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Survey paper

Improving accuracy, complexity and policy relevance: a literature survey on recent advancements of climate mitigation modeling

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Abstract: Process-based Integrated Assessment Models (IAMs) play a crucial role in climate agenda-setting and progress monitoring. They advise climate negotiations, inform nationally determined contributions (NDCs), and help create scenarios for central banks. Recent developments have enhanced IAMs' policy scope and accuracy, including the incorporation of industrial policies, improved sectoral details, and modeling of consumer behavior. Despite these advancements, challenges remain, particularly in improving spatio-temporal and sectoral resolution, adapting to fast-changing sector-specific policies, and addressing complex dynamics beyond the traditional techno-economic cost-minimization framework. This literature review explores Directed Technical Change (DTC) growth models, Agent-Based Modeling (ABM), and game theory to complement mainstream IAM approaches, especially in integrating political economy considerations. DTC emphasizes the role of public research and development (R&D) investment in supporting early-stage mitigation technologies. ABM highlights the decision-making processes and behaviors of heterogeneous agents, while game theory examines market dynamics, such as newcomer vs. incumbent competition, strategic pricing, and resource extraction. While these models cannot replace IAMs, they can broaden the scenario design space and improve the complexity and policy relevance of IAM-based mitigation modeling.

Keywords: climate mitigation modelling; process-based integrated assessment models; directed technical change; agent based models; game theory

1. Introduction

Mitigating climate change and guiding the global economy towards sustainability requires swift, coordinated action from governments, international organizations, the financial sector, companies, civil society, workers, and citizens. To coordinate such diverse actors, a quantitative and actionable roadmap for climate mitigation is essential. Over the last two decades, process-based integrated assessment models (IAMs) have become a key tool in climate policy, particularly in the IPCC WG III report. IAMs have taken on the dual role of setting agendas and monitoring climate mitigation progress [1], advising governments and financial institutions worldwide on climate policy and investment.

However, in recent years, some review articles [2–8] have highlighted several important limitations of IAMs. They identify areas where IAMs fail to effectively set agendas and monitor progress, even within their optimization-based framework. They also point to the limitations of the IAM methodology, and suggest other dynamic modeling methods, particularly for addressing the political economy aspects of the transition. Among critical literature, a consensus is emerging that when it comes to modeling disruptive technical innovation, heterogeneity of actors, processes of technology lock-in, and other disruptive or non-equilibrium aspects of the transition, IAMs are not the best-suited tool.

Despite their shortcomings, IAMs remain a key tool for setting benchmark pathways for global energy and land-use transitions. Their ability to generate internally consistent, flow-based global pathways of energy and agricultural production, as well as emissions under emission constraints, gives them a strong future role in advising climate policies (Section 2). Any competing model will face similar challenges IAMs face today, namely computing self-consistent flows of energy and emissions under constraint, addressing data availability within the sectors, and balancing the tradeoff between broad spatio-temporal scope and granular resolution. In this regard, dynamical methods are unlikely to replace IAMs in providing a comprehensive range of quantitative services, from setting national and sectoral policy targets to exploring trade-offs in technology choices. Given the limited carbon budget under the Paris Agreement, even equilibrium-based IAMs can model radical transition pathways, reflecting significant departures from the status quo [9, 10]. Moreover, IAMs are increasingly incorporating dynamical models to model sectoral dynamics, such as those used in transport and industry (see Section 2.4.3).

Given these considerations, it is important to ask: *Which limitations should IAMs address, considering their dual role of setting the mitigation agenda and monitoring progress? Which can be addressed with existing methodology, and which cannot? Where IAMs have inherent limitations, what alternative tools can complement them? What questions do these tools address, and how can they enhance IAM pathways?* To answer these questions, we first survey recent advancements in IAMs, focusing on energy systems. In Sections 2.1–2.3, we provide a mechanistic explanation of how IAMs model the energy transition, aiming to increase the transparency of these complex models. We also highlight the limitations of the market-based policy interpretation of IAM based mainly on highly aggregated CO_2 pricing, which struggles to meet the challenge of fast-changing policy realities and to generate adequate volume of investment. In Section 2.4, we outline three interlinked limitations of IAMs that can and should be addressed within the current methodological framework. The main critique focuses on improving IAMs' ability to better represent a broader range of real-world policies—beyond CO_2 pricing—and incorporating them into standard pathways with greater accuracy, reflecting a deeper understanding of regional energy policies, sectoral dynamics, and technological diffusion.

Alongside the critical review of recent advancements of IAMs, we provide a literature survey on three dynamic methods that can complement mainstream IAM analysis: Directed Technical Change (DTC) (Section 3), Agent-Based Modeling (ABM) (Section 4), and Game Theory (Section 5). Given IAMs' limitations in capturing political economy, these approaches offer a better way to model innovation processes, heterogeneity, and strategic interactions. We have chosen them both because of their frequent appearances in the critical literature, and also of their ability to address key aspects of political economy missing from IAMs. Drawing on the authors' diverse expertise, we propose concrete ways to integrate elements of these dynamic models into IAMs.

Compared to previous critical IAM literature, our review makes two main contributions. First, we offer an "insider" perspective on IAM modeling, focusing on the energy system, and explaining the mechanisms behind mitigation modeling, along with its strengths and shortcomings. Second, we differentiate three types of limitations in current climate mitigation modeling: 1) limitations that mainstream process-based IAMs can address within the existing equilibrium framework; 2) limitations IAMs cannot resolve due to methodological constraints, but which can be complemented by dynamical models and other quantitative tools; and 3) limitations common to all quantitative models, yet critical for understanding how to successfully mitigate climate change (see summary Figure 1). The first critique does not undermine the value of IAM benchmark pathways, but calls for more accurate, real-world oriented benchmarks with actionable policy levers. The second critique focuses on connecting IAM benchmarks with real-world political economy, assessing not only CO_2 prices, equity, or investment, but also innovation and growth. Lastly, we highlight the general limitations of quantitative models. While some models address political economy and behavioral aspects (limitation 2), all quantitative models struggle to capture the complex social processes behind past transitions and the institutional change needed to combat climate change, underscoring the need for a broader, interdisciplinary approach.

2. Current methodology of modeling climate mitigation – opportunities and challenges

2.1. IAMs, their policy roles and policy questions

As the primary tool for climate mitigation modeling, process-based IAMs have widespread policy impacts. In recent years, they've shaped regional and national climate policies, including the EU Emission Trading System (EU-ETS), the "Fit for 55" package, the EU 2040 GHG reduction target, and China's 2060 net-zero goal [11–14]. IAMs also support the 127 central banks and supervisors, plus 20 observers in the Network for Greening the Financial System (NGFS), in conducting climate stress tests and assessing climate-related risks [15].

IAMs compute global climate pathways under various socio-economic scenarios, mainly population and GDP growth projections. The more complex, energy-engineering-focused IAMs—the so-called "process-based" IAMs—include detailed energy and land-use systems, which contain all the emitting sectors [7, 16]. Their outputs—"scenario pathways"—show how energy and food demand change with GDP and population, and match these with resource extraction and production capacities. IAMs also estimate required green investments and compute equilibrium prices of energy, providing useful metrics for analyzing the economic implications of the transition.

There are two key questions IAMs are especially suited to answer:

1) **Agenda-setting**: What are the sectoral emission and capacity deployment targets needed to meet a Paris Agreement-aligned climate commitment? What global and regional investment levels are required? What sector-specific policies (e.g., CO_2 prices, energy taxes, subsidies) can support green technology competitiveness and drive consumer adoption?

2) **Monitoring progress**: Given current technological development and implemented policies, what is the projected global warming outcome? Can major emitting regions meet net-zero targets by mid-

Model	Limitation which can be overcome within current framework			Inherent limitations of optimization approach which require dynamical models		
	Challenges for IAMs	Solution or complementary method	Section	Challenges for IAMs	Solution or complementary method	Section
IAM	Highly aggregated CO_2 pricing tools is less flexible at responding to disruptive technology changes and rapid energy price changes	Validate with lightweight bottom-up techno-economic analysis for specific technologies and sectors; using IO model to assess interaction between CO_2 prices and inflation	2.3.1	Portraying the political economy of profit-lead innovation and economic growth, explicit modelling of innovation process, knowledge build-up and depreciation	Growth models with directed technical change, two-factor learning curve, learning and forgetting curve	3
	Slow at shifting from market-primacy to investment-primacy policy tools to set ambitious climate investment agenda	Improve modelling on demand-sector granular capacity investment requirement, implement endogenous technical change	2.3.2	Portraying process-based transition dynamics involving heterogeneous decision-makers and non-smooth dynamics; Depicting dynamics of baseline "business as usual" pathway, where national policies are implemented	Agent-based modeling	4
	Coarse spatio-temporal resolution, limited national and sectoral policy insights in high resolution	Soft-coupling to power sector dispatch models, downscaling via post-processing	2.4.1	Portraying strategic considerations in climate mitigation	Game theory	5
	Need for sector granularity and policy diversity beyond CO_2 prices in order to monitor policies already implemented	Incorporate granular sectoral models (optimization or dynamical models)	2.4.2-3	*Challenge for all current models including IAMs:* portray complex social changes underlying changing industrial regime, articulate process of institutional change	An interdisciplinary approach including economic and industrial history, sociology, etc	6

Figure 1. An overview of the different types of IAM limitations and the solutions and complementary approaches which can address them.

century under current NDCs? How much emission reduction will these policies achieve if fully implemented?

While stylized IAMs like DICE and RICE have contributed to climate policymaking, this review focuses on process-based IAMs due to their detailed energy systems and broader policy impact [7]. Since IPCC scenarios mostly rely on five or six global process-based IAMs [17], we focus on models like REMIND and MESSAGE to explain IAM methodology [18, 19], due to their large contribution to the last IPCC AR6 scenarios, as well their ability to pass the scenario vetting tests [17]. Even though there is some methodological diversity among process-based IAMs (e.g., [20]).

2.2. *Modeling energy system in IAM*

The energy "supply side" of IAMs typically models a linear chain of energy conversion, starting from primary energy extraction (e.g., oil or coal), which is converted into a secondary energy carrier (e.g., coal burned to generate electricity), and then to a final energy carrier, which is transported to users (e.g., electricity transmission). The "demand-side" sector (e.g., buildings, transportation, and industry) then takes over, where the final energy carrier is converted into usable energy, products, and services. For example, a given amount of final energy (coal or hydrogen) delivered to steel plants produces one ton of primary steel (industrial product). Electricity can be used to generate heat via heat pumps, which maintains a fixed indoor temperature (energy service, measured in "heating degree days"). In transport, electricity or diesel fuel powers a vehicle to provide transportation service, measured in "moving one ton of freight or one passenger for one kilometer". An example diagram from the IAM REMIND is shown in Figure 2.

It is important to distinguish between final energy carrier demand and energy service demand, as electrification or efficiency technologies can reduce final energy use without decreasing energy service demand (e.g., in electrifying transport). An additional layer of efficiency exists between final energy and energy service ("energy usage efficiency" in Figure 2). For example, with the same energy service demand (e.g., indoor temperature in winter), a well-insulated house requires less final energy than a poorly insulated one.

As energy is converted linearly in the energy system, IAMs track the emissions of greenhouse gases in all world regions through usually non-region-specific benchmark emission factors for the energy conversion and usage processes. In addition, soft-linking energy system IAMs to land-use IAMs can help assess the impact of climate mitigation on the global food system, e.g., through the large-scale use of biomass as a carbon-neutral fuel [21, 22]. Energy and land-use sectoral emissions from the modeled systems are connected to a simplified climate model, which informs users about the climate outcomes of a given scenario, e.g., climate forcing and global average temperature.

IAMs have a long-term temporal scope due to the cumulative impact of greenhouse gases like CO_2 and N_2O. They also cover large geographical areas, typically modeling the entire globe. Functionally, IAMs use numerical solvers to determine the most cost-effective climate mitigation pathway under exogenous emission constraints. For example, under a 1.5°C or well-below-2°C target, a cumulative GHG or CO_2 emission budget—based on the latest IPCC WGI results—is imposed on a baseline energy and land-use system, with regional growth and population scenarios, usually extending to the end of the century. Under these constraints, the model computes the long-term "least-cost" path across the entire time horizon. Due to their computational simplicity, IAMs are well-suited for setting climate mitigation agendas and providing benchmarks for global technological deployment.

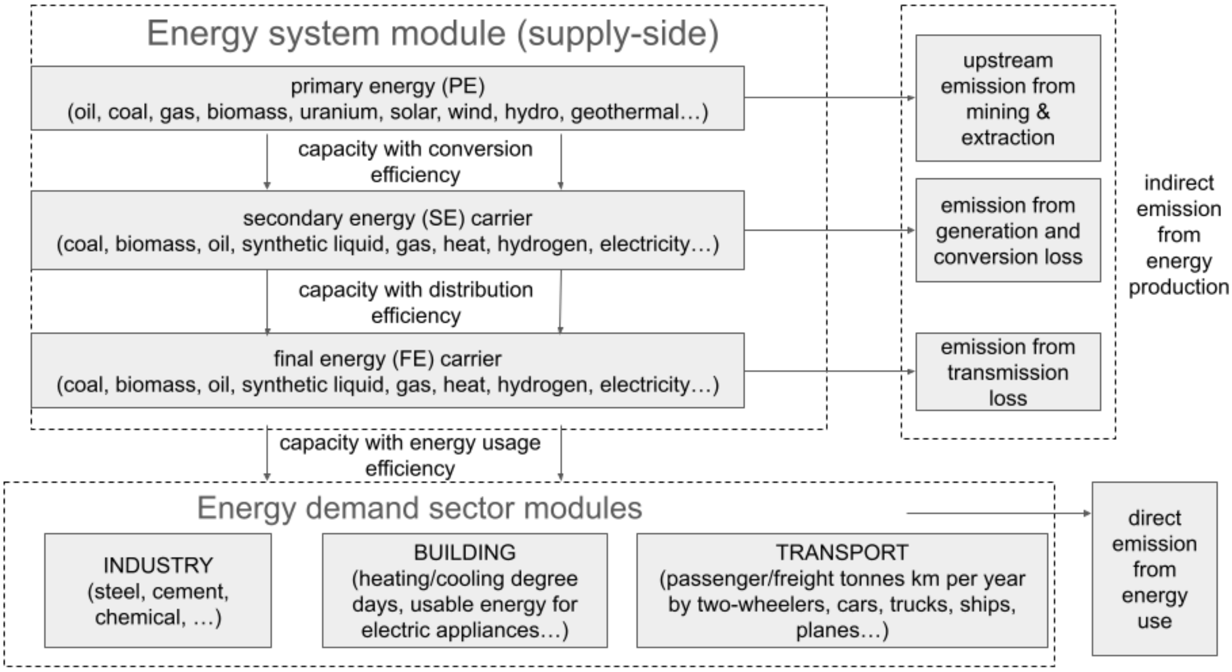

Figure 2. A diagram shows the linear conversion from primary to secondary energy, then to final energy, and eventually to energy services or usable energy in the end-use sectors in a state-of-the-art process-based IAM, REMIND [19]. Each stage of the linear conversion involves several different types of technologies (e.g., oil to electricity conversion corresponds to a diesel generator, coal to hydrogen conversion corresponds to coal gasification), which are not shown separately in the figure. Each technology has capacity and generation variables associated with it, which are endogenous and can respond to pricing or non-pricing policies or constraints.

At their core, mainstream process-based IAMs are constrained optimization models. In this framework, the objective function is typically welfare, which is maximized. This is equivalent to energy system cost minimization under certain assumptions [23]. The decision variables are long-term annual capacities, and the extraction or generation of energy and agricultural goods. The main constraints include energy demand, historical capacities, GHG emissions, and resource endowments. The Lagrangian multipliers of supply-demand balance equations for different products are interpreted as their equilibrium prices. Constrained optimization simulates the equilibrium state of energy and agricultural markets, where supply equals demand. This simplifies the complex problem of numerically solving coupled differential equations in high-dimensional systems to calculating the steady state through optimization.

The equilibrium prices generated by IAMs typically reflect perfect competition, meaning that prices equal levelized production costs. Under market equilibrium and perfect endogeneity (i.e., when no additional constraints are imposed on decision variables), cost always equals price in the model. This is guaranteed by the Karush–Kuhn–Tucker condition in constrained optimization, as shown for the electricity sectors in the studies by C. C. Gong, et al. [23, 24]. The market-equilibrium formulation reflects the idea that perfectly competitive markets force producers to “race their price to the bottom”, driving profits to zero. However, this is a simplification of real-world agricultural and energy markets, where varying degrees of imperfect competition, strategic price-setting, and profits arise, depending on the pricing power of large producers, regulatory regimes, and geopolitical factors. These limitations of IAM methodology can be sometimes addressed by other dynamical models (Section 5.3.1).

In the energy demand sectors, which lie “outside” the energy supply side, IAMs typically use nested production functions with CES. The “CES tree” nodes represent production functions in various sectors, with branches showing their inputs and outputs. An example of a CES tree for the industry sector in the IAM model REMIND is shown in Figure 3. The CES elasticity parameter σ represents the exogenous, often time-dependent elasticities of substitution between upstream node branches, indicating how easily the model can switch between different (energy) inputs to maintain output at a given time based on input price changes. This CES-based structure for demand sectors is linked to the “supply-side” linear energy system module, as shown in Figure 2. When the supply side adjusts its optimal mix (e.g., due to emission constraints, CO_2 prices, or subsidies), the prices of alternative fuels in the CES node change accordingly. As a result, technology choices in end-use sectors may shift—for example, from oil boilers to heat pumps powered by cheaper electricity from renewables. This incentivizes more investment in heat pumps and renewable electricity, while reducing investment in crude oil, refineries, and oil boilers. Fuel switching can be simulated not only with CO_2 prices, but also with a mix of pricing, taxes, subsidies, interest rate policies, and regulations to achieve similar outcomes (see Section 2.4.3).

2.3. Emission abatement dynamics in IAMs and recent challenges

In IAMs, emission constraints drive transformations in the energy and land-use systems. While IAMs now use a range of policy tools including regulations and bans, most scenarios still rely primarily on endogenous carbon pricing to drive this transformation. These price-based policies then indirectly promote fuel-switching, technology learning, energy efficiency, and occasionally material efficiency improvements. A simple graphic illustrating abatement dynamics in IAMs is shown in Figure 4.

The mechanism works as follows: IAMs begin with a starting CO_2 price path, applied to per ton of carbon emitted. The model iterates this path until a desired climate target is met (e.g., < 2°C warming, emissions budgets, etc.). The CO_2 price increases the cost of emitting fuels and processes, making green alternatives cheaper in comparison, prompting the model to invest in them. Over time, cumulative investments in renewables trigger endogenous learning through a “learning-by-doing” function (one-factor learning curve (OFLC)), which reduces costs for fast-learning technologies. This reflects the “perfect foresight” in IAMs with long-term time horizons. IAMs also model the spillover effect, where investments in renewables in one region lower costs in others. Lastly, energy and energy intensive product prices change under policy, leading to demand responses in CES nodes. Higher energy prices can induce energy and material efficiency improvements, or simply reduce demand, while lower prices stimulate demand growth.

Assessing the endogeneity of efficiency improvements in IAMs requires understanding that sector dynamics respond heterogeneously to price mechanisms, depending on how each sector is modeled and the diversity of policies applied. For example, in the current version of the IAM REMIND, price-induced electrification is particularly prominent in the industry and building sectors, which have CES-based structures. In contrast, the transport sector’s response to price changes is less pronounced [25].

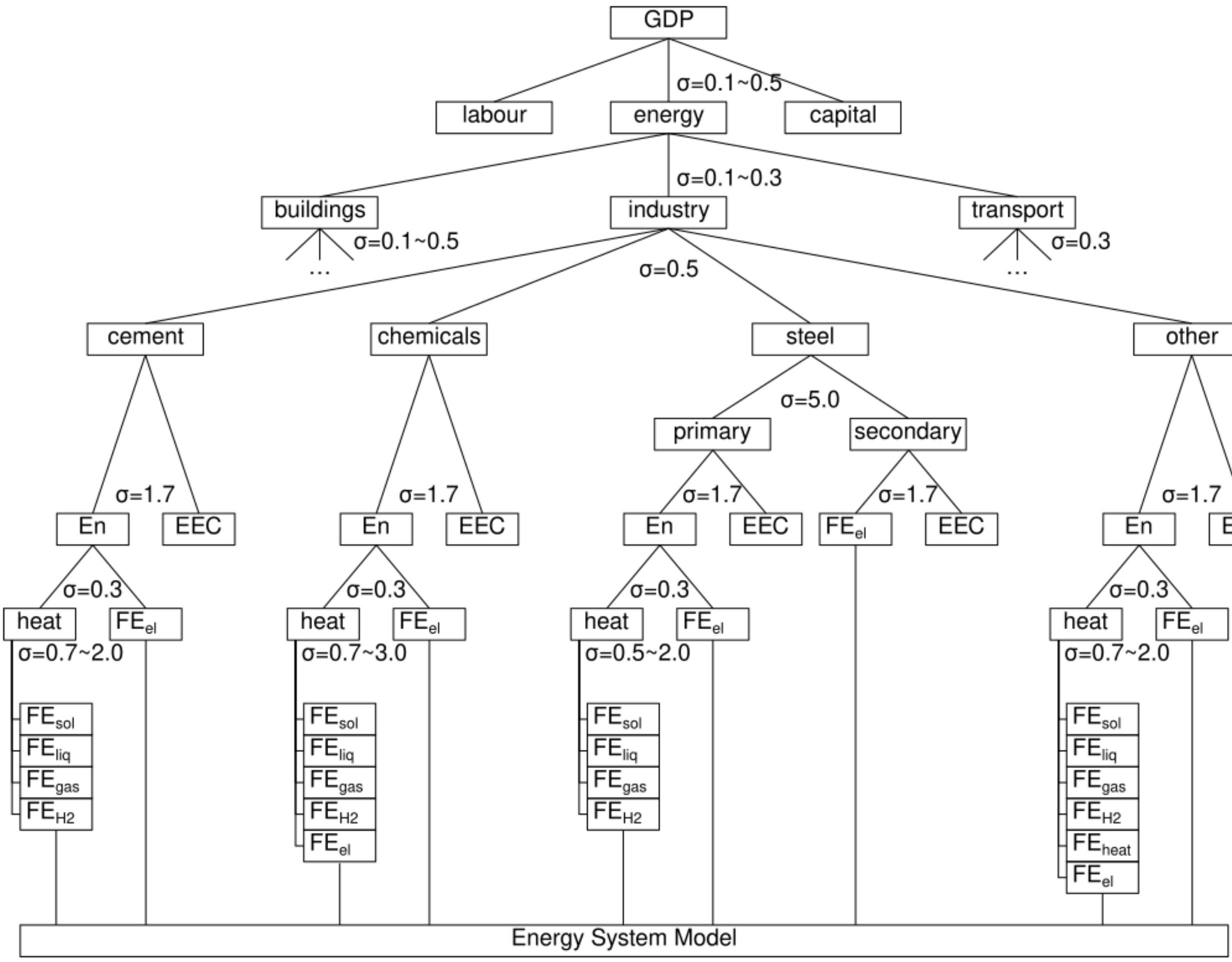

Figure 3. A diagram showing the nested CES tree structure portraying the economics of the industry sector of an IAM, REMIND [19]. EEC: energy efficiency capital (see Section 2.3); En: energy; FE: final energy; sol: solid; liq: liquid; el: electricity; H2: hydrogen; σ: exogenous elasticity of substitution.

This is because REMIND models the global transport sector separately, using a dynamic model with explicit technology diffusion, which is then coupled to the main energy system. The diffusion rate of electric vehicles (EVs) depends on factors like fuel price, capital cost, driving range, and charging infrastructure. While the CO_2 price can slightly incentivize electrification by raising gasoline costs, its impact on EV diffusion is minimal, as the shape of the diffusion curve is mainly controlled by parameters not linked to the energy system module. Thus, the large efficiency gains from vehicle electrification are primarily driven by policies other than the CO_2 price.

2.3.1. Limitations of the aggregate CO_2 price in adapting to ongoing technology innovation and rapid energy price changes

Despite the simplicity of the CO_2 price-based mechanism in models, applying it in real-world policymaking presents several issues. The CO_2 price typically reflects the marginal abatement cost—the cost of reducing one more ton of emissions. In this framework, the sector with the lowest abatement

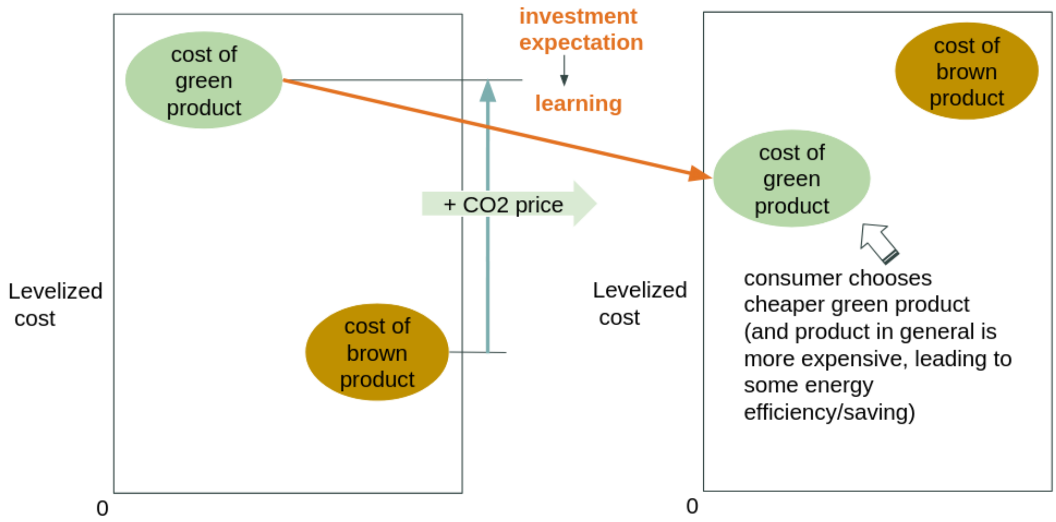

Figure 4. A diagram showing the application of the CO_2 price creates an "investment expectation" in IAM, which triggers fuel switching, endogenous learning and energy efficiency. For simplicity, this relation holds for a one-region model, where the effects of trade and resource scarcity are neglected. Left: the comparison of the levelized cost of the green product before the CO_2 price is applied. Right: after a CO_2 price is applied to greenhouse gas-emitting products. The learning in this particular example does not lead to a decrease in the price of the green product such that it becomes cheaper than before. As a result, demand is reduced due to price-demand elasticity.

cost is usually targeted first, sidestepping the politically sensitive question of which sector should transition early. However, the economy-wide CO_2 price in IAMs is highly aggregated and applied uniformly across the entire system, often to hundreds or thousands of processes. This can create challenges for policymakers navigating a fast-changing environment, where disruptive innovations, political economy factors, and fossil fuel producers' strategies to influence prices can rapidly alter abatement dynamics.

First, disruptive innovation and learning could rapidly reduce the cost of low-emitting products, making them cost-competitive with incumbent technologies (e.g., wind, solar, batteries, and electric vehicles). In this case, an effective CO_2 price may not be necessary in the near future for these sectors, and other priorities—such as infrastructure build-out speed, critical mineral supply, financing, and just transition policies for non-competitive industries—will become more important. Second, due to political economy considerations, subsidies may be needed as a short-term incentive before a CO_2 price can be applied, as part of "policy sequencing". However, one cannot directly use the IAM aggregate CO_2 price as a subsidy, even if it can be translated to a per-capacity or per-generation unit. Instead, the specific costs of production within the model need to be examined. However, understanding these costs and their sub-components is not straightforward in IAMs. Finally, when fossil fuel prices rise—like the current energy crisis in Europe—an increased CO_2 price could exacerbate inflation in sectors like household heating and electricity, unless supported by active policies for electrification and fuel switching. This is analyzed extensively in the study by I. Weber, et al. [26], via IO models of price pass-through in each sector. However, reducing the CO_2 price too much risks relaxing sectoral targets and widening the price gap between sectors. A more targeted approach based on process-specific cost analysis is needed. Conversely, if fossil fuel prices collapse due to oversupply or inability to compete with green fuels, CO_2 prices must rise to maintain the competitiveness of green products. This latter example highlights the need for integrating with models that allow for demand-supply imbalances and where game-theoretical approaches, based on cash-flow analysis, can be applied (Section 5.3.1).

Besides the more granular sectoral models (see Section 2.4.3), one alternative approach to analyzing the more specific key components of sectoral abatement dynamics is simply to decompose output prices into input prices and costs, which can help policymakers better understand what drives the cost differences between dirty and green options. There is a rich literature based on this type of bottom-up techno-economic analysis for the levelized costs of brown vs. green processes [27]. While this method lacks the sectoral interactions that IAMs more comprehensively portray, it is, depending on the application, more lightweight, and its results are more straightforward to interpret due to the limited numbers of parameter input and assumptions. The changes in prices due to economy-wide inter-sectoral interactions can always be derived from IAM results and incorporated into such bottom-up analyses as an additional sensitivity parameter.

2.3.2. Limitations of CO_2 price in generating adequate volume of effective investment

A successful theory of change—depicted in Figure 4—which relies on CO_2 pricing as the primary driver of fuel switching, technology learning, and efficiency, assumes that the government will credibly signal to investors that the CO_2 price will eventually reach levels necessary to achieve net-zero emissions. This would compel companies, asset managers, and funds to align their investments accordingly, leading to large-scale manufacturing and deployment of green technologies. However, in reality, this is not guaranteed. The key motivator for investment—profit—is not modeled in IAMs, and non-profit-driven public investment is also seldom addressed. Therefore, interpreting IAMs solely through a market-based lens, with CO_2 pricing as the main policy lever and ignoring the sources of investment, presents an incomplete theory of change and results in a slow, uncertain transition.

However, recent expansions in sectoral details and the implementation of endogenous learning in IAMs could theoretically improve this situation by supporting an investment-primacy policy interpretation, moving beyond a market-primacy approach. This interpretation is made possible by incorporating fiscal and financial policy tools based on investment variables derived from the IAMs' transition pathways. These variables represent the necessary investments to meet stringent mitigation targets and reduce the cost of renewables (especially if IAMs include endogenous technical change). In policy terms, they provide investment estimates for climate fiscal policies. This shift from carbon pricing to investment reflects a broader transformation from a neoclassical paradigm to a more diversified policy discourse following the great financial crisis [28]. However, the methodological advancements required for this interpretation are still incomplete, as most process-based IAMs include detailed capital expenditure variables only on the energy supply side, with limited detail on the demand side (due to a lack of demand-side granularity in CES-based formulations) (see Section 2.4.3).

2.4. *Recent advancements and further challenges in improving the accuracy and quality of IAM benchmark pathways*

To fulfill the dual roles of agenda-setting and monitoring progress, IAMs must continually improve their methodology. We highlight three key areas: 1) increasing resolution in the power and industrial sectors to enhance the accuracy of mitigation pathways; 2) broadening and diversifying the technological scope; 3) systematically exploring and implementing policies beyond carbon pricing. The third aspect is closely linked to the first two. While IAMs have made recent advances in these areas, challenges persist, and a coordinated approach within the IAM community is needed. A lack of policy diversity risks widening the gap between IAMs' primary policy levers and real-world policies, especially as the US and China implement major industrial policies to support renewable industries and new supply chains. Increasing spatio-temporal resolution and sectoral granularity is crucial for modeling non-pricing policies. Thus, resolution remains the biggest barrier to the quality and accuracy of global scenario pathways and meeting IAMs' dual goals.

2.4.1. Further development on increasing spatial, temporal and sectoral resolution

Global process-based IAMs, whether focused on energy supply or demand, require higher resolution in technology, spatial, temporal, and sectoral dimensions. This is especially urgent for electricity generation on the supply side. Since the lowest-cost electricity worldwide comes from intermittent solar and wind, the optimal power sector solution is inherently spatio-temporally complex. Most global IAMs fail to capture this complexity due to computational constraints. With typical 1-year resolution and 5- to 10-year time steps, IAMs cannot accurately represent weather fluctuations affecting wind, solar, and battery output, or demand-side flexibilization. This results in inaccurate capacity and investment projections, which can materially impact policymaking [29]. Policy tools like capacity market mechanisms are also difficult to assess in coarse-grained IAMs. Spatially, regions in IAMs are typically treated as "copper plates", with no explicit representation of electricity grid networks. This limits the modeling of grid constraints and expansion and renders it difficult to project future electricity prices, which increasingly depend on specific locations.

To respond to this challenge, many IAMs have explored the explicit incorporation of high-resolution dynamics in the power sector [23, 30–36]. C. C. Gong, et al. [23] in particular, presents a bidirectional iterative soft-coupling approach which can be shown to be mathematically consistent with mapping the Lagrangian function of two constraint optimization problems of different scales. Using this and other similar formulation, coupling long-term IAMs with a complete set of energy sectors such as extraction sectors and demand sectors, to spatially and temporally detailed power sector models becomes feasible. Once further developed, this improvement could pave way to the combined long-term planning and short-term operation of a future complex power sectors with high shares of intermittent resources, and help evaluate the climate impact on power demand and supply which requires high resolution time series (e.g., air condition use during heat waves or decreased hydroelectric output due to droughts).

On the demand side, increasing granularity could improve the interpretation of IAM results [3]. IAMs also need to become more granular to monitor climate progress. A lack of resolution could create a widening gap between IAM policies and real-world policy implementation, as many newly proposed or enacted national investment and regulatory policies are highly granular, targeting specific sectors or technologies. These include policies on energy efficiency standards, targets for specific appliances or vehicles, tax exemptions, price caps on certain goods, waste reduction, and more [37].

In advanced IAM versions, it is possible to replace a CES branch with process-based systems or substitute an entire sector's subtree with a high-granularity model, soft-coupled to the IAM. Process-based and diffusion models offer clear advantages over older CES formulations. Granular demand-side modules not only provide more policy levers, such as capacity limits and subsidies, but also enhance accuracy by including material costs, capacity factors, and stock consistency. By incorporating actual production-level technology, capital expenditures for new processes are accounted for—particularly important for capital-intensive electrification processes. For example, ArcelorMittal and Acciaierie d'Italia each received around 1 billion euros in subsidies for new direct reduced iron (DRI) plants. The development of non-pricing industrial policies and efforts to increase granularity in IAMs are closely linked—without granularity, IAMs cannot effectively simulate industrial policies. For recent applications of granular models in IAMs, see Section 2.4.3. While some granular sectoral components have been integrated into standard IAMs, many are still under development.

Although energy efficiency is endogenously modeled in IAMs, often times they are not explicitly modeled as a technology type. For example, Figure 3 shows the implementation of such a stylized "energy efficiency capital" (EEC). This is a highly stylized way to indicate that models can invest in this node to increase energy efficiencies according to certain elasticity. As a result, there is no capital expenditure or operational cost associated with this stylized formulation, nor are there capacity targets which can be created due to there being no explicit technologies. This lack of granularity could impact the accuracies of assessing of GHG-emission reduction costs [38].

In addition to increasing spatial and sectoral resolutions, another dimension for increasing granularity is to resolve detailed economic sectors' energy use and emission. This is typically carried out through post-process down-scaling. Recent studies have focused on downscaling energy variables to the sector level using input-output (IO) models linked to IAMs [39–41]. Although this approach has limitations, such as the inability of historical IO tables to fully capture long-term structural economic changes, it represents a promising frontier in refining sectoral energy processes, including emissions across scopes 1, 2, and 3.

The post-processing approach has also been used to geographically downscale global mitigation pathways to the country level. Studies by F. Sferra, et al. [42, 43] applied the SIAMESE method, which allocates energy consumption from regions to countries based on price equilibrium, converting it into emissions, along with statistical (algorithmic) down-scaling. Although finer geographical resolution is theoretically possible within IAMs, it is constrained by computational resources. A major challenge is the lack of historical energy data for many countries, especially in the Global South and many middle-income nations, where such data is unavailable or of low quality.

2.4.2. Expand IAMs' technological scope and model the role of innovation policy

In the energy system part of IAMs, policy pathways are typically based on assessing mature mitigation technologies and their market competitiveness. However, to meet stringent mitigation targets, a broader portfolio of mitigation technologies should be considered in default or bespoke scenarios, with an emphasis on supporting emerging innovations. Early-stage technologies are often excluded from IAMs, either because they are still precommercial, recently commercialized (e.g., sodium batteries), or are only deployed at small scales. Less mature technologies such as silicon-based alternative cement, advanced nuclear, nuclear marine propulsion, thermal energy storage, advanced geothermal, and industrial electrification [44] are often deemed too niche or immature for inclusion in mainstream scenarios such as MESSAGE or REMIND [18, 19]. The notable exception is novel carbon dioxide removal (CDR) technologies, including direct air capture, bioenergy with carbon capture, enhanced weathering, ocean alkalinization, and biochar, which are increasingly featured in IAM scenarios [45, 46].

Excluding technologies not fully commercialized makes IAMs less relevant for policies supporting technologies through the so-called "valley of death" in innovation theory, which describes when technologies mature, emerge from the laboratory, but the generally risk-averse private capital is not able to scale it up and introduce it into the market [47]. If a novel technology is excluded from the model, IAMs cannot suggest policies for R&D or deployment. Although IAM modellers may take a conservative approach due to uncertainties around costs, safety, and scalability, this introduces subjective judgments. IAM teams with limited resources may lack the capacity to prioritize pre-commercial technologies, even if viewed as "game-changing" by other stakeholders. For example, emerging technologies such as sodium batteries, brick-based heat storage, copper-based wind turbine magnets, or thorium reactors could be added, especially under strict emission budgets. Uncertainty around electrolytic hydrogen could be hedged by incorporating direct electrification methods such as molten oxide metallurgy. Broader collaboration with engineering and industrial communities may be needed to assess the costs and mineral requirements of emerging technologies.

Most process-based IAMs focus primarily on scaling up mature, commercialized technologies through endogenous or exogenous "learning by doing" [48], without addressing the policies that enable these technologies to succeed in the first place. In Section 3, we introduce the DTC model, which explicitly depicts knowledge innovation and accumulation. Within the existing IAM framework, it is also possible to implement the "two-factor learning curve (TFLC)", based on empirical studies of technology learning [49, 50], and applied in both stylized and process-based IAMs [48, 51, 52]. The two factors are "learning by doing" (learning through capacity accumulation) and "learning by researching" (learning through knowledge accumulation).

In addition to the learning curve, the "forgetting curve" has been formulated for technologies that have experienced a loss of accumulated (often tacit) knowledge [53–56]. This is especially applicable to the nuclear industry. After decades of underinvestment in human and physical capital in the U.S. and Europe, newly built nuclear power plants face high costs. Applying the forgetting curve to older industries, where experienced workers have retired, and new skills are required, has significant implications for policies aimed at reducing the costs of these technologies.

2.4.3. Expand IAMs' scope for sectoral policies beyond carbon pricing

Empirical research linking past policy implementation to emission reductions shows that CO_2 pricing and non-pricing regulatory policies are effective as part of a broader policy mix, rather than standalone measures [57]. The CO_2 price is considered the most economically efficient policy instrument under the neoclassical IAM framework. However, its effectiveness depends on how investors react to future carbon price expectations. If the policy fails to credibly signal a rising future price, the scheme will be ineffective, leading to market failures [58]. In such cases, additional policy instruments are needed, such as emission intensity regulations, subsidies, direct investment, technology bans, and energy efficiency mandates [58, 59].

Recent advancement in IAM modeling has shown rich implementation beyond carbon pricing. Although not widely used in current IAM scenarios, where carbon pricing is the main climate instrument

[60, 61], energy supply-side subsidies and quantity targets can be modeled [62–65]. On the demand side, IAMs have employed technology-diffusion models (e.g., "logit models") for the transport sector to simulate transformation, incorporating a broader range of vehicle types and policy instruments, such as vehicle subsidies, technological diffusion, producer mandates, purchase subsidies, and technology bans [66–72]. For industry sectors, IAMs can model technology bans, retrofitting existing processes, or creating entirely new methods for producing steel or cement [73]. Shaohui Zhang, et al. [25, 74, 75] have applied the linearized and process-based approach to the case of steel sector in IAMs.

Endogenous material efficiency can sometimes be modeled to incorporate circular economy policies. However, this requires additional modeling of material flows within a sector, as the viability of material substitution or efficiency is highly dependent on end-use applications and contexts. For example, scrap steel is only suitable for making long products like concrete reinforcement bars due to trace contamination during recycling, the removal of which requires innovative technologies [76, 77]. Material Flow Analysis (MFA) has been coupled with IAMs in the studies by Paul Stegmann, et al. [75, 78, 79]. Without MFA, it is difficult to integrate circular economy measures into climate pathways. Even with MFA, it is essential to explicitly model the abatement cost curves of separate industrial processes, their innovation learning potential, and the global diffusion of "best practices" of production.

2.5. Inherent methodological limitations and need for complementary approaches

Although process-based IAMs' demand sectors increasingly incorporate dynamical aspects (as the case with transport), at their core—specifically in energy systems and land-use—they remain fundamentally market equilibrium models. As such, they face long-standing criticisms for their inability to capture profit, strategic pricing, and other non-equilibrium market phenomena and behaviors [80]. Given the political economy of growth and industrial competition on one hand, and behavioral inertia and institutional bottlenecks on the other, it is clear that neither the market-equilibrium nor the single-agent assumptions in IAMs hold [60, 81] (see also Section 4). This need for complementary approaches has been recognized by the IAM community, and conceptual frameworks for iteration or integration have been proposed [5, 82, 83]. However, concrete collaborations between the IAM community and political or social sciences are still in the early stages, largely due to differences in underlying approaches and assumptions [82, 84].

The lack of scenarios that account for breaks and disruptions is considered an inherent weakness of IAMs [85–88]. However, despite being equilibrium models, IAMs' technical pathways are not always slow-moving and smooth. In fact, under stringent temperature stabilization scenarios, such as 1.5°C or well-below-2°C end-of-century targets with low temperature overshoot, energy variables like fossil fuel consumption can sharply decline from their current upward or stagnating trajectories in the near term, with dramatic reductions occurring by mid-century [9, 10]. This has even led some to question the feasibility of such pathways [89, 90].

While critical literature highlights the importance of disruption in the transition process or macro conditions [85–88], it's important to assess the benefits of replacing IAMs' near-term disruptive pathways with smaller breaks or longer plateaus using non-equilibrium methods. After all, a non-equilibrium model doesn't automatically offer more policy insights than an equilibrium one. The effectiveness of either approach depends on its accuracy, scope, and ability to assess concrete policies. Discontinuous diffusion processes, like stagnation and lock-in, are perhaps better suited for portraying baseline dynamics—such as the "business-as-usual" or "national policy implemented" (NPi) scenarios—rather than creating ambitious long-term climate pathways. Given political economy constraints, transitions in scenarios without a climate budget won't happen smoothly. This is where integrating dynamic models with IAMs could make baseline scenarios more realistic and informative.

One thing is clear: IAMs are not models of politics and power, and they may never be. Explicitly modeling politics, institutions, and behaviors is beyond IAMs' methodology, the core of which is designed to inform users of engineering benchmark for deploying green technologies under climate constraint. However, IAMs can be improved in terms of political economy dynamics by incorporating other quantitative models. In this paper, we suggest three alternative methods—DTC, ABM, and game theory—as valuable additions to the mitigation research toolbox. While not an exhaustive list of complementary approaches, these models address some of the gaps between IAMs and complex policy realities, potentially guiding IAM scenario design or even being soft-coupled with IAMs. While these models have their own limitations [80], they can model various aspects of political economy. Despite successful applications, such as [91], soft-coupling political economy models with IAMs remains a new and emerging field that requires further research.

3. Growth Models with Directed Technical Change

3.1. Introduction and empirical support

DTC models, building on endogenous growth theory, emphasize how economic incentives and policy interventions can actively direct technological progress in specific directions [92]. Unlike earlier models that treat technological change as exogenous or passive, DTC models focus on the strategic decision-making of firms and investors in response to policy signals, accounting for the heterogeneity of technologies and the allocation of R&D efforts among them. Government interventions such as subsidies, taxes, and regulations are pivotal in guiding innovation toward cleaner technologies, recognizing the influence of path dependency shaped by existing infrastructures and institutions [93].

While both DTC models and IAMs with endogenous technical change (ETC-IAMs) aim to project energy technology transitions under various policies, they differ significantly in their methodological approaches. IAMs often focus on how overall technological progress is stimulated by economic activities and policies but treat innovation as a relatively passive and uniform process [5]. In contrast, DTC models involve detailed modeling of the innovation process, capturing how policies can unevenly impact the attractiveness of various technologies, thus influencing the direction and pace of technological advancements. In IAMs, the investment expectation is simply assumed (see Figure 4), based on the existence of a credibly communicated future CO_2 price path that leads to the net-zero goal. In DTC models, investment is profit-driven and modeled more explicitly. Endogenous technological learning remains a complex topic and an active area of research in energy system modeling as well as in IAMs [94]. Here, we focus on applying DTC and endogenous technological learning in IAMs.

Recent empirical studies strongly support the Directed Technological Change (DTC) framework, highlighting the crucial role of targeted economic incentives and policy interventions in steering innovation toward clean energy technologies. Beyond energy prices, environmental policies such as carbon pricing mechanisms have significantly boosted low-carbon innovation. The EU-ETS serves as a prime example, with regulated firms showing increased patenting activities in low-carbon technologies compared to unregulated firms [95]. A recent analysis further demonstrated that carbon pricing mechanisms in the European Union have amplified patenting activity in low-carbon technologies, reinforcing the connection between price signals and innovation pathways. The phenomenon of path dependency within the DTC framework is also empirically supported. Philippe Aghion, et al. [96] demonstrated that firms with a history of clean innovation are more likely to continue on this path, with initial policy support, such as carbon taxes, playing a pivotal role in shaping firms' innovation trajectories toward sustainability.

Moreover, research underscores the risk of fossil fuel market dominance without targeted support, potentially locking economies into carbon-intensive pathways. Daron Acemoglu, et al. [97] found that the natural gas boom in the United States temporarily reduced coal use but ultimately slowed renewable energy innovation. This highlights the importance of pairing carbon pricing with targeted subsidies for renewables to sustain a long-term shift toward clean energy. These insights align with the DTC perspective, emphasizing the need for policies that go beyond market signals alone.

In addition to price-based incentives, government investment in R&D and targeted subsidies plays a significant role in accelerating the adoption of clean technologies. The International Energy Agency (IEA) [98, 99] emphasizes that effective allocation of public funds in research, development, and demonstration (RD&D) for emerging energy technologies is crucial for overcoming initial cost barriers, ensuring that clean technologies can compete with established, carbon-intensive ones. This targeted support is especially vital for addressing innovation gaps in harder-to-abate sectors like heavy industry and long-haul transport. Addressing innovation market failures, empirical research underscores the effectiveness of clean R&D subsidies in stimulating innovation, particularly among smaller firms. Sabrina T Howell [100] found that government grants significantly increase the likelihood of small firms securing venture capital and succeeding in innovation activities. Moreover, clean technologies generate higher knowledge spillovers compared to conventional technologies, reinforcing the argument for R&D subsidies within the DTC model [101].

3.2. Embedding DTC into IAMs

With the empirical support discussed above, it is pertinent to explore the integration of Directed Technological Change (DTC) modeling into the IAM framework. This integration requires the development of methods to incorporate DTC principles into IAMs, taking into account the specific structural features and assumptions of each model. This approach would enable an enhanced representation of innovation dynamics and policy impacts while maintaining consistency with the established IAM frameworks. A foundational model within environmental economics that utilizes DTC principles is the framework developed by Acemoglu, Aghion, Bursztyn, and Hemous (AABH) [102]. This model differentiates between innovations that complement existing technologies and those that aim to replace them, focusing on the potential for clean technologies to displace their polluting counterparts. The AABH model highlights how targeted policies can transform the energy landscape, contrasting with approaches that assume technological change occurs exogenously or passively.

The AABH model considers a scenario where a final good Y_t is produced using clean (Y_{ct}) and dirty (Y_{dt}) inputs, described by a CES production function:

$$Y_t = \left(Y_{ct}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{dt}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{3.1}$$

where ε is the elasticity of substitution between clean and dirty inputs ($\varepsilon > 1$ indicates they are gross substitutes). Emissions are directly linked to the consumption of dirty inputs:

$$P_t = \xi Y_{dt}, \tag{3.2}$$

with ξ representing the emission coefficient per unit of dirty input. Innovation in both clean and dirty sectors drives productivity, represented by:

$$Y_j = \frac{1}{1-\beta} L_j^{\beta} \int_0^1 A_{ji}^{\beta} x_{ji}^{1-\beta} \mathrm{d}i, \quad \text{for } j \in c, d, \tag{3.3}$$

where L_j denotes the labor allocated to the sector j, A_{ji} is the technology level for intermediate good i in the sector j, and x_{ji} is the quantity of intermediate good i used in the sector j. The parameter β represents the output elasticity with respect to labor.

Scientists choose to innovate in either clean or dirty sectors. The expected profits for a scientist in the sector j are:

$$\Pi_{jt} = \eta_j \left(1+\gamma\right) \beta \, p_{jt}^{\frac{1}{\beta}} L_{j,t} A_{j,t-1} = \frac{\eta_j \beta p_{ij} Y_{jt}}{1 + \gamma \, \eta_j \, s_{jt}}, \tag{3.4}$$

where η_j is the probability of successful innovation in a sector j, p_{jt} is the price of output in the sector j, s_{jt} is the research effort, and γ is a parameter representing the size of innovation steps. The profit ratio between clean and dirty sectors is:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d} \left(\frac{p_{ct}}{p_{dt}}\right)^{\frac{1}{\beta}} \frac{L_{ct}}{L_{dt}} \frac{A_{c,t-1}}{A_{d,t-1}}. \tag{3.5}$$

This expression indicates that the sector with higher existing technology levels $A_{j,t-1}$ and greater profitability attracts more innovation efforts, leading to a self-reinforcing cycle of technological advancement—an example of path dependence. Without policy intervention, the dirty sector may continue to dominate due to its established technological advantage and higher immediate returns on investment. To overcome this inertia, the model suggests policies such as:

- **Clean Research Subsidies** (α_c): Increasing the expected profits from innovating in the clean sector by subsidizing R&D, encouraging a shift in innovation efforts toward clean technologies.

$$\Pi_{ct} = \left(1+\alpha_c\right) \eta_c \left(1+\gamma\right) \beta \, p_{c,t}^{\frac{1}{\beta}} L_{c,t} A_{c,t-1},$$

- **Carbon Taxes** (τ) Internalizing environmental externalities by raising the costs of dirty inputs, reducing the profitability of the dirty sector and making clean technologies more competitive.

These interventions adjust the profit incentives, making it more attractive to innovate in the clean sector and addressing the market's inherent bias toward established, carbon-intensive technologies. The AABH framework thus emphasizes that effective policy measures are crucial for guiding innovation toward sustainable technologies, rather than relying solely on market forces.

The AABH model's emphasis on the role of policy in shifting profitability and directing innovation toward cleaner sectors is a key insight from the DTC framework. While some IAMs may not explicitly model profits, they can capture similar dynamics by representing how policies such as carbon pricing and subsidies alter the cost-effectiveness of low-carbon technologies. Incorporating an explicit representation of R&D dynamics, including knowledge accumulation and depreciation, is crucial for IAMs to effectively assess the impact of these policies on the direction and pace of technological change. Integrating insights from DTC models can further enhance the representation of directed technical change in IAMs, enabling a more comprehensive assessment of the long-term implications of climate policies and the potential for a sustainable energy transition.

3.2.1. The WITCH model – an example of DTC application in IAM

Integrating Directed Technological Change (DTC) principles into an Integrated Assessment Model (IAM) involves embedding mechanisms that allow for directed innovation, where R&D allocation and technological advancements are endogenously shaped by policy and market incentives. The WITCH model (World Induced Technical Change Hybrid), developed by Bosetti et al. ([103, 104]), provides a prominent attempt at this integration. It combines a top-down intertemporal optimization framework with a bottom-up representation of the energy sector, modeling ETC and DTC principles explicitly within an IAM framework.

In the WITCH model, regions allocate R&D investments across energy technologies, enhancing energy efficiency and reducing low-carbon technology costs. This aligns with DTC principles by focusing on targeted technological advancements. Policy measures like carbon pricing, subsidies, and regulations drive these investments, facilitating cleaner energy transitions. Subsidies are particularly impactful, as they reduce the effective cost of R&D in targeted sectors, thereby incentivizing higher investment levels and accelerating knowledge stock accumulation. The model also captures technology externalities, such as international knowledge spillovers, which enable shared advancements and further support global climate and innovation goals.

Formally, the impact of subsidies on R&D investment can be expressed as follows:

R&D Investment Function with Subsidies: When subsidies (S) are applied, they reduce the net cost of R&D for firms or governments. The effective R&D investment in a sector can be modeled as:

$$I_{RD}^{\text{net}} = (1 - S) \cdot I_{RD}$$

where I_{RD}^{net} represents the adjusted R&D investment after subsidies, with S as the subsidy rate (e.g., $S = 0.3$ for a 30% subsidy).

Knowledge Stock Accumulation with Subsidies: Knowledge stock K in a sector accumulates over time through R&D investments. With subsidies, this accumulation is accelerated:

$$RD_{t+1} = RD_t + \gamma \cdot I_{RD}^{\text{net}}$$

Here, γ is a productivity parameter that translates R&D into knowledge stock.

Learning Curves and Cost Reductions: Subsidies also impact learning curves by enabling greater R&D investment, leading to faster cost reductions in technology. For example, a two-factor learning curve might capture this as:

$$C_{t+1} = C_t \cdot (I_{RD}^{\text{net}})^{-\delta}$$

where C represents technology cost, which declines more rapidly as effective R&D increases.

Additionally, WITCH models learning-by-doing, where accumulated experience in deploying a technology reduces costs over time. This effect, coupled with R&D subsidies, supports substantial long-term cost reductions in clean technologies, making them more competitive with conventional options. The model also accounts for international technological spillovers, allowing one region's R&D advancements to benefit others and emphasizing the role of global cooperation.

The WITCH model's results demonstrate that combining carbon pricing with targeted R&D subsidies effectively directs technological change toward low-carbon solutions. Early focused investments in clean R&D can substantially reduce long-term mitigation costs by accelerating technological advancements and decreasing future abatement expenses [104]. This strategic integration underscores the benefits of policies that simultaneously incentivize R&D and promote international collaboration, establishing a robust framework for addressing climate change through directed innovation.

4. Agent-Based Modeling

IAMs often overlook the heterogeneous processes of technological adoption within social and institutional contexts. Factors such as government institutions [105] and infrastructure availability [106] significantly influence how new technologies spread or encounter barriers in international and domestic markets. Accurately capturing these dynamics is critical for modeling the green transition.

To model these path-dependent, explosive, or disruptive dynamical processes, introducing heterogeneous actors and agents in simulations is essential. ABM offers a computational method rooted in complexity science, focusing on the individual behaviors of agents and their interactions within a system [107]. Unlike conventional economic modeling techniques that rely on aggregate data and the concept of a singular "representative agent", ABM adopts a detailed, bottom-up approach. This method is particularly useful for modeling systems with heterogeneous agents, nonlinear interactions, and adaptive behaviors. Consequently, ABM is well positioned to provide an in-depth analysis of the green transition—a process characterized by the different influences of various actors whose distinct behaviors collectively dictate the pace and path of environmental progress [108, 109].

4.1. Core Tenets, Strengths, and Weaknesses of Agent-Based Modeling

Agent-Based Modeling is grounded in three core tenets: individual agents and their decision-making capacities, heterogeneity among actors, and interactions leading to emergent systemic patterns. ABM delineates individual agents—including private individuals, businesses, and government bodies—each endowed with specific attributes and decision-making abilities. This granularity allows for a detailed representation of how different entities influence and are influenced by their environments.

ABM acknowledges and embraces the inherent heterogeneity among agents, such as differences in preferences, financial and regulatory constraints, and reactions to various incentives. Understanding this diversity is essential for capturing the full spectrum of potential outcomes and identifying strategies that leverage it. Furthermore, ABMs map the interactions among agents within their ecosystems, uncovering emergent systemic patterns or behaviors that may not be immediately apparent. By modeling these interactions, ABMs reveal how individual behaviors aggregate to produce collective outcomes, such as tipping points in technology adoption or shifts in market dynamics.

For instance, an ABM studying EV adoption might demonstrate how initial government subsidies create a critical mass of EV users, leading to network effects that lower costs and increase convenience for subsequent adopters, resulting in a market-wide shift toward EVs. By focusing on these core tenets, ABM provides a robust framework for exploring and understanding the complex, dynamic processes that drive the transition to more sustainable and resilient systems. These principles enable ABM to offer deep insights into the interactions and behaviors that shape real-world outcomes, making it a powerful tool for policymakers and researchers aiming to address environmental and economic challenges.

The inherent strengths of ABM lie in its strong ability to represent complex systems characterized by numerous interacting participants, complex feedback loops, and the integration of technological, social, and economic factors [110, 111]. These models are particularly pertinent in identifying emergent outcomes or critical thresholds arising from the aggregated actions of individual agents, providing invaluable insights crucial for navigating the green transition. Notwithstanding its merits, ABM faces certain challenges. It requires extensive data on agent behaviors, preferences, and interaction patterns, which can be difficult to obtain. Simulating large populations of agents over extended periods demands considerable computational resources. Moreover, ensuring that ABMs produce realistic and reliable outcomes necessitates meticulous validation efforts, often employing empirical data and thorough sensitivity analyses to enhance the model's credibility [112].

Despite these challenges, ABMs can be instrumental in deepening our understanding of sub-processes already identified in global IAM pathways, such as technology lock-in and institutional bottlenecks in specific regions and sectors. ABMs have been applied to sectors where heterogeneous decision-making is significant, such as building renovation [113], national policies on coal phase-out [114], and bottlenecks in granting permits for renewable capacity and power grids [115]. These sub-processes can be soft-coupled to IAMs by implementing bounds and constraints in the sector or region that match certain scenario outcomes from these sub-processes, or by directly incorporating ABM formulations into IAM submodules.

4.2. ABM in energy systems and integration with IAMs

ABMs have been applied across various energy sectors, including power, transport, and buildings, allowing for a potential linkage or integration with energy systems in process-based IAMs. For instance, in the power sector, ABMs model interactions between producers, consumers, and grid operators to simulate how policy changes, technological advancements, and consumer behaviors affect renewable energy adoption and grid stability [116]. In urban settings, ABMs have been used to model the adoption of sustainable transportation, capturing commuter behaviors and interactions to assess the impact of policies on the uptake of public transit and cycling infrastructure [117]. ABMs also provide insights into consumer behavior related to sustainable goods, considering factors like social influence, environmental consciousness, and policies such as green labeling [118].

In particular, ABM-IAM integrations, or "ABIAMs", can introduce heterogeneous agents (e.g., firms, households, financial entities) and enable adaptive, non-equilibrium dynamics, shocks, and complex policy testing. Much of this work is currently conducted with stylized IAMs rather than process-based IAMs. Nevertheless, aspects of this research can inspire integration approaches aimed at improving specific aspects of process-based IAMs.

The Dystopian Schumpeter meets Keynes (DSK) model by Lamperti and colleagues expands the Keynes+Schumpeter framework to include climate effects, innovation dynamics, and the financial sector's role in low-carbon transitions [119, 120]. By simulating green financial regulations, such as carbon-risk-adjusted credit ratings, it highlights impacts on both financial stability and climate resilience.The ABM-IAM model by Safarzyńska and van den Bergh [121] integrates income inequality and R&D-driven technological innovation to show how these factors affect carbon costs and policy effectiveness [121], particularly the social cost of carbon. The CFHS model by Michał Czupryna et al[122, 123] emphasizes regional dynamics in agriculture, productivity, and energy. It features a detailed energy sector with multiple resources and models regional energy transitions in response to resource depletion. The GRSW model by L. Gerdes et al. [124] addresses global inequality, examining disparities between developed (North) and developing (South) regions. By integrating localized pollution effects on labor productivity, it underscores the socioeconomic costs of regional pollution and the challenges of equitable climate policy.

Recent ABIAM applications reflect their growing role in climate policy analysis. Christoph Schimeczek et al. [125]'s AMIRIS model uses an ABM approach to simulate electricity markets and assess renewable energy integration, while the MUSE framework by Sara Giarola et al. [126] examines global energy transition scenarios, focusing on technology adoption and investment. Leila Niamir et al. [127] integrate ABMs with computable general equilibrium models to explore individual actions on emissions, emphasizing behavioral change for climate targets. In urban systems, Christina Nageli et al. [113] employ ABMs to assess how building renovation rates and technology adoption influence emissions. Further, Karolina Safarzyn´ska [128] investigate how revenue-redistributive carbon taxes mitigate income inequality and enhance resilience, while Jinkun Dai et al. [129, 130] focus on individual land-use decisions and sustainable agri-food systems. Finally, Alessandro Di Noia et al. [131] explore coastal climate adaptation through ABMs, showing how individual and collective actions shape resilience in vulnerable areas.

Future development of ABIAMs holds significant potential for refining the granularity of energy system modeling, multi-sectoral economic structures, and land-use dynamics by exploring several key areas. These areas include more sophisticated energy sector representations, integration of resource flows, expanded financial system modeling, and incorporation of DTC mechanisms. As Karl Naumann-Woleske [132] highlights, models such as CFHS [122] and ACCLIMATE [133] have made notable advancements, but further development could improve these frameworks. Integrating aspects of resource extraction, emissions-intensive processes, and end-of-life waste management will be crucial, particularly as resource constraints impact the feasibility and timing of energy transitions [134, 135]. Insights from industrial ecology, emphasized by Naumann-Woleske [132], could enrich ABIAMs by applying frameworks like the stock-flow-service nexus [136] and incorporating social factors that influence demand. This integration would allow ABIAMs to more accurately capture the complex interplay between socioeconomic systems and resource use, addressing both material and social constraints on sustainable development.

Rewriting state-of-the-art process-based IAMs to include multiple agents in the global energy and land-use system is challenging due to their broad scope and limited data in developing countries. However, there are three ways IAMs and ABMs could be integrated. First, IAMs or down-scaled IAMs can identify key abatement dynamics in sectors within a region. ABM scenarios can be constructed based on these, focusing on hard-to-abate sectors where diverse policy proposals can be tested for heterogeneous actors. Second, where computational resources allow, IAMs can be soft-coupled to ABMs of sectoral processes to produce baseline or NPi pathways. These models would reflect non-smooth adoption under existing policies, likely resulting in a slower process and higher baseline temperature estimates, which could inform other climate-related fields, such as impact and adaptation. Third, ABMs can be used to explore climate resilience. When climate damages are incorporated into IAMs, adaptation adoption is highly heterogeneous. ABMs can simulate adaptation dynamics based on income, exposure, and vulnerability, with the varying abilities of agents to adapt potentially amplifying or dampening overall climate-related damage on GDP.

Not every demand-side energy sector requires ABM to describe its dynamics in integration with IAMs. For example, technological diffusion in the building and transport sectors differs from that in industrial sectors. ABM studies in these sectors focus on technology adoption by heterogeneous user groups or across diverse applications. In contrast, industrial sectors spread production techniques and exchange information through specialized associations and conferences, involving fewer decision makers. Depending on the tradability of the industrial good, producers often compete on efficiency and cost, leading to a more homogeneous adoption process. However, even within a single sector, different production processes can diffuse in varied ways. For instance, as Steve Pye et al. [137] shows, iron and steel methods like the oxygen furnace, direct reduction iron, and continuous casting diffused differently across regions. In this case, a single logit curve can effectively model diffusion using adoption year and speed, with regional industries behaving more like a single agent than multiple ones.

5. Game Theory

5.1. Introduction to game theory

Game theory, recognized for its thorough examination of strategic interactions in various fields, is crucial for understanding environmental sustainability. Depending on the game, it can analyze market dynamics, entry strategies for emerging industries, and the complex behavior of entities within competitive settings. Game theory can provide insights into decision-making influenced by the expectations of others' actions. This analytical tool helps navigate the intricate journey towards sustainable practices, shedding light on the challenges and opportunities of the green transition. In IAMs, game theory has also been applied to model trade, such as using Nash equilibrium [138].

Game theory is a systematic approach used to analyze the interactions between two or more players to understand their behavior under defined circumstances. The importance of considering strategic interactions in analyzing climate issues has a long-standing tradition [139–143].

Recent economic research on global warming policies has extensively concentrated on mitigation strategies. Recent contributions of game theory to environmental economics have explored various areas such as international climate agreements, the allocation of carbon credits, and the strategic interactions between countries in reducing emissions. Additionally, game theory has been applied to analyze cooperation and competition in the development and adoption of green technologies, the management of common resources, and the role of incentives in encouraging sustainable practices. These insights help to better understand the dynamics and challenges of implementing effective global warming policies. However, despite the extensive use of game theory in environmental economics and green transitions, it's important to note that many models discussed within game theory may not integrate economic, environmental, and resource dynamics into a single framework. Nonetheless, game theory can be crucial as a tool for assessing the long-term implications of energy transitions. Policy insights derived from game theory can help policymakers understand the behaviors of actors in the green economic transition, therefore devise better policy strategies to encourage the adoption of sustainable and environmentally friendly innovation. In this way, game theory insights can complement the more static IAM policy targets, and increase the policy relevance of quantitative models.

Incorporating the principle of dynamic interactions, game theory recognizes that decisions are made within a network of strategic considerations, influenced by both current and anticipated future scenarios. The work by E. Saltari et al. [144], on "A Nash equilibrium for differential games with moving-horizon strategies", serves as a notable example. Their study introduces a framework for understanding strategic decisions in a dynamic context, offering an algorithm to calculate Nash equilibrium for differential games. By employing nonlinear model predictive control methods, their research highlights the continuous evolution of strategic decision-making in uncertain and shifting environments. This progress in game theory, enhancing our understanding of the interactions between the economy and the environment, strengthens our ability to address complex challenges in environmental sustainability. It represents a crucial step towards a more sustainable future, particularly in addressing uncertainties and policy impacts.

Game theory can be applied to both cooperative and non-cooperative scenarios. Among recent contributions of game theory to environmental economics, Bruno Nkuiya [145] examined how the anticipation of abrupt environmental damage shifts can influence the behavior of non-cooperating countries. However, IAMs, which capture the feedback between the economy and climate change damages, often need to be linked to game-theoretic modules of coalition formation to study the stability of agreements [146]. In recent years, various climate models have been employed to study the prospects of cooperation. In this context, Giovanni Di Bartolomeo et al. [147] employed an approach that incorporated both economic activity and the climate system. Their study compared individual emission levels generated by polluters acting non-cooperatively with those under cooperative solutions, highlighting the differences in outcomes between these approaches.

5.2. Game theory and climate change

As mentioned, game theory offers valuable insights into the strategic interactions among players in the context of climate change. By modeling various scenarios, it helps us understand how countries, organizations, and individuals make decisions related to climate policies and resource management. Recent papers have expanded on these themes, offering new perspectives and solutions in different areas.

Nicola Acocella et al. [148] assessed strategic interactions in environmental governance, highlighting policy trade-offs. Their formal policy game illustrated potential conflicts between central and local authorities, revealing how coordination failures can lead to suboptimal provision of natural resources and environmental protection. Addressing carbon emission reduction remains a global priority, with cap-and-trade regulations widely adopted to achieve this objective. Chuyu Sun et al. [149] developed two evolutionary game models to examine the effects of carbon tax and carbon emission trading policies within the context of fiscal subsidies. Their study explores how integrating these policies with subsidies can more effectively promote the development of renewable energy, with a particular focus on wind power. Kai Kang et al. [150] investigated the impact of cap-and-trade regulations on carbon emission trading efforts between suppliers and manufacturers, using an evolutionary game model to examine their investment decisions. Moreover, Ming Zhong et al. [151] applied cooperative game theory to develop a comprehensive economic scheduling model for demand response within the context of carbon trading. The goal was to optimize both collective and individual gains across various scenarios. The study revealed that incorporating the carbon trading mechanism led to reductions in system operating costs and carbon emissions, demonstrating favorable outcomes for both economic and environmental objectives.

Within the context of green supply chain management, Rui Zhao et al.[152] applied game theory to examine the strategies that manufacturers adapt to minimize the environmental risks associated with material life cycles and reduce carbon emissions. Kourosh Halat et al. [153] employed a Stackelberg game framework involving both the government and the green supply chains (GSC). In this setup, the government aims to maximize social welfare, while the GSC focuses on minimizing its costs. The study investigates how coordination and carbon regulations affect inventory costs, carbon emissions, and the government's objective function.

Reyer Gerlagh, et al. [154] introduced a novel dynamic game, known as the green transition game, which combines elements of coordination games and public good games, including considerations of free-rider incentives. This dynamic three-player stag-hunt game captures aspects of transitioning from a carbon-intensive economy to a green economy. Furthermore, Michael Finus et al. [155] demonstrated that stable coalitions tend to be larger in the Stackelberg scenario compared to the Nash-Cournot scenario within the context of the standard international environmental agreement game.

Additionally, Rui Bai et al. [156] utilizes game theory to illustrate that green finance plays a substantial role, both theoretically and empirically, in fostering green innovation. These findings underscore the critical role of government regulations and incentive mechanisms in shaping environmental policies and promoting sustainable practices. Moreover, environmental regulations play a crucial role in effectively mitigating pollution. Game theory, renowned for its robust theoretical foundation and modeling capabilities, has been extensively utilized to study competition in environmental regulation (ER) for pollution control [157].

In this context, Rafaela Vital Caetano et al. [158], investigated how carbon taxes and custom duties on polluting imports can prevent the transfer of polluting industries from developed to developing countries, using game theory and a dynamic game with incomplete information. Analyzing 24 developed and 18 developing countries, the study highlights the role of energy transition and recommends stricter regulatory frameworks to attract clean FDI and enhance the deterrent effect of carbon taxes.

Additionally, game theory plays a vital role in understanding geopolitical competition, providing valuable insights into the strategies and decisions of various global actors. In the context of electricity grids and geopolitics, Songying Fang et al. [159] employed a game-theoretic framework to explore the potential outcomes of synchronizing the Baltic electricity grid with Europe while simultaneously desynchronizing it from Russia's BRELL network. This analysis aimed to enhance energy security for Estonia, Latvia, and Lithuania. In the context of electric power markets, Steven A. Gabriel et al. [160] presented a mixed-integer linear programming model designed for a Stackelberg game within network-constrained industries. The model is applied to both a three-node example network and a fifteen-node Western European grid. The results highlight the model's effectiveness and its potential for addressing larger-scale problems in the future. Furthermore, rare earth and critical materials play a crucial role in consumer products, green technologies, and military applications today. In this context, among recent studies, Benteng Zou et al. [161] analyzed the U.S.-China competition for rare earth elements from a dynamic game perspective. The findings indicated that the U.S. should delay production until its rare earth reserves align with China's. While China's monopolistic supply isn't influenced by the chosen strategy, the duopolistic Markovian approach initially proves more profitable than an open-loop commitment. However, as competition continues, the situation reverses, with both countries ultimately benefiting more from committing to an open-loop supply strategy. Using an international relation perspective, Maciej Filip Bukowski [162] explores the complexity of the geopolitics of climate change, framing it as a "wicked problem" due to the multitude of variables and conflicting national interests involved. It argues that applying concepts from Game Theory, specifically the Nash Equilibrium, could help reconcile competing geopolitical interests and support the achievement of global climate goals, such as reducing GHG emissions and decarbonizing the economy.

5.3. Incumbents vs. newcomers game in the green transition

The role of newcomers in the green transition is crucial, as they introduce innovative technologies and approaches that can accelerate progress towards sustainability. Understanding their impact is essential for shaping effective policies and strategies. Building on game theory, a focused application of this framework is illustrated through the dynamics of incumbents vs. newcomers in the green transition. Depending on the technique used, these competitive scenarios may involve either a single player acting strategically or both incumbents and potential market entrants engage in a strategic battle, each aiming for profit maximization. In a game-theoretic analysis of incumbents vs. newcomers, incumbents usually move first, but since they are playing in a game, they have to take the reaction of the newcomers into account. This strategic interplay underscores the dynamic nature of market competition, where incumbents' decisions not only shape their own outcomes but also influence the strategic responses of newcomers, shaping the overall market landscape. In this type of game, the core players can be identified as:

- Incumbents, Leaders, or Cartels: In the context of the green transition, depending on the game, these players typically set prices or determine extraction and exploitation paths.
- Newcomers, Followers, or Fringes: These players, which may consist of small groups or individual entities, react to decisions made by the incumbents and aim to challenge their positions within the market.

In an analysis of incumbents versus newcomers, game theory can provide valuable insights into two key aspects:

5.3.1. Setting the price in the game

Incumbents can use strategic pricing to prevent new competitors from entering the market, as seen in dynamic limit pricing games. Incumbents can set prices with the intent to deter new entrants, who, as fringe players, are forced to adapt their strategies accordingly. This strategic interplay gains additional complexity with the growing emphasis on sustainability, prompting incumbent firms to reassess their market strategies to align with environmental goals.

Among recent studies, this theme is illustrated by W. Semmler et al. [163]. This research addresses the confrontation between incumbent fossil fuel entities and emerging renewable energy firms, by employing a game-theoretic lens to examine the entry barriers and financial accessibility disparities between dominant companies and new entrants. Through these dynamics, the study highlights how financial differences shape the competitive battlefield in the energy sector's pivot towards sustainability. Hassan Benchekroun et al. [164] investigates a game between oligopolistic fossil fuel suppliers, fringe suppliers, and producers of a renewable substitute. The findings highlight economic rather than physical exhaustion of non-renewable resources under cost assumptions, and identify a phase of limit-pricing where both fossil and renewable suppliers remain active.

5.3.2. Setting the extraction path in the game

In the strategy of determining how to extract a shared resource, a leading firm often takes the lead, markedly influencing the market direction. This leadership involves strategically deciding how fast and in what manner to extract resources, affecting not only the company's path but also the overall market environment. New entrants typically assume the role of followers, adjusting their strategies based on the leading firm's decisions. These dynamics highlight the complex interplay between leadership, market response, and competition, especially relevant in the development of green technologies and efficient resource use.

Key academic contributions illuminate the intricacies of this strategic framework. For example, F. Groot et al. [165] presented a scenario in which the leading firm determines the pace of resource extraction while tacking the resource's value into account. This approach outlines the market's sequential and responsive nature, with new entrants tailoring their strategies to the leader's decisions. Among recent contributions, B. Minooei Fard et al. [166], employed game theory to explore the competitive dynamics in the Rare Earth Elements (REEs) market, investigating the behavior of China and other market players. This research examines the strategies around pricing, resource extraction, and supply chains used by China and other global players, highlighting the tactics for preserving market control and the consequences of resource scarcity.

5.3.3. Effect of policy

Additionally, it is important to note that public policy plays a crucial role in influencing the interaction between incumbents and newcomers, especially in the context of promoting or hindering the green transition. Government policies can incentivize sustainable practices, encourage innovation in green technologies, or impose regulations that level the playing field for newcomers. Conversely, policies favoring incumbents may hold back competition and prevent the adoption of environmentally friendly solutions. Thus, the interplay between incumbents and newcomers is not only shaped by market dynamics, but also by the broader regulatory environment set by public policy. In this context, we can refer to W. Semmler et al. [163], which demonstrates how market outcomes can be influenced by environmental public policies that support renewable energy firms.

One area where the impact of public policy is particularly significant is in the green supply chain. Jiuh-Biing Sheu et al. [167] employed a three-stage game-theoretic model to examine how green supply chain participants respond to competitive pressures under government interventions. Their findings indicate that the government should implement green taxation and subsidies to ensure that the profits from green-product production remain positive. Among recent contributions, Seyed Reza Madani et al. [168] focused on governance policies that promote the production of greener, more sustainable products. They developed a mathematical model where the government acts as the leader, and two competing supply chains, green and non-green, are the followers. The study discussed pricing policies, greening strategies, and governance tariffs in the context of supply chain competition. Moreover, Xin Chen et al. [169] investigated the impact of subsidy strategies on the green supply chain by developing a three-stage Stackelberg game model involving the government, manufacturers, and retailers. Their study analyzed the effects of policy interventions, including cost, R&D, and sales subsidies.

5.4. Enhancing IAMs with game-theoretic frameworks

IAMs typically simulate market equilibrium, assuming symmetrical information among players. However, the rapid advancement of mitigation technologies and the growing complexity of the technological and supply-chain landscape make this assumption increasingly unrealistic. Climate policies are tightening globally and becoming more intertwined with geopolitical and national security issues. In this context, information asymmetry among players is common. Game-theoretic frameworks can help conceptualize the complex and dynamic interactions in climate mitigation research, enhancing the policy relevance of IAMs. For instance, the IAM WITCH has incorporated game theory to model coalition formation for achieving ambitious climate action [170]. We propose a few concrete policy research questions that could, in theory, be addressed by integrating game theory with IAMs.

- **Producers' strategic approaches to price setting:** Due to rapid technological progress in transport electrification, demand growth in fossil fuel sectors is already slowing. As mitigation requires a rapid phase-out of fossil fuels, this process accelerates in IAM scenarios. This could lead to situations where fossil fuel prices fall below production costs. As IAMs are equilibrium models, they cannot simulate prices below production costs. However, limit pricing games can provide a qualitative decreasing price trajectory for fossil fuels, which can be quantified by producers' cash flow. The resulting price can be fed back into IAMs, altering competition dynamics between green synthetic liquid fuels and fossil fuels, potentially making the green alternative less competitive, requiring more policies. Price-setting could also apply to green energy producers, where firms may adjust heterogeneous pricing strategies, particularly in export sectors like Chinese solar panel exports [171]. Detailed IAM pathways can incorporate such pricing dynamics, leading to near-term adjustments in technology diffusion but potentially having long-term path-dependent effects.
- **Supply-chain management:** Aggregated IAMs cannot capture the full complexity of interactions within green supply chains. Game-theoretic studies [152, 153] demonstrate how supply chains respond to government interventions and green policies. These studies offer detailed insights into how stakeholders interact under competitive pressures and regulatory interventions, highlighting the trade-offs businesses face when adopting sustainable practices. In this context, carbon price or total investment variables derived from IAM benchmark pathways can be integrated into game-theoretic analyses of supply chains, considering strategic interactions under policy-driven scenarios.
- **Geopolitical competition:** Optimization-based IAMs often struggle to fully simulate the complex and evolving nature of geopolitical competition over energy resources, whereas game-theoretic approaches offer detailed insights into strategic moves and interdependencies between nations. For example, decisions on rare earth element markets, as analyzed by B. Minooei Fard et al. [166], or the synchronization of electricity grids, as examined by Songying Fang et al. [159], involve strategic choices made to secure energy autonomy or align with politically favorable regions. By integrating these insights from game theory, IAMs can enhance their realism, accounting for the interactive and competitive aspects of international energy security. For instance, if one country heavily invests in renewable energy to reduce fossil fuel dependence, IAMs can use game-theoretic models to predict how neighboring countries might respond. This allows IAMs to simulate energy policy adjustments as countries aim to maintain competitive balance,

secure supplies, or align with renewable energy leaders. By incorporating such strategic insights, IAMs can model a broader range of potential outcomes, reflecting the dynamic geopolitical nature of energy policies, rather than relying on static assumptions.

- **Strategic interaction around green technology choice:** IAMs typically lack regional growth motives and technological specialization based on existing technology stocks. Game-theory models, however, suggest that regions may form "technology clusters", where industries focus on advancing technologies in which they have a perceived competitive advantage. For example, Japanese car manufacturers prioritize hydrogen fuel-cell vehicles, German carmakers focus on synthetic fuel, coal-dependent countries may support synthetic ammonia or biomass co-firing, and Saudi Arabia might specialize in carbon capture and storage. These technology choices often deviate from cost-optimal options like electric vehicles or widespread wind and solar deployment. Nonetheless, by pursuing these strategies, regions with existing industrial advantages can secure a substantial share of the green energy market or dominate specific segments of future supply chains, shaping technology development in their favor. Less-developed regions, reliant on capital and technology transfers from more industrially advanced ones, may also be influenced by these suboptimal technology choices. This dynamic can impact the diffusion of green technologies in IAMs, such as their speed and direction, i.e. technology adoption does not occur uniformly but follows networks shaped by economic and geopolitical relations.

6. Concluding remarks and outlooks

6.1. Integration of political economy into climate mitigation modeling

As Bruno Turnheim et al. [172] points out, "governing open-ended, uncertain, contested, disruptive change processes is very different from governing the efficient exploitation of relatively stable systems, which dominated in previous decades in many countries." Process-based IAMs, using mainstream environmental economic frameworks, have inherent limitations in capturing disruptive, heterogeneous, and path-dependent dynamics in structural transitions. This gap is increasingly recognized within and outside the IAM community. In this paper, we survey recent developments in mainstream climate mitigation modeling while drawing on critical IAM literature. By introducing three complementary dynamical methods, we propose new approaches for integrating political economy aspects into IAMs' scenario designs and pathways.

In this critical review, building on a more comprehensive introduction to IAM methodology compared to previous literature, we propose several ways to improve the existing framework. First, enhance the quality of pathways by increasing IAMs' temporal, spatial, and technical resolution through both hard and soft coupling, and gradually replace coarse CES-based formulations with process-based ones. Second, improve the depiction of technological innovation by expanding IAM technology portfolios and implementing two-factor learning curves (and possibly a "learning and forgetting curve" to capture knowledge depreciation). Third, incorporate dynamic models, particularly for demand sectors, diversify the policy mix in IAM pathways to systematically include regulatory, investment, and infrastructure policies, and develop alternative ambitious climate scenarios where carbon pricing is not the main driver, but part of a broader policy mix.

To integrate political economy aspects into IAMs, we propose three dynamic models that address key limitations. These models focus on the political economy of innovation, heterogeneous adoption dynamics, and strategic responses in the green transition. The DTC model links profit, investment, innovation, and growth, with features like knowledge stock accumulation, depreciation, and endogenous growth from innovation that can be incorporated into IAMs as stand-alone components. ABMs model transitional dynamics as a heterogeneous diffusion process, refining IAM baseline dynamics by modeling the impacts of existing climate policies on different groups in a more realistic way. ABMs can also examine the heterogeneous response to climate damage and adaptation based on wealth and income, feeding back into IAMs through economic growth, energy and food demand. Game-theoretic models could enhance IAMs by simulating strategic interactions in pricing dynamics, supply chains, and geopolitical competition. For example, limit pricing games can model price declines in fossil fuels, while game theory can show how countries and firms navigate competitive pressures and policy interventions. Additionally, game theory can explain regional technological specialization and innovation, illustrating how countries prioritize certain green technologies based on competitive advantages, influencing global technology adoption in IAM scenarios.

While we cannot comprehensively cover all the latest advancements or critiques of IAMs, nor provide an exhaustive discussion of dynamic models, we hope this paper offers valuable insights and concrete suggestions for advancing the research agenda in climate mitigation modeling. In our last reflection, we would like to highlight that there exist limitations common to all quantitative models to portray key aspects of climate mitigation, which is related to institutional change, as well as endogenizing the role of finance and debt in relation to growth.

6.2. Future research on endogenizing institutional change, growth and finance

Over the past three decades, IAMs and other quantitative models have gained traction within policy and research communities. However, their real-world impact remains limited in effectively coordinating rapid and global climate action, due to various internal and external factors [6]. Beyond their limited depiction of political economy, a key challenge for successful climate mitigation is modeling institutional behavior change. A simple coupling of IAMs with political economy models, as frequently suggested in the critical literature, does not adequately endogenize institutional change—an essential component for understanding how an existing industrial regime is destabilized, phased out, and replaced by a new one, especially when considering past cases from industrial history [173, 174]. To give an example, the previous lack of endogenous modeling for coal phase-out policies and power sector transitions led to unrealistic coal phase-out pathways in IAMs [90]. Although recent efforts have integrated political economy constraints, such as the diffusion and adoption of coal phase-out pledges [91], these hybrid models still remain highly aggregated [80] and fail to capture the complex social and political processes underlying the adoption of such policies or their regional diffusion.

As Michael Grubb et al. [6, 60] suggest, understanding these processes requires economic thinking beyond the neoclassical framework to endogenize institutional change. While many social theoretical frameworks analyze industrial regime and policy changes (e.g., those mentioned in the studies by Anders Enggaard Bødker et al.[175, 176], we propose Masahiko Aoki's game-theoretic framework for studying institutional change in the "post-carbon" transition. This dynamical model of institutions resists full mathematical formulation. Known as the "equilibrium-summary-representation" approach, it provides a process-based model for institutional evolution [177–179]. In essence, institutions are neither the equilibrium outcome of the game, nor the set of rules of the game, but a system of shared beliefs and "summary representations"—compressed information about the game's equilibrium—that coordinate them. Together, the "summary representations" that coordinate shared beliefs and the shared beliefs themselves contribute to the collective sustaining and remaking of the institution.

Under Aoki's framework, creating a shared belief about the equilibrium of the new rules is key to driving institutional change. In terms of climate mitigation, the institutional change needed for successful climate mitigation requires coordinated cognitive shifts among participants, i.e., creating shared beliefs, which have a substantive base. How the "post-carbon" game's rules would look like are currently only communicated through quantitative "compressed information", in the form of scenario pathways of IAMs and results from dynamic models. By providing an internally consistent "summary representation" of a green future, these models have played (or were expected to play) a crucial role in coordinating this shared belief about how a "post-carbon" game will unfold. Aoki's framework also make more obvious and explicit the observation that IAM results cannot be interpreted as an equilibrium of the world post-carbon. Since mitigation models—whether dynamic or optimization-based—cannot be expected to portray a real equilibrium where global society achieves ambitious climate targets, as the politics and rules of the game are constantly evolving. No models can predict the changing structure of power over the next 20 years, let alone 50 or 80 years.

Hence, we are to interpret the quantitative results from the models as a form of "compressed information" about how the post-carbon game will be played, and not the equilibrium of the outcome. However, there are at least two difficulties on how such model results could then coordinate shared beliefs. First, due to the aggregate, engineering-focused, and static nature of many quantitative models, the full implications of these pathways for the actors shaping a new "post-carbon" rule, as well as their evolving strategies, are difficult to articulate. Second, the representation of the rule in the "post-carbon" world currently lacks a substantive base. For a world meant to embody sustainability and equity, there has been a lack of sufficient international policies to ground these compressed visions—policies such as loss and damage funds, green finance, and grants for the least-developed countries. This results in a vicious cycle—a lack of substantive policies that back up a supposed shared vision, leads to denial or doubt about the "summary representation" regarding the post-carbon world (e.g. climate models and transition pathways), which then in turn leads to increasing difficulties in coordinating shared beliefs among actors to create endogenous institutional change.

However, if the quantitative models (or any analytical models) can credibly and precisely articulate, what the equilibrium of the "post-carbon" rule may be, and the more shared beliefs are grounded in common values such as equity, fairness, feasibility, growth, and resilience, the easier the shared beliefs about the post-carbon world can be coordinated. To create a "summary representation" of how the new "post-carbon" game will unfold, IAMs and quantitative models are just one way to coordinate beliefs. Other academic works using different analytical methods from diverse disciplines are also needed to explore these implications from various perspectives.

Lastly, as many studies highlight, technological innovation, economic growth, debt, and finance are intricately interlinked and must be considered together in a comprehensive climate mitigation framework [2, 8, 180]. The relationship between growth, debt, and emissions is complex, shaped by financial structures, fiscal policies, inequality, investment, and technology choices [181–184]. Since IAMs play a role in both setting targets and monitoring progress, understanding and endogenizing economic growth is crucial, as uncertainties in growth rates directly affect energy demand projections. To better understand growth, finance, technological innovation, and emissions, IAMs must go beyond simplistic GDP-emission decoupling and incorporate frameworks like Keynesian or post-Schumpeterian models

[180, 185, 186].

Use of AI tools declaration

The authors declare they have used Artificial Intelligence (AI) tools for the purpose of English editing.

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Conflict of interest

The authors declare no conflict of interest.

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