thing that should be borne in mind is that the computer science meaning of the terms *verification* and *validation* is quite different from the meaning usually given in the social sciences. Nevertheless, both terms are used in social simulation, often with disparate semantics.

For the classical theory of computation, the role of program verification is to ascertain the validity of certain output as a function of given input, regardless of any interpretation given in terms of any theory or any phenomenon not strictly computational. The execution of a program is understood, in this sense, as a calculus of formal inference, which manipulates symbols without regard to their content.

Another kind of experimental evaluation, which may be confounded with the latter, is called program validation. The role of validation is to ascertain that the execution of a program behaves according to the relatively arbitrary expectations of the program end-users.

In their book (Nigel and Troitzsch, 2005), Nigel Gilbert and Klaus Troitzsch state that in the case of SocSim (and MABS) verification is difficult since many simulations include random number generators; hence, every run is typically different and only the distribution of results can be theoretically anticipated. One hence needs to "debug" the simulation carefully; this may be done using a set of test cases, for instance those corresponding to boundary conditions and/or threshold values, when the outcomes values can be easily predicted. A good practice is to repeat these test cases whenever a major change in the model is done, to ensure that the outcomes are still correct. If possible, an automatic mechanism to run the test suite and record the results is desirable; this mechanism may even highlight differences that need attention, using a version control system, as provided in some programming environments, to identify the versions responsible for the results.

On the other hand, validation aims to assess whether the simulation is a good model of the target phenomena: if a model can be relied on to reflect the behaviour of the target, then we can say that it is "valid".

Typically, validation is performed by comparing each simulation result, on an individual basis, with the corresponding real value. Several statistical methods can be used for this purpose, such as R2 and mean absolute error. It should be emphasized, however, that this type of point-to-point validation is rarely obtained in scenarios with random variations of their conditions; particularly in chaotic systems, small fluctuations in the initial conditions change dramatically the system final trajectory (Sterman, 2000). Thus, usually a simulation model is considered sufficiently faithful when it presents the same variations observed in the real world in the frequency, amplitude and phase of the system's oscillations.

According to Nigel and Troitzsch (2005), validation is extremely hard in SocSim, for several reasons:

- sometimes, both the model and the target are likely to be stochastic processes, and consequently validation would depend on the expected statistical distribution of the output measures. Unfortunately, in SocSim these distributions are rarely known in advance and are not easy to estimate;
- many simulations are path-dependent, i.e., their outcomes depend on the initial conditions, and these latter may be very sensitive to the values of some models's assumptions;
- there are always some aspects of the target that are irreproducible by the model;
- sometimes, the model may be correct, but the data about the target are not, or are a result of some assumptions and estimations.

Artificial social models, as shown in section 1.3, do not refer to a concrete target, and in this case verification and validation are hardly distinguished.

Once a model is verified and validated, one needs also to perform a *sensitivity analysis*, i.e., trying to infer the extent to which the behaviour of the simulation is sensitive to the initial assumptions which have been made. The user must change the initial conditions and parameters of the model by a small amount, rerun the simulation, and observe eventual sensible differences in the outcomes. This is done repeatedly, while systematically changing the parameters. In SocSim, as the number of parameters is very high, this leads to a combinatorial explosion. One technique to avoid this problem is to vary these parameters randomly, thus generating a distribution of outcomes.

Model calibration is another important issue in any simulation experiment. It consists on adjusting an already existing model to a reference system. In general, this is done by adjusting model parameters to a set of given samples from the reference system. A formal approach to simulation calibration is proposed in Hofmann (2005), where the author shows that this problem is NP-complete.

Regarding MABS calibration, a nice work is described in Fehler, Klügl and Puppe (2006). The authors state that calibration of MABS models pose big problems for standard calibration techniques, due to the large parameter search spaces, long simulation run times, different observation levels upon which the model needs to be calibrated and uncertainties in the structural model design. Regarding this latter, sometimes it is not clear what properties and behavior, i.e. modeled structure of the real-world agent, that actually lead to the measurable aggregate values.

Therefore, this leads to a rather high uncertainty about a valid model structure and consequently about a valid parameter setting. In their work, they present some methods to improve the calibration process of agent-based simulations.

Another interesting approach is presented in Windrum, Fagiolo and Moneta (2007), where the authors describe three alternative methodological approaches used in agent-based economics to calibrate and empirically validate agent-based models.

2.3 Readability and repeatability

A criticism that MABS methods suffer, when compared to traditional analytical methods, is the issue of repeatability of experiments. While a mathematical equation generates the same solution as many were the times it resolves, it probably does not occur with a simulation.

The ODD (Overview, Design concepts, and Details) protocol (Grimm et al., 2006) was published in 2006 to standardize the published descriptions of individual-based (IBM) and agent-based models (ABMs). The primary objectives of ODD are to make model descriptions more understandable and complete, thereby making ABMs less subject to criticism for being irreproducible. According to the authors, “the basic idea of the protocol is always to structure the information about an ABM in the same sequence.”

The protocol is composed of seven elements, which can be grouped into three blocks:

- the Overview block consists of three elements: Purpose, State variables and scales, and Process overview and scheduling. They provide an overview of the overall purpose and structure of the model;
- the Design concepts block provides a common framework for designing and communicating ABMs. The protocol also include some checklists related to such design concepts, that are not mandatory, but give a better idea of the design philosophy: emergence, adaptation, fitness, prediction, sensing, interaction, stochasticity, collective and observation;
- the Details block specifies information about the initialization, inputs and eventual submodels.

In 2010, the protocol was reviewed and gained an update, due to some feedback suggestions given by the protocol users (Grimm et al., 2010). Figure 3 presents the original and updated elements of the protocol.

FIGURE 3
The seven elements of the original and updated ODD protocol

	Elements of the original ODD protocol (Grimm et al., 2006)	Elements of the updating ODD protocol
Overview	1. Purpose 2. State variables and scales 3. Process overview and scheduling	Purpose Entities, state variables, and scales Process overview and scheduling
Design Concepts	4. Design concepts • Emergence • Adaptation • Fitness • Prediction • Sensing • Interaction • Stochasticity • Collectives • Observation	4. Design concepts • Basic Principles • Emergence • Adaptation • Objectives • Learning • Prediction • Sensing • Interaction • Stochasticity • Collectives • Observation
Details	5. Initialization 6. Input 7. Submodels	5. Initialization 6. Input data 7. Submodels

Source: Grimm et al. (2010).

3 MABS PLATFORMS

In this section, we present the main characteristics of some of the most used computational tools to implement MABS. We start by characterizing the pattern that the development of these platforms has followed. We then detail six platforms, chosen by their different main concepts, underlying programming languages and programming skills required from the users. We then conclude by presenting a comparative analysis of these tools.

1.1 Historical evolution

As pointed out by Nigel and Bankes (2002), the evolution of MABS platforms have followed the same pattern previously traced by statistical software.

In a first phase, started in the early 1990s, most researchers developed their models *using conventional programming languages*, such as C, Java and Smalltalk. Such an approach presented many disadvantages: basic models and algorithms had to be continuously reimplemented, graphical libraries were not adapted to dynamic modeling and understanding and accessing the code was a task limited to the experts on the language and/or the compiler.

In a second phase, *libraries of routines* were designed and implemented, so that they could be more easily included in one's own purpose-build program. Although having a great advantage compared to the task of writing (and validating) an own program, they still required a suitable programming knowledge from the developer in order to use/adapt/enhance the library code.

Finally, the breakthrough came with the design and development of *packages*', i.e., a set of routines assembled and accessed by a common standardized user interface, of which SPSS and SAS are the best-known early examples. Obviously, this approach has a limitation: quoting the authors of the article, "However, to ensure that they are sufficiently straight-forward for the target audience, some sacrifices in functionality have had to be made."

We have had a great advance in the last 10 years since the publication of this article. Several MABS platforms have been proposed in this period. In the following subsections, some of these platforms will be described, highlighting their major characteristics. This description is based on the documentation of the platforms and on some surveys (Railsback, Lytinen and Jackson, 2006; Allan, 2010). After presenting the platforms, we provide in section 3.8 a comparative analysis of their characteristics.

3.2 Swarm

Swarm[3] (Minar et al., 1996) was the first agent based modeling and simulation platform released. It was created at the Santa Fe Institute in 1994, and it was specifically intended for artificial life and complex systems applications. Recently, the project development and management moved to the Swarm Development Group.

Swarm was designed as a general language and toolbox for MABS, intended to be used in different scientific domains. In its design, there is a clear conceptual separation between the pieces of software that implement a model and those others aimed for observing and conducting experiments on the model. Differently from other platforms, this distinction between the actual model and the software needed to observe and collect its data facilitates to change one part without influencing the other.

Another key concept is the design of a model as a hierarchy of *swarms*. A swarm is composed by a set of objects and a schedule of the actions that these objects execute. Swarms can be defined hierarchically: they can contain lower level swarms, and be part of higher level swarms. In this way, emergent phenomena can be easily modeled. When composing these swarms, their corresponding schedules are conveniently integrated. A very simple model, for instance, may be formed by one single "model swarm" associated to an "observer swarm", that serves to assess the model behavior.

Swarm was designed before the domain of Java as a standard object-oriented language, and it was implemented in Objective-C, since this language, differently

3. Available at: <http://savannah.nongnu.org/projects/swarm>.

from C++ for instance, do not have strong typing, and hence allows that a model schedule can request some actions to a list of objects of unknown types. By using its own internal data structures and memory management to implement model objects, a user is able to design observer swarms that implement "probes", thus allowing users to monitor and control any simulation object. These objects can provide both real time data presentation and storage of data for later analysis.

Swarm provides a set of libraries for building models and analyzing, displaying and controlling experiments on those models. Since these libraries are coded in Objective-C, a user would have to program in this language to modify/enhance these libraries. Recently, a version called Java Swarm was designed to provide, with as little change as possible, access to Swarm's Objective-C library from Java. However, this is not a Java version of the platform: it simply allows Java code to pass messages to the Objective-C library with workarounds to accommodate strong typing in the Java language.

Swarm is probably still the most powerful and flexible MABS platform. However, it has a very steep learning curve. In order to use efficiently the platform, a modeler must have at least some previously acquired programming skills in Objective-C, and possibly in Java, and must be familiar with object-orientated design.

3.3 Repast

RePast[4] (Recursive Porous Agent Simulation Toolkit) (North et al., 2005) is a platform that was developed at the Social Science Research Computing Lab of the University of Chicago. It seems that its development aimed different objectives: *i*) to implement in Java a system whose functionality would be equivalent to Swarm; *ii*) to provide libraries and tools specifically designed for the social science domain; and *iii*) to deliver a system that would enable inexperienced users to build models more easily.

Repast did not adopt all of Swarm's design choices: for instance, it does not implement swarms. It is a Java-based platform, and hence the user developing a simulation ideally needs skills to program this language.

The authors report in North, Collier and Vos (2006) three implementations for the system: *i*) Repast for Java (Repast J), the original Java language implementation of the Repast specification; *ii*) Repast .NET, a Microsoft .NET implementation of the Repast specification written in the C# language; and *iii*) Repast for Python Scripting (Repast Py), which is a rapid application development (RAD) tool for producing Repast simulations in which agent behavior is scripted using the Python computer language. As a RAD tool, Repast Py differs significantly

4. Available at: <http://repast.sourceforge.net>.

from Repast J and Repast.NET. In Repast Py, user services are presented in a visual manner through a separate application whereas Repast J and Repast .NET are frameworks that are accessed through standard programming languages such as Java or C#. It is quite useful for novices when they need to begin to construct a simulation model.

More recently, a new release was delivered, called Repast Simphony (Repast-S). This free and open source toolkit was developed at Argonne National Laboratory, and it presents several tools for visual model development, visual model execution, automated database connectivity, automated output logging, and results visualization. Finally, there is also a C++ based implementation release, called Repast for High Performance Computing (Repast-HPC), which is intended to be used in massive simulations running in distributed computers. This release, however, do not present all then graphical interfaces of the other releases.

Quoting Railsback, Lytinen and Jackson (2006):

> Repast-S probably now has the greatest functionality of any AMBS package. It supports a wide range of external tools for statistical and network analysis, visualization, data mining, spreadsheets, etc. Point and click modeling in 2D and 3D is supported. Models can be checkpointed in various formats including XML. The discrete event scheduler is concurrent and multi-threaded, various numerical libraries are available, e.g. for random numbers and distributed computing is supported using the Terracotta Enterprise Suite for Java.

3.4 Mason

Mason[5] (Luke et al., 2005) is an open source and free Java-based platform, developed by a joint effort of two units of George Mason University: the Computer Science Department and the Center for Social Complexity. It is not based on any other previously developed toolkit. It is a general purpose platform, not aimed to a specific domain.

The main goal of the system is to offer a more concise and performant (faster) option to Repast. It focusses on models whose simulations take a long time, that are computationally demanding, and that involve a huge number of agents whose number of interactions is very high. Design choices seem to have been driven largely by the goals of maximizing execution speed and assuring complete reproducibility across hardware. Hence, the ability to dynamically attach/detach graphical interfaces to a simulation and to resume/stop a simulation while moving it among different computers was considered a priority requirement in its design. Consequently, core models run independently of visualization modules.

5. Available at: <http://cs.gmu.edu/_eclab/projects/mason>.

In summary, Mason is a fast, easily extendable, discrete event MABS platform written in Java. It was designed to serve as the basis for a wide range of MABS tasks, ranging from swarm robotics to machine learning and to social complexity environments. Mason contains both a model library and an optional suite of visualization tools in 2D and 3D.

3.5 NetLogo

NetLogo[6] (Wilensky, 1999) is a MABS platform originally conceived in 1999 by Uri Wilensky, developed at the Center for Connected Learning and Computer-Based Modeling, Northwestern University. NetLogo, which originally was called StarLogoT, is a high level platform, and provides a simple yet powerful programming language, built in graphical interfaces and comprehensive documentation.

The platform is based on the Logo language, which is a dialect of Lisp; consequently, it does not present all the rich control and commands of a standard programming language. NetLogo aimed to develop a certain class of models, i.e., agents that move and act concurrently on a spatial grid, and whose behaviors result from local interactions.

Quoting Allan (2010), "NetLogo clearly reflects its heritage from StarLogo as an educational tool, as its primary design objective is ease of use. Its programming language includes many high level structures and primitives that greatly reduce programming effort." Hence, it is the ideal platform for modelers that do not have programming skills and for beginners in the field.

NetLogo is a really professional platform, both in its product design and associated documentation. It also comes with a library of models, containing a huge set of pre-written simulations addressing different domains in the natural and social sciences, including biology and medicine, physics and chemistry, mathematics and computer science, economics and social psychology.

An example of use of the NetLogo platform, in the context of game theory and learning, is presented in section 5.2.

3.6 Cormas

Developed by the Green team in CIRAD, France, whose main interest is to develop and test models for managing natural renewable resources, Cormas[7] (Bousquet et al.,1998) is a powerful platform when one wants to focus on interactions between stakeholders about the use of natural renewable resources.

6. Available at: <http://ccl.northwestern.edu/netlogo/>.
7. Available at: <http://cormas.cirad.fr>.

According to the information available in the project site:

> Cormas is a simulation platform based on the VisualWorks programming environment which allows the development of applications in the object-oriented programming language SmallTalk. Cormas pre-defined entities are SmallTalk generic classes from which, by specialization and refining, users can create specific entities for their own model.

The Green team is influenced by the ideas of two different research associations: the International Society of Ecological Economics (ISEE) and the International Association for the Study of Common Property (IASCP). The former is interested to integrate ecological systems within economic frameworks, and their models are often based on dynamic systems modeling to represent the flow of energy, information or money. The latter focus on the management of common property, particularly renewable natural resources, whose techniques are quite often based on game theory in which individual behaviors and interactions are taken into account. Lastly, a regional approach uses GIS (Geographical Information Systems) as its main modeling tool. Cormas was therefore developed to cope with these different influences.

Particularly, the group has developed a framework called *companion-modelling* (Barreteau, 2003), which enables stakeholders to decide long-term objectives on the basis of a shared conception of how the present situation should evolve. The entire mediation approach presupposes that the stakeholders are well informed of the issues dividing them and of the fact that they all have an interest in solving the original problem. From a technical point of view, the framework uses both MABS and role-playing games. Other authors called this junction of technologies as *participative simulation* (Guyot and Honiden, 2006).

An example of use of the Cormas platform, in the context of participative simulation, is presented in section 5.3.

3.7 Gama

Gama[8] (Grignard et al., 2013) is a MABS platform developed by several teams under the umbrella of the IRD/UPMC international research unit UMMISCO, comprising the Vietnam National University (Vietnam), CNRS/University of Rouen (France), CNRS/University of Toulouse 1 (France), University of Can Tho (Vietnam) and CNRS/University Paris-Sud (France). It is one of the more recently developed MABS platforms.

Gama's main two differences with respect to other MABS platforms are *i*) a richer integration of geographical vector data (series of coordinates defining geometries); and *ii*) the facility to define multi-level models. By using a modeling

8. Available at: <http://doc.gama-platform.org/>.

language based on XML, called GAML, the platform facilitates the definition of rather complex models, which integrates individual agents, other entities of different scales and geographical vector data. By providing such integration, Gama allows the use of more powerful tools, like Geographic Information Systems (GIS) spatial analysis, to manage these data.

According to the authors, there are three different ways to integrate geographical vector data in a MABS platform, from a simpler to a richer representation:

- geographical vectors can simply be read/written from/to external files and databases, thus integrated seamlessly to the underlying platform;
- the platform can represent these data as a "background layer", constituted of geographical objects. Agent can thus move, evolve and interact according to the constraints defined in this layer;
- an *agentification* process is carried out, meaning that each geographical object is considered as an agent as well.

Regarding multi-scale representation, the platform enables to model an "agent" to represent any individual or aggregation/structure of individuals of the reference system, at any spatial scale and across different time horizons. In this way, the modeler can choose freely the reference entities that will be represented by agents; the choice depends exclusively on the abstraction level that the modeler wants to work with.

According to the authors, current MABS platforms lack support to represent these multi-level structures as explicit entities in the model, as well as tools to detect them. Consequently, when modelers need to represent these structures and follow their dynamics during the simulation, they face some difficulties. The development of the Gama platform intends to cover this gap.

3.8 Comparative Analysis

The set of ABS and MABS platforms presented in the last subsections is far from being complete. In fact, in the last fifteen years the community has developed a huge number of libraries, toolkits and platforms, each one with different purposes and characteristics: some are built for general purpose modeling, while others focus on a particular domain; some are open source, some are closed source, and others are proprietary; some of them offer a simple user interface, while others require from the user skills in programming techniques.

As a consequence, several surveys were produced to compare ABS and MABS platforms, in order to make it easier for a modeler to choose which would be the "best option" for modeling his problem. Unfortunately, there is not an easy answer for this question, since we can compare these platforms along different dimensions and aiming to different purposes.

Perhaps the most seminal survey was the one produced by Railsback, Lytinen and Jackson (2006). These authors examine in detail four platforms: NetLogo, Mason, Repast, and Swarm. To illustrate how difficult is to compare these systems, the authors showed that they differ even in the terminology adopted, as shown in figure 4.

FIGURE 4
Terminology difference among platforms

Concept	Term			
	MASON	NetLogo	Repast	Swarm
Object that builds and controls simulation objects	model	observer	model	model swarm
Object that builds and controls screen graphics	model-WithUI	interface	(none)	observer swarm
Object that represents space and agent locations	field	world	space	space
Graphical display of spatial information	portrayal	view	display	display
User-opened display of an agent's state	inspector	monitor	probe	probe display
An agent behavior or event to be executed	steppable	procedure	action	action
Queue of events executed repeatedly	schedule	forever procedure	schedule	schedule

Source: Railsback, Lytinen and Jackson (2006).

In order to evaluate how easy would be for a modeler to use such platforms, they created a template, called "StupidModel", composed of various levels, and they used their experience in simulating this model to evaluate and compare the platforms. In each new level, more capabilities were added in order to see how the platforms performed when dealing with more complex issues. In the first level, for instance, they checked just the underlying environment and verified how the agents were displayed in their environment. In level 2, agent had more actions added to their repertory and they examined how the scheduling of these actions was implemented by the different platforms. They finished by reaching 15 different levels, through which they examine characteristics such as environmental issues, model structure, agent scheduling, file input and output, random number generation, and statistical capabilities.

A second survey was presented in Tobias and Hofmann (2004). It compares four different Java-based SimSoc platforms, using three different criteria that were conveniently weighted to give a final result: *i*) general criterion, composed of license, documentation, support, user base and future viability; *ii*) modeling and experimentation criterion, composed of support for modeling, support for simulation control, support for experimentation, support for project organization, ease of use, support for communication and ease of installation; and *iii*) modeling options criterion, composed of large number of complex agents, inter-agent communication, generation of agent populations, generation of networks, management of spatial arrangement, and dynamic structure change. By combining and weighting these criteria, Repast was the highest scored platform, as shown in figure 5.

FIGURE 5
Weighted total scores of the evaluated simulation frameworks

Criterion	RePast	Swarm	Quicksilver	VSEit
General (78)	71	62	48	44
Support for modeling and experimentation (186)	113	95	94	80
Modeling options (168)	127	109	99	103
Total	**311**	**266**	**241**	**227**

Source: Tobias and Hofmann (2004).

In Castle and Crooks (2006), the authors were interested in finding principles for MABS with the aim of developing geospatial simulations, in particular to aggregate Geographical Information Systems (GIS). However, according to the authors, “GIS are not well suited to dynamic modeling (e.g. ABM). In particular, problems of representing time and change within GIS are highlighted”. Having this goal in mind, they analyzed several MABS platforms. Figure 6 presents the results obtained for some shareware/freeware simulation/modeling systems.

More recently, in Nikolai and Madey (2009) one can find a kind of compilation/extension of these previous surveys, considering both additional criteria and other platforms. The authors have analyzed fifty three different platforms, and examined the following five main dimensions: *i*) language required to program a model and to run a simulation; *ii*) operating system required to run the toolkit; *iii*) type of license that governs the toolkit; *iv*) primary domain for which the toolkit is intended; and *v*) types of support available to the user.

Another excellent recent survey is the one presented in Allan (2010), where the author has analyzed thirty one MABS platforms, and more thirteen generic multi-agent systems frameworks. The author also presents some applications of MABS in different areas as biology, chemistry, security and supply chain. Some issues about performing MABS in high-performance computers (HPCs) are also addressed.

4 OTHER TECHNIQUES

In this section, we present other computational techniques that may be used to model and analyze complex systems. In particular, we will address two techniques: machine learning and social networks. As these techniques have a huge theoretical background, we have chosen just to introduce their main ideas in a very high-level abstraction level and present some computational tools that could implement some algorithms useful for complex systems.

FIGURE 6
Comparison of shareware/freeware-simulation/modelling systems

Open Source Simulation/Modelling Systems			
	SWARM	MASON	Repast
Developers	Santa Fe Institute / SWARM Development Group, USA	Center for Social Complexity, George Mason University, USA	University of Chicago, Department of Social Science Research Computing, USA
Date of Inception	1996	2003	2000
Website	<http:/www.swarm.org>	<http://es.gmu.edu/~eelab/projects/mason>	<http://repast.sourceforge.net>
E-mail List	<http://www.swarm.org/mai lman/listinfo>	<https://listserv.gmu.edu/archives/mason-interest-l>	<https://lists.sourceforge.net/listis/listinfo/repast-interest>
Implementation Language	Objective-C / Java	Java	Java / Python / Microsoft.Net
Operating System	Windows, UNIX, Linux, Mac OSX	Windows, UNIX, Linux, Mac OSX	Windows, UNIX, Linux, Mac OSX
Required programming experience	Strong	Strong	Strong
Integrated GIS functionality	Yes (e.g. Kenge GIS library for Raster data: <http://www.gis.usu.edu/sw arm)>	None	Yes (e.g. OpenMap, Java Topology Suite and GeoTools). Repast simulations can also be run within ArcGIS through an extension called Agent Analyst
Integrated charting / graphing / statistics	Yes (e.g. R and S-plus statistical packages)	None	Yes (e.g. Colt statistical package, and basic Repast functionality for simple network statistics)
Availability of demonstration models	Yes	Yes	Yes
Source code of demonstration models	Yes	Yes	Yes
Tutorials / How-to Documentation	Yes	Yes	Yes
Additional information	Minar et al. (1996)	Luke et al. (2004)	Agent Analyst Extension <http://www.institute.redlan. ds.edu/agentanalyst> Useful weblog: <http://www.gisagcnts.blogsp ot.com>

Source: Castle and Crooks (2006) adapted from Najlis, Janseen and Parker (2001); Parker (2001).

4.1 Machine learning

In the last decade, society has produced huge amounts of data. Interestingly, from a user point of view, both an absence of data and many non-processed (raw) data are quite equivalent: data are useless, unless we extract information from them; by information, we mean to find regular patterns underlying these data.

According to Mitchell (1997) and Witten and Frank (2011), the goal of machine learning (ML) is to build efficient algorithms that change their behavior with experience, in a way that makes them perform better in the future.

4.1.1 Basic concepts

There are basically three ML paradigms:

- *supervised learning*, where correct examples, i.e., (input, output) pairs are presented to the system;
- *reinforcement learning*, where just a performance indicator (good, bad) is presented to the system;
- *unsupervised learning*, where no prior information is given to the system, who looks for regularities and statistical measures to learn.

Inductive learning is a type of supervised learning, where the system tries to find a concept description that fits the data. In other words, the system tries to build an hypothesis to map inputs to outputs, generalizing the training examples presented to the system.

Clustering is a type of unsupervised learning, where the system tries to group similar instances into clusters. Depending on the model adopted, these clusters may be disjoint/overlapping, deterministic/probabilistic and flat/hierarchical.

These two techniques are the best candidates to be used in complex systems and MABS. The first normally is used to help to design different agents stereotypes, representing real agents in the simulated environment. The second technique is used to identify emergent patterns produced by the simulation in the meso and macro levels.

As mentioned by Witten and Frank (2011), ML is deployed in several practical applications, like processing loan applications, screening images for oil slicks, electricity supply forecasting and diagnosis of machine faults, among others.

4.1.2 Implementing machine learning

Classical algorithms for inductive learning are fully described in the litterature, like ID3 (symbolic) and Neural Networks (non-symbolic).

This is also the case for clustering, including the well known k-means algorithm. This algorithm tries to group data into a predefined number of k clusters. The algorithm considers the clusters to be disjoint, deterministic, and flat. Basically, its steps are the following:

1) Choose initially k cluster centers, for instance randomly;
2) Assign instances to clusters, based on their distance to the cluster centers;
3) Compute centroids of the clusters;
4) Repeat previous steps until obtaining convergence.

The algorithm basically minimizes an instance squared distance to cluster centers. Results can be very sensitive to the initial choice of seeds, and sometimes the algorithm can stop at a local minimum. A good technique to increase the chance of finding the global optimum is to restart the algorithm with different random seeds.

One important aspect in using k-means is to choose "the best" k. Possibles techniques include: *i*) to choose a k value that minimizes cross-validated squared distance to cluster centers; *ii*) to use penalized squared distance on the training data; and *iii*) to apply k-means recursively, starting with $k = 2$, and to stop increasing its value based on some evaluation error (Hall et al., 2009).

There are other well-established hierarchical, agglomerative, and incremental clustering algorithms available in the literature. A more detailed description of such algorithms may be found in Mitchell (1997) and Witten and Frank (2011).

4.1.3 Weka

Perhaps the best well-known repository for ML is Weka[9] (Hall et al., 2009). According to the information available in the site:

> Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from your own Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes.

Weka was developed by the Machine Learning Group at the University of Waikato, New Zealand. The name Weka comes from a flightless bird with an inquisitive nature, found only on the islands of New Zealand.

Weka is open source software issued under the GNU General Public License. It may be used for Data Mining, and can be applied to process Big Data. Recently, the authors have provided a 5 week MOOC, called "Data Mining with Weka", which contains video lectures and other useful information for using the repository.

9. Available at: <http://www.cs.waikato.ac.nz/ml/weka/>.

4.2 Social Networks

In their book (Wasserman and Faust, 1994), Wasserman and Faust characterize social network analysis as the following:

> Social network analysis is based on an assumption of the importance of relationships among interacting units. The social network perspective encompasses theories, models, and applications that are expressed in terms of relational concepts or processes. Along with growing interest and increased use of network analysis has come a consensus about the central principles underlying the network perspective. In addition to the use of relational concepts, we note the following as being important:
>
> - Actors and their actions are viewed as interdependent rather than independent, autonomous units ;
> - Relational ties (linkages) between actors are channels for transfer or "flow" of resources (either material or nonmaterial);
> - Network models focusing on individuals view the network structural environment as providing opportunities for or constraints on individual action;
> - Network models conceptualize structure (social, economic, political, and so forth) as lasting patterns of relations among actors.

The unit of analysis in network analysis is not the individual, but an entity consisting of a collection of individuals and the linkages among them.

4.2.1 Basic concepts

According to Gretzel (2001), several types of social relations can be represented through network data, like social roles (boss of, teacher of, friend of), affective relations (likes, respects, hates), and cognitive relations (knows, views as similar), among others.

From a formal point of view, social networks can be represented by graphs, where nodes represent individuals and links their relations. By adopting such representation, one can profit from the huge amount of available graph algorithms in order to calculate some network interesting properties. From an implementation point of view, due to performance issues, graphs may be implemented by matrices.

According to Wasserman and Faust (1994), the main concepts and levels of analysis in the domain are the following:

- main concepts
  - *Actor/Node/Point/Agent:* social entities such as persons, organizations, cities, etc;
  - *Tie/Link/Edge/Line/Arc:* represents relationships among actors;
  - *Dyad:* consists of a pair of actors and the (possible) tie(s) between them;

    - *Triad* : a subset of three actors and the (possible) tie(s) among them;
    - *Subgroup:* subset of actors and all ties among them;
    - *Group:* collection of all actors on which ties are to be measured;
    - *Relation:* collection of ties of a specific kind among members of a group;
    - *Social Network:* finite set or sets of actors and the relation or relations defined on them.
- levels of analysis
    - *Actor level:* centrality, prestige and roles such as isolates, liaisons, bridges, etc;
    - *Dyadic level:* distance and reachability, structural and other notions of equivalence, and tendencies toward reciprocity;
    - *Triadic level* : balance and transitivity;
    - *Subset level* : cliques, cohesive subgroups, components;
    - *Network level* : connectedness, diameter, centralization, density, prestige, etc.

Other interesting references to social network analysis are Borgatti, Everett and Freeman(2002); Hanneman and Riddle (2005) and Carrington, Scott and Wasserman(2005). An interesting recent work focusing on how social network analysis can be used to craft strategies to track, destabilize, and disrupt covert and illegal networks is described in (Everton, 2012).

4.2.2 Implementing social networks

In Kirschner (2008), an overview of the most common SocNet platforms is presented. The report was developed by the Philanthropy and Networks Exploration,[10] a partnership between the Packard Foundation and Monitor Institute, whose aim is to investigate how networks can facilitate greater philanthropic effectiveness.

The analysed platforms were identified from several sources, including the literature survey presented in Huisman and Duijn (2005). They were divided in four groups (Kirschner, 2008):

- *Advanced Academic platforms*: often used in academic environments, these tools aim to deal with sophisticated types of social network analysis, generally prioritizing performance as opposed to usability. User guides and help files are not comprehensive or are written for more sophisticated

10. Available at: <http://www.philanthropyandnetworks.org>.

audiences. Examples are UciNet/NetDraw, Guess, Iknow, NetVis module, Otter, Pajek, SoNIA;

- *Advanced Accessible platforms:* used in more general settings, including corporate environments, these tools tend to be more intuitive and easier to use than the tools for academic applications. Software help files are more comprehensive and user guides are written for a general user audience. Examples are NetMiner, Visone, InFlow (Valdis Krebs), Network Evaluation Tool (Rob Cross), Sentinel Visualizer;
- *Simple Easy to Use platforms:* these tools can be used by users less familiar with social network analysis, they are built without complex functionality and are very easy to navigate and use. Help files are simple and clear. An example is Smart Network Analyzer;
- *Online Visualization tools:* these tools are used to analyze existing data made available by users, and are quite often simple to use, with intuitive functionality. Examples are Xigi.net, TouchGraph, Network Genie.

In the sequence, we will detail two of these platforms.

4.2.3 UciNet/NetDraw

UciNet[11] is a downloadable software program that can read and write social network data files. NetDraw is bundled with UciNet and it is used to read and display network visualizations. UciNet is widely used in academia: its file format can be used with a number of other analysis and visualization platforms.

Although primarily used in academic environments, UciNet is also used by consultants that have developed customized versions of the software to suit more specific needs. UciNet is free for individual use, but has a cost for a business license.

Its main advantages are the following: *i*) it is flexible and can import data from different files formats, including Excel; *ii*) it supports more complex types of network analysis; and *iii*) it is compatible with many different visualization platforms.

On the other hand, its major drawbacks are the following: *i*) it is more difficult to use for simple social network analysis tasks; *ii*) the online help resources are intended for more sophisticated audiences; *iii*) it is quite difficult to filter data that is being viewed; and *iv*) NetDraw's visualization does not allow output formatting.

A nice chapter describing how to get started in UciNet/NetDraw, among other tools, is presented in Everton (2012).

11. Available at: <http://www.analytictech.com>.

4.2.4 NetMiner

NetMiner[12] is a software tool for exploratory analysis and visualization of network data. It can handle large amounts of data and enables the user to conduct both simple and more advanced types of analysis, including a number of statistical procedures. Data can be visualized based on several different types of network visualization algorithms, and statistical results can be charted using graphs.

NetMiner is suitable for a range of audiences including academic, corporate, and general consumer. It is a proprietary platform, but student use licenses are very cheap.

Its main advantages are the following: *i*) it presents a convenient and intuitive user interface, easy to use for less advanced users; *ii*) it offer a good user support through help files built into the platform, as well as documentation on using the software online; and *iii*) it offers advanced functionalities to conduct multiple types of statistical analyses and visualizations.

A drawback is the fact that it requires a basic level of technical sophistication and familiarity with social network analysis.

5 MABS APPLICATION EXAMPLES

In this section, we present very briefly three different MABS application examples to illustrate how this technique can be efficiently used in different complex systems scenarios. These applications were chosen because they address different goals, as discussed in section 1.3, and use different platforms, as discussed in section 3.

5.1 Social Networks

PartNet+ (Monteiro, 2004; Monteiro and Sichman, 2005) is a multi-agent-based simulation tool whose aim is to understand partnership formation among heterogeneous agents. It is an extension of a previous tool, called PartNet, developed by Conte and Pedone (1998).

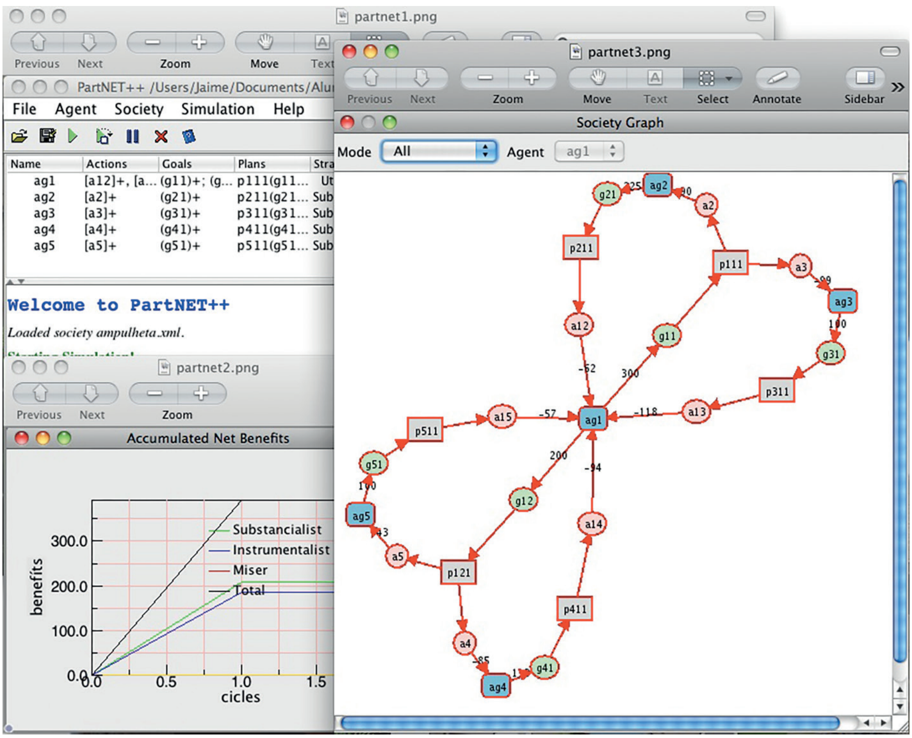
The simulator implements a social reasoning mechanism based on dependence networks, developed by Sichman (Sichman et al., 1994) and inspired on Castelfranchi, Conte and colleagues' dependence theory (Castelfranchi, Micelli and Cesta, 1992; Conte and Castelfranchi, 1992). By representing internally the goals, plans, actions and resources from each other, agents can detect their complementarity regarding the actions and resources they need in order to achieve their goals, and calculate who are the agents they depend on and who are the ones who are more susceptible to cooperate, i.e., those who also depend on them. Based on this calculus, agents

12. Available at: <www.netminer.com>.

interact by sending proposals to each other, in order to establish partnerships to achieve each other's goals.

FIGURE 7

PartNet+ interface



Source: Monteiro (2004).
Publisher's note: image whose layout and texts could not be formatted and proofread due to the technical characteristics of the original files provided by the authors for publication.

When choosing preferred partners, each agent in PartNet+ follows a strategy that dictates what kind of partnerships will be sought. There are three different strategies available, that cover most of the reasonable stereotypical choices that an agent may have when choosing partnerships:

- *Utilitarians*, that try to maximize the importance of the achieved goal while minimizing the cost of the action used;
- *Substantialists*, that choose partnerships with most important goals, no matter what the cost is;
- *Misers*, that seek the partnerships with minimum cost, no matter the goal importance is.

In figure 7, we can see the PartNet+ interface. In the main window, the simulation parameters like the agent's goals, plans and actions can be set and simulation be controlled. Additional overlay windows show graphics containing the simulation results, as the accumulated net benefit, and the dependence graph, enabling the user to visualize what dependence relations have been used in partnerships.

As discussed in section 3.1, one may use different approaches to implement MABS. In the case of PartNet+, the simulator was developed using the Java programming language. This choice was made because there was already a version of the original software to calculate dependence relations and networks available in this language. Hence, it may be the case that a legacy piece of software can determine such a choice.

Using the types proposed in section 1.3, the goal of the simulation was to implement a socio-cognitive model. Validation was not addressed by the behavior of individual agents, but rather by some aggregated values. An example of an hypothesis that was tested and validated, as expected by previous results in social sciences, is that substantialists gets better accumulated net benefits when there are more goals in the society.

This application is an illustration of the use of multi-agent-based simulation techniques in the social networks domain, namely to predict partnerships formation between agents in self-centric networks.

5.2 Game theory and learning

In Nardin and Sichman (2012), we present a simulation model for a land expropriation scenario. Such model integrates both concepts of *coalition* and *trust*, allowing the analysis of how trust influences coalition formation in the case of land expropriation.

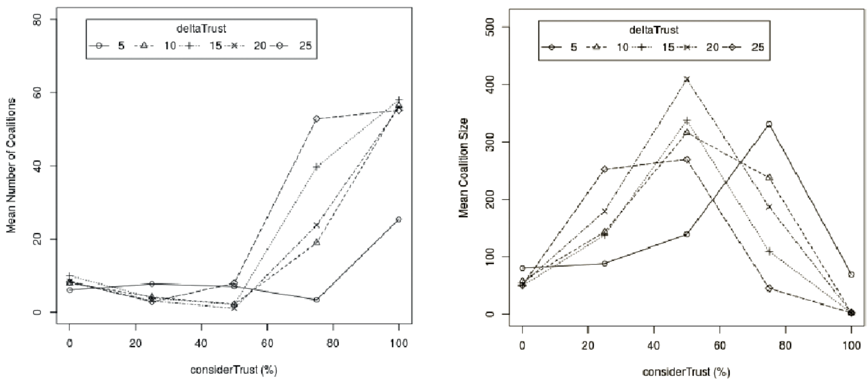
The environment consists of a population of self-interested agents, representing landowners, that are positioned in a square lattice which represents the land properties. Each landowner agent interacts with its neighbors by playing the Prisoner's Dilemma, choosing either to cooperate or to defect.

Initially, agents play independently of each other, but by analyzing their outcomes they may decide to join (or leave) a coalition. Members of a coalition cooperate with the other coalition members and defect with other agents that do not belong to the coalition. Moreover, a model parameter *tax* represents the amount that coalition members must pay for their leader in order to have the right to remain in the coalition.

The decision to join, to remain or to leave a coalition is largely based on the trust value that the landowner has gathered about its coalition leader. Such value is updated in each round, mainly based on the received payoff from the coalition leader. This variation depends on a model parameter called *DeltaTrust*, that represents the agents' *trust volatility* of their coalition leaders. Hence, when agents join a coalition they attribute an initial trust value to the coalition leader, which may increase or decrease depending on the coalition outcome. If this trust value reaches a minimal threshold, which a model parameter called *trustThreshold*, the agent decides to leave the coalition.

The main objective of the work is to identify the influence that trust exerts on landowners coalition formation, by varying the trust input parameter values and analyzing the coalition formation macroscopic patterns, calculated by considering the average value of the 10 executions of each simulation scenario. A parameter *considerTrust* represents the percentage of agents that take the notion of trust into account to decide to join, remain or leave a coalition. We were particularly interested in evaluating three macroscopic patterns at the end of the simulation: the number of remaining coalitions, their sizes, and the number of *Independent* agents. For that, three different agent trust intolerance levels were considered, corresponding respectively to *trustThreshold* values of 25 (liberal), 50 (moderate), and 75 (conservative).

FIGURE 8
Number and size of coalitions x considerTrust [tax = 25% and trust Threshold= 75]



Source: Nardin and Sichman (2012).
Publisher's note: image whose layout and texts could not be formatted and proofread due to the technical characteristics of the original files provided by the authors for publication.

Briefly speaking, the results showed that for high *tax* rates, above 50%, the system was highly dynamic, with a rapid formation and dissolution of small coalitions, and a great number of independent landowners. However, when the *tax* was set to 25%, the macroscopic behavior varied depending on the combination of the model parameters, in particular of the *trust Threshold* value. This can be observed in figure 8. In particular, in fully heterogeneous scenarios, where only half the agents take trust into account to decide to remain or leave a coalition and when *trust intolerance level* and *trust volatility* are high, respectively 75 and 20 (figure 8), fewer coalitions remained, with a higher number of agents. These values indicate that in conservative landowners and low tax scenarios, the moderate use of trust is beneficial to the formation of bigger coalitions.

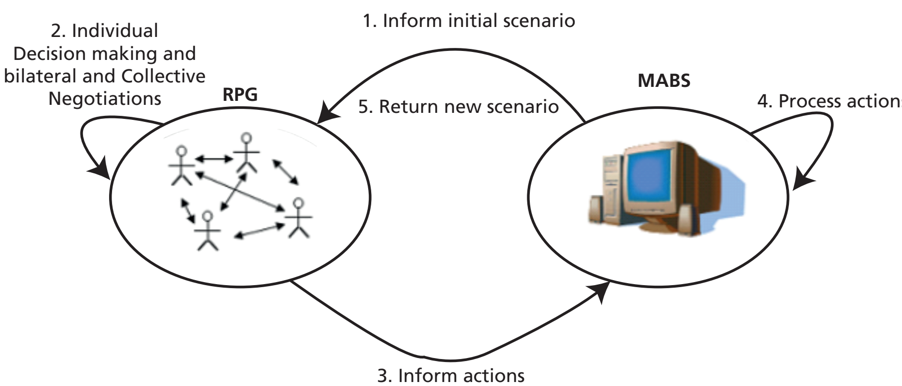
In this application, simulations were performed using NetLogo (Wilensky, 1999), described in section 3.5. It also implemented a socio-cognitive model, as mentioned in section 1.3. Validation was addressed just by comparing different models' outputs, using statistical techniques, as presented above.

This application is an illustration of the use of MABS techniques that combines game-theoretic and learning approaches, namely to predict agent coalitions stability in an expropriation land scenario.

5.3 Participative simulation

In Adamatti, Sichman and Coelho (2009), we describe a methodology called GMABS (Games and Multi-Agent-Based Simulation) that integrates MABS and Role-Playing Games (RPG) techniques. It was applied in a participative simulation scenario, whose goal was to evaluate the impact of the agents' actions in the environment. It combines the dynamic capacity of MABS with the discussion and learning capacity of RPG. This methodology is illustrated in figure 9, and is composed of 6 steps:

FIGURE 9
GMABS methodology



Source: Adamatti, Sichman and Coelho (2009).

1) Players receive all the information about the game: the roles they can assume, the actions and rules available to these roles, their common environment, and the topological constraints. When the game starts, each player defines the role he/she is going to play. At that time, each participant knows what actions he/she can execute, and the benefits and/or damages their actions can cause to the common environment.

The initial scenario also defines where the participants are physically located within the common environment and what their initial possessions are, like money, land, etc.;

2) In this step there are three different activities:

   a) Players may reason and decide about individual actions that just depend on themselves. As an example, in the natural resources domain, land owners may change their land use;

   b) Players have all the necessary information to initiate bilateral negotiations with each other. In order to negotiate, they may exchange information and make their decisions, according to the rules that must be followed by the roles they are playing. In the natural resources domain, for instance, land owners can sell their plots. Normally, these two previous activities (a and b) take place simultaneously, and their duration is defined in the beginning of the game;

After deciding about their individual actions and concluding the bilateral negotiations, players can negotiate about collective strategies for the next rounds. These collective strategies should benefit everyone or just a subgroup of players. Once more considering the natural resources domain, players are able to demand improvements in infrastructures, more jobs, lower tax values, and so on. This negotiation process of collective strategies is just a "predisposition" to define future actions: players are not really committed to keep their word and really use these strategies in further rounds. This process is very important for each player to better understand the others' objectives and strategies;

3) Players inform to the MABS tool, possibly mediated by a human operator, which individual actions were chosen and which bilateral negotiations were concluded;

4) The MABS tool computes the data, and as a result the players' actions may modify the initial scenario. Therefore, the environment properties are modified, which implies the modification of each player's data;

5) The MABS tool gives the new scenario back to the players, once again mediated by the operator. If the game deadline is not reached or the maximum number of rounds has not been achieved, the game returns to step 2.

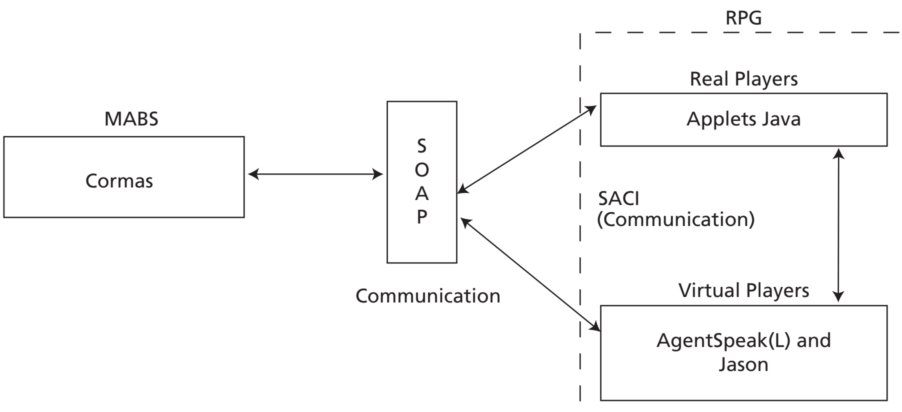
6) If the game has reached its end, a debriefing session is carried on.

Using GMABS, two prototypes in the natural resources management domain were developed. The first prototype, called JogoMan, is a paper-based game: all players need to be physically present simultaneously in the same place, and there is a minimum needed number of participants to play the game.

In order to avoid this constraint, a second prototype, called ViP-JogoMan, was built. This second prototype enables the insertion of *virtual players* that can substitute some real players in the game. These virtual players can partially mime real behaviors and capture autonomy, social abilities, reaction and adaptation of the real players.

The BDI (Belief-Desire-Intention) architecture [51] was chosen to model these virtual players, since its paradigm is based on core concepts that easily map to the language that people use to describe their reasoning and actions in everyday life. ViP-JogoMan is a computer-based game, in which people play via Web, players can be in different places and it does not have a hard constraint regarding the minimum number of real players. The architecture of Vip-JogoMan is presented in figure 10.

FIGURE 10
Vip-Jogoman Architecture



Source: Adamatti, Sichman and Coelho (2009).

In this application, the agent-based simulations were performed using Cormas (Bousquet et al.,1998), described in section 3.6. The application's goal, as mentioned in section 1.3, was to implement participatory simulation. Validation was addressed by questionnaires and by comparing the number of negotiations between the agents, in different settings, with or without the presence of virtual agents.

Briefly speaking, the results obtained have shown that the use of behavioral profiles based on BDI architecture to model and implement virtual players seems to be well suited to make their decisions believable, since most real players did not identify the virtual players during the tests. Moreover, in some particular scenarios, the simple presence of virtual players has enhanced the number of negotiations between the agents.

This application is an illustration of how the use of MABS techniques, combined with RPG, can help the concertation of social actors aiming to improve the quality of water in metropolitan regions.

6 CONCLUSIONS

In this chapter, we addressed the question of how to build operational models and implementations of complex systems. We have described several techniques and tools that could be used for this goal; we have focused on MABS platforms, since we believe that these are the most suitable tools to implement such systems. We would like to finish this chapter by quoting Robert Axelrod (Axelrod, 1997), when he has given his influential opinion on the important role of simulation in science:

> Simulation is a third way of doing science. Like deduction, it starts with a set of explicit assumptions. But unlike deduction, it does not prove theorems. Instead, a simulation generates data that can be analyzed inductively. Unlike typical induction, however, the simulated data comes from a rigorously specified set of rules rather than direct measurement of the real world. While induction can be used to find patterns in data, and deduction can be used to find consequences of assumptions, simulation modeling can be used as an aid intuition.

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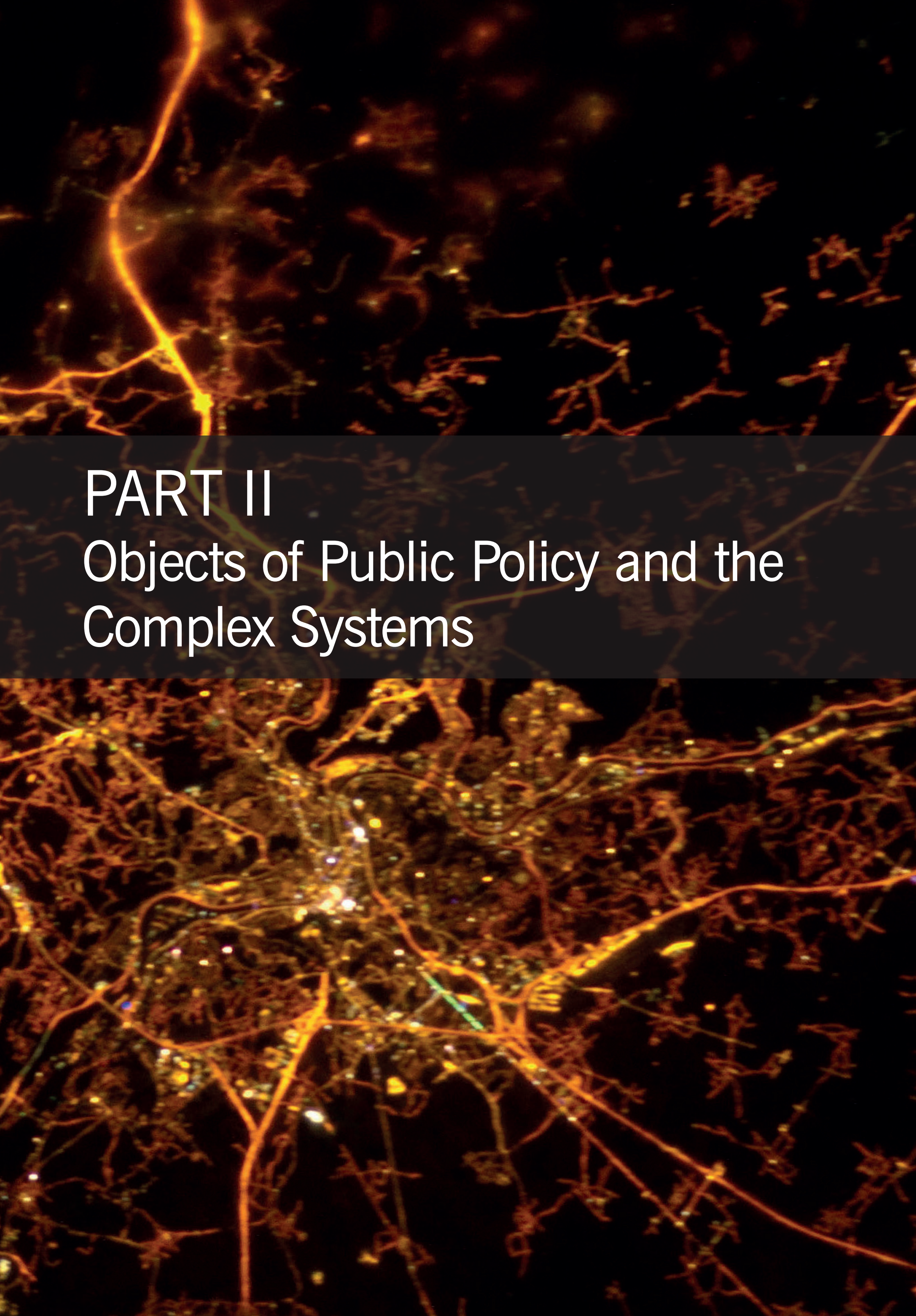
PART II
Objects of Public Policy and the Complex Systems



CHAPTER 6

UNDERSTANDING THE ENVIRONMENT AS A COMPLEX, DYNAMIC NATURAL-SOCIAL SYSTEM: OPPORTUNITIES AND CHALLENGES IN PUBLIC POLICIES FOR PROMOTING GLOBAL SUSTAINABILITY

Masaru Yarime[1]
Ali Kharrazi[2]

Complex systems are characterized by the interactions between heterogeneous agents and the surrounding environment, emergence and self-organization, the importance of non-linearity and scaling, the use of simple rules, the emphasis on dynamics and feedback, and the notions of adaptation, learning, and evolution (Furtado and Morita-Sakowski, 2014). In this sense, our environment can be regarded as a complex system in which inputs, including materials, energy, and biological species, undergo dynamic, complex transformation involving natural and social interactions, producing outputs as a result (Fath, 2015). It is crucial that during this process the environment endures and maintains its vital functions in the presence of various kinds of fluctuations and disturbances, which would involve a considerable degree of uncertainty.

Contemporary environmental challenges require new research approaches that include the human dimension as an essential part when studying the natural environment (Bodin and Tengö, 2012). It is therefore increasingly recognized that our environment should be understood as coupled human and natural systems or social-ecological systems, involving complex and diverse patterns and processes (Ostrom, 2009). As such, its proper analysis requires effective integration of the concepts and methodologies employed in natural and social sciences. While several conceptual frameworks have been recently developed for integrating human society with nature, there remains a significant extent of potential available for making progress on methodological and theoretical approaches to examining the complexities of social-natural interdependencies and interactions quantitatively.

Recent case studies covering different parts of the globe reveal that couplings between human and natural systems vary across space, time, and organizational units

1. Graduate School of Public Policy (GraSPP), University of Tokyo, Japan. Department of Science, Technology, Engineering and Public Policy (STEaPP), University College London, United Kingdom. E-mail: <yarimemasa@gmail.com>.
2. Graduate School of Public Policy (GraSPP), University of Tokyo, Japan. Advanced Systems Analysis Program, International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria. E-mail <ali@pp.u-tokyo.ac.jp>.

(Liu et al., 2007). They exhibit key characteristics of complex systems, including nonlinear dynamics with thresholds, reciprocal feedback loops, time lags, resilience, heterogeneity, and surprises. Coupled human and natural systems in the past also have legacy effects on present conditions and future possibilities. Hence it is important to deal with our environment as a complex adaptive system, the sustainability of which is as a dynamic, continuous process, not as a static state of the system, with significant implications when we consider public policies.

For exploring the sustainability of our environment, sustainability science has been proposed as a new academic field, specifically aimed at understanding the fundamental character of complex interactions between natural and social systems (Kates et al., 2001; Clark and Dickson, 2003; Komiyama and Takeuchi, 2006; Kajikawa et al., 2007; Jerneck et al., 2011; Yarime et al., 2012). The primary interests of sustainability science include dynamic interactions between natural and social systems, vulnerability or resilience of the nature-society system, scientifically meaningful limits or boundaries, system of incentive structures, involving markets, rules, norms, and scientific information, and integration of operational systems for monitoring and reporting on environmental and social conditions. Hence the challenge of sustainability requires an appropriate and effective use of data, information, and knowledge on diverse aspects, ranging from the nature to economy and institutions (Yarime, Takeda and Kajikawa, 2010).

As a variety of academic disciplines including natural sciences, engineering, and social sciences are involved in sustainability science, various types of concepts and methodologies have been proposed so far. Despite the diversity in approaches, the systemic character of sustainability is emphasized in most of the approaches. Many issues related to sustainability are mutually connected and interdependent; climate change and biodiversity loss are among the prime examples of complex linkages and interactions, which requires systemic understanding and interventions. It is also recognized that long-term time frameworks are fundamental in sustainability. As sustainability concerns impacts and influences in the future, dynamic processes of change and transformation are of critical importance, with the issue of equity between different generations inherently involved. The dimension of action-oriented research is also emphasized. Implementing knowledge for strategies and public policies is explicitly expected to address the pressing sustainability challenges our societies face.

Systems approaches to sustainability requires us to take into account the relationship between system sustainability and renewal of components (Voinov and Farley, 2007; Voinov, 2008). Systems are parts of hierarchies where systems of higher levels are made up of subsystems from lower levels, and renewal in components is an important factor of adaptation and evolution. If a system is sustained for too long, it borrows from the sustainability of a super-system and rests upon lack of sustainability in subsystems. By sustaining certain systems beyond their renewal cycle, the sustainability of larger, higher level systems could be compromised. This is illustrated clearly by biological organisms, which undergo continuous replacement at the level of cells. Also the collapse and renewal of firms and industries would be necessary to sustain the vitality of the larger economic system in a capitalist economy, as discussed in Schumpeter's theory of creative destruction.

To systematically analyze the complexity of coupled natural-social systems, it is useful to regard them as networks (Janssen et al., 2006). The ecosystems, for example, can be considered as networks of material or energy flows such as food webs or nutrient exchanges (Ulanowicz, 1986). For natural-social systems, a theoretical framework building on the rapidly growing interdisciplinary research on complex networks has been developed to define and formalize ways in which societies and nature are interdependent (Bodin and Tengö, 2012). A set of basic building blocks, each of which represents a simplified social-ecological relationship of two social actors and two ecological resources, can show all possible patterns of the natural-social system characterized by social and ecological connectivity, resource sharing, and resource substitutability. Based on that unit of analysis, an empirical case study was conducted on the network of a rural agricultural landscape in southern Madagascar by utilizing theoretical insights related to the management of common-pool resources and meta-population dynamics.

The dynamics of network systems can be represented by two complementary aspects of growth and development (Fath, 2015). Growth is a quantitative change in a system property as measured by an extensive variable such as total system throughput, which is the sum of all exchanges within the system and between the system and its outside. Development is a qualitative change in the system as measured by an intensive variable such as information or network connectivity or cycling. As in physics, the total capacity of some feature is the combination of how much and what quality, an extensive variable times an intensive variable. Therefore, when we try to understand the nature of a network system, it is important to consider both growth and development, in other words, quantitative and qualitative dimensions. Considering this perspective, we can distinguish two dimensions in the sustainability of a coupled natural-social system, that is, a quantitative or extensive dimension, which encompasses the total resource throughput within the system, and a qualitative or intensive dimension, which describes the robustness or resilience of the system of resource flows (Kharrazi, et al. 2013).

A number of natural as well as social processes tend to accelerate its own growth in a way that actively drains the broader system (Ulanowicz, 1995). It is hence important to understand the dynamic mechanism of positive feedback which can erode systemic sustainability. These processes include the following phases: selection, a natural tendency to augment elements that increase flow through the epicenter circuit and to eliminate elements which do not; increasing efficiency honed by this selection and elimination; self-amplifying growth created by increasing efficiency, influx and pull; erosion of the surrounding network caused by the massive draw of resources into the epicenter hub; brittleness caused by the elimination of backup resilience; and rigidity cause by increasing constraints on options and behavior. There are many examples in which this dynamics of positive feedback can be demonstrated to function in the natural environment (Goerner, Lietaer and Ulanowicz, 2009). The massive algae bloom in the Gulf of Mexico today shows what happens when unchecked growth in one circuit creates a resource concentrating vortex that actively erodes the broader network upon which systemic health ultimately depends. Fertilizer and agricultural wastes flowing down the Mississippi River triggered massive algae growth that has depleted nearly all the oxygen in water, which caused an equally massive die-off of marine life, notably fish, shrimp and shellfish.

Therefore, in response to the challenge of establishing the sustainability of our environment as coupled human-natural systems involving complex and dynamic interactions, it is increasingly recognized that decision makers in the public as well as private sectors need to take the issue of strengthening resilience seriously, particularly in the context of climate change, biodiversity loss, and disaster risk reduction (PwC, 2013; World Bank, 2013). While there is no single definition of this important concept that can be applied universally and the methods to quantify and measure the progress of this concept are still in their infancy, here we conceptualize resilience as a balance between efficiency and redundancy (Goerner, Lietaer and Ulanowicz, 2009; Lietaer, Ulanowicz and Goerner, 2009; Ulanowicz et al., 2009). Efficiency is defined as the network's capacity to perform in a sufficiently organized and efficient manner as to maintain its integrity over time. Redundancy is considered to be the network's reserve of flexible fallback positions and diversity of actions that can be used to meet the exigencies of novel disturbances and the novelty needed for on-going development and evolution. Understanding the tradeoff between efficiency and redundancy for resilience would help us design public policies for the environment towards a more appropriate balance.

The study of resilience has developed rather independently in various academic fields, including, notably, engineering and ecology (Folke, 2006). Accordingly, the current literature on resilience can be grouped into two overarching categories of engineering resilience and adaptive or evolutionary resilience (Holling, 1996). In engineering resilience, the aim is to develop the capacity to withstand a stress and to return to what is considered as a normal state. Engineering resilience can be easily understood in its application to transportation infrastructure. For example, under the stress of a heavy snowstorm, flood, fire, or earthquake, infrastructures such as bridges, roads, and highways are designed to withstand various levels of such stress and return to a normal functioning state. In this definition of resilience, the main idea is to restore normal conditions.

This definition, however, has its limitations. Systems that are subject to a stress may in fact continue to survive, but at a notably altered state and far from their normal conditions. In other words, the concept of resilience also needs to incorporate the element of adaptability. Here, the objective becomes the resilience of a function that would make the system continue to operate under the existence of changes and disturbances. Various vital functions in our day-to-day lives such as waste disposal, emergency medical services, and policing, for example, dispose the notion of having a concrete normal state. Rather than maintaining an identical state, the resilience of these functions needs to be measured in their ability to continue delivery and operation after a stress or shock to the function of the urban system. In this context, resilience would be different from just returning to what is perceived as normal, but instead indicates an adaptive capacity to reorganize into a different operating structure while maintaining the function.

Adaptive or evolutionary resilience allows for a system to maintain distinct configurations. In ecological studies this is known as multiple attractors, where an ecosystem can switch from one resilient configuration to another, each of which maintains a distinct ecological equilibrium. The existence of multiple attractors is not limited to ecosystems and can be related to all systems. By defining the various possible attractors of a system, one can predict with more precision what configurations the system will switch to after a disturbance or stress to its system. This is extremely useful for quantifying the adaptive aspect of resilience. To identify the various attractors of a system, however, is a challenging task. First, the long-term records of the system's behavior might be unavailable. Second, a certain system can simply be too complex to identify its various attractors or even evolve into new attractors. Third, the magnitude and nature of the stress to a system may also be unique and without any precedence.

In the absence of a reliable measurement of resilience, especially adaptive resilience, it is important to understand the dimensions that influence the general resiliency of a system. The principles for building resilience in social-ecological systems suggest us to maintain diversity and redundancy, manage connectivity, manage slow variables and feedbacks, foster complex adaptive systems thinking, encourage learning, broaden participation, and promote polycentric governance systems (Biggs, Schlueter and Schoon, 2015). A careful examination of these principles will allow policy makers to assess whether the resilience of a system is properly managed and maintained. Particularly important approaches would include increasing the diversity and redundancy of the components of a system, managing connectivity and modularity in the system, and improving feedbacks within the system for regulatory response. Knowledge of these approaches for a given system provides policy makers with powerful tools to manage resiliency within a system in order to withstand a shock or disturbance, reduce risks, improve recovery, and enhance regulatory feedback.

Diversity is an important concept with strong applications in various disciplines. As a basic definition, diversity is the degree of variation in a system. This can include the degree of variation in components maintaining similar functions, which can be called functional diversity, and that in the components maintaining different responses to disturbances, which is response diversity (Folke et al., 2004). Diversity allows a system to be more flexible in its options when faced with a disturbance.

For example, by promoting diversity in energy systems, both in terms of energy production and energy consumption, the resilience of these systems will be increased as a result. This can be achieved in terms of advancing technological diversity, where, in addition to the traditional energy supplies of oil, natural gas, coal, nuclear, and hydro, new technologies, most of which would be related renewable energy sources, are developed and diffused. These new types of technologies include solar, wind, geothermal, biomass, and ocean power technologies for generating energy. Diversity can be further promoted by using a wide variety of energy sources at multiple scales, for example, solar panels owned by households or a small and medium-sized enterprises operating a wind farm. Diversity both in technology, that is, functional diversity, and also in different scales, which means response diversity, will permit for a more flexible response to disturbances.

From the perspective of ecology, biodiversity can be considered to be the generator of redundancy as well as efficiency, thereby contributing to improving the resilience of the ecosystem.[3] Biodiversity can make an ecosystem more resistant to impacts, that is, more resilient, as it allows for different responses and redundancies. Redundancy can be considered as the ability of different species to hold key positions; given their biochemical, morphological or behavioral differences, diverse species are not equally impacted by a single external shock. On the other hand, biodiversity allows for the colonization of different ecological niches; in other words, different species may use different forms of matter and energy. Yet the residuals of a species may become inputs for other species. This allows for efficiency gains, at least to a certain extent. Excessive diversity in biological species would make the connections and interactions between them within the ecosystem so complex that the efficiency of the transfer and use of matter and energy would be reduced after reaching a particular point. In terms of transferring matter and energy, generally it would be more efficient when the network structure of pathways are relatively simple and straightforward (Ulanowicz, Bondavalli and Egnotovich, 1996; Goerner, Lietaer and Ulanowicz, 2009).

Connectivity within a system can be understood well by introducing the concept of modularity. Modularity refers to the degree to which a system's components can be decomposed into separate individual units but also matched

3. We are grateful to Dr. Bernardo Furtado for pointing out this important aspect of biodiversity.

and recombined. Modularity can help contain the spread of a shock or disturbance through a system. For example, the breakout of a deadly virus or fire is more likely to be contained with the implementation of modular mechanisms such as quarantines and firebreaks. A system with too much or too little modularity has fundamental trade-offs. On the one hand, a system with too much modularity will not benefit from economies of scale associated with larger scale systems. On the other hand, a system with little modularity might be prone to cascading failures where a shock or disturbance can spread with high speed throughout the system.

In the context of energy systems, distributed energy systems where electricity is generated from many small energy sources is very modular. Currently, most countries generate electricity in very large scale and centralized location, e.g. gas or nuclear power plants. While these plants maintain the benefits associated with economies of scales, they are also unsecure, brittle and prone to failure in case of a disturbance. A related concept to modularity and distributed energy systems is the micro grid. The micro grid, which has received a particular attention since the North India blackout in 2012, envisions a localized collection of energy generation, storage, and transmission which, while connected to the traditional centralized grid, is mainly targeted to a specific geographical area. In the wake of a disturbance or shock in the centralized grid, the link between the micro grids can be disconnected, and thereafter the micro grid can function autonomously on its own. Micro grids and distributed energy systems allow for greater modularity and subsequently more reliable energy in lieu of disruptions.

Feedback refers to the transfer of changes in one part of a system to other parts. A resilient system maintains strong feedback mechanisms for identifying thresholds and regulating the system's ability to move from one trajectory to another. Feedback is a common phenomenon in natural systems. Especially in evolutionary biology and ecological fluctuations, regulatory feedback mechanisms are fundamental to the resilience and survival of systems. In human systems feedbacks lead to learning and self-organization towards different solutions or attractors as the new conditions arise. In traditional energy systems, there is very little regulatory feedback. Specifically, there is little real-time information exchange on the level of energy supply and demand. This lack of information necessitates a constant oversupply of electricity incurring high costs. Furthermore, without dynamic information there is little regulatory control of the system to avoid collapse in case of a disturbance. To address the need for regulatory feedback in energy systems, what is described as smart technologies is now increasingly being utilized for this purpose. Smart meters involve real-time sensors that enable two-way communication between the meter and central system, functioning as the cornerstone of the proposed smart grid system. A smart grid is a modernized electrical grid that leverages the constant feedback of information from all of its meters, sensors, and devises for quick regulatory reaction to both technological and human behavior. These smart energy technologies and systems are expected to improve the resilience of energy systems, in addition to contributing to the three targets of sustainable energy, that is, providing access to energy for all, increasing energy efficiency, and promoting renewable energies (Secretary-General's High-Level Group on Sustainable Energy for All, 2012; United Nations, 2014).

The ecological information-based approach, derived from the probability theory and the graph theory, can be utilized for quantitatively analyzing the overall structure of a system in which nodes are connected with each other through flows between them in a network (Kharrazi et al., 2013; Kharrazi et al., 2014). This approach adopts a system-oriented paradigm that emphasizes holistic properties of a network. Those properties may not be evident from focusing on parts of the network in isolation, requiring, instead, consideration of the transfers between nodes. This approach is well established in ecology, for example, for investigating food webs, comparing ecosystems, and measuring stress levels in an ecosystem. This approach has been recently employed to quantitatively explore the resilience of network systems from the perspective of their structural and organizational relationships (Goerner, Lietaer and Ulanowicz, 2009; Lietaer, Ulanowicz and Goerner, 2009; Ulanowicz et al., 2009).

While the ecological information-based approach has been mainly applied to ecological systems, there have been very few attempts to apply it to coupled natural-social systems so far (Bodini, Bondavalli and Allesina, 2012; Tumilba and Yarime, 2015). The characteristics of natural-social systems can be examined in details by utilizing this methodology. In particular, it would be very useful to explore the applicability of the normative criteria which have been derived from sustainable ecological systems for evaluating the sustainability of natural-social systems. The trends in the system-level measurements can also reveal the efficiency and redundancy dimensions of the resilience of such complex systems from a long-term perspective. An analysis of complex natural-social systems with the ecological information-based approach would be best illustrated in the field of resource networks.

Global resource networks, with the intertwined nature of environmental impacts of production, trade, and consumption, pose significant knowledge gaps relating to the complex connections and interactions in natural-social systems (Tukker and Jansen, 2006). Ecological footprint accounting has been proposed as a comprehensive resource accounting tool that compares demand for renewable natural resources and services with the ability of the biosphere to generate them (Borucke et al., 2013). As the ecological footprint is a measure of consumption that incorporates information on domestic production as well as international trade, comparing total demand, that is, ecological footprint of consumption, with demand met from domestic production, which is ecological footprint of production, and the regenerative capacity of the domestic biosphere, biocapacity, allows a classification and assessment of risk in a country (Hill Clarvis et al., 2014). While the difference between the ecological footprints of consumption and production represents a country's net trade in renewable natural resources and services, which would be subject to risks linked with availability and prices of resources on international markets, the difference between the ecological footprint of production and biocapacity represents either an overuse of domestic bioproductive land and marine areas or a reliance on global commons to absorb waste in the form of carbon dioxide emissions.

Different countries exhibit a wide range of resource profiles (United Nations Environmental Programme Financial Initiative and Global Footprint Network, 2012). For example, Brazil possesses the largest amount of biocapacity of any country in the world and is a biocapacity creditor. In contrast, Japan demands seven times more biocapacity than it has within its borders. There are also significant variations in how the ecological footprint and biocapacity situations have evolved among the countries. While Japan's ecological footprint has remained stable over the past two decades, the biocapacity of Brazil has declined to less than half of that of 20 years ago, due to its growing consumption and exports. As the role of trade varies from one country to another, Brazil is a net exporter of commodities derived from natural resources as measured by its biocapacity, whereas Japan is a net importer.

As illustrated in the ecological footprint approach, previous approaches to quantifying the sustainability of coupled natural-social systems tended to focus on the accounting of various kinds of volume, primarily focusing on the availability of resources and the amount of consumption (Kharrazi et al., 2014). Therefore the main attention has been paid to how to increase a system's growth, without giving sufficient consideration to negative effects of excessive growth of the system concerned. Sustainability, however, also requires resilience as a critical dimension to maintain the functioning of the system by withstanding disruptions and disturbances. As the origins of production, routes of trades, and destinations of final consumption of resources constitute a very complex network, the ecological information-based approach can provide a useful framework for examining the resilience of the global resource systems with quantitative measurements.

The global resource systems can be understood as networks with nodes of countries and flows of water, energy, biodiversity, and various types of natural resources embodied in goods traded between different countries in the world. A better understanding of global networks of them, which collectively can be called natural capital, allows us to evaluate the resilience of the complex social-ecological system. Although researchers have traditionally used a single region input-output analysis to capture embodied flows, the accelerating globalization of economic activities has made production and consumption spatially separate. Despite the increased global economic connectivity, consumers have not evolved in line with the origin of production, and the relationships between origin and destination have become obscure and difficult to see. Studies comparing multiple versus single region input-output analysis demonstrated that multipliers and embodiments between these two methods could substantially differ from one another (Wiedmann et al., 2007).

The ecological information-based approach can be applied to analyze the structural resilience of networked systems in which virtual flows of resources connect in complex ways (Kharrazi et al., forthcoming). From this perspective, we can consider the possibility of absorbing shocks and disturbances in the global energy systems through trade networks connecting different countries and regions with diverse endowments and environments, wich could be analogous to virtual power plants connected with each other (Yarime et al., 2014). Given the diversity in the characteristics of countries and regions with regard to economic, social, and environmental conditions, the sustainability of global resource systems can be promoted through networks involving diverse geographical locations.

More generally, this approach to promoting the sustainability of natural-social systems through network governance will have significant implications for public policies at the global level. Network governance intends to address the grand challenge of global sustainability by identifying potentials and problems in different locations within the network, depending upon the availability and specificities of natural capital, including energy reserves, water stress, and biodiversity. By pursuing complementarities between weaknesses and strengths present in the network from a systemic perspective, it would be possible to coordinate our technologies, behavior, and institutions collectively so that the sustainability of the whole system will be enhanced. The possibilities and challenges in network governance need to be explored for obtaining implications for public policies in pursuing sustainability at the national as well as global levels.

The sustainability of our environment as a complex natural-social system requires that the system is durable and stable for generations with a sufficient capacity of resilience. Research findings in the field of sustainability science about change, disturbance, uncertainty, and adaptability emphasize the capacity to reorganize and recover from change and disturbance without a collapse of the system; in other words, we need to establish a system that is "safe to fail" (Ahern, 2011). Strategies and public policies for building resilience capacity would require multi-functionality, redundancy and modularization, bio and social diversity, multi-scale networks and connectivity, and adaptive planning and design.

In the context of establishing governance for sustainability, earth system governance is understood as "the sum of the formal and informal rule systems and actor-networks at all levels of human society that are set in order to influence the co-evolution of human and natural systems in a way that secures the sustainable development of human society" (Biermann, 2007). Governance for sustainability thus can be defined as formal and informal networks with interactions among actors, and systems composed by them, that influence sustainability by integrating various dimensions (Shiroyama et al., 2012). Hence network governance for sustainability requires knowledge integration as a means to deal with diverse and uncertain dimensions of sustainability and multi-actor governance involving public-private collaboration and multi-level interactions. That would be crucial in reaching consensus on concrete actions among different stakeholders for designing and establishing sustainability. As our environment is inherently embedded in coupled natural-human systems with all the complexities and uncertainties, any implementation of policies aimed at achieving sustainability in the systems demands serious engagement and active collaboration of stakeholders, which will contribute to moving towards societal transformations.

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CHAPTER 7

THE COMPLEX NATURE OF SOCIAL SYSTEMS

Claudio J. Tessone[1]

1 INTRODUCTION

In many cases, social and economic systems are composed by agents (be they individuals, firms, countries etc.) whose actions cannot be considered in isolation. Instead, their state (opinion, choice, health state, wealth) and concomitant behaviour is influenced by the state of others. As an outcome of the interaction, the global properties of these systems are not just the aggregation of individual behaviour, but richer. When this occurs, it is said that such a system is *complex*.

Some aspects of social systems exhibit large-scale regularities, like the emergence of languages, social norms and cultural traits. They also display persistent inhomogeneities, like social segregation and inequality of wealth distribution. In some cases, they evince evolving patterns, like waves of product adoption, spikes of attention in social media, disease propagation, or cascade of bankruptcies in financial crises. All these are paradigmatic examples of systems that can be studied by recourse of stylised models whose constituents are simple, yet the outcome of their interaction is a rich emergent behaviour. In this chapter, I will review complex systems models that account for the above mentioned behaviour.

The following is not conceived as a comprehensive review of the approaches to social systems from a complex science point of view. Achieving this would be impossible in its bounded extension. Therefore, it is structured to serve as a gateway to the actual sources containing the relevant research. In the following sections, I will introduce what can be considered the set of most paradigmatic models and ideas in this realm, and also some of the main conclusions that can be drawn for them, and some interesting extensions.

1.1 Complex systems models

A model is an abstract, and to some extent idealised, description of reality that still captures a specific phenomenon. It is therefore limited by construction. This is true in particular for the complex systems approach to social systems.

1. Chair of Systems Design, D-MTEC – ETH Zürich Weinbergstrasse 56, CH-8092 Zürich, Switzerland. URPP Social Networks, Universität Zürich. Andreasstrasse 15, CH-8050 Zürich, Switzerland.

Models in this realm are not intended to reproduce *society* as a whole, but to shed light on mechanisms behind social phenomena. Therefore, along this chapter I will refer to the subject of study as *social systems* or, when appropriate, *socio-economic systems*.

On the one hand, a wealth of studies have analysed complex systems from theoretical and methodological points of view in mathematics and physics. As an example, complex systems appear naturally in statistical mechanics, the branch of physics that studies the global properties of systems composed of many interacting elements. This kind of research complements collective behaviour described in social sciences and economics. From an epistemological point of view, however, natural and social sciences approach research differently, and each of them has resorted on tools and methods normally used and accepted in their own discipline. While in some cases it is crucial for the discipline that new research is placed in existing logical frameworks with the aim of being formally sound in the context of what is already known, in others the researchers lack the quantitative tools needed to extend the qualitative description of phenomena into quantitative knowledge.

Research in complex social systems should be a cross-disciplinary endeavour, but the rule rather than the exception has been for the knowledge to remain within each discipline. It is important to mention that in some cases, different disciplines have resorted on the same tools to reach some level of description of disparate systems. These advances, unfortunately, have been almost systematically overlooked by the other fields, frustrating the cross-pollination between them. It is important for researchers and practitioners to bear this in mind while delving on what is already known.

This chapter is organised as follows. In section 2, I review the key ingredients of social systems that make them amenable to a complex systems approach: finiteness, heterogeneity and interaction. Then, section 3 contains some of the most paradigmatic models of complex social systems and the realm of their application. The following section 4 overviews the network of interactions in social systems with some of its topological properties and mechanisms behind them. The final section 5 provides an outlook of the complex systems approach to social systems.

2 COMMON FEATURES OF SOCIAL SYSTEMS

There exist common traits to socio-economic systems that render them unique. One of them is the pervasive *heterogeneity* of its elements, which can be either intrinsic or an outcome of the dynamic evolution of the system. This is in stark contrast with classic systems in natural sciences, where either the elements are identical (like atoms or molecules), or they can be described by a representative element (like in biological models where the heterogeneity between individuals of the same species can be often neglected). Depending on the context, the constituents can be named agents, individuals, voters, nodes, etc. I will use these terms interchangeably. Another important characteristic was already advanced above: the current state of an agent, the action it performs and its outcome depend, either directly or indirectly, on the actions of other agents in the system. Regardless of how simple is the individual behaviour of the system constituents, complex behaviour is triggered by the *interaction* between them. Finally, these systems are *finite*, and in some cases very small. Therefore, the actual results can greatly differ from those expected from studying the (in some cases mathematically tractable) infinite-size limit.

One of the important questions addressed when modelling socio-economic systems is how they react to external influences. By this, it is understood that the agents under study do not act just based on their internal state and the interactions they have with others. In many cases, the agents are subject to influences that are common to all the system constituents. These are *signals*, which can be of different origins. From a modelling point of view, a change in policy is exactly a signal applied to a social system. It can be common to all agents, or act differently on different agents, but it is in general exogenous to the system. Another example of these signals is the role of advertisement and/or media in costumer behaviour or public opinion.

2.1 Finite size

Researchers in statistical physics are used to taking routinely the limit of infinite-size (what in that realm is called *thermodynamic limit*) in which the number of constituents N goes to infinity (Pathria, 1996). When methods of statistical physics are applied to explain the properties of macroscopic matter, it is clear that the number N is always finite, but very large (think of the Avogadro number 6.023×10^{23}). Consequently, the nowadays widely used computer simulations of physical systems always struggle to get to larger and larger systems with the continuous increasing demand in computer resources.

When studying problems of interest in social sciences (Ball, 2003; Castellano, Fortunato and Loreto, 2009; Weidlich, 2002), the fact that the number of agents considered can never be that large has to be taken into account. In most cases, realistic values of N range in the hundreds or thousands, reaching at most a few million. The thermodynamic limit might no be justified in this case, as the results in that limit can vary with respect to those of finite-size systems. For infinite systems, normally deterministic descriptions can be formulated. However, if the system is finite, an intrinsic randomness persists, what is sometimes called *demographic noise*

(Nisbet and Gurney, 1982). Furthermore, new and interesting phenomena can appear depending on the number of individuals or agents considered. For example, it can create a strong non-linear response to a small external signal (Tessone and Toral, 2005) or oscillatory behaviour in cooperation models (Bladon, Galla and McKane, 2010).

2.2 Heterogeneity

Another of the properties that make socio-economic systems a challenging and exciting realm of research is the inherent heterogeneity of its constituents. When considering systems composed of voters, investors, firms or countries, it is clear that all the elements are not identical, but clearly diverse (Page, 2011). This heterogeneity cannot be neglected, as it is an integral part of the agents. When modelling in a quantitative way these systems, a simple replacement of one agent's characteristics by a kind of average or representative value may limit excessively the descriptive power of the model. Indeed, in some cases, the extent of this diversity is so large that such substitution is also inaccurate from a conceptual point of view.

The sources of heterogeneity at individual level may differ depending on the system under consideration. Often, heterogeneity is due to an intrinsic (or previously acquired) property of the agent. For example, when the system under consideration is a process of opinion formation, different people have disparate preferences (based on idiosyncrasy, cultural background, etc.) (Castellano, Fortunato and Loreto, 2009); this preference can play a role in their process of decision making (Schneider and Stoll, 1980). In other cases, heterogeneity is something that builds up during the evolution of the system. For example, in a social context, the number of social contacts (being in real life or in on-line social media) spans several *orders of magnitude* (Newmann, 2010), even if for all individuals, it starts from an empty set.

One of the crucial insights brought by complex systems modelling is the following: in many social systems, heterogeneity is not something that, while present, simply distorts or blurs the outcome obtained if identical representative agents replace a diverse population. Instead, heterogeneity can crucially affect their observed properties, and be the source of *a priori* unexpected phenomena in socio-economic systems.

2.3 Network of interaction

Central to social systems is that their constituents do not act in isolation: Agents interact with others (Bavelas, 1948; Wasserman and Faust, 1994). With whom do agents interact, how do these interactions change global properties of the system (Boccaletti et al., 2006), and how (Holme and Saramaki, 2012) and why (Galeotti et al., 2009) do they appear or disappear are questions that must to be assessed to have a proper understanding of the system under consideration. In some cases, it is possible to assume that an agent interacts with all the others. This is the case, for example, in price formation in open markets, where the demand by one individual affects the price for the others. In social systems, it occurs when individuals react to aggregated information at the population level, like in polls, etc.

In most systems, however, agents interact only with a subset of others and these interactions can be decomposed into dyadic[2] exchanges. In these cases, these relations can be described as a *network*, whose *nodes* are the agents of the system and the *links* (or *edges*) between them describe the interactions. Some simple examples are: in opinion formation, an individual may discuss the issue at stake with his acquaintances which amount to a restricted subset of the whole system. Other examples of particular relevance are that of networks of proximity (for processes opinion formation), and that of sexual contacts (for the unfolding of disease propagation).

3 COMPLEX SOCIAL SYSTEMS

The opinions held by individuals and decisions are not the simple outcome of their own reflections, but to some degree are affected by those of their environment, on what is termed social influence. Social influence can be readily observed in common collective decision processes, e.g. political polls (Mutz, 1992), panic stampedes (Helbin, Farkas and Vicsek, 2000), cultural markets (Salganic, Dodds and Watts, 2006), or aid campaigns (Schweitzer and Mach, 2008). Some of these collective decisions can trap a population in a suboptimal state, for example in a financial bubble due to financial actors' herding behaviour (Prechter, 2001). Alternatively, they may steer a system into positive directions, such as increased tax compliance rates (Wenzel, 2005). However, understanding how such collective decisions are formed, evaluating their benefit for the population, and even directing their outcomes, is conditional on quantifying how people perceive and respond to social influence.

Based on incomplete information, how does an agent make his decision on a particular subject? A utility maximisation strategy is impossible because in many social situations the private utility cannot be quantified easily. In order to reduce the risk of making the wrong judgement, it seems to be appropriate to copy the decisions of others. Such an *imitation* strategy is widely found in cultural evolution and recognised as such more than a century ago (Tarde, 1903): Humans imitate the behaviour of others to become successful

2. Dyadic refers to interactions involving only two individuals or agents (from dyad, or pair).

or just to adapt to an existing community (Dugatkin, 2000). A voluminous Literature has studied the effects of imitative and herding behaviour in the most variegated contexts. Imitation is in general an interesting example of complex bahaviour. On the on hand it is a local rule, but it can indeed create collective phenomena, like consensus.

The following are models that explain complex social phenomena, and go beyond this simple example.

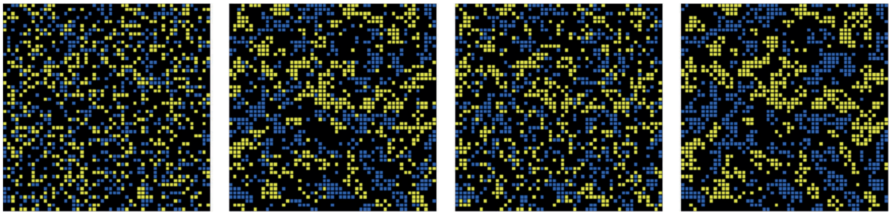
3.1 Social sciences and emergent phenomena

The fact that social systems exhibit a behaviour that nowadays would be termed as "complex" was indeed recognised by social scientists and economists long ago. Most of the times, the portrayal of the properties of such systems remained, however, at the descriptive level. There are few counter-examples that do not follow this rule, and provide sound insights of mechanisms underlying phenomena with very simple and elegant considerations. These models have become paradigmatic in the context of complex social systems and have triggered numerous extensions. I briefly review those that are among the most important ones, with the intention that the interested reader will deepen the information provided here by following the concomitant references.

3.1.1 Schelling's model of segregation

In modern societies is it not uncommon for people to segregate themselves into neighbourhoods with others that share some common trait like skin colour, country of origin, religion, etc. This effect is in some cases the result of some kind of discrimination – for example, when a correlation exists between income and racial group belonging. Beyond these external factors, Thomas Schelling (1969;1971) showed that a bias in the preference of individuals to be surrounded by others which belong to his same group, is enough to give raise to segregation at the global level (Schelling, 2006).

FIGURE 1
Snapshots of the evolution of the Schelling model in a bidimensional lattice



Obs.: A population initially distributed largely in a homogeneous manner eventually segregates into well-defined domains where a clear local majority emerges.

There is a crucial insight about this setting (Schelling, 1969): "Locally, in a city or a neighborhood, a church or a school, either blacks or whites can be a majority. But if each insists on being a local majority, there is only one mixture that will do it: complete segregation." When the dynamics is run on this model, even a small preference to be surrounded by others of the same group is enough to trigger a situation where agents form segregated clusters. Only those near an interface between the two groups may still have an incentive to move.

This model is paradigmatic of the complex systems research that pervaded other areas of social systems later: There is no need to understand all the factors behind people moving around, nor to have a detailed description of their spatial configuration, to learn that a simple local decision is enough to produce the macroscopic behaviour observed. Empirical analyses (Clark, 1991) have shown that the basic mechanism is at work in reality. The phenomenology observed was later shown to be connected to coarsening phenomena (Dall'Asta, Castellano and Marsili, 2008; Vinkovic and Kirman, 2006), even if criticised for its intractability (Stauffer, 2012).

3.1.2 Granovetter threshold model

The segregation model previously discussed has imprinted in it the concept of local spatial interactions. Some years later, Granovetter (1978) introduced a celebrated model for decision making processes. In it, each individual has an idiosyncratic *threshold*; if the number of agents in the group who have decided the opposite to him exceeds said threshold, then the agent will change his decision and conform with the opposite one. The original context of application encompassed: *i*) diffusion of birth control techniques (where different thresholds may arise from different cultural backgrounds, position in the local hierarchy, own preferences etc.); *ii*) strikes, where workers will attend to see how many others have already committed to participate; *iii*) "chain migration"; *iv*) educational attainment, where the local cohort will condition the decision to pursue higher levels of education, etc.

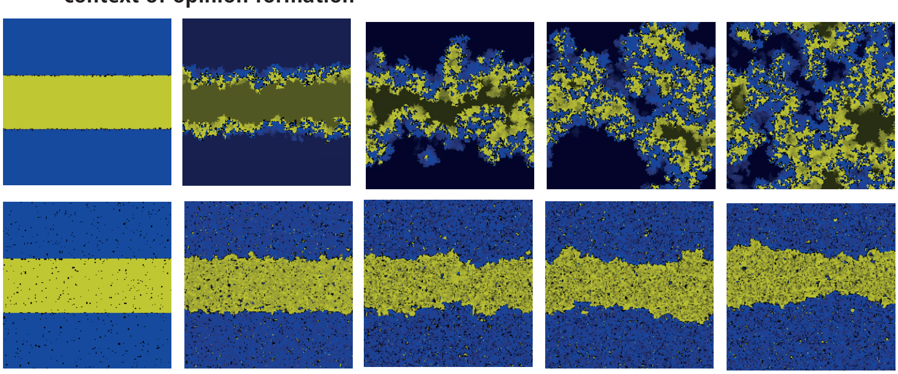
The ingredients of the model are minimal, indeed: Consider a system composed of N agents, each one endowed with a threshold θ_i. These agents have to make a decision, e.g., on whether to participate (+) or not (–) in a riot. Initially, all agents are in state (–). At each time, each agent confronts the fraction of agents who have already decided to participate in the riot N_+/N with his own threshold θ_i. If $N_+/N \geq \theta_i$, then the agent decides to participate as well. It is rather obvious that, in an homogeneous system with $\theta_i = \theta_0$, $\forall i$ and $\theta_0 > 0$, nobody would join the riot. As a second example, let us consider the situation $\theta_i = (i - 1)/N$, i.e. a uniform threshold distribution in the interval $[0, (N-1)/N]$. In this case, all agents end up rioting. As a third example, let us consider a small modification of the second case. Now, all agents but one have the thresholds as in the second case; the sole change is that agent $i = 2$ has a threshold $\theta_2 = 2/N$ (cf. this with $\theta_2 = 1/N$ in the second case). In this latest scenario, the number of agents joining the riot is only one individual, the one with threshold equal to 0. According to Granovetter the media could report the latter two examples – composed to most practical matters by identical crowds – respectively, in the following way: "a crowd of radicals engaged in riotous behaviour", and "A demented troublemaker broke a window while a group of solid citizens looked on". This enormous macroscopic change appears due to tiny differences in individual composition of the two crowds.

The formal solution of this model is very simple. Let $f(\theta)$ be the distribution of thresholds for the agents. The total number of individuals joining the riot will be given by the smallest threshold θ' that verifies

$$\int_0^{\theta'} f(\vartheta)d\vartheta = \theta', \text{ and } \int_0^{\theta''} f(\vartheta)d\vartheta > \theta'' \quad \forall \theta'' < \theta'. \qquad (1)$$

The beauty of Granovetter's insight comes from the recognition of the dramatic impact that intrinsic or acquired heterogeneity at individual level may have at the aggregated one. It also shows that out of social interaction, completely divergent macro-states can emerge.

FIGURE 2
Temporal evolution of two models exhibiting complex behaviour, normally used in the context of opinion formation



Obs.: The two opinions are shown in blue and yellow, while the more time an agent has kept his opinion, the darker the square is. The upper row shows the time evolution of the Voter model when the network of interactions is a square lattice. It is apparent that the well-defined interface which signals the initial condition dissolves, giving rise to an interface between the two states which grows over time. The lower row, presents the results of the Ising model (whose interpretation is also discussed in the text) which exhibits a different phenomenology.

3.2 Opinion formation models

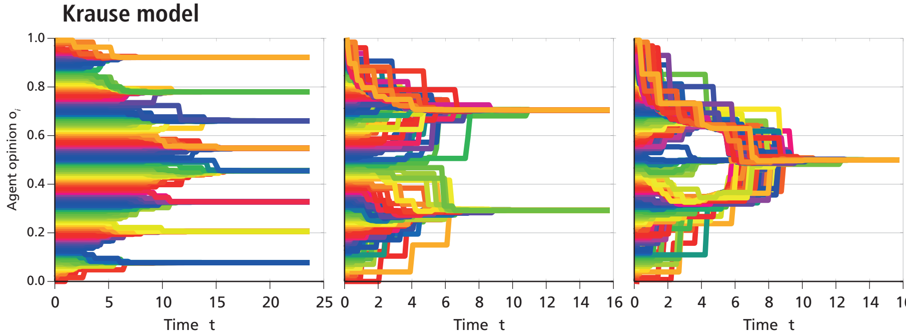
In order to understand the intrinsic properties of systems comprised of many individuals, a number of models have been developed to describe opinion spreading in a social context. It is important to bear in mind that many of them where proposed *ad hoc*, without any sociological insight preceding them. This does not demerit, however, the insights that they provided in key mechanisms of opinion formation.

3.2.1 The voter model

Early approaches in the social sciences showed that the existence of positive social influence (i.e. imitation behaviour) tends to establish homogeneity (i.e. consensus) among individuals (Abelson, 1964; French, 1956). The “voter model” (Liggett, 1995), also shows this behaviour. From a complex systems point of view, the voter model has been a paradigm for studying opinion dynamics (Holyst, Kacperski and Schweitzer, 2001), coarsening phenomena (Dornic et al., 2001), and spin-glasses (Fontes et al., 2001; Liggett, 1995).

The dynamics of the voter model can safely be regarded as the simplest implementation of an imitation process: Let us consider a system composed of N agents which can have one of two opinions $s_i \in \{-1, 1\}$. The agents are connected by a network of interactions N. At each time step, an agent is picked at random and imitates the opinion of one of his neighbours (also selected as random).

FIGURE 3
Results for the evolution of agent's opinion for the Bounded Confidence Hegselmann-Krause model



Source: Hegselmann and Krause (2002).
Obs.: The three panels present the evolution for different values of the threshold E above which no exchange in agent's opinion take place. Respectively the values are E = 0.05 (left panel), 0.18 (centre) and 0.25 (right). The number of agents in the system is N = 128.

Its simplicity allows for many analytical calculations (Liggett, 1995; Redner, 2001). For example, for regular networks (i.e. those where all the agents have the same number of connections to others) this model has the property of magnetisation conservation (Castellano, Vilone and Vespignani, 2003; Frachebourg, Krapivsky and Ben-Naim, 1996), which means that – when averaging over multiple realisations of the evolution – the relative proportion of individuals holding each opinion does not change with time. A corollary of this property is that a system with a density N_1/N of agents having opinion 1 will reach consensus at such opinion with a probability N_1/N. When run on a finite system, this reaches consensus in a finite time. How does the consensus time depend on the underlying network (Castellano, Vilone and Vespignani, 2003; Suchecki, Eguíluz and San Miguel, 2005; Wu, Huberman and Adamic, 2004). was extensively studied. For heterogeneous networks (Suchecki, Eguíluz and San Miguel, 2005), the exact dynamic rule fundamentally alters its behaviour, and the network topology can slow-down the ordering dynamics and may even lead to a disordered system where no consensus is reached (Sood and Redner, 2005).

3.2.2 Ising model and opinion formation

The voter model corresponds to a variety of models where the individuals are faced with a dichotomy. This scenario is the simplest decision making set-up, and it also provides a plethora of phenomena arising from it. In Physics, in a different context, the celebrated *Ising model* (Brush, 1967) was studied for decades as a source of emergent behaviour, in particular for the existence of a transition from disordered (so-called *paramagnetic*) to ordered (*ferromagnetic*) macroscopic states depending on the level of randomness in the system (which acts as a control parameter). This model resorts on the representation of the constituents as two states and these elements are connected through a network defining the interactions. Depending on the randomness, connected nodes are more likely to end up in a configuration where they have the same state. To which extent does this coherent state extend within the system, ultimately determines the degree of global order. When the decision is not between two choices, but among several, the setting is known as the *Potts model* (Wu, 1982).

The knowledge on this model allowed for complementary approaches to the dynamics of opinion formation, in the form of the *Weidlich model* (Weidlich, 1991). In this set-up, the description is not based on the single-element state, but on the densities of constituents in each one. It is therefore equivalent to Master equation approaches,[3] and population level dynamics.

Even if reviled as a *typical physicist's approach to social systems*, the Ising model (and its applications to social systems) showcases a problem faced often: different

3. A master equation (Gardiner, 1983) is a mathematical description very common in the physics literature where the dynamics of a system composed by many elements is written in terms of the proportion of elements that are in a given state. A simple example would be, in a discrete opinion formation model, a formulation in terms of the ratio of individuals who hold each opinion. At this macroscopic level, the dynamics can be written as a function of the transition probabilities from one state to the others.

terminology used to describe the same systems in different disciplines. Consider a coordination game played by bounded rational agents where the probability of selecting one of the two (indistinguishable) strategies is chosen with a probability following Logit dynamics on the expected pay-off. Formally, this model is exactly the same as the Ising.

3.2.3 Minority opinion spreading

The model introduced by Galam (2002; 2008) to describe the spreading of a minority opinion, incorporates basic mechanisms of social inertia, resulting in democratic rejection of social reforms initially favoured by a majority.[4] In this model, individuals gather during their social life in *meeting cells* of different sizes where they discuss about a topic until a final decision, in favour or against, is taken by the entire group. The decision is based on the *majority rule* such that everybody in the meeting cell adopts the opinion of the majority. Galam introduced the idea of "social inertia" in the form of a bias corresponding to a resistance to reforms (Galam, 2004a) or favouring prejudices (Galam, 2003). Therefore: in case of tie within a group, one of the decisions is systematically adopted.

The dynamics of the model is as follows: There is a population of N individuals who randomly gather in "meeting cells", simply defined by the number of individuals that can meet there; a_k is then the probability that a particular person is found in a cell of size k. The persons have a binary opinion – (+) or (–) – about a certain topic. At time $t = 0$, one sets $N_+(0)/N$ to an arbitrary value. The agents are then distributed randomly among the different cells. The basic premise of the model is that all the people within a cell adopt the opinion of the majority of the cell. Furthermore, in the case of a tie (which can only occur if the cell size k is an even number), one of the opinions is systematically adopted. Once an opinion within the different cells has been taken, time increases and the individuals rearrange by distributing themselves again randomly among the different cells. For a wide range of distributions $\{a_k\}$, this model has three fixed points: two stable ones at $N+ = N$ and $N+ = 0$ and an unstable one, the *faith point*, at $N_+/N = p_C < 1/2$. Hence, the dynamics is such that

$$\lim_{t\to\infty} N_+(t) = \begin{cases} N \quad if \quad N_+(0)/N > p_c \\ N \quad if \quad N_+(0)/N < p_c \end{cases}. \tag{2}$$

Therefore, the main finding of this model is that an initially minority opinion, corresponding to $N+(0)/N < 1/2$ can win in the long term.

4. For reviews around this family of models, the interested reader can refer to Galam (2004b; 2008; 2012).

3.2.4 The response to common signals

Regarding the effect of signals (that may represent advertisement or changes in policy) in social systems, it is important to recall that they are heterogeneous. In a general setting, it was shown that heterogeneous systems exhibit a maximum response to an external common signal, as a function of the degree of diversity of the constituents (Tessone et al., 2006). This phenomenon was shown to occur in different models of opinion formation (Galam, 1997; Tessone and Toral, 2009; Vaz Martins, Pineda and Toral, 2010). The same phenomenon occurs if, instead of idiosyncratic heterogeneity, the source of disorder is a different one, like the existence of repulsive interactions within the system. In a social context, these repulsive interactions would represent contrarians, i.e. individuals that oppose any type of consensus (Galam, 2004a; Stauffer and Sá Martins, 2004) or that intend to destabilise the system itself, such as the Joker-like players studied in the context of social dilemmas (Arenas et al., 2011).

3.2.5 Continuous opinion models

In some cases, the individual opinion must be modelled not as a discrete choice but in terms of a continuous variable. This is the case, for example, when individuals must answer quantitative questions they do not know the answer of and can only formulate an educated guess. When exposed to the opinion of others, on average, the change in opinion of an individual is proportional to the distance to the average opinion of others (Mavrodiev, Tessone and Schweitzer, 2012).

Long before these empirical studies, different models were proposed to study this scenario. One archetypical example is the Hegselmann-Krause bounded confidence model (Hegselmann and Krause, 2002). It runs as follows: There are N agents with an opinion $o_i \in [0, 1]$. At each time, an agent is picked at random and updates his opinion according to the rule

$$o_i(t+\delta t) = \sum_j \Theta\left(\varepsilon - \left|o_j - o_i\right|\right) o_j, \qquad (3)$$

where Θ is the Heaviside step function. Simply stated, agents will move towards the average opinion of all the other agents whose opinion is not farther than ε from theirs. ε represents what the authors named *confidence level* of the agents. The rationale behind the model is that individuals do not take into consideration the opinions of others who are far enough from theirs.

Some intuition of the phenomenology of this model can be obtained by observing figure 3. If the confidence level is small (left panel) individuals rarely change their opinion and interact with the few who have a close enough opinion; in this case, multiple opinions survive, in a regime akin to *plurality*. For increasing values of ε the number of clusters reduce, traversing a regime where only two irreconcilable opinions, with similar support survive. For even larger values of confidence level, agents are influenced by a larger set of agents, with more diverse opinion, and then consensus is reached (right panel). Close to the transition towards consensus, an interesting phenomenon is observed (middle panel): Agents first create two main clusters, and individuals with an opinion close to 1/2 even break away, depending on which side of the separatrix they are. Then, after the two clusters are formed, they converge again towards a final state of full consensus.

Another celebrated model in this line is that of Deffuant et al. (2000) and Weisbuch et al. (2002) which exhibits a similar behaviour.[5]

3.2.6 Cultural traits and language dynamics

Robert Axelrod (1984; 1997) introduced a model for the generation and diversification of different cultures. It was born out of the observation that differences between cultures do not disappear at all despite the fact that people tend to become more alike in their beliefs, attitudes and behaviour when they interact.

Specifically, in Axelrod's model each agent is characterised by a set of F cultural features, each one of them can adopt any of q different traits. The state of agent i defined by the F variables $(\sigma_{i,1}, \ldots, \sigma_{i,F})$. Agents interact by means of a network of interaction. Then, the dynamics is as follows, two neighbouring agents i and j are selected at random. Their *overlap* l_{ij} is the number of common features, $\ell_{ij} = \sum_k \delta_{\sigma_{ik},\sigma_{jk}}$. With a probability l_{ij}/F, the value of one of the not yet common features is transferred from one agent to the other, so increasing the overlap by one. This process is then repeated. Eventually, a frozen state is reached in which no possible evolution is possible. In such a frozen state, neighbouring sites have either an overlap equal to 0 or to F. The relative size of the largest cluster of agents sharing all cultural features, S_{max}/N is a measure of the cultural diversity. $S_{max} = N$ identifies a monocultural or *globalised* state. On the other hand, if $S_{max} = O(1)$, the state that can be qualified of culturally diverse or *polarised*.

This model was widely studied, showing the existence of a transition between the two cultural states (Castellano, Marsili and Vespignani, 2000; Vilone, Vespignani and Castellano, 2002), where in presence of *cultural drift* – fluctuations in the cultural traits – the multicultural state disappears for sufficiently large systems (Klemm et al., 2003; 2005) and also in presence of mass media (González-Avella et al., 2007).

5. For a complete survey of models of continuous opinion dynamics, the interested reader may refer to Lorenz (2007).

3.3 Strategic behaviour

Cooperation is an abundant phenomenon in social systems, but in most game-theoretical approaches *defection* should be the rational strategy to choose (Axelrod, 1984; 1997; Axelrod and Dion, 1988; Huberman and Glance, 1993; May, 1987). In order to solve this paradox, a vast literature has proposed modifications to the classical approach. The normal set-up to study this phenomenon is the analysis of games where agents have to choose a strategy; depending on the choices of others they get a given pay-off or reward. A wealth of studies involve 2 × 2 games, i.e. two agents play a game while having to decide between two choices (Camerer, 2003; Gintis, 2009; Myerson, 1991), in some contexts interpreted as cooperation or defection. Based on the strategies, the pay-off structure ultimately determines the kind of game under consideration (Stark, 2010). The most studied model is the so-called "prisoner's dilemma" where the Nash equilibrium is pure defection.

Another interesting example is that of public goods games (Kagel and Roth, 1995), where a population of *N* agents have to take one of two possible actions $\sigma_i \in \{0, 1\}$ (cooperation and defection, respectively). The utility function for agent i is defined by

$$\pi(\sigma_i) \equiv -c\sigma_i + r/N \sum_{j=1}^{N} \sigma_j, \qquad (4)$$

where *c* is the contribution to the public good, $r > 1$ is a gain factor by the public good. It is easy to see that the optional strategy is free riding if $c > r/N$, because the costs are more than the eventual gains. How to trigger cooperation in such a situation has been a withstanding question in this area of research.

In general the emergence of cooperation can be the result of: Changes of the pay-off structure, repeated interactions, spatial distribution of agents, agent migration etc. (Hauert and Szabó, 2005; Nowak, 2006; Szabó and Fath, 2007). Also, it was found that people often condition their behaviour on the cooperativeness of others or on their beliefs about others' actions, in a phenomenon termed *conditional cooperation* (Fischbacher, Gachter and Fehr, 2001; Keser, 2002).

4 NETWORK OF INTERACTIONS

Some properties have been found to be widespread in social and economic interactions (Boccaletti et al., 2006). Take for example the degree, the number of connections each node has as defined by the network, i.e. the size of the neighbourhood of said node. One of the typical properties of the networks analysed is that the degree usually has not a typical magnitude, but it is very diverse, spanning even several orders of magnitude. This usually translates in very broad degree distributions in real-world networks. Another property that is pervasive is that, within the network, any pair of agents are separated by a distance that is very small compared with the network size, and regardless of how much the network grows, these distances barely change. Interestingly, and with the advent of the pervasive use of on-line social networks, people has become aware (at least from an intuitive point of view) with these concepts: Nowadays, the fact that some individuals have very few social contacts, while others have thousands is of no surprise; something similar happens with the six degrees of separation, originated in the foundational works by Milgram (1967; Watts and Storgatz, 1998).

These properties and others related to the network structures have been shown to completely alter the global properties of the systems under consideration (Dorogovtsev, Goltsev and Mendes, 2001). In general, social sciences have restricted their analyses to describe properties of real-world networks, while developing a large body of knowledge on the topological traits that allow to describe and quantify these and other properties existent in real-world networks (Bollobás, 2001; Wasserman and Faust, 1994). On the other hand, the literature on complex networks has focused on understanding the properties of highly stylised models. However, in general, only plausibility arguments have been used and over-used to justify them (without micro-foundation or link to real-world data).

4.1 Small-world effect

The small-world effect is the property of the networks of social interactions (among others) by which their diameter (i.e. the maximum distance between any two nodes) is very small, when compared to the number of nodes in the network. The basic idea comes from the original empirical study by Stanley Milgram (1967). He distributed letters in central states of the United States with instructions that they should reach a given person in Boston (north-east). In principle, the individuals with the letters did not know the final recipients, but they were instructed to forward the letter to some acquaintance they thought may know how to deliver it. Two important things occurred: First, around a fifth of all the letters arrived; those which arrived passed (on average) through around six intermediate individuals. Second, in several cases the second last recipient (before arrival) was the same person (i.e. there are very well-connected individuals in the social network).

In a very simple mathematical construct, Watts and Storgatz (1998) demonstrated how the small-world property can emerge. I.e. starting from an arbitrary topology, the introduction of few random links connecting distant nodes is enough to dramatically decrease the average distance in a network.

4.2 Scale-free degree distributions

In the context of biological evolution, a ground-breaking work by G. Udny Yule (1925) showed that a heterogeneous, heavy-tailed distribution can emerge out a simple stochastic process. It is a kind of urn model,[6] related to the Pólya process[7] and can be simplified into the following: First of all, species are grouped in genera. Over time, by mutation of one of the existing species, new ones appear. At a constant rate λ_Y, this speciation process generates a new species belonging to the same genus as the parent species. Otherwise, at a rate μ_Y, the speciation event generates a new species that belongs to a new genus.

The Yule model is multiplicative, in the sense that the probability that a new species belongs to a given genus is proportional to the number of species the genus already contains. In other words and context, this model epitomises the concept of the rich gets richer effect. Let ki be the number of species belonging to genus *i*, and let $p(k)$ be the probability that a genus has size k. Yule showed (Aldous, 2001; Yule, 1925) that, for very long times, the distribution is given by

$$p(k) = \frac{\Gamma\left(1+\rho_Y^{-1}\right)}{\rho_Y} \frac{\Gamma(k)}{\Gamma\left(k+1+\rho_Y^{-1}\right)}, \tag{5}$$

where $\rho_Y = \lambda_Y / \mu_Y$. This solution means that for large values of k, asymp-totically, the distribution follows a scale-free distribution (Caldarelli, 2007; Sornette, 2006), $p(k) \propto k{-}(1+1/\rho_Y)$. This distribution is scale-free in the sense that by rescaling the variable k by a factor $\lambda > 1$, it results in

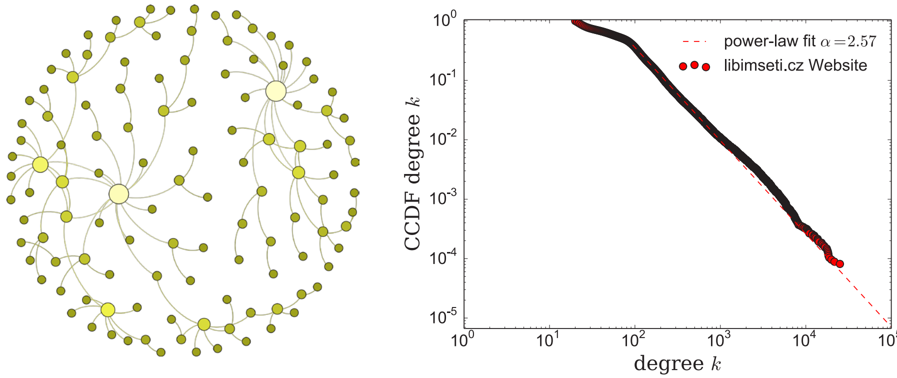
$$p(\lambda k) \propto (\lambda k)^{-(1+1/\rho Y)} \propto k^{-(1+1/\rho Y)} \propto p(k). \tag{6}$$

This property is also usually referred to as scale invariance. The intrinsic mechanism of the Yule model was rediscovered in the context of what nowadays would be called scientometrics, and termed the Matthew effect (Merton, 1968). In this work, Robert Merton writes "The Matthew effect consists in the accruing of greater increments of recognition for particular scientific contributions to scientists of considerable repute and the withholding of such recognition from scientists who have not yet made their mark".

6. In general an urn model (Johnson and Kotz, 1977) refers to a mathematical construct that can be abstracted into scenario where marbles are extracted sequentially from an urn. The rules that define the mechanism by which new marbles are added to the urn between successive extractions, ultimately determine the statistical properties of the sequence of marbles obtained.

7. The Pólya process (Sprott, 1978) is a simple urn model defined as follows: an urn contains marbles with two different colours. At each step, a marble is removed and a new marble with same colour as the removed one is added to the urn. This produces a process by which the more marbles were removed of a given colour, the more likely it is that successive marbles will be of the same colour.

FIGURE 4
Typical scale-free network



Obs.: Typical scale-free network, where hubs – nodes which are heavily connected to the rest – can be seen in lighter colour. (right) Cumulative degree distribution of the network of social contacts in the Czech dating platform "L´ıb´ım se ti" (Kunegis, Groner and Gottron, 2012) as of 2011. The network consists of 220 970 users (nodes) and 17 359 346 connections (edges). The dashed line represents a power-law fit equivalent to $p(k) \propto k^{-\alpha}$, following Newman (2005), it is found $\alpha = 2.57$ and $k_{min} = 93$.

Publisher's note: image whose layout and texts could not be formatted and proofread due to the technical characteristics of the original files provided by the authors for publication.

The preferential attachment (Barabási and Albert, 1999) follows a related idea. Let us consider a network that grows in a discrete time-scale. Initially, the network has m_0 nodes with an arbitrary topology. At every time step, a new node is added to the network and generates m links to existing nodes; the probability p(i ←→ j) that the new node i connects to another one j is given by

$$p(i \leftrightarrow j) = \frac{k_j + a}{\sum_{j'=1}^{i-1} (k_{j'} + a)}. \tag{7}$$

The parameter a reflects the initial attractiveness of nodes, even if not connected to any other. Like in the Yule model, the more links (what previously was a species) a node (genus) has, the more likely it will recruit new links (species). In this setting, the degree distribution obeys

$$p(k)\, \alpha\, \frac{\Gamma(k+a)}{\Gamma(3 + a/m + k + a)}. \tag{8}$$

The case studied in the original paper by Barabási and Albert has $a = 0$, which means that the degree distribution for large degrees simplifies to $p(k) \propto k^{-3}$. The networks produced by the latter model have a low clustering, and have an average path length $\bar{\ell}$ that grows with the network size N as Barrat, Barthélémy and Vespignani (2008), $\bar{\ell} = ln(N)/ln(ln(N))$.

It is important to stress that the preferential attachment model is not a realistic model of network growth. Arguing that individuals enter, for the sake of an example, on an on-line social network one at a time and create links to existing users and with no further link dynamics from their side is not an accurate description of reality. But acknowledging that, allows us to recognise something crucial of complex systems modelling. Preferential attachment captures a mechanism: Users are more likely to be known (or be "attractive" to others) the more acquaintances they already have. This can be due either to: *i*) new users are more likely to know someone who has several acquaintances; and *ii*) an extroverted person will be signalled by a large social neighbourhood and will be more likely to increase it even further. Then, the emergent property of this model (the scale-free degree distribution) is a characteristic likely to be found in any network where a property like preferential attachement is at play.

The model of preferential attachment was extended to encompass different and more realistic scenarios (Allard and Marceau, 2011; Dorogovtsev and Mendes, 2001; 2002; Dorogovtsev, Mendes and Samukhin, 2000; Tessone, Geipel and Schweitzer, 2011). It was also analysed and validated in contexts like collaborations (Barzel and Barabási, 2013; Capocci et al., 2006; Vespignani, 2011), sexual contact network (Jones and Handcock, 2003; Liljeros et al., 2001), etc.

From a procedural point of view, it is important to stress that empirical validation of scale-free distributions is a line of research in itself. Originally, inherited from the physics literature, simple regressions were performed, and accepted as standard. It is unfortunately not unheard of papers where the claimed scale-free behaviour extend indeed very few data points. The reader will recognise that doing so is in blatant contradiction with equation 6. Nowadays, it is widely accepted that this approach can lead to wrong conclusions (Newman, 2010), and therefore more sophisticated tools have been developed (Newman, 2005).

4.3 Temporal networks

In many cases of interest, the network of interactions is not static, but it changes over time. A very simple example is found in the network of social interactions: A person, regardless of the amount of social acquaintances he has, does not maintain a continuous interaction with all of them. Instead, at any point in time he may be either isolated, or interacting with a limited subset of his social neighbourhood. If he is speaking to a friend, he has a single active contact. Another example is that of scientific collaborations: Even very prolific scientists can only maintain a rather limited set of concurrent research projects with others. In these cases, the agents have a constrained amount of resources they can allocate to links, either because of limited capacity or limited cognitive abilities.

In spite of this fact, most modelling approaches either consider that the underlying network of interactions does not evolve, or that its evolution occurs at a time-scale which is much slower than that of the dynamical process taking place on the studied network. In the latter cases, the network exhibits a slow evolution that can be considered a simple perturbation when related to the complete structure. This also applies to a strand of research that has focused on network co-evolution where the states of its constituents determine the changes in topology, until a kind of stationary topology (and concomitant macroscopic state) is reached.

When the network evolution is observed, many systems exhibit patterns of interaction that are largely sparse and volatile. Sparsity is a common trait in the instantaneous realisation of the network if links are costly, or when the nodes have some kind of capacity constraints. Volatility refers to the fact that in real-world temporal networks, edges tend to have low persistence when compared to the observation period of the network evolution. This means that a network is volatile if it is possible to define a decay time after which the observed network topology largely differs from the previously observed one.

The realisation that the network is not a static construct but evolving has profound implications on the properties of the system under study (Holme and Saramaki, 2012). A simple example suffices to give an intuition of the effects that can be found in this scenario: The process of disease propagation where the vector of transmission is physical contact between an infected individual and a healthy one. Given that infection can only take place over active contacts, if the typical cycle of infection-recovery were much faster than the network dynamics, any infection would not propagate throughout the population and die after some time, propagating only over this tenuous, effectively static network (Tessone and Zanette, 2012; Zanette and Risau-Gusmán, 2008).

4.4 Multiplex and interconnected networks

In the descriptions so far, it is important to note that the nodes represent a unique type of component and a single type of connection exists between them, conforming the edges. Mainly during the last lustrum, the study of the so-called multi-layer networks (Kivela et al., 2014) has gained massive momentum. Take as a simple example a social network; acquaintances in this setting can be originated by different communication channels, not exclusive but at the same time not akin: e-mail, on-line social network contacts, phone calls, and face-to-face contacts are all different aspects of communication. These facets may not be taken as equivalent, depending on the problem studied on said multi-faceted social network. For example, information flow in such a network may require a proper modelling where the different channels of communication have their own intrinsic characteristics.

Another example of a system that can be represented as a multi-layer network is that of human mobility by public transport in large cities, where nodes represent public transport stops. There, it is possible to travel between nodes by different means of transportation: Underground, train or bus. All these are intrinsically different edges and a proper study mandates to take this point in consideration. In both previous examples, the networks under consideration have an additional property: Nodes in all layers are the same; in this case the system is called a multiplex network (Boccaletti et al., 2014).

In other situations, the networks in the different layers are composed of nodes of different nature. Take for example economic transactions (which may be taken as edges) and individuals (as one type of nodes) and their working places (as another). Edges will exist between different individuals, individuals and their working place, and between the nodes representing firms and the public sector. This is a simple example of an interconnected network.

The phenomenology of all these family of systems is very rich: When do interconnected networks behave as a single one, or independently (Radicchi and Arenas, 2013)? How do opinion dynamic models behave in these networks? How robust or fragile are such systems to the removal of nodes? All these questions have been targeted in the Literature and constitute important milestones in the understanding of the phenomenology of interconnected networks.

5 OUTLOOK

Many social systems are intrinsically complex. At the same time, they have a multitude of details that render their complete description an unattainable task. The works summarised in this chapter highlight the fact that stylised models can capture mechanisms behind some of their observed properties. Importantly, when these mechanisms are at work, the microscopic details become unimportant to have a qualitative understanding of the subject under consideration. These insights are crucial to realise that a parsimonious approach is of great value for this kind of systems. Practitioners and policy makers must bear in mind always the essential complex nature of the systems they are faced with. Understanding these phenomena is of crucial importance, but this does not mean resorting solely in simple models as a complete description of reality. This is not, as explained throughout this chapter, the intention of the complex systems approach.

As of this writing, there is an almost complete transition towards digital storage of information and, at the same time, more facets of human activity take place on-line. This fact spawns challenges from the most disparate points of view (social, economic, legal), but constitutes a huge possibility to gain more insight on the mechanisms underlying socio-economic processes. With continuous access to data, this can be done at two levels: First, from a qualitative point of view, the different mechanisms can be first individualised and formalised. Second, after this knowledge is consolidated, a more quantitative approach (with the additional advantage that it is now grounded in theory) can take place with huge implications for different actors of our society, ranging form policy making by governments to development opportunities for business (like in partnerships and marketing campaigns).

The research in this realm is largely interdisciplinary. However, crucial effort has to be taken by the research community and practitioners not to overlook the knowledge from the different fields. This requires an additional attention, but it is an efficient way to facilitate cross-pollination of the ideas between the involved disciplines. Part of the problem lies on the different terminology used in the different areas, with disparate constructs to elicit similar concepts. Also, it is needed that a larger extent of the research in this area is the outcome of interdisciplinary collaborations. In this way, different disciplines would enrich complex social systems research with diverse, yet complementary approaches. Different threats exist: On the one hand, the danger of research that only aims towards one of the disciplines involved, becoming effectively compartimentised. This limits greatly the reach in other communities, and also by construction is of limited interest only for the own discipline.

For a quantitative understanding of the phenomena observed in social systems, complementary tools – beyond the minimalistic complex systems approach – are needed. Even in this set-up, it is of primary importance not to populate the models with unnecessary details that convey no information nor predictive power to them.

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CHAPTER 8

THE ECONOMY AS A COMPLEX OBJECT

Orlando Gomes[1]

1 INTRODUCTION

Every day, millions of firms and millions of households around the world select, among many available options, which actions to undertake in order to fulfill their own economic goals. Any attempt to understand and explain such a wide and heavily interconnected system of human relations is a challenging task that the science of economics is pursuing since its inception in the eighteenth century.

Perfect rationality is the central assumption in economics; it is, in fact, the element that allows to distinguish this scientific field from any other dealing with the behavior of human beings or other living organisms. Economic agents are rational in their decisions and also in the way they perceive the future. The *Homo-Economicus* formulates rational expectations, in the sense that this entity is capable of using efficiently all the available information in order to avoid incurring in systematic mistakes, when predicting the future. Taking, as the main premise of economic analysis, the agents' unlimited capacity to apprehend the reality may be somehow interpreted as simplistic. However, it is precisely such premise that has driven the economic science in the last few decades, allowing it to approach many puzzling and important issues arising from empirical observation.

There is an immediate corollary of the rationality assumption: agents pursuing identical goals will act exactly in the same way and, therefore, the aggregate economy might be understood through the examination of the behavior of a representative agent. The representative firm will maximize profits given expected revenues and its cost structure; the representative household will formulate a consumption plan in order to maximize intertemporal utility; the representative government agency will establish policy goals and it will use the available resources to attain them. The representative agent paradigm has served as the benchmark for a whole generation of brilliant economists to launch the ideas that constitute today the foundations of economic analysis. In this group of scientists one can include such important

1. Lisbon Accounting and Business School of the Lisbon Polytechnic Institute (ISCAL-IPL) Av. Miguel Bombarda 20, 1069-035 Lisbon, Portugal. E-mail: <omgomes@iscal.ipl.pt>; Business Research Unit of the Lisbon University Institute (BRU-IUL).

names as the ones of Paul Samuelson, John Hicks, Kenneth Arrow, Gerard Debreu, Franco Modigliani, Robert Solow, Milton Friedman and Robert Lucas.

Economics has progressed a lot: real life intricate mechanisms have been reduced to simple mathematical models that, in turn, became powerful tools to address many relevant economic issues. The main achievement of modern economics was, then, its ability to explain how a typical agent, endowed with material resources and human skills, is capable of evaluating the costs and benefits of any decision and to choose the option involving a lower opportunity cost; knowing how such agent effectively acts, one might extrapolate the behavior of the global economy. Therefore, by taking fully rational economic agents with identical features, the science of economics has apparently discovered a formula that is suitable to understand many meaningful real-world events.

Despite the relevant progresses made by the economic science in the past, it is by now relatively consensual that it is necessary to start to look beyond the fully rational representative agent structure of analysis. Some authors, as Colander et al. (2004), Delli Gatti et al. (2010), Holt et al. (2011), and Kirman (2012) believe that a new era of economic thought is emerging; an era where conventional neoclassical economics is giving place to an interpretation of the human behavior in which one finds room for diversity, heterogeneity, adaptability and complexity. The economy should be interpreted as a complex system, a system where agents with different capabilities, different endowments and different preferences interact to generate a result that is not known a priori and that is the direct outcome of how the interaction process unfolds.

In this chapter, the reasons why one should interpret the economy as a complex object are dissected. It is shown that the economic science is making a gradual transition to a science of complexity, that macro events are necessarily the outcome of how micro units interact at a local level, and that a complexity approach is flexible enough to explain many relevant aggregate events as long periods of departure of key macro variables relatively to their equilibrium values. The remainder of the chapter is organized as follows. Section 2 reviews the contemporaneous literature on complexity economics. Section 3 explains why one should interpret the macro economy as a complex system. In section 4, a powerful tool that allows to address the economy as a complex object is approached, namely complex networks, which might be addressed in the context of agent-based models. Section 5 illustrates how a relatively simple model involving local interactions between heterogeneous agents might lead to a long-term result that can be classified as a complex outcome. Section 6 concludes.

2 COMPLEXITY IN ECONOMICS: THE EMERGENCE OF A NEW PARADIGM

According to Tesfatsion (2006), the economy can be qualified as a complex system for two complementary reasons: first, because a large number of individual units engage in systematic relations at a micro level; second, because local interactions generate global regularities that involve emergent properties, i.e., properties that are unique to the established pattern of interaction and that, consequently, do not depend solely on the intrinsic features of the involved individual units.

The concept of complexity involves many dimensions and it needs to be carefully dissected. In what concerns economics, and in order to rigorously define the economy as a complex system, the following properties emerge as relevant (see Arthur et al., 1997; Martin and Sunley, 2007; Fontana, 2008).

2.1 Heterogeneity

Heterogeneity is the main driver of economic relations; these relations, e.g. trade realtions, simply would not exist if all individuals shared the same preferences, endowments and skills. The economy is a system constituted by a large number of components, with each component possessing its own features.

The attempt of the economic theory in building its reasoning in turn of the explanation of the behavior of a rational representative agent, as argued in the introduction, thus neglecting all possible sources of heterogeneity, might be interpreted as a relevant fragility. As Bouchaud (2009) remarks, there is an impossibility in this reductionist approach: the behavior of the crowd is, in its essence, different from the behavior of the individual; collective action has a logic of its own, a logic that can only be understood by allowing for agent heterogeneity.

2.2 Decentralization

The economy is a self-organized decentralized system. The aggregate outcome is the result of the free initiative of each individual agent who acts with the purpose of serving her own individual goals, and this occurs without the need for intervention of any outside entity or central planner. The idea of decentralized equilibrium is an ancient concept in economics that many of its most prominent scientists have recurrently recovered. For instance, Friedrich von Hayek (1967) talked about the existence of a spontaneous order, according to which the observed laws of motion are the outcome of the interaction established among self-interested agents. In Hayek's view, the economy is understood as a complex web of relations and transactions in an environment that is similar to what we can define as a complex network or complex object.

Contemporary approaches to complexity continue to highlight the nature of the economy as a decentralized network. It is the case of Ashraf et al. (2012), who interpret market relations as the outcome of the behavior of profit-seeking business firms. Each individual firm will act with the purpose of serving its own objectives; however, by doing so a coherent macro pattern of transactions will emerge. Global regularities are not the result of central coordination; on the contrary, no one will evidence the ability to gather the immense knowledge and power that are required to control market relations and, hence, the aggregate patterns that possibly emerge are often beyond the comprehension of each individual agent.

2.3 Evolution

The economy is a dynamic system within which individuals adapt and learn. The interaction process shapes the way agents act, because they evolve as the relations between them unfold. A complex system is necessarily formed through evolution. Simple organisms give place to more sophisticated entities as they adapt in the context of a constantly changing environment. A Darwinian process of survival of the fittest takes place in the economy in the same way it occurs in many other contexts. The evolutionary process is a lengthy process that adds successive layers of complexity to the pre-existent web of interactions.

The sophisticated market institutions, financial institutions or regulatory entities we have in today's economy are the result of a gradual and incremental evolution. Hodgson and Knudsen (2010) designate the process of system evolution leading to the sophistication of complex networks as generative replication. The term replication relates to the idea that from one stage to the next some information is passed on, i.e., a new system has always some features of the previous systems that originate it. Nevertheless, a new system rarely just replicates the precedent one; it typically adds something new. A generative process is a process that builds on past generations to present a new improved version of the reality; it is a process that is able to introduce innovation, it is a process of creative destruction. Under the discussed perspective, one might claim that the economy is an increasingly complex system that has arrived to the current state of complexity after millions of years of evolution.

2.4 Path-dependence and non-equilibrium dynamics

As implicitly mentioned in the previous point, the economic system is historically determined. The current state of a system has singular features that are determined by the particular events that have promoted it. History will not necessarily repeat itself and therefore there are no reasons to believe that a given economic scenario observed in the past will occur in the future with the exact same features. It is the set of specific conditions attached to the character of the agents, to the institutional context, to the dynamics of interaction and to the environment in which interaction takes place that will determine economic outcomes and it is in fact implausible that such huge amount of requisites might appear in a recurrent form.

Because of the previously stated and because agents adapt, learn and evolve, the economic system does not have the tendency to remain in an equilibrium position or rest in a stationary state. Interaction in complex environments will seldom produce a steady-state outcome. Even apparently simple models built on the notion of local interaction among heterogeneous agents might generate, according to Brunn (2002), a complex and irregular dynamic behavior, where the values of the underlying variables fluctuate forever without ever converging to a stationary state. Furthermore, in complex environments new patterns of interaction might emerge after thousands of periods of starting running a simulation, even when no external event disturbs the system.

Note that the above observations go against the most basic foundations of the neoclassical economics of the representative agent, which believes that equilibria are inherent to economic relations and that the trajectories of variables are solely determined by the initial conditions and by simple rules of motion, which allow, from the start, to predict with accuracy how those trajectories will evolve and where the system will rest in the so called long-term steady-state.

The mentioned features, namely the four properties that were characterized above, clearly qualify the economy as a complex object. Based on these features, many authors, e.g., Markose (2005), McCauley (2005), Velupillai (2005) or Rosser (2010), have attempted to conceive a notion of complexity able to reveal itself appropriate to address economic events. Such notion involves considering three different categories: connective complexity, dynamic complexity and computational complexity.

The first concept, connective complexity, highlights that what truly shapes the behavior of the elements of a system are the relations that are established among them and that the evolution of the system is the direct outcome of the links that emerge and vanish, within a given network, at each time period. More than the individual features of each single element, it is the logic of interaction that matters. This interpretation of a complex system is the one pioneered by Simon (1962), who also reflected on the limits of rational thinking; the notion of bounded rationality opens the door for agent heterogeneity and, consequently, attributes meaning to the distinct forms of contact across different agents.

Dynamic complexity is related to the properties of the dynamic equations one takes to describe the evolution of the economic system. Economics is a science that heavily resorts to dynamic systems to interpret the reality. These systems are typically simple, involve linear relations and imply convergence towards a fixed-point steady-state. However, when escaping the straightjacket of homogeneous behavior and full rationality, one encounters intricate nonlinear dynamic relations across economic variables, which lead to systems with non conventional long-term outcomes, particularly a-periodic cycles and chaotic motion. As Day (1994) highlights, a dynamic system can be interpreted as complex when it generates, for its endogenous variables, a motion pattern that is not regular, i.e., that is not a fixed-point or a periodic cycle. Chaos is associated with complexity because it reflects a long-term result of irregular bounded instability that is determined by the initial conditions of the system. Chaotic systems are characterized by sensitive dependence on initial conditions, meaning that two different initial states, no matter how close to each other, will generate completely different long-term irregular fluctuations.

A third notion relates to computational complexity. Work in this area goes back to the influential contribution of Shannon and Weaver (1949) concerning the theory of information. In this context, complexity is attached to the concept of entropy. Entropy, in turn, is associated with how hard it is to process information. The higher the level of entropy, the more complex the respective system will be. Since it deals with the capacity to treat information, computational complexity raises a pertinent question concerning the way in which conventional economic theory addresses its challenges: if agents are rational and optimize their behavior, they will employ all their effort and resources in searching for the optimal solution. Within a complex system involving entropy, the computational effort required to attain the optimal solution may be so high that it becomes unreasonable, from a cost-benefit point of view, to search for such outcome. Then, in the context of a complex environment, the decision-maker faces a trade-off between finding the best solution and the employment of the resources required to attain it.

The above arguments point to the unequivocal idea that the economy should be approached under a complexity perspective. However, as pointed out before, conventional economic thought has avoided this approach. One of the reasons for mainstream economics to be detached from a complexity perspective relates to the conservative attitude of the economists and their difficulty in accepting the techniques and tools that other sciences have developed and have to offer. Economics is today the science of logical and coherent models, models that are rigorous from a conceptual point of view and where the notions of rationality, equilibrium, optimization and efficiency dominate. To go beyond this paradigm, the obsessive search for the optimal behavior must be discarded in favor of a multidisciplinary approach that gives relevance to experimentation and to the careful analysis of institutional factors.

One of the scientific fields that can best assist economics in the quest for a complexity paradigm is physics, where long ago the mechanical view of the world that economics continues to adopt has been replaced by an agent-based interpretation.

A new field of knowledge, dubbed econophysics, has emerged with the intention of offering new insights on how economic issues can be approached. An inductive reasoning is adopted, strongly based on the observation and measurement of collective behavior. The science of econophysics was born and developed with the contributions of Mantegna and Stanley (2000), Gallegatti et al. (2006), Rosser (2008) and Yakovenko (2009), among others. The introduction of physics in economics is useful for a better understanding of how spontaneous orders emerge in the markets; physics has a long tradition in examining self-organized, adaptive and evolutionary systems and its tools can be easily adapted to understand and interpret the human behavior under a setting of interaction.

Triggering a change of paradigm in a scientific field is, certainly, a huge and hard task. Economists are locked in their own methodology and techniques and will probably offer some resistance to the adoption of new approaches. Fortunately, the perception of the world as a complex entity is something that many other fields of knowledge (not only physics but also, e.g., biology or psychology) have already accepted, having developed a significant set of tools that are now available for economics to address and explore their own issues in the scenario in which they truly arise, namely a complex scenario composed by multiple heterogeneous and interacting parts.

Furthermore, there is a methodological issue with conventional economics that has prevented it to progress to a science of complexity. Economics is typically approached as a deductive science, i.e., a science that begins by establishing hypotheses, over which a model is constructed and where, at the end, the model is confronted with the reality. Empirical concerns only arise at the last step of the process to confirm the assumptions that one has established in the beginning. Under such a process, the reality is forced into the model and economics becomes the science that explains what one wants to observe from the start, in alternative to the science that begins by observing facts and that constructs models to explain such facts.

An inversion of paradigm is necessary, i.e., economics needs to adopt an inductive methodology, starting from observing and exploring real facts and then proceeding to their explanation. Interpreting the economy as a complex object requires this methodological change.

3 THE COMPLEX MACRO SYSTEM

Since its early days, economic thought has always been concerned with the evident complexity of market structures and market relationships (see Colander, 2008, for a detailed study on how economic scientists have approached, in many occasions, complexity issues). In fact, some of the most prominent classical economists, e.g., Adam Smith, David Ricardo or Alfred Marshall, saw the economy as an entity governed by interaction, evolution, learning, adaptation and path dependence. But they also argued in favor of establishing some simplifying assumptions with the goal of discerning order where only an uncoordinated multitude of relations was apparent.

One should not forget, though, as emphasized by Colander and Rothschild (2010), that the major contributors for the economic theory, including those that published their work across the twentieth century, namely John Maynard Keynes or Milton Friedman, never hid behind simple mechanical models to disguise the complexity of the economy. The contributions of those authors are in depth critical evaluations about the functioning of the economic system, which were, on posterior dates, transformed by their successors into basic and stylized models of analysis that could be brought into the classroom and used for policy implementation. The Keynesian IS-LM model is a good example of how a detailed inspection about the functioning of the macro economy was reduced to a couple of simple relations that are useful for an aggregate analysis, but where many questions about the behavior of the agents that generated them are forgotten.

Macroeconomics became strongly attached to the traditional concept of general equilibrium models in which agent heterogeneity and adaptability are absent. Nevertheless, this is the field in which a complexity approach is most urgent. The macro economy is the result of multiple interactions that are aggregated in order to explain the behavior of the economy as a sole entity. A rigorous aggregation exercise requires understanding with detail what the term microeconomic foundations truly means. In a complexity perspective such foundations relate to the identification of different groups that behave distinctively and of the interactions that are established within each group and across groups.

Macroeconomics must be an applied science for which the observation of the structure of economic relations and of patterns of interaction should precede the construction of an empirically based model, that can be used for policy evaluation and policy implementation. Above all, one must avoid incurring in a fallacy of composition: in the macro economy, the whole is far from being the sum of the parts; when agents establish economic relations they are creating a unique reality that goes beyond the characteristics of each individual entity.

Progressively, agent-based numerical simulations and simple and stylized models from physics are replacing, as analytical tools, traditional macroeconomic models in which agents are endowed with unlimited computing abilities and where aggregation is a naïve process of augmenting the scale of the analysis. Those tools are well suited to deal with heterogeneity and interaction, allowing to highlight the fundamental fact: the behavior of the whole economic system is not inferable from the behavior of a single agent. Wagner (2012) sees the relationship between micro and macro phenomena as non-scalable, i.e., macro events cannot be inferred from the behavior of the micro units, because they are of a higher order of complexity. This author considers that the macro economy is a complex ecology of plans where micro units can generate different macro patterns in response to different interaction processes.

In Lengnick (2013), an agent-based macroeconomic model is built with the objective of comparing aggregate consequences of local interaction with the results of a conventional dynamic stochastic general equilibrium framework. Running the model, the author finds that coordination failures may deviate the economy from an equilibrium position, although a spontaneous order generating such equilibrium result is also feasible. Either way, the important idea is that the macro level equilibrium is not imposed on the economic structure; if it arises, it is the natural outcome of a series of interaction processes.

Other attempts of addressing the macro economy as a complex system have focused particular attention on financial and credit markets. The flexibility of agent-based macro models in introducing complicated and unexpected out-of-equilibrium dynamics over simple theoretical structures have made them the ideal setting to address and study extreme financial circumstances, as market crashes, bubbles or bank runs. Thus, it is no surprise that various authors have attempted to carefully dissect the anatomy of credit and financial networks with multiple interacting units. It is the case of Gallegatti et al. (2003), Iyetomi et al. (2009), Bargigli and Gallegatti (2011) and Grilli et al. (2014), who have searched for the sources of instability in financial and credit markets and for the channels that link the credit system to the macro economy, in order to explain observed fluctuations, both in periods of economic normality and also, with special emphasis, in phases of deep recession.

Most of the effort in theoretic macroeconomics across the last few decades has been related with the quest for the true micro foundations of macro behavior. Models that integrate complexity features apparently provide a relevant starting point for such endeavor. Complex systems are intrinsically models that are built upon the observation of the patterns of interaction among individual agents. They are also models equipped with the ability to generate an integrated view of the system and to search for collective patterns. It is in this way that the macro economy emerges and evolves. It is not forced from the outside; it is generated as individual relations turn into collective patterns of interaction within the erected framework of analysis.

4 AGENT-BASED MODELS AND COMPLEX NETWORKS

The analysis of the economy as an evolving complex entity requires the use of specific techniques that go beyond the conventional tools to which this science typically resorts. Many authors, e.g. Tesfatsion (2003), Gaffeo et al. (2008), Farmer and Foley (2009) and Fagiolo and Roventini (2012), stress that agent-based models are the ideal setting to put into perspective complex economic relations. Agent-based models are collections of algorithms or procedures that provide flexible structures to explore how local interactions originate a two-way feedback between the microstructure and the regularities that emerge at a macro level.

Such models are implemented as computational experiments that create flexible virtual worlds that, once generated, evolve over time with complete autonomy, i.e., their dynamics are solely driven by the interaction of the system's inhabitants with no need for external or central coordination. The modeler is just called for setting the initial conditions, and no posterior intervention of her part is required. When setting the initial state, agents are endowed with a set of characteristics that allow to classify them as economic agents: they will be guided by their own interests, they will choose rationally, they will be able to communicate with those who surround them, and they will be able to adapt to their environment and to act strategically. In these models, agents are not optimizers, they are constrained by local information sets and they select the best possible option from a few lines of action they can follow.

In agent-based models, even extremely simple frameworks might lead to complex dynamics. Interaction creates a unique and unrepeatable history and models might run forever without ever reaching a steady-state (out-of-equilibrium dynamics persist); it is often possible to find relatively long periods with large deviations relatively to a benchmark fixed-point equilibrium (what is useful, e.g., to explain the occurrence of recessions in the aggregate economy). Nevertheless, regular large-scale patterns might also emerge in this kind of models, i.e., one might discern the existence of a given degree of coordination arising from a complex interaction market structure.

In Helbing and Balietti (2012), it is emphasized that one of the most salient features of agent-based modeling is its versatility. This approach may be applied to a wide variety of economic and social issues where complexity is necessarily present (e.g., financial markets, social conflict, managerial decisions, urban development, or globalization) and it can also use different modeling strategies; for instance, automated systems might be created from a set of logical rules regardless from any underlying structure or, alternatively, the agent-based environment might be supported on a network of relations. Therefore, a significant part of agent-based modeling, in the context of complexity analysis, relates to the formation and evolution of networks. Economic networks are particularly relevant, because truly understanding economic relations demands a capacity to put into perspective how each and every agent is connected and what drives the formation and the dissolution of links among interacting agents.

In what follows, complex networks are addressed, under the perspective that they constitute a relevant tool for complexity analysis. They are well equipped to deal with local interactions among heterogeneous agents and, therefore, to approach the economic system as a complex object. Basically, complex networks are a large collection of nodes, representing the relevant entities or agents, that are connected by links that translate the nature of the relations between the nodes. Bargigli and Tedeschi (2014) highlight the relevance of building networks to explain the interconnections in the economy. The most meaningful idea that one must take into account when modeling the economy as a complex network is that the topological structure of such network is systematically changing as the links that associate agents with each other are constantly forming and breaking.

What distinguishes economic networks from networks in other areas of knowledge is that links exist or not as a consequence of a cost-benefit analysis that self-interested agents undertake given their own expectations about future events. Networks evolve endogenously as local interaction among rational, though not hyper-rational, agents unfold. The central question in economic networks is what forces underlie the establishment of links between any two individuals? What affinities can we encounter among those who choose to be in contact or are put together by chance?

Technically, a complex network corresponds to a graph $G=(N,L)$ where N and L are two sets. Set N contains the nodes, vertices or points of the network and L corresponds to the links or edges that connect the nodes. Thus, the elements of L will correspond to pairs of elements of N. The first set contains N elements: $N\equiv\{n_1,n_2,\ldots,n_N\}$ and the second set is of order L, i.e., contains L elements: $L\equiv\{l_1,l_2,\ldots,l_L\}$. According to Bocalletti et al. (2006), what distinguishes a complex network from a simple graph is the specific set of features of its topological structure. A complex network is composed by thousands or millions of nodes and links and it has an irregular and constantly evolving structure. Approaching such type of network is a complicated task, but it is precisely the challenge that is worth facing, because those are precisely the characteristics that define the economy as a complex object.

In economic networks, nodes represent households, firms, financial institutions and government agencies and departments; the links are the real and monetary flows that connect the agents. This description appears to be close to the one of the well known circular-flow diagram through which economic principles are introduced to students. In fact, an economic network is a circular-flow diagram, but an extremely detailed one, where in principle a high degree of heterogeneity across each class of agents is allowed for. This lack of homogeneity is not restricted to the nature of the nodes, it has to do also with the specific features of the links. An economic network is an inhomogeneous web of relations, in the sense that the degree of a node, i.e., the number of direct connections with other vertices, varies across nodes.

Economic networks share most of the properties of other real-world networks that connect human beings and the institutional arrangements created by them. One of these properties is that the degree distribution, i.e., the fraction of nodes sharing a same degree, is power-law shaped. This signifies that in actual networks one rarely encounters a random and relatively homogeneous distribution of links; there will be some nodes that will dominate, concentrating a large number of edges to other points in the network, while the large majority of the nodes have associated only a few links. A network involving a power-law degree distribution is designated as a scale-free network; economic networks are, undoubtedly, scale-free networks. Another important feature of economic networks, common to other interaction structures in society, is that, no matter how large the network is, one often finds relatively short paths between any pair of nodes; this is known as the small-world property. Economic networks are, effectively, small-world networks.

The structure of the economy should be interpreted also as a weighted network. This means that links across nodes vary in their intensity and relevance. There are strong and weak links across agents and the analysis of the network should be able to cope with this diversity. Furthermore, in economic networks there is a tendency for the formation of communities, clusters or cohesive subgroups, i.e., relatively small groups that share strong ties across their members. A group of tightly connected nodes is likely to create some specific features as fads or new habits, which can on a second stage spread to the rest of the network. The strength of the links and its degree distribution are not static features of the economic network; the intensity of connections may be reinforced or fade away with the passage of time, existing connections may disappear completely and new ones are likely to be formed. Therefore, the economy is not only a complex network; it is a systematically evolving organism that can decisively change shape in a few time periods.

Analyzing a network with the features one has enumerated in the previous paragraphs appears to be an extremely demanding task. A compromise between comprehensiveness and tractability is required to reduce the diversity of node characteristics and link properties to an intelligible small set of regularities. In the next section, a complex network scenario is taken to illustrate the behavior of economic agents. Agents will be classified in terms of their confidence or sentiment towards the future performance of the economy and their sentiments may change as a result of local interactions. Although this corresponds to a minimal structure of analysis, it is sufficiently comprehensive to cover most of the complexity features one has previously mentioned, namely agent heterogeneity, local interaction and decentralized decisions, adaptability and evolution, and out-of–equilibrium dynamics.

5 AN ILLUSTRATION: COMPLEX DYNAMICS IN A SIMPLE SENTIMENT MODEL

Economic complexity may be addressed by constructing large-scale networks that contemplate a large portion of the most meaningful observable interaction processes. Typically, these network relations can be subject to analysis only resorting to computer simulations, through which the model is run in order to identify significant regularities. Nevertheless, complex is not a synonymous of complicated; one does not need to have an immensely large set of relations to approach economic phenomena as complex phenomena.

This section proposes a simple model aimed at addressing sentiment switching under a complexity perspective. Economic agents change their perspective about future economic events as a result of local interactions, although, in some circumstances, the global result might feedback into agents' decisions. Although very simple and stylized, we will argue that the model contains the assumptions and leads to the results that correspond to the features of complex systems we have characterized so far. This model is inspired on the literature about rumor spreading on complex networks, a literature that was pioneered by Daley and Kendall (1965) and Maki and Thompson (1973), and that has counted with many important contributions in recent years, e.g., Zanette (2002), Nekovee et al. (2007), Huo et al. (2012) or Wang et al. (2013).

Consider a network with an undefined but large number of nodes. Each node will contain an agent. Agents will be heterogeneous in the sense that they will possess different sentiments about the future state of the economy (e.g., about future output growth or future inflation). Agents are split into five categories: neutral, weakly optimistic, strongly optimistic, weakly pessimistic and strongly pessimistic. At each date t, each agent will assume one of the characterized positions and the following shares will correspond to the percentage of individuals in each of them: x_t (neutral), z_t^ω (weakly optimistic), y_t^ω (strongly optimistic), z_t^ζ (weakly pessimistic), y_t^ζ (strongly pessimistic). Naturally, $x_t + z_t^\omega + y_t^\omega + z_t^\zeta + y_t^\zeta = 1$. We also define the share of optimists as $\omega_t \equiv z_t^\omega + y_t^\omega$ and the share of pessimists as $\zeta_t \equiv z_t^\zeta + y_t^\zeta$.

This is a cellular automata network, where each node is in one of the five possible states at date t but where the contact among agents in different nodes might induce a change of category or state for the next period. In what follows, a series of rules for sentiment switching through local interaction will be applied. These are necessarily stylized rules that serve the illustrative purpose of our exercise, but that could be made more realistic, for instance, by proceeding with a rigorous empirical inquiry of how sentiments change when two individuals with different sentiments meet. The rules that will be adopted are the following:

1) When two neighbors, *i* and *j*, are in the same state and meet, they will remain in that specific category with a one hundred percent probability:

$$x(i) + x(j) \xrightarrow{1} x(i) + x(j)$$

$$z^{\omega}(i) + z^{\omega}(j) \xrightarrow{1} z^{\omega}(i) + z^{\omega}(j)$$

$$y^{\omega}(i) + y^{\omega}(j) \xrightarrow{1} y^{\omega}(i) + y^{\omega}(j)$$

$$z^{\zeta}(i) + z^{\zeta}(j) \xrightarrow{1} z^{\zeta}(i) + z^{\zeta}(j)$$

$$y^{\zeta}(i) + y^{\zeta}(j) \xrightarrow{1} y^{\zeta}(i) + y^{\zeta}(j)$$

2) When one of two neighbors, *i* and *j*, is strongly optimistic or strongly pessimistic, and meets an individual with the opposite sentiment, they remain in their original sentiment classes, with probability 1:

$$y^{\omega}(i) + y^{\zeta}(j) \xrightarrow{1} y^{\omega}(i) + y^{\zeta}(j)$$

$$y^{\omega}(i) + z^{\zeta}(j) \xrightarrow{1} y^{\omega}(i) + z^{\zeta}(j)$$

$$z^{\omega}(i) + y^{\zeta}(j) \xrightarrow{1} z^{\omega}(i) + y^{\zeta}(j)$$

3) When two neighbors, *i* and *j*, meet, one of them with a neutral sentiment and the other with a weak sentiment towards pessimism or optimism, the neutral sentiment becomes pervasive, with probability $\theta \in (0,1)$:

$$x(i) + z^{\omega}(j) \xrightarrow{\theta} x(i) + x(j);\; x(i) + z^{\omega}(j) \xrightarrow{1-\theta} x(i) + z^{\omega}(j)$$

$$x(i) + z^{\zeta}(j) \xrightarrow{\theta} x(i) + x(j);\; x(i) + z^{\zeta}(j) \xrightarrow{1-\theta} x(i) + z^{\zeta}(j)$$

4) When two neighbors, *i* and *j*, in the same sentiment category, meet and one of them has a strong sentiment and the other a weak sentiment, the sentiment of the first will weaken, with a probability $\sigma \in (0,1)$:

$$y^{\omega}(i) + z^{\omega}(j) \xrightarrow{\sigma} z^{\omega}(i) + z^{\omega}(j);\; y^{\omega}(i) + z^{\omega}(j) \xrightarrow{1-\sigma} y^{\omega}(i) + z^{\omega}(j)$$

$$y^{\zeta}(i) + z^{\zeta}(j) \xrightarrow{\sigma} z^{\zeta}(i) + z^{\zeta}(j);\; y^{\zeta}(i) + z^{\zeta}(j) \xrightarrow{1-\sigma} y^{\zeta}(i) + z^{\zeta}(j)$$

5) When one of two neighbors, *i* and *j*, is strongly optimistic or strongly pessimistic, and meets an individual that has a neutral sentiment, the first is potentially capable of converting the second into that sentiment category, i.e., the second agent becomes also a strong believer of the respective sentiment; this occurs with a probability $\lambda \in (0,1)$:

$$y^{\omega}(i) + x(j) \xrightarrow{\lambda} y^{\omega}(i) + y^{\omega}(j);\; y^{\omega}(i) + x(j) \xrightarrow{1-\lambda} y^{\omega}(i) + x(j)$$
$$y^{\zeta}(i) + x(j) \xrightarrow{\lambda} y^{\zeta}(i) + y^{\zeta}(j);\; y^{\zeta}(i) + x(j) \xrightarrow{1-\lambda} y^{\zeta}(i) + x(j)$$

6) The most sophisticated rule we adopt respects to the meeting between agents *i* and *j*, when they are in opposite sides of the sentiment barricade and they are both weak believers. In this case, they can be converted to the neighbor's sentiment category, with a probability $\rho \in (0,1)$, if a specific set of conditions are met. In particular, in this case we take a feedback process from the macro to the micro level that translates in the following conditions: if, simultaneously, the global share of optimists is increasing and the global share of pessimists is decreasing, the optimist agent will be able to transform the pessimist into an optimist; the opposite occurs when the global share of optimists is decreasing and the global share of pessimists is increasing. Individuals will remain in the original positions if none of the two stated conditions is satisfied. Symbolically:

$$\omega_t > \omega_{t-1} \wedge \zeta_t < \zeta_{t-1}:$$
$$z^{\omega}(i) + z^{\zeta}(j) \xrightarrow{\rho} z^{\omega}(i) + z^{\omega}(j);\; z^{\omega}(i) + z^{\zeta}(j) \xrightarrow{1-\rho} z^{\omega}(i) + z^{\zeta}(j)$$

$$\omega_t < \omega_{t-1} \wedge \zeta_t > \zeta_{t-1}:$$
$$z^{\omega}(i) + z^{\zeta}(j) \xrightarrow{\rho} z^{\zeta}(i) + z^{\zeta}(j);\; z^{\omega}(i) + z^{\zeta}(j) \xrightarrow{1-\rho} z^{\omega}(i) + z^{\zeta}(j)$$

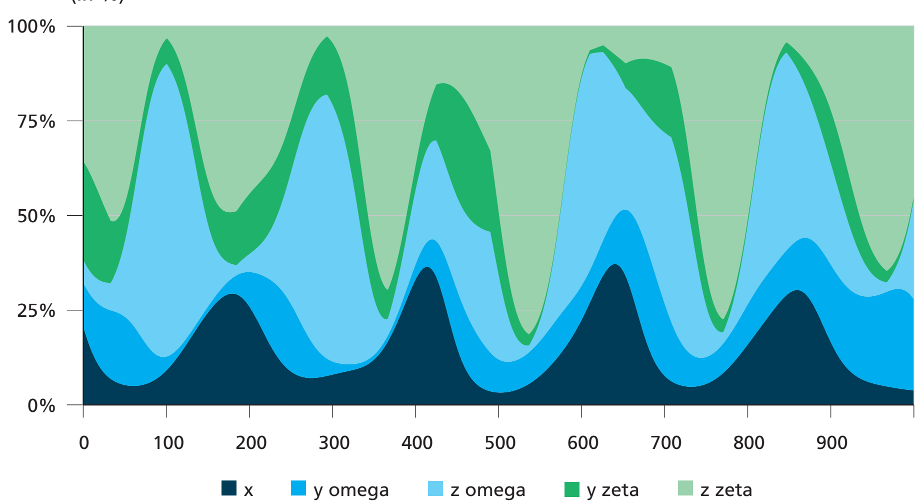
Taking the hypothesis of homogeneous mixing, i.e., that meetings occur randomly across the population, and normalizing the number of contacts per unit of time to 1, the above information can be transformed into a relatively simple system of difference equations that respect to the evolution of densities of agents in the various categories. In the current case, the system under evaluation will be,

$$x_{t+1} - x_t = [\theta\,(z_t^{\omega} + z_t^{\zeta}) - \lambda\,(y_t^{\omega} + y_t^{\zeta})]\,x_t$$
$$y_{t+1}^{\omega} - y_t^{\omega} = (\lambda x_t - \sigma z_t^{\omega})y_t^{\omega}$$
$$z_{t+1}^{\omega} - z_t^{\omega} = (\sigma y_t^{\omega} - \theta x_t \pm \rho z_t^{\zeta})\,z_t^{\omega}$$
$$y_{t+1}^{\zeta} - y_t^{\zeta} = (\lambda x_t - \sigma z_t^{\zeta})\,y_t^{\zeta}$$
$$z_{t+1}^{\zeta} - z_t^{\zeta} = (\sigma y_t^{\zeta} - \theta x_t \mp \rho z_t^{\omega})\,z_t^{\zeta}$$

In this set of equations, the plus/minus signs in the third and fifth equations obey to the conditions previously imposed to the interaction between agents with opposite weak sentiments. To approach the model's dynamics, one could proceed with a typical analytical study of existence and stability of the respective long-term equilibrium. However, given the peculiarities of the specified interaction process, such equilibrium will be irrelevant, because the system will not remain on it. Out-of-equilibrium dynamics will dominate, as a few numerical examples allow to illustrate.

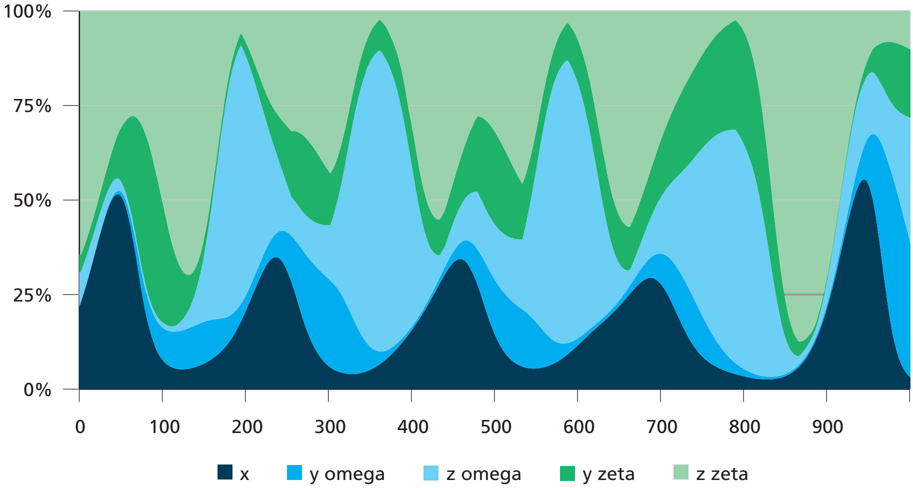
To visualize the dynamics of the proposed interaction network model, one needs to specify parameter values and initial values for the endogenous variables of the system. Consider the following array of parameters, $(\theta, \sigma, \lambda, \rho) = (0.05, 0.075, 0.15, 0.1)$. For this, as for a large majority of combinations of admissible parameter values, one finds that in the long-run, after the transient phase is complete, the system will remain in a non equilibrium position, with irregular cycles persisting over time. Waves of optimism and pessimism emerge, in this way, as the result of the mere interaction among neighbors combined with a localized feedback effect from the global economy over micro decisions. Figures 1 to 4 present the outcome of the model for 1,000 observations obtained after excluding the initial transient phase. Each graphic is obtained from a different set of initial conditions. They are all such that $y_0^\omega = z_0^\omega = (1 - x_0)/3$ and $y_0^\zeta = z_0^\zeta = (1 - x_0)/6$, with $x_0 = 0.25$, $x_0 = 0.5$, $x_0 = 0.75$, $x_0 = 0.9$, for each case.

FIGURE 1
Percentage of agents in each sentiment category (*x0* = 0.25)
(In %)



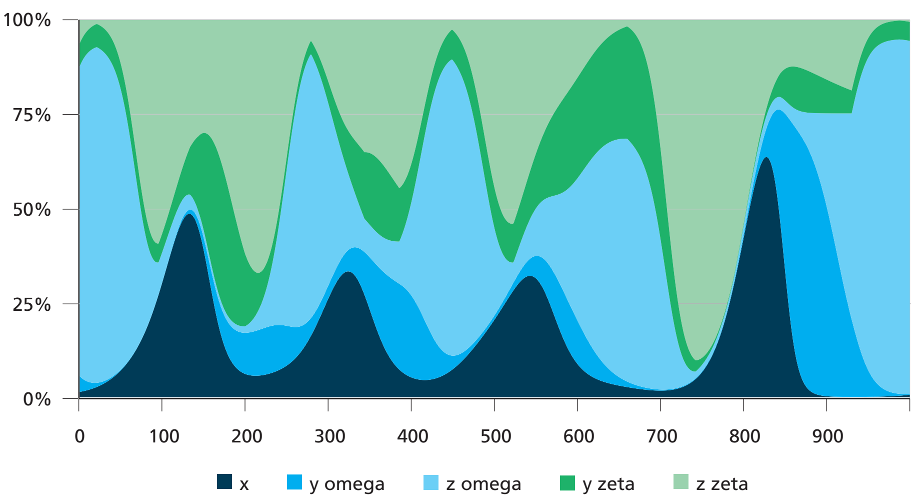
Elaborated by the author.

FIGURE 2
Percentage of agents in each sentiment category (*x0* = 0.5)
(In %)



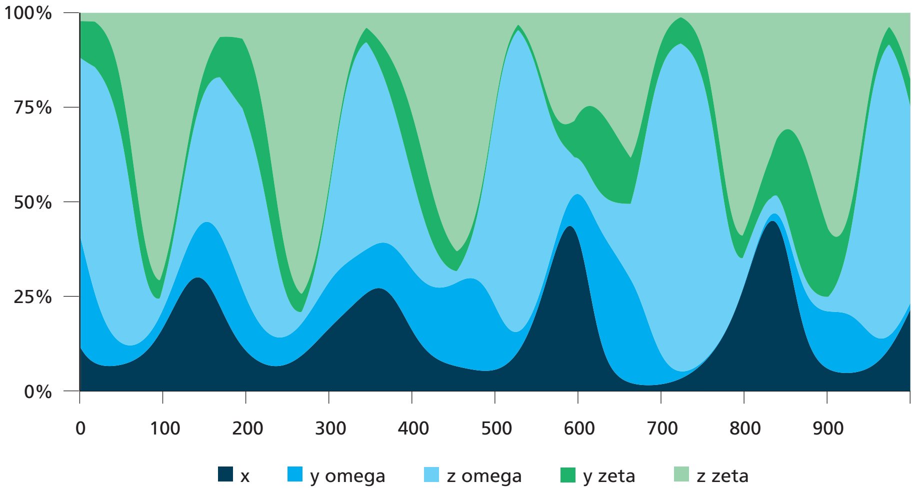
Elaborated by the author.

FIGURE 3
Percentage of agents in each sentiment category (*x*0 = 0.75)
(In %)



Elaborated by the author.

FIGURE 4
Percentage of agents in each sentiment category (*x*0 = 0.9)
(In %)



Elaborated by the author.

This illustrative example of how a complex system might work has achieved the intended goals. Starting from a minimal complex structure with agent heterogeneity and local interaction, an evolutionary network emerged. In this network agents learn, adapt and evolve as they establish relations with each other, and there is no tendency for the system to remain in an equilibrium position, since agents can always go back to a prior sentiment position depending with who they interact next. This out-of-equilibrium result evidences how complexity might emerge from a small set of interaction rules.

The implications of a model as the characterized one are huge. By focusing on changing sentiments, it says that periods of optimism and pessimism are not just the result of observable economic conditions and of the probabilities regarding how they will evolve in the future. It is the structure of the contacts among agents that will determine their confidence levels. Waves of optimism and pessimism are pervasive because agents are permanently in contact and can be influenced by others. Animal spirits are, thus, present in the economy and may help explaining short-run macro performance.

6 CONCLUSION

This chapter put into perspective the reasons why one should interpret the economy as a complex object and discussed how the science of economics might gain the status of a science of complexity. In Arthur (2013), the complexity status of economics is synthesized on the idea that the economy is permanently in motion and perpetually under construction and renewal. Economic relations do not have to do with determinacy, equilibrium, order or static outcomes, as the traditional approach to economics suggest; the economy is organic, contingent on past events, evolutionary and open to innovation. In a word, the economy is complex.

The complexity approach is progressively gaining a rightful place on economic thought. This is due to its realism, i.e., to the ability of explaining how global regularities are generated by local strategic actions and how such regularities feedback into the behavior of individual agents, creating a competing and evolutionary environment where non-equilibria are the norm; new structures are persistently being formed and emergent phenomena arise in a recurrent basis. The correct keywords to describe what an economy truly is are change, creation and evolution. These are all concepts that only a complex perspective might encompass.

The mentioned realism comes necessarily with a cost. Bringing complexity to economics implies looking at the regularities of typically large-dimensional structures of interaction, that in many occasions cannot be addressed resorting to analytical models; computer simulation is the only viable form of approaching the specified complex networks. This is not necessarily a problem; fortunately, today computers exist and they constitute a powerful additional tool that scientists have at their disposal not only to process data but also to explore new ideas and generate and test new theories. This is occurring in many scientific fields and economics does not have to be an exception. Nevertheless, the sophistication of the assumed structures of analysis does not exclude the possibility of addressing the strong ideas of complexity (heterogeneity, decentralization, evolution and path-dependence) under a relatively simple framework; this has been done in section 5 of the chapter, where the mentioned ideas were exemplified taking into consideration a simple sentiment-switching model built upon a small set of difference equations.

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CHAPTER 9

MODELING THE ECONOMY AS A COMPLEX SYSTEM[1]

Herbert Dawid[2]

1 INTRODUCTION

Most of the economic systems of interest, like firms, markets, and even more so whole economies, are characterized by the interaction of a large number of heterogeneous individuals who take a plethora of decisions of different kinds to produce and exchange a large variety of goods as well as information. These transactions are governed by institutional rules which might vary significantly between different regions, industries, time periods and other contexts. Based on this economic systems must certainly be seen as very complex systems, which makes it extremely challenging to derive any insights of general validity about the (future) dynamics of key economic variables or the effect of certain economic policy measures. Such insights are however of crucial importance for providing the public with reliable predictions, at least of a qualitative nature, about the set of future economic developments that seem possible and, maybe even more importantly, for providing policy makers with reasonable predictions about the expected impact of different policy measures at their disposal. Generally speaking such insights can be obtained in an inductive way by generalizing results obtained from (past) empirical evidence or by building models that try to capture the crucial features of the system under investigation. In this chapter the focus is entirely on the second of these options, namely the model-based analysis of economic dynamics.

Any economic model is built on assumptions about a number of key issues. It has to be clarified what type of agents are included in the model (firms, households, banks, etc.), which properties characterize the different types of agents (and the differences between individual agents of the same type), what kind of goods (including labor, information, etc.) are exchanged between individuals, what kind of rules govern these exchanges and, finally, how individual agents determine their actions. Although economic models vary a lot with respect to the first of these issues (depending on the area of application), most standard models in the economic

1. I am grateful to Simon Gemkow, Philipp Harting, Michael Neugart and Sander van der Hoog for many fruitful discussions and their cooperation in developing the Eurace@Unibi model discussed in parts of this paper.

2. Department of Business Administration and Economics and Center for Mathematical Economics (IMW), Bielefeld University, P.O. Box 100131, 33501 Bielefed. Email: <hdawid@wiwi.uni-bielefeld.de>.

literature rely on rather similar assumptions with respect to the other issues. In a large part of the literature it is assumed that agents of the same type are identical (the so-called "representative agent") or vary only with respect to a single parameter (e.g. initial endowment, productivity, risk attitude), they exchange goods on frictionless spot markets that always clear and, most importantly, their behavior is determined according to some equilibrium concept. Equilibrium behavior requires that every agent maximizes some (inter-temporal) objective function given her rational expectations, which means that each agent is able to correctly predict the strategies of all other individuals in the economy.[3] These assumptions allow to build models that address involved economic issues that can be analyzed by solving a relatively small set of (inter-temporal) first order conditions, budget constraints and market clearing conditions. Given the vast complexity of economic systems such a parsimonious approach is very tempting since it allows to clearly identify in a transparent way key mechanisms responsible for certain economic phenomena. The focus of analysis is typically on long-run steady states or balanced growth paths and in many cases, the long run behavior can be characterized by analytical means or by efficient numerical methods. Also, relying on a small common core of key assumptions allows for relatively easy comparability across models and lowers the entry barriers of working with different models once the basic logic of the equilibrium concepts and the dynamic optimization methods have been understood.

A prime example in this respect is the use of dynamic stochastic general equilibrium models as workhorse models for economic analysis in general and policy analysis in particular for a wide variety of economic issues. For this class of models not only a common core model structure has been adopted, but there also exist standard calibrations of the model based on the objective to match certain (macroeconomic) empirical regularities, which can be used as the basis for extensions and variations of the model. However, as has been argued repeatedly (Kirman, 1992; Colander et al., 2009; Fagiolo and Roventini, 2012) the core of standard assumptions is strong and in many cases seems to be at odds with empirical observations on the micro level. This applies in particular to the assumption that individual behavior is determined by (infinite horizon) dynamic optimization under perfect information about the structure of the surrounding economic system and perfect foresight about the strategies of all other agents in the economy determining their current and future behavior. Also in many domains the core models had to be adjusted by extensions, like price stickiness (Calvo pricing) or very myopic rule-of-thumb consumers, for the models to generate dynamics which are qualitatively consistent with empirical evidence on the macro level. These extensions

3. Clearly, there are important and large streams of literature where several of the assumptions listed here are relaxed, like the search and matching literature (relaxing the assumption of frictionless spot markets) which by now is the standard approach for the theoretical analysis of labor markets.

however seem to be rather ad hoc, with no empirical foundations on the micro level, and also seem to be inconsistent with the frictionless equilibrium paradigm that otherwise underlies these models. Finally, the fact that oscillations, booms and busts, in these models typically can be produced only through the introduction of a persistent stream of exogenous shocks has been criticized, since in this way this class of models can contribute little to the understanding of the mechanisms that generate economic fluctuations. Gaining a better understanding of these mechanisms would however be important in order to be able to evaluate potential implications of policy measures or institutional adjustments for the stability of the economy. In particular in the aftermath of the financial and economic crisis that started in 2008 a number of policy makers have expressed concern about the ability of standard models available to support them in dealing with the crisis and in putting policies in place which should prevent future crises.[4]

In recent years a growing community of economists has developed modeling approaches which take the complexity of economic systems more explicitly into account and try to derive insights about emerging economic dynamics on the market-industry and macroeconomic-level by explicit aggregation of dynamically changing behavior of populations of (heterogeneous) agents of different types. Pioneering work with such an agenda are the evolutionary industry models of Nelson and Winter (Nelson and Winter, 1982) or the early work in and around the Santa Fe Institute (Arrow et al., 1988; Arthur et al., 1997; Fontana, 2010). Following such an approach allows to capture explicitly the channels and institutional rules through which individual agents interact and gives the modeler a large freedom with respect to modeling individual behavior. This freedom is not necessarily a blessing since it raises the issue of wilderness or even arbitrariness of model assumptions. It will be discussed in the next section how the literature is dealing with this serious issue. The focus in this class of models is not restricted to long run steady state considerations, but typically an explicit account of the emerging economic dynamics, including transient phases is given. An analytical treatment of such complex dynamical systems is in general very challenging, which implies that computer simulations and numerical analysis play an important role in the examination of such models. From the perspective of the evaluation and design of economic policy measures the properties of the complex systems approach sketched above are for several reasons particularly attractive.

4. The most prominent statement in this respect is from the former ECB president Jean-Claude Trichet, who (when still in office) stated at an ECB Central Banking Conference in November 2010: "When the crisis came, the serious limitations of existing economic and financial models immediately became apparent. (…) Macro models failed to predict the crisis and seemed incapable of explaining what was happening to the economy in a convincing manner. As a policy-maker during the crisis, I found the available models of limited help. In fact, I would go further: in the face of the crisis, we felt abandoned by conventional tools. (…) We need to deal better with heterogeneity across agents and the interaction among those heterogeneous agents. We need to entertain alternative motivations for economic choices. (…) Agent-based modelling dispenses with the optimisation assumption and allows for more complex interactions between agents. Such approaches are worthy of our attention." Available at: <http://www.ecb.europa.eu/press/key/date/2010/html/sp101118.en.html>.

- In many instances short and medium run effects of policies are as relevant as the long run, which makes it important to be able to evaluate policy effects with different time horizons. Also policy effects are often most relevant in situations far off the long run equilibrium, e.g. in crises.
- Understanding the effects of policies on individual behavior might be a bad predictor for policy implications on the aggregate level. It is important to capture the heterogeneities between individuals as well as feedbacks between micro behavior and macro outcomes and networks between economic agents.
- Long run properties of emergent economic dynamics can be crucially affected by temporary imbalances, potential lock-ins and path-dependencies (hysteresis). Hence, transient dynamics have to be explicitly considered for a thorough policy analysis.
- Policy effects often crucially depend on characteristics of the institutional setup they are applied in. Therefore, an explicit representation of institutional setup (market rules etc.) is required.
- If economic decision makers react in a bounded rational way to their economic environment and to economic policy measures (e.g. using behavioral rules), then policy models which are normative from a policy perspective should capture such reactions (rather than the reaction "in equilibrium").

This brief discussion highlights the potential of a modeling approach which treats the economy as a complex system. In the next section I will discuss in more detail several important issues associated with the use of models of this kind. The focus here will be on computational models, which represent a vast majority of the literature in this area. Due to reasons of tractability analytical approaches could so far only be applied to rather simple versions of heterogeneous agents models. Theses analyses employ Markov theory (Dawid, 1999), methods developed in statistical physics which allow to derive the dynamics of certain moments of the distributions of key variables (Alfarano et al., 2008; Delli Gatti et al., 2012) or methods developed for a particular type of approach like network models (Newman, 2010; Jackson, 2010).

2 COMPUTATIONAL METHODS FOR MODELING COMPLEX ECONOMIC INTERACTIONS

The majority of models describing the economy as a complex system with emerging dynamics relies on computational agent-based models. I abstain here from an extensive general discussion of the different interpretations of the defining properties of agent-based models in the literature, but rather provide a simple list of key characteristics of agent-based models as they are understood in this chapter:

- Each relevant economic actor is represented by an agent, which means that in general there are many agents of each type in the model. Agents are potentially heterogeneous with respect to initial endowments, characteristics and decision rules.
- Decision making by agents is determined by behavioral rules, which might be adjusted over time due to learning.
- Agents interact through explicitly given interaction protocols (market rules, information flow channels, etc.)
- Dynamics on the meso-(market/industry) and on the macro-level is generated by aggregating over the actions/stocks of all agents in the model.

Generally speaking agent-based computational models are set up by determining the characteristics and decision rules of agents and the interaction protocols. In order to run the models a parameter constellation has to be chosen as well as the initial values of all the endogenous variables in the model. Given this initial condition the model is then simulated and the time series of the relevant variables are stored, where this might be done for the whole set of individual agents or in some reduced form by storing only the dynamics of the distribution of the variable across agents or only certain moments of this distribution.[5] As discussed for example in LeBaron and Tesfatsion (2008) or in Farmer and Foley (2009) agent-based models indeed have the potential to address many of the problematic issues about economic modeling discussed in the previous section. However, as for any modeling approach, the design and analysis of such models requires a high degree of scrutiny and care in order to be able to generate reliable results and insights of general interest. In what follows I highlight a few key aspects of building agent-based models and give some pointers to approaches developed in the literature.

2.1 Markets and economic transactions

A first key issue in designing an agent-based model is the question how interactions of agents in markets and similar environments should be captured. A pure micro-founded bottom-up approach would require that the modeler has to define the explicit protocols according to which potential buyers and sellers meet and the terms of the interactions (e.g. prices, quantities) are determined. If such a bottom-up approach is followed then the requirement of empirical grounding of the analysis (which will be further elaborated on below) requires that the model captures the main institutional features of the market under consideration.

5. See Tesfatsion (2006) for an extensive introduction and discussion of agent-based modeling in Economics.

Clearly such features vary substantially between different types of markets and indeed agent based modelers have developed quite variable approaches to capture typical features of financial markets (LeBaron, 2006), labor markets (Neugart and Richiardi, 2014), electricity markets (Li et al., 2011) or markets for standard (storable) consumption and investment goods (Dawid et al., 2014a). These models among other approaches incorporate auctions of different types, order books or search models with limited information and bargaining as well as outlets with posted prices repeatedly called on by consumers.

Incorporating such detailed representations of the interaction structure on the market into an agent-based model typically introduces frictions and potential rationing on both sides of the market into the model. Hence, such an approach typically requires that agents hold stocks of the goods traded (which evolve over time) and that it is clearly spelled out how agents react to rationing. The last part is particularly relevant for firms if rationing appears on factor markets, thereby forcing them to adjust their production processes. Furthermore, the amount of frictions arising in the market might depend quite strongly on details of the interaction protocol. For example, the frictions arising in a labor market model where searching unemployed apply to posted vacancies of multiple firms depend on the number of simultaneous applications workers send, the heterogeneity of information about vacancies across workers, the heterogeneity of firms with respect to their ranking of applicants and other aspects for which it is quite challenging to obtain empirical evidence.

Although the requirement to match empirical stylized facts (like the average overall frictions on a market) provides some guidance how these aspects of the model should be chosen, the pure bottom-up approach clearly induces a considerable degree of complexity in modeling market interactions. Whether the introduction of such complexity is adequate and necessary depends on the context and aim of the analysis. Indeed there are numerous examples of agent-based papers in which reduced form representations, like standard market clearing conditions, rather than explicit market models are used to determine market outcomes, because the focus of the studies is such that a detailed description of the market interactions does not seem to add relevant insights (Nelson and Winter, 1982; Arthur et al., 1997; Dawid and Reimann, 2011). Clearly, the appropriate modeling choice depends crucially on the research questions to be addressed by the model.

2.2 Individual agent behavior and learning

As discussed in the previous section, a key aspect of any economic model is the way individual decision making is captured. In dynamic equilibrium models it is assumed that the behavior of all actors is determined by maximization of the own (intertemporal) objective function using correct expectations about the behavior of the other actors. It is quite debatable in how far such dynamic equilibrium analysis provides a descriptive theory of individual behavior. First, dynamic equilibrium requires that all agents have sufficient information about the entire economic system to be able to fully understand not only the own dynamic decision problem but also that of all other agents in the economy. Arguably, in most relevant economic settings such information is not available to individual decision makers. Second, there is empirical evidence suggesting that individuals do not rely on long-term dynamic optimization (Noussair and Matheny, 2010) and do not hold rational expectations (Hommes et al., 2005). Because it is part of the agenda of the agent-based approach to use models which aim to be descriptive also on the micro level, these observations suggest to look for alternatives. Furthermore, in a setting where agents differ in several dimensions and interact in complex environments the calculation of dynamic equilibrium behavior is often infeasible, even if up-to-date numerical methods are employed.[6]

In the agent-based literature, individual behavior is determined by behavioral rules, where this term should be interpreted in a rather broad sense. In particular, the term behavioral rule does not rule out optimization of the decision maker. Actually, there are numerous examples of heuristics used as behavioral rules, which rely on optimization of some objective function within a simplified "internal model" of the economic environment constructed by the decision maker using available data. Determining a suitable approach for designing the behavioral rules is a major modeling issue and the "Wilderness of bounded rationality" (Sims, 1980) is a serious concern. Different approaches to model boundedly rational behavior and its adaptation have been put forward in the agent-based literature. Most of these approaches are based on the conviction that the behavioral rules used in agent-based models should have some kind of empirical foundation in a sense that they try to capture key aspects of the behavior of corresponding agents in the real world. Several of the approaches developed in the literature, although not all of them, also take into account that rules might be adapted over time and provide models of how agents adjust their decision rules.

The most suitable approach for providing empirical or theoretical foundations for certain types of rules depends strongly on the type of agent that is to be modeled. Describing the decision rule of an individual choosing a consumption good is very different from capturing the rule determining the interest rate decisions of a central bank. In fact, the interest rate decision of a central bank is one of the few types of decisions where there are publicly documented decision rules (like the Taylor rule), which have been employed at least to some extent by actual decision

6. This observation can be nicely illustrated by considering the Eurace@Unibi model discussed in section 3.2, see footnote 14.

makers (central banks) and have been introduced in a wide range of Economic models.[7] Such rules can be easily implemented in an agent-based model. If we consider decisions taken by individuals rather than an institution, like a central bank, such documentation of the rules or processes leading to a decision is missing.

An obvious candidate to obtain empirically grounded insights into the decision processes of individuals in different economic frameworks is the consideration of experimental evidence. Early work in this domain is surveyed in Duffy (2006) and recently efforts have been intensified to systematically use experiments in order to obtain insights about the rules according to which individuals make decisions and build expectations. For example Arifovic and Ledyard (2010, 2012) put forward Individual Evolutionary Learning as a computational model of adaptive learning which, under proper calibration, fits well the experimental data about behavior in different mechanism design contexts. Empirically oriented examination of individual decision heuristics has also been an active field of research in psychology for many years (Gigerenzer and Gaissmaier, 2011), but so far the insights obtained there have been hardly incorporated in agent-based models in Economics. Concerning expectation formation extensive experimental work has been carried out to identify a set of expectation formation rules employed by individuals in different contexts (Hommes, 2011) and these insights have been used in the design of agent-based models with a focus on expectation dynamics.

An alternative approach for providing empirical grounding for individual decision rules incorporated in agent-based models is the repeated interaction between the modeler and real world stakeholders during the model design process. As pointed out for example in Janssen and Ostrom (2006) such an approach is primarily suitable if the model is developed in a very specific context with a relatively small number of relevant stakeholders which can be consulted. Examples of agent-based models that have been developed with such a close engagement of stakeholders can be found in D'Agostini et al. (2003) or Gaillard et al. (2014).

Also the description of firm behavior in agent-based models typically relies on a rule-based approach. In this sense the literature follows arguments put forward e.g. in Nelson and Winter (1982) that in many institutions, including firms, over time decision rules[8] evolve, which have turned out to be successful in the past and therefore are employed, and maybe adjusted over time, to determine the firms actions in a complex and dynamic environment. There is substantial variance in the way this general idea has been implemented in concrete models. A number of models use fixed behavioral rules, which are based on anecdotal evidence and

7. The extent to which the Taylor rule has been used or is currently used by central banks is however a matter of debate (see Taylor, 2014).
8. Nelson and Winter (1982) strictly speaking describe the evolution of "routines".

plausibility considerations (Delli Gatti et al., 2008; Ashraf et al., 2011), whereas in other contributions only the basic structure of the behavioral rules are given and some learning algorithm is used to adjust these rules over time.[9] For example Dosi et al. (1999) or Midgley et al. (1997) demonstrate that such an approach can give rise to firm behavior which seems to match well observable behavior of firms in markets. A slightly different approach for modeling firm behavior in agent-based models is put forward in Dawid and Reimann (2004; 2007) and elaborated in Dawid and Harting (2012). This approach termed the "Management Science Approach" incorporates relatively simple decision rules matching standard procedures of real-world firms in the agent-based model. There is a rich literature on (heuristic) managerial decision rules in many areas of management science including pricing, production planning or market selection and the idea is to use these heuristics in the model of the firms. A concrete example of a behavioral rule determined according to the Management Science Approach will be discussed in section 3.2 in the framework of the description of the Eurace@Unibi model. Although it certainly cannot be assumed that all firms in the economy rely on such standard managerial heuristics, capturing the main features of such heuristics when modeling the firm adds a strong empirical micro-foundation to the agent-based modeling approach. As has been shown in Dawid et al. (2014a) in the context of the Eurace@Unibi model (discussed in more detail below) the empirical micro-foundation of the approach is complemented by a good match of a number of empirical stylized facts about industry and firm dynamics as well as distributional properties.

2.3 Parametrization, calibration and fit to empirical data

Agent-based models are usually characterized by a relatively large set of model parameters and often exhibit nonlinear complex dynamics. Both of these features make it notoriously difficult to pin down the set of parameter values which provide a close match between the behavior of the model and the real-world system that is modeled. In order to reduce the number of "free parameters" usually a certain subset of parameters for which direct empirical measurements are available (e.g. depreciation rates, tax rates, etc.), are directly estimated using empirical data. Concerning the determination of the remaining model parameters a number of issues arise. First, a clear definition has to be provided what is meant by a "good match" between model output and empirical time series. Different approaches have been developed in this respect – see Windrum et al. (2007) for a more extensive discussion. In a series of papers presenting "history-friendly-models" a particular context, like the evolution of the biotech industry or the PC industry,

9. The set of algortihms that have been used to describe the updating of rules includes genetic algorithms (Dawid, 1999); classifier systems (Arthur et al., 1997) and genetic programming (Chen and Yeh, 2002).

is considered and the goal is to develop a model which reproduces the qualitative patterns of industry evolution observed in this particular context (Malerba et al., 2001; Malerba and Orsenigo, 2002). Typically it is however not exactly quantified what defines a "good reproduction".

For agent-based models with a more general scope, like macroeconomics or financial markets, the most common approach to pin down the parameters is "indirect calibration" (Windrum et al., 2007). A set of empirical stylized facts is chosen, which the model is supposed to reproduce, and then ranges for the parameters are identified where the model output meets this goal.[10] Problematic about this approach is that at this point no clear consensus concerning the set of stylized facts to be considered in the different areas of applications has emerged. A few stylized facts, have become standard requirements in some areas (e.g. business cycle properties, firm size distributions, volatility clustering in financial markets), but there is a considerable freedom of choice for the individual modeler who might be tempted to put the main focus on stylized facts the own model is particularly good at reproducing. On the other hand, the fact that some of the developed agent-based models are able to reproduce a broad set of empirical stylized facts at different levels of aggregation (see Dosi et al., 2010; Dawid et al., 2014a) is certainly one of the factors contributing strongly to the credibility not only of the particular parameter set chosen but also of the model design and the modeling approach as such.

However, it has to be acknowledged that also in the indirect calibration approach common quantifiable criteria under which circumstances a given stylized fact is considered to be reproduced by a model are largely missing. Apart from the challenge to quantify similarity between simulated time series and empirical data (see Marks, 2013), there are issues of comparability of time units in the simulations with the real world and of the selection of the simulation time window to be used for comparison with the data (transient dynamics vs. (ergodic?) long run properties). Furthermore, often the requirement of reproducing stylized facts still allows for a large set of potential parameter settings. Ideally, qualitative statements derived using the model, for example about the effects of certain policies, should be tested for robustness across this set of potential parameter settings, however such extensive robustness checks are often infeasible. Alternatively, estimation methods could be used to determine the parameter setting that fits the data "best" thereby providing a unique default parameter setting. Due to the particular properties of agent-based models (many parameters, complex maybe non-ergodic dynamics, lack of analytical representations of the dynamics) this is however a very challenging and computationally intensive endeavor. A first step towards the development

10. A particular careful exercise of this kind has for example been carried out in Ashraf et al. (2011) using United States Data.

of estimation methods for agent-based models has been made in Grazzini and Richiardi (2014), however it is not clear in how far these methods can be applied to larger agent-based models.

Overall, the attention paid to linking agent-based models to data has strongly increased in recent years, and although systematic estimations of the models put forward in the literature are at this point largely missing, the research field seems to be moving towards establishing a strong empirical foundation for the employed models.

2.4 Policy analysis and market design using ACE models

Many of the agent-based models in the literature have been developed with the aim to explore effects of certain policy measures or changes in the design and regulatory framework of certain markets. Establishing sound and transparent results about the effects of such measures in an often complex stochastic model is not a trivial issue. The two main challenges are to establish in a statistically rigorous way the effect of the considered measures on the key variables of interest and to provide a clear understanding of the economic mechanisms responsible for the policy effects, such that the results do not seem to emerge from a "black box" which does not allow for an intuitive understanding of what is driving the results.

Given that agent-based models in general describe stochastic dynamic processes, where a change in policy is often captured by some parameter variation, measuring policy effects comes down to showing that the considered parameter changes have statistically significant effects on certain relevant indicators. In the literature often some aggregate indicators are considered, like average growth rate or average values of a variable during a small time window at the end of the run. Such approaches condense information about a single run to a one-dimensional variable. Batch runs with and without policy are carried out and standard (non-parametric) tests can then be used to test whether the considered indicator is influenced by the considered policy in a statistically significant way. Whereas this procedure is rather straight forward, a more controversial question, related to the calibration issues discussed above, is whether it is sufficient to provide such tests for a given parameter setting or whether the batch of runs with and without policy should rather be based on different parameter settings sampled from the space of "plausible" parameter constellations.

An alternative way to measuring policy effects, which has been chosen in many papers, is to graphically present average trajectories of key variables of interest together with confidence bands for batch runs with and without the policy, thereby indicating for which policies the dynamics of the model changes in a significant way. In Dawid et al. (2013; 2014b) a dynamic statistical model based on penalized splines is introduced as a tool to capture in a rigorous statistical way the dynamic effects of policies. Under this approach spline functions, capturing the (size of the) dynamic effects of each considered policy measure, are estimated based on a set of simulation runs carried out under different policy scenarios. Confidence intervals for each spline function can be provided and this allows to obtain insights about the size and the statistical significance of the different policy effects at each given point in time.

The second challenge for an agent-based policy analysis is the determination of the main economic mechanisms responsible for the established aggregate policy effects. Typically this challenge is tackled by establishing chains of effects triggered by the policy on a set of micro and meso level variables. Such chains of effects are constructed by considering statistical tests and measures, such as (lagged) cross-correlation functions, or graphical presentations of time series. Systemic and general approaches for establishing such causal chains in the framework of agent-based models are however largely missing.[11]

3 EXAMPLES OF AGENT-BASED ANALYSES

3.1 Effects of specific policies and regulatory measures in particular markets and industries

As discussed above, agent-based models, by their very nature, are well suited to capture specific structures and institutional features of particular markets. Hence, this modeling approach has been used to study market design and policy issues in a variety of specific markets and industries. In this section I briefly review two recent examples of such analyses. The first example (Geankoplos et al., 2012) examines factors that could have avoided the bubble and crash in the housing market and the second example provides a detailed description of a particular energy market as a testbed for potential regulatory reform measures. Additional examples of detailed market studies not reviewed here include different aspects of financial markets (see LeBaron, 2006), special segments of the labor market (Haruvy et al., 2006), the Computer-Industry (Malerba et al., 1999; 2001) and the Biotech-Industry (Malerba and Orsenigo, 2002) or lottery markets (Chen and Chie, 2008).

Geanakoplos et al. (2012) present a relatively simple agent-based model of the Washington D.C. area housing market which is able to reproduce a substantial set of stylized facts on this market including the boom and bust between 2000-2010. The authors motivate the use of an agent-based approach for modeling the housing market by the observation that for many years agent-based models have

11. There are a few attempts in the literature, like the regression tree approach (Vallee and Yildizoglu, 2006), but no widely accepted method has emerged so far.

outperformed alternative approaches in the prediction of mortgage prepayment rates. The housing market model focuses on home buying and selling of households, where demand and supply is determined by the formation of new households and the moving of existing households, respectively, as well as rent/own decisions. The rules determining bids and asks on the market have very simple structure and are strongly based on empirical micro-level data on income, wealth and behavior in the Washington D.C. area. Also the financing of the homes is modeled in a simple empirically grounded way, where also potential rationing of households is captured. It is reported that the model is not only able to endogenously reproduce the boom and bust dynamics between 2000-2010 but also additional empirical observations like units sold, time on the market or the ratio between the sold price to original list price. Using this model the authors argue that the degree of leverage rather than the dynamics of interest rates was the driving factor underlying the housing bubble.

Leigh Tesfatsion with several co-authors has developed AMES (Agent-Based Modeling of Electricity Systems), an agent-based model of a wholesale power market which captures many key features of the electricity markets in several United States regions.[12] In particular, the recommendations for wholesale power market design by the United States Federal Energy Regulatory Commission (FERC) are taken into account as well as the fact that there are limited supply capacities at a given location (called grid bus) and limited capacities in the grid linking the buses, which might lead to congestion. The agents in the model are the Independent System Operator, whose goal it is to maximize total net surplus in the market, as well as a number of energy generators, with heterogeneous cost and capacity structure, who put supply offers in the day-ahead market. Finally, there are traders, who put demand bids on the day-ahead market and sell to consumers. In addition there is an exogenous time varying demand at the different locations (which might or might not be price sensitive). Following the FERC recommendation the day ahead market is operated using local marginal prices, which means that the price at a given location and point in time is the lowest cost of providing an incremental unit of power at this location and time. Generators learn and adjust their behavior (offer price and quantity) according to an algorithm similar to Simulated Annealing, where the impact of the current fitness (called propensity score) of an action on the probability to be chosen increases over time. The very specific application domain of the model allows the authors to calibrate the model to empirically relevant parameter settings.

Li et al. (2011) show that strategic capacity withholding of generators arises in this setting and also establish that there is positive correlation of prices with

12. See Li and Tesfatsion (2011); Li et al. (2011).

marginal costs across locations. This implies in particular that strategic capacity withholding has spillover effects on prices in other locations. The authors argue that such spillovers have important implications for the design of policies mitigating market power. The AMES model has also been used in a number of additional papers as a testbed for studying various concrete market design issues for wholesale power markets.[13]

3.2 Effects of (combinations of) policies in the framework of closed (macro) models

The majority of recent agent-based work addressing economic policy issues has been carried out in a macroeconomic context. Both the issues addressed in this work and the complexity of the underlying models varies quite substantially between the different contributions.

In a contribution which relies on a relatively minimalistic macroeconomic model Arifovic et al. (2013) analyze the effect of social learning for monetary policy. They consider a standard New Keynesian model including a Taylor rule with the extension that household-firms are heterogeneous with respect to their forecasts about the perceived law of motion of the economy. They update the forecasts based on a social evolutionary learning algorithm. The paper shows under which circumstances in such a setting with social learning rational expectations equilibria and sunspot equilibria can be learned. Similar in spirit is Arifovic et al. (2010) where the issue of credibility of policy announcements is studied in an extension of the simple Kydland-Prescott style framework. Individual households/workers have heterogeneous attitudes towards the policy announcements (some believe them, some do not) and adjust these attitudes based on the imitation of relatively more successful agents in their population. It is shown that in such a setting, a boundedly rational policy maker, which has to rely on imperfect information about the evolution of the credibility of her announcements, is able to induce outcomes that Pareto dominate the unique Nash equilibrium outcome of the static version of the model. In somehow related approaches Anufriev et al. (2013) or DeGrauwe (2012) introduce heterogeneous expectation dynamics into otherwise standard dynamic equilibrium models to study the implications of such expectations on economic dynamics and stability.

Whereas in these contributions heterogeneity and agent-based modeling has been embedded in an otherwise rather simple and reduced form model of the macroeconomy, a number of recent papers have carried out policy analyses in the framework of macroeconomic models where all sectors of the considered

13. Extensive material about the AMES model and its applications are available at: <http://www2.econ.iastate.edu/tesfatsi/AMESMarketHome.htm>.

economy are modeled in a bottom-up agent-based manner. Dosi et al. (2010; 2013; 2014).carry out analyses of fiscal and monetary policy measures in a family of closed agent-based models labeled as “Schumpeter meeting Keynes” (K+S) models. The basic structure of the considered economy is that capital-good firms performing R&D offer a heterogeneous range of machine tools to consumption good firms, which use capital and labor input produce a homogenous consumption good. Firms finance their production and investment choices employing internal funds as well as credit provided by the banking sector. Government expenditures (unemployment benefits, bank bailouts, interest on public debt) is financed by taxes collected from households, firms and banks. In each of the papers mentioned above the authors demonstrate that the model can replicate a large set of empirical stylized facts on different levels of aggregation, such as typical growth paths, business cycle properties, macroeconomic correlates, and cross-sectional distributions. In Dosi et al. (2010) a strong complementarity between demand oriented fiscal policies and the effectiveness of Schumpeterian policies facilitating the adoption of new technologies is established. A main insight in Dosi et al. (2013) is that fiscal policies dampen business cycles and reduce unemployment as well as the likelihood of experiencing a huge crisis. It is also shown that long-term growth can be positively affected by fiscal policy, where this effect is particularly strong if the income distribution is skewed toward profits. Dosi et al. (2014) extend this analysis by exploring the effects of combinations of monetary and fiscal policy. They find that policy mixes associating unconstrained, counter-cyclical fiscal policy and dual mandate monetary policy are particularly suitable for stabilizing the economy.

Delli Gatti et al. (2008) in a book as well as in a set of related papers (Riccetti et al., 2013; Delli Gatti et al., 2010), use agent-based models featuring a credit market and a goods market to address issues related to the interplay between financial and real market instabilities. In Riccetti et al. (2013) the real side of the model is kept very simple relying on the key assumption that the scale of activity of a firm, in particular the level of production, is an increasing function of its “net worth”. Firms have leverage targets based on which they determine their investments. They take loans from banks to finance (parts of) these investments, where the structure of the bank-firm network evolves endogenously over time. The market environment is assumed to be risky (stochastic prices) and therefore firms are repeatedly hit by (good and bad) shocks. Interest rates charged by banks depend on the financial situation of the bank and the firm asking for credit. The model gives rise to a financial accelerator and potential bankruptcy chains. Riccetti et al. (2013) study among other issues the impact of pro-cyclical compared to fixed leverage targets and analyze the effects of monetary policy. One important implication of their analysis is that the central bank should also consider the effect on the leverage of firms when deciding monetary policy changes. In Mandel et al. (2014) the financial architecture of Delli Gatti et al. (2010) is integrated in a standard real business cycle model. They characterize scenarios where convergence to equilibrium prices is observed in their agent-based setting and show that when financial constraints become binding a positive feedback loop between disequilibrium and financial fragility emerges, in line with Minsky's Financial Instability Hypothesis. Small price variations can trigger financial imbalances that get amplified by a financial accelerator. Furthermore, they demonstrate that the structure of the financial network affects aggregate volatility because it impacts the speed of convergence to and the stability of equilibrium.

Ashraf et al. (2011) use a carefully calibrated agent-based macroeconomic model to explore the implications of different banking regulation schemes. They highlight the important role of banks for the economy's performance and show that banking regulation in normal times hardly affects macroeconomic stability while in bad times more stringent regulation has a detrimental effect on the economy as it suppresses lending to firms in need. Related issues have also been analyzed in an agent-based framework by Teglio et al. (2012) who mainly focus on the macroeconomic effects of financial regulations. Klimek et al. (2014) propose a simple agent-based model, which incorporates households, a single production sector and banks. Using this model they analyze the effects of three different crisis resolution mechanisms on economic and financial dynamics. In their setting a bankrupt bank can either be shut down via a purchase and assumption transaction, it can be bailed-out using taxpayer money, or it may be bailed-in in a debt-to-equity conversion. Their analysis implies that, whereas in strong economies (high productivity, low unemployment) bankrupt banks should be closed, in the face of weaker economic outlooks the bail-in mechanism seems most attractive. Tax-payer financed bail-outs should according to their analysis never be applied.

An agent-based macroeconomic model developed with the goal of exploring environmental policy issues is the Lagom model (Wolf et al., 2012). In the Lagom model, technology choice, household consumption, firms' mark-ups, and wages are determined using genetic algorithms. The different sectors of the model are linked by input-output tables, which are initialized based on real world data. The inclusion of a representation of local emissions induced by economic activity opens up the possibility to consider different types of economic policy measures also from an environmental perspective.

3.2.1 An illustrative example of an agent-based policy model: Eurace@Unibi

The Eurace@Unibi model (Dawid et al., 2012; 2014a) also falls in the category of agent-based macroeconomic models and has been developed with the particular aim to provide a unified framework, which allows for the analysis of a wide range of policy issues including fiscal policies, innovation policies, labor market policies or cohesion policies. Furthermore, financial-market and credit-market regulations can be studied in this framework. The focus lies on the interplay of labor markets, industry dynamics, technological change and growth. The model describes an economy containing labor, consumption goods, capital goods, financial and credit markets in a regional context. The economy is inhabited by numerous instances of different types of agents: firms (consumption goods producers and capital goods producers), households and banks. Each of these agents is located in one of the regions. Additionally, there is a single central bank and a government that collects taxes and finances social benefits as well as potentially some economic policy measures, where policies might differ between regions. Finally, there is a statistical office (Eurostat) that collects data from all individual agents in the economy and generates aggregate indicators according to standard procedures. These indicators are distributed to the agents in the economy (who might use them e.g. as input for their decision rules) and also stored in order to facilitate the analysis of the simulation results.

Firms in the consumption goods sector use capital goods combined with labor input to produce consumption goods. Capital goods are offered in different qualities (vintages) by capital goods producers, where the technological frontier (i.e. the highest available vintage) moves stochastically upwards over time. The labor market is populated with workers that have a finite number of general skill levels and acquire specific skills on-the-job, which they need to fully exploit the technological advantages of the capital employed in the production process. Every time when a consumption goods producer invests in new capital goods it decides which quality of capital goods to select, thereby determining the speed by which new technologies spread in the economy. In this way the model captures in a simple way the linkages between skill dynamics, labor market dynamics and technological diffusion in an economy.

Consumption goods are sold at local market platforms (called malls), where firms store and offer their products at posted prices and consumers come to buy goods. Labor market interaction is described by a simple multi-round search-and-matching procedure. Wages of workers are determined, on the one hand, by the expectation the employer has at the time of hiring about the level of specific skills of the worker, and, on the other hand, by a base wage variable, which is influenced by the (past) tightness of the labor market and determines the overall level of wages paid by a particular employer. Banks collect deposits from households and firms and provide loans to firms. There is a financial market where shares of a single asset are traded, namely an index bond containing all firms in the economy. The dividend paid by each share at a certain point in time is determined by the sum of the dividends currently paid by all firms. This simple representation of a financial market is not suitable to describe speculative bubbles in the financial market, but captures important feedbacks between firm profits and households income, in a sense that fluctuations of dividends affect only the income of a particular subgroup of households, namely the owners of shares of the index bonds. The central bank provides standing facilities for the banks at a given base rate, pays interest on banks' overnight deposits and might provide fiat money to the government.

The spatial extensions of the markets differ. The capital goods market is global meaning that firms in all regions buy from the same global capital goods producer and therefore have access to the same technologies. On the consumption goods market demand is determined locally in the sense that all consumers buy at the local mall located in their region, but supply is global because every firm might sell its products in all regional markets of the economy. Labor markets are characterized by spatial frictions determined by commuting costs that arise if workers accept jobs outside their own region. It is assumed that firms have access to all banks in the economy and, therefore, credit markets operate globally.

Following the Management Science Approach presented in section 2 the decision rules of firms and households in the Eurace@Unibi model are based on empirically founded heuristics described in the relevant literature.[14] This includes in particular price and quantity determination and market selection of firms or consumption and savings decisions of households. To illustrate the Management Science Approach I briefly sketch the behavioral rule determining firms' pricing decision. In the model consumption goods firms adjust their prices once a year, which is in accordance with empirical data. In order to determine the new price they follow a heuristic described in the managerial literature on strategic pricing, for example in Nagle et al. (2011, chapter 6). Each firm carries out "simulated purchase surveys" among a random sample of households, to obtain an estimation of how the demand for its product would react to price changes. It combines this estimation with a prediction of changes in total costs associated with different adjustments in output in order to calculate expected profits over a fixed planning horizon for a set of potential price changes. The price is chosen such, that it maximizes discounted profits over the planning horizon.

The Eurace@Unibi model endogenously (without external aggregate shocks) generates economic fluctuations that match empirical stylized facts with respect

14. Coming back to the discussion in section 2 of problems associated with the assumption of (dynamic) equilibrium behavior, it should be noted that in this model such an assumption would give rise to extremely complex and intractable dynamic optimization problems for the different types of agents. Considering, for example, firms' choice of investment (size and vintage) at a given point in time, each firm would have to consider the future dynamics of the distribution of skills in the workforce as well as the distribution of future investment paths of all firms (which in general will differ across firms since they are heterogeneous with respect to current structure of capital stock and labor force) and also the corresponding developments of pricing decisions by competitors and the evolution of demand (which is endogenous). Even if a single firm would know the strategies of all the other agents (which clearly would be a rather unrealistic assumption) the dimension of the state space and the complexity of the induced dynamics would prevent the determination of the intertemporally optimal strategy for this infinite horizon problem.

to business cycle characteristics, as well as with respect to serial correlation and amplitude ratios between output and key variables, such as consumption and investment. The firm size distributions emerging from the model resemble those found in empirical studies and also firm level features, such as persistent price dispersion combined with counter-cyclical mark-ups and persistence of firm market shares, are found in simulation data generated with the Eurace@Unibi model in accordance with the empirical literature. The same holds true for standard observations in labor markets, such as the Beveridge curve (Dawid et al., 2012; Dawid et al., 2014a) for a discussion of these issues. Finally in Dawid et al. (2013) it is shown that a standard calibration of the model also produces patterns of income-inequality comparisons across economies that match those observed in different parts of the European Union. The fact that all these different kinds of stylized facts can be reproduced by the model strongly suggests that the approach to build an economic model with strong empirical micro foundations was successful in capturing key mechanisms that drive the dynamics of real world economies.

A wide variety of policy issues related to labor market design, skill formation and income inequality has been studied using the Eurace@Unibi model.[15] To provide one example I briefly discuss the examination of the effectiveness of different types of cohesion policies with respect to convergence of regions in Dawid et al. (2014b). Motivated by the main instruments used by the European Union (European Fund for Regional Development, European Social Fund) the effects of two types of policies are compared: technology policy, providing subsidies to firms in an economically lagging region which invest in technologies at the technological frontier, and human capital policy, inducing an improvement of the distribution of general skills in the workforce in the target region. Two different setups are considered, where in the first setup the labor markets are fully integrated, such that there are small frictions and all workers have almost unhindered access to both local labor markets. In the second setup the labor markets are completely separated and workers can only work in their home region.

Employing the penalized spline approach, sketched in section 2, in the paper first the estimated dynamic effects of the policies on key variables, such as regional per-capita output, are presented. Based on this the mechanisms driving these results are carved out by studying the effects of the policies on a set of micro and meso level variables, such as technology choices, base wage offers and relative prices of different firms, as well as skill evolution, firm choice and consumption decision of consumers. The main results of the analysis are that the human capital policy is only effective, in terms of fostering cohesion, if labor markets are separated. If labor markets are integrated, output actually falls in the lagging region at which

15. See Dawid et al. (2014a) for a survey.

the policy is targeted. Technology policies speed up convergence for integrated and separated labor markets. The negative implications of the human capital policy under open labor markets arise even though the direct goal of improving the level of specific skills and of the vintage choice in the lagging region is reached. The negative effects of the policy for the target region are due to the induced changes in the labor market tightness in that region, which have implications for wage dynamics, (relative) goods prices, demand shifts and investments.

This analysis is extended in Dawid et al. (2013), where the effectiveness of technology policies is studied in more detail. In particular, it is shown in this paper that the positive convergence effects of technology policy arise only if the technology choice of a large fraction of firms who receive investment subsidies can indeed be positively influenced. If a large fraction of firms receive subsidies although they do not invest at the frontier (i.e. choose the best available vintage), than the effectiveness of the policy found in Dawid et al. (2014b) disappears. Furthermore, in Dawid et al. (2013) the implications of the policy are not only studied with respect to average output per capita in a region but also with respect to income inequality in the regions. This highlights the potential of agent-based policy models to simultaneously consider different aspects of policy effects and in particular to examine distributional issues which cannot be studied in representative agent models.

4 DISCUSSION AND CONCLUSIONS

The discussion in this chapter is based on the insight that the economy and its main components, such as markets and industries, are complex systems, and on the main question of how much of this complexity we should attempt to capture in models when examining economic issues. In particular, sections 2 and 3 have discussed an agent-based bottom-up modeling approach, where a lot of attention is paid to the behavior of individual economic actors and their interaction. Section 2 has made clear that a number of serious challenges have to be faced when developing models of this kind. This concerns the foundations for the representation of individual behavior as well as the empirical calibration and the systematic analysis of such models. The overview of existing agent-based analyses in economics in section 3 has shown that, in spite of the fact that these models share the same modeling approach, the actual degree of complexity varies quite substantially among different agent-based models. Depending on whether the focus of analysis is on one particular economic phenomenon in a specific market or on a better understanding of the emerging feedbacks between the real and financial sectors models with different degrees of granularity seem appropriate. The discussion in section 3 highlights the usefulness of a computational agent-based approach in several domains of application. Arguably, much simpler mainstream models would have a hard time addressing several of the issues dealt with in the examples presented. I would not necessarily conclude from this argument that the more complex computational models are in general more suitable than the main-stream models for economic policy analysis, but rather that there seem to be important economic issues where relevant new insights can be obtained using a modeling approach which treats the economy as a complex interactive system.

The examples presented in section 3 provide some indication of the type of economic issues where the application of agent-based models seems particularly promising. First, the area of market design should be mentioned. The ability of agent-based models to capture in some detail the institutional details of particular markets and also to potentially involve stakeholders in the design of the behavioral models of market participants makes agent based models a particularly suitable tool to explore expected implications of changes in market design or regulatory rules and to communicate such expected implications to policy makers. In fact, agent-based models have been applied with substantial success in this domain. Second, agent-based models, which explicitly represent the heterogeneity of agents with respect to different characteristics, are natural candidates to address distributional issues. Gaining a better understanding of the processes responsible for inequalities of different kinds within and across regions has been a main topic of economic research for years and it seems that the importance of this topic is still increasing. Agent-based models should be able to play an important role in this discourse. They allow to capture key mechanisms that are responsible for the emergence of differences between firms or households, as well as for the evolution of particular linkages and interaction patterns and for the occurrence of lock-ins and path dependencies. The papers briefly reviewed in section 3 give an indication of the potential of agent-based models in this respect, but it seems that this potential so far has not been fully explored.

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CHAPTER 10

CITIES AS COMPLEX SYSTEMS

Luís M. A. Bettencourt[1]

1 INTRODUCTION

Cities and urbanization pose some of the greatest and most important challenges to our understanding of human social systems and for effective policy (UN-Habitat, 2009). The roots of these difficulties lie in the nature of cities as complex objects. These are systems of interacting people and social organizations in dense built spaces serviced by infrastructure and managed by social and political organizations (Bettencourt, 2013a). Attempts to better manage cities along only a few of these facets often fail. A more holistic understanding of cities, where all these aspects of urban life come together, is just now emerging. Its main findings and their implications for public policy are the focus of this paper.

Most of urban planning history is concerned with identifying the fundamental nature of cities (Lynch, 1981; Mumford, 1961). On the one hand, cities – at least in their modern form – are handled in practice as vast land-use systems to be designed and managed according to best practices from engineering and applied economics. This means that urban planning and policy are primarily defined in terms of the allocation of land, the design of transportation systems and the development of urban services according to the best technology available and under physical, political and budgetary constraints. As I discuss in this paper, many of these operational issues can often be defined conceptually as "simple" problems and be tackled using well-known strategies from engineering, which are increasingly possible to implement in standard ways thanks to progress in informational and communication technologies.

While this practically minded approach describes most of the short-term activities of city administrations, there is much more to cities than that. This becomes critical when we consider urban issues over long time horizons and in places where engineering practices fail (Bettencourt, 2014a). Then, the emphasis shifts to a different kind of problem that deals typically with human socioeconomic dynamics: for example, issues of urban poverty, (un)employment, crime and violence, economic growth and environmental sustainability. Needless to say, these problems are "complex": they require that we understand their history and context; we do not know how to solve them using standard recipes.

1. Santa Fe Institute. 1399 Hyde Park Rd, Santa Fe NM, 87501, USA.

Most cities – their civil societies, economic agents and political organizations – struggle with such complex problems. Failure to deal with these issues undermines the future development of any city as well as its day-to-day management. Tackling complex problems requires a different set of approaches, based in the appreciation for the massively interconnected character of urban social and infrastructural networks and their dynamics over time. Complex problems emphasize dynamics of social and economic self-organization, such as markets and civic life, not top-down design.

The perspective of *cities as complex systems* emphasizes the connections between these various components of the city to identify important new relations in urban organization and dynamics that can also enable more successful and sustainable solutions (Bettencourt, 2013b). The aims of approaching cities as complex systems are therefore more ambitious than most urban planning practice, as we would like to create a theory of the role of urban areas in human societies, emphasizing human agency and a person' s ability to learn, be creative and take part in social organizations (Bettencourt, 2013a; 2013b). We would also like to understand better how urban physical space and service delivery influence and facilitate such social dynamics and, in turn, come to define their success metrics. Although the strategy of complex systems to create this holistic view of cities goes beyond other urban disciplines (sociology, economics, engineering, etc.) its objective is to create a simpler quantitative synthesis of the nature of cities, for example by leveraging physical and operational constraints on underspecified social and economic models and vice-versa. Considerable progress in understanding cities as complex systems – both empirically and theoretically – has been made over the last decade and will be briefly described below (Bettencourt, 2013a; 2013b). These new insights allow us to discuss how to deal with complex problems in general, and the specific circumstances when such issues can become "simple".

In practical terms, this paper analyzes the problem of conceptualizing and managing cities from the point of view of these two different perspectives: its simpler, shorter-term technical management and its longer-term complex challenges (Bettencourt, 2014a). I will articulate these views of the city starting with a brief historical overview of how cities have been perceived in urban planning and policy. I will then discuss in what precise sense cities are complex systems. This includes an emergent new empirical and theoretical understanding of the characteristics of cities and their consequences for how urban areas of different sizes pose different challenges to the planner. I will then return to the tension between engineering solutions and complex systems approaches to show when each is necessary and how complex systems may become simple problem and vice-versa.

2 A BRIEF HISTORY OF CONCEPTS OF THE CITY

Cities are one of the most fundamental units of human societies. Historically, the city as a political unit existed well before nations. Early cities were important religious and defensive centers as well (Mumford, 1961). But it is the city as a socioeconomic unit that is most important today.[2] Cities concentrate and accelerate social and economic outputs of modern nations, including gross domestic product (GDP), to a much larger extent than they concentrate population (Bettencourt, 2013a; Bettencourt et al., 2007; Bettencourt and West, 2010). They also create the conditions for more broadly based human development, as spatial proximity can facilitate modern service delivery and the mobilization and evolution of social and political organizations to solve difficult human problems (Holston, 2008).

Despite their fundamental role in human history and in contemporary development, cities have defied integrated understanding, capable of identifying systematic solutions to problems of urban governance. For example we do not know in detail what is the infrastructure necessary for a well functioning city or how to compute the full inclusive costs and benefits of urban services. We also do not know how such services should change in detail in response to economic and population growth. Answers to these questions rely heavily on past practices, not so much on a deep understanding of the processes that take place in cities.

Historically, we have used various metaphors to try to understand the essential features of cities. So for example, as early as the 4th century BCE, Aristotle and Plato debated the properties of the political city in light of analogies to a family or an insect colony.[3] Commonly, urban planners view cities as vast engineering problems and adopt, in their work, principles similar to those used to stabilize and run complicated machinery, such as airplanes or power stations (Lynch, 1981). This is what Kevin Lynch referred to the view of the city as a "machine" (Lynch, 1981). The machine metaphor for the city was central to modernist architecture and planning but, where implemented, has lead to dysfunctional social designs that also result in ineffective land uses and large transportation costs, pollution and congestion.

Another tradition in architecture and planning emphasizes the organic character of cities in analogy to organisms or ecosystems (Lynch, 1981; Sitte, 1889; Geddes, 1915; Jacobs, 1970). Finally, in an age of pervasive telecommunications, we may think of cities as networks for information exchange, perhaps analogous to nervous systems (Castells, 1989).

The city is all of these things, of course, but none of them in particular (Bettencourt, 2013a; Lynch, 1981): as a complex system it has its own organization and dynamics. It also has a function that sets it apart from other complex systems, as we shall discuss below. Misapplied simplistic metaphors have, in fact, led to many planning disasters, in terms of outcomes surely, but also to huge opportunity

2. Cities, defined as functional urban areas (the implicit definition I will use here), are integrated socioeconomic units in terms of labor markets, meaning the spatial area and populations spanned by a set of frequent commuting flows. Examples are Metropolitan Areas in the USA.

3. Aristotle, *Politics (Books 1, II).*

costs for developing better urban environments. The challenge for a modern science of cities is to define urban issues in their own right and to seek integrated solutions that play to the natural dynamics of cites in terms of human development and economic growth, while avoiding negative unintended consequences, such as violence, exclusion or pollution (Bettencourt, 2013a).

The modern view of *cities as complex systems* started to emerge in the 1960s both in the United States and in developing countries, especially in Latin America. This was a time of great urban challenge worldwide. In the United States, cities underwent massive infrastructural interventions under the general epitome of "urban renewal". In many other nations, particularly in Europe and Latin America, this was also a time of fast urban growth that, in many cases, lead to the informalization of urban labor and housing often in the form of vast slums (favelas in Brazil). Many of the major issues with cities today have their roots in the transformations that took place during this period and their legacy of social and economic disparities and segregation (Wilson, 1990).

In the United States, the perspective of cities as complex systems arose partly as a reaction to the pure infrastructural solutions of the urban renewal movement. At this time, the concept of "organized complexity" was coined by Warren Weaver, in a now famous Rockefeller foundation report in 1958 (Weaver, 1958), and appropriated by Jane Jacobs in her landmark book *The Death and Life of Great American Cities* in 1961 (Jacobs, 1961). For Jacobs, *organized complexity* was the keystone concept that allows us to make sense of the fine social and spatial fabric of large cities. The structure and dynamics of this fabric, she proposed, was the basis of urban economic and civic successes. These ideas have now become the starting point for a new generation of urbanists and planners, and we have come to refer to cities as "complex adaptive systems".

In developing cities, concepts of complex systems stemmed from the consideration of more practical issues, namely how to deal with the pervasive growth of slums in places such as Mexico City (Sudra, 1976) or Mumbai (SPARC, 1985). Following a few empirical early studies of neighborhoods, John F. C. Turner wrote several influential pieces about housing for the poor as a mechanism for human development and emphasized its connections with other aspects of daily life (Turner, 1977), coining in the process the idea of "housing as a verb". In this way, the ideas that urban lives entangle all aspects of the city, from health and education to services and transportation, started to be taken seriously, at least in principle, in formulating urban policies.

As policy prescriptions, these new approaches were geared towards the urban evolution of (poor) neighborhoods, instead of previous practices such as forced evictions, which tended to make problems recur (Rogler, 1967). Several formalizations of these policies such as "sites and services" (Mayo and Gross, 1987) as well as better-designed public housing policies for "slum-upgrading" became the common practice and by and large are the norm today.

However, observing over thirty years of mixed outcomes in terms formal policies for public housing and sites and services (Mayo and Gross, 1987), raises fundamental questions about their viability and financial sustainability. As middle income countries, such as Brazil or South Africa, embark in some of the largest projects in public housing in the world, such questions loom large: For example, why is public housing so difficult to "get right"? Why have so many projects, especially in the United States and Europe failed, while public housing is a resounding success in many nations in Asia?

Answers to these question require that we understand better the nature of cities as complex systems and the many interdependences between the physical city, its infrastructure and services and the socioeconomic life of people in urban areas (Bettencourt, 2013a). It also requires that we can formalize ways to learn from urban interventions, a topic to which we will return later.

3 WHY ARE CITIES COMPLEX SYSTEMS?

Complex adaptive systems, and cities in particular, have a number of properties that distinguish them from simpler physical systems and that make their management by conventional methods especially difficult. These properties can be summarized in terms of five general properties (Bettencourt, 2013a; 2013b; Jacobs, 1961): *i*) heterogeneity; *ii*) interconnectivity; *iii*) scale; *iv*) circular causality; *v*) development.

First, *heterogeneity* refers to the fact that large cities are very diverse. This has a positive and a negative side: heterogeneity may refer to economic capabilities, such as types of professions or businesses, but also to wealth disparities (inequality), to race and ethnicity, etc. For example, larger cities disproportionally attract foreign and distant migration and thus tend to have a more diverse cultural and ethnic composition. Cities are also spatially very different from place to place and from person to person. There are poor and rich neighborhoods, there are commercial and residential parts of the city. There are also public spaces that are used much more intensely than others (Whyte, 2001) and by different groups of people. This makes standardized approaches to planning and policy very problematic and potentially wasteful. They risk failing to generate appropriate solutions because they target an average situation that is rare and uncharacteristic of any specific place or social group. As we shall see, there is a major need for detailed information about the people and neighborhoods to be affected by urban interventions. Obtaining such information has been traditionally difficult and time-consuming and, perhaps for these reasons, has rarely been done. However, thanks to new information and communication technologies the situation is changing.

Second, everything in a city is subtly *interconnected* in networks: Issues of economic development or health are connected to physical places and to urban services, and these in turn to budgets at the individual and municipal levels. How may we disentangle some of these issues so that we can develop practical solutions that are not overwhelmingly complicated?

Third, the character of cities changes with their *scale*, usually measured by population size: Larger cities are on average spatially denser and make more intense use of their infrastructure (e.g., more cars per road surface), leading to a different structure of both benefits and costs. Larger cities are more productive economically but also more expensive in terms of cost of living. Thus, dealing with issues of cities is in general a scale dependent problem. Planning, in this light, must recognize how urban space and infrastructure are used, adapt to different intensities and management costs over the lifecycle of solutions, and be able to change as cities grow.

Fourth, virtually all issues of cities, like other complex systems, show *circular causality*: for example, is a city richer because it has better infrastructure? Or does it have better infrastructure because it is richer? Is a city more violent because it has higher inequality? Or is it the other way around? This poses an important challenge to designing policy interventions: it is hard to obtain results along a single dimension without generating unintended consequences in other aspects of urban life. This issue calls for urban planning that is attentive, and explores, the creation of virtuous cycles of change. For example, as a society develops there is a general interplay between the quality and cost of urban services and the city's socioeconomic development,[4] where positive change in the physical and infrastructural aspects of the city are necessary to support its socioeconomic dynamics and vice-versa. Urban planning that captures and understands this type of circular causality is much more likely to be successful and financially sustainable.

Finally, people, businesses and the city itself *develop* over time, so that any policies today should promote a mixture of old and new uses and positive change well into the future. This is a challenge because we must envisage future land-uses, social organizations and technologies that we cannot yet conceive of in the present. This emphasizes the idea of a city as a process, rather than an object. For urban planning and policy embracing the idea of continuous and open-ended development means that it should recognize the nature of individual and human change in the city and act to reinforce its positive aspects, while discouraging its negative consequences. This is quite different from creating a static design and requires instead that planners seek and can access information about the detailed lives of their citizens, neighborhoods and businesses.

4. Such virtuous cycles of development do, in some cases, also run in the opposite direction, leading to vicious cycles of blithe and decay. This sort of dynamics has been invoked to explain the crises of post-industrial cities such as Detroit (Wilson, 1990), where unrecovered costs for services have led to the degradation of their quality via cut-backs, including, crucially, equitable justice and law enforcement, which has led to population and job loss, which in turn erodes the tax base for services, and so on.

4 THE PROPERTIES OF CITIES AS COMPLEX SYSTEMS

Cities not only share all the properties described above with other complex systems, they express them in certain specific ways, to which I now turn.

Urban areas exist over a large range of populations, from small towns with a few tens of inhabitants to megacities with tens of millions. It has been know to geographers and regional economists for many decades now that cities of different population sizes have different properties in terms of their relative political and economic roles. These ideas have been often described under the concept of urban hierarchy (Berry, 1967). Urban hierarchies capture the observation that larger cities in an urban system (nation) contain all the functions of smaller ones but not vice-versa. In other words, we may only find a specialized hospital, opera house, or a stock-exchange in a sufficiently large city, where we will also find a little bit of farming. Larger cities, in this way provide services for smaller towns in their territory, and exchange such services by those of sectors that while present are de-emphasized as they grow, such as food and energy production and some forms of manufacturing.

In this way the issue of city scale and that of heterogeneity are intimately connected. This gradual differentiation of functions with population size calls for a systematic understanding of cities in terms of differences in their internal structure but also of what changes in their organization as their size varies.

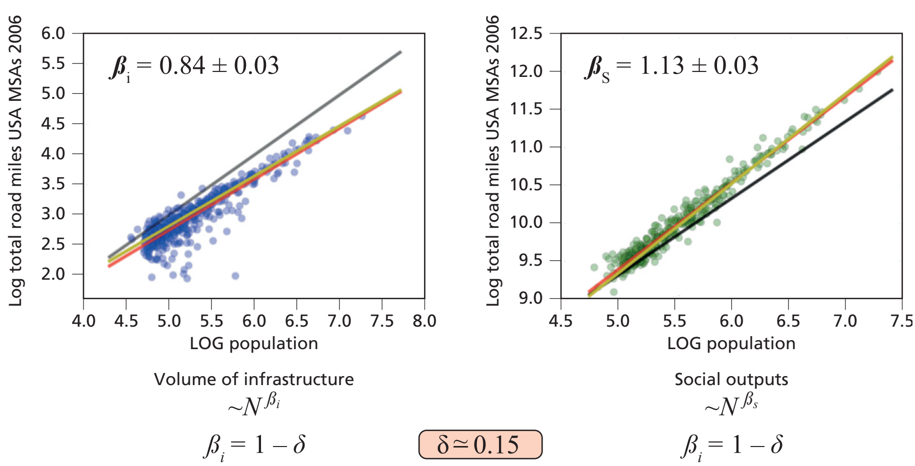
The study of how the properties and structure of cities change with their size is known as *scaling*. Scaling is one of the main analytical tools of complex systems as it can be applied to all kinds of different problems, provided there is sufficient data. For example, scaling analysis has often been applied to many-body problems in physics such as gases or liquids, or to more complicated systems such as stars, organisms, ecosystems or, indeed, cities. All these systems show scaling, meaning that empirical analyses show that their average properties are continuous functions of system size. Simpler physical systems, such as an ideal gas, show *extensive* properties (energy, entropy) that are simply proportional to the size of the system (Bettencourt et al., 2014). But complex systems typically show different (*non-extensive*) behavior, where their properties vary non-linearly with size as they grow. This will be important for cities, as I show below, because it is the reason that makes smaller urban areas qualitatively different from larger ones and that requires a different approach to their problems.

When a system scales, it manifests consistent properties across the range of sizes it can take. This tells us two main things. The first is that all instances of a type of system express the same underlying local dynamics. So, scaling, such as it is shown in figure 1, tells us that we can approach the problem of what cities are by looking at settlements of all sizes and search for the same kind of processes happening in all of them. This is important because smaller cities are often simpler to analyze. The same can be said for organisms, ecosystems, etc. What this says for cities is that their most basic units have similar behavior across all places, specifically that social life and physical places take essentially the same form in small towns and in large cities. The differences that do arise between larger metropolis and small towns are then the result of how these elementary dynamics elaborate and compose across scales.

The second consequence of scaling tells us about this cumulation and captures the true collective nature of cities. Because different types of complex systems have different emergent collective properties, scaling also tells us what is different about them, even though they may all *scale*. For example, the different way in which cities or organisms use energy as their size changes tells us that they have different dynamics (Bettencourt, 2013a; Bettencourt et al., 2007).

The main advantage of a scaling analysis of a system of cities is that it provides a very simple set of analytical tools that reveal many non-trivial aspects of urban areas that are general to all places. After identifying the properties common to all cities in the system, it also provides a procedure for singling out what is unique and special about each place (figure 1).

FIGURE 1
Nonlinear scaling of infrastructural and economic properties of cities



Obs.: The left panel shows the road surface of United States metropolitan areas, which scale sublinearly (β<1) according to a power law relation. Analogously the GDP of United States metropolitan areas grows superlinerly on average with population size with an exponent β>1. Both exponents for the volume of infrastructure and for social outputs deviate from unity (linear, black line) by the same amount in the negative and positive directions (yellow line), respectively. The deviations from the red line (best fit) value of β (value shown in each panel) are approximately normally distributed, but their values are very persistent over time with characteristic timescales of the order of decades.

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Let me start by describing some of the main empirical findings of scaling analysis applied to cities, and then proceed to explaining these properties in light of theory.

For example, analysis of socioeconomic outputs of cities as a function of their size shows that they increase per capita with city size, increasing by 10%-20% as the size of the city is doubled (Bettencourt, 2013a; Bettencourt et al., 2007). This includes quantities such as the size of the urban economy (GDP), its labor productivity (wages), its violent crime rates and measures of innovation, such as patents or employment in certain professions.

On the other hand we also observe that the volume of built space and infrastructure decreases per capita by a similar amount (Bettencourt, 2013a; Bettencourt et al., 2007). For example the area of roads per capita decreases by 10%-20% with each doubling of city size. The total area of roads and infrastructure is also connected to built space (Bettencourt, 2013a; Angel et al., 2011), which varies with city size in a similar way, as measured by satellite imagery around the world. These characteristics appear to be general properties of cities that apply equally well to China and the United States or Brazil and Germany, though national levels of wealth and infrastructure (the intercepts in figure 1) vary and change over time (Bettencourt, 2013a; Bettencourt et al., 2014). These two parameters both go up with development, while crime and other negative consequences of large-scale socialization go down.

This is why the main challenges of small cities are different from those of larger ones. Larger cities need to be able to control higher levels of crime per capita and to manage their infrastructure and services more intensely and often with new technologies to keep up with higher usage rates. Smaller cities, on the other hand, don't have these problems to the same extent and instead struggle with issues of lack of high value-added socioeconomic activity and the results of low-density land uses.

The compound effect of higher average wealth per capita and smaller space is that land rents increase faster than incomes (Bettencourt, 2013a). This has a varied set of important consequences for urban planning and for the shape of the city in space more generally. The response to land rents that increase faster than incomes with city size is typically of two types: first people can live in less space, second more floor space can be added per unit of land by building multi-story units, provided construction costs are not too high. These are typical features of large cities, leading to a more intense use of space. The consequences for city administrations (and real estate entrepreneurs) are that the capitalization of land is an effective means for cost recovery. As land appreciates faster than incomes as cities grow, the revenues allow cities to sustain larger and more professional administrations and develop better services.

The deviations from scaling relations (residuals of a log-log linear fit, see figure 1) are also interesting as they express local effects characteristic of each city, away from the expectation from their population size. Such residuals are not random numbers, though they obey simple statistics well described in general by a Gaussian distribution[5] (Gomez-Lievano, Youn and Bettencourt, 2012; Bettencourt et al., 2010). Instead they provide a city-size independent of urban performance for each city relative to all others in the same urban system (Bettencourt et al., 2010). Moreover, such deviations change over time only very slowly, so that a city that is richer or poorer than the expectation for its size today is likely to continue to be so for perhaps a few decades (Bettencourt, 2013a; Bettencourt et al., 2010). This means that fundamental urban change is slow and happens on timescales of several electoral cycles – thus, the consistency of certain urban policies over the long term is an important ingredient for steering change in the right direction.

It is interesting to summarize these empirical results in light of new theory for the nature of cities as complex systems and the five properties of cities described in the previous section. Recently proposed theory (Bettencourt, 2013a) describes cities in terms of network models of socioeconomic interactions and infrastructure and gives predictions for the value of scaling exponents (elasticities).

A detailed mathematical treatment of these ideas will not be developed here, and the interested reader is referred to the original sources (Bettencourt, 2013a). Basically the scaling properties of cities can be obtained through assuming four simple properties, common to all cities: *i*) that city populations are mixing, meaning that one can in principle meet anyone else in the city; *ii*) that the built space in cities is set by decentralized infrastructure networks that grow with the city; *iii*) that human effort is conserved across city sizes; and *iv*) that the socioeconomic products of cities are proportional to the overall rate of social interactions in these spaces.

These ideas can also be stated in a slightly different way: if humans benefit, on average, from interacting with others, then the problem to be solved is how to create a set of processes in space that makes such interactions possible at a cost that is commensurate with their benefits. This is the general problem that cities solve: they structure space and human spatial densities in such a manner that the costs of running the city (especially the transportation of people, goods, energy and information) scales in the same way as the rate of social interactions (Bettencourt, 2013a), while preserving human effort. These ideas propose, in particular, that the scaling properties of cities are the result of increasing rates of social interaction per capita with the size of cities. We have directly tested this hypothesis using cell phone networks, where each person's contacts can be measured directly; results are in good agreement with theory (Schläpfer et al., 2014; Andris and Bettencourt, 2014).

5. This is a lognormal distribution in the original variables (Bettencourt et al., 2014; Gomez-Lievano, Youn and Bettencourt, 2012; Bettencourt et al., 2010; Schläpfer et al., 2014).

The final ingredient is what happens to human social networks as interaction rates (network degree) increase. Here, we can naturally connect back to foundational ideas from economics and sociology, and specifically with concepts of the division of labor (Smith, 1776), which in modern terms we think of as a division of knowledge (Arrow, 1962). We observe, in agreement with the more qualitative ideas of urban hierarchy mentioned above, that in larger cities there is greater diversity of professions, business types, etc. (Bettencourt, Samaniego and Youn, 2014; Youn et al., 2014). The presence of larger human capital is often invoked by urban economists as the proximate reason why larger cities show greater labor productivity. But the idea then is that it is the possibility of social contact with more people that encourages each individual to specialize and learn and become more interdependent with others. In this process new knowledge is created that can lead to new economic growth (Bettencourt, Samaniego and Youn, 2014; Bettencourt, 2014b).

Thus, cities create the conditions for larger rates of socioeconomic interaction with others (larger markets, amount other things) and encourage the generation of new knowledge and its recombination, through specialization and interdependence of both individuals and organizations (firms, non-profits, government agencies, etc.).

We now see how the five properties of cities introduced above are interdependent: city size (*scale*) allows, in principle, for greater *interconnectivity* between people, along a larger number of dimensions made possible by learning and specialization (*heterogeneity*). The causality between these processes is circular as interdependence (social connectivity) is necessary to allow specialization and specialization leads to more advanced knowledge, with greater economic value that can sustain enabling social and physical infrastructure. As these processes iterate over time and deepen, more knowledge can be created and embodied in individuals and socioeconomic networks leading to economic growth and human *development*, not only at the level of single cities but of urban systems through the structure of urban hierarchies.

These effects, on average, all follow from a scaling theory of cities (Bettencourt, Samaniego and Youn, 2014; Bettencourt, 2014b). However, the detailed stochastic processes by which individual lives are woven in cities and can lead to these aggregate results remains to be investigated in greater detail. In particular, it is important that we better understand why, despite the possibility of larger rates of interaction, many cities in developing nations remain poorer than their developed counterparts. This is thought to be in part the consequence of limitations to the processes described here. As a result, many individuals in developing cities find it difficult to shift their lives away from pure survival and onto more entrepreneurial and more creative activities that can cumulate knowledge and lead to systematic change in terms of human development and economic growth.

In this way the interplay between infrastructure, urban services and human creativity and agency comes back into focus. In particular, the ability for cities to identify problems that they can solve by engineering solutions is essential in order to liberate the socioeconomic potential of their citizens. This then is the long-term strategic role of urban planning and policy to which we now return.

5 IMPLICATIONS FOR URBAN PLANNING AND POLICY

We now turn to the practical implications of cities as complex systems for planning and policy. Our considerations will be mostly strategic, as the design of each policy naturally requires tailoring interventions to local information, the consideration of budget constraints, political context, etc.[6]

Specifically, in this section I try to answer three questions that are at the root of the main difficulties of managing cities and promoting positive change: *i*) How to design approaches that take the dynamic interconnections and heterogeneity of cities into account? 2) When is it appropriate to use practices from engineering; and conventional policy to tackle urban problems? 3) How to deal with the more "complex problems" that characterize so much of the social and economic fabric of cities?

The second and third questions are easier to answer. I define *i*) "simple problems": as those that can be tackled using methodologies from engineering and *ii*) "complex problems" as those require the full consideration of methods from complex systems. I will now describe what makes a problem fall in one class or the other and the strategy to solve each type.

Simple problems are not necessarily easy to solve: They are "simple" because their structure is clear and amenable to solutions that fall within the logic of engineering theory, which is familiar to policy makers and urban planners (Bettencourt, 2014a). Such problems can be addressed in standard ways that are minimally culturally sensitive. Examples are how to run a bus system or waste collection.

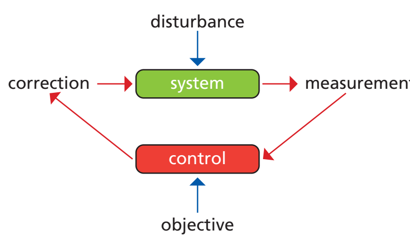
We can identify when a problem is simple through three necessary properties (Bettencourt, 2014a): *i*) the existence of well-defined, measurable performance metrics, against which the solution is to be assessed on a frequent basis; *ii*) the means to act on the system to move it towards fulfilling its performance metrics; *iii*) the ability to act fast enough, so that the solution remains simple. What I just described may be formalized in terms of a feedback-control loop (Åström and Murray, 2008), which can be implemented by an algorithm, a human or a dedicated organization.

6. This is the sense in which scientific theory never fully determines engineering solutions or policies. However, scientific insights are essential to reduce the space of possible policy and engineering designs and, often, to the conception of entirely new technical solutions to problems that have been intractable in the past. Consider, for example, attempting to go to the Moon without knowledge of the laws of motion and gravity.

For example, when running a bus system, we may consider the waiting time at a bus stop as a performance metric. Let's say that we want the average waiting time to be 5 minutes or less. We can measure the average waiting time in BRT (Bus Rapid Transit) stations where people tap into bus platforms and then adjust the bus speeds and frequency (through communication and dispatching) on a continuous basis to fulfill these metrics. If waiting times become too long or irregular the dispatching and adjustment of speed becomes more difficult and riders will be less satisfied with the service because of longer waiting times, but also because of greater uncertainty and the system will be harder to manage and sustain financially. Thus, effective operation, leading to sustained and predictable quality of service, requires active system management on the time scale of minutes or faster. Otherwise the system falls apart and becomes unmanageable.

Another important but very different example of policy as a feedback-control loop is monetary policy, whereby central banks adjust interest rates to stave off inflation and stimulate economic growth. This is an example of a national (not urban) policy, whereby a once complex issue – controlling inflation – has been rendered simple.

FIGURE 2
The structure of policy as a feedback control loop



Obs.: Such solutions reflect engineering theory about how to operate complicated systems in simple ways. Crucially it requires a clear measurement of properties of the system and its comparison with a desirable objective, the capacity of acting on the system by a controller to correct its state toward the objective and the ability to act fast enough so that the response from the system remains simple.
Publisher's note: image whose layout and texts could not be formatted and proofread due to the technical characteristics of the original files provided by the authors for publication.

The critical aspect of these solutions, that is not explicit in figure 2, is the importance of fast, timely response on the part of the planner. As I will discuss below, all "simple" systems are complex in the long-run and typically display instabilities even on relatively short timescales. The ability to act on the system before any such instabilities develop is critical. For example, a monetary policy that lets inflation rise too far may then overdo its correction measures, take the system under recession and eventually deflation, for which its means to act (loan rates) are ineffective. As a result, a good policy when applied fast enough becomes absolutely ineffective if applied on timescales where the system's response is no longer controllable by simple means.

Where they work, engineering-type policies of this type allow for extremely effective problem-solving that liberate us from the most essential elements of survival such as transportation, water, electricity, waste removal, climate control, etc. This is essential to allow a society to dedicate its time to activities with greater socioeconomic value that are enablers of its own growth and development (Bettencourt, 2014b).

All simple problems are complex to begin with and become complex again over the long-run. To explain what I mean, consider again the example of a bus system. The design of BRTs, made famous by Curitiba in Brazil and Bogotá in Colombia, is a good example. Before these novel systems were conceived a bus line consisted of a set of vehicles running on roads, stopping at bus stops along a route and attempting to stick to pre-defined schedules. But the deficiencies of such traditional systems in terms of high-costs and low-speed, especially in large congested cities, led to such innovative solutions as dedicated bus lanes and elevated platforms that function more like those of a subway system. At first, the problem of running a cheap and effective bus system in a congested city was complex because it depended on the behavior and cooperation of bus riders, car drivers, and many other factors. But through experimentation and invention, these problems were overcome. As a result, the problem of running a BRT becomes simple(r). Having such a system in place, we can now implement the process of dispatching buses or adjusting their speed to minimize waiting and travel time as described above. Because this system is now "simple" and, certainly less exposed to uncertainties of human behavior, computational techniques such as simulation and agent-based models also become useful in developing and testing methods of management. All this, put together, allows for a virtuous cycle of improvements and the exploration of further efficiencies.

In the long-run, the problem of operating a transit system becomes complex again: It will be entangled with public expectations rising in tandem with economic growth and human development. This will require faster, more point-to-point, more comfortable solutions. At present this means that taxis, cars or even helicopters, become preferable for a richer and more time conscious population. How to develop a financially sustainable public transit system for a rich society, where time and comfort are paramount, remains an open problem and goes far beyond exploring greater efficiencies in BRT systems. Recent trends of rising car ownership in traditionally transit-oriented cities such as Singapore or Curitiba are evidence of this issue (Marques, 2010; Mahbubani, 2014) as are world record-breaking traffic jams in the large cities of middle-income countries, such as Beijing or São Paulo.

If "complex" urban problems are inevitable – then how should we deal with them?

In explicit form this question goes back to the 1970s when the term "wicked problems" was coined to describe many of the difficult socioeconomic issues faced by cities (Rittel and Webber, 1973). Wicked problems, where originally defined, much as I did for complex systems, as problems with circular causality and very large (combinatorial) problem spaces. Thus, it may seem at first that such problems are just impossible to solve. What does the study of complex systems tell us about how they can be handled in practice?

The short answer is that such problems are to be solved through *self-organization* (Bettencourt, 2014a). This is also the answer from economics, though in a more limited context (Hayek, 1945). The role of markets or, more generally, of networks of individuals and organizations who integrate and use information available to them, but not to anyone in its totality (such as the planner), is the way in which wicked problems are tackled in practice. This does not guarantee optimal solutions in general, but results instead in a distributed and robust way to handle problems.

Self-organization places the emphasis on human agency and creativity and on effective social organizations, capable of coordinating their knowledge and action through signals, such as prices. As we should know from the idea of market failures in economics, this is not always possible and relies in particular on low transaction and coordination costs.[7]

From this point of view, there are two main challenges to effective self-organization: *i*) the *problem of information*, necessary to design and prioritize urban interventions; and *ii*) the *problem of learning* from policies as they are implemented.

Both these problems run much deeper than may appear from a practical point of view. Some thought about the difficulties involved transforms the practice of urban policy away from a static design problem towards one that is essentially to do with coordination of information and action across levels of organization: from the individual and neighborhood to the municipal governments, and beyond. This also means that local conditions (cultural, technological, budgetary) are very relevant at this stage of problem solving (Brenman and Sanchez, 2012).

For example, at low development it is common that some scarce urban services are shared among a large number of households. Consider, for example, water points: How many should there be in a neighborhood? The answer from the point of view of the utility depends on the capital and maintenance cost of the service. But from the point of view of users, waiting time, distance and reliability (maintenance) are essential: it maybe that more water points developed at higher capital costs can provide a better service and be better maintained because they incur less use each and

7. For several aspects of market failures, see <http://en.wikipedia.org/Niki/Market_failure>.

because a smaller group of users may confer a sense of responsibility and ownership.[8] How is the planner to know that in advance? In practice, some of the *information* for the initial design is to be found in the community to be served, and then is to be *learned* through the assessment of the service along several dimensions over time. Because governments and planning authorities are often not well equipped to deal with these issues, the development of successful urban planning and policy is difficult and requires the acquisition of organizational and technological sophistication.

Thus, the *problem of information* is simple enough to understand: how can a planner at the municipality know enough about the lives of people, say, in a particular neighborhood, in order to know how to design the best possible policy intervention in such a place?

In general, this is actually very difficult – there is a world of difference between implementing a standard solution (say in terms of transportation, water, electricity) and devising a plan that is at once most helpful to the community it serves and realizable in term of affordability, cost recovery and maintenance. Such a problem is not necessarily made simpler by common practices of participatory planning, such as holding community meetings, unless these can be made to be an effective way to acquire the necessary information.

From the point of view of populations a similar problem arises: How is a community, motivated to facilitate municipal work, to know how to collect its local information and communicate it in a way that can help planners?

This issue is a formal problem of coordination and has been dealt with in complex systems: The problem boils down to developing the ability to solve local problems in a way that integrates bottom-up processes of knowledge and data collection and top-down agency (Brenman and Sanchez, 2012). In other words, it is essential that communities to be served can contribute relevant information about their priorities in terms of service quality and quantity and financial capacity, and that such information is incorporated in the planning of a service by the municipality.

This poses the challenge of how to share information among very different organizations. Several experiments, typically in poor slum neighborhoods, have pointed to some interesting solutions to this problem that play both to the self-interest of communities to be served and to the need of the city for adequate information. They have demonstrated that the best way to bridge these different levels organization is through data, that often can be collected by communities, but that must be verifiable by third parties. This can transform a difficult political confrontation about general issues into a simpler negotiation around more objective facts and choices.

8. A reasoning of this kind has lead to a massive program to replace public toilets by private ones in Pune, India, for example. See <shelter-associates.org>.

New information and communication technologies can also play a role in reducing the difficulties of carrying out these processes. It has now become possible to generate census-like surveys according to simple standardized procedures, using paper and pen methods or electronic devices, and to collect spatial geo-coded information in inexpensive and extremely accurate ways. Because these methods are easy to share through new online platforms[9] they allow for much lower coordination costs than in the past, and the simple tracking of services both from the logistic and socioeconomic perspectives. Such methods are becoming more widespread, but are still relatively new. Middle-income countries, such as Brazil (Perlman, 2010), have a unique need and opportunity to use them to track their large investments in slum/neighborhood upgrades and public housing, as well as in more general service delivery contexts.

This brings us then to the issue of *learning*. Learning is essential because it provides the opportunity for planners, governments and researchers to solve problems effectively and improve their practices from experience as they go. This requires the formalization of interventions in cities in terms of clear, measurable outcomes and the ability to collect information along the way. This means that knowledge about the nature of urban development in many places can be compared and assessed and that the search for possible solutions everywhere can tap onto the wealth of knowledge generated in many other places. While learning is certainly happening already through myriads of interventions in many places, it is very hard to assess each of these policies objectively and for third parties, not directly involved in them, to learn from such experiences. Thus, one requires an integrated way to share procedures and assessments of urban policies such that the sum total of the resulting knowledge actually cumulates (Ostrom, 2009).

The answer to the first question, at the beginning of this section, now comes in to focus. Self-organization mechanisms play out to existing knowledge and capacities and to their expansion and improvement. Effective policy that encourages self-organization must reinforce positive cycles of circular causality in heterogeneous environments, where some solutions to the targeted problems are likely to already exist locally somewhere in the city (Perlman, 2010). For example, even poor cities have more developed neighborhoods where standards of service provision are higher: the question of expanding services may then be primarily about scaling and replicating such local operational capacity more widely. Thus, the answer is often to take advantage of socio-economic dynamics that are already present in some form in the system, while creating the conditions for such capacity to expand and improve, rather than try to develop new *tabula rasa* solutions. One reason for this is that local solutions are much more likely to be well adapted to local contexts and needs than imported recipes. But the ultimate reason

9. See our current work at: <http://www.santafe.edu/research/informal-settlements>.

is that the acquisition of information and learning by diverse agents in the city is the basis for the fundamental solution of many different problems and should itself be the primary target of policy.

In summary, the practical lessons from regarding cities as complex systems are that the capacity to both treat simple and complex problems in cities must coexist, and the planner must be able to shift between these two perspectives as she takes at once a practical approach to particular, clear and present problems or a longer, more strategic view towards the development of the city over decades.

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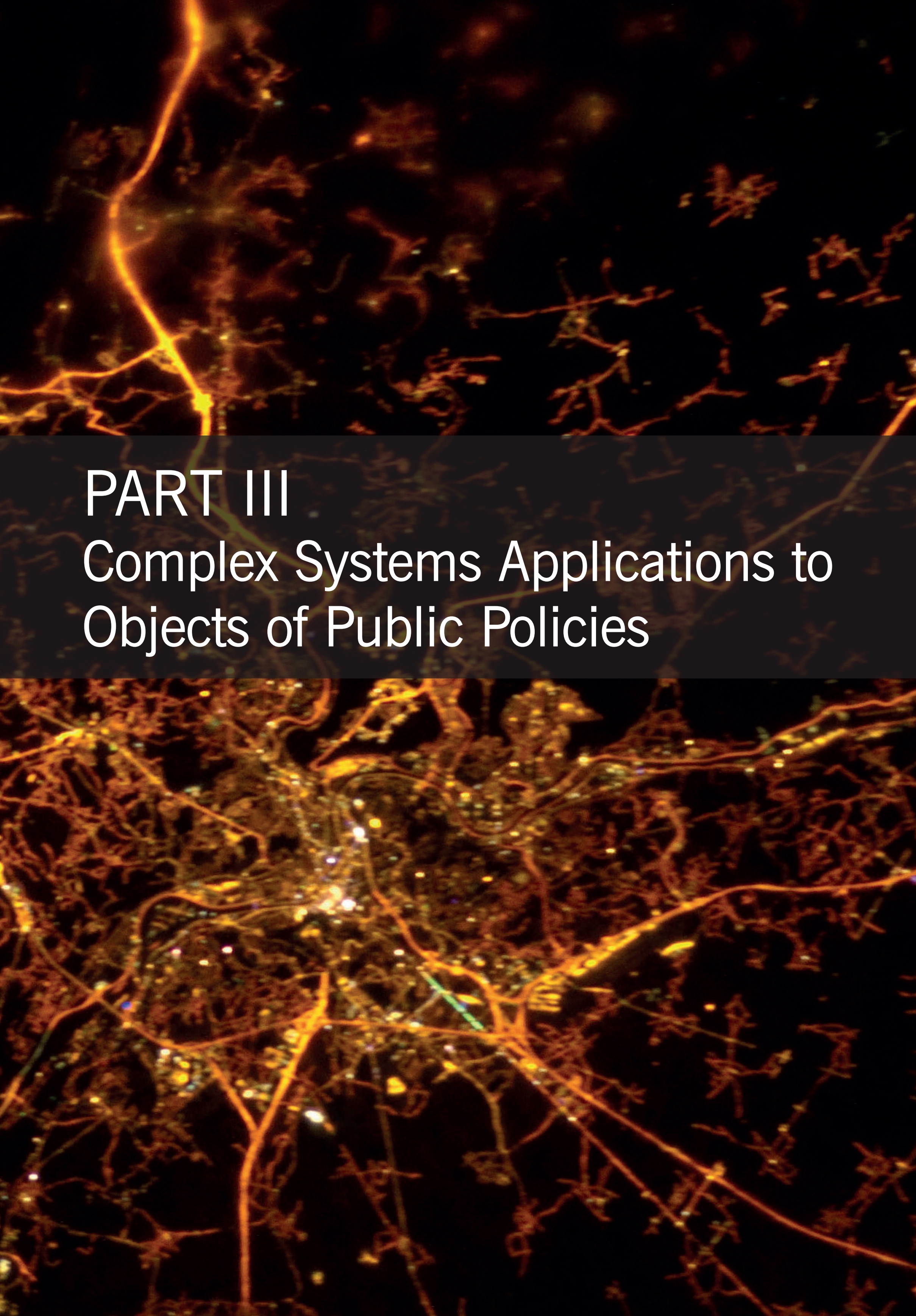
PART III
Complex Systems Applications to Objects of Public Policies



CHAPTER 11

COMPLEXITY THEORY IN APPLIED POLICY WORLDWIDE

Yaneer Bar-Yam[1]

1 INTRODUCTION

Globalization, including transportation, communication, economic and social integration, imply that seemingly local policies can have far-reaching consequences. Under these conditions what appear to be autonomous decisions by national authorities can have global impacts. How can we identify those impacts? Dependencies in networks and the patterns of behavior that are caused by them are the subject of complex systems science (Bar-Yam, 1997; 2002). Complex systems are systems in which the collective behavior does not satisfy the central limit theorem, i.e. components are neither independent nor fully dependent. One of the central methodologies of complex systems science, multiscale analysis (Bar-Yam and Bialik, 2013; Bar-Yam, 2004; 2002), can be used to identify the complex relationships between the behavior of parts and the whole. The overall complexity of a system, or the amount of information required to describe a system, can be analyzed as a function of scale. If the parts of a system are independent, then the whole system exhibits fine scale random behavior. If the parts are correlated, the system has large scale coherent behavior. If the parts are interdependent, the system can perform complex behaviors that can be characterized to identify key properties.

Focusing on the largest scale behaviors in relation to finer scale component behaviors enables understanding how external forces and internal self-organization together comprise the behavior of the system. The impact of policy interventions, past and intended, can be characterized. Policies that change a particular behavior must have the necessary scale of intervention, while those that change complex behaviors must have the necessary ability to respond to different conditions – an effective intervention must be at least as complex as the target system.

The literature on complex systems science has become large with both scientific studies and applications to real world problems.[2] The following sections will illustrate how complex systems science and multiscale analysis have been used by the New England Complex Systems Institute to develop important insights and inform policy making decisions in our complex interdependent world. In section 2,

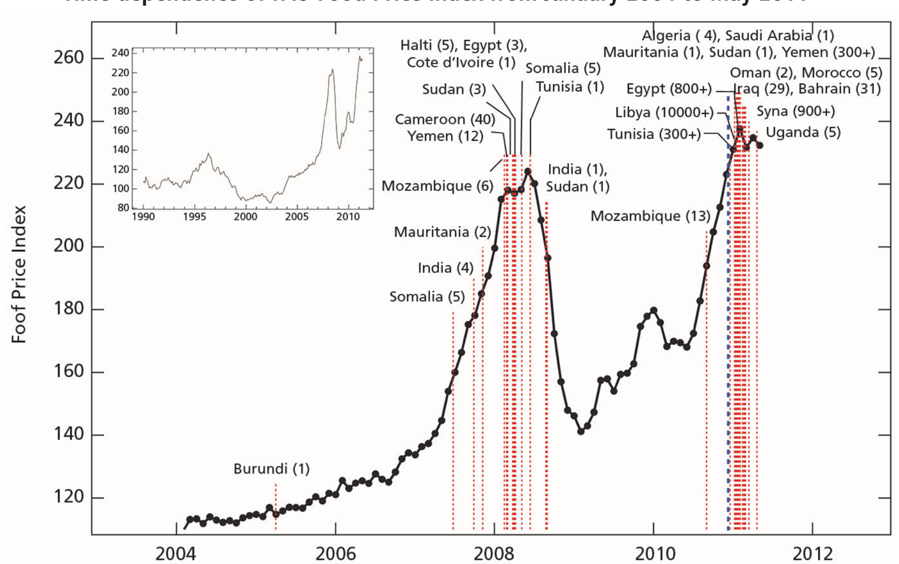
1. New England Complex Systems Institute 210 Broadway, Cambridge, MA 02139.

2. Complexity Digest. Available at: <http://comdig.unam.mx>.

we describe the role of spiking food prices in political instability, including the Arab Spring. In section 3, we identify U.S. ethanol mandates and commodity market deregulation as the primary causes of the rising food prices that sparked unrest. In section 4, we outline how we can characterize panic in equity markets and its impact on market behavior. Section 5 describes the consequences of interdependence for systemic risk and the financial crisis. In section 6, we consider the role of ethnic geography on ethnic tension and violence, using peaceful Switzerland as a case study to show how peaceful coexistence can be achieved. Finally, in section 7, we show how increasing global transportation actually changes the types of diseases that are present, leading to vulnerability to extinction through outbreaks of highly lethal, rapidly spreading diseases. The Ebola epidemic of 2014 is an example of the risks that we are facing. Section 8 provides a brief summary.

2 THE FOOD CRISES AND POLITICAL INSTABILITY IN NORTH AFRICA AND THE MIDDLE EAST

FIGURE 1
Time dependence of FAO Food Price Index from January 2004 to May 2011



Source: Lagi, Bertrand and Bar-Yam (2011).
Obs.: Red dashed vertical lines correspond to beginning dates of "food riots" and protests associated with the major recent unrest in North Africa and the Middle East. The overall death toll is reported in parentheses. Blue vertical line indicates the date, December 13, 2010, on which we submitted a report to the U.S. government, warning of the link between food prices, social unrest and political instability. Inset shows FAO Food Price Index from 1990 to 2011.
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In 2011 protest movements became pervasive in countries of North Africa and the Middle East. These protests were associated with dictatorial regimes and were often considered to be motivated by the failings of the political systems in the human rights arena. We demonstrated that food prices are the precipitating condition for social unrest and identified a specific global food price threshold for unrest. We projected that, even without sharp peaks in food prices, within just a few years the trend of prices would reach the threshold. This pointed to a danger of spreading global social disruption. Our predictions have been realized (Merchant, 2014).

Historically, there are ample examples of "food riots" with consequent challenges to authority and political change, notably in the food riots and social instability across Europe in 1848, which followed widespread droughts. While many other causes of social unrest have been identified, food scarcity or high prices often underlie riots, unrest and revolutions. Today, many poor countries rely on the global food supply system and are thus sensitive to global food prices. This condition is quite different from the historical prevalence of subsistence farming in undeveloped countries, or even a reliance on local food supplies that could provide a buffer against global food supply conditions. It is an example of the increasingly central role that global interdependence is playing in human survival and well-being. We can understand the appearance of social unrest in 2011 based upon a hypothesis that widespread unrest does not arise from long-standing political failings of the system, but rather from its sudden perceived failure to provide essential security to the population. In food importing countries with widespread poverty, political organizations may be perceived to have a critical role in food security. Failure to provide security undermines the political system's very reason for existence. Once this occurs, the resulting protests can reflect the wide range of reasons for dissatisfaction, broadening the scope of the protest and masking the immediate trigger of the unrest.

Human beings depend on political systems for collective decision making and action and their acquiescence to those systems, if not enthusiasm for them, is necessary for the existence of those political systems. The complexity of addressing security in all its components, from protection against external threats to the supply of food and water, is too high for individuals and families to address themselves in modern societies (Bar-Yam, 1997). Thus, individuals depend on a political system for adequate decision making to guarantee expected standards of survival. This is particularly true for marginal populations, i.e. the poor, whose alternatives are limited and who live near the boundaries of survival even in good times. The dependence of the population on political systems engenders its support of those systems, even when they are authoritarian or cruel, compromising the security of individuals while maintaining the security of the population. Indeed, a certain amount of authority is necessary as part of the maintenance of order against atypical individuals or groups who would disrupt it (Lagi, Bertrand and Bar-Yam, 2011a). When the ability of the political system to provide security for the population breaks down, popular support disappears. Conditions of widespread threat to security are particularly present when food is inaccessible to the population at large. In this case, the underlying reason for support of the system is eliminated, and at the same time there is "nothing to lose," i.e. even the threat of death does not deter actions that are taken in opposition to the political order. Any incident then triggers death-defying protests and other actions that disrupt the existing order. Widespread and extreme actions that jeopardize the leadership of the political system, or the political system itself, take place. All support for the system and allowance for its failings are lost. The loss of support occurs even if the political system is not directly responsible for the food security failure, as is the case if the primary responsibility lies in the global food supply system.

The role of global food prices in social unrest can be identified from news reports of food riots. Figure 1 shows a measure of global food prices, the UN Food and Agriculture Organization (FAO) Food Price Index and the timing of reported food riots in recent years. In 2008 more than 60 food riots occurred worldwide in 30 different countries, 10 of which resulted in multiple deaths, as shown in the figure. After an intermediate drop, even higher prices at the end of 2010 and the beginning of 2011 coincided with additional food riots (in Mauritania and Uganda), as well as the larger protests and government changes in North Africa and the Middle East known as the Arab Spring. There were comparatively fewer food riots when the global food prices were lower. Three of these, at the lowest global food prices, are associated with specific local factors affecting the availability of food: refugee conditions in Burundi in 2005, social and agricultural disruption in Somalia and supply disruptions due to floods in India. The latter two occurred in 2007 as global food prices began to increase but were not directly associated with the global food prices according to news reports. Two additional food riots in 2007 and 2010, in Mauritania and Mozambique, occurred when global food prices were high, but not at the level of most riots, and thus appear to be early events associated with increasing global food prices.

These observations are consistent with a hypothesis that high global food prices are a precipitating condition for social unrest. More specifically, food riots occur above a threshold of the FAO price index of 210 ($p<10^{-7}$, binomial test). The observations also suggest that the events in North Africa and the Middle East were triggered by food prices. Considering the period of time from January 1990 to May 2011 (figure 1 inset), the probability that the unrest in North Africa and the Middle East occurred by chance at a period of high food prices is $p<0.06$ (one sample binomial test). This conservative estimate considers unrest across all countries to be a single unique event over this period of just over twenty years. If individual country events are considered to be independent, because the precipitating conditions must be sufficient for mass violence in each, the probability of coincidence is much lower.

A persistence of global food prices above this food price threshold should lead to persistent and increasing global unrest. Given the sharp peaks of food prices we might expect the prices of food to decline shortly (Lagi, Bertrand and Bar-Yam, 2011a). However, underlying the peaks in figure 1, we see a more gradual, but still rapid, increase in food prices during the period starting in 2004. It is reasonable to hypothesize that when this underlying trend exceeds the threshold, the security of vulnerable populations will be broadly and persistently compromised. Such a threat to security should be a key concern to policymakers worldwide. Social unrest and political instability of countries can be expected to spread as the impact of loss of security persists and becomes pervasive, even though the underlying causes are global food prices and are not necessarily due to specific governmental policies. While some variation in the form of unrest may occur due to local differences in government, desperate populations are likely to resort to violence even in democratic regimes. We successfully predicted a breakdown of social order as a result of loss of food security, based upon historical events and the expectation that global population increases and resource constraints will lead to catastrophe.

3 THE FOOD CRISES: A QUANTITATIVE MODEL OF FOOD PRICES INCLUDING SPECULATORS AND ETHANOL CONVERSION[3]

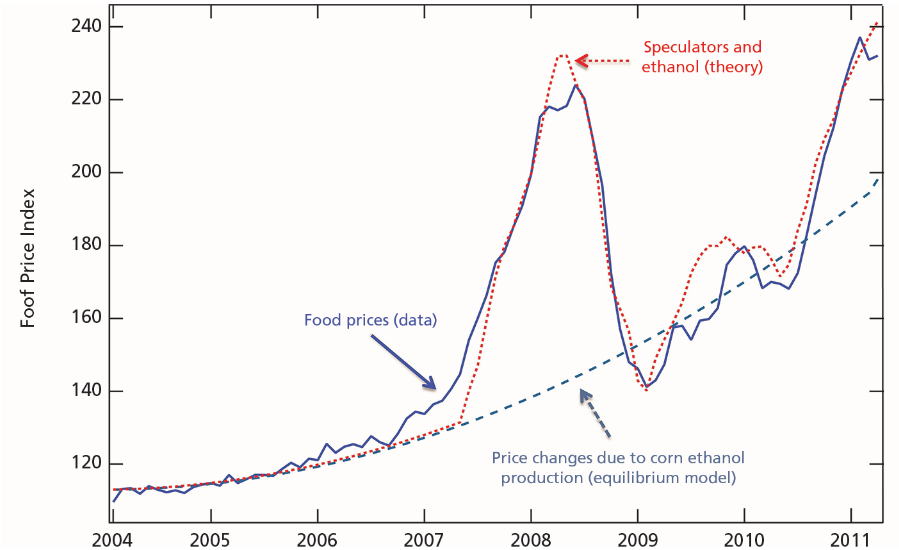
In 2007 and early 2008 the prices of grain, including wheat, corn and rice, rose by over 100%, then fell back to prior levels by late 2008. A similar rapid increase occurred again in the fall of 2010. These dramatic price changes have resulted in severe impacts on vulnerable populations worldwide and prompted analyses of their causes. Among the causes discussed are: *i*) weather, particularly droughts in Australia; *ii*) increasing demand for meat in the developing world, especially in China and India; *iii*) biofuels, especially corn ethanol in the United States and biodiesel in Europe; *iv*) speculation by investors seeking financial gain on the commodities markets; *v*) currency exchange rates; and *vi*) linkage between oil and food prices. Many conceptual characterizations and qualitative discussions of the causes suggest that multiple factors are important. However, quantitative analysis is necessary to determine which factors are actually important and which are not. While various efforts have been made, no analysis thus far has provided a direct description of the price dynamics. We have produced a quantitative model of price dynamics demonstrating that only two factors are central: speculators and corn ethanol. We introduced and analyzed a model of financial speculator price dynamics describing speculative bubbles and crashes. We further showed that the increase in corn to ethanol conversion can account for the underlying price trends when we exclude speculative bubbles. A model combining both the shock due to increasing ethanol conversion and speculators quantitatively matches food price dynamics. Our results imply that changes in commodity market regulations that eliminated restrictions on investments and government support for ethanol production have played a direct role in global food price increases.

3. Lagi, Bertrand and Bar-Yam (2011b).

The analysis of food price changes immediately encounters one of the central controversies of economics: whether prices are controlled by actual supply and demand, or are affected by speculators who can cause "artificial" bubbles and panics. Commodity futures markets were developed to reduce uncertainty by enabling pre-buying or selling at known contract prices. In recent years "index funds" that enable investors (speculators) to place bets on the increase of commodity prices across a range of commodities were made possible by market deregulation. The question arises whether such investors, who do not receive delivery of the commodity, can affect market prices. One thread in the literature denies the possibility of speculator effects in commodities. Others affirm a role for speculators in prices, but there has been no quantitative description of their effect. The rapid drop in prices in 2008, consistent with bubble/crash dynamics, increased the conviction that speculation is playing an important role. Still, previous analyses have been limited by an inability to directly model the role of speculators. This limitation has also been present in historical studies of commodity prices. For example, analysis of sharp commodity price increases in the 1970s found that they could not be due to actual supply and demand. The discrepancy between actual prices and the expected price changes due to consumption and production was attributed to speculation, but no quantitative model was provided for its effects. More recently, statistical (Granger) causality tests were used to determine whether any part of the price increases in 2008 could be attributed to speculative activity. The results found statistical support for a causal effect, but the magnitude of the effect cannot be estimated using this technique.

We developed a model relating speculation to prices and analyzed its price dynamics. The model describes trend-following behavior and can directly manifest bubble and crash dynamics. In our model, when prices increase, trend following leads speculators to buy, contributing to further price increases. If prices decrease, the speculators sell, contributing to further price declines. Speculator trading is added to a dynamic model of supply and demand equilibrium. If knowledgeable investors believe supply and demand do not match (as inferred from available information), there is a countering (Walrasian) force toward equilibrium prices. When prices are above equilibrium these investors sell, and when below these investors buy. The interplay of trend following and equilibrium restoring transactions leads to a variety of behaviors depending on their relative and absolute strengths. For a sufficiently large speculator volume, trend following causes prices to depart significantly from equilibrium. Even so, as prices further depart from equilibrium the supply and demand restoring forces strengthen and eventually reverse the trend, which is then accelerated by the trend following back toward and even beyond the equilibrium price. The resulting oscillatory behavior, consisting of departures from equilibrium values and their restoration, matches the phenomenon of bubble and crash dynamics. The model clarifies that there are regimes in which speculators have distinct effects on the market behavior, including both stabilizing and destabilizing the supply and demand equilibrium.

FIGURE 2
Food prices and model simulations (2004-2011)



Source: Lagi, Bertrand and Bar-Yam (2011).
Obs.: The FAO Food Price Index (blue solid line), the ethanol supply and demand model (blue dashed line) – where dominant supply shocks are due to the conversion of corn to ethanol so that price changes are proportional to ethanol production – and the results of the speculator and ethanol model (red dotted line) – which adds speculator trend following and switching among investment markets, including commodities, equities and bonds.
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Aside from the high price peaks, the underlying trends of increasing food prices match the increases in the rate of ethanol conversion. We constructed a dominant supply shock model of the impact of ethanol conversion on prices, accurately matching underlying price trends and demonstrating that the supply and demand equilibrium prices would be relatively constant without the increase in corn to ethanol conversion. We then combined the effects of speculators and corn to ethanol conversion into a single model with remarkably good quantitative agreement with the food price dynamics. The unified model also captures the way speculators shift between equities and commodities for maximum projected gains. Final results are shown in figure 2.

4 PREDICTING ECONOMIC MARKET CRISES USING MEASURES OF COLLECTIVE PANIC[4]

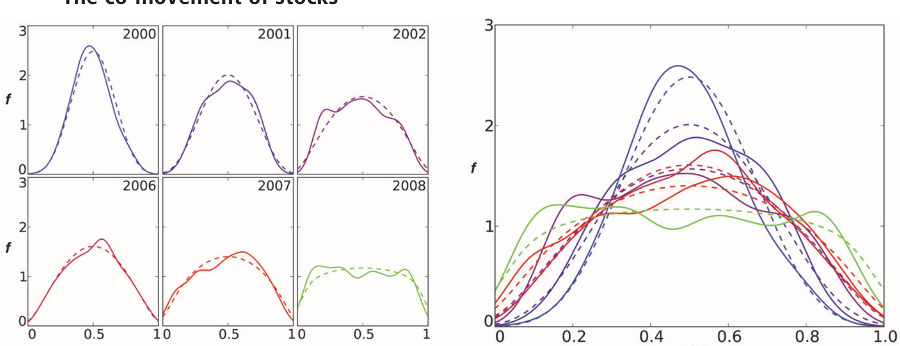
In sociology (Wolfenstein, 1957; Smelser, 1963; Quarantelli, 2001; Mawson, 2005), panic has been defined as a collective flight from a real or imagined threat. In economics, bank runs occur at least in part because of the risk to the individual

4. Harmon et al. (2011).

from the bank run itself – and may be triggered by predisposing conditions, external (perhaps catastrophic) events or even randomly. Although empirical studies of panic are difficult, efforts to distinguish endogenous (self-generated) and exogenous market panics from oscillations of market indices have met with some success, though the conclusions have been debated. Market behavior is often considered to reflect external economic news, though empirical evidence has been presented to challenge this connection. Efforts to characterize events range from the Hindenburg Omen to microdynamic models and to the demonstration that market behaviors are invariant across many scales. Panic can be considered a critical transition for which early warnings are being sought. The "collective flight" aspect of such a transition should be revealed in measures of mimicry that is considered central to panic. We used co-movement data to evaluate whether the recent market crisis and earlier one-day crashes are internally generated or externally triggered. Based upon a hypothesis about mimicry, we constructed a model that includes both mimicry and external factors and tested it empirically against the daily extent of co-movement. Our objective was to determine the relative importance of internal and external causes, and, where internal causes are important, to find a signature of self-induced panic which can be used to predict panic.

The literature generally uses volatility and the correlation between stock prices to characterize risk. These measures are sensitive to the magnitude of price movement and therefore increase dramatically when there is a market crash. Studies find that, on average, volatility increases following price declines, but do not show higher volatility is followed by price declines. We are interested in the extent to which stocks move together. The extent of such co-movement may be large even when price movements are small.

FIGURE 3
The co-movement of stocks



Source: Harmon et al. (2011).

Obs.: Plotted is the fraction of trading days during the year (*f*, vertical axis) in which a certain fraction of stocks (*k*/*N*, horizontal axis) moved up. Empirical data are shown (solid lines) along with one-parameter theoretical fits (dashed lines) for the years indicated. Three years are omitted that do not differ much from the year immediately preceding and following them. Right panel combines all of the years shown. Stocks included are from the Russell 3000 that trade on the NYSE or Nasdaq. Curves are kernel density estimates with Gaussian kernels. Fits pass the X 2 goodness-of-fit test (the deviation of the data from the theoretical distribution is not statistically significant at the 25% level).

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Indeed, even when price changes are small, we expect that co-movement itself is the collective behavior that is characteristic of panic or panicky behavior that precedes a panic. Thus, rather than measuring volatility or correlation, we measured the fraction of stocks that move in the same direction. We found that this increases well before the market crash, and there is significant advance warning to provide a clear indicator of an impending crash. The existence of the indicator shows that market crashes are preceded by nervousness that gives rise to following behavior – increased collective behavior prior to a panic.

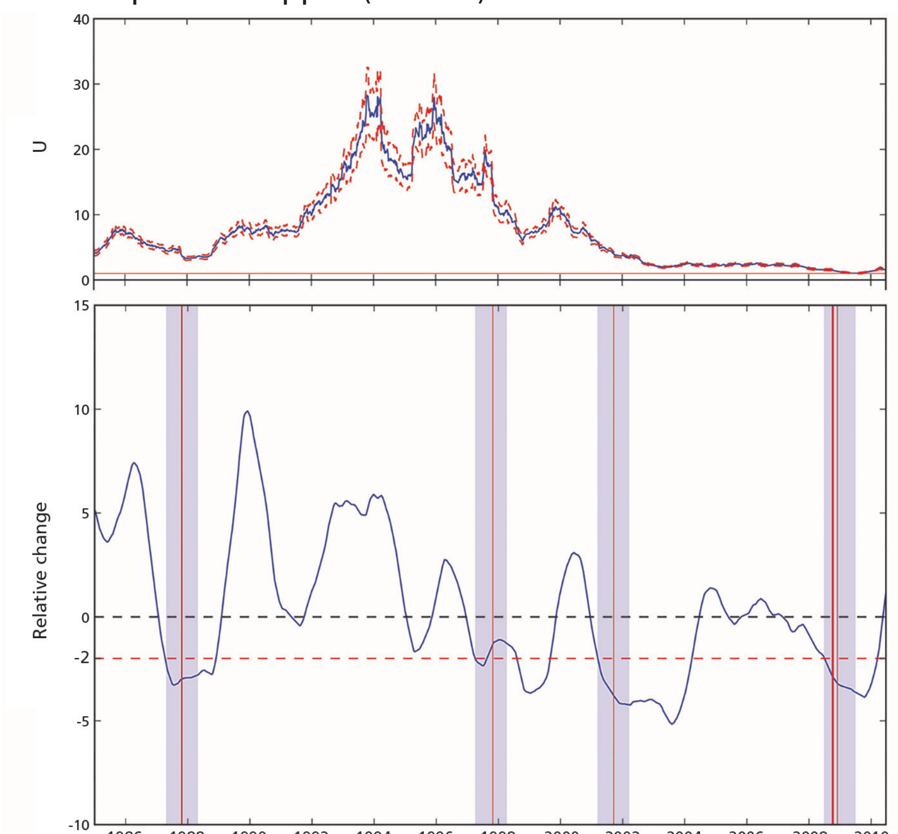
We consider the "co-movement" of stocks over time by plotting the number of days in a year that a particular fraction of the market moves up (the complement moving down). Intuitively, if substantially more or less than 50% of the market moves in the same direction, this represents co-movement. As shown in figure 3, the results indicate that in 2000, the curve is peaked near 1/2, so that approximately 50% of stocks are moving up or down on any given day. Over the decade of the 2000s, however, the curve became progressively flatter – in 2008 the likelihood of any fraction is almost the same for any value. The probability that a large fraction of the market moves in the same direction, either up or down, on any given day, increased dramatically. Such high levels of co-movement may manifest the collective behavior we are searching for.

To quantitatively describe co-movement, we start from a behavioral economics model of a single stock that describes trend-following "bandwagons." It has been shown that investors can benefit from trend-following. Moreover, there is no need for the change to be based upon fundamental value for it to provide benefit to the investors. When individuals observe that a stock increases (decreases) in value, and choose to buy (sell) in anticipation of future increases (decreases), this self-consistently generates the desired direction of change. Such a "bandwagon" effect can undermine the assumptions of market equilibrium. We hypothesized that this trend-following mimicry across multiple stocks can cause a marketwide panic, and we built a model to capture its signature. We assume that investors in a stock observe three things, the direction of their stock, external indicators of the economy and the direction of other stocks. The last of these is the potential origin of self-induced, market-wide panic.

To model the co-movement fraction, we represent only whether a stock value rises or falls. This enables us to directly characterize the degree to which stocks move together and not how far they move at any particular time. Stocks are represented by nodes of a network and influences between stocks by links between nodes, an appropriate representation for market analysis. We consider both fully and partly connected networks. Every day, each of the N nodes is labeled by a sign

(+/–) indicating the daily return of the stock. Market dynamics are simulated by randomly selecting nodes which maintain their current sign or randomly copy the sign of one of their connected neighbors. To represent external influences, we add nodes that influence others, but are not themselves influenced, i.e. "fixed" nodes. The number of fixed nodes influencing in a positive direction is *U* and the number influencing in a negative direction is *D*. The effective strength of the positive and negative external influences is given by the number of these nodes. External influences of opposite types do not cancel; instead larger *U* and *D* reflect increasing probability that external influences determine the returns of a stock independent of the changes in other stocks. This is the conventional view that news is responsible for the market behavior. Good news would be represented by *U* greater than *D*, bad news by *D* greater than *U*.

FIGURE 4
Model parameter – top panel (1986-2010)



Source: Harmon et al. (2011).
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We have previously proposed this model as a widely applicable theory of collective behavior of complex systems. Successful matching to data will be a confirmation of this theory. It has also been previously identified as a model of conformity and non-conformity in social systems, and it has been studied in application to evolutionary dynamics. If we consider a more complete model of influences, in which investors of one stock only consider specific other stocks as guides, we have a partly connected network. We have studied the dynamics of such networks analytically and through simulations, and the primary modification from fully-connected networks is to amplify the effect of the external influences. As the links within the network are fewer, the network can be approximated by a more weakly coupled, fully connected network, with a weakening factor given by the average number of links compared to the number of possible links. Similarly, if only a subset of the external influences are considered relevant for the return of a specific stock, the relative strength of the external influences can be replaced by weaker, uniform external influences. Otherwise, for many cases, the shape of the distribution is not significantly affected. The model thus measures the relative strengths of the internal and external influences rather than the absolute strength of either. The models robustness indicates a universality across a wide range of network topologies, suggesting applicability to real world systems.

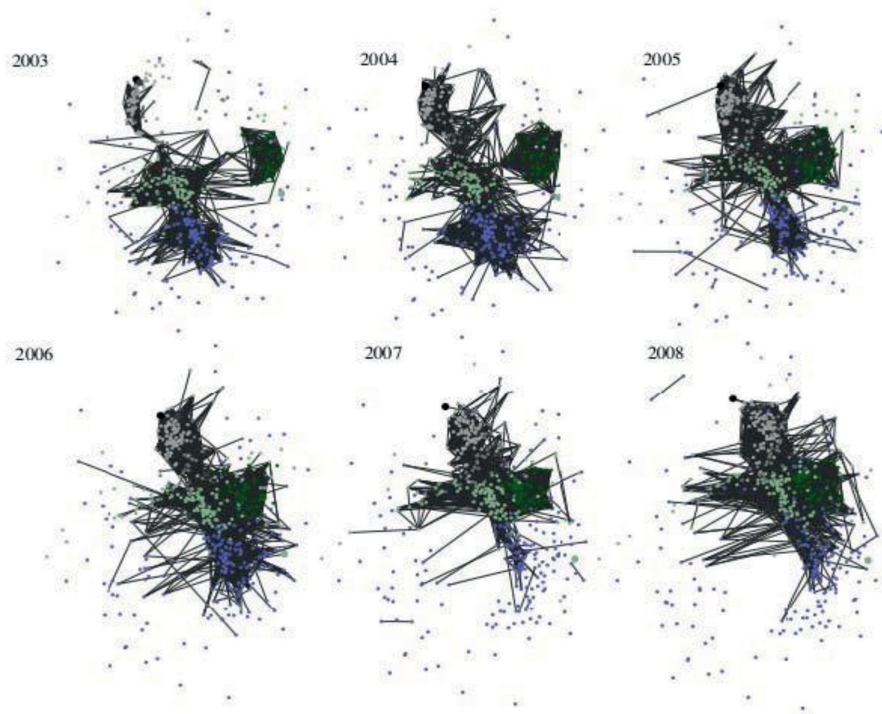
Compared with recent empirical market data in figure 3, the model fits remarkably well. A Gaussian model fits the early years, less well in the final years, and does not fit 2008. The good agreement of our model is obtained with equal up and down influences, $U = D$, which is the only adjustable parameter. When $U = 1$, as was the case in 2008, a transition to crisis can be expected. Figure 4 shows the one-day crashes leading up to crisis.

5 NETWORKS OF ECONOMIC MARKET INTERDEPENDENCE AND SYSTEMIC RISK[5]

The global economy is a highly complex system whose dynamics reflect the connections among its multiple components, as found in other networked systems. A common property of complex systems is the risk of cascading failures, where a failure of one node causes similar failures in linked nodes that propagate throughout the system, creating large scale collective failures. Economic risks associated with cascading financial losses are manifest in the recent economic crisis and the earlier Asian economic crisis, but are not considered in conventional measures of investment risk.

5. Harmon, Stacey and Bar-Yam, 2010.

FIGURE 5
Network of correlations of market daily returns for years as indicated (2003-2008)



Source: Harmon et al. (2010).
Obs.: Dots represent individual corporations colored according to economic sector: technology (blue), basic materials including oil companies (light grey) and others (dark grey), and finance including real-estate (dark green) and other (light green). Links shown are the highest 6.25% of Pearson correlations of log (p(t)/p(t – 1)) time series, where p(t) are adjusted daily closing prices of firms, in each year. Larger dots are spot oil prices at Brent, UK and Cushing, OK (black) and the price of ten year treasury bonds (green).
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A central question is the role that complex systems science can play in informing regulatory policy that preserves the ability of markets to promote economic growth through freedom of investment, while protecting the public interest by preventing financial meltdowns due to systemic risk.

Characterizing the network of economic dependencies and its relationship to risk is key. The dependencies among organizations involve large numbers of factors, including competition for capital and labor, supply and demand relationships among organizations that deliver common end products or rely upon common inputs, natural disasters and climate conditions, acts of war and peace, changes of government or its policies including economic policy such as interest rates, and geographic association. Quantifying such dependencies, e.g., through Leontief models, is difficult because many of the dependencies are non-linear and driven by socio-economic events not included in these models. Also, behavioral economics suggests that under some conditions collective investor behavior, e.g., from perceptions of value, may have significant effects. Reflecting both fundamental and behavioral interactions, correlations in market value of firms can serve as a measure of the perceived aggregate financial dependence and quantify “herding” behavior in collective fluctuations. Moreover, price correlations are directly relevant to measures of risk.

We constructed a network of dependencies among 500 corporations having the largest stock trading volume, augmented with several economic indices (oil prices and bond prices reflecting interest rates). We formed a network where links are present for the highest correlations in daily returns in each year from 2003 to 2008. In order to display the effect of changes over time, we constructed a single network over all years, with each corporation in a particular year represented by a node linked to itself in the previous and next year. Each year is separately shown in figure 5. We included only economic sectors that are significantly self-correlated, as the larger network constructed from the entire market obscures key insights. Previous correlational analyses have described how correlations may arise from external forces across the market – arbitrage pricing theory (Chamberlain and Rothschild, 1983; Ross, 1976) – or used correlations to characterize sectors and market crashes – econophysics (Mantegna and Stanley, 2000; Onnela et al., 2003). This work lacks an understanding of the economic origins of changes in dependencies and their policy implications. We examine variations of within-and between-sector correlations, arising from non-linear effects, for information about changes in economic conditions prior to and during the economic crisis.

The study of network community properties often requires careful analysis. In our case, the observations we describe are manifest visually and were also tested statistically. In particular, apparent trends were tested using the *t*-statistic of differences in link densities within and between sectors (merging), or the minimum of this statistic between one sector and each of the others (self-clustering). Sectors are statistically linked (unlinked) to an index if the *t* -statistic comparing links to the index relative to the link density of the graph is above 4 (below 2).

Limiting investments (i.e., limiting capital-to-asset ratios) in order to moderate risk directly influences opportunities for growth. However, our results also point to a different strategy, which recognizes that financial institutions cross-link otherwise weakly correlated economic sectors. The key is that economic couplings among companies propagate the effect of failures. If economic entity G fails in a financial obligation to entity H, the impact on H may affect other entities J and K, that are linked to H, even if their activity has nothing to do with G. Conversely, while a small capital-to-asset ratio may be risky for a particular institution, if the investments are within a particular economic sector the failure of that institution is unlikely to cause economy-wide repercussions. Thus, segregating financial relationships, particularly among activities that are not otherwise related, or are weakly related, reduces systemic risk.

The idea that separations between components of the financial sector contribute to economic stability was a key aspect of legislation to stabilize the American banking system after the market crash of 1929. The Glass-Steagall Act of 1933 separated investment banking from consumer (retail) banking to prevent the fluctuations from other parts of the economy affecting consumer banking. This Act was progressively eroded until its repeal in 1999. Other historical forms of separation imposed by law or by practice included the separation of savings and loan associations and insurance providers from commercial and investment banking, as well as geographic separation by state. While many effects contribute to correlations in economic activity, nonlinearities associated with investment during market declines support the historical intuition that regulating these dependencies is more critical than regulating those arising from, e.g., supply chains. One of the arguments in favor of deregulation was that banks, by investing in diverse sectors, would have greater stability. Our analysis implies that the investment across economic sectors itself creates increased cross-linking of otherwise much more weakly coupled parts of the economy, causing dependencies that increase, rather than decrease, risk. Quite generally, separation prevents failure propagation and connections increase risks of global crises. Subdivision is a universal property of complex systems. An increase in separation of financial services is likely to entail costs, and the cost-benefit tradeoffs of imposing particular types of separation are yet to be determined.

In summary, complex systems science focuses on the role of interdependence, a key aspect of the dynamical behavior of economic crises as well as the evaluation of risks in both "normal" and rare conditions. We have analyzed the dynamics of correlational dependencies in rising and falling markets. The impact on the economic system of repeals of Depression-era government policies is becoming increasingly manifest through scientific analysis of the current economic crisis. This study suggests that erosion of the Glass-Steagall Act, the consolidation of banking functions and cross sector investments eliminated "firewalls" that could have prevented the housing sector decline from triggering a wider financial and economic crisis.

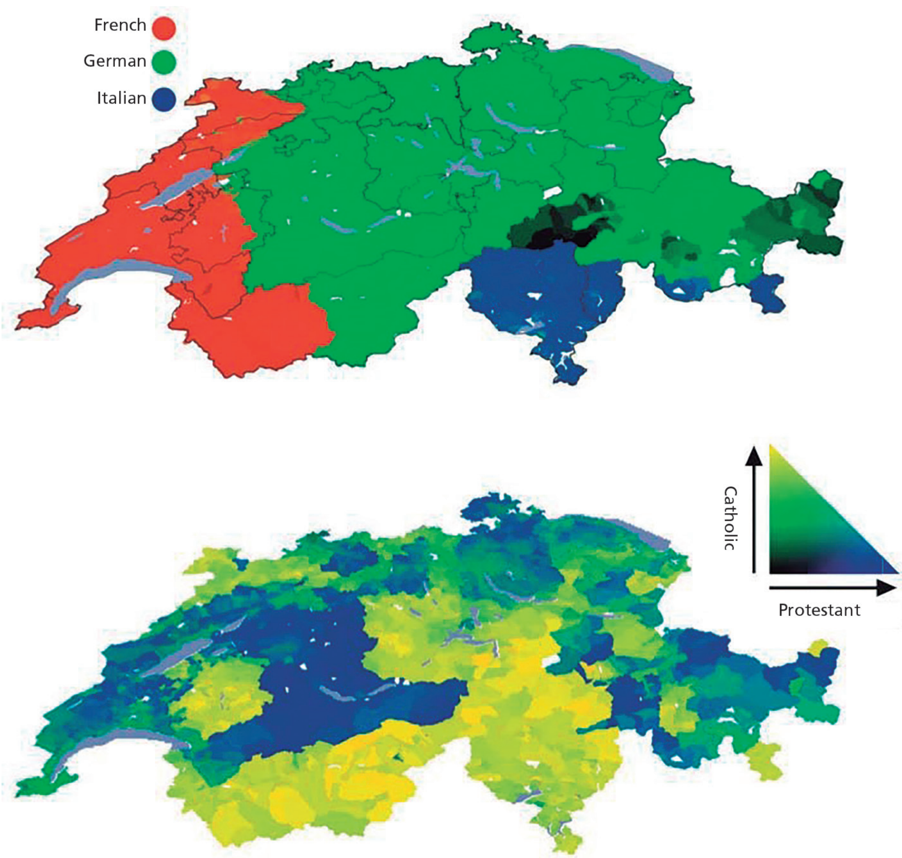
6 GOOD FENCES: THE IMPORTANCE OF SETTING BOUNDARIES FOR PEACEFUL COEXISTENCE[6]

Efforts to resolve conflicts and achieve sustained peace are guided by perspectives about how conflict and peace are based in interpersonal and intergroup relationships, as well as historical, social, economic and political contexts. We have introduced

6. Rutherford et al., 2014.

a complex systems theory of ethnic conflict that describes conflicts in areas of the former Yugoslavia and India with high accuracy. In this theory, details of history and social and economic conditions are not the primary determinants of peace or conflict. Instead, the geographic arrangement of populations is key. Significantly, our theory points to two distinct conditions that are conducive to peace – well mixed and well separated populations. The first corresponds to the most commonly striven for peaceful framework: a well integrated society. The second corresponds to spatial separation, partition and self determination – a historically used but often reviled approach. Here we consider a more subtle third approach, that of within-state boundaries in which intergroup cooperation and autonomy are both present. The success of this approach is of particular importance as the world becomes more connected through international cooperation. As illustrated by the European Union, the role of borders as boundaries is changing.

FIGURE 6
Maps of Switzerland showing the 2000 census proportion of linguistic groups and catholics and protestants



Source: Rutherford et al. (2014).

In order to evaluate the role of within-state boundaries in peace, we considered the coexistence of groups in Switzerland. Switzerland is known as a country of great stability, without major internal conflict despite being home to multiple languages and religions. Switzerland is not a well-mixed society, it is heterogeneous geographically in both language and religion (figure 6). The alpine topography and the federal system of strong cantons have been noted as relevant to coexistence; their importance can be seen in Napoleons statement, after the failure of his centralized Helvetic Republic, that nature had made Switzerland a federation. But the existence of both alpine and non-alpine boundaries between groups and the presence of multiple languages and religions within individual cantons suggest partition is not essential for peaceful coexistence in Switzerland. In identifying the causes of peace, the literature has focused on socio-economic and political conditions. These include: a long tradition of mediation and accommodation; social cleavages that cross-cut the population rather than coincide with each other; unwritten and written rights of proportionality (fairness) and cultural protectionism; a federal system with strong sub-national units; a civil society that fosters unity; direct democracy through frequent referenda; small size; historical time difference between cleavages in language and religion; neutrality in international warfare; and economic prosperity (Lijphart, 1977; Schmid, 1981; Martin, 1931; Steiner, 1974; Glass, 1977; Linder, 2010; Head, 2002; McRae, 1983). Geography plays an unclear, presumably supporting, role in these frameworks. The analysis of coexistence in Switzerland is also part of a broader debate about whether social and geographical aspects of federalism promote peace or conflict (Christin and Hug, 2006).

We analyzed the geographical distribution of groups in Switzerland based solely upon the hypothesis that spatial patterns formed by ethnic groups are predictive of unrest and violence among the groups. The model also allows that topographic or political boundaries may serve as separations to promote peace. We test the ability of the theory to predict peaceful coexistence in the context of internal country boundaries in Switzerland. Where explicit boundaries do not exist, such as in mixed cantons where alpine boundaries are absent, violence might be expected, and the results of the model in these areas serve as a particularly stringent test of the theory. In most such cases, violence is not predicted, consistent with what is found. In one area, a significant level of violence is predicted, and in fact violence is actually observed. The analysis sheds light on the example of Switzerland as a model for peaceful coexistence. The precision of the results provides some assurance of the usefulness of the theory in planning interventions that might promote peace in many areas of the world.

We briefly summarize five categories of distinct successful comparisons between model predictions and the observed data that are contained in the results.

Our examination of linguistic and religious groups in Switzerland included cases where violence is predicted without the presence of boundaries, but is mitigated by the consideration of topographical and political boundaries appropriate to linguistic and religious groups, respectively.

1) Topographical boundaries reduced violence between linguistic groups. This occurred along: *i*) Alpine boundaries of the Swiss Alps between German-speaking and Italian-speaking populations; *ii*) Alpine boundaries between German-speaking and French-speaking populations; and *iii*) Jura range boundaries between German-speaking and French-speaking populations.
2) Political boundaries reduced violence between religious groups. This is the case both for *i*) canton boundaries and for *ii*) circle boundaries in the canton of Graubunden. Our analysis also identified locations in which our model does not predict violence despite linguistic or religious heterogeneity and no explicit boundaries.
3) The straightness of the boundary prevents violence between linguistic groups in Fribourg/Freiburg.
4) Isolation of a Protestant population on an appendage from the Catholic majority prevents violence in Fribourg/Freiburg. We also identified one area at the highest level of calculated residual propensity to violence and it corresponds to an area of unresolved historical conflict.
5) The northeastern part of the canton of Bern is the location of both the highest prediction of propensity to violence, and a real-world history of intergroup tension. The unique condition of the conflict in this part of Switzerland and its correspondence to the prediction by the model provides additional confirmation of the model.

Our research has consistently identified improperly aligned boundaries as a key underlying cause of localized ethnic violence. Using policy to establish clear borders and regional autonomy offers an avenue to ending sectarian conflict.

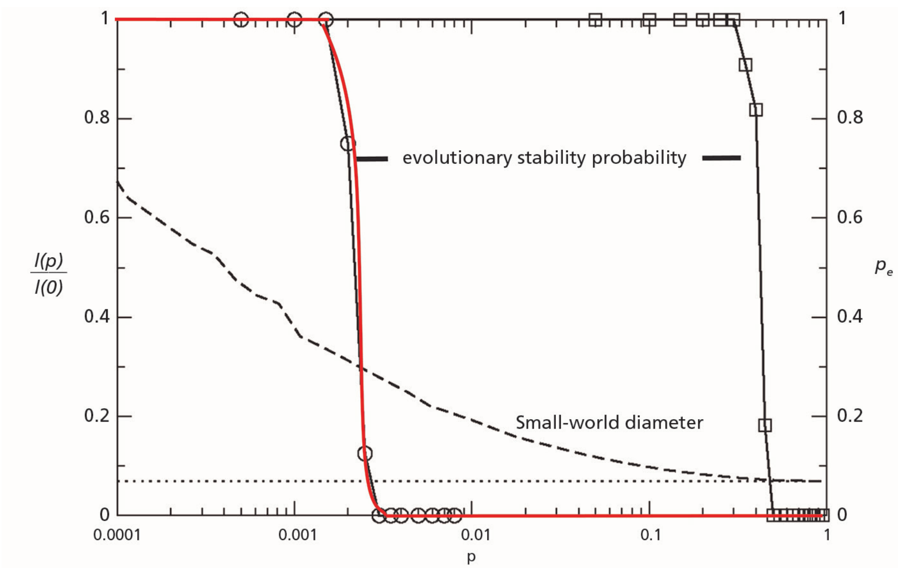
7 LONG-RANGE INTERACTION AND EVOLUTIONARY STABILITY IN A PREDATOR-PREY SYSTEM[7]

We have modeled the behavior of predators and pathogens in spatially extended evolutionary models. Our results suggest that such models are relevant to studies of systems with long-range interactions. There is a transition that occurs from coexistence to global extinction. This transition can be sudden and can occur

7. Rauch and Bar-Yam, 2006.

even in systems that already have a significant density of long-range interactions. Thus, one should not conclude that a system that already has long-range mixing will be stable to additional mixing.

FIGURE 7
Evolutionary stability on a two-dimensional Small-World network



Source: Rauch e Bar-Yam (2006).
Obs.: The probability *pe* that predator and prey coexist for 100,000 generations, as a function of *p*, averaged over 11 runs, for g = 0.05 (circles) and g = 0.2 (squares) (depletion rate v = 0.2, lattice size L = 250). Note the logarithmic scale of *p*. We identify the point of transition to instability pc as the density such that for all p>pc, pe<1 / 2. For comparison, the average path length l (p) between nodes is plotted as a fraction of l (0) (dashed line, same scale). For comparison, the dotted line shows l (1) / l (0), that is, the value for a random network.
Publisher's note: image whose layout and texts could not be formatted and proofread due to the technical characteristics of the original files provided by the authors for publication.

According to our simulations, when global mixing increases beyond the critical density, overexploiting predator or pathogen strains escape local extinction and replace sustainable strains globally, leading to their own extinction and decimation of the prey population. Our results apply directly to simple evolutionary models, but similar considerations apply to the phenomena of emergent diseases (such as Ebola, SARS and Avian Flu), most of which evolve on short time scales, and may also apply to invasive species, which have been of widespread ecological concern. While the demonstration that some long-range connections do not always destabilize evolving systems provides some reassurance, the danger from additional connections suggests that a system may cross the transition and become unstable with little warning as global mixing increases in frequency (see figure 7).

Our results predicted the outbreak of Ebola in West Africa and suggest the need for concerted response, including medical developments and, perhaps, societal changes. Due to increasing global transportation, human beings appear to have crossed the transition to large pandemics. Preventive actions should be taken that either limit global transportation or its impact.

8 CONCLUSION

We have demonstrated that policy decisions made by governments and regulatory bodies can have far-reaching consequences in the modern world. An understanding of complex systems methods and concepts, especially multiscale analysis, network structures and nonlinear dynamics, enables analysis that can inform effective real world decision making. One nation's energy subsidies can cause global food prices to spike, setting off political unrest halfway around the world. Financial markets that become too interdependent have a high risk of cascades, and collective panics cause global crises. Ethnic violence can be largely predicted from ethnic spatial geography and alleviated by policies that allow for local autonomy. Global connectedness promotes the existence of virulent diseases that can cause devastating global pandemics. Complex systems science has a proven record of predicting and explaining the causes of global phenomena. Policy makers and regulators who seek to achieve specific objectives or to more generally improve economic and social systems can benefit from the insights of targeted studies.

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CHAPTER 12

COMPLEX SYSTEMS MODELLING IN BRAZILIAN PUBLIC POLICIES

Bernardo Mueller[1]

1 INTRODUCTION

The purpose of this chapter is to assess the use of complex systems modelling and techniques in public policies in Brazil. Although the interest in complex systems has grown tremendously in the past two decades, the actual application of this approach by governments in public policies is still relatively rare. Brazil is no exception: I have not found any example of an explicit use of complex system thinking in any public policy in this country. This absence is likely due to the relatively early stage of the diffusion of these ideas, as complexity is still a young science which has only recently started to gain more widespread exposure. In order to assess the potential for using complex systems modelling in public policy in Brazil this paper investigates where research is being done on these topics in Brazilian universities and research institutes. It is probable that many of these endeavors will be the seeds that may eventually lead to pioneering applications in specific areas of public policy. This research has incentives to search for those areas where the need for innovative ideas is more salient and where complex systems approaches have the greatest potential.[2] In addition, the paper considers which areas of public policies in Brazil could, given their nature and characteristics, most benefit from complex systems modelling. Together, this mapping of the early research and of the potential policy areas should indicate where we should expect practical uses of complex systems approaches to eventually emerge in Brazil.

In order to do this section 2 first describes the model of public policies that currently dominates in Brazil. If complex systems are to be introduced in the policy realm this is the dominant scenario this approach will be faced with. Section 3 then briefly discusses why this dominant style of policy-making often fails in situations that have characteristics of complex systems. Section 4 illustrates the kind of problems that tend to arise when policy areas

1. Dept. of Economics, University of Brasilia.

2. The choice of research area is also determined by what is available in the literature worldwide, so that some research in Brazil may simply be following what is being done elsewhere rather than trying to address the most pressing problems in the country.

with complex characteristics are treated with traditional policy instruments that presuppose perfect control and management. This is done by giving the example of one concrete policy that has failed and another that has succeeded in Brazil, respectively, land reform and conditional cash transfers. Section 5 then presents the list of areas where research is currently being done on the practical application of complex systems to public policy in Brazil. The policy areas that have not been the focus of any complex system research but where this approach offers some promise are discussed in section 6. Finally, section 7 considers the prospects for the future.

2 THE NATURE OF PUBLIC POLICIES IN BRAZIL

In order to understand the potential of complex systems modelling for public policies in Brazil, it is necessary to first consider the nature of the policymaking process that is dominant in the country today. Every country has a policymaking process that is shaped by political institutions that influence who are the relevant actors, what are their powers, what are their preferences and how they interact. In this section I start by briefly describing the main political institutions that shape the policymaking process in Brazil. I then describe the pervading public policy model that determines how public policies are created, implemented and evaluated. It will be seen that this model is quite antithetical to the notion of complex systems and how much they can be controlled, which suggests that the introduction of complex systems thinking will necessarily be a strong departure from the current practice.

The key political institution that determines the nature of policymaking in Brazil is the high level of presidential power. The Executive has a series of proactive and reactive powers, as well as a series of political instruments and resources to acquire support in Congress and other arenas. This allows it to set the political agenda and in normal circumstances approve most of its proposals (Alston et al. 2008). Although electoral rules lead to a party system composed of multiple parties, the Executive is generally able to put together a majority coalition that grants it high levels of governability. While this implies that the Executive has preponderant influence over public policy, a series of checks and balances seeks to assure that this power is not abused. These checks and balances come in the form of, among others, an independent judiciary, a free and combative press, independent public prosecutors, a professionalized bureaucracy (for Latin American standards), a diverse and vibrant civil society and a highly hardwired budget that predetermines over 90% of expenditures. The upshot of strong presidential powers together with strong checks and balances has been high levels of governability with ever strengthening governance and rule of law. This has led to unprecedented reductions of inequality and poverty and reasonably disciplined fiscal and monetary policy that have kept inflation under control since 1995. This state of affairs, however, has not yet translated into exceptional levels of economic growth – Brazil´s performance has been mediocre compared to most other Latin American countries.

Alston et al. (2014) interpret the overarching beliefs that pervade Brazilian society since 1995 as a belief in fiscally sound social inclusion. This belief emerged as a reaction to the perverse experiences with authoritarianism (1964-1985) and hyperinflation (1985-1994). Since 1995 this belief has been constraining and shaping what can be done in the policy realm independent of which party is in power. This means that public policy focuses on inclusion, equality and participation, but always subject to a hard budget constraint. Social groups are given varied institutionalized points of entry to participate in the process of policymaking and implementation, such as through councils, partnerships and other participatory institutions (Pires, 2011). States and municipalities play important roles in some policy areas, such as education and health, but under the shadow of the Executive that centralizes much of the decision making and constrains these subnational units through laws, such as the Fiscal Responsibility Law, and several forms of auditing and regulation. Both the content and form of policy in Brazil must be compatible with the belief in sustainable social inclusion and the institutions to which it has given rise. Any prospect for the use of complex systems approach will have to be compatible with these beliefs and institutions.

Taking the beliefs and institutions as given, what is the specific model of public policies that is dominant in Brazil today? Like much of the world Brazil was highly influenced by the rise of New Public Management in the early 1990s. A large reform in 1995 sought to modernize the public administration system and make it more efficient, flexible and streamlined, reducing the role of the state in implementing policy (Abrúcio, 2007). This new approach to public policy sought to break away from the centralized, hierarchical, rigid and non-responsive style that pervaded most public bureaucracies by incorporating many characteristics of private firms, such as competition, incentives, decentralization, and focus on the clients and its core competencies. In particular, this type of public management puts great emphasis on setting targets, planning, regulating (as opposed to command-and-control), collecting data and being evidence-based, result driven and focused on efficiency. Whereas these means can often be valuable and effective, the way in which they have been conceived and interpreted often presuppose unrealistic capacity to obtain and process information and are overly optimistic regarding the ability to control, intervene and fine-tune the policy and its consequences. When the policy area has the nature and characteristics of a complex system, this level of apprehension and control are often unlikely given the uncertainty and limited information inherent in the process. The next section discusses this fundamental incompatibility between this style of public policy management in domains that have complex characteristics. The subsequent section then gives some concrete examples.

3 PUBLIC POLICIES IN COMPLEX SCENARIOS

Because complex systems are composed of large numbers of heterogeneous agents acting locally by following simple rules under limited rationality, without central control and in constant adaptation and learning there is a basic contradiction with the standard notion of policy that presumes that optimal planning decisions can be made by considering all options *ex-ante*, weighing costs and benefits, and factoring in uncertainty by assigning probabilities to every possible contingency. Further, the traditional approach to policymaking requires setting specific and quantifiable targets and objectives, presupposing a very tight level of control at each stage of formulation and implementation, with constant feedback allowing for fine-tuning to correct any deviation from the predetermined path. Although some policy domains have characteristics that are amiable to such an approach, the same is not valid for domains that have the characteristics of complex systems. Even these complex policy areas can often follow dynamics with stable equilibria and predictable behavior, but they are subject to phase transitions where they acquire periodic, complex or chaotic behavior, where there is no telling what the system will do, except by letting it run. That is, the results of public policies are often emergent phenomena that are surprising and unexpected, and cannot be anticipated or prescribed. Much of the failure of public policies, both in Brazil and elsewhere, is due to the reductionist attempt to deal with complex phenomena using assumptions and instruments that are only appropriate for non-complex, albeit complicated, problems.

The existence of this fundamental contradiction does not imply that the policymaker is impotent to seek objectives and try to influence the system. Although it might not be possible to assure specific targets, predetermining exactly how they will be reached, complex systems can be influenced to lead to results that have the properties that the policymaker may prefer. According to Page (2013),[3] "an actor in a complex system controls almost nothing, but influences almost everything." By affecting the properties of the system, such as interdependence, diversity, connectedness and adaptability, the system can be made to have the desired properties. Interventions can thus be achieved even though specific results may not.

3. Scott Page. 2013. *Understanding Complexity*. The Great Courses, lecture 12. Available at: <http://www.thegreatcourses.com/tgc/courses/course_detail.aspx?cid=5181>.

What is needed, therefore, to deal with complex systems is a revision of the assumptions and expectations of what it means to do public policies in such circumstances. This involves a new understanding of what is possible and of how results can be judged. Because complex systems follow an evolutionary logic, they naturally involve much error, failure, waste and redundancies, and rarely reach globally optimal solutions. These characteristics do not fit with the traditional notion of public policies, where there is an expectation of absolute control and efficiency. In dealing with complex systems it is not possible to simply ignore these characteristics and try to suppress them. Instead it is necessary to recognize them and take them into account when creating the policies. Perhaps one of the main impediments to the adoption of complex systems modelling in the public policies of countries like Brazil will be the need for the culture change in the understanding of the nature of what can and cannot be done in public policies in complex domains.

4 THE DIFFICULTY OF TRADITIONAL PUBLIC POLICY IN A COMPLEX DOMAIN

In order to illustrate how an approach to public policy that relies on control, prediction and high levels of information can be prone to failure when that policy has the characteristics of a complex system this section briefly describes the attempts at land reform in Brazil. Subsequently, a comparison will be made with a distinctively more successful policy area: conditional cash transfers.

Brazil has historically been one of the countries with the highest level of land ownership concentration in the world. The perverse social and economic consequences of this state of affairs have been recognized as early as the 19th century and land reform objectives were already enshrined in the 1946 constitution. Because land reform naturally entails redistribution it is a controversial and ideologically charged issue that has always featured prominently in Brazilian political debate. The military coup of 1964 was partly prompted by rural conflict and land reform was the flagship policy of the new democratic regime that took its place in 1985. Whereas the military sought to implement a land reform in order to achieve greater productive efficiency, the new democratic republic sought to promote social justice by transferring land to the masses of landless peasants. Neither regime, however, nor any government that has come to power since, has succeeded in implementing a successful land reform, despite the fact that all have tried and invested vast resources in doing so. Since the early 1990s organized groups of landless peasants (in particular the MST – Landless Peasant Movement) have devised means of pressuring the government to expedite the process of reform by invading unproductive land and occupying it until the government effects the expropriation and transfer. This strategy works not by force, but rather because the electorate approves of land reform and the commotion created by the invasions, which often involve conflict and violence, are broadcast nationwide by the press and embarrass the federal government which is rightly seen as not fulfilling its duty to undertake the reform. As a result of this pressure, an area equivalent to France, Portugal, Austria and Ireland has been redistributed to over one million families of landless peasants in the past two decades.

With such staggering numbers, why is it that I am claiming that land reform has been a failed policy? And what is it about this policy area that gives it the characteristics of a complex system? Regarding the first question, it has to be noted that the ultimate objective is not simply to redistribute land from unproductive uses to landless peasants, but rather to do so in such a way that creates a viable class of family farms that are able to insert themselves in the market and become self-sustaining. This objective has not been achieved. Most settlement projects through which land has been redistributed have failed at becoming emancipated from government subsidies, with the original beneficiaries frequently selling or abandoning their plots, often leading to reconsolidation of the farms to more viable minimum sizes under the ownership of larger landowners with more wealth and experience. Despite the huge area of land that has been redistributed in the past decades by land reform programs, today more than half of agricultural production in Brazil is undertaken by an impressive 0.62% of the producers (Alves and Dias, 2010). Clearly this is not indicative of a successful policy that was meant to prompt a less unequal rural sector.

So what went wrong with this process of public policy? Although some of the blame of the failure of the early attempts at reform (pre-1995) can be traced to the ability of landowning interest groups to block policies contrary to their interests, the same cannot be said of the efforts since 1995 when the government was fully invested in seeing the reforms through (due to the electorate's manifest preferences for land reform that were expertly exploited by the MST's strategy of invasions and public demonstrations). If the government really wanted to achieve the reform's objectives and actually invested the political and budgetary resources into the process, why did results and methods go so wildly awry? To see that in fact the government had very little control over the process, note that the original conception of the policy is that a large cadaster would be made of all the landless peasants and of all potential unproductive properties, which the land reform agency would use to expropriate and match one with the other. Because the pace of land reform under these rules was grudgingly slow, the landless peasants realized they could expedite the process by invading and occupying rather than waiting for the government to come around. As the countryside became spotted with rural conflict since the early 1990s, government has been running around reactively trying to set out the fires by expropriating land and creating settlement projects at an ever increasing pace. However, the lack of control over the process is such that the more effort and resources it expends, the greater the incentives for more invasions (Alston, Libecap and Mueller, 1999; 2000; 2012).

One of the major problems was that the entire political debate about whether the government was making a suitable effort at land reform was framed along one single metric; the number of families settled in that given year. The government, the landless peasant movements and the press all focus on this single measure to determine if land reform is or is not being done. The government makes electoral promises of thousands of families settled per year, the organized peasants denounce that the real number settled is below that promised and the press mediates by focusing on that sole dimension. Thus the incentives for the government were to make ambitious promises and deliver by skimping on the quality of the land and the essential post-settlement follow-through.[4] Once a family was given land their number was tallied in the overall statistics and the government would hurry off to give land to other landless peasants. But without the crucial subsequent assistance from the program, large numbers of settled peasants were unable to subsist and ended up selling or abandoning their land. But because the political debate did not focus on this margin of the program there were few incentives for the government to act otherwise. As most of the better available land had been distributed, and most of the potential beneficiaries with the aptitude for agricultural work had been settled, the government had to tap into less productive and more distant land (often in the Amazon) and into the masses of urban poor (which had little intention or ability to stay on the land), thus compounding the probability of failure to generate productive family farms. It is true that in the process of land reform a large redistribution of resources was made in benefit of an underprivileged part of society. However, the way this was done involved tremendous waste in terms of violence, uncertainty and human displacement, not to speak of environmental damage.

Quite realistically an equivalent amount of redistribution could have been achieved at a much lower cost and suffering by simply making direct cash transfers as is shown to be possible by the *Bolsa Familia* program through which approximately 15 million families in Brazil receive small transfers conditional on actions such as keeping their children in school. The *Bolsa Familia* program is considered highly successful in having helped reduce inequality in Brazil in the past decade and also in reducing poverty, with almost none of the perverse incentives that this kind of program can often elicit (Soares, 2014). The success of this policy has made it a poster child often cited by the World Bank and other international organizations and has been copied by several other nations (Lindert et al., 2007).

4. Whereas the *Bolsa Familia* program (described below) also incited a political debate around the single metric of the number of beneficiaries, in this case the ultimate objective was effectively the transfer of resources and only secondarily other objectives such as keeping children in school. Thus the government faced incentives to actually accomplish the program's objectives, rather than striving towards a misleading goal as in the case of land reform.

Fully explaining the success of *Bolsa Familia* (BF) and the failure of land reform requires much analysis and data that is beyond the scope of this chapter. Nevertheless, it is useful to compare these public policies from the perspective of how much they approximate the characteristics of complex systems. Both are social policies that seek to reduce poverty and inequality by transferring resources to the poor. Both involve millions of beneficiaries spread out over vast areas of over 5,500 municipalities. And both have high political visibility and impact. Yet, whereas land reform is centralized in the hands of a single federal agency, the implementation of BF by the federal government co-opted the subnational governments – states and municipalities – to participate voluntarily through schemes where local governments are rewarded based on results. While the federal government retains the task of selecting the families and transferring the cash directly through ATMs, local governments administer and maintain a single dynamic cadaster that is essential in providing the information of who is in the program and whether the conditionalities are being met (Cunha and Câmara Pinto, 2008). By transferring the cash directly to the beneficiary the program avoids having the proceeds or the credit hijacked by intermediaries, a traditional problem in this type of policy. In land reform, on the other hand, the government has never managed to create a working land cadaster, which is a crucial step for a large scale reform. Besides the logistic problems of mapping out boundaries and ownership over a continental country with a highly convoluted history of squatting and land-grabbing, there is always resistance from landowners that fear the use of the information for tax purposes or expropriation. Thus, while good levels of information are available in the BF policy domain, it is lacking land reform. Furthermore, the essential task of transferring relatively small stipends in cash is relatively simple and unopposed compared to the problem-fraught task of *i*) taking land from one agent; *ii*) displacing large groups of often diverse individuals from other regions onto that land; and *iii*) seeing to it that they are able to settle in, adapt and eventually become productive and sustainable in competitive markets despite the lack of experience. Clearly there is much more that can go wrong in one policy area than the other, especially given that while BF has practically no opposition and receives international acclaim, land reform is historically an embattled and conflict-ridden. Furthermore, while in BF mayors competed to be seen as promoters of the policy (De Janvry, Finan and Sadoulet, 2012), land reform politics is embroiled in interest group competition, ideology and misinformation.

The point is not that land reform cannot be done, but rather that the type and scale of land reform that was tried did not match the realities of this complex policy area. The policy is information-intensive when information is scarce; it tries to centralize a policy that is inherently local; it assumes the ability to control the process when in reality it can only act reactively; it requires measurement and evaluation along a series of diverse and subtle margins, while in reality a single and imprecise metric is used (the number of settled families); it deals myopically with a policy area that unfolds over the long-term. Given these characteristics it is clear that a land reform policy with a chance of succeeding in Brazil would necessarily have to look much different from that which was tried. In particular it would have to incorporate the fact that it this policy area is in many ways a complex system.

5 APPLICATIONS OF COMPLEX SYSTEMS IN BRAZILIAN PUBLIC POLICIES

This section compiles all the evidence encountered of research being done in Brazil on themes related to complex systems. If complex system approaches for public policy are to emerge in Brazil it is probable that they will trace their roots to previous research done by individuals and groups in academia and research institutes. That is, the research presented here can be seen as possible precursors to actual practical applications in public policy. Partly the distribution of studies documented here will reflect the developments in the international literature. But they should also partly mirror areas and problems where the applications of these methods are more promising for Brazilian circumstances. The studies are presented in subsections grouped by public policy area. To be included each item must necessarily deal with themes related to Brazilian public policies through a complex system approach. This includes both theoretical and empirical pieces, but those that are purely abstract and do not link to any problem or issue in this country have not been included. Clearly this list provides only a snapshot of what is naturally a dynamic process that is expected to grow substantially in coming years.

5.1 Land use and urban planning

This policy area involves the planning and regulation of land use and occupation in urban areas. It involves issues of sprawl, slums (*favelas*), density, and congestion, among many others. Cities are clearly complex systems composed of diverse, heterogeneous agents interacting locally according to simple rules and leading to self-organization and spontaneous order that routinely defies attempts at central planning and top down control. With an urbanization rate of 81% Brazil is eminently urban and its cities suffer from all modern pathologies, such as pollution, crime, congestion, segregation, sprawl, loss of public space, deficient public services, etc. Public policy in this area is generally done at the local level through local master plans, zoning laws and other legislation, with monitoring by a diverse set of agencies and organizations, from municipal secretariats, to district attorneys and the police. Most of the studies found in this area seek to model the complex nature of city organization and evolution through instruments such as cellular automata, agent-based models and network theory, all of which are well suited to capture cities endogenous self-organizing properties.

CHART 1
Land use and urban planning

	Authors	Title	Reference
1	Bommel, P., Poccard-Chapuis, A.B. Coudel, E.	An ABM to Monitor Landscape Dynamics and to Undertake Collective Foresight Investigations in the Amazon	Proceedings of the Third International Workshop on Social Simulation (BWSS 2012).
2	Delaneze, M.E., Riedel, P.S., Marques, M.L., Ferreira, M.V., Bentz, C.M.	Modelagem espacial utilizando autômato celular aplicada à avaliação das mudanças do uso e cobertura da terra no entorno da faixa de dutos Rio de Janeiro	Proceedings of the XV Simpósio Brasileiro de Sensoriamento Remoto – SBSR, Curitiba, PR, Brasil, 2011.
3	Feitosa, F.F., Le, Q.B., Vlek, P., Monteiro, A.M.V., Rosemback, R.	Countering Urban Segregation in Brazilian Cities: Policy-oriented Explorations Using Agent-based Simulation	Environment and Planning B: Planning and Design, 2012.
4	Furtado, B.A, van Delden, H.	Modelagem Urbana e Regional com Autômatos Celulares e Agentes: Panorama Teórico, Aplicações e Política Pública	IPEA, Discussion Paper n. 1576, 2011.
5	Furtado, B.A.	Modelling Social Heterogeneity, Neighborhoods and Local Influences on Urban Real Estate Prices: Spatial Dynamic analyses in the Belo Horizonte Metropolitan Area, Brazil	Faculty of Geosciences, Utrecht University, Netherlands Geographical Studies 385, 2009.
6	Lim, K., Deadman, P.J., Moran, E., Brondizio, E. McCracken, S.	Agent-Based Simulations of Household Decision Making and Land Use Change near Altamira, Brazil	In (ed.) H.R. Gimblett, Integrating GIS and Agent-Based Modeling Techniques for Simulating Social and Ecological Processes, Santa Fe Institute, Studies in the Sciences of Complexity, 2002.
7	Mello, B.A., Cajueiro, D.O., Gomide, L.H.B. Vieira, R. e Boueri, R.	Teoria de Redes Complexas e o Poder de Difusão dos Municípios	IPEA, Discussion Paper n. 1484, 2010.
8	Saraiva, M.V.P.	Simulação de Crescimento Urbano em Espaços Celulares com uma Medida de Acessibilidade: Método e Estudo de Caso em Cidades do Sul do Rio Grande do Sul	Master's thesis. Programa de Pós-Graduação em Arquitetura e Urbanismo. Universidade Federal de Pelotas, Pelotas, 2012.
9	Soares-Filho, B.S., Pennachin, C. L., Cerqueira, G.	DINAMICA – a stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier	Ecological Modelling, v. 154, Issue 3, Sept. 2002.

Elaborated by the author.

5.2 Economic growth and development

This is a broad and diverse policy area that has many overlaps with other areas. It deals with policies linked to activities related to the components of GDP, i.e. consumption, investment, government expenditures and exports/imports, as well as the short-term determinants of these, such as fiscal and monetary policy, and the long-term determinants, such as institutions, rule of law and beliefs. Traditional economic theory is generally reductionist and believes that cause and effect can be modelled analytically and tested with data in detailed and linear ways, leading to policy recommendations to promote growth and development. The analysis rests on the assumption of strong rationality and focuses almost exclusively on equilibrium outcomes. The papers here, instead, treat the economy as a complex system composed of heterogeneous agents acting locally, with limited information subject to learning and adaptation, leading to hard to predict emergent phenomena, e.g. development or crises. The Hausman et al. project makes clever use of network and evolutionary theory (the adjacent possible) to create a clever index of complexity for countries, which outperforms other indices in explaining the disparity in economic growth across countries.

CHART 2
Economic growth and development

	Authors	Title	Reference
1	Hausmann, R. et al.	The Atlas of Economic Complexity	Cambridge MA: Puritan Press. 2011. <http://atlas.media.mit.edu/>
2	Vasconcellos, T.	O Índice de Complexidade Econômica: Uma Revisão Teórica e Aplicações ao Caso Brasileiro	Monograph. Departamento de Economia da Universidade de Brasília, 2013.
3	Dataviva.	Ferramenta que disponibiliza dados oficiais sobre exportações, atividades econômicas, localidades e ocupações de todo o Brasil	<http://dataviva.info/2014>
4	Alston, L.J., Mello, M.A., Mueller, B. e Pereira C.E.	Beliefs, Leadership and Critical Transitions: Brazil 1964-2014	Princeton University Press. 2015
5	Mueller, B.	Emergence and Evolution of Beliefs and Institutions in Development	Working Paper. Dept. of Economics, Universidade de Brasilia. 2014.
6	Possas, M.L. e Dweck, E..	Ciclo e Tendência num Modelo Micro-Macrodinâmico de Simulação	<www.ie.ufrj.br/datacenterie/pdfs/seminarios/pesquisa/texto1610.pdf.2006>

Elaborated by the author.

5.3 Epidemics and infectious diseases

The spread of disease over space and time is an important policy concern in all countries. Traditional epidemiological models such as SIR – susceptible, infected, resistant – fail to appropriately incorporate spatial dynamics that are at the heart of these problems. Complex system approaches are better able to deal with the emergent phenomena contained in epidemics, such as tipping points. Many of the sources found in this topic were thesis/dissertations from engineering or physics rather than from public health or medicine.

CHART 3
Epidemics and infectious diseases

	Authors	Title	Reference
1	Alvarenga, L.R.	Modelagem de Epidemias através de Modelos Baseados em Indivíduos	Master's thesis. Programa de Pós-graduação em Engenharia Elétrica – Universidade Federal de Minas Gerais. 2008.
2	Carvalho, A.M.	Dinâmica de Doenças Infecciosas em Redes Complexas	Doctoral thesis. Programa de Pós-Graduação em Física da UFRGS. 2012.
3	Nepomuceno, E. G.	Dinâmica, Modelagem e controle de epidemias	Doctoral thesis. Universidade Federal de Minas Gerais (UFMG). 2005.
4	Possas, C.A.	Saúde no ecossistema social: enfrentando a complexidade e a emergência de doenças infecciosas	Cadernos de Saúde Pública. v. 17, n. 1, Jan./Feb. 2001.
5	Jacintho, L.F.O., Batista, A.F.M., Ruas, T.L., Marietto, M.G.B., Silva. F.A.	An agent-based model for the spread of the Dengue fever: a swarm platform simulation approach	Proceedings of the 2010 Spring Simulation Multiconference (SpringSim '10). Society for Computer Simulation International, San Diego, CA. 2010.
6	Takahashi, C.C., Takahashi, F.C., Alvarenga, L.R., Takahashi, R.H.C.	Estudo do tempo de erradicação de epidemias em modelos baseados em indivíduos	Proceedings of the XVII Congresso Brasileiro de Automática. 2008.

Elaborated by the author.

5.4 Public health

Although it may not be readily apparent, public health is one of the most prototypical complex adaptive systems with networks of networks that cannot be decomposed into their constituent parts without losing information on their crucial interrelations (Rouse, 2008). At the same time this policy area is one of the most problematic public policies in most countries, including Brazil. Few references were found using complex systems approaches, which suggests a vast area to be filled by future complexity research.

CHART 4
Public health

	Authors	Title	Reference
1	Almeida-Filho, N.	A Saúde e o Paradigma da Complexidade	Cadernos IHU, n. 15. 2006.
2	Pinheiro Filho, F.P., Mori Sarti, F.	Falhas de Mercado e Redes em Políticas Públicas: Desafios e Possibilidades ao Sistema Único de Saúde	Ciência & Saúde Coletiva, v. 17, n. 11, Noviembre, p. 2981-2990. 2012.

Elaborated by the author.

5.5 Environment and climate change

Climate change and environmental problems may be the quintessential complex system challenge in the coming decades given the magnitude of the phenomena and the diversity and global interrelatedness of the agents and their actions. Traditional policy approaches that rely on command and control, as well as those that seek to develop market incentives have proven woefully inadequate. There is already a movement in academia towards recognizing the complex nature of the problem, as in these manifestos urging for different approaches: Levin et al. (2013) and Jordan et al. (2011). Brazil has always been a crucial country in environment-related issues due to the Amazon forest, large population and large fresh water reserves. In particular it would be natural for there to be studies on deforestation, for which complex system approaches are particularly well suited.

CHART 5
Environment and climate change

	Authors	Title	Reference
1	Andrade, P.R., A.M.V. Monteiro and G. Camara.	From Input-Output Matrixes to Agent-Based Models: A Case Study on Carbon Credits in a Local Economy	Proceedings of the Second International Workshop on Social Simulation (BWSS 2010).
2	Costa, A.C. da R., Mota F.P., Dimuro, G.P., Santos, I.	Um framework para simulação de Políticas Públicas aplicado ao caso da Piracema, sob o olhar da Teoria dos Jogos	Brazilian Conferences in Intelligence Systems, 2012. <http://www.lbd.dcc.ufmg.br/colecoes/enia/2012/0027.pdf>
3	Mello, R.F.L.	Em busca da sustentabilidade da organização antropossocial através da reciclagem e do conceito de auto-eco-organização	Dissertation. Universidade Federal do Paraná. 1999.

Elaborated by the author.

5.6 Financial markets and crises

The financial crises of 2008/2009 made it evident that the core models of traditional finance – DSGE and VAR models – based on equilibrium concepts and often on Gaussian statistics, were inappropriate representations of the real world being unable to deal with large unpredictable events. The literature applying methods related to complex systems – often done by physicists – is already well developed. Several researchers in Brazil have already sought to apply these methods to Brazilian markets, making it one of the most developed areas of complexity studies in Brazil.

CHART 6
Financial markets and crises

	Authors	Title	Reference
1	Gleria, I., Matsushita, R. Silva, S.	Scaling Power Laws in the São Paulo Stock Exchange	Economics Bulletin 7.3: 1-12. 2002.
2	Matsushita, R., Silva, S. Figueiredo, A., Gleria, I.	Log-Periodic Crashes Revisited	Physica A 364: 331-335. 2006
3	Matsushita, R., Silva, S. Figueiredo, A., Gleria, I.	Hurst Exponents, Power Laws, and Efficiency in the Brazilian Foreign Exchange Market	Economics Bulletin 7.1: 1-11. 2007.
4	Tabak, B., Takami M.Y., Cajueiro, D.O.	Quantifying price fluctuations in the Brazilian stock market	Physica A: Statistical Mechanics and its Applications, v. 388, Issue 1: 59-62. 2009.
5	Tabak, B.M., Cajueiro D.O., Serra, T.R.	Topological Properties of Bank Networks: The Case of Brazil	Int. J. Mod. Phys. C 20, 1121. 2009.
6	Cajueiro, D. O., Tabak, B.M.	Possible causes of long-range dependence in the Brazilian stock market.	Phys. A, v. 345, Issue 3-4: 635-645. 2005.
7	Cajueiro, D. O. and Tabak, B. M	The role of banks in the Brazilian interbank market: Does bank type matter?	Phys. A 387, 27, 6825-6836. 2008.

Elaborated by the author.

5.7 Agent-based modelling and computer simulation

This subsection covers references that are primarily concerned with the method of simulating public policy (i.e. agent-based modelling) and only secondarily with the public policy itself. These studies are useful for they help advance and help diffuse the methods that can then be used by others primarily interested in the results for the policy area proper. Three editions of the Brazilian Workshop for Social Simulation[5] have been held in 2008, 2010 and 2014, spearheading the effort to push this literature forward in Brazil. Most of the papers are methodological and not related to public policies, but nevertheless are important for advancing this field of research in Brazil (in this chapter we include only those that are related to public policies).

5. See <http://bwss2012.c3.furg.br/>.

CHART 7
Agent-based modelling and computer simulation

	Authors	Title	Reference
1	Andrade, A.A., Frazzon E.M.	Simulação Baseada em Agentes: Para a Análise de uma Cadeia Global de Suprimentos	XXXII Encontro Nacional de Engenharia de Produção, Bento Gonçalves, RS, October 15-18. 2012.
2	Sichman, J.S., Rocha Costa, A.C., Adamatti, D., Dimuro, G.P.	An Overview of Social Simulation Research in Brazil	Proceedings of the Third International Workshop on Social Simulation (BWSS 2012).

Elaborated by the author.

5.8 Crime and urban problems

This category is related to cities, but focuses on specific problems that arise when large number of highly connected heterogeneous agents interact in close proximity, with crime being the major related area of public policy. Crime and public safety are major problems in Brazilian cities and there is great scope for analyzing crime through the perspective of complex systems.

CHART 8
Crime and urban problems

	Authors	Title	Reference
1	Berger, L.M. Borenstein, D.	An Agent-Based Simulation of Car Theft: further evidence of the rational choice theory of crime	Economic Analysis of Law Review, V. 4, nº 1, Jan-Jun.: p. 103-119. 2013.
2	Pint, B., Crooks, A., Geller, A.	Exploring the Emergence of Organized Crime in Rio de Janeiro: An Agent-Based Modeling Approach	Proceedings of the Second International Workshop on Social Simulation (BWSS 2010).

Elaborated by the author.

5.9 Energy, transportation and infrastructure

Most infrastructure public services are organized in networks, i.e. telecommunications, transportation, electricity, gas, sewage, etc. There is a large international literature applying complex systems approaches to infrastructure and there is much scope for using these methods in Brazil. This country has massive problems in this public policy area, with underinvestment and infrastructure shortfalls often seen as a major impediment to growth.

CHART 9
Energy, transportation and infrastructure

	Authors	Title	Reference
1	Avancini, D.P.	Demanda por transporte rodoviário urbano: um modelo computacional baseado em agentes	Monograph. Universidade Federal de Santa Catarina. 2013.
2	Zopelari, A.L.M.S., Silva Cesar, A.	Competitiveness and Social Inclusion within National the Programme for Production and Use of Biofuels: Negative Feedbacks on Profitability Awareness in Sharp Institutional Settlements in Brazil South Region Concerning Soybean Oil	Proceedings of the Third International Workshop on Social Simulation (BWSS 2012).

Elaborated by the author.

5.10 Social networks

Brazilians are massive users of social media and the country is even quite advanced in the use of these technologies for the purposes of e-government and public policies. Social media are ideally understood as complex systems, given their interdependence, connectedness and non-linear dynamics. There is therefore the scope for research in this area through a complex system lens.

CHART 10
Social networks

	Authors	Title	Reference
1	Barbosa Filho, H., Lima Neto F.B., Fusco, W.	Migration, Communication and Social Networks; An Agent-Based Social Simulation	Complex Networks: Studies in Computational Intelligence, v. 424, p. 67-74. 2013.
2	Marteleto, R.M.	Análise de Redes Sociais – Aplicação nos Estudos de Transferência da Informação	Ci. Inf., Brasilia, v. 30, n. 1: 71-81. 2001.

Elaborated by the author.

6 DISCUSSION

The previous section has shown that, in keeping with the transdisciplinary nature of complex systems science, there is reasonably good coverage in the Brazilian literature of themes that are important in this country's public policies, even if the total number of references is still relatively low in most of them. There are, nevertheless, several conspicuous absences, that is, areas of public policies that are very important in Brazil but for which no research was found. The most glaring, perhaps, is education, which is unanimously understood by Brazilian society as the number one area where government investment should concentrate. Other areas of public policies that are generally important in Brazil and that have not yet been covered by this research are; deforestation, biodiversity, innovation, industrial organization, pollution, traffic, land reform, social assistance (i.e *Bolsa Familia*), racism and other social pathologies, among others. Also there is practically nothing in the area of political science, such as elections, political platforms, etc.

This chapter has shown that it is still early days for complex systems in Brazil. Not only are there no cases of public policies explicitly using these approaches, but even in the area of research and academia there is still very little being done. Clearly adoption is still in the flat part of the S-shaped diffusion curve that this approach is likely to go through in the coming years. The conference on "Modeling Complex Systems for Public Policy" organized by IPEA – the federal government`s economic research institute – for which this chapter has been produced, is likely to be a historic landmark in that path.

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CUNHA, R. E.; PINTO, B. H. C. **Programa Bolsa Família como estratégia para redução da pobreza e da desigualdade no Brasil e os processos de cooperação e coordenação intergovernamental na sua implementação**. In: CONGRESSO INTERNACIONAL DEL CLAD SOBRE LA REFORMA DEL ESTADO Y DE LA ADMINISTRACIÓN PÚBLICA, 13. Buenos Aires, nov. 2008.

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JORDAN, T. E. et al. Recommendations for Interdisciplinary Study of Tipping Points in Natural and Social Systems. **Eos Transactions American Geophysical Union**, v. 91, n. 16, p. 143-144, 2011.

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CHAPTER 13

COMPLEXITY METHODS APPLIED TO TRANSPORT PLANNING

Dick Ettema[1]

1 INTRODUCTION: THE TRANSPORT SYSTEM AS A COMPLEX SYSTEM

Over the past decades, complexity theory has received increasing interest in the scientific and policy arena, and has led to applications in fields such as management and organisational science, economics (Cilliers, 2001); urban planning (Brian Arthur, 2007; Batty, 2007; Bettencourt, 2014); and transportation (Frazier and Kockelman, 2004). Importantly, cities, of which the transportation system makes up an elementary part, are increasingly regarded as complex systems (Bettencourt, 2014). The complexity of cities is defined by Bettencourt (2014) by five characteristics: heterogeneity, interconnectivity, scale, circular causality and development. While heterogeneity and interconnectivity refer to individual agents and their interactions (see Bettencourt, 2014 for a detailed discussion), development and circular causality refer to the processes going on in cities, that materialise on more aggregate levels, for instance as land use patterns, economic growth or congestion. An important notion of the complexity of cities is that developments take place as a result of actions between agents in a variety of domains, implying that urban developments are the outcome of intertwined social, economic, technological and ecological processes.

In a more formal sense, Manson (2001) mentions the relevant notion of aggregate complexity, which implies that the state of the system at a particular time is the product of the behaviour of individual elements (agents) in the system. These agents' behaviour is guided by certain rules and mutual interactions, but agents are not aware of the behaviour of all other agents in the system. Feedback effects exist in the sense that individual agents may respond to the aggregate state of the system. The aggregation of individual behaviours leads to emergent outcomes on the level of the aggregate system, which may be highly nonlinear. In a similar vein, forces outside the system may trigger a chain effect of responses at the individual level, eventually leading via a series of feedback effects, to a shift to a new state at the system level (dissipation). The industrial revolution, caused by new technologies, is a typical example of this. An important notion in this respect, is that a complex system does not exist in isolation, but exists in an environment that exerts forces and influences on the complex system. An important decision is therefore how the boundaries of the system are defined, and whether influences are regarded as external or as part of the system.

1. Utrecht University.

From the above, it follows that the transport system has properties of a complex system. It includes multiple agents, including the users of the system (pedestrians, cyclists, public transport users, car drivers and passengers) making decisions about whether, when, where and by which mode to travel. Aggregate system characteristics emerge from the aggregation of such behaviours, such as traffic loads and congestion levels on roads and patronage levels of public transport systems. Users respond to the state of the system when making their decisions. They may respond to congestion levels by changing trip frequency, destination, travel mode or travel time. However, also public authorities and service providers may be regarded as agents in a complex transport system. They decide about construction of infrastructure and provision of public transport services, at least partly responding to current traffic load and patronage levels. Also, the transport system may become dissipative in response to new technologies. For instance, the industrial production of cars and subsequent mass motorisation have led to a radical shift in modal split and trip lengths in many countries (Van Wee, 2014). This example also illustrates the need to properly define the boundaries of the system. For instance, mass motorisation has caused, but has also been stimulated by the process of urban sprawl, suggesting that the transport system might be extended to also include urban development, households' residential location decisions and agents such as real estate developers. At the same time, it is noted that societal, economic and technological developments, which emerge outside the transportation field, may exert significant influence on the use of the transportation system. For instance, urban lifestyles may become more favourable among young adults, placing a lower emphasis on car use and the car as a status symbol (Frändberg and Vilhelmson, 2014). Also, new information and communication technologies may accommodate new forms of organizing travel, for instance by implementing flexible, mobile internet platforms for car sharing (Hansen et al., 2010). In addition, economic development and its spatial manifestation in the form of job locations, will have a major impact on the demand (in time and space) of commuter and business trips, but is inherently difficult to forecast (Dawid, 2014). Finally, changing work habits combined with increasing ICT use may moderate the effects of economic development on business and commute traffic (Alexander et al., 2010; Aguilera, 2014).

Traditionally, transportation planners have aimed at accommodating individuals' demand for travel in order to facilitate their achievement of individual, social and economic goals. The main preconditions are typically to guarantee a minimum level of accessibility for all and to avoid congestion, safety risks and pollution leading to health hazards. Typically, they have followed an engineering approach, based on the assumption that the demand for travel can be determined (and forecasted) based on the spatial distribution of population, jobs and facilities. To this end, traffic models have been applied, which have accounted for the emergence of congestion as an aggregation of individual trip making decisions. However, the range of complex effects in the transport and land use system is potentially much larger, and may extend to aspects such as pollution and health, housing markets, equity and exclusion effects and sustainability issues. In recognition of this complexity, traditional traffic models have been extended to more comprehensive land use transport interaction (LUTI) models, using individual (agent-based) representations of individuals, households, dwellings and firms. While these models can account for a wider range of interactions and feedback effects, these increased range of options comes at the cost of increasing data hunger and reduced certainty about the validity of the outcomes. Also, one may be critical as to what extent major drivers of changes in travel behaviour (such as economic growth, changes in societal norms or changes in business models of transportation firms) are well represented in traffic models or agent-based LUTI models. A major issue is therefore how existing model applications should be valued in the context of the complexity of cities and transportation systems, and how these models can be applied to explore the effects of complex processes inside and outside the transportation domain on the transport system.

The aim of this chapter, therefore, is to give an overview of traffic and transport simulation models, their options to describe complex effects of policies or autonomous trends, and discuss the implications for policy makers. The paper is structured as follows. Section 2 discusses the main characteristics of complex methods in transport planning. Section 3 discusses implementation issues related to these methods. Section 4 outlines implications for the transport system, followed by urban and societal implications in section 5. Section 6 discusses some recent developments in the development of complex systems in transportation.

2 MAIN CHARACTERISTICS OF EXISTING COMPLEX METHODS IN TRANSPORT PLANNING

Over the past decades various planning support tools have been developed that take into account the complexity of the transport system, as described above. These tools operate on different scales and assume different system boundaries. We will discuss the following tools, with increasing spatial scale and complexity:

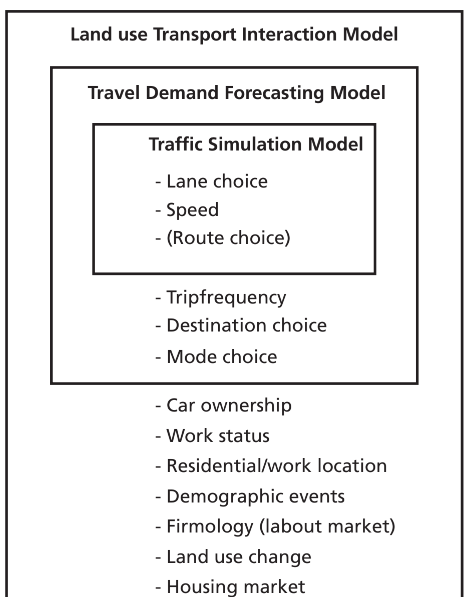
1) Traffic simulation models;
2) Travel demand forecasting models;
3) Land use transport interaction (LUTI) models.

These models can be thought of as nested in each other, with an increasing number of agents' decisions being represented (figure 1). Since LUTI models obviously include the widest range of responses, they can also account for the widest range of complex, emergent effects, especially including interactions between the transport system on the one hand and the housing market, labour market, car fleet, energy system and land use system on the other hand. A relatively strong emphasis is therefore placed on discussing LUTI models throughout the chapter.

2.1 Traffic simulation models

Traffic simulation models (Barcelo et al., 2005; Rieser et al., 2007) describe how individual vehicles manoeuvre from a given origin to a destination in a road network. The most recent models include a representation of individual vehicles, which are equipped with a set of "behavioural" rules such as choosing speed and driving lane in response to other vehicles on the road and choosing and adjusting the route to the destination. In addition, for each vehicle an origin and destination is given. Typically, these models assume that the number of trips between origins and destinations as well as their departure time are given. In addition to individual vehicles, the models may include a representation of equipment such as traffic lights, which may also in a dynamic sense respond to the (simulated) vehicles on the road.

FIGURE 1
Nested system of transport models



Traffic simulation models typically display emergent characteristics (traffic load and speed per link), resulting from the behaviours of the individual vehicles. While such characteristics may also be obtained from aggregate algorithms defining the relationship between traffic loads and speeds, traffic simulation models do so in much more detail and may also account for detailed network effects, such as queues blocking upstream crossings. Recent traffic simulation models are capable of simulating traffic flows based on an individual representation of cars for larger urban areas. Rieser et al. (2007) describe an application based on a representation of individual vehicle for the whole country of Switzerland. An important limitation of traffic simulation models is that decisions such as trip generation, destination choice, mode choice and departure time choice are exogenous, thus assuming that individuals do not respond to congestion on these dimensions. This may lead to an overestimation of congestion and travel times, since in reality individuals will consider such options to avoid overlong travel times.

2.2 Travel demand forecasting models

Other than traffic simulation models, travel demand forecasting models (TDFMs) describe trip generation, destination choice, mode choice and departure time choice of trips (McNally, 2008; Yai, 1989). The traditional version of TDFMs are four stage models, which model the four aspects of each trip (generation, destination, travel mode and route) subsequently and independently of each other. Also, different trip purposes (commuting, business, other) are modelled independently of each other. This results in an origin-destination matrix of trips, that is typically input to traffic simulation models. TDFMs (e.g. Algers, 1995; Jovicic and Hansen, 2003) include a set of discrete choice models describing the aforementioned behaviours as a function of personal characteristics and characteristics of the transport system such as travel time and travel cost. These models are applied on a representation of the population in a system of traffic zones. This can be done in different ways. Traditionally, models of trip frequency, destination and mode are applied for a number of different household and individual types in each zone, resulting in probability distributions. Given the numbers of each household type in a zone, this results in an overall distribution of trips by destination and mode. More recently, agent-based models have been developed with a representation of individual travellers, defined by residential zone and socio-demographic characteristics (e.g. the RAMBLAS model, Veldhuisen et al., 2000). For each agent, trip frequency, destination and travel mode are then determined individually. An agent based representation of trip making offers the advantage of a greater flexibility and a more straightforward linkage to modules that forecast aspects such as residential relocation, job change etc. (see also section 2.3).

TDFMs can be regarded as complexity methods in the sense that aggregate distributions of trips emerge from (semi)individual decisions of trip frequency, destination and mode choice. In addition, TDFMs include feedback effects in the sense that individual decisions are affected by system level outcomes, which are however limited to travel time changes caused by congestion levels. Like traffic forecasting models, TDFMs typically tend to develop into an equilibrium situation, since the feedback effects have a dampening effect: congestion leads to a choice for different destinations, modes and travel times, leading to lower congestion levels. The boundary of the system is drawn around the current population and their residential location, of which behavioural rules and aspect such as car ownership are assumed invariant, and a transport and infrastructure system that is constant. As a result, external forces such as changes in technology, labour markets or the housing market, which may lead to radically different behavioural rules and outcomes, are not very well represented.

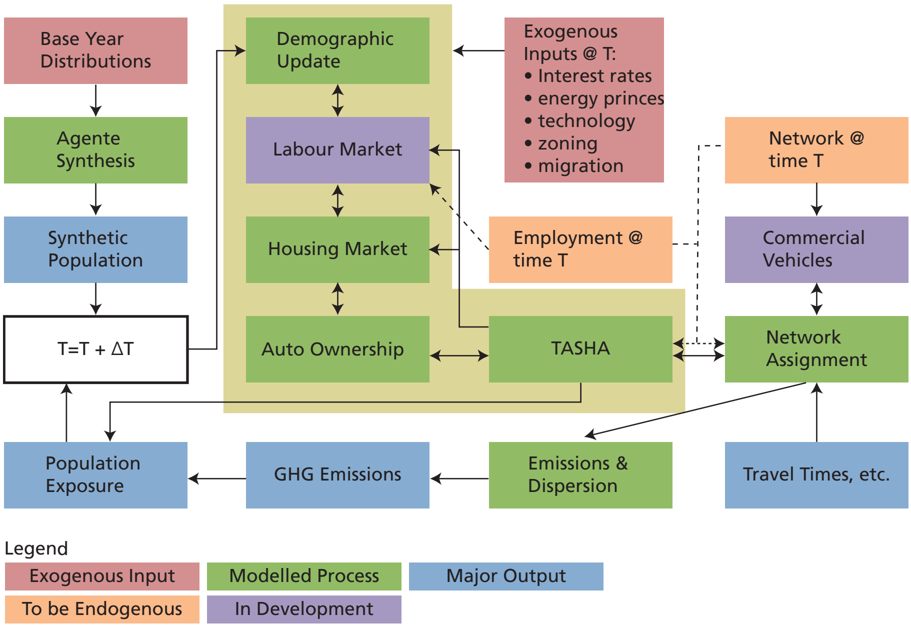
A trend taking place over the last decades is the gradual replacement of the traditional four stage models with so called activity-based travel demand models (Ettema and Timmermans, 1997; Arentze et al. 2000; Bowman and Ben-Akiva, 2000). Without discussing the technical aspects of activity-based models in detail, the main principle underlying activity-based models is that travel is derived from activity participation, implying that in order to understand travel, the total activity pattern should be taken into account. This has various consequences. First, travel decisions for one trip may be related to travel decisions for another trip. The most obvious aspect is timing, since the timing of trips depends on the ordering of activities. However, also destination choices for various activities may be interdependent, e.g. if the location of shopping trips is dependent on the work location. Another dimension of (most) activity-based models is that travel decisions are made at the household level. This implies allocation of certain activities (e.g. shopping or serve passenger trips) to specific household members, but also the decision of who will use household vehicles. As compared to four stage models, activity-based models logically include a wider range of statistical models, such as trip chaining models, activity scheduling models, and time use and duration models. As a consequence, they are better able to represent certain emergent effects, where policies or developments in one domain have implications in another domain. For instance, activity-based models have the potential to forecast the effect of changes in time regimes (school or work hours) on trip timing, the effect of female work status on males' shopping behaviour or the effect of shopping location choice on commute travel mode.

2.3 Land use transport interaction (LUTI) models

LUTI models (Wegener, 2013) include a representation of travel behaviour by a TDMF model, but this representation is embedded in, and interacts with, a representation of the spatial distribution of people, jobs and economic activities. Basically, LUTI models describe households' demographic processes (birth/death rates, household formation and dissolution), locational decisions (residence, jobs, changes in work status) and vehicle holding decisions, as well as economic processes such as job development in different locations and the development of land prices and residential development. These processes are influenced by travel times and accessibility levels described by an embedded TDFM. In most cases, economic and housing market developments are represented by economic input-output models. Recently, however, also agent-based simulation based systems, such as UrbanSim (Borning et al., 2008), ILUTE (Chingcuanco and Miller, 2012) and ILUMASS (Strauch et al., 2005) have been developed.

As an example of an agent-based LUTI model, the structure of the ILUTE system is outlined in figure 2. ILUTE (Chingcuanco and Miller, 2012) includes a representation of individual households, made up of individuals, and defined by age, gender, education, work status and car ownership. In addition, there are representations of individual dwellings (defined by type, size, location and price/rent), individual firms offering jobs (with specified experience and knowledge level) and land owners/developers who take decisions about real estate development and land use change. A suite of models is implemented to describe the behaviour of individuals and households, which mostly imply some form of interaction with other types of agents. An activity-based model (TASHA) is included that describes activities and travel decisions of households and individuals (see section 2.2.). A demographic simulation model describes the aging of individuals from year to year, as well as events such as dying, giving birth, marriage and household formation, household dissolution. Given the agent based structure, this implies the existence of a "market" of singles and a match making mechanism. To describe location and relocation decisions, a housing market simulation module keeps track of vacancy and occupancy of dwellings, and the matching between vacant dwellings and households aspiring another dwelling. Importantly, this matchmaking implies a price setting system that responds to the supply of and demand for dwellings of different types in different areas. In a similar sense, a module exists that describes the development of firms an jobs as a function of larger economic trends (Harmon, 2014) and makes matches between individuals with a certain level of skills and experience and jobs of certain requirements. ILUTE (as other agent-based LUTI models, such as UrbanSim) is set up in a modular fashion, which allows for a relatively straightforward linkage to other, dedicated models. For instance, ILUTE has been linked to emissions models to forecast individuals exposure to pollutants during their daily activity pattern, and to models of dwelling energy consumption to forecast urban energy consumptions.

FIGURE 2
Outline of ILUTE model system



Source: Chingcuanco and Miller (2012).

It will be clear that LUTI models can also be regarded as complex systems and that they represent the widest range of potential reactions to changes in the economy, demography or institutional system, not only by individuals and households, but also by economic agents and developers/policy makers. For instance, households may decide to relocate, change jobs or acquire/dispose vehicles in response to changes in accessibility. Likewise, changes in the location of jobs resulting from changes in accessibility can be represented, as well as changes in housing prices or urban development. As a result, agent based LUTI models are less likely to develop into an equilibrium state that is relatively similar to the initial state, and more likely to represent transitions to fundamentally different states. For instance, since LUTI models describe urban development, vehicle owning decisions and travel behaviour, they would technically have been able to describe the related and reinforcing processes of increasing car ownership and urban sprawl.

Another important characteristic of agent based LUTI models is their dynamic character. They simulate changes in urban development, demographics, housing and work locations and travel patterns for a series of years, implying that agents' decision in year *t*+1 are conditional on aggregate system characteristics (travel times, prices, available dwelling, jobs etc.) in year *t*, which in turn accumulate from individual agents' decisions. This dynamic approach allows to model the temporal dimension of responses to policies. For instance, it has been found that responses to office relocation in terms of mode choice may lag behind up to five year, since a behavioural response may necessitate changes in household organisation, car ownership or residential relocation. While traditional equilibrium models would predict an immediate change to a new equilibrium, agent based dynamic models are better able to describe the stepwise process leading to the final outcome.

3 IMPLEMENTATION ISSUES

Developing traffic simulation models, TDFMs and LUTI models can be split into two major components:

1) Developing a representation of relevant structures and agents.
2) Developing a representation of behavioural rules of the agents, their mutual interactions and relevant feedback effects.

Following the development of the model it needs to be calibrated to verify if outcomes are generated with a reasonable degree of reliability. Finally, scenarios need to be developed for the application in order to evaluate policy alternatives. These stages will be discussed subsequently.

3.1 Representation of structures and agents

The structures to represent depend on the type of model. In case of traffic simulation models, the structure includes a representation of the road network in terms of links and nodes, and link characteristics such as travel speed and layout (e.g. width). Such data will in most cases be available in digital form at planning agencies. The structure may also include signalling equipment such as traffic lights and their specification. The software managing the signalling equipment can nowadays directly be linked either to physical detectors, as well as to traffic simulation software. In addition, origin and destination zones are defined, and the number of cars travelling between these zones through the network. Depending on the scale of the application (ranging from a single trajectory to a whole region) OD matrices can be derived from traffic counts or from an existing regional TDFM. Main agents are vehicles, the drivers of which are equipped with behavioural rules (see 3.2).

In TDFMs, the structure includes a representation of an area divided into traffic zones, which include a specific population, producing a number of trips for various purposes. In addition, a representation of travel times by various modes, for different times of the day is needed. For public transport these are derived from existing (and possibly adjusted to represent scenarios) time table information. For car, these are derived from travel times as calculated on a network (e.g. used in the traffic simulation models).

If necessary, these time may be adjusted based on the outcome of a traffic assignment or traffic simulation, to account for the effect of congestion on car travel times.

For agent based LUTI models, additional structures are needed, also based on a zonal representation of the study area. Typically, these include households and individuals with their working status, vehicle ownership and income, but also representations of the housing market and of the economy (firms and jobs) in each zone. Agent based models require a population of individual households with all relevant characteristics specified on the individual level. Such data is seldomly available from official records. The usual approach is then to use synthetic populations (Zhu and Ferreira, 2014). In synthesizing populations, a set of individuals with specific characteristics is generated such that the aggregate distributions of age, gender, education etc. meet the actual distributions. Iterative proportional fitting is the most used method to generate synthetic populations, and can be applied to households/individuals as well as dwelling units. In essence, the same approach might be used to firms, but given the much lower number of firms per zone this poses difficulties. As a result, ILUTE and UrbanSim have so far modelled the labour market as a population of jobs, rather than a population of firms offering jobs. Likewise, while urban development and land use change are the result of decisions made by agents such as policy makers, real estate developers etc. these decisions are much less frequent and more complex in nature than e.g. household relocation or individual mode choice decisions. These processes are therefore mostly dealt with in a more stylized fashion. The most common approach is to model for zones or parcels in the modelling system, the probability of conversion into another land use type. Various statistical approaches (versions of discrete choice models) have been used for this purpose (Zollig Renner and Axhausen, 2013; Shen et al., 2014; Bhat et al., 2014).

3.2 Developing behavioural rules and feedback effects

For traffic simulation models, car drivers are equipped with rules regarding the choice of speed and lane and route. These rules may be derived from experiments where drivers are observed in simulators, but are often chosen by the modeller based on prior experience of what produces a realistic outcome. Feedback is modelled automatically, since vehicles respond to the position and speed of other vehicles in the network.

In TDFMs, behavioural rules concern choices of *i*) making a trip for a specific purpose; *ii*) a departure time of the trip; *iii*) a destination; and *iv*) a travel mode. Typically, these choices are modelled with econometric discrete choice models, which describe the choice as an outcome of the characteristics of the choice alternatives. The traditional version of these models was the multinomial logit model (MNL), which had, however, the undesirable property that the ration of the choice probabilities of two alternatives is independent of the presence of a third alternative (also known as the red bus/blue bus problem). This property is undesirable since it may be expected that alternatives that share more common characteristics (e.g. bus and tram) are expected to substitute for each other relative to a more different alternative (e.g. car). In addition, travel choices on different dimensions were traditionally assumed to be independent of each other (i.e. described by separate MNL models), whereas in reality they may be related. For instance, the travel mode may depend on the choice of destination and vice versa. To account for such substitution and interdependency effects, more advanced model specification have been developed such as nested logit models (Ben-Akiva and Lerman, 1985) and mixed logit models (e.g. Hess and Polak, 2006). Also, in the context of spatial choice, MNL models fail to account for spatial autocorrelation, which has led to the development of alternative GEV choice models (Bekhor and Prashker, 2008).

The parameters in the choice model need to be estimated based on observed choices. These may be choices actually made and recorded in surveys or travel diaries (revealed preference), but also choices made under hypothetical conditions, presented in a survey (stated preference). The main feedback mechanism is travellers' response to congestion. This is represented adjusting car travel time for congestion following the traffic assignment, which will influence the choice of trip-making, destination, departure time or mode, depending on the travel time coefficient.

Agent-based LUTI models include additional models for households behaviour (car ownership, housing location and housing type, work status) which are typically also based on discrete choice models. These are mostly based on observed choices obtained from surveys. Housing market and economic developments are also assumed to follow specific rules. Since a detailed discussion of the calibration of these models is beyond the scope of this chapter, the reader is referred to Chingcuanco and Miller (2012), Strauch et al. (2005), Borning et al. (2008) and Ettema et al. (2007) for detailed illustrations.

3.3 Scenario development

Complex traffic and travel models are applied to make predictions of the outcome of interventions or assumptions made about the future. The predictions often concern the traffic loads on roads or patronage levels of public transport. Usually, the aim is not so much to predict exact outcomes, but to gain an insight into the differences between different policy alternatives. In any case, applying a traffic or transport model to make predictions requires that structures and agents are specified for a future situation. Usually, the infrastructure and transport services are specified according to the interventions of which the effects needs to be forecasted. However, other inputs, such as the population per zone, the development of firms, jobs and residential areas also need to be specified. To this end, modellers mostly rely on external forecasts from demographic and economic models as well as on policy plans that specify the development of residential and commercial areas in future years. With increasing forecasting horizons, it is useful to apply different scenarios of e.g. economic development, to test outcomes under different external circumstances.

In practice, travel demand forecasting scenarios are often based on extrapolation of current demographic and economic trends. For instance, Arentze et al. (2008), forecast the transportation implications of an aging population, based on extrapolations of labour force participation and behavioural parameters. These exercises are typically aimed at predicting a likely outcome, as a relatively marginal change from the current situation or baseline scenario. However, regarding cities (and their land use and transport systems) as complex systems would suggest that interactions between various system components and agents could lead to unexpected outcomes that would differ fundamentally from straightforward extrapolations. Examples of such interactions include the effect of ICTs on personal and delivery travel, which may, depending on the context, substitute, modify or stimulate travel (Mokhtarian, 2009). TDFMs and LUTI models are not well suited to represent such interactions, and their use in exploring such scenarios would require the formulation of additional assumptions, which should be included in the model structure. In a similar vein, Cervero (2008) notes that conventional TDFMs are not well suited to capture the effect of neighbourhood scale land use strategies. He advocates the use of dedicated add-ons to conventional models to represent the interaction between neighbourhood characteristics and travel behaviour.

4 MODELLING BENEFITS FOR THE TRANSPORT SYSTEM

Transport providers and infrastructure developers may benefit from traffic simulations, TDFMs and LUTI models in various ways. In essence, these models deliver insight in the effect of operational variables, such as prices, travel speeds, frequencies under different scenarios. This allows providers and developers to invest in the most cost effective way in infrastructure and services. Cost effectiveness can be defined in a purely economic or in a societal sense. In an economic sense, the models can predict how many travellers will use a service (e.g. a bus line or a toll road) and what revenues will be made. Hence, profitability of investments can be estimated a priori. In a societal sense, the benefits of investments can be assessed. For instance, effects of new infrastructure and services can be assessed in changes in trip frequencies, mode use and consequently changes in congestion and travel times. Both the travel time gains and the accommodation of so called latent demand are considered to be social benefits, which are often quantified to monetary values based on willingness-to-pay methods. This allows authorities to trade off investments against societal benefits in cost-benefit analyses.

Another benefit of traffic and transport models is that travel behaviour, traffic loadings and congestion under different longer term scenarios can be explored. Think for instance of different demographic and economic scenarios. The models can then give an indication to what extent the transportation system can provide inhabitants sufficient accessibility to fulfil their needs, but also whether the transportation system is economically sustainable under scenarios of income change, demographic transition and urban development.

5 MODELLING IMPACTS FOR CITY AND SOCIETY

While the preceding paragraph discussed the assessment of outcomes for the transportation system, traffic and transport models can also be used to assess the impact of policies and autonomous developments for wider urban and societal issues.

First, traffic and transport models can be used to assess changes in accessibility (e.g. due to changes in congestion levels). For instance, when planning an urban extension, travel models may give an indication of the expected travel volumes but also the accessibility to specific services for the new inhabitants. These changes in accessibility may be linked to access to specific services for specific groups, such as the accessibility of healthcare for non-motorised/vulnerable groups (Nemet and Baily, 2000). In this way more specific societal issues can be addressed, also in relation to equity considerations. On the other hand, accessibility is relevant to service providers to determine their catchment area and market potential. For instance, retailers may use accessibility measures to determine the number of potential customers. Firms may be interested in the accessibility to skilled labourers within a certain travel time. Thus, traffic and transport models may be used to assess whether a region will remain economically viable and attractive to firms from a transportation point of view (see Wheaton, 2004 for a more stylized modelling effort).

Second, traffic and travel models predict traffic flows, which in turn result in negative outcomes such as local pollution and noise. The predictions may then serve to calculate concentrations of pollutants and noise volumes and assess the consequences for exposure and public health. Linking such outputs to the spatial concentration of different population segments, for instance health hazards of vulnerable groups can be determined (e.g. Pearce et al., 2006). Hatzopoulou et al. (2007) integrated an activity based travel model (TASHA) with emission models in order obtain a dynamic and detailed account of traffic generated emissions by location and time of day. In addition, they confronted these emissions with the locations of individuals according to their simulated activity patterns, rather than with their home locations, to get a more realistic estimate of the impact of emissions.

Finally, since traffic and travel models predict travel by various travel modes, they can be used to assess to what extent people will use active travel modes such as walking and cycling. Given the worldwide concern about overweight and obesity, active travel is increasingly seen as an important way of counteracting these effects, as indicated by numerous studies (Saelens and Handy, 2008; Boarnet et al., 2011; Van Wee 2014). Assessing the effects of land use and transport interventions on active travel therefore is an important benefit of transport models.

The same holds by and large for policies aiming at more sustainable forms of travel behaviour. While a shift from less (car) to more sustainable travel modes (public transport, cycling, walking) may be enforced by economic means (Bonsall and Willumsen, 2014), land use policies are increasingly seen as a promising road toward more sustainable travel practices (Van Wee and Handy, 2014). Given that traffic models and TDFMs describe mode choice behaviour based on the spatial distribution of individuals' residences and potential destinations, they may prove valuable in assessing land use policies aiming at a shift toward more sustainable travel modes.

As discussed previously, LUTI models extend the set of responses as compared to TDFMs, by allowing for responses such as changes in car ownership, residential location and job change. This is relevant since it has been found that individuals' and households' responses use a variety of strategies to facilitate their desired travel pattern and respond to changes in travel or personal conditions (Oakil et al., 2014; Cao and Mokhtarian, 2005). In addition, LUTI models allow to investigate the interaction with other markets, such as the housing market, real estate market, labour market and the regional economy, which may respond to changes in the transportation context, as well as influence it. The literature presents some examples of the added value of LUTI models in this respect.

Erdogan et al. (2013) apply a LUTI model to show how changes in fuel prices do not only have direct effects on trip frequency, mode and destination choice, but also on longer term choices regarding residential and work location. Through the real estate and housing market, higher fuel prices might even lead to denser urban developments.

However, also infrastructural policies may have indirect effects, through their impact on households' and firms' locational decisions. Guerra (2014) describes an empirical study of the metro extension (Line B) in Mexico City. He reports that the metro extension attracted a significant share of new travellers, who previously did not use the car. There were land use effects in the form of commercial densification around new metro stations. Again, LUTI models provide a promising tool for assessing both the transport and the land use effects.

Another highly relevant topic is the effect of rising income levels in developing countries leading to sharp increases in car ownership in countries such as Colombia (Gomez-Gelvez and Obando, 2013), China (Cervero and Day, 2014) and Brazil. Notably, the effects differ between contexts. While Gomez-Gelvez and Obando describe that car ownership in Bogota primarily increases as a result of an increase in the number of households, the number of cars per households in the Chinese context has substantially risen, leading to an increase in suburban development and urban sprawl. Cervero and Day conclude that transit oriented development may play a role in at least dampening the massive increase in car ownership and use in China. However, quantifying the effect of TOD requires jointly modelling the effects of households' car ownership and location decisions, as well as their daily travel, where congestion may have a significant impact on these decisions. LUTI models may provide a fruitful tool to assess the joint effects of these developments.

6 INNOVATIONS AND CHALLENGES IN TRANSPORT MODELLING

Complex transport models have been subject to various innovations over the past decades. In general, most of these innovations include a trend toward more complexity (in terms of more interaction and feedback between system elements) and more detail, which reinforce each other.

Traffic simulation models have profited from advances in computing power and data organisation, and are increasingly capable of modelling larger regions, up to a whole country such as Switzerland (Meister et al., 2010).

In TDFMs, two important trends are observed. First, a switch from the traditional four-step model, in which trips are modelled independently of each other, to activity-based models, in which trips form part of activity patterns. This has the important implication that the scheduling of trips becomes more realistic and that their timing can be predicted with more accuracy. Recently activity-based models, such as TASHA, have been extended to create activity schedules not only at the individual, but also at the household level, implying that household interactions can be modelled more reliably. A second trend is a trend toward fully individual micro-simulation instead of producing distributions for specific population segments per zone. This trend is facilitated by increasing computing power and data storage capacity.

Finally, complex transport models profit from the increasingly detailed data becoming available these days. The data concern very detailed data about transportation infrastructure and land use, available up to the parcel level. Combined with the individual representation of agents (travellers) this allows for a more detailed and a more varied representation of travel behaviour.

Given the progress in transport and land use modelling over the past decades, the question can be raised how state-of-the-art transport and land use models should be judged in the broader context of the complexity of cities, of which transportation systems are a part. A key issue in this respect is whether transportation should be considered a simple or a complex problem (Bettencourt, 2014). A simple problem is a problem that is well-defined in terms of performance metrics and that offers fast and direct actions to move it toward the desired end state. A complex system, on the other hand, involves much more interactions, circular causalities and a vast problem space with many uncertainties (Bettencourt, 2014). Consequently, what actions can be used to influence the system and what their effect will be is much less readily evident.

Traditionally, transport planners have approached transportation planning as a simple problem. Travel demand and travel behaviour were assumed to follow in a straightforward way from the spatial organisation and the characteristics of the transport system. For instance, changes in travel time or costs lead to changes in travel volumes and modal split in a well-defined and expected way. In addition, transportation planners have assumed that the transportation system tends to a state of equilibrium, rather than focussing on developments of the system in response to external forces. In particular, they have used a small set of explanatory variables to extrapolate current correlations to future conditions, assuming that travellers' preferences and needs are invariant.

While this approach has definitely had many merits in providing insights when planning infrastructure in concrete settings, it also poses limitations to the way we think about the transportation system in an uncertain future. As a matter of fact, the complexity of urban societies leads to developments that make the assumptions on which transport and LUTI models are built questionable. Changes in the population composition, partly due to international migration, will lead to changes in people's needs and preferences, also with regard to travel. For instance, societal norms towards sustainable or healthy lifestyles may change, with implications for the use of sustainable and healthy travel modes. Complex social processes of opinion and norm diffusion (Tessone, 2014) may play a role here. Also, using mobile ICT platforms, the organisation of transport services may fundamentally change, leading to bottom up initiatives for e.g. developing car and ride sharing programmes (Hansen et al., 2010). Also in this case, social interactions will fuel the diffusion and adoption of such systems. Further spread of mobile ICT tools and services may not only change our organisation of the work and private sphere, but also lead to changes in the way we perceive travel time and make travel decisions (Lyons et al., 2007). Lastly, the development of electric vehicles and automated vehicles may radically change the way we choose to travel and use our travel time, but also our decisions whether to own, share or hire a vehicle (Pendyala, 2014). Again, however, the speed and extent of diffusion of such new systems is the outcome of complex social and economic processes. While each of the above may have a significant to major impact on future travel, existing transport and LUTI models are not equipped to deal with them, since they are based on the extrapolation of the current organisation of the system and current needs and preferences.

The question thus remains what tools transport planners can use to explore and anticipate such uncertain futures. A first option would be to use agent-based LUTI models, but to apply them for specific sensitivity analyses. Rather than aiming to forecast the most likely outcome, one may aim to find sets of parameters and inputs that lead to a radical shift in transport and land use or, in other words, lead to a dissipative outcome. Given these dissipative sets, a next analysis would involve an exploratory analysis of how such changes in preferences or input variables may come about. For instance, a low value of travel time for car users might be brought about by the introduction of automatic vehicles, allowing one to work or recreate while driving. As another example, extreme costs of transport might be related to scarcity of fossil fuels. Such analyses might give planners insight into what factors are likely to lead to major changes in the land use and transportation system. A second option to explore uncertain futures might be to directly study the diffusion of new technologies and forms of organisation, such as car sharing schemes or electric vehicles. Using models of market diffusion (Shaheen and Cohen, 2007; Jansen and Jager, 2002), the likelihood of such new developments to take off and policies stimulating them can be studied. Likewise, studying and modelling the diffusion of a change in attitudes (Tessone, 2014; Nowak et al., 1990) in a population may add to our understanding of how sustainable and healthy lifestyles pervade in population segments.

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CHAPTER 14

EDUCATION AS A COMPLEX SYSTEM: IMPLICATIONS FOR EDUCATIONAL RESEARCH AND POLICY[1]

Michael J. Jacobson[2]

1 INTRODUCTION

Scientific study of the behavior of complex physical and social systems over the past three decades has lead to significant insights about the world that classical approaches tended to over simplify or to ignore (Bar-Yam, 2003). However, Jacobson and Wilensky (2006) have noted that the application of complexity perspectives to educational research and policy is at an early stage. Given this backdrop, the primary goals of this chapter are to discuss four main areas: *i*) education as a complex system; *ii*) complexity and methodologies for studying education; *iii*) educational systems research and educational policy; and *iv*) challenges of learning about complex systems and implications. These areas are considered in turn, followed by concluding remarks.

There has been a shift in the fields of the learning and cognitive sciences and educational research over the past decade from earlier work on learning concepts about complex systems to the application of perspectives about complex physical and social systems to enhance educational research and to inform policy.[3] One indication of this latter trend is reflected in the use of complexity concepts by researchers who are studying education that have important implications beyond just an enriched technical vocabulary for researchers. For example, Bereiter and Scardamalia have argued that:

> As complex systems concepts such as self-organization and emergence make their way into mainstream educational psychology, it becomes increasingly apparent that there are no simple causal explanations for anything in this field. In general, what comes out of a socio-cognitive process cannot be explained or fully predicted by what goes into it. Creative works, understanding, and cognitive development are all examples

1. This chapter will incorporate material (with permission) from Jacobson and Wilensky (2006), Jacobson and Kapur (2012), and Jacobson, Kapur, and Reimann (2014). I wish to acknowledge my research colleagues and collaborators over the years who have helped me learn and deepen my understanding of the intricacies and wonders of complex physical and social systems, especially Manu Kapur, Uri Wilensky, and Yaneer Bar-Yam.

2. Centre for Research on Computer Supported Learning and Cognition (CoCo) Faculty of Education and Social Work The University of Sydney Sydney, NSW 2006, Australia. E-mail: <michael.jacobson@sydney.edu.au>.

3. For an overview, see Jacobson and Wilensky (2006).

of complex structures emerging from the interaction of simpler components (Sawyer, 1999; 2004). Learning itself, at both neural and knowledge levels, has emergent properties (Bereiter and Scardamalia, 2005, p. 707).

Lemke and Sabelli further observe:

> The education system is one of the most complex and challenging systems for research. Much as we know about cognitive aspects of learning, pedagogical strategies, and reform implementation, we currently lack the modeling capability needed to help practitioners and policymakers explore the potential impact of proposed interventions, since efforts in this area are still at a very preliminary stage of development (Lemke and Sabelli, 2008, p. 128).

From these two perspectives, if current learning and educational research has established that there are "no simple causal explanations for anything in this field", then the policy corollary is that there are no simple policies for educational initiatives and interventions. To address the implications of this policy corollary, I first consider how to view education as a complex system followed by an overview of current methodological approaches for conducting education research used to inform policy.

2 EDUCATION AS A COMPLEX SYSTEM

An important framework has been articulated by Lemke and Sabelli (2008) for viewing education systems and educational reform initiatives from a complexity perspective, which has five main components: *i*) system definition; *ii*) structural analysis; *iii*) relationships among subsystems and levels; *iv*) drivers for change; and *v*) modeling methods. For the purposes of this chapter, the first three components are most relevant, and are briefly summarized in turn.

2.1 System elements

Lemke and Sabelli define an educational system in terms of its constituent elements and environmental dynamics, such as institutions and social practices, sources and users of information, and human and material resources. The elements to be included in an educational system must be tightly coupled and interdependent. For example, students are a critical element in the system and they learn in a variety of contexts, such as in formal learning environments with teachers at schools and universities and in informal learning environments of science museums, mass media, print publishing, and increasingly, online Internet mediated sources. Other elements (i.e., stakeholders) in educational systems can include school boards and trustees, government education authorities, research institutions, sponsors of researchers, and communities.

Another aspect of an educational system is *levels of organization*. This must be viewed not simply as control hierarchies of lines of authority, but also in terms of emergent patterns and processes at mezzo and macro levels of the system. There are also information and material resources that flow across adjacent and non-adjacent levels of an educational system. For example, at one level, the individual grades of a student are sent to parents, as well as being transformed and reorganized through pattern-recognition that extracts only relevant information for the dynamics of the next higher levels of the school, district, state, or country.

2.2 Structural analysis

The hierarchies of formal organizations provide one way to view an educational system, such as individual students and teachers, student groups, classrooms, departments, schools, and –depending on terms used in different national systems – districts, states or provinces, and the entire national system. Lemke and Sabelli (2008) propose that a *structural analysis* would take into account the different timescales that different levels of the system function at, and would analyze the dynamic processes within, and emergent properties across different system levels.

Also critical in defining an educational system is the *range of timescales* of the critical processes. As a central goal of an educational system is fostering individual learning, relevant timescales span milliseconds of neuronal synaptic interactions and cognitive processes, to minutes for individual students and student-teacher conversational interactions, to hours of the school day, to months of school terms, to a year at a grade level, to years of primary, secondary, and tertiary education, and to years and decades of policy implementations at national levels.

A structural analysis of an educational system must also be concerned with issues such as the exchange of information that ranges from classroom activities over periods of minutes to curriculum change processes occurring over periods of years. Another issue concerns how particular conceptual understandings might develop from learning events in classrooms or a laboratory and from experiences in hallways, cafeterias, and outside of school. The development of long lasting identities, attitudes and values also occur in the context of networks of social interactions between peers in a class, in the local community, and in virtual social networks of online communities. A structural analysis should also be concerned with how the developmental emergence of identities, attitudes, and values that occurs over years will affect decisions and actions adults might make in very short timescales of seconds, minutes, or hours. At higher system levels, such analyses can examine how community problems and changing national priorities influence the overall agendas and programs of the larger educational system. Similar issues related to teachers could also be analyzed, such as interactions in terms of different timescales with students, supervisors and administrators, teacher educators, curriculum developers, educational publishers, and university researchers.

2.3 Relationships among subsystems and levels

Critical in the analysis of complex systems are the relationships within and across subsystems and levels. Lemke and Sabelli (2008) argue that of particular importance are the levels above and below a specific focal level of interest. A teacher interested in implementing a new teaching approach, for example, might consider a level below – how students might respond – and a level above – how the principal might view the new approach.

More generally for educational systems, the next higher level of the organization might generate positive or negative feedback that could enhance or constrain how the dynamics at the focal level unfold. In a similar manner, subsystems at a level lower might also provide feedback interactions that could influence the behaviors at the focal level. Also of interest in looking at the relationships across system levels are the degrees of freedom that exist after constraints are accounted for.

Critical to understanding educational subsystems and levels are the kinds of matter and information that are exchanged, such as classrooms with computers, tables, and seating from the school administration and aggregate school performance reports provided to policy makers. These interactions across subsystems and levels might be tightly coupled, such as when school funding used to purchase computers is linked to specific targets for school performance in reports or large-scale national or international educational assessments.

In closing this section, there is a further general property of complex systems that is of relevance to research and policy involving educational systems, *the dialectical co-existence of linearity and non-linearity* (Jacobson and Kapur, 2012):

> The complexity of emergent behavior comes from the co-existence of linearity and non-linearity across and within multiple levels or scales of an open system. Indeed, because of this, complex systems exhibit seemingly opposing properties and behaviors: randomness and order, predictability (e.g., attractors, highly connected nodes or hubs) and unpredictability, coherence and incoherence, stability and instability, centralization and decentralization, and so on. It is not one or the other, it is *both* (Kauffman, 1995, p. 310).

3 COMPLEXITY AND METHODOLOGIES FOR STUDYING EDUCATION

Accepting the perspective that education in modern societies should be viewed as complex systems is important for academic research exploring how educational systems function and behave in terms of relevant subsystems and levels, feedback and information flows, emergence, and so on. Also, of particular importance to this volume, a complexity perspective has implications for policies regarding educational systems at national and local levels. In fact, these two areas are connected in that the information flows available to policy makers are constrained by the types of methodologies that have been developed and validated by academic research.

Broadly speaking, existing methodological approaches for educational research fall into two main categories: *quantitative* and *qualitative* (Firestone, 1987). Quantitative approaches (including quasi-experimental) are pervasively used in educational research (Kapur *et al.*, 2007; Suthers and Hundhausen, 2003). Rooted in a positivist philosophical tradition, quantitative methods typically seek to establish causal or quasi-causal explanations of design or intervention effects versus control or comparison conditions . In contrast, qualitative approaches have a phenomenological philosophical basis that seeks to describe and to understand educational contexts and environments. Although there are educational researchers who exclusively use only one of these methodologies, since the late 1980s it has become increasingly common for researchers who study learning to use both quantitative and qualitative methods in a complimentary manner in order to understand the educational issues being investigated from the different types of information generated by these two methodological perspectives.

However, an important question must be asked. Are the existing quantitative and qualitative methodologies used in educational research – whether separately or in combination – in fact sufficient for providing appropriate information and understandings of the dynamics of educational systems viewed from the complexity perspectives outlined in the previous section?

Unfortunately, the answer is "no". This is because the major mathematical tools used in quantitative methods (e.g. differential equations, statistical modeling) are fundamentally *linear* tools that work by breaking a system into its components or parts, studying the parts individually, and then adding the parts together to form the whole. However, emergent phenomena generally have *nonlinear* properties that cannot be analyzed by "adding up the parts" as the patterns at the macro-level of complex systems generally have *different* properties than the constituent parts at the micro-level of the system. As Holland (1995, p. 5) explains, "nonlinearities mean that our most useful tools for generalizing observations into theory – trend analysis, determination of equilibria, sample means, and so on – are badly blunted".

Finally, there is another important limitation that cuts across both quantitative and qualitative approaches: they are largely limited *to explaining and understanding what has already emerged* (Epstein and Axtell, 1996). For example, once patterns or organizations (e.g., opinions, norms, convergence in group discussions) emerge, they can be subjected to quantitative methods to explain aggregate-level relationships. At the same time, qualitative methods can be employed to gain rich descriptions and understandings of the trajectories that led to emergent organizations. However, if one could unwind time, *the same trajectory may not have unfolded even if one started with similar initial conditions* (Kauffman, 1995). Part of what makes an emergent pattern irreducible and therefore its own shortest description is its high sensitivity to initial conditions. Consequently, to understand an emergent phenomenon, one needs to understand and explain not only the trajectory of evolution that *actually* unfolds but also the possibility space of trajectories of evolution that could unfold. Thus, relying mainly on quantitative and qualitative approaches places limitations on understandings of the possibility space over which an emergent phenomenon may unfold.

Realizing that quantitative and qualitative approaches each have value for educational research, there have been calls for greater integration of these approaches moving forward (Firestone, 1987). However, there is an imperative for a methodology that not only builds on quantitative and qualitative methods but that is also able to appropriately investigate the emergence of learning given the argument that both the quantitative and the qualitative approaches – alone or combined – have limitations for this undertaking.

In Jacobson and Kapur (2012), *agent-based modeling* (ABM) is proposed as a methodological *complement* to quantitative and qualitative approaches in educational research given that it is increasingly being used not only in the natural sciences (Jackson, 1996) but also in economics (Arthur, Durlauf and Lane, 1997), sociology (Watts and Strogatz, 1998), socio-cultural psychology (Axelrod, 1997), organizational science (Carley, 2002), just to name a few areas. Grounded in complexity theory, ABM is providing important theoretical and empirical insights into the dynamics of complex systems (Eidelson, 1997).

ABMs, when integrated with quantitative and qualitative approaches, can potentially reveal insights that may otherwise remain elusive about the dynamics of emergence in learning processes and environments, much like how qualitative methods can reveal insights into a phenomenon that may not be possible with the use of quantitative methods alone. We are beginning to see examples of educational and learning research in which ABMs and other modeling techniques are being used as an important methodological compliment to traditional approaches, which is discussed in the next section.

4 FROM RESEARCH TO POLICY: TOOLS TO STUDY EDUCATION AS A COMPLEX SYSTEM

As noted above, Lemke and Sabelli (2008) argue that there was a critical need for modeling capabilities that could inform practitioners and policymakers about how proposed educational reform interventions might unfold. Recent work indicates important progress is being made to address this important need.

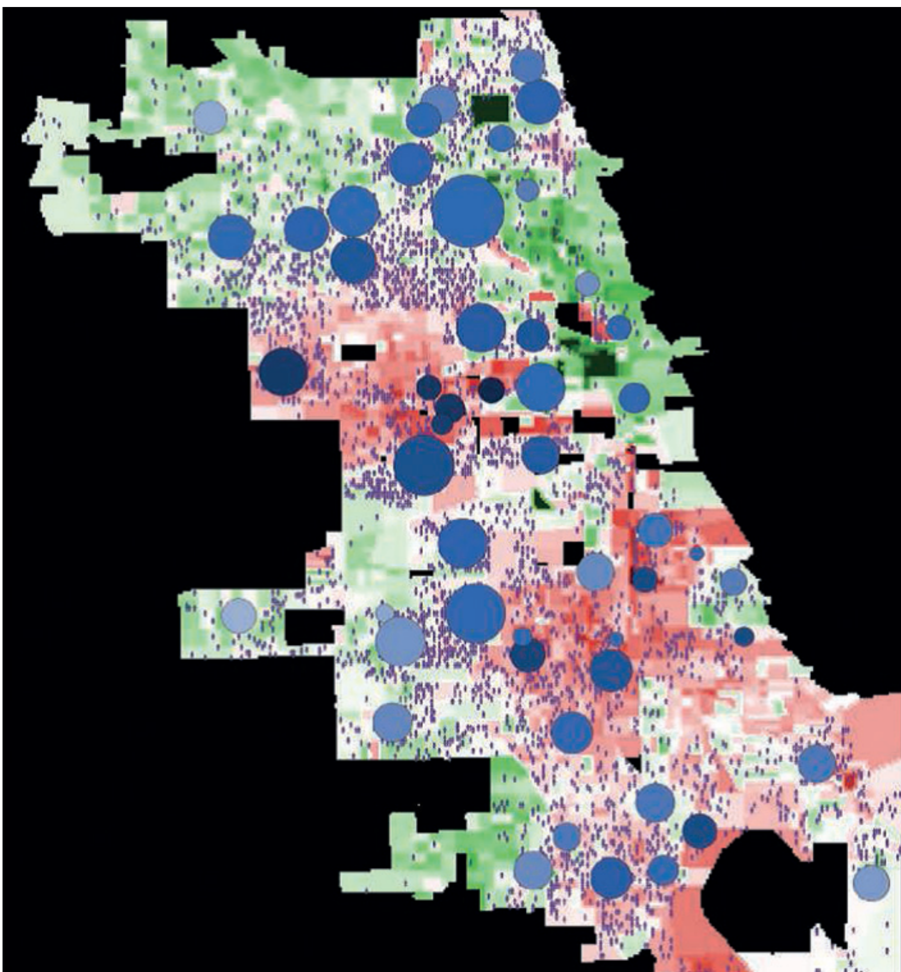
Maroulis *et al.* (2010) provide an overview of research involving the application of complex systems perspectives, especially computer modeling, to educational and policy research. They note, for example, that researchers are using new visualization tools to examine longitudinal network data in which macro-level outcomes such as classroom discipline emerge from micro-level conversational interactions of students. Other researchers in sociology are using computer modeling to identify macro-level social groups that emerge from local interactions of students in school networks, rather than using a priori student categories such as “athletes” or “scholars” (Frank *et al.*, 2008). Maroulis *et al.* (2010) observe that visualization and computer modeling approaches such as these can be used on existing data, and thus represent important new analytical tools for researchers who are studying educational complex systems.

In terms of research into policy and educational reforms, Maroulis *et al.* (2014) report on their work using ABMs to study initiatives to provide parents with school choice in the United States. Briefly, proponents of school choice reform argue that competition introduced by allowing parents to select the schools their children attend will lead to better schooling and incentives for school reform. In contrast, opponents of this type of reform claim resources are drained away from schools and that school quality is thus hurt not helped, by such a reform. Research into this issue since the 1990s had employed standard quantitative and qualitative methods, but these studies have provided inconclusive and even conflicting findings.

Maroulis *et al.* (2014) investigated this policy debate by creating ABMs of a school district’s transition from a local neighborhood school “catchment area” system to a school choice system. The agents in the system were schools and students. School agents varied in terms of the quality and building capacity of existing schools, and new schools that entered into the system by imitating top existing schools. Student agents varied in their ability and background, and they would rank schools in terms of achievement and geographic proximity. The academic achievement of the student agents combined individual traits and the “value added” by the quality of the school they attended. Real data from Chicago Public Schools was used to initialize the model (see figure 1).

Analysis of the ABM identified dynamics not revealed in previous quantitative and qualitative research. Specifically, model runs demonstrated that the timing of new schools entering the system was a critical factor. The overall system improves because new schools entering the system imitate the top existing schools. However, a high emphasis on achievement at the schools leads to new schools entering the system earlier, which resulted in lower achieving new schools. Thus, there was a paradoxical mismatch between the macro-level and micro-level behaviors of the system in that increasing the emphasis on school achievement at the household level did not generally lead to increasing achievement at the district level. From a policy perspective, results of using this ABM suggest the critics of school choice reform were correct that school achievement in the overall system would not rise. However, the reason proposed by the critics – draining of resources away from existing schools – was not actually the causal factor; rather, it was the timing of new schools entering the system. This ABM of the Chicago Public School system also provided insights into other systemic effects, such as policy approaches to minimize the unintended transfer of top students to private schools where vouchers issued by the government were used to pay for the private schooling (Maroulis *et al*., 2010).

FIGURE 1
Visualization from agent-based model of school choice in Chicago, Illinois



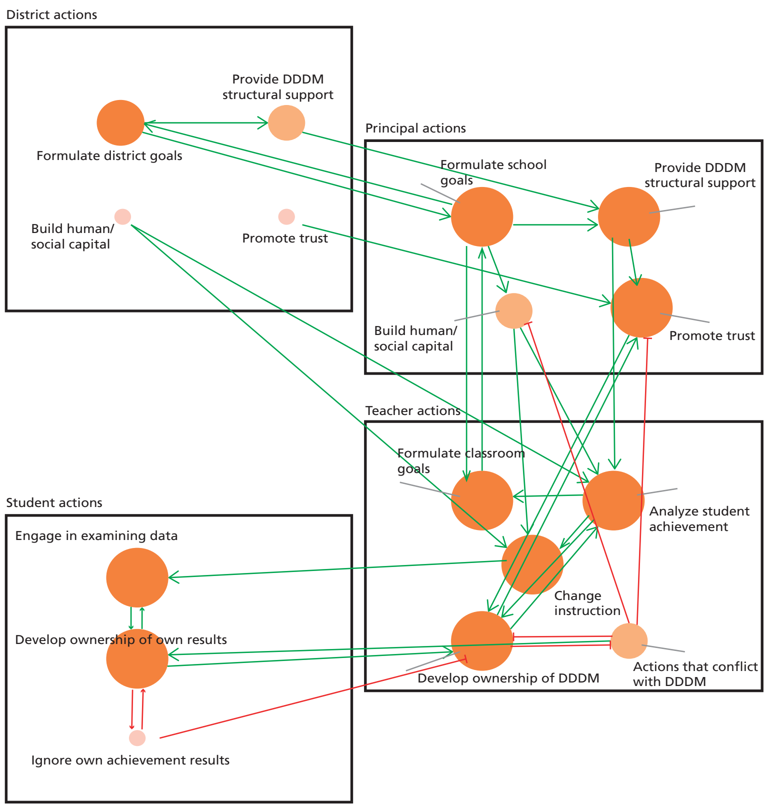
Source: Maroulis *et al*. (2014).

Obs.: Small dots represent students, large circles represent schools, circle size represents academic performance, and dark red and dark green colors show high and low poverty areas respectively.

Levin and Datnow (2012) provide another example of the use of computer modeling to explore the influence of principal leadership related to implementing a high school reform. An educational reform approach involving Data Driven Decision Making (DDDM) has been found to be an effective approach for guiding educational decisions. The data used to inform the development of the ABM – which Levin and Datnow refer to as a *multi-mediator model* (MMM) – was drawn from a case study of an urban school in the United States where the use of DDDM had been found to influence positive school outcomes. The MMM allows the manipulation of interactions between the district administration that wishes implement the DDM reform, the actions of the principal as the site leader promoting the DDDM reform, the principal's interactions with teachers within the school, and the interactions of teachers with their students.

FIGURE 2

A multi-mediator model of DDDM educational reform, including principal, teacher, student, and district actions



Source: Levin and Datnow (2012).

The MMM model developed by Levin and Datnow is shown in figure 2. Green lines show positive feedback between the network nodes in the model, and red lines show negative feedback. The model also illustrates across level feedback interactions, such as positive feedback between the District Actions "provide DDDM structural support" to the Principal Actions "provide DDDM structural support". However, note that there is negative feedback between Principal Actions "build human social capital" and "promote trust" and Teacher Actions "actions that conflict with DDDM". Consistent with the qualitative case study data, the models runs revealed that it is necessary for the principal to do *both* "build human social capital" and "promote trust" in order for the DDDM reform initiative to be sustainable. One may view the persistence of the DDDM reform as a type of phase transition in the school system. Going beyond the data, the MMM may then be used to explore "what if" scenarios. For model runs where the principal only engages in one or the other of these two actions, the MMM suggests that there would be a high probability that a DDDM reform would fail; that is, there would *not* be a phase transition in the school system. Future research is needed involving other case studies, including some with a school where DDDM was not successfully implemented to see if there is a "fit" between the new data and the MMM, with the possibility that the MMM may need to be revised to account for additional factors and dynamics in the new cases.

These projects represent proof-of-concept research that illustrates how the use of computer modeling, particularly ABMs, can provide research and policy insights about complex educational systems. In this brief overview of this very early research, it is clear that complexity-based computer modeling approaches can provide analytics and information that goes beyond traditional quantitative and qualitative educational research approaches. As Jacobson and Kapur (2012) observed, these projects use modeling methods to compliment and extend traditional educational research methodologies, not to replace them. Considerable work is now needed to develop and validate modeling approaches that would meet the needs of policy makers and practitioners. Still, these early efforts are quite promising and future research in these areas is clearly warranted.

5 CHALLENGES OF LEARNING ABOUT COMPLEX SYSTEMS AND IMPLICATIONS

In this chapter, I have argued that research into the dynamics and properties of complex physical and social systems is relevant for understanding important characteristics of educational systems. Further, there is now a body of research that has demonstrated ways in which complexity conceptual perspectives and methodologies can in fact be effectively used to study aspects of educational systems that compliment existing educational research approaches.

However, although complex systems are commonly experienced, research indicates that there are significant differences in ways that experts and novices think about complex systems (Hmelo-Silver, Marathe and Liu, 2007; Jacobson, 2001). This is not surprising as currently core ideas about complex systems (e.g., self-organization, chaos, emergence) and research methods (e.g., agent-based modeling) are currently not systematically taught in any of the science curricula of major OECD countries. This is an issue as it means the majority of non-scientist adults (i.e., former students) who might be involved in professional areas, government policy organizations, or political service are unlikely to have had any direct exposure to complexity perspectives as part of their formal schooling. To address this issue, there is a case to be made about the need to make changes to science standards, to develop new curricular materials, to educate and prepare teachers to teach new advanced knowledge areas such as complex systems, to develop relevant assessments, and so on, all of which are all areas that have policy implications. One step in this direction is the Next Generation Science Standards (National Research Council, 2013), which does provide recommendations for starting to teach complexity concepts at pre-university levels in the United States. The learning of complexity concepts and methods may also be an issue for many practicing social scientists who might be involved with doing research about educational systems, which has implications for professional development at this time.

There is a broader and perhaps deeper learning challenge concerning complexity perspectives beyond conceptual understanding, which is the epistemic implication of complex systems theory and methods. A key, and perhaps counterintuitive, epistemic aspect of complex systems views is that the apparent complexity in the behavior of many complex systems may be described in terms of the interaction of system elements based on relatively simple rules. This perspective seems implicit in views of Simon (1996, p. 1): "The central task of a natural science is to make the wonderful commonplace: to show that complexity, correctly viewed, is only a mask for simplicity; to find pattern hidden in apparent chaos". I call this the *simplicity-complexity* epistemic view.

Complexity perspectives represent a challenge to what I believe is a reasonably common epistemic view of *complexity-complexity*, which is that complex systems such as educational researchers study must have "complex" explanations whereas simple systems would, of course, have simple explanations. Indeed, a *complexity--complexity* epistemic bias – and its corollary, a *simplicity-simplicity* epistemic bias – would seem to be obvious characteristics of "common sense." For example, a simple machine such as a pulley may be explained as a robe wrapped around a wheel with a grove to raise or lower something, whereas the behavior and operation of a complex machine such as a modern jet airliner could only be explained with complex concepts from physics (i.e., Bernoulli effect), engineering and materials science, business models to finance and maintain, and so on.

While there has been no direct research into this conjecture, I believe that many educational researchers and probably policy agency individuals tend to have epistemic commitments to the *complexity-complexity* bias. If this is so, then an important epistemic challenge of complexity perspectives for educational research and for policy makers is that one does not necessarily need complex explanations for complex behavior; such behavior may very well be explained from the “bottom up” via simple, minimal information, such as utility functions, decision rules, or heuristics contained in local interactions (Nowak, 2004). Of course, it may be that future educational research into educational complex systems may or may not align with a simplicity-complexity epistemic view. Still, being aware of epistemic assumptions such as these has value to educational researchers and education policy makers.

6 CONCLUSION

In closing this chapter, I revisit questions that were posed by Lemke and Sabelli (2008):

> Can the new tools of complex system analysis help us understand the potential impact on the educational system of new technologies and help us predict the paths that different efforts at systemic reform follow? (…) Can they help us identify critical relationships within the educational system that resist systemic change or afford opportunities for new alternatives? (…) If the answers to any of these questions are to be “yes”, we will require collaboration within a diverse new community of researchers seeking a common framework for sharing ideas from different disciplines and approaches to both complex system analysis and to education.

It would seem that now several years since these questions were posed, we can in fact say a provisional “yes” to several of them. Given this positive affirmation, and given the range of educational needs and challenges in the 21st century, both in developed and developing countries, there is an urgent need to foster a broader awareness of the intellectual and methodological tools of complexity for applicability to the study of educational systems. There is a similar concurrent urgency for politicians and other stakeholders in education who shape educational policy as well. It is hoped that this chapter will contribute to the dialog to advance awareness of both the urgency and the opportunities of viewing education as a complex system.

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CHAPTER 15

COMPLEX APPROACHES FOR EDUCATION IN BRAZIL

Patrícia A. Morita Sakowski[1]
Marina H. Tóvolli[2]

1 INTRODUCTION

Education systems encompass a large number of heterogeneous agents, whose interactions give rise to learning, teaching, cognition and education. They are comprised of interconnected layers, each of which provides support and restraints to the others. Through mechanisms of feedback and adaptation, these systems and their agents co-evolve. All these features make education systems complex.

The heterogeneous agents in an education system are, for example, students, teachers, and parents. Every student learns in a different way, every teacher has his/her methods of teaching, and every parent raises his/her child in his/her distinct manner. Learning emerges not only from information passed from teachers, but as the result of interactions between students and other individuals, both in formal and informal environments.

Education systems are comprised of various interconnected layers. In a macro perspective, they involve government institutions, such as the Ministry of Education and the network of schools and universities. However, the ministries of Finance, Health and Transport, among others, can also be considered part of this system, as they influence the allocation of financial resources, the health conditions to the population, and the accessibility to schools, respectively.

In a lower level, schools cannot be separated from the context in which they exist. Out-of-school factors, such as the safety of the neighborhood or the social-economic standing of the community, impact the attendance of students and their academic performance. Similarly, higher education influences and is influenced by basic education.

At the interpersonal level, students interact with their peers, teachers, parents, school managers and the community as a whole, while at the intrapersonal level, learning results from mental processes influenced by personal interests, personal

1. Researcher and Chief of The Planning and Institutional Articulation Advisory Board (Aspla/Ipea).
2. Research Assistant at Ipea.

history, hormone levels, working memory and other specific features in response to stimuli from the environment.

Educational features in a society emerge thus from the interaction of all these different scales, which cannot be isolated from each other. Due to the complex nature of educational systems, traditional linear methodologies are not sufficient to capture their dynamics. The presence of multiple causalities and non-linearity might even put in doubt the external validity of results obtained in rigorous randomized controlled trials, as controlling for all key variables might be unattainable in educational research (Cohen, Manion and Morrison, 2003).

Given the complex nature of education, complex systems' methodologies can help analyze education in different ways. First, simply understanding the complex nature of educational systems might help researchers refrain from having a mechanistic view of education, governed by simple causalities and levers that lead to predictable results.

Second, modeling education can provide a better comprehension of the dynamics of the system. By trying to identify the key elements and rules within a system, one can little by little understand how the different agents interrelate as well as simulate possible outcomes of a given intervention, for instance. In this respect, the role of models as theory communicators should be emphasized (Heemskerk, Wilson and Pavao-Zuckerman, 2003). By means of collaborative research, models can be improved, at the same time enriching the understanding of the phenomena.

The availability of loads of data on education also makes viable association studies. Machine learning techniques and network analysis can provide valuable insights into general trends or specific aspects to be furthered studied. Besides, tackling the complexity of educational systems might be the way of finding simple solutions (Berlow et al., 2014). For example, by understanding the network of relationships involved in the system, one could identify the central nodes or leverage points through which changes could be brought upon.

It is important to mention that complex systems methodologies are not a substitute for traditional educational research methods, though, but a complement to them. Knowledge about educational systems might emerge from the combination of evidence-based research, traditional quantitative and qualitative methods, associative studies and modeling.

As presented in the previous chapter, considerable amount of research has been done exploring the complex nature of educational systems, learning and teaching worldwide. In Brazil, however, this area is still incipient. The aim of this chapter is to analyze what has been done in the area in the country so far and to explore how the complexity approach can help education in Brazil. Following this introduction, section 2 focuses on the use of complexity concepts to think education in a more theoretical sense. Section 3 presents applications of complex systems' methods and methodologies in the country. Finally, section 4 discusses why the complexity approach seems particularly suitable for analyzing and helping improve education in Brazil.

2 COMPLEX THINKING IN EDUCATION

The discussion of the complexity perspective in Brazil has particularly been marked by the contributions of the French philosopher and sociologist Edgar Morin. Many studies have been focused in discussing complexity concepts and the need to rethink education, with a special concern on reframing pedagogical practices. This new perspective challenges the traditional paradigm based on instructive theories, and proposes a new paradigm from the epistemological postulates formulated in the biological and quantum theories.

The traditional or Newtonian-Cartesian paradigm has as main postulates the fragmentation and the dualistic view of the universe. It has influenced the education, the schools and the pedagogical practices worldwide (Behrens and Oliari, 2007). The pedagogical practices have been built upon a Cartesian view of dichotomy of the dualities, such as subject-object, part-whole, rational-emotional, local-global, ignoring the interconnection between these binary pairs. What is seen is the subdivision of knowledge in areas, institutes, and departments, in which principles like fragmentation, division, simplification and reductionism are dominant, resulting in a de-contextualized pedagogical practice (Santos, 2008). These principles, brought about the disciplinary structure of knowledge, made knowledge lose its meaning (Petraglia, 1995).

According to Araújo (2007), the pedagogical practices have emphasized instructive aspects in the place of creative, reflexive, constructive and cooperative aspects, producing *i*) a rigidity process, a transmission of content that favors the memorization of isolated information; and *ii*) a process that ignores the context, the involvement of the students, and their heterogeneity.[3] The student is seen as a spectator; someone that must copy, memorize, and reproduce the information passed on by the teacher (Behrens, 1999).

In general, most teachers tend to perceive and represent the world through the classical physics' lens, by which reality is seen as stable, predictable, and predetermined. In contrast with the traditional paradigm, the quantum and biological theories present some epistemological principles, such as the dialogical and uncer-

3. Araújo (2007), particularly interested in the emergent challenges of the online education, notes that there are distance learning courses that still present a disciplinary structure, strongly marked by the instructive vision. For the author, instructive models are scientifically archaic, and they tend to simplify the process of knowledge construction. This implies the need to investigate the use of technologies in distance learning courses from an e-learning perspective, allowing the construction of an autonomous thought.

tainty, which help us to rethink education and to reframe the pedagogical practices (Moraes, 2004a). Some of these principles are briefly presented below.

2.1 The dialogical principle

Morin (2011) points out the dialogical principle as an important complexity concept. This principle refers to the capacity of association between two items that are antagonistic and at the same time complements. For example, order and disorder are antagonistic, but they can be complements in some situations, by collaborating and producing organization and complexity, in such a way, that there is duality within the unity.

Considering the dialogical principle, Guimarães et al. (2009) argue that the involvement of opposites implies the valuing of pedagogical practices that take into account conflict; that observe the whole, the parts and interaction of the parts, instead of isolating them. By this view, the fragmented curriculum would be replaced by a curriculum that enables communication and dialogue among wisdoms, promoting the construction of the whole.

2.2 The complementarity of opposites

Related to the dialogical principle, there is the idea of complementarity of opposites.[4] In the educational context, Santos (2008) calls attention to the dichotomization and emphasis in only one attribute of the binary pairs, such as rationality, what contributes to an unilateral view and an incomprehension of the learning process. As a result, the students are not able to articulate the diverse individual dimensions. By this scenario, Santos (2008, p. 77) proposes an articulation of the binary pairs, so as to obtain a more complete view of the phenomena being observed. For the author, "reason without emotion does not capture the human characteristic, while emotion without reason leads to nowhere."

Another example is the binary order-disorder. For Santos (2008) there is a symbiotic relationship of interdependence between order and disorder. In relation to educational management, she argues that:

> order is represented by legislation and by organization, legal and bureaucratic norms, curricular structure. In the management of this organization, the disorder and the ambiguity arise, introduced by the subjects that give dynamicity to the model of functionality and rationality of the system. Human beings, with their diversity, give support and functionality to the management of the organization. People's behavior in the institution is a mixture of dependence and autonomy (another binary pair). Order is desirable, but disorder, spontaneity, disobedience, provide vitality to the institution, although, in excess, lead to its disintegration (Santos, 2008, p. 78).[5]

4. The principle of complementary of opposites was proposed by the Danish physicist Niels Bohr, by which he argues that wave and particle composes the same reality (Santos, 2008).
5. All quotes in this chapter were translated by the authors.

2.3 Uncertainty and nonlinearity

These ideas lead us to the importance of uncertainty and non-linearity. As pointed out by Santos (2008), the principle of complementarity of opposites argues for the articulation of dualities, such as certainty and uncertainty, denying a reductionist and deterministic view. The uncertainty concept goes against the dichotomized dualistic view, which emphasizes only order and certainty. The school maintains a scenario of certainty by repeating norms, values, and social sanctions, and by following the institutionalized rules, such as evaluation rules, in a way that the teacher's behavior becomes predictable. Most of the time, teachers disregard the uncertain and complex characteristics of the knowledge building process, depersonalizing and homogenizing the students. Santos (2008), by considering that the characteristics of the subject, of the knowledge and of the society are dynamic, argues that the articulation of certainty and uncertainty in the pedagogical practices is fundamental.

Besides, the uncertainty concept opposes the linear causality view grounded in the Cartesian rationality, by questioning the stability, the determination and foreseeability of the phenomena (Moraes, 2004a; 2004b). Non-linear dynamics counteract the pedagogical practices based on instructive theories that comprehend the knowledge building process as linear, and that do not account for the collaborative and interactive learning (Araújo, 2007).

2.4 Organizational recursion

Another important complexity concept is organizational recursion. According to Morin (2011, p. 74), a recursive process is "a process in which the outcomes and effects are at the same time causes and inputs of what had produced them". The recursive principle breaks up with the idea of cause and effect, by presenting the cyclic concept that everything that is produced returns on what had produced it.

This idea is congruent to the educational system if we consider it as a system that self-organizes; in the sense that a student is an outcome of a determined educational system, and at the same time the student influences the system. Therefore, the retroactive relations between the student and the system make the system evolve and develop (Moares, 2004a).

The same idea is seen when we talk about the construction of knowledge. According to Bonilla (2002), information and knowledge are related. But since meaning lays within the interpreter, information only gains meaning within a human context. Knowledge then would be the process of attributing meaning to information; and this would occur in the interactions among the agents, and interactions between agents and the world. Therefore, the construction of knowledge comprehends a recursive organization, in which agents transform knowledge, and knowledge transforms the agents that had produced it.

2.5 The autopoiesis principle

Related to organizational recursion is the principle of autopoiesis formulated by the Chilean biologists and philosophers Maturana and Varela.[6] This principle refers to an autonomous unit that constitutes itself as a network of components production, in which each component participates recursively in the same network. That is, there is no separation between the product and the producer; in such a way that the autopoietic organization is itself the product of its operations (Varela et al., 1974; Maturana and Varela, 1995).[7]

Based on this idea, Moraes and Torre (2006) argue that learning implies autopoietic processes, since knowledge and learning are interpretative and recursive processes, produced by the agent when he/she interacts with the environment. The authors call attention to the impossibility to predict what happens with the student only by observing the environment in which he/she is embedded, since the environment does not determine, but it can only unleash the changes on the cognitive-emotional structure of the student. This implies that a teacher's dynamics can work well with a specific group of students, but not with another group.

In accordance with Moraes and Torre, Santos (2008) argues that for the pedagogical practice this implies that the professor should adopt a methodology that pushes the students to produce knowledge by their own. The professor would facilitate the dialogue among the wisdoms, respecting the heterogeneity of each student, since each student has his/her own way of learning and of solving problems. By considering that the environment influences the individual, Santos (2008) emphasizes that knowledge should be seen as a result of the entanglement of physical, biological and social aspects. For her this implies the need to reframe the perception's concept.

2.6 Hologramatic principle

The last principle presented here is the hologramatic principle. Proposed by Edgar Morin (2011), the hologramatic principle refers to the idea that the part constitutes the whole, and the whole constitutes the part. The author uses the idea of

6. Maturana and Varela, aiming at comprehending the living being organization, postulate the autopoietic principle, affirming that all living being is an autopoietic organization. The cell, for example, "is a network of chemical reactions which produce molecules such that: *i*) through their interactions generate and participate recursively in the same network of reactions which produced them; and *ii*) realize the cell as a material unity" (Varela et al., 1974, p.560).

7. The main difference between the former organizational recursion and the autopoiesis is how the authors understand autonomy per se. Morin (2011) considers a relative autonomy – the individual is indeed dependent on the environment –, while Maturana and Varela (1995) admit an absolute autonomy. For them, each autopoietic unit presents a particular structure, and when the autopoietic unit interacts with the environment, the structure of the environment does not determine; but it only unleashes structure changes of the unit. That is, due to the autopoiesis organization, the system is autonomous of the environment. The system and environment are interrelated but not dependent; each system operates independent from the other.

the physical hologram to argue that the smallest image's point of the hologram contains almost the whole information of the represented object.

This goes against the current disciplinary structure of knowledge, based on Cartesian orientations, in which it is believed that the sum of the parts listed in the curriculums is equal to the whole knowledge. This disciplinary structure hinders the student to establish relationships between the knowledge obtained (Santos, 2008). Considering that to understand the parts, one needs to understand the inter-relationships between the parts and the whole, Santos argues that in order to explain isolated phenomena, the context is essential. For the author there is the need to invert the binary part-whole, and to interconnect the fragmented totality.

One way to overcome the current fragmented disciplinary structure, and to articulate the opposites is transdisciplinarity. Transdisciplinarity points out that what seems contradictory in one level of reality, may be coherent in another level of reality; meaning that there is no absolute truth, but instead relative truths, subjects to constant changes. As such, transdisciplinarity offers a wider understanding of reality; reality assumes a wider meaning (Santos, 2008).

From the transdisciplinarity view, knowledge is seen as a web of connections, a network. Knowledge is multidimensional, given the different levels of reality in the cognitive process (Santos, 2008). For Santos, by following traditional pedagogical practices, teachers tend to disregard the hologramatic principle, and not to articulate the diverse wisdoms in the construction of a multidimensional knowledge. Given the complexity of the phenomena, understanding an object in its diverse dimensions, requires both transdisciplinary knowledge and transdisciplinary observers. As put by the author:

> Transdisciplinarity maximizes learning by working with images and concepts that mobilize mutually mental, emotional and body dimensions, intertwining horizontal and vertical relations of knowledge. It produces situations in which there is larger involvement of students in their own construction of meanings (Santos, 2008, p. 76).

3 COMPLEX SYSTEMS' METHODS AND METHODOLOGIES IN EDUCATION

The previous section presented a discussion on the use of theoretical concepts of complexity to think education in Brazil. This section focuses on the applications of complex systems' methods and methodologies in education in Brazil. These applications can be divided in two main groups: those predominantly related to modeling and those mostly related to data availability. The separation is mostly for analytical reasons, as these two groups are fundamentally intertwined and interconnected. Modeling encompasses Cellular Automata and Agent-Based Modeling; System Dynamics; Network Analysis; and Intelligent Tutoring Systems, while

Educational Data Mining; Learning Analytics, and Data Visualization compose the second group.[8]

3.1 Agent-based models and cellular automata

In Brazil, agent-based models and cellular automata have been used mostly for teaching complexity concepts, Science and Maths at different educational levels. Xavier and Borges (2004), for instance, discuss the use of cellular automata for teaching about emerging patterns and complex behavior to students in the last year of basic education. Uehara and Silveira (2008) focus on the application of cellular automata for teaching Calculus in Computer Science undergraduate courses. Other examples include the use of computational modeling and simulation for teaching Physics (Gomes and Ferracioli, 2002), Chemistry (Recchi and Martins, 2013), Biology (Pereira and Sampaio, 2008), and Environmental education (Santos et al., 2001).[9]

The software Netlogo is popular in many of these applications. Recchi and Martins (2013), for example, used Netlogo to teach Chemistry and Science in an undergraduate course. In the course, the students were asked to develop projects using the Netlogo software. One interesting study conducted by one group of students simulated the diffusion of AIDS. By doing this, the students were able to better understand the concepts and mechanisms of infectious disease, as well as the factors that contribute to its proliferation. As such, the software promotes a dynamic learning process, in which the student is able to intervene and interact with the software, and to construct knowledge by him/herself.

The use of cellular automata and agent based modeling for teaching is also thorough abroad. A research project at Stanford University, for instance, promotes the use of computational models to link physical and virtual experiments in Science classes (Blikstein, 2012). In contrast to Brazil, agent-based models have been more directly applied to analyze educational policy abroad. Maroulis, Bakshy, Gomes and Wilensky (2010) simulate an agent-based model in order to investigate the impact of choice-based reforms in Chicago public schools (see previous chapter), while Millington, Butler and Hamnett (2014) use an agent-based model to analyze the impact of distance-based school-place allocation policies in the United Kingdom. Similar kinds of study have not been found in the country.

8. For more information on methods and methodologies of complex systems, see chapter 3.

9. The use of games in education can also be considered a simulation based approach and is gaining popularity in Brazil (Borges et al., 2013).

3.2 System dynamics

As OECD (2009, p. 10) puts it,

> Dynamical systems models are generally sets of differential equations or iterative discrete equations, used to describe the behavior of interacting parts in a complex system, often including positive and negative feedback loops. They are used to enable simulation of, among other things, the results of alternative system interventions (for example, which incentives are most likely to yield adoption of alternative energies by consumers and power companies). They have also been used to anticipate unintended consequences of policies (for example, the impact of increased availability of health insurance on decreases in preventive health behaviors).

Only one application of System Dynamics to educational policy was found in Brazil. Concerned about a possible failure of reaching the enrollment goal established in the National Education Plan (NEP),[10] Strauss and Borenstein (2014) applied the dynamic systems methodology to better analyze and understand the dynamics of the higher educational system in Brazil. They developed a model that allowed them to simulate the behavior of many variables, such as government regulation, demand and supply, and the private and public sector, in order to analyze the effects of different policies. The scenario analysis enabled a better understanding of the dynamic behavior of the higher educational system in Brazil, giving support to the development of effective strategies and the improvement of educational policies.

One similar example abroad is the work by Murthy et al. (2010) who use a system dynamics simulation model to analyze and plan future investments of a distance education program at a leading engineering institute in India. Other related papers (Al Hallak et al., 2009; Dahlan et al., 2010; Rodrigues et al., 2012) use the system dynamics approach as decision support systems for higher education management.

3.3 Network analysis

Different examples of network analysis applied to education were found in Brazil. Mesquita et al. (2008) apply the methodology of network analysis to investigate the organization and potential action of a group of teachers, technicians, coordinators and schools directors from the municipal schools of the city of Fortaleza, who have as common goal the socio-educational inclusion of individuals with special needs. By identifying each actor's role, the size and density of the network, and the key actors that sustain and may expand the network, the analysis supports the construction of effective actions that can foster a better functioning of the group. This involves stimulating the sharing of information and experiences in order to promote the inclusion of individuals with special needs.

10. The PNE (2011/2020) establishes the goal of increasing the liquid enrollment rate of higher education to 33% of the population between 18-24 years-old (Ministério da Educação, 2011).

Aquino Guimarães et al. (2009) apply network analysis in order to examine the network of graduate programs in management in Brazil. Given the lack of academic research tradition in the area, the authors consider that articulation among the graduate programs would increase national publications in management and consolidate this scientific field in the country. That is, a strong and dense network, regarding the diversity of grounded edges and the number of actors (programs) involved respectively, tend to promote an increase in the amount and quality of scientific production.

Therefore, a better understanding of the graduate programs' network allows that each program identifies its role in the network and its potential contributions for the strengthening and expansion of the network. Besides, it contributes to the formulation of more adequate public policies, by providing important information to the development of graduate programs in the country (Aquino Guimarães et al., 2009).The study shows that the network of graduate programs in management in Brazil is weak and diffuse, what indicates that there are few partnerships and shared activities among the programs. Besides, the nature of the institution, whether public or private, seems not to be an important factor for the constitution of the network. By the study, Aquino Guimarães et al. (2009) argue that institutional policies that may foster the practice of joint researches and the exchange of professors and students should be taken into account as a way to increase cooperation and the strength of the graduate programs' network.

A similar study investigates the network of research institutes of public and social management in Brazil (Rossoni et al., 2008). The analysis demonstrates a diffuse network, in which the stronger links lie between institutions within the same state. Besides, the structure of the network is related to the scientific production index of each research institution. In the same line, Silva et al. (2006) use the network analysis method to examine the co-authorship network of professors in the postgraduate program of information science.

Another interesting application examines interactive systems and Learning Objects (LOs) in the teaching and learning process. Rossi et al. (2013) use the network analysis method to evaluate learning from the use of a game that exercises mathematical operations with fractions. The method allowed the authors to analyze students' participation in the game and their performance, and to identify learning deficiencies within a group of students.

Further studies using network analysis could encompass the use of contagion and opinion formation[11] models to analyze how education propagates in society.[12]

11. See chapter 7 on the complex nature of social systems.

12. For a more general overview of the use of network analysis on educational research, see Daly (2010) and Carolan (2013).

3.4 Intelligent tutoring systems

Intelligent tutoring systems are linked to the application of artificial intelligence to education and can be described as "computer software designed to simulate a human tutor's behavior and guidance" (Educause, 2013, p. 1).[13] Intelligent tutoring systems differ from other computer-aided instruction, in that they are able to interpret complex student responses and they learn as they operate. This means these systems do not merely check whether an answer is right or wrong, but identify where in that response the student has gone wrong. Also, they can adjust their knowledge base using data generated by students using the system, and alter their tutoring behavior in real time to be more effective (Educause, 2013). Massive online courses (MOOCS), such as Coursera and Edx are examples of computer-aided instruction, as they do not adapt according to student's behavior. They consist mostly of pre-recorded videos and exercises whose content does not change based on how students respond. They do have the potential to turn into intelligent tutoring systems though.

The best example for intelligent tutoring systems in Brazil is arguably "geekie".[14] Geekie is an intelligent tutoring system developed in the country, which offers computer-aided tutoring for students connected to the internet. In 2014, Geekie partnered with the Secretariat of Education of different states in Brazil to offer its intelligent tutoring system for free for students to prepare for ENEM (Exame Nacional do Ensino Médio), a national exam taken by students to enter university. When the student first logs into the system, he or she takes a diagnosis test, based on which the system identifies the student's difficulties and proficiency level in different content areas and builds a personalized study plan. The students' progress reports are sent to teachers and managers, so that they can adapt their lesson plan accordingly. In its website, Geekie states that the system has had an impact on 13 thousand public schools and over 2 million students.

Research on intelligent tutoring systems is plentiful in Brazil and tends to be concentrated in Computer Science Departments. The Brazilian Symposium and the Brazilian Congress on Informatics in Education (SBIE and CBIE), for instance, bring together much of the research in the area. Bittencourt et al. (2009) and Brusilovsky and Peylo (2003), for example, build adaptive learning platforms, which use data from the student to provide a customized learning experience.

Müller and Silveira (2013) use a recommendation technique – analogous to the ones employed to suggest products to consumers – in order to suggest users in a system that might help others in solving a particular problem. In other words, the system uses social matching to support the formation of pairs. The system

13. More information on intelligent tutoring systems can be found in Koedinger et al. (2013).
14. Available at: <www.geekie.com.br>.

is aimed at teachers that might be having difficulties using a computer-teaching platform. When a teacher has a doubt, the system helps finding a person with a similar system configuration and skill level to help solve the first teachers' question.

3.5 Learning analytics and educational data mining

All these intelligent tutoring systems, MOOCs, and other educational technologies are producing vast amounts of data, that can help understand how students learn and, by doing this, enable more intelligent, interactive, engaging and effective education (Koedinger et al., 2013).

Data mining and analytics refer to "methodologies that extract useful and actionable information from large datasets", such as the aforementioned ones. When these methodologies are applied to education, they are referred to as educational data mining and learning analytics (Baker and Siemens, 2014).[15]

Baker and Siemens (2014)[16] categorize the key methodologies in the field in five main groups: prediction methods, structure discovery, relationship mining, distillation of data for human judgment and discovery with models. The main models for prediction are classifiers, regressors and latent knowledge estimation. For example, by studying students' data, one can try to identify students with a higher risk of dropping out; and by analyzing students' answers, one can estimate latent knowledge. Structure discovery encompasses clustering, factor analysis, social network analysis, and domain structure discovery. In an exercise to which students answer in different ways, clustering techniques can help identifying a cluster of wrong answers and detecting concepts that are being misunderstood, so that videos can be sent to students to clarify such points. Relationship mining involves four main groups: association rule mining, correlation mining, sequential pattern mining, and causal data mining. Distillation of data for human judgment is related to visualization[17] strategies to present data to educators in a timely fashion, such as heat maps, learning curves and learnograms. Finally, discovery with models involves the use of a prediction model inside another prediction model, or within a relationship mining analysis, for example.

Big data in education seems to be the area which has advanced the most. In the world, Learning Analytics and Educational Data Mining have been used, for example, to study online courses, to support the development of more effective e-learning systems, and to explore how children "game the system" (Baker and Yacef, 2009; Kotsiantis, 2012; Siemens and Baker, 2012). Eye tracking data and

15. For more on the development of the two communities – Learning Analytics and Educational Data Mining – and their differences, see Siemens and Baker (2012) and Baker and Siemens (2014).

16. The paper provides detailed explanations and examples of applications of these methodologies.

17. The issue of visualization is discussed in more details in the following section.

movement sensors have been used to give insights into the very learning process taking place when a child is doing an assignment (Blikstein, 2011); and machine learning has been used to help predict when a student will drop-out or fail school (Bayer et al., 2012; Márquez-Vera et al., 2013).

In Brazil, though, such applications are scarcer, although still plentiful. Kampff (2009) tried to identify characteristics and behavior of students who had a higher risk of failing in a virtual learning environment. The system then alerted the teacher that the student might need some special attention and suggested what the teacher could do based on previous experiences. Pimentel and Omar (2006) used students' data to identify the relationship between cognitive and metacognitive skills, that is: does what we believe to know relate to what we actually know? Finally, Rigo et al. (2014) discuss improvements needed in the application of educational data mining, such as the implementation of interactive solutions, so that results can effectively support the detection of behavior linked to dropping out of school.

3.6 Visualization

Loads of data on education might be available, and powerful models might help simulate policy interventions and understand education mechanisms better. These efforts will have minor contributions though, if stakeholders cannot understand what all these data and models are saying. This is why the distillation of data for human judgment mentioned in the previous section is crucial.

As Rand (chapter 2) puts it, stakeholders and decision makers need to understand the analyses in order to make appropriate decisions. "In some cases, they do not have the complex systems *literacy* necessary to understand the results. Education (about complex systems) will help this, but so will increased efforts in visualization, since visualization can make results and models easier to understand."

Gentille also emphasizes the importance of visualization and interactivity: "Thought must be given to how simulation results are presented to stakeholders, minding their interests, salience and experience. Promote ad-hoc data exploration because it facilitates model verification, validation and knowledge discovery" (Gentile, 2014).

One of the most prominent examples in Brazil regarding visualization is the site Qedu.[18] Qedu is a free open-access portal, which presents information on school quality for the federal, state, municipal and school level. Basically, it brings together all data that are being generated by different learning assessments

18. Available at: <www.qedu.org.br>.

conducted in Brazil, and presents them in an easier and more manageable way for the ample public to understand.

The portal shows, for example, that only 12% of children in the last year of basic school in Brazil reached adequate learning in Maths in 2011. It also allows the user to see how this percentage varies per state. In Alagoas and Amapá, for instance, this percentage (3%) is the lowest in the country, while the states of Minas Gerais (22%) and Santa Catarina (17%) show the best results. When zooming in the state of Minas Gerais, though, the results per city are very heterogenous. In Gameleiras, in the North of the state, this percentage is 3%, while in Coronel Xavier Chaves, also in the North, this percentage is 85%. Besides, the site allows the user to see the result as far as the level of the school. This can be an important instrument for parents and the population in general to accompany the performance of students, to help them choose schools and demand from them, and to be an active agent who can try to influence the educational system.

4 DISCUSSION

This chapter provided an overview of the application of the complex systems' approach to education in Brazil. The first part explored the use of complexity concepts and views to think education in a theoretical sense, while the second focused on applications of methods and methodologies. This analysis brought up a couple of insights for teaching, learning and for educational policy in Brazil, which are discussed in this section.

First, teaching students and stakeholders complexity concepts might be relevant. As Rand (*Complex systems: concepts, literature, possibilities and limitations*, chapter 2 of this book) puts it, from a young age people tend to develop a deterministic and centralized mindset, that is, they expect systems to have deterministic rules that govern their behavior and that there is a central controller in most systems. However, most complex systems show the opposite. Therefore, exposing students to complexity concepts might help counteract this tendency.

Also, complex systems methods can be considered relatively new in educational research in Brazil. Researchers with a thorough knowledge of the theme are relatively scarce and there is less tradition of quantitative or computationally intensive approaches in education research. Actually, most of the applications tend to come from computer science rather than education departments. Teaching educators complex systems concepts and familiarizing stakeholders with its terms and methodologies might thus be an important step towards improving educational research, which can bring important insights to educational policy.

Second, promoting a transdiscilipinary curriculum at the student level and conducting interdisciplinary analysis at the policy-research level might be crucial to promote effective learning and to tackle the complex nature of educational systems.

As Carter and Reardon (2014, p. 16, our griffon) comment on educational inequality:

> *The multidimensional problems of inequality require multidimensional solutions*, perhaps developed through innovative, interdisciplinary collaborations between seasoned researchers and the next generation of researchers. As we move forward, tackling inequality through research, policy, and practice mandates *an ecological approach that attends to the multiple, interlocking domains of inequality.* Mixed-method research projects, in particular, may be necessary to produce both generalizable findings and deeper insight into the subtle, often invisible social mechanisms that shape individuals' lived experiences.

Third, it seems important to recognize and incorporate students' heterogeneity in educational practice and research. Given the high levels of inequality in Brazil, taking students' heterogeneity in account is critical.

Forth, computational modeling and simulation are powerful tools to teach complex concepts at the student level, and to analyze complex problems at the research and policy level. Models can help understand underlying mechanisms and be used as decision support tools.

Fifth, network analysis can be employed for promoting system's resilience, identifying key nodes, and promoting information flow. On the data side, data are precious resource to improve knowledge about learning and to validate and improve models. Visualization efforts are crucial though to promote information flow and learning within the educational system and the emergence of bottom-up solutions.

Finally, gearing education policy and practice towards personalized learning, that is "instruction that is tailored to learning needs, tailored to learning preferences, and tailored to the specific interests of different learners" (Pea et al., 2014, p. 13), might be an interesting path to follow. Personalized learning supports learning for all students and is argued to improve educational performance, to promote cost efficiencies through educational productivity and organizational optimization, and to accelerate educational innovation (Pea et al., 2014, p. 13).

This seems to make particular sense in Brazil, given the mentioned heterogeneity of students, that encompasses different aspects, such as socio-economic background and intrinsic individual characteristics. One aspect worth pointing out is the heterogeneity present within classes in Brazil, given the high school year distortion in the country. In 2011, 15% of students from the 1st to 5th grade (primary school) were two or more years behind the appropriate grade; 28% of students from the 6th to 9th grade (middle school); and 30% of students of high school (Qedu). This scenario results from both failing school years and dropping out.

A continuous progression policy was adopted in some states in Brazil to improve this situation. After evaluating the program, Menezes-Filho et al. (2008) state that

> findings point to a higher promotion rate and a lower dropout rate at the urban state schools that adopted the program. The school performance impact estimates point to a significant reduction in proficiency of 8th grade secondary education students, whereas the impact for 4th grade students was not significant (Menezes-Filho et al., 2008).

This suggests that the continuous progression policy might be important towards promoting attendance and avoiding dropout, but that it is insufficient. In this sense, personalized learning could be complementary towards learning and proficiency, by incorporating students' heterogeneity; and by being scalable if implemented by means of intelligent tutoring systems.

Acemoglu et al. (2014) argue that "web-based education will have broadly equalizing effects. Not only will human capital around the globe be enhanced,[19] but human capital inequalities may also decrease." We think that personalized learning is a good opportunity to help develop human capital and diminish educational inequalities in Brazil. At the same time, it is important to point out that it is also a risk. If we do not keep up with the new developments in education and do not work on the infrastructure issued for this view to develop for the population at large, these advances could have the very opposite effect.

Finally, it is important to highlight that the aforementioned insights are possible paths derived from the complex systems' approach to education. Further investigation is warranted to confirm the validity of these aspects.

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19. For the impact of the internet on the concentration of economic activity, see Forma et al. (2014) and Sakowski (2014). Forma et al. (2014) argue that "The rate of patent growth was faster among countries who were not leaders in patenting in the early 1990s but were leaders in internet adoption by 2000, suggesting that the internet helped stem the trend towards more geographic concentration" and that "(…) the internet could act as a broad force for weakening the links between the geography of inventive activity and spatial patterns of downstream use of it."

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CHAPTER 16

OVERCOMING CHAOS: LEGISLATURES AS COMPLEX ADAPTIVE SYSTEMS

Acir Almeida[1]

1 INTRODUCTION

This chapter argues that legislatures are complex adaptive systems and briefly assesses the potential contribution from the complexity approach for the analysis of the evolution of legislative institutions, understood here as a system of formal and informal law-making rules. It also shows how this approach sheds light on the evolution of law-making patterns in post-1988 Brazil, at the national level.

The complexity approach mobilizes concepts, theories and methodologies from many different scientific fields for the study of processes and patterns from *complex adaptive systems*. A system is considered complex if it is composed of a large collection of diverse, interdependent agents, not subject to centralized control. One crucial property of a complex system is that the results that emerge from the interactions amongst its agents cannot be understood by simply "adding up" the behaviors of its individual parts. A complex system is adaptive if it is continually self-organizing in response to the results it generates and to changes in its environment (Eidelson, 1997; Holland, 1992).

A democratically elected legislature is a complex adaptive system. It is composed of many heterogeneous agents who, in principle, are not subject to centralized control. These agents have individual goals, but cannot achieve them by acting in isolation from one another – given the collective nature of legislative decisions, every one of them needs the cooperation from at least a certain number of others. However, since legislative resources (e.g., plenary time) are limited, not all goals can be realized in a timely fashion. Hence, the complex nature of legislatures lies on the strategic interactions legislators need to engage in with each other to advance their goals.

Three collective problems are especially relevant for law-making purposes: the rational use of legislative rights; the acquisition and dissemination of information about the expected impacts of alternative policies; and the stability of collective

1. Institute for Applied Economic Research (Ipea). E-mail: <acir.almeida@ipea.gov.br>.

decisions. If not properly dealt with, these problems may lead, respectively, to legislative paralysis, policies with highly uncertain consequences, and unstable collective decisions. In their worst form, these features may render the legislature ineffective as a law-making body or, more generally, dysfunctional as a system.

Legislators solve these collective problems by regulating the exercise of their legislative rights. In other words, they adopt *legislative institutions*, here defined as: a collection of rules and procedures defining who can do what, when, and how in regards to law-making; that are recognized and shared by all individuals from the relevant population; and, finally, that are relatively resilient to the idiosyncratic preferences of these individuals (March and Olsen, 2006, p. 3-4; North, 1990, p. 3-6).

Most frequently, legislative institutions have a formal nature – i.e., they assume the form of rules that are openly written in official documents and are enforced through official channels. But this is not always the case: norms and conventions are also important determinants of the functioning of many democratic decision-making systems. Equally important is that informal institutions may very well shape how formal institutions work (Helmke and Levitsky, 2006). Another important feature of legislative institutions is that they often have distributive effects – they serve the interests of some groups at the expense of the interests of others (Knight, 1992, chap. 2). As result, underlying legislative institutions there is a constant conflict between forces of change, on one side, and of preservation, on the other. And the result of such conflict may manifest itself on the formal or informal elements of the institutions, or even on how they interact with each other.

We know a great deal about the efficiency-enhancing and stability-inducing properties of different legislative institutions. However, much less is known about their dynamics. How do these institutions evolve? What are the forces that promote or hinder institutional adaptation? How is this process of adaptation influenced by the broader political environment? We believe the complexity approach offers a potentially useful conceptual toolbox to understand this dynamic process.

The remaining of this chapter has the following structure. The second section explains the complex nature of legislatures by analyzing the main collective action and social choice dilemmas legislators face, and also explains why these problems may turn the legislature into a dysfunctional system if they are not properly dealt with. The third section describes the two main organizational models that the literature identifies as institutional solutions to those collective and social choice problems. The forth section addresses the question of the evolution of legislative institutions, pointing both to the limitations of traditional approaches in explaining the emergence and change of institutions and to recent developments towards a complexity-oriented approach. The fifth section briefly indicates possible applications of this approach to the analysis of the evolution of legislative institutions in post-1988 Brazil. The sixth section closes the chapter with a brief summary.

2 LEGISLATIVE CHAOS

For the sake of argument, it is fruitful to begin by imagining a legislature in its "state of nature". This is the situation in which "all business is conducted in the plenary session (no committees) and members' ability to talk and make motions is largely unrestricted and unregulated" (Cox, 2006, p. 141). Therefore, for any bill to become law in a state-of-nature legislature it needs to go through one (and only one) simple process: it must be formally proposed, discussed and then voted upon in the plenary session, where it must gather the support from a majority.

In this hypothetical state, the use of plenary time becomes a collective dilemma – i.e., a conflict between group goals and individual self-interest. Since there is only so much that can be done in any plenary session, the number of relevant policy decisions per session depends on how efficiently the plenary time is used. Absent any restriction on the use of legislative rights, every legislator is likely, on the one hand, to present to the plenary as many bills as sees fit and, on the other hand, to make as much use as she can of plenary time in order to block or delay any bill she does not agree with. Each member thus realizes that her optimum bargaining strategy is to block any other bill unless her bills are approved. The most likely result under these conditions is legislative paralysis (Cox, 2006, p. 143).

Even if legislators manage to collectively use plenary time rationally, there is still a second collective dilemma faced by a state-of-nature legislature, namely, the acquisition and dissemination of relevant information about the consequences of alternative policies (Krehbiel, 1991). Modern legislatures must make several complex policy choices concerning many different policy areas, but most legislators have scarce if any information about the consequences of those policies. Poorly informed decisions have higher risk of generating results quite different from the ones intended, and this represents a loss of utility for all interested parties. However, given that the acquisition of information requires time and effort, individual legislators have strong incentives to free ride on the knowledge of others. Moreover, the unequal distribution of private information raises the additional problem of opportunism, with more informed legislators trying to influence the choices of less informed ones by withholding relevant information. Thus, in the legislative state of nature policy decisions are likely to be made under condition of high uncertainty, leading to policies with poorly predictable outcomes.

Now, suppose those two collective problems are solved, such that legislators are able to make well informed decisions in a timely fashion. Even under these conditions, they may not be able to come to a coherent collective choice amongst the bill, some amended version of it, and the status quo. The reason is that majority rule decision may fail to yield a choice option that is majority-preferred to every other available option (Black, 1948). This result, called "majority cycling", was later encompassed by Arrow's famous General Impossibility Theorem, which states that no collective choice rule exists satisfying a set of reasonable conditions, and that the particular condition violated by the method of majority rule is the transitivity of collective preference (Arrow, 1963).[2] Moreover, it has also been demonstrated that it is possible in multidimensional choice settings to find a sequence of pair-wise majority votes that leads to the collective choice of virtually any available option (McKelvey, 1976). These results imply that majority-rule decisions are inherently unstable and that virtually anyone of the choice options may obtain. For these reasons, majority decisions are said to be inherently chaotic.[3]

In principle, legislators could benefit from spontaneous cooperation, by engaging in logrolling – i.e., deals of the form "I'll vote later for your bill if you vote now for mine" (Tullock, 1981). By voting in favor of issues they care less in exchange for votes on issues they care more, legislators might be able to enact legislation and reduce the risk of cycles. The problem is that legislative bargains are fragile in terms of durability and enforceability – nothing precludes legislators from reneging on present deals by joining a different coalition in the future (Weingast and Marshall, 1988).

Majority decisions are not subject to cycles when the choice options can be aligned along a single policy dimension and voter preferences are single-peaked, such that, for every voter, any option closer to the one regarded as ideal is preferred to more distant ones. When these conditions obtain, majority rule yields an equilibrium outcome, the option closest to the voter whose ideal policy occupies the median position on the relevant dimension (Black, 1948). Nevertheless, if the choice involves more than one policy dimension – which is often the case –, majority rule equilibrium only obtains under very stringent assumptions about the locations of voters' preferences (Plott, 1967).

These collective and social choice dilemmas reflect the complex nature of legislatures. The three problems associated with the dilemmas (paralysis, uncertainty, and cycling) imply that policy-making in a state of nature legislature – i.e., when there are no restrictions on the use of individual legislative rights – is expected to be ineffective and virtually chaotic: important, controversial policies should only

2. A preference order is transitive if, for any three alternatives A, B, and C, the conditions $A \geq B$ and $B \geq C$ imply $A \geq C$, where "$\geq$" means "is preferred as much as". For collective preferences, transitivity may not hold, as in the case of three individuals (I1, I2, and I3) with preference profiles I1: $A \geq B \geq C$, I2: $B \geq C \geq A$, and I3: $C \geq A \geq B$, which lead to the following (intransitive) majority preference: $A \geq B \geq C \geq A$.

3. The term "chaotic" is used here in the social choice tradition, referring to the unpredictability and instability of majority voting when the policy space is multidimensional. Not to be confused with the property of having a trajectory very sensitive to small perturbations in initial conditions.

rarely come to a vote; whenever they did, legislators would make poorly informed choices; and such choices should be quite unstable and difficult to predict.

Real-life legislatures, however, rarely are ineffective or chaotic. This contradiction between theory and practice spurred scholars to investigate which aspects of legislatures solve collective dilemmas and induce decision-making stability. What they found is that the answer lies in the set of institutional arrangements that invariably underpin the operation of majority rule (Shepsle and Weingast, 1994). Such arrangements, which are self-imposed by legislators, solve those collective problems by constraining the use of legislative rights. They generate order and effectiveness in an otherwise chaotic collective body. The next section briefly describes two ideal type configurations of these institutional arrangements.

3 TWO MODELS OF LEGISLATIVE ORGANIZATION

A common feature of real-life legislatures is that, on the one hand, legislators have equal voting rights but, on the other, they have unequal agenda-setting rights. "Agenda-setting" refers to the control over the flow of bills to the plenary and the procedures under which they are considered in this arena. They include, for example, rights to propose legislation, to expedite, to block or to delay the vote on bills, and to determine the terms of the debate and the nature of legislative amendments.

The distribution of agenda-setting rights is tightly associated with how legislatures organize their business. There are two ideal type models of legislative organization, defined according to the degree of concentration of those rights: the committee model, in which agenda-setting powers are dispersed across autonomous legislative committees, each with the monopoly over some set of policy areas; and the cartel party model, in which those powers are concentrated in the hands of the majority party leadership.

3.1 The committee model

The committee model has the following characteristics: *i*) there are a number of standing committees, each with exclusive jurisdiction over one or a few policy areas; *ii*) legislators self-select themselves into the committees whose jurisdictions they care most about; *iii*) committees have the exclusive right to propose legislation in their jurisdictions; and *iv*) only amendments relevant to the bill under consideration are allowed in the plenary.

In this stylized model, the legislative process has the following sequence: *i*) once a bill is proposed, it is sent to the committee which has jurisdiction over its issue; *ii*) the committee decides by majority rule whether or not to send the bill (or a modified version of it) to the plenary; *iii*) if it does, the plenary then votes on the bill and the amendments eventually offered to it. Note that, if a bill contains more than one policy issue, each issue is considered separately in the committee with jurisdiction over it.

By means of the committee system, legislators are able to avoid decision-making paralysis and instability (Shepsle, 1979). As discussed above, vote trading is not a solution for legislative paralysis when there is no mechanism to prevent legislators from reneging on their promises. The committee model functions as such mechanism: given the committee's monopoly over the agenda within its jurisdiction, it has the power to veto any bill that is contrary to its interests, thus making reneging on legislative deals ineffective. Moreover, since different policy issues are assigned to different committees on a one-to-one basis and only germane amendments are allowed, majority decisions are always restricted to a one-dimensional choice space, a situation for which (assuming single-peaked preferences) we know there is one equilibrium solution: the median preference on the dimension.

Another relevant aspect of the committee model is its role in motivating the endogenous production and dissemination of relevant information about the relation between policies and their results (Krehbiel, 1991). Since legislators self-select themselves into committees, these are supposedly composed of legislators with a high interest on their respective issues, with more motivation to incur the costs of becoming better informed. However, for this motivation to be effective, legislative majorities need to avoid tampering with committee bills in the plenary. For this purpose, majorities impose restrictions on themselves, which may apply to their rights of amendment or to call a vote on bills already approved in committee. The committee's agenda power and the restrictive procedures under which its bills are deliberated in plenary induce the committee to produce and disseminate information.

3.2 The cartel party model

In the cartel party model, control of the legislative agenda is concentrated in the hands of the leadership of the majority party or coalition, and it is exercised through the appointment of loyal delegates to offices with agenda-setting powers, like the chairmanships of the legislature and the committees. Through this cartelization of agenda-setting offices, the majority party pushes its own initiatives onto deliberation and blocks bills and motions that it opposes from ever coming to a plenary vote (Cox and McCubbins, 1993).

The effectiveness of the cartel party model, however, depends on the party leadership having the means to prevent opportunism amongst its ranks, by keeping its delegates and the rank-and-file in line, behaving according to the party's collective interests. For this reason, party members usually entrust their leaders with punishment mechanisms, like the power to expel members from legislative caucuses, to deny them re-nomination to the party electoral list, or to deny them future office opportunities.

The cartel party model prevents legislative paralysis both because it deprives minorities from the means to block or delay bills and because the propositions that come to the plenary are those for which the members of the majority party have previously agreed upon. Independently of how agenda power is distributed, the model also avoids decision-making instability, since only the preference of the majority party is decisive, as long as its members vote together, as a unified block. In addition, since the party benefits electorally from the reputation of producing "good policies" (at least in the limited sense of accomplishing the intended results), party leaders have incentives to stimulate the acquisition and dissemination of relevant information within the party's ranks.

Either the committee model or the cartel party model can, in principle, solve the collective problems faced by legislators. These models can be thought of as the two extremes of a hypothetical continuum, from the most decentralized to the most centralized form of legislative organization, respectively. Actually, only a handful of cases seem to fit well these two ideal types. One classical example of committee model is the United States' lower chamber, the House of Representatives, before the 1970s. The British House of Commons has always been an exemplary case of the cartel party model. Most modern democratic legislatures, however, fall somewhere in between these two extremes (Mattson and Strom, 1995).

4 EMERGENCE AND CHANGE OF LEGISLATIVE INSTITUTIONS

If legislatures are complex *adaptive* systems, then we should take seriously the question of how legislative institutions evolve. This requires understanding legislative change as a dynamic and endogenous process. However, even though we know a great deal about how different organizational models solve the collective problems legislators face, much less in known about how the institutions that characterize these models emerge and change. In what follows, I briefly discuss the existing literature about the evolution of legislative organization and the potential contributions from the complexity approach.

4.1 Rational choice institutionalism

The conventional approach in analyses of the evolution of legislative institutions is rational choice institutionalism (RCI). This is a micro-level perspective that emphasizes individual forethought, calculation, and rational purpose. From this view, institutions are equilibrium solutions to collective problems, which emerge and change as a result of individuals' goal-oriented choices. Over time, institutions may generate a host of unforeseen consequences that, in turn, may motivate individuals to make further institutional changes.

There are three competing rational choice theories about legislative organization, each giving emphasis to different actors or goals. The *distributive* and the *informational* theories offer alternative explanations for the emergence of a strong committee system. According to the first, legislators empower committees in order to secure the production of particularistic policies for their constituencies (Shepsle, 1979; Weingast and Marshall, 1988). Assuming that legislators' main motivation is to get reelected and that for achieving this goal they need to advance the interests of some minority of constituents, the distributive theory postulates that each legislator will try to form a winning coalition, which requires exchange and cooperation. As discussed above, a system of heterogeneous committees that, nonetheless, are internally homogeneous (in terms of the issues that mostly interest their members), coupled with a strong agenda-setting power over the bills under their specific jurisdictions, enables the formation of durable logrolling coalitions. Therefore, from the distributive theory, we should thus expect the committee system to be strong and autonomous when legislators have more particularistic or heterogeneous policy preferences.

The informational theory argues that legislators create strong committee system to enable them to make informed public policy choices (Krehbiel, 1991). It assumes that legislators' main concern is with the uncertain consequences of their policy decisions and, as previously discussed, it considers the reduction of legislative uncertainty the main collective action problem. By delegating agenda powers to committees, the plenary motivates their members both to acquire expert knowledge about particular policy areas and to disseminate it to the legislature as a whole. So, if policy uncertainty is high, such as in periods of rapid social and economic change, committees tend to be granted more power.

The distributive and the informational theories assume that parties are irrelevant for the explanation of legislative organization. Alternatively, the *cartel party* theory postulates that a majority party or coalition is the organizing force and that it designs legislative institutions in order to achieve its collective policy goals (Cox and McCubbins, 1993). The key assumption of this theory is that legislators' electoral fortunes strongly depend on their parties' reputation amongst voters. Therefore, the main collective problem faced by legislators is to build and preserve a (good) policy-related reputation for their parties. Thus, party members delegate legislative powers to party leaders, especially control over nomination to the offices that dictate the legislative agenda, enabling the latter to enforce intra-party cooperation. The committee chairmanship is one of such offices. In fact, the cartel party theory does not require committees to be weak – only that they not be autonomous. Strong committees may be a means for parties to maintain control over legislative decisions.

Thus, according to these theories, it is more likely that the organization of a legislature is closer to the committee model when: *i*) legislators' policy preferences are more particularistic; or *ii*) they do not form clear partisan clusters and policy uncertainty is high. On the other hand, legislative organization is more likely to be closer to the cartel party model when legislators' preferences are more universalistic and form clear partisan clusters.

The *conditional party government* theory articulates these conditions into an account of how legislative organization changes over time (Aldrich, 1994; Rohde, 1991). It assumes that legislatures are organized by parties into committees, and it argues that they alternate between periods of party government and periods of committee government, depending on the degree of intra-party cohesion and party divergence. When there is a majority party or coalition and an opposition whose members' preferences form two distinct clusters – i.e., there is high within-group homogeneity and high between-group heterogeneity – the incentives for majority members to delegate to their party leader are stronger and, therefore, the conditions for party government are optimal. In this case, members of the majority party are willing to grant more agenda-setting power to their leadership. On the other hand, to the extent that the preferences of majority and minority party members overlap, there are fewer incentives to centralize power in the hands of the party leadership and, therefore, conditions are more favorable for committee government.

All these theories share the view that legislative institutions are static equilibrium solutions to collective problems. There are at least three limitations from this perspective in what concerns the question of institutional evolution. The first is that the view of institutions as *solutions* to certain problems has a functionalist nature – i.e., it tends to assume that the institutions' (expected) benefits are crucial for their adoption and persistence, ignoring the possibility that these benefits may be unintended consequences. Besides, the notion of "solution" is hard to reconcile with the possibility that legislators may be locked in inefficient equilibria, which may eventually make the legislature decay into a dysfunctional system (Pierson, 2000).

The second is that the *equilibrium* view does not require understanding the processes that lead to particular equilibria or that may disturb the equilibrium once achieved. This makes the process of institutional change of relatively minor interest for rational choice institutionalists and, consequently, inhibits theoretical progress on the subject.

The third limitation is that the *static* view cannot accommodate endogenous change. Change, therefore, can only be motivated by factors exogenous to the institutions under study. In this regard, the conditional party government theory is based only on changes in the distribution of legislators' policy preferences, which is, itself, the product of electoral outcomes – by definition, a variable exogenous to the legislative process. These three limitations make RCI ill-equipped to tackle the question of institutional evolution.[4]

4.2 Historical institutionalism

In political science, "historical institutionalism" (HI) is the one approach that has had the most success in exploring institutional change (Pierson, 2000; Steinmo *et al.*, 1992; Thelen, 1999). It is a macro-level perspective that stresses the extent to which institutions evolve in ways unplanned and undirected by the people composing them. It is not that human action is irrelevant for institutional development – it is simply that the process is not explicitly controlled by individuals. Instead of viewing institutions as static equilibrium solutions, HI sees them as the dynamic legacy of concrete historical processes.

In fact, HI scholars see political and social phenomena through the same lens of complexity scholars. In the words of Lewis and Steinmo (2010, p. 243):

> historical institutionalists are like the environmental biologist who believes that to understand the specific fate of a particular organism or behavior, one must explicitly examine that organism or behavior in the ecology or context in which it lives. This implies a different scientific ontology than that commonly found in the hard sciences of physics and chemistry. While objects in the physical world often adhere to constant "laws" of nature, biological organisms often defy attempts to reduce them to their essential components because of their complexity. Historical institutionalism is rooted in a similar ontological shift in social science (Lewis and Steinmo, 2010, p. 243).

HI makes use of concepts like "path-dependence" and "punctuated equilibrium," that convey the ideas, respectively, that future developments are conditioned by past trajectories and that long periods of small, incremental change may be interrupted by brief periods of radical, discontinuous change. Related to path-dependence, there are also the concepts of "critical juncture" and "feedback." The first expresses a defining moment in the evolution of an institution, in the sense that it constitutes the starting point for a path-dependent process. The second concept expresses a phenomenon whereby each successive step along a particular path produces consequences that help either to sustain (positive feedback) or to undermine (negative feedback) that path.

Most applications of this approach, however, are directed to the explanation of the persistence of macro institutional arrangements, often over very long periods of time. In these applications, change tends to follow a punctuated equilibrium

4. As a matter of fact, the editors of a relatively recent book that applies rational choice theories to the political and institutional history of the U.S. Congress conclude that "legislative scholars [should] develop more dynamic theories that account for institutional and behavioral change" (Brady and McCubbins, 2002, p. 472).

model, in which there are brief moments of human agency and choice, when one set of institutions is replaced by another. Such model thus suggests that institutional arrangements either persist or break down. For this reason, applications of HI tend to obscure endogenous sources and mechanisms of persistence and change. Not surprisingly, this approach has been criticized for not properly specifying the links between micro-behavior and sources of institutional change.

There have been some efforts to put together the insights from RCI and HI in order to better articulate the micro-foundations of institutional change. An important contribution is Greif and Laitin (2004). They offer a rational choice theory of endogenous institutional change that builds on ideas from HI, particularly the notion of feedback effects. Their main innovation is to redefine exogenous parameters as endogenous variables (called "quasi-parameters"), which shift marginally by equilibrium behavior in a way that allows either for (endogenous) institutional change or persistence. However, it is not clear how these endogenous forces can be identified *ex ante*.

The recognition that institutional change is not only the product of exogenous shocks, but that it is also embedded in the ways in which agents interact with one another and their environment, implies making a serious effort in understanding endogenous processes of institutional evolution.

4.3 Towards an evolutionary institutionalism?

If we want to take institutional evolution seriously, a promising starting point is the conceptual toolbox from evolutionary theory. Indeed, recent developments in the institutionalist literature have been in the direction of evolutionary theory, motivated particularly by the ideia that, instead of focusing exclusively on either macro-structure or micro-behavior, we should focus on the interactions between these two levels to understand how institutions evolve. Some political scientists make the case that the shortcomings from HI may be successfully addressed by making full use of the conceptual tools from evolutionary theory (Blyth *et al.*, 2011; Lewis and Steinmo, 2010; 2012; Lustick, 2011).

Basically, an evolutionary theory has two pillars: a mechanism of transmittable variation, that generates units with transmittable differences; and a mechanism of selection, that determines the relative success with which these differences propagate. An evolutionary explanation requires some specification about how variation occurs, so that objects with observable differences are produced through some process. It must also explain how selection occurs – i.e., how some principle operates to select certain variations and not others – and how variations that have been selected are reproduced.

How does this explanatory scheme translate to the case of institutional change? Variation refers to some agents occasionally acting differently from institutionalized expectations. Selection refers to the adoption of the same deviant behavior by other agents from the relevant population. If the agents that adopt the deviant behavior do better (on average) than the others, then this behavior is likely to propagate and lead to changes in expectations and, finally, to institutional change. But, if they do not do better, the deviant behavior is not likely to propagate and, therefore, the institution will remain stable.[5]

Mahoney and Thelen (2010) provide a theory of endogenous institutional change that is reasonably close to the evolutionary model. In their theory, both the political context (environment) and the institution shape the type of relevant agent that emerges in any specific institutional context, and the kind of strategy (deviant action) this agent is likely to pursue to produce change. The relevant aspect of the political context is the strength of veto possibilities for defenders of the institutional status quo, whereas the relevant aspect of the institution is the level of discretion in its interpretation and enforcement. Different combinations of strong/weak veto possibilities and low/high discretion give rise to different types of change agents and possible modes of institutional change. The four modes specified by the authors are: displacement of the previous rules by new ones; the attachment of new rules to existing ones (layering); the changed impact of existing rules (drift); and the changed enactment of existing rules (conversion).

In addition to providing an explicit account of an endogenous process of change, Mahoney and Thelen's model offers at least two other interesting insights for understanding the evolution of institutions. First, their model not only emphasizes the underlying conflicts between challengers and defenders of existing institutions, it also takes into account that "the success of various kinds of agents in effecting change typically depends crucially on the coalitions they are able to deliberately forge or that emerge unexpectedly in the course of distributional struggle" (Mahoney and Thelen, 2010, p. 29). This coalition-building process and the success in forging a pro-change majority may be thought as the selection process in evolutionary theory. The second interesting element from the model is that it acknowledges that some changes do not necessarily manifest themselves on the formal aspects of the rules – i.e., they may be informal too (the authors denominate this process "conversion").

Mahoney and Thelen's model seems very promising for the analysis of the evolution of legislative institutions. Actually, in his analysis of institutional innovation throughout the history of the U.S. Congress, Schickler (2001) identifies some

5. Note that an evolutionary theory does not require analogs to the mechanisms that are relevant for biological evolution. It also does not imply any idea of progress ahead at the evolutionary path. And, finally, it does not need to be functionalist.

patterns of institutional change that are consistent with the model. Specifically, he finds evidence that political entrepreneurs played an important role in aligning multiple interests behind important changes. This result is consistent with the idea of change agents building pro-change coalitions. He also finds that changes seeking to promote a single interest typically provoked a response from members that sought to protect competing interests. This result, for its part, is consistent with the assumption of distributive conflict. Another pattern consistent with the theory is that institutional change often involved superimposing new arrangements on top of preexisting structures intended to serve different purposes (layering).

But, the model does have one important analytical shortcoming: it does not specify how agents' preferences concerning institutional maintenance and change are formed. The authors simply define different types of actors based on whether or not they seek to preserve the institution and whether or not they abide by the institution. But they offer no clue about how these actions (and the underlying preferences) relate to the outcomes of the institution and environmental conditions. This severely limits the understanding of endogenous mechanisms of change.

To be sure, this is a problem that all current theories of institutional evolution share. Rational choice theories assume a constant and universal set of preferences. Although HI scholars are interested in explaining why preferences vary across time and space, they have little to offer in terms of an explanation of human motivations, beyond the general point that history shapes preferences. Notwithstanding, there is a growing optimism that evolutionary theory may provide significant contributions when it comes to explaining the formation of political preferences (Lewis and Steinmo, 2012).

Another potential contribution from evolutionary theory refers to the multilayered view of institutions that several scholars have adopted. Ostrom (2005), for example, distinguishes between "operational", "collective-choice", and "constitutional" rules, which govern, respectively, daily interactions, the choice of operational rules, and the choice of collective-choice rules. In order to analyze how rules are formed at one level, the higher levels rules are considered (temporarily) fixed. The process of institutional change thus unfolds somewhat like this: each individual calculates her expected costs and benefits from an institutional change, and if a minimum coalition necessary to affect change agrees to it, an institutional change can occur. What constitutes a "minimum coalition" is determined by the higher-level rules – for example, in a dictatorship the dictator alone might constitute a winning coalition; in a democracy, a majority would constitute a winning coalition. Therefore, institutional change depends both on the decision makers assessment of how the change is likely to affect them and on higher-level rules. This complex, multi-layered view of institutions is the kind of complex system to which evolution theory adds insight, as its tools were specifically designed to integrate levels of analysis by connecting individuals to populations.

In sum, evolutionary theory, which is the approach used to analyze the dynamics of complex systems, offers one potentially fruitful approach to the explanation of how legislative institutions emerge and change.

5 THE CASE OF LEGISLATIVE INSTITUTIONS IN POST-1988 BRAZIL

This section makes the point that national legislative institutions in post-1988 Brazil are undergoing a major structural change and then briefly explores how the insights from the complexity approach may be useful for understanding this transformation.

5.1 Characterizing the institutional change

The formal law-making rules adopted by the members of the Brazilian Congress in 1988-1989 and that consolidated the transition to the current democratic regime have some features that disperse and others that concentrate power. Power is dispersed in the sense that the committee system has a key role in the ordinary legislative process. With a few exceptions, every bill is supposed not only to be examined and discussed in standing committees, but also to be conclusively voted on.[6] The plenary can override the committee's decision, but it requires a majority to approve a petition for the bill to have a final floor vote. Moreover, committee seats and chairmanships must be allocated to parties proportionally to their legislative size, ensuring representation of the minority opposition on key committee posts.

However, the rules also concentrate extraordinary agenda-setting powers on the presidency of the Republic and the congressional party leadership. The president has the power to issue decrees with immediate force of law on relevant and urgent matters, which must be voted on in the plenary, after being analyzed by *ad hoc* committees.[7] The president also has the power to invoke urgency procedures for any government bill, implying that if Congress does not vote on it in 45 days it is precluded from deliberating on any other bill.[8] Party leaders, for their part, have the power to represent backbenchers on urgency petitions to discharge any bill from committee and bring it to an immediate vote on the floor, at any time.[9] These three agenda-setting devices can be used to bypass the committee system and

6. Article 58 of the 1988 Brazilian Constitution (CF/1988), Art. 24 of the Standing Orders of the Chamber of Deputies (RICD), and Art. 91 of the Standing Orders of the Federal Senate (RISF).

7. Art. 62 of the CF/1988, and Resolution 1-1989 of the Brazilian Congress.

8. Art. 64 of the CF/1988.

9. Art. 155 of the RICD and Art. 336 of the RISF.

thus to appeal directly to the plenary floor, determining on what issues Congress must decide and when.

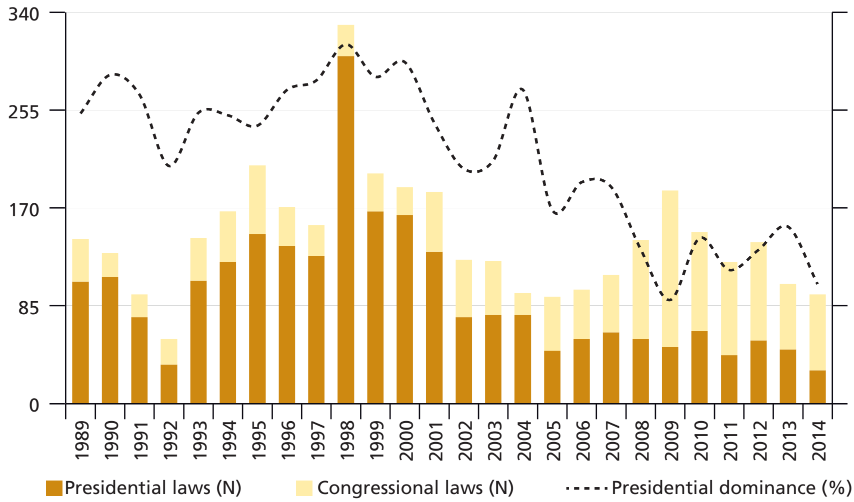
In the first fifteen years after the adoption of the formal rules, decree and the congressional urgency procedure were used intensely to advance the executive's agenda, leading to strong presidential dominance in law-making and a subordinate, if not minor, role to congressional committees (Figueiredo and Limongi, 2007; Pereira and Mueller, 2004). From 1989 through 2006, the president issued and Congress accepted an average of 6.9 non-budgetary decrees per month, comprising 72% of all non-budgetary presidential initiatives enacted into law by Congress.[10] Moreover, amongst the non-budgetary presidential bills that were enacted into law in the same period, 58% were approved in the Chamber under its urgency procedure. This led Congress to enacting into law a number of presidential initiatives three times lager than the ones proposed by its own members (most of them, by the way, were not even fully analyzed by the committee system).

For reasons that are not yet entirely clear, Congress seems to have delegated control of the legislative agenda over to the executive and this despite the fact that no president has had a single party majority. A necessary condition for this delegation to be successful seems to be the cooperation between the president and congressional party leaders, in the form of president-led majority coalitions (Figueiredo and Limongi, 2007). Interestingly, the only time when this cooperation did not function was under the administration of President Collor de Mello (1990-1992). This was also a time when the executive experienced its poorest legislative performance.

In the last decade or so, a rather radically different law-making pattern seems to be consolidating, even though the basic features of the formal institutional set-up have remained stable and presidents have consistently formed majority governing coalitions. First, presidential dominance has progressively given place to congressional dominance. Graph 1 depicts the annual counts of presidential and congressional non-budgetary laws (main vertical axis) and the rate of presidential dominance vis-à-vis Congress (secondary vertical axis), measured as the percentage of presidential initiatives amongst those laws. Beginning in the year 2002, there was a substantial decrease on the annual number of laws originated from the presidency and, beginning in 2008, the number of laws originated from Congress experienced a sharp increase. These two movements have made the legislative dominance of the president to fall from the annual average of 78% in the period 1989-2001, to 60% in 2002-2007, and finally to 37% in 2008-2014.

10. Data computed by the author, based on the following sources: Câmara dos Deputados (no date), Cebrap (no date), and Senado Federal (no date). The counts of presidential laws include the different versions of decrees that were continuously reissued for several months (Amorim Neto and Tafner, 2002, p.10).

GRAPH 1
Annual counts of non-budgetary laws initiated by the president and by Congress, and annual rate of presidential dominance (1989-2014)



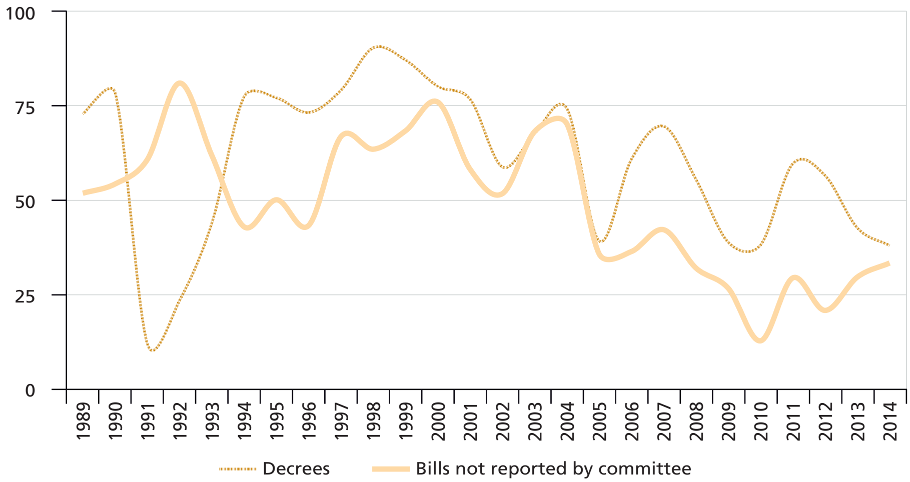
Source: Amorim Neto and Tafner (2002, p. 10); Câmara dos Deputados ([no date]); Senado Federal ([no date]).
Elaborated by the author.
Obs.: The counts of presidential laws include the different versions of decrees that were reissued.

The legislative process of non-budgetary presidential initiatives has also changed with a more active role for the committee system nowadays. As it can be observed in Graph 2, beginning in the early 2000s, there has been a moderate reduction in the percentage of presidential laws enacted by decree and a substantial reduction in the percentage of presidential bills (enacted into law) that were not reported by at least one of the committees to which they had been referred to in the Chamber of Deputies. The first of these percentages decreased from the annual average of 67% in 1989-2001, to 62% in 2002-2007, and then to 47% in 2008-2014. The second decreased from 60%, to 51%, and, finally, to 26%, respectively.

There is also evidence that the Chamber has been increasingly delegating the final decision over bills increasingly more to committees. Graph 3 shows the annual number of bills from the presidency and from Congress conclusively approved by the Chamber's committee system, as a percentage of the laws that in fact could be subjected to this process.[11] It is clear that legislation initiated by both the president and the members of Congress has been increasingly decided upon exclusively by committees. This pattern does not vanish with the exclusion of non-controversial honorific (mostly from Congress) and administrative (mostly from the presidency) legislation.

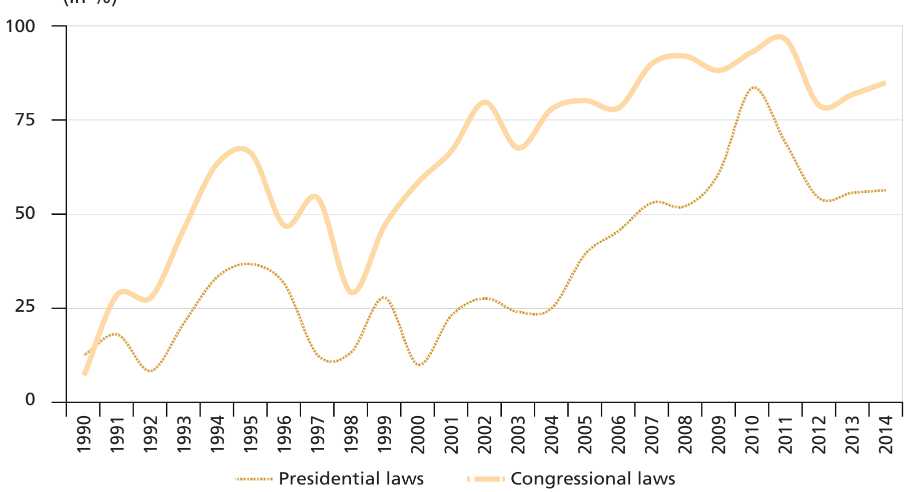
11. It excludes laws initiated by decree, budgetary laws and other much less frequent cases, as detailed in Art. 24 of the RICD.

GRAPH 2
Annual percentages of non-budgetary presidential laws that were enacted by decree and of non-budgetary presidential laws enacted by statute that were not fully reported by the Chamber's committee system (1989-2014)
(In %)



Source: Amorim Neto and Tafner (2002, p. 10); Câmara dos Deputados ([no date]); Centro Brasileiro de Análise e Planejamento (Cebrap, [no date.]); Senado Federal ([no date]).
Elaborated by the author.
Obs.: The counts of presidential laws include the different versions of decrees that were reissued.

GRAPH 3
Annual percentage of laws that were enacted conclusively by committee, by initiator (1990-2014)
(In %)



Source: Author's own elaboration based on Câmara dos Deputados (no date), Cebrap (no date), and Senado Federal (no date).
Elaborated by the author.
Obs.: Only laws originally proposed after 1989.

Admittedly, fine-grained data are still necessary, particularly about the new role played by congressional committees, it seems fair to conclude that law-making in the Brazilian Congress has gone through a major transformation, from an initially executive-dominated process, in which decisions were predominantly made on the plenary, with few opportunities for standing committees to perform their advisory role, to one in which Congress is more proactive and committees are prominent players. Although the formal institutional set-up has remained fairly stable, the set of rules and organized practices under which the "law-making game" is played have changed, thus making it appropriate to conceptually characterize that transformation as a case of institutional change.

As the following sections will try to show, there are several indications that the change in Brazilian legislative institutions has several traits that render it a promising case for the application of the complexity approach or, more specifically, the evolutionary view of institutional change.

5.2 A static perspective

In terms of the theoretical models discussed above, in section 3, one promising interpretation of the phenomenon is that law-making in the Brazilian Congress has become less like the cartel party model and more like the committee model. In other words, it is possible that the main agent towards whom control of the legislative agenda is delegated has shifted, from the president (the leader of the cartel) to committees.[12]

According to the conditional party government thesis (section 4.1), which is a theory of institutional change based on the RCI approach, the most likely reason for that shift is some (exogenous) change on the distribution of legislative preferences, one that implies higher divergence within the governing coalition or lower divergence between government supporters and oppositionists. In fact, there was one such change in Brazilian politics, coinciding with the appearance of the new law-making pattern. In 2003, after eight years under the control of the center-right Brazilian Social Democracy Party (PSDB), the presidency passed to the leftist Workers' Party (PT). For almost all its term, the PSDB headed a center-to-right majority coalition composed of three to four other parties. All governing coalitions formed since 2003 (and up to this date), however, were much more heterogeneous, including not only leftist but also center-right parties, with six to nine partners. Based on the records of voting behavior in the Chamber, there is strong evidence

12. On the application of the cartel thesis to the Brazilian political system it is important to have in mind two aspects: although no presidential party have controlled a majority of seats, majority governing coalitions are systematically formed under the leadership of presidents; and where a legislator stands relative to presidential policies seems to be the most informative signal about her policy preferences (Santos, 2003, cap. 2). For these reasons, for the members of the governing coalition the president is the functional equivalent of the party leader in the cartel thesis, in terms of the logic underlying the decision to delegate agenda-setting powers.

that the PSDB-led majority coalitions behaved as a legislative cartel until 2000, but there is no evidence that any majority coalition formed after 2000 behaved as such (Amorim Neto *et al.*, 2003, p. 563; Santos and Almeida, 2009, p. 98). Therefore, the change in the president-led majority coalition from relatively homogeneous to highly heterogeneous should explain the decentralization of agenda-setting powers from the presidency to congressional committees, as would predict the conditional party government thesis.

Nevertheless, there are some indications that the increasing reliance on the committee system was not so much a purposeful choice (as would be assumed by the RCI approach), but rather an unanticipated consequence of previous institutional choices (and, thus, more consistent with the HI view of institutional change). Moreover, the record of rules and practices concerning the legislative process of decrees shows that, besides the abrupt transformation materialized through the constitutional reform of 2001, there were also equally relevant piecemeal and subtle changes, more in line with the adaptive processes studied by the evolutionary view of institutional change. These points are illustrated next, by means of a brief description of the evolution of the rules and practices of the "decree game."

5.3 An evolutionary perspective

Whatever the reasons that led the constituents to grant constitutional decree authority to the president, it seems to have made very much sense at the time.[13] During most of the second half of the 1980s, Brazil had been under a severe and persistent economic crisis, with very high inflation. The dominant strategy of stabilization policies was shock therapy, and three different traumatic attempts had already failed since 1986. Given the complex, urgent, and uncertain nature of such policies, and the lack of congressional expertise on the issue, delegating control of the legislative agenda to the president probably had seemed natural. After the promulgation of the constitution, the country had two more experiences with economic shock therapy (in 1989 and 1990), and both relied heavily, again, on presidential decrees.

Originally, the 1988 Constitution stated that the president could issue decrees (*Medidas Provisórias* – MPVs) on relevant and urgent matters, and that they should be approved by the full Congress (i.e., by majorities of deputies and senators at the same plenary session) within 30 days, otherwise they would become invalid. Nonetheless, the critical economic context offered a good justification for presidents to test the limits of this delegation. Amongst the very first decrees issued by President Sarney (1985-1990), one hardly could be considered relevant or urgent

13. For a discussion of the alternative explanations for the delegation of decree authority to the Brazilian president, see Almeida (1998, ch. 2).

(MPV 10, from October 1988) and another one was reissued on its expiration date, after Congress had failed to vote on it (MPV 29, from January 1989). The first of these "deviations" was promptly accepted by Congress, and until today there has been no systematic use of the relevance and urgency clause to discipline the use of decrees. The second deviation, the reissuing of decrees, on the other hand, was the object of a report from a special joint committee, which stated that, until Congress regulated the matter, the president could reissue non-voted decrees as long as its text remained the same.[14]

Notwithstanding the initial leniency of Congress with the use of decrees, it managed to make a stand against several abuses by President Collor (1990-1992). It effectively resisted decrees that encroached congressional exclusive jurisdiction over the penal issues (MPVs 153 and 156, from March 1990) and the reissuing of a rejected decree (MPV 185, from May 1990), which eventually led the Chamber's Committee on Constitution and Justice (CCJ) to approve a bill restricting decree authority on June 6, 1990 (*Folha de São Paulo*, June 8, 1990, p. A-5). The new Congress that convened in February, 1991, immediately passed the bill in the Chamber, though it was never brought to a vote in the Senate. In any event, it was probably enough since the use of decrees dropped dramatically for the remainder of Collor's term.

Congress loosened the grips once again in 1994, when the issuing of new decrees and the reissuing of non-voted decrees became a regular practice, such that in the next seven years (even after inflation was stabilized) it escalated up to the point where decrees were only rarely voted by Congress and most were reissued for at least seven consecutive months (and many of which a text different from previous versions).

The reissuing of decrees was debated in Congress during the whole period and an amendment to the Constitution was approved by the Senate on May, 1997, with the support from the same majority coalition that accepted the indefinite reissuing of decrees in the first place. But it was only on September, 2001, that Constitutional Amendment 32 was finally approved by Congress. It basically *i*) explicitly prohibited the reissuing of decrees; *ii*) expanded to a total of 120 days the expiration of non-voted decrees; *iii*) required decrees to be voted on first in the Chamber and then in the Senate, instead of in the full Congress; and *iv*) blocked plenary deliberations on any other item if there was any decree awaiting a vote and that had been issued for more than 45 days. The 2001 reform was effective in halting the reissuing of decrees and, although their use remains a controversial issue, since then there has been no major change in the use of this powerful agenda-setting device.

14. Report n. 1-1989, from February 1989.

Several aspects of the above sequence of events and practices can be interpreted under the light of evolutionary theories of institutional change. Mahoney and Thelen's (2010) theory, for example, offers interesting insights on the evolution of the "decree game." Decree authority has experienced changes of two types: conversion (the new practices adopted in the early years) and displacement (the 2001 constitutional reform). The first type was promoted by the president, whereas the second, by a congressional majority.

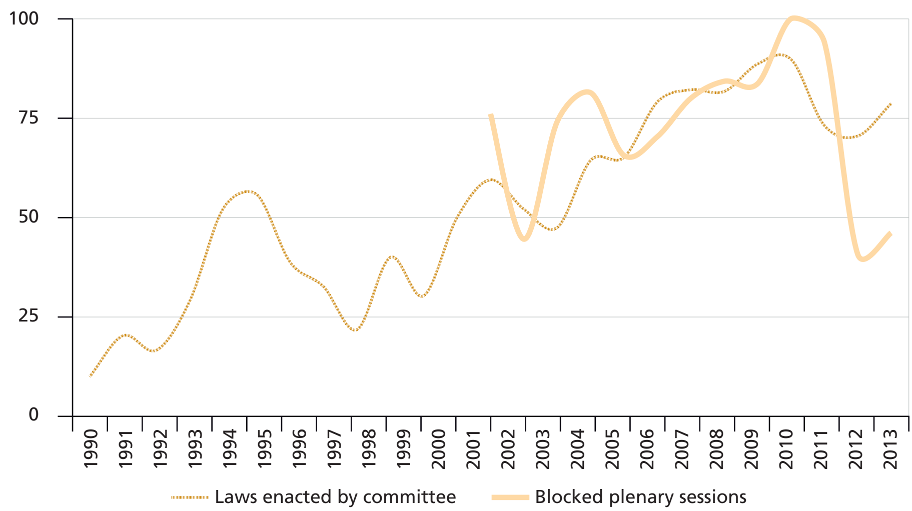
According to the theory, conversion results when change agents act as opportunists, a situation that corresponds to a target institution that has high level of discretion in interpretation or enforcement and to a political context of weak veto possibilities for defenders of the status quo (e.g., low probability of a congressional majority rejecting decrees). In the case of decrees, the Constitution allowed much discretion on its interpretation since there is no definition of which matters are "relevant and urgent" and there was no explicit restraint on the reissuing of decrees. The second type of institutional change (displacement) results when change agents act as insurrectionaries, which corresponds to a target institution with low discretion in interpretation and enforcement, and weak veto possibilities for defenders. This type matches the reaction of Congress, in 2001, when an extraordinary majority was formed to change the constitution and to explicitly prohibit the reissuing of decrees.

Another relevant aspect that calls attention when the dynamics of the institutional change in considered is that the relation between the 2001 reform (the one that restricted the president's decree power) and the strengthening of the committee system that is observed afterwards, is not straightforwardly explained. As discussed above, according to the static view of the conditional party government theory, these events can be interpreted as the two sides of the same coin, in the sense that they reflect different movements towards the same end (a shift in agenda-setting powers from the president to the committee system).

Moreover, the literature about Congress has identified a more direct linkage between those events. The reform generated the unanticipated consequence that plenary sessions became frequently blocked by decrees not voted on in the 45 days' time (Pereira, Power and Rennó, 2008). In 2002, for example, 76% of the Chamber's ordinary plenary sessions were blocked. One solution adopted by both the Chamber and the Senate to circumvent the blockage of plenary sessions was the transfer of final decisions on bills to the committee system, which contributed to bringing standing committees to the forefront of the legislative process (Machiaveli, 2009, p. 123-128; Santos, 2007, p. 56).

There is evidence, however, that the strengthening of the committee system had been under way long before the 2001 reform and that it has persisted on its own. Graph 4, below, depicts, for the Chamber, the annual percentages of non-budgetary laws that were conclusively voted on in committees (relative to all laws that could have been subjected to this process) and of blocked plenary sessions. It is clear that, even before blocking became a problem, laws were increasingly being enacted exclusively by the committee system. Moreover, even though blocking has decreased sharply in the years 2013 and 2014, the tendency to delegate final decisions to committees persisted.

GRAPH 4
Annual percentages of laws that were enacted conclusively by committee and of blocked plenary sessions, Chamber of Deputies (1990-2014)
(In %)



Source: Câmara dos Deputados ([no date]); Cebrap ([no date]); Senado Federal ([no date]).
Elaborated by the author.
Obs.: Only laws originally proposed after 1989.

In sum, the transformation of legislative institutions in post-1988 Brazil presents several elements that render it a promising case for the application of the complexity approach. The evolution of the law-making game is full of adaptations triggered by deviating behaviors that seemed to work well for the interests of a congressional majority. Moreover, the strengthening of the committee system has been a gradual, long-term process, but that probably was (unintentionally) boosted in the aftermath of the 2001 reform.

6 SUMMARY

This chapter has made the point that legislatures are complex adaptive systems. They are complex because they are composed of many diverse, interdependent agents (the legislators) who are not subject to centralized control. In order for legislatures not to become dysfunctional or chaotic, its members need to overcome a series of social choice and collective action dilemmas. To circumvent these problems, members adopt legislative institutions, formal or informal rules that structure the law-making process by defining who can do what and when.

Legislative institutions vary according to the degree to which they concentrate agenda-setting rights, with the committee model at the most decentralized end and the cartel party model at the most centralized end. Two important and still unresolved theoretical questions concerning legislative institutions are why and how they change along these two extremes. This chapter explored the contributions of dynamic, evolutionary theories of institutional change. These theories focus on the adaptive nature of complex systems, like legislatures.

The evolution of Brazilian legislative institutions after 1988 was offered as a potentially interesting case study for exploring the application of evolutionary theories of institutional change. The point was made that this case presents several elements that render it a promising case for the application of evolutionary theory and, more generally, the complexity approach.

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CHAPTER 17

THE TERRITORY AS A COMPLEX SOCIAL SYSTEM

Marcos Aurélio Santos da Silva[1]

1 INTRODUCTION

The concept of territory as a social construction, bounded by a geographic space, increasingly predominates in the elaboration process of public policies for sustainable regional development (Saquet, 2010; Boueri and Costa, 2013). It is in the social dimension, supported by public policies, that arises the bottom-up development and the organized and articulated local initiatives which trigger territorial socio-political-economic events (Claval, 2008).

The territory arises, thus, as the integration mechanism for public actions, because it is considered that, at some time, all government interference will take effect and will be influenced by it. The spatial character of public policies is a reality, especially when dealing with issues of regional development. In Brazil, some Ministries have used the territorial approach to leverage policies, plans and programs of development, with emphasis on: the National Regional Development Policy of the Ministry of National Integration (MIN), the National Plan for Water Resources of the Ministry of the Environment, and the Program of Territorial Development of the Ministry of Agrarian Development (Matteo et al., 2013).

However, Ministries do not share the same concept of territory. While the MIN develops its national policy for regional development bolstered by the promotion of the economic dynamism of micro and meso Brazilian regions, the Ministry of the Environment has been working with the territory bounded by river basin and has as goals, among others, the decrease of extreme hydrological events and conflicts about water. The Ministry of Agrarian Development (MDA), through its Department of Territorial Development (SDT), has as goal the sustainable development of contiguous rural areas. These areas must present some characteristics, such as: strong presence of family farming, low population density (< 80inhab/km^2), and an "active civil society".[2] Based on these indicators the SDT/MDA created the Rural Territories that constitute groups of municipalities and their

1. Computer Scientist, MSc. in Applied Computing, researcher at Embrapa Tabuleiros Costeiros – Av. Beira Mar, 3250, Aracaju, SE, 49025040. E-mail: <marcos.santos-silva@embrapa.br>.

2. Active civil society means that there are many organized social groups which represent the civil society and that they interact and make formal and informal communicative connections to make collective decisions.

neighbors which share some commonalities regarding economic, cultural or historical identities (Brasil, 2005).

Some challenges arise when analyzing the territory under the bias of its social dimension. Despite being a strong concept in geography, the territory still needs to develop its bases in other disciplines such as sociology and economics (Abramovay, 2007; Signoret, 2011). In fact, the territory can be considered a complex system with the subject, the social actor or a set of social actors, being in the center of the process of territorialisation (Moine, 2006; Leloup, 2010; Queirós, 2010; Encarnação et al., 2010; Lima, 2011; Signoret, 2011). Signoret (2011) argues that the territory is a process of adhesion of some collectivity to a common project linked to economic activities or simply to a historical cultural legacy that reinforces the elements of identity and belonging. However, despite this progress, many questions are still open when it comes to the analysis of territorial systems: what would be a suitable theoretical-methodological framework for this study? If the territory is a fuzzy social construct, how to map these spatially located social phenomena? Trying to answer these questions, this chapter integrates some concepts of geography, sociology, and computing to structure a scientific basis for the study of the territory via the systemic approach.

Thus**,** the territory will be analyzed as a socioterritorial complex system, where the social relations will be studied in the light of the Sociology of Organized Action (Crozier and Friedberg, 1977; Moine, 2006; 2007). This social theory has been formalized in mathematical terms, Sociology laboratory (Soclab) framework,[3] so as to allow a systematic observation of the social systems (Sibertin-Blanc, Amblard and Mailliard, 2006; Sibertin-Blanc et al., 2013). The process of social modeling using the Soclab framework has been applied to some analysis' problems of territorial collective action, such as: a water management in France (Adreit et al., 2009; Casula, 2011; Baldet, 2011) and the mapping of territorial institutional social relations in the Southern Rural Territory of Sergipe (Silva, Sibertin-Blanc and Gaudou, 2011; Silva et al., 2014; Silva, 2014).

Using the concepts and techniques discussed here, this chapter intends to contribute to the formulation of a theoretical-methodological framework for the evaluation of socioterritorial systems which allows the development of diagnostics, as well as the analysis of the consequences of territorial public policies. This chapter will also: demonstrate how the territory and its social components can be systemically analyzed, by the definition of the socioterritorial system; present the Soclab framework, which is a formalization of the Sociology of Organized Action used for analysis of socioterritorial systems; and show some applications of socioterritorial analysis by the Soclab framework.

3. The term Sociology laboratory framework (Soclab framework) corresponds to a method of sociological research based on systemic modeling and computational simulation. However, the term Soclab is also used to describe the software that assists this process, the Soclab software.

The chapter is organized as follows: section 2 presents the socioterritorial systems, where the territory is treated as a concept and defined in the light of the theory of systems; section 3 introduces the Sociology of Organized Action social theory that will be used as reference in our territorial sociological analysis; section 4 unveils the Soclab framework; it describes the metamodel SOA/SCA, its mathematic formalization, the methods of modeling (identification of social actors, resources and their relations) and social simulation (social game); section 5 investigates the prisoners' dilemma according to the Soclab framework; section 6 shows an example of a hypothetical socioterritorial system modeling and simulation; section 7 presents some applications of the Soclab framework to socioterritorial systems, emphasizing the analysis of social power relations in the Southern Rural Territory of Sergipe; section 8 provides the final considerations.

2 SOCIOTERRITORIAL SYSTEM

This section presents a territorial definition based on the social systemic approach, the socioterritorial system. This idea is supported by the fact that the social dimension plays a key role in modern territorial development and that the territory must be treated as a concept and investigated from a sociological perspective.

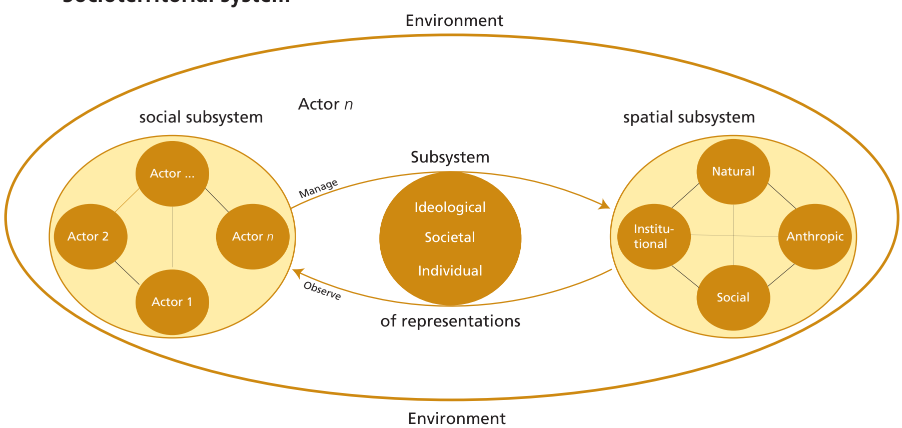
The influence of decisions' decentralization on collective actions focused on regional development is growing due to the complexity of interdependencies among the social actors and the public power at various scales (Claval, 2008). One of the basic premises of this new model is the bottom-up endogenous development, which emerge from local actions and consultations, in addition to the agreements and balances of opposing political forces that are nourished of regional dissemblances, such as cultural identity and history. Then, it is necessary to study the territory considering the dynamics of its social dimension, in addition to its biophysical attributes and its political and administrative divisions.

Saquet (2010) has produced an in-depth analysis of the evolution of the territory as a concept and concludes that there is a need for a focus on social relations, with an emphasis on systemic and integrative approaches. Leloup (2010) highlights the importance of social relations in territorial analytical study as well as the coordination among the actors in the process of territorial development. The author, as well as Lima (2011), emphasizes the following requirements for the composition of a territory: the subject, the social actors with certain autonomy; a common project; a geographical limit; and some territorial regulatory process. According to Signoret (2011), territory only exists if there is a collective project that assembles the people around a common theme and that increases the social interdependence.

The territory is not only the landscape where social relations happens, but also the result of this complex social network which composes it.

In the conceptual territorial systemic model proposed by Moine (2006; 2007), see figure 1, it is observed three subsystems that communicate with each other and form the socioterritorial system, they are: the subsystem of social actors, which brings together communicational processes, strategic decision-making and governance; the spatial subsystem that gathers components of lived space; and the subsystem of representations that acts as an ideological, societal and individual filter between the two other subsystems. According to Moine (2006, p. 126; emphasis added), "*le territoire est un systéme complexe évolutif qui associe un ensemble d'acteurs d'une part, l'espace géographique que ces acteurs utilisent, aménagent et gérent d'autre part*". [4]

FIGURE 1
Socioterritorial system



Source: Adapted from Silva et al. (2014).
Elaborated by the author.

The three subsystems designed by Moine integrate the spatial dimension (local, where social actors act on the real space; and global, where social actors decide about the designed space); the temporal dimension (past, present and future); and the organizational dimension, conditioned by the governance system. The socioterritorial system can then be seen as a complex social system, relatively stable, where the social game occupies a central role. According to Moine (2007, p . 41), "*il s'agit d'un ensemble humain structuré qui coordonne les autres actions de ses participants par des mécanismes de jeux relativement stables et qui maintient sa structure, c'est-à-dire*

4. "the territory is an evolutive complex system that associates a set of social actors on the one hand, and the geographic area that these social actors use, modify, and manage on the other hand".

la stabilité de ses jeux et les rapports entre ceux-ci, par des mécanismes de régulation qui constituent d'autres jeux".[5]

Unlike other approaches in geography (Cole, 1972; Christofoletti, 1979), the method discussed here focuses on social actors, who are responsible for territorial governance, be it public or private. Geographic systems as cities, forests and agricultural areas, for example, have the following properties of complexity: indeterminate nature of the causes of the observed phenomenon; impossibility of understanding the problem by isolating its parts; self-organization from the interaction among the various parts of the system; feedback as a reorientation mechanism around the goal of the system; autoregulatory process as a way of maintaining the system; and recursion, which is the definition of the system by itself.

The study of socioterritorial systems requires the addition of the social dimension (social systems) to the geographic systems. This means that new elements of complexity must be added to this analysis, they are: the undefined, unstable and poorly structured character of relations among people and groups, conditioned by different values and cognitive systems; the constant presence of counterintuitive and not expected effects of social actions; the conflict as a constant; and a high degree of nested subsystems with high temporal variability.

Socioterritorial system differs from socio-ecological systems in some aspects. Socio-ecological systems have a predominantly local scope, they usually deal with the optimization of the use of a single natural resource, and they are well defined as, e.g., irrigation systems, fisheries, forestry and extractive activities. In these cases, it is possible to model and simulate the system of collective action and decision-making based on specific criteria such as, e.g., the flow of water, the availability of fish, the deforestation rate or the limit of collection rate in extractive activities. Poteete, Janssen and Ostrom (2010) developed a comprehensive work on modeling and simulation of socio-ecological systems. Similarly, the companion modeling uses the role playing game and simulation of socio-ecological systems to facilitate the negotiation process among the social actors (Étienne, 2010).

Socioterritorial systems have fuzzy borders at a regional scale, and additionally the involved resources go beyond the natural ones. Here, the central issue is governance, sociopolitical power relations in a broad sense. The decision-making procedures are not fully known and informal relations have a great relevance. It is not possible to apply optimization solutions to these socioterritorial systems; the main goal, instead, is to understand its social structure, the relations between the social actors, and its operation on issues that affect the collectivity.

5. "...it is a human agglomerate structured that coordinates the actions of its members by means of game engines (social), relatively stable, and that it maintains its structure, i.e. the stability of these games and the relationships between them, by regulatory mechanisms that constitute other games".

It is concluded that the socioterritorial system can be defined as a complex system, composed of three subsystems (social, representation and spatial), that has as its main objective the regional sustainable development. The phenomenon to be observed is the emergence and maintenance of the social power relations that give governance structure and some social cohesion to the territory. Despite showing diffuse borders and few formal rules, the socioterritorial system can be analyzed as a whole with low cohesion but with clear objectives.

Faced with the need to analyze the territory as a social system by means of a systemic modeling process, it is necessary to choose a social theory that meets the following requirements, it must: be adherent to the systemic thought; emphasize the political social system; and be sufficiently comprehensive to aid the process of understanding not strongly structured social systems. The Sociology of Organized Action (SOA) or Strategic Analysis initially proposed by Crozier and Friedberg (1977) and developed by Friedberg (1993) proved to be in line with the theory of systems (Roggero, 2000); prioritizes informal aspects, i.e. informal management practices and behavior modeling of social systems; and, is sufficiently generic to assist in the process of construction of knowledge about organizations with diffuse borders. Besides, this theory has been applied to the analysis of territorialized problems (Adreit et al., 2009; Sibertin et al., 2013; Casula, 2011; Baldet, 2011; Silva et al., 2014; Silva, 2014).

3 SOCIOLOGY OF ORGANIZED ACTION (SOA)

This section will present the Sociology of Organized Action social theory, its components, premisses and a proposal connection mechanism with the socioterritorial system.

The Sociology of Organized Action (SOA) is based on the study of the organization as a political system, consisting predominantly of power relations among social actors. The SOA has the following principles (Sibertin et al., 2013): *i*) the organization is a social construct, produced by the social actors. In other words, it is self-determined and independent of the external environment. The organization is not only the product of formal standards, but the integration of informal and formal rules; *ii*) the social actor always have enough freedom to achieve their own objectives, as well, it will never become a mere organizational instrument; *iii*) the strategies of social actors are characterized by mobilization of resources to carry out some form of power over the other to achieve their own goals, which are not always in line with the aims of the organization; and *iv*) it is assumed a minimum collective order, which is established by the various interdependencies among the relations of power and dependence.

Crozier and Friedberg (1977) observed the organization (formal or informal) as a social construct, not natural or spontaneous, consisting of a finite set of social actors which share one or more objectives. The actions of the social actors are limited or shaped by formal standards of organization and cultural traditions which have evolved historically. The personal choices that arise from circumstantial situations or which are motivated by internal values also limit the action of each social actor. Each actor will have a certain capacity of action that will guide the definition of his strategies in the social game that, in turn, seeks to balance the collective objectives and individual aspirations.

Thus, the coordinated collective action needs a stabilization mechanism that assists the balance of forces in the social game. In this case, the power acts as a regulator and is defined by the authors as "(...) *la possibilité pour certains individus ou groupes d'agir sur d'autres individus ou groupes*" [6] (Crozier and Friedberg, 1977, p. 65). This action on another individual means to establish a connection, an agreement, a contract between the two. The power can be seen as a consensual relationship and not as an attribute, static and unchanging, of each social actor. These power relations will be, therefore, the structure by which social actors will act. However, the foremost component of this theoretical formulation is the 'uncertainty zone'.

In fact, each social actor will have one or more uncertainty zones as factors for integration within a structured field of action in the social game. The uncertainty zones can be interpreted as a resource controlled by a social actor and needed by others, such as, for example, a specific technical knowledge, a moral ascendancy of an individual in a particular group, the ability to punish etc. Whereas in this social game there is no absolute submission of any social actor. Each social actor will have at least an element of persuasion, uncertainty zone, that he will explore at the moment of elaboration of their strategies. The uncertainty zones are a key concept in SOA. In fact, social actors create interdependence by means of these zones which generates more engagement and social cohesion. These uncertainty zones will structure the power relations that may congeal over time and generate resistance to change.

According to Crozier and Friedberg (1977) the social game unfolds through a System of Concrete Action (SCA) which is nothing more than the context where the social actors and their relations of interdependence are immersed. According to Silva et al. (2014, p. 67):

> SCA is an open system, which disregards the other systems whose actors are part (environment) and that represents an intelligible simplification of the real world from the formalization of the structure of the field of action in study. The SCA assumes a minimum of flow of information and mutual understanding among the actors.

6. "(...)the possibility of certain individuals or groups to act over other individuals or groups".

> One of the assumptions of the SCA is that the actor is heuristically rational and seeks the realization of its objectives that are defined within a changing context. The social actor acts, rationally, in function of their assumptions about their partners, and of their interpretations of the actions of them. The focus of the SCA is on the local actions that are, at the end of the process, responsible for the emergence of the social system. To model a SCA it is necessary to identify the actors and their intentions, the relations of control and dependence in relation to the uncertainty zones, in addition to the repertoire of possible strategic behaviors.

It is noteworthy that the majority of territorial public policies aims the sustainable territorial development. This development would be based on the decentralization of governance, in terms of increased social engagement in decisions on the territory, the expansion of the level of communication between the social actors and the construction and expansion of social networks. In fact, in addition to the economic system and the human-nature system, it has been the territorial political system that regulates the power relations that constraint the governance process (Silva et al., 2014).

Therefore, it is seen that the social game is the connecting element between the socioterritorial system and the SCA. The socioterritorial system can be seen as an organization characterized by fuzzy borders and internal rules. In this system the informal rules or historical-cultural behavior are more relevant than any structure or formal rule.

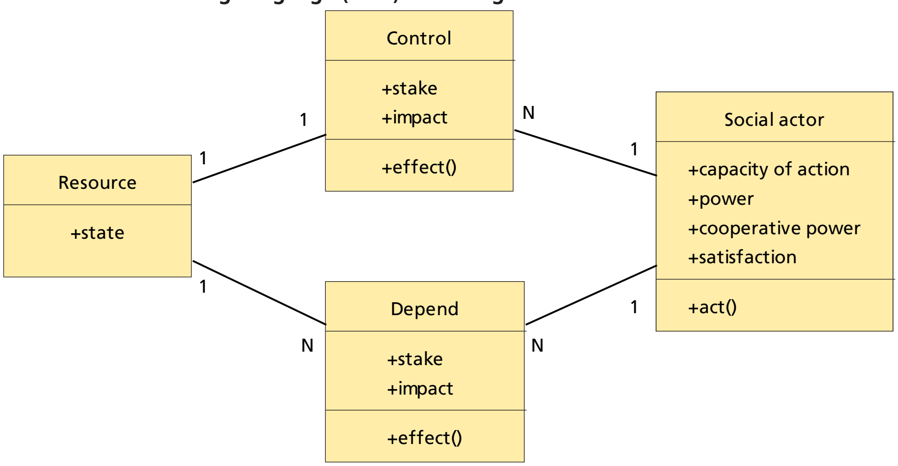
One of the challenges of bringing together socioterritorial systems and SOA/SCA is the correspondence between the social system and the space subsystem. The geographic space or the space subsystem can be considered in three ways: *i*) as an element contributing to the spatial dependence of social actions, so the location could facilitate the cooperation or not by means of physical proximity among the social actors, which may be represented by social relations; *ii*) as a resource or geographic object, which may be represented by means of "uncertainty zones"; and *iii*) as an externality that presses the socioterritorial system which can be another social system, a uncertainty zone controlled by an external social actor or a relation between an element of the system and an external one.

The next section will unveil the Soclab framework that formalize and implements the core conceptions of the SOA/SAC.

4 THE SOCLAB FRAMEWORK

The System of Concrete Action has formalized by Sibertin-Blanc, Amblard and Mailliard (2006); Sibertin-Blanc et al. (2013), by means of the Soclab framework, to allow the theoretical study of computational modeling of social organizations, as well as to serve as a reference for empirical researches on the field. The metamodel SOA/SCA (figure 2) is composed of two central entities, social actor and resource[7] ("uncertainty zone"), and two entities that links each other and which denotes the relations of dependence and control of one or more social actors with respect to a given resource (Sibertin-Blanc, Amblard and Mailliard, 2006). The entity resource represents the uncertainties zones in SOA/SCA and has as attribute its state, which indicates the degree of access of social actors to it.

FIGURE 2
Unified Modeling Language (UML) class diagram for the SOA/SAC metamodel



Source: Adapted from Sibertin-Blanc et al. (2013).
Elaborated by the author.

4.1 Notation and terminology[8]

Formally the Soclab can be defined as follows:

- a set A of N social actors, $A = \{\alpha_1, \alpha_2, \dots, \alpha_N\}$.
- a set R of M resources, $R = \{r_1, r_2, \dots, r_M\}$, represented by the vector of states.
- $\mathbf{r} = [\lambda_1, \lambda_2, \dots, \lambda_M]^T$, where λ_m represents the level of access to the resource r_m, $\lambda_m \in [-10, 10]$. The value λ_m indicates the space of behavior or the level of access to the resource r_m by other social actors. In spite of the

7.In the original proposition the resource is called relation. However, it has preferred the term "resource" because it is more clear and refer directly to what it actually represents. The social relation is given by means of shared resources, i.e. when a social actor is related to another means that it controls a resource that is used by the other or vice versa.

8. The notation used in this work differs from that presented in Sibertin-Blanc, Amblard and Mailliard (2006) and Sibertin-Blanc et al. (2013). The changes occurred in order to provide more concise equations and provide clarity to the social simulation algorithm.

numeric value, λ_m has an qualitative interpretation, i.e. , values close to -10 denote difficulties in access to the resource, values around zero indicates the neutrality of the access to the resource, and values close to 10 demonstrate a good level of access to the same.

- the relations of control: $A \rightarrow R$, if $\alpha_n \rightarrow r_m$, then α_n controls r_m , i.e., the value λ_m of resource r_m is determined by α_n,. Each social actor must control at least one resource.
- the relations of dependence: $A \leftarrow R$, if $\alpha_n \leftarrow r_m$, then α_n depends on r_m.
- a stake matrix **S**, where $s_{mn} \in [0, 10]$ and $\sum_{m=1}^{M} s_{mn} = 10$, where for each dependency relationship between a social actor α_n and a resource r_m will be assigned a stake s_{mn} so that the sum of all stakes for each social actor must be equal to 10. Each social actor will be responsible for the distribution of these stakes.
- a set E of F effect functions, $E = \{e_1, e_2, \ldots , e_F\}$, one for each relation of dependence and control. All functions are continuous with domain $D \in [-10, 10]$ and image $I \in [-10, 10]$. For each dependency relationship, the function computes the effect of resource r_m on the social actor α_n that depends on or controls, it having as independent variable the state of the resource λ_m. For each relation of dependence it is possible to calculate the impact, I_{mn}, of the resource r_m on the social actor α_n, $I_{mn} = e_{mn}(\lambda_m)s_{mn}$.
- a matriz $\mathbf{W}_{NxN}$ of solidarity where $w_{ij} \in [-1, 1]$, $\Sigma w.j = 1$. Being that values close to -1 symbolize a certain hostility toward the social actor α_i with the actor α_j, the value 0 denotes indifference and values around 1 mean a high degree of solidarity. The matrix **W** is not symmetrical, because each social actor defines a degree of solidarity in relation to the others, i.e. each row i of the matrix represents how the social actor α_i observed the degree of solidarity with him in relation to the others.

4.2 The social actor

The social actor is the agent that controls at least one uncertainty zone, or resource in the adopted terminology. It can be an individual or a group, has goals and collaborates directly or indirectly with the socioterritorial system. The strength of the link between the social actor and the social system depends on the number of connections among social actors and resources. For each social actor you can compute their capacity of action C_n (Eq. 1) and power P_n (Eq. 2), the first being the sum of effects weighted by the respective stakes of relations that he depends on, and the second the sum of effects weighted by the respective stakes of relations that he controls. The cooperative power P_n^c (Eq. 3) can be calculated in a similar way to the P_n , but considering only the sum of the positive effects. These values should be computed and compared considering the same value of **r**.

$$C_n = \sum_{\forall r_m \in R | a_n \leftarrow r_m} I_{mn} \tag{1}$$

$$P_n = \sum_{\forall r_m \in R | a_n \rightarrow r_m} I_{mn} \tag{2}$$

$$P_n^c = \sum_{\forall r_m \in R | a_n \rightarrow r_m \wedge I_{mn} > 0} I_{mn} \tag{3}$$

$$S_n = \sum_{j=1}^{N} C_n w_{nj} \tag{4}$$

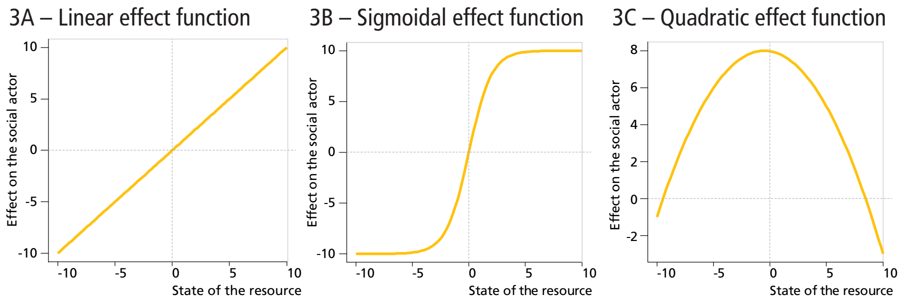
If the matriz of solidarity **W** is taken into account, it is possible to compute the values of satisfaction S_n perceived by the actor α_n (Eq. 4). While the capacity of action quantifies the freedom of action of the social actor, the satisfaction corresponds to the value that will guide their behavior on the basis of the capabilities of the other actors. However, if the solidarities are not considered **W** = diag(1) and $S_n = C_n$.

4.3 The resource ("uncertainty zone") and the effect functions

The resources may be concrete elements such as financial, material or human resources, but also services such as consultancy, technical support, political support etc. Moreover, the geographic space location is a important matter and, thus, it is possible to map these spatial elements as resources since they are controlled by a social actor and shared directly or indirectly by a set of other social actors. The resource is the means by which the social actor establishes the relationship of control and dependence, and your state will define the level of access to it by the social actors.

For each resource, the social actor will specify a value, s_{mn}, which correspond to the level of need for the achievement of their specific goals, measured by the level of satisfaction or capacity of action. To compute the effect a function must be defined, called effect function, which, for each resource-social actor relation, will define the level of effect in the interval [-10, 10] based on the state of the resource, which also varies in the interval [-10, 10]. The curve of the effect function may take any form, however, to simplify the process of interpretation of the results it can be restricted to linear, sigmoidal or quadratic (figure 3).

FIGURE 3
Some examples of effect functions



Elaborated by the author.

The effect function should be interpreted as follows. In the case of a linear curve, passing through the origin of the graphic (figure 3A): the greater the access to the resource, broader will be the effect on the social actor, and vice-versa, and at the origin of the graphic both the access and the effect can be seen as indifferent. In the case of a sigmoidal curve (figure 3B), also passing through the origin: this means that you have a behavior analogous to the linear curve, but with upper and lower limits, i.e., this means that the social actor is sensitive to variations of access to the resource near the origin of the graphic. For a quadratic function with the curve facing down and maximum on the y axis (figure 3C): in this case the effect on the social actor is maximum for the indifferent level of access to the resource and tends to decrease when the level of access to it increases or decreases.

The process of social modelind by Soclab framework should be considered in conjunction with traditional methods of social research. The Soclab framework, however, facilitates and systematize the process of data collection and organization. In Annex A there is a template of a research form to assist the data collection process via interviews, application of questionnaires or, even, based on the experience of the modeler. The software Soclab[9] can be used as technical support to the development of the model and subsequently as the means by which the analysis of the structure, the states of the resources and of the simulations will be performed.

4.4 The social game (the social simulation algorithm)

The Soclab framework defines the social dynamics as being an iterative process where social actors change the state of the resources which they control to achieve their ambitions. This process stops at a particular configuration of states

9. Available at: <http://soclabproject.wordpress.com/>.

of resources, where there is no more interest on the part of the social actor to change their behavior based on their current satisfaction. In computational terms, this behavior is represented by a simulation algorithm where social actors can be implemented as objects endowed with characteristics such as capacity of action, power, cooperative power and satisfaction. Each social actor, or object, will act based on a set of rules created during the simulation process by a reinforcement learning technique. Each rule consists of three components: a vector $\boldsymbol{\varepsilon}$, $\boldsymbol{\varepsilon} = [e_1, e_2, \dots, e_q]^T$ whose values correspond to the value of the effect function of the resources that it depends on; another vector $\boldsymbol{\delta}$, $\boldsymbol{\delta} = [\delta_1, \delta_2, \dots, \delta_p]^T$, whose values correspond to the increment, positive or negative, on the resource states that the social actor controls; and a variable F that indicates the strength of the rule. The values of increments and strength are updated every step of the algorithm by Eqs. 5-7, respectively.

$$\delta_{qn}(t) = 2TX(t)\omega,\ \omega \in [-1,1] \tag{5}$$

$$f_1(t) = \left(1 - TX_n(t)\right)f(t-1) + TX_n(t)RR_1\Delta S_n(t) \tag{6}$$

$$f_2(t) = f(t-1) + TX_n(t)(1 - RR_2)\Delta S_n(t) \tag{7}$$

Where $\Delta S_n(t)$ represents the variation in satisfaction of the actor after the application of the rule in time t and ω a random value between -1 and 1. The function $f_1(t)$ is applied to calculate the strength of the rules that are applied at time t-1, while the function $f_2(t)$ to upgrade the strength of the rules applied at time t-2.

4.4.1 Psycho-cognitive parameters

The Soclab framework includes in the simulation algorithm four psycho-cognitive parameters: tenacity, T_n, reactivity, R_n, discernment, D_n, and distribution of reinforcement, $\{RR_1, RR_2\}$, for each social actor α_n. The tenacity takes an integer values between one and ten and determines how much the social actor will explore new rules to achieve his ambition, $K_n(t)$. The higher T_n, greater will be the processing time of the algorithm searching for a solution. The reactivity is also an integer constant, assumes values between one and ten and determines the importance that the social actor attaches to the present and the past in the learning process. The higher the value of R_n, smaller will be the memory which refreshes the exploitation rate, TX_n, and his ambition, $K_n(t)$, the lower the value of R_n, greater will be the importance of the past. The discernment is an integer constant, assumes values between one and five and is used to calculate the threshold γ, Eq. 8, that will be used to define if one rule is applicable or not. So, if the euclidean distance weighted by the stakes between the actual situation[10] and the situation of the rule is less than γ then this rule may be chosen as appropriate. The distribution of reinforcement indicates the percentage of reward that will be given to the rules which led the social actor to a good situation, close to the ambition. At time *t+1* the social actor realizes the effect of the last action track via your satisfaction or capacity of action, and at time *t+2* the actor perceives as the other reacted to their action at time *t*. The distribution of reinforcement of each rule will be divided to these two moments, RR_1 and RR_2, so that you can focus on the immediate perception by assigning a higher percentage for RR_1, or vice-versa, by assigning a greater percentage value for RR_2. The default values are 50% and 50 %.

$$\gamma = \frac{\|S_{n\,max} - S_{n\,min}\|}{D_n} \tag{8}$$

$$C_{n\,max} = \sum_{a_n \leftarrow r_n} \max\{I_{mn}\} \tag{9}$$

$$S_{n\,max} = \sum_j^N C_{n\,max} w_{nj} \tag{10}$$

$$C_{n\,min} = \sum_{a_n \leftarrow r_n} \min\{I_{mn}\} \tag{11}$$

$$S_{n\,min} = \sum_j^N C_{n\,min} w_{nj} \tag{12}$$

4.4.2 Exploitation rate and ambition of the social actor

The rate of exploitation, $TX_n(t)$, of a social actor, $TX_n(t) \in [0.1; 0.9]$ (Eq. 13), determines the way in which the value of ambition, the strength of each rule and the intensity of the action of a new rule will be calculated. The exploitation rate is calculated from the immediate rate of exploitation (Eq. 14), $TXI_n(t)$, calculated at each step of the simulation as a function of the distance between the current situation and the ambition of the social actor, as well as his tenacity.

$$TX_n(t) = \left(1 - \frac{R_n}{10}\right) TX_n(t-1) + \frac{R_n}{10} TXI_n(t) \tag{13}$$

$$TXI_n(t) = 0.1 + \left[\frac{0.8}{1 + e^{\left(-(T_n * (10 - T_n) + 10)) * (dif_n(t) - \frac{10 - T_n}{10}\right)}}\right] \tag{14}$$

The ambition of a social actor, $K_n(t)$, is the level of satisfaction or capacity of action desired by him and varies over time. The ambition starts with the maximum value of satisfaction (Eq. 15) or capacity of action (Eq. 16). For the remaining steps it is considered two situations. First, if the social actor not achieved its ambition, then,

10. Represented by the vector containing the values of the effects of all the relations between the social actor and the resources that he depends on.

the ambition will decrease as a function of the distance between the current situation and the ambition, as well as the exploitation rate according to Eq. 17. If the social actor has reached or exceeded its ambition it will increase according to the Eq. 18.

$$K_n(0) = C_{n\,max} \tag{15}$$

$$K_n(0) = S_{n\,max} \tag{16}$$

$$K_n(t) = K_n(t-1) - \left[\left(1 - TX_n(t)\right) * \left(\frac{R_n}{100}\right) * dif_n(t)\right] \tag{17}$$

$$K_n(t) = K_n(t-1) + \left[\left(S_n(t) - K_n(t-1)\right) * \left(\frac{R_n}{100}\right)\right] \tag{18}$$

The difference between ambition and satisfaction, $dif_n(t)$, is calculated as a ratio between the satisfaction and the ambition that indicates the part of the satisfaction which the actor has in relation to its ambition (Eq. 19).

$$dif_n(t) = \frac{K_n(t-1) - S_n(t)}{K_n(t-1) - S_{n\,min}} \tag{19}$$

4.4.3 The simulation algorithm

The simulation algorithm is based on the reinforcement learning paradigm, is guided by trial and error and can be summarized in three steps: *i*) perception of social actor; *ii*) decision-making by the social actor; *iii*) execution of the action by the social actor. The ultimate goal of the algorithm is to find a final situation of states of resources **r** such that there is no more interest of each actor in act, i.e., changing states of resources that he controls. At the stage of perception the actor calculates his satisfaction and compares it with his ambition $K_n(t)$. The distance between one and another will determine how the actor will behave in the next phase. At the stage of decision the actor evaluates which rule apply from a list created in the reinforcement learning process. During the execution phase of the action the social actor applies the rule chosen and changes the values of the states of the resources he controls.

The simulation algorithm can be summarized as follows (El Gemayel, 2013, p. 99):

> **define** T_n, R_n, D_n and $\{RR1, RR2\}_n$ for each social actor α_n
>
> **initiate r** at random
>
> **compute** the satisfaction $S_n(0)$ for each social actor (Eq. 4)
>
> **compute** the ambition $K_n(0)$ (Eqs. 15-16)
>
> **compute** $dif_n(0)$ (Eq. 19)

initiate $TX_n(0)=TXI_n(0)$ (Eqs. 13-14)
for each discrete time t **do**

for each social actor αn **do**

1) **calculate** $S_n(t)$ *(Eq.4)*; $dif_n(t)$ *(Eq. 19)*
2) **update** $K_n(t)$ *(Eqs. 17-18)*; $TX_n(t)$ *(Eq. 13)*
3) **update** the strength of the applied actions (Eqs. 6-7)
4) **select** applicable rule where ‖actual-situation n – *rule.* ε ‖
5) **if** no selectioned rule **then**

   creates *new rule*

   rule. ← *actual-situation*$_n$

   rule. ← (t)(Eq. 5)

   rule.Strength ← *0*

6) **choose** one rule among the ones with the highest strength or the new one

end-for

for each resource r_{m} **do**

update the values of the states of the resources according to the values σ of the choosen rules

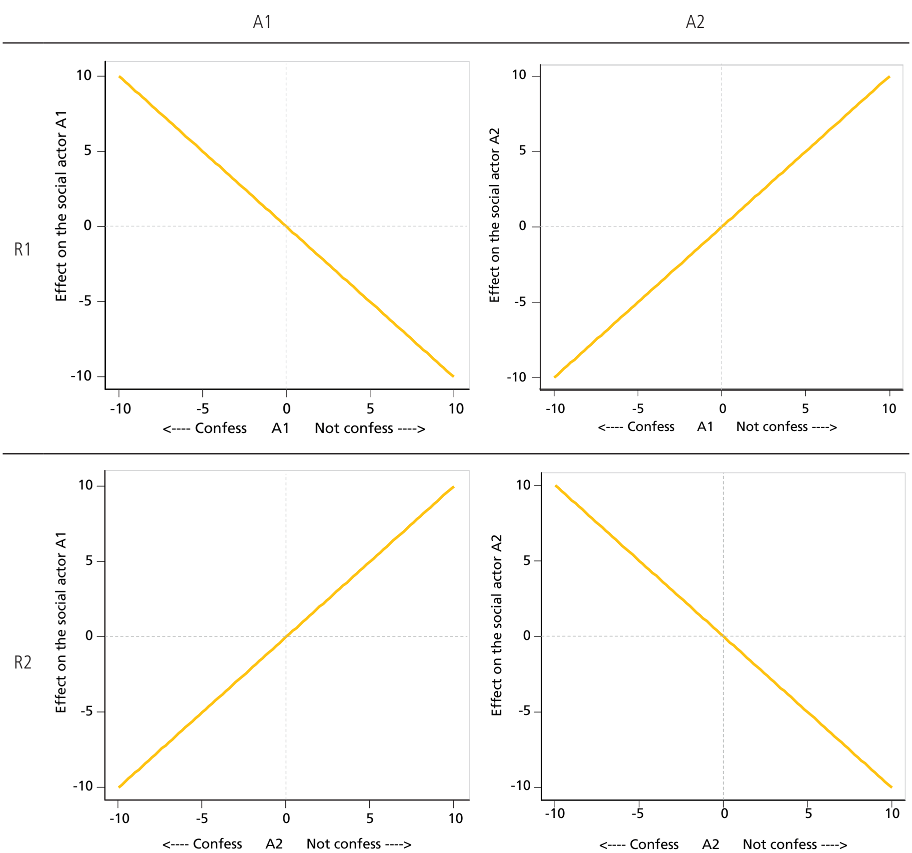
end-for

end-for

5 THE PRISONER'S DILEMMA ANALYSIS THROUGH THE SOCLAB FRAMEWORK

The functions of C_n and S_n can be interpreted as utility functions, as well as are defined in the game theory. So, it is worth to analyze the prisoner's dilemma from the Soclab perspective (El Gemayel, 2013). Consider, therefore, two social actors A1 and A2, suspects and prisoners in two incommunicable and separate jails. Both can confess (C) or not confess (CN) the "delict", and for each combination of choices of these two prisoners there will be a positive or a negative return in terms of time of conviction for each of them. If both deny the crime the joint penalty assigned to them will be the minimum, when both confess the joint penalty is maximized, when one confesses and the other does not, the first will receive the minimum sentence and the other the maximum penalty.

GRAPH 1
Effect function for all relations



Elaborated by the author.

In this situation the uncertainty zone controlled by each social actor is their choice to confess or not. At the same time that each prisoner controls their uncertainty zone, he depends on the status of the situation of the uncertainty zone controlled by the other, then it is observed a situation of interdependence between these two social actors. The distribution of the stakes will follow this situation, because no matter the decision of A1, despite controlling his own uncertainty zone, is the state of the uncertainty zone of A2 that will define the satisfaction of A1.

In this way, A1 assigns the weight (stake) one for the resource that he controls, R1, and the weight nine to the resource controlled by A2, and vice-versa. The resources R1 and R2 will assume states in the interval [-10,10] in a way that negative values mean confess and positive values mean do not confess. It has opted for linear effect functions that behave inversely for each resource and for each social actor as shown in graph 1. Observing R1, it is noticed that A1 will have more positive effects if he confess independent of the choice of A2, state of R2. The same happens with A2 for R2 and R1 (El Gemayel, 2013).

Table 1 shows the capacities of action (C_n) calculated from a combination of particular values of R1 and R2. If it is considered the overall C_n, which is the algebraic sum of the capacity of actions of the social actors, the best case happens when both not confess (80,80) and the worst case, when both confess (-80, -80), that corresponds to the Nash equilibrium (Dutta, 1999).

TABLE 1
Satisfactions for social actors A1 e A2 considering particular values of R1 and R2

		R2 states		
		-10	0	10
	-10	-80/-80	10/-90	100/-100
R1 states	0	-90/10	0/0	90/-10
	10	-100/100	-10/90	80/80

Elaborated by the author.

The social simulation, considering different values of the stake distribution, shows that the social game changes according to how social actors weight the relevance of the resources that they control and depend on. The table 2 presents the results of simulations performed using the Soclab software for the social system presented above. According to El Gemayel (2013), it has considered the same values of discernment (D_n=*1*), tenacity (T_n=*5*), reactivity (R_n=*5*) and distribution of reinforcement $\{RR_1=s_{nR1}*10\%,\ RR_2=s_{nR2}*10\%\}$ for both social actors. The simulation has performed one hundred simulations with 200,000 steps each one at most.

The distribution of stakes denotes how a social actor will face the social game. If someone puts more stakes on the resources that he depends on it means that he expects a cooperative game, otherwise, if he puts more stakes on the resources that he controls, then the game will be a non-cooperative one. The simulations have performed varying the stakes for each social actor from zero to one, or from totally cooperative (0/10) to totally non-cooperative (10/0), according to the table 2. The results showed that: the capacity of action is maximum in the extremes and decreases until the minimum value, zero, when the stakes are equally distributed; the final states for the resources stabilizes positively for cooperative social games and negatively for non-cooperatives ones; and it needs more steps of simulation to reach the equilibrium when the stakes are equally divided.

TABLE 2
The results of the social simulation for the prisoner's dilemma taking into consideration the variation of the stakes distribution

	Stakes distribution of social actor A1 for the resources R1 and R2										
	<- Totally cooperative				Nash equilibrium			Totally non-cooperative ->			
	0/10	1/9	2/8	3/7	4/6	5/5	6/4	7/3	8/2	9/1	10/0
Capacity of action for A1 (average)	100	80	60	40	20	0	20	40	60	80	100
State of the relation R1 (average)	10	10	10	10	10	-10	-10	-10	-10	-10	-10
Number of steps needed for the convergence (mean)	1060	5646	13644	18446	19486	21183	17232	14766	11888	6320	25

Elaborated by the author.
Obs.: It is shown only the results for the social actor/resource A1/R1 because this social game is symmetric, so the results for A2/R2 are exactly the same.

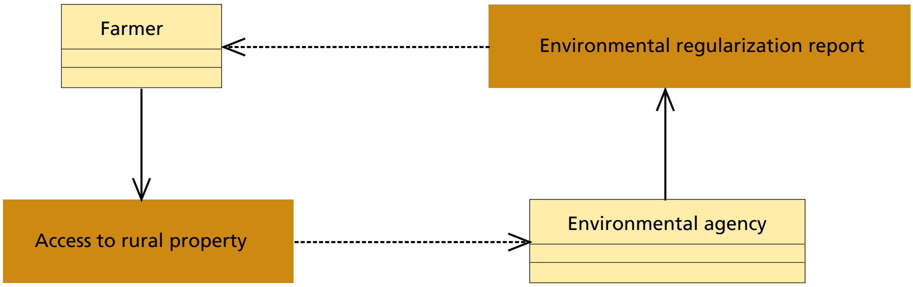
It is important to notice that the social game in the Soclab framework tries to reach a stable state observing the sum of the all social actors' capacity of action/satisfaction. The table 2 shows that, in this social game, this stability is equivalent to the Nash equilibrium only when the stakes are equally distributed.

In sum, this exercise showed that the Soclab framework can be a suitable tool to design social games and, by the effect functions, to generate payoff matrices.

6 EXAMPLE OF A HYPOTHETICAL SOCIOTERRITORIAL SYSTEM

Consider a socioterritorial system composed of two social actors, the farmer and the environmental agency. The first controls the resource "access to rural property" while the second controls the resource "environmental regularization report" (figure 4). The environmental agency must have physical access to the resource controlled by farmers, while the farmer needs to regularize their property to have access to financial resources. Although it seems a win-win game, if the farmer fully facilitates the access of the environmental agency it may compromise its production and consequently his income; if the farmer completely block the access he will not have the means to finance their activities. On the other hand, the environmental agency cannot fully exercise its supervisory power because it can lead to mistrust the farmer that may eventually block the access to the rural property. The environmental agency, then, would seek to maintain a level of access to this resource controlled by farmers to achieve, at least, the minimum goals of the agency.

FIGURE 4
UML diagram for the hypothetical model of the hypothetical socioterritorial system



Elaborated by the author.

Once defined the social actors and the resources that make up the system, it is necessary to proceed with the distribution of stakes for each resource, i.e., define the weight of each resource for each social actor within the socioterritorial system (table 3). Although dependent on the environmental regularization, the farmer allocates more stakes, six, for the resource "access to rural property", because the risk of having their economic activity blocked by environmental monitoring prevents him from giving more attention to resource controlled by the environmental agency, four stakes. In turn, the environmental agency depends almost entirely on the "access to rural property", eight stakes, in order to attain the internal goals of the agency through the "environmental regularization report", two stakes.

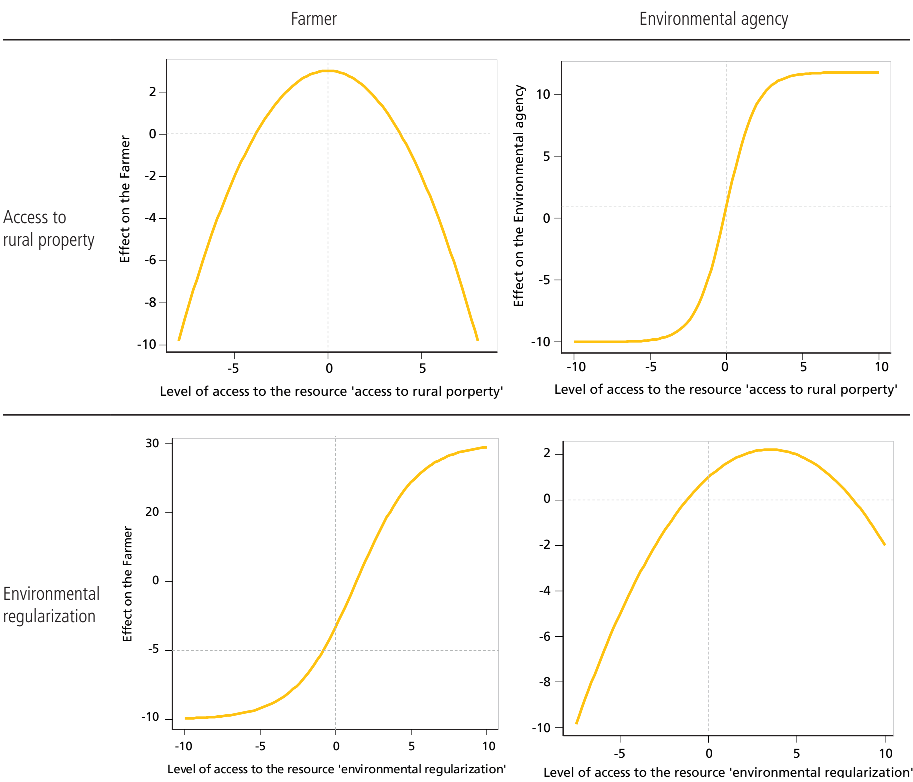
TABLE 3
Distribution of stakes by resource

	Farmer	Environmental agency
Access to rural property	6	8
Environmental regularization	4	2

Elaborated by the author.

The effect functions describe, by means of a continuous curve with domain and image in the range [-10,10], the effect of the resource on the social actor that depends on it. In this hypothetical case, it has four effect functions as shown in graph 2. The effect function of the farmer for the resource "access to rural property" is quadratic and means that the effect increases if the access to this resource is near to zero (neutrality). The effect function of the same actor for the resource "environmental regularization report" is sigmoidal, i.e., the greater the access to this resource greater will be the effect on the rural producer. For the environmental agency the effect function for the resource "access to rural property" is also sigmoidal with lower and upper limits equal to -8 and 8, this means that the greater the access to rural property better will be the impact on the agency. However, for the resource "environmental regularization report" the agency has its peak in return for a certain access, the minimum goal of the environmental agency, and decays to the other states.

GRAPH 2
Effect functions for each relation social actor – resource



Elaborated by the author.

After running the simulation algorithm for this case it has observed that the socioterritorial system reached its stability in an average of 11,843 steps, for the states of "access to rural property" and "environmental regularization report" equal to 4.18 and 5.95, respectively, with an individual capacity of action equal to 104.93 and 76.48 for the actors farmer and environmental agency, respectively (table 4). These values correspond to 66% and 68% of the percentage equivalent to the maximum possible capacity of the actions of the respective actors.

The analysis of the capacity of actions and states for the various iterations of the simulation algorithm, see table 4, show that the environmental agency has less freedom because it depends on a restricted resource. The resource "access to rural property" varied less because it will be in a narrow limit that the farmer can achieve the best of their capacity of actions.

TABLE 4
Mean and standard deviation for capacity of actions and resources for converged situations from the simulation algorithm

		Mean	Standard deviation
Capacity of action	Farmer	104.93	5,26
	Environmental agency	76.48	2,19
State of the resources	Access to rural property	4,18	0,47
	Environmental regularization	5,95	1,20

Elaborated by the author.

7 APPLICATIONS OF THE SOCLAB FRAMEWORK IN SOCIOTERRITORIAL SYSTEMS

The empirical origin of SOA and its formalization through Soclab framework allowed the application of this theoretic-methodological approach in some territorial problems of analysis of collective action (Adreit et al., 2009; Casula, 2011; Baldet, 2011; Silva, Sibertin-Blanc and Gaudou, 2011; Silva et al., 2014; Silva, 2014). These applications can be considered as analysis of power relations in socioterritorial systems and presents certain general characteristics such as: are inserted in contexts of territorial multidisciplinary research; are exploratory and not conclusive approaches; to some extent, the social actors related to agriculture, the main human activity which modifies the natural environment, are present in the governance of the all analysed socioterritorial systems.

The next two subsections will briefly review these works and describes in some detail a case study about the analysis of power relations in the Southern Rural Territory of Sergipe, Brazil.

7.1 A brief review

Although the Soclab framework had been elaborated to deal with any kind of collaborative social studies the main focus has been the analysis of socioterritorial systems. Casula (2011) used this approach to investigate the social structure around the water management in Corse, France, and showed that it increase our capacity of understanding the microfoundations of the overall behavior of that kind social system.

Adreit et al. (2009) applied the Soclab in sociological analysis of the behavior of social actors tied to agriculture in the river basin Adour-Garonne, southwest of France. This is a vulnerable area in terms of pollution of rivers and their tributaries mostly due to agricultural activity. According to the authors, although the Soclab framework be more appropriate for exploratory analysis of the social structure and their power relations around a particular set of resources, it is possible to use the results of modeling and simulation to take concrete decisions. Thus, from the analysis of the capacity of action and power, according to the definitions of Soclab, the authors evaluated the acceptability and applicability of public policies elaborated to reduce the pollution of the rivers.

Baldet (2011) and Sibertin-Blanc et al. (2013) analyzed the conflicting relations between social actors involved in the prevention and management of flood risk in the basin of the river Touch, southwest of France. This scenario has two groups of social actors, those who represent the municipalities of agricultural areas and those who represent the municipalities of the metropolitan area of Toulouse. The first are obliged to reserve part of their arable area to prevent flooding in urban areas, represented by the second group. The solution adopted was the change in perspective regarding the interpretation or conceptualization of the river, it should be managed as an integrated element in an ecosystem and not simply as a continuous flow of water. The social actor SIAH, intermunicipal association for the management of the river Touch, was responsible for this perspective change.

In this study the Soclab framework has been used to evaluate four hypotheses: *i*) the social actor SIAH, according to the actor-network analysis, is an obligatory passage to the other; *ii*) the social actor SIAH holds the means to introduce significant changes in the management of flood risk; *iii*) the social actor SIAH has allies with enough power to impose his strategy; and *iv*) the agreement on the "Territorial Public Interest" extinguished the main conflicts in territorial system. The authors validated the first three hypotheses and concluded that the social actor SIAH has enough power to drive the paradigm shift and that this power is purely cooperative. In spite of this, the paradigm shift hasn't ended the conflict between these two opposing groups.

7.2 The Southern Rural Territory of Sergipe, Brazil

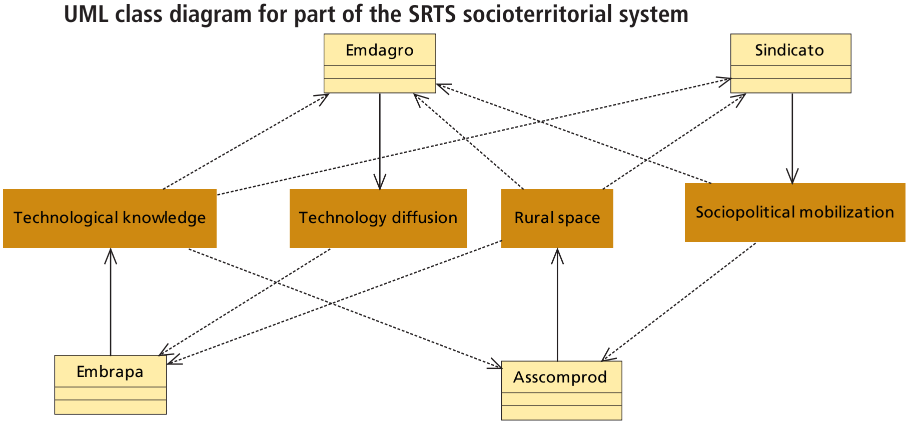
Silva et al. (2014) applied the Soclab framework in modeling the Southern Rural Territory of Sergipe (SRTS), which is part of the Sustainable Rural Development Public Policy of the Ministry of Agrarian Development (MDA). This empirical research had as objective the survey of the main social actors and their relations of interdependence in order to serve as a possible baseline for future analyzes of the impact of territorial policy of the MDA. The analysis took as a point of departure the territorial council, which is responsible for the coordination and governance of the SRTS.

The Southern Rural Territory of Sergipe, Brazil includes twelve municipalities. The total population comprises 278,955 inhabitants, of which 44% resides in rural areas. It has more than a thousand settled families and 20,599 rural properties attached to the familiar agriculture. The agriculture (orange and coconut) and livestock are the main rural economic activities (Siqueira, Silva and Aragão, 2010).

The Ministry of Agrarian Development (MDA) created the SRTS in 2007. To rule this new entity, it has created a council, composed of representatives from institutions tied to the familiar agriculture, to design a plan for a sustainable territorial development. Despite some initiatives, this process is still going on. In general, it has perceived a fragile social engagement around the territorial council and a sectoral bias that isolates the territory from other economic, environmental and social actions.

The research has executed by means of interviews, questionnaires and documental analysis and the first social actors and resources draft became visible in Silva et al. (2014). This paper showed that some social actors, associated with the environmental conservation and to the economic activities, does not take part in the SRTS council and that there was not a strong engagement among the communitarian rural associations and the council. So, it has decided to model only the relations among social actors that have strongly tied with the SRTS Council. The solidarities were not considered, so $S_n = C_n$.

FIGURE 5
UML class diagram for part of the SRTS socioterritorial system



Elaborated by the author.

7.2.1 The model

It has assumed that: the behavior of social actors which are part the same group is homogeneous enough to allow us to represent it by only one social actor (e.g., associations, unions, majors, banks and municipal councils); it is possible to identify informal relations among social actors by yours institutional resources.

Figure 5 shows part of the UML class of the SRTS socioterritorial system. In this graphic some social actors have represented (Emdagro, Sindicato, Embrapa and Asscomprod) as well as their resources and the links among them.

The chart 1 shows the social actors from the SRTS and the resources controlled by them (Silva, 2014). For each resource it has defined a range of accessibility which denotes whether one resource is available or not and in what extent.

CHART 1
The list of social actors and their resources

Social actor	Social actor's description	Resource	Resource's description and accessibility
Pronese	The Company for Sustainable Development of the State of Sergipe manages programs and activities in rural areas with a focus on poverty reduction, managing credit programs and design of environmental management plans.	Consulting on SD	Consulting on sustainable public policies for rural areas. There is no restriction to access this resource, so the accessibility is in the range [-10,10].
Emdagro	The Agricultural Development Company of Sergipe works with the family farming and sustainable agriculture.	Technical assistance and rural extension	The lack of structural capacity limit the access to it and prevents a greater commitment of Emdagro with their customers, so there is some restriction to access it [-8, 8].
		Technology diffusion	Range of access is [-10,6].
Asscomprod	The communitarian/producers associations organize the community politically and administratively.	Rural space	The access may not be complete and is rarely inaccessible, [-9,9].
Banco	The Banco do Nordeste, the World Bank and the Banco do Brasil finances low cost projects for local sustainable development.	Financial resources	The range of access is [-6,6].
Condem_ Cmds	The Economic Council for Municipal Development / The Municipal Council for Sustainable Development.	Plan for municipal development	The plan for municipal development by CONDEM/CMDS. It can assume extreme situations, [-10,10].
Prefeitura	City hall	Public policies for municipal's sustainable development	This resource can assume extreme situations, [-10,10].
Sindicato	Rural workers' Union.	Sociopolitical mobilization	Meant sociopolitical mobilization as the ability of the Rural workers' Union to mobilize people for the defense of the union ideology. Range of access is equal to [-9,9].
Embrapa	Brazilian Agricultural Research Corporation.	Technological knowledge	The access to it is extremely limited due to various social and not social aspects of our society, [-5,5].

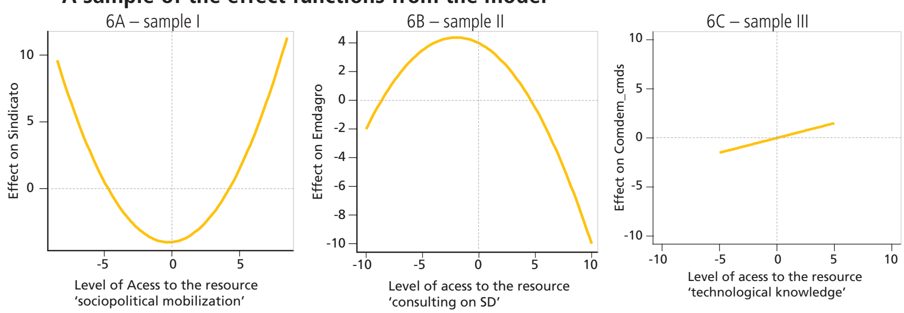
Source: adapted from Silva (2014).
Elaborated by the author.

The stakes of the social actors have distributed to all resources according to a cooperative social game, so each one put more stakes on resources controlled by others. As expected, Embrapa is the least dependent on the others. As an agrarian research organization with a limited capacity to technology diffusion its stakes were put on resources controlled by the Emdagro and in the rural space controlled by the Asscomprod (Silva, 2014).

The effect functions are illustrated in figure 6. The effect of the resource "sociopolitical mobilization" on the Sindicato social actor reflects that it will be negative only for a situation where people are apathetic, the value of this resource is around zero. Otherwise, this social actor, which represents the rural's labor force, will get positive effects for negative values of the resource, which means sociopolitical demobilization or vulnerability, and for positive values, which means a completely social engagement (figure 6A).

Figure 6B shows the effect of the resource "consulting on SD", controlled by Pronese, on the Emdagro. The parabolic curve shows that the extreme difficulty of access this feature negatively affects Emdagro, as well as the abundant supply, because Emdagro not have the means to reach the demand generated by the unrestricted access to the resource. The impact will be positive only for intermediate situations, so a restricted access can be a turning point and forces the Emdagro to assume the role of consultant in sustainability. The effect will also be positive for slightly easier access situations, as this would generate requests of feasible actions by the Emdagro.

FIGURE 6
A sample of the effect functions from the model



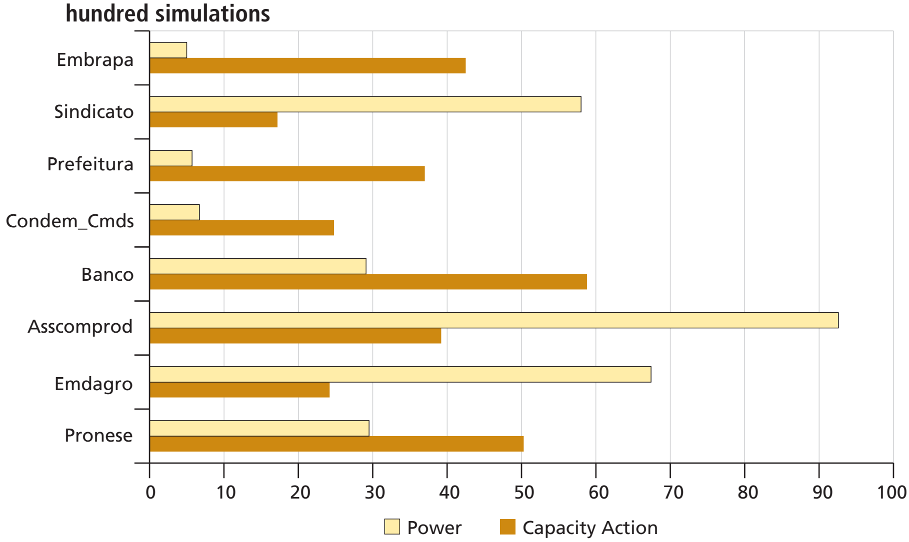
Source: Silva (2014).
Elaborated by the author.

The last graphic is a good example of a restricted resource, range from -5 to 5 (figure 6C). This short straight line shows that the effect of the "technological knowledge" on Comdem_cmds is almost insignificant, or that this social actor does not use such kind of information in the decision making process.

7.2.2 The simulations

To perform the social simulation to check if this socioterritorial systems is stable or not, and to see how is the distribution of power and capacity of action among social actors it has used the Soclab software. It has considered default values for all psycho-cognitive parameters and performed 100 simulations with 200,000 steps each one at most. The social simulation algorithm reached the stability in 98% simulations with an average steps of 73,883.

GRAPH 3
The average value of capacity of action and power for stable social games after one hundred simulations



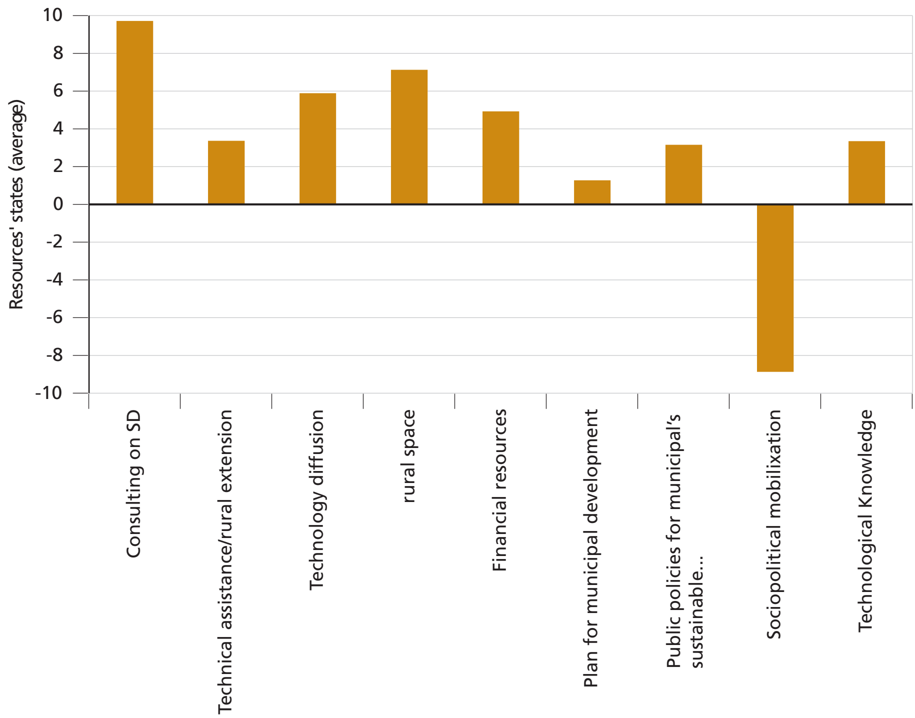
Elaborated by the author.

The graph 3 shows the average values for capacity of action and power for all social actors. The Banco, the Pronese and the Embrapa have high scores for capacity of action (55.09, 49.30 and 41.23, respectively), this means that they have more chances to cooperate with others. The Sindicato is the social actor with the worst capacity of action (16.70), this suggests that the Sindicato is somehow locked and placed with a limited space of action. Despite of the centrality and importance of the Emdagro it has a small capacity of action (20.62), so the two resources controlled by this actor do not give him the necessary capacity due to its opposition to others actors and its limitation to attend the demand for rural assistance. Analogically, the same occurs to the Prefeitura and to the Condem_cmds.

The most powerful social actors are the Asscomprod (92.6), the Emdagro (67.4) and the Sindicato (58), this means that they control important resources and which maximize the impact on each of these social actors. In fact, the Asscomprod controls a key resource, "rural space". The Embrapa (5), the Prefeitura (5.7) and the Condem_cmds (6.7) have the worst values for the variable power.

Only two resources presented a greater access to it after converging simulations, "consulting on SD" controlled by the Pronese and "rural space" controlled by the Asscomprod (graph 4). In fact, they are key social actors that shares their resources without restriction. Some resources' states stabilized in the neutral region, around zero, this means that this socioterritorial system shows some kind of indifference toward local initiatives (plan for municipal development, public policies for municipal's sustainable development) and to the technological developments.

GRAPH 4
The average value of the resources' states for stable social games after one hundred simulations



Elaborated by the author.

7.2.3 Territorial public policy assessment and some remarks about this case study

A comprehensive assessment of a territorial public policy is a tough task and it demands a multidimensional approach to take into account as many as possible aspects of the reality to be understood. The Soclab framework address part of this challenge but does not offer a falsifiable and conclusive method. However, it showed to be effective to systematize the information from sociological studies, to map social relations, to evaluate the stability of these interdependences, and to construct a baseline for future comparisons of different relational states for the same socioterritorial system.

In our case study, the Soclab framework showed some evidences that the SRTS socioterritorial system could be interpreted as a stable organization, that presents some characteristics which must be addressed in order to explain the overall functioning of the system, such as: it showed to be, to some extent, sectorial, so privileging only matters related to the family farm group; there are some resources with restricted access; and, there is a power/capacity of action distribution imbalance among the social actors. Obviously, one way to change this scenario is adding new social actors to bring a new structure to the social game by changing the formal and informal rules of the territorial council.

Silva (2014) evaluated two scenarios for this socioterritorial system by changing a effect function and the range of access to a resource. All the results have evaluated/validated by researchers with enough expertise to judge the plausibility of the simulation outputs.

8 FINAL CONSIDERATIONS

Although there are already mechanisms of territorial observation, it is important to emphasize the need for interdisciplinary methods that integrate the different concepts of areas of the guiding principles of sustainable development. In this chapter the theory of systems is used as the common thread of connection between the social system of actors, their relations of power and space system through the Soclab framework. The socioterritorial system approach can be modeled for different purposes and proved to be applicable in the processes of territorial public policy evaluation.

The analysis of power in socioterritorial systems through SOA allows the establishment of the interdependencies between the various social actors through the relations of control and dependence on the "uncertainty zones" which can serve as subsidies for studies in the areas of social networks and social cohesion. The strategic analysis does not allow one to conclude categorically if some sociterritorial system will reach or not your goals, but if he has the necessary conditions for this instead.

The conceptualization territorial proposal by Moine shows a tendency to focus the analysis of the human-space interaction in the system of social governance. However, this new direction adds to the process of territorial analysis the challenge to integrate the space system to the social system. This work has been simplified this task through the mapping of geographic elements as relations and resources in the Soclab framework.

The modeling process through the Soclab framework presents increasing difficulty as the number of social actors and resources are added to the model. The main difficulties are the construction of the effect functions that requires deep knowledge of the problem and the analysis of the results of the simulation for the cases with multiple actors and resources. In fact, the simulation algorithm has exponential complexity which imposes limitations of computacional processing simulation.

One of the main applications of the Soclab framework is in the exploratory analysis of the social relations to search: whether or not the socioterritorial system is stable and in what conditions it occurs; if there is an imbalance in the distribution of power between social actors, which can explain, among other things, the indifference of certain actors; and the establishment of a baseline for comparative purposes. Of course, the use of Soclab framework also creates a standardized record of territorial sociological investigations.

The process of social modeling and simulation creates opportunities and challenges for research and development in various areas, such as: a multivariate statistical analysis of the results of the simulation; the evolution of the link between the spatial system and the social system; the spatialisation of the results and subsequent connection with models of land use; the analysis of the social system by means of other social theories; and the design of systems of analysis and monitoring of territorial public policies.

Finally, it is expected that the method of modeling and simulation exposed in this chapter could collaborate in the process of understanding the complex socioterritorial systems as well as assisting the government in the planning and development territorial public policies.

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ANNEX A

TABLE A.1
Simplified suggestion of a survey form for the construction of socioterritorial model (mainly, the effect functions) based on Soclab framework

Social Actor:_______________________________	Relevant resources ("uncertainty zones") for the social actor		
	A	B	C
1. What resources are needed for the completion of their tasks and achieve their goals?			
2. Who controls the resources?			
3. How important is the resource for your activity? (0.10)			
4. Describe your behavior in the case of restricted access to feature			
5. Evaluate the effect of the behavior described in item 4 in its activity (-10.0)			
6. Describe your behavior for the case of unrestricted access to feature			
7. Evaluate the effect of the behavior described in item 6 in its activity (0.10)			
8. Describe your behavior for the case of neutral situation with regard to access to feature			
9. Evaluate the effect of the behavior described in item 8 in its activity (-10,10)			
10. What is the situation usal with regard to access to the resource?			
11. Evaluate this situation in terms of impact on their activity (-10,10)			
12. For each social actor assign a value which represents a solidarity degree with the others. Values close to -1 means a situation of conflict, values close to zero denote neutrality or impartiality, while values close to 1 correspond to a cooperative relationship.			

	Social Actor A	Social Actor B	Social Actor C	Social Actor D	Social Actor E	Social Actor F
Solidarity						

Source : Sibertin et al. (2013).

The values of question 3 should be normalized so that the sum of all and peer assessment resulted to the social actor is equal to ten. Questions 4 to 11 should be used for the construction of the effect functions. The values of the question 12 will be used to construct the matrix $\mathbf{W}_{NxN}$.

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Supervision
Everson da Silva Moura
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