A Model of Endogenous Technological Change Through Uncertain Returns on Learning (R&D and Investments)

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Abstract

A model is presented that endogenizes the two most important sources of technological change—uncertainty, and technological learning through research and development (R&D) and learning by doing (investments)—into an intertemporal optimization framework. Mathematically, the resulting problem is one of non-convex, non-smooth, stochastic optimization. The simple, stylized sectoral (energy) model includes one demand and one resource category. The model selects from three competing technologies, which differ in their current costs and in their (uncertain) potentials for future cost reductions through learning. The resulting model fully endogenizes the process of technological change, which is driven by expected, but uncertain, returns from investments into R&D and niche-market applications. These in turn can render new technologies increasingly competitive, ultimately leading to pervasive diffusion. The model, while definitely oversimplified, nevertheless allows several robust conclusions. First, it was possible to find an operable analytical solution for an optimization problem that simultaneously involves stochasticity (uncertainty) as well as non-convexity (increasing returns through technological learning). Second, the S-shaped patterns of technological entry and diffusion endogenously generated by the model are consistent with those observed historically and in the empirical literature on technological diffusion. Third, the model illustrates the possibility of wide-ranging technological outcomes resulting from even small differences in initial conditions and the (uncertain) rates of technological learning. Fourth, the resulting diffusion of new technologies of our model can yield pronounced discontinuities in the environmental performance of technologies. For instance, future emissions could decline radically even in absence of environmental constraints.
endogenous technological change presented here.

Yet, for all these arguments and evidence technological change has largely been treated as exogenous in existing models. This is true of models developed within the tradition of growth theory and associated production function models (so-called “top-down,” models), as well as those developed within an systems engineering perspective (e.g., detailed sectoral “bottom-up” optimization models). In both modeling traditions, technological change is either reduced to an aggregate exogenous trend parameter (the “residual” of the growth accounts), or introduced in form of numerous (exogenous) assumptions on costs and performance of future technologies. Common to both modeling traditions is that the only endogenous mechanism of technological change is that of progressive resource depletion and resulting cost increases. Such constraints which are at odds with historical experience (cf. Barnett and Morse, 1967) trigger both substitution of factor inputs as well as the penetration of otherwise uneconomic technologies. These are either represented generically as aggregates in form of so-called “backstops” (a term coined by Nordhaus, 1973), or through detailed assumptions on numerous technologies individually.

Perhaps one of the reasons for this apparent impasse is that both modeling traditions usually operate within an optimization framework. However, in reality, future characteristics of technologies are not known ex ante, but result from the (uncertain) results of intervening actions (R&D and investments), i.e. technological learning. Endogenization of uncertainty and of R&D and technological learning into models is therefore mathematically cumbersome involving stochasticity and recursive formulations.

Technological learning is a classical example of increasing returns, i.e. the more learning takes place, the better a technology’s performance. It is the technology counterpart of the increasing returns resulting from the accumulation of knowledge or increases in human capital that are the focus of endogenous growth theory (e.g. Romer, 1986, and 1990; or Grossman and Helpman, 1991) and as discussed increasingly also in the technology domain (cf. Arthur, 1983, and 1989).

Our paper and model aims to make a contribution in the domain of endogenizing technological change as arising from uncertain technological learning. As such, the model formulation complements more traditional approaches of induced technical change focusing on relative resource and factor endowments
2 Sources of Technological Change

In this Section we discuss two (interrelated) sources of technological change: Uncertainty and learning. Uncertainty, its associated economic risks and opportunities, as well as the strategies adopted in face of both risks and opportunities are a main driver of technological evolution. Learning itself is seen as a result of both the classical "learning by doing" (read: commercial investments) as well as of research and development (R&D), and demonstration efforts (in niche markets), subsumed here under the heading of RD&D. All these components are interrelated and have to be considered holistically as has been repeatedly argued by critics of "linear" models of innovation (cf. OECD, 1992), a point which we take up in our model formulation, where both R&D and investments taken together are modeled as a single learning process whose actual outcome is however subject to uncertainty. Learning is not only the main endogenous mechanism for reducing uncertainty, but is also a means of improving technical, economic, sometimes even social, characteristics of new technologies that are the main drivers for their widespread diffusion.

2.1 Uncertainty

There is only one certainty related to technological change: the technology of tomorrow will be different from that of today. But to what extent, and by which concrete configurations? The importance of technological uncertainty has been recognized and explored ever since the earliest days of global environmental modeling (e.g., Nordhaus, 1973; Starr and Rudman, 1973). Different approaches have been followed for analyzing the impacts of technological uncertainty including the formulation of alternative scenarios (e.g., IIASA-WEC, 1995); model sensitivity analysis (e.g., Nordhaus, 1973, 1979); and sensitivity analysis based on expert polls or Delphi-type methods (e.g., Manne and Richels, 1994).

In each of these types of analysis the subjective choice of the technological uncertainty range investigated is made either by the modelers themselves in the sensitivity analysis, or by the experts polled. Also, whereas scenarios or sensitivity analyses yield insights into the variations in model outcomes that result from changes in input assumptions, technological uncertainty is not endogenized into the decision rules (usually based on some optimization criterion) that have been employed in the models. In other words, although
A general methodology for endogenizing uncertainty in optimization problems is described in Ermoliev and Wets (1988) and an improved algorithm was suggested by Ermoliev (1995). It was applied in a sectoral (energy) model using stochastic optimization by Golodnikov et al. (1995) and Messner et al. (1996).\(^2\) (See also Grübler and Messner, 1996.) There, the subjective nature of defining technological uncertainty ranges is replaced by an empirical approach, that draws on a detailed statistical analysis (Strubegger and Reitgruber, 1995) of investment costs of current and future energy technologies derived from engineering studies. The resulting empirically derived uncertainty distributions are incorporated directly into the optimization algorithm of the model—i.e., into its underlying decision-making rule. This is done through adding a risk term\(^3\) in the objective function that integrates (weighted by probabilities) stochastically drawn data samples into the final solution. The algorithm assures short computation time and full endogenization of uncertainty in the model solution\(^4\).

The stochastic model responds to a frequent criticism of traditional optimization models: the inappropriate assumption of a decision-making agent that operates under perfect foresight. Through endogenization of uncertainty, decision making in the model no longer operates under perfect foresight. The model behavior thus approximates the outcome of real-life decision-making situations in which different economic agents with different expectations and risk attitudes show persistent differences in strategies and investment behavior that result in technological diversification.

Model simulations illustrate that compared with traditional deterministic model representations, which assume perfect foresight, endogenization of technological uncertainty yields more diversified technological configurations. Even more important, the model results reveal a pro-innovation bias and no risk aversion in investments into technological change. Diversification thus becomes the optimal response strategy in face of technological uncertainty.

However, model simulations also illustrate that the inclusion of uncertainty leads to technological diversification only along the lines of incremental innovations—in other terms, to technology changes within a “technolog-

\(^2\) A similar type of application using the MARKAL model is reported in Fragnière and Haurie (1995).

\(^3\) This term represents the economic costs (added to the objective function) if a technology turns out to be more expensive than expected.

\(^4\) For details see Golodnikov et al. (1995); Messner et al. (1996); and Ermoliev and Wets (1988).
nological learning has since been analyzed empirically for manufacturing and service activities including aircraft, ships, refined petroleum products, petrochemicals, steam and gas turbines, and broiler chickens. Learning processes have also been documented for a wide variety of human activities ranging from success rates of new surgical procedures to productivity in kibbutz farming and nuclear plant operation reliability (Argote and Eppe, 1990). In economics, “learning by doing” and “learning by using” have been highlighted since the early 1960s (see e.g., Arrow, 1962; and Rosenberg, 1982). Detailed studies track the many different sources and mechanisms of technological learning (for a succinct discussion of “who learns what?” see Cantley and Sahal, 1980).⁵

Learning phenomena are generally described in form of “learning” or “experience” curves, where typically the unit costs of production decline at a decreasing rate as experience is gained. Because learning depends on the actual accumulation of experience and not just on the passage of time, learning curves are generally measured as a function of cumulative output. Frequently, the resulting exponential decay function is plotted with logarithmically scaled axes so that it becomes a straight line (see Figure 2). Because each successive doubling takes longer, such straight line plots should not be misunderstood to mean “linear” progress that can be maintained indefinitely. Over time, cost reductions become smaller and smaller as each doubling requires more production volume. The potential for cost reductions become increasingly exhausted as the technology matures.

Technological learning is a classical example of “increasing returns”, i.e., the more experience is accumulated, the better the performance, the lower the

reached 41 units in 1974. It subsequently dropped to 6 units in 1977, and then increased again thereafter. The drastic reduction in output led to large scale layoffs and the initially gained experience was lost with the staff turnover. As a result, the planes built in the early 1980s were in real terms (after inflation) more expensive than those built in the early 1970s.

⁵A stylized taxonomy of technological learning mechanisms includes inter alia: learning by upscaling (e.g., steam turbines or generators), learning through mass production (e.g., the classical Model T Ford), and learning through both increasing scale and mass production, referred to here as “continuous operation”, i.e., the mass production of standardized commodities in plants of increasing size (e.g., transistors, or base chemicals like ethylene or PVC, where cost reductions through learning have been particularly spectacular, cf. Clair, 1983). This simple taxonomy is confirmed by a statistical analysis of learning rates across many technologies and products (Christiansson, 1995). Learning rates are typically twice as high for “continuous operation” as for either upscaling or mass production alone.
costs of a technology, etc. However, because accumulation of experience takes ever longer (cf. the increasingly “packed” spacing of observations towards the 1990s in Figure 2) and is more difficult to achieve, learning itself shows decreasing marginal returns.

Figure 2 plots the costs of photovoltaic cells per (peak) kW capacity as a function of total cumulative installed capacity for Japan. Starting off from extremely high costs of some 30,000 Yen (in 1985 prices) in the early 1970s, costs fell dramatically: from 16,300 Yen in 1976 to 1,200 Yen in 1985 (i.e., a factor close to 14 in less than 10 years), and then further to 640 Yen in 1995 (another factor 2 within the next 10 years). The resulting learning rate of a 36 percent reduction in costs per each doubling of cumulative installed capacity is at the higher end of the range of learning rates observed in the empirical literature (cf. Argote and Eppele, 1990; and Christiansson, 1995). This high learning rate however is less surprising considering the infancy of the technology and the significant progress through R&D\(^7\) that should, in fact, not be separated from “learning by doing” via investments, a point to which we return below.

Despite overwhelming empirical evidence and solid theoretical underpinnings, learning phenomena have been explicitly introduced only into few models of intertemporal choice. The most likely explanation for this paucity of model applications is the difficulties of dealing algorithmically with the resulting non-convexities of the problem solution. A first detailed model formulation was suggested by Nordhaus and Van der Heyden (1983) to assess the potential benefits of enhanced R&D efforts in new energy technologies such as the fast breeder reactor. A first full scale operational optimization model incorporating systematic technological learning was developed by Messner, 1995 (see also Nakicenovic, 1996). In a mixed-integer formulation, learning rates for a number of advanced electricity generating technologies were introduced into a linear programming model of the global energy system. These learning rates were assumed to be known ex ante. Hence, future technology costs depend solely on the amount of intervening investments that lead to increased experience (installed capacity), that, in turn, stimulates learning and subsequent cost reductions.

The model by Messner (1995) demonstrated the feasibility of including

\(^7\)Note in particular the substantial cost decreases between 1973 and 1976 prior to any installation of demonstration units.
sider uncertainty explicitly. Second, viewing technological change as result of R&D and investments, it is insufficient to consider only investments, even if investments constitute the dominant share in total expenditures into new technologies. Both domains are considered explicitly in the model presented here.

2.2.2 Learning through (Applied) R&D

The importance of RD&D (research, development, and demonstration) as source of technological change is evident and needs no further discussion here. The demonstration component of RD&D, which takes up the highest share in total RD&D costs, is well captured in the learning curve formulation presented above. However, one needs also to consider R&D (research and development) costs explicitly. In other words: include applied research\textsuperscript{10} efforts in our considerations here.

As a representative conceptual and empirical model we follow the formulation of Watanabe (1995), who draws on the experience with MITI’s “sunshine” technology program. The data are particularly suited for illustrating our main argument because they include both public and private R&D expenditures and are also exceptionally comprehensive. (As a rule it is very difficult to get a complete overview of technology specific R&D expenditures by private industry.) The Watanabe model has also the added benefit of empirical parametrization obtained through statistical/econometric analysis of long time-series data. We use the example of photovoltaic cells (PVs) as illustration.

In essence, the model of applied R&D (see Figure 3) describes a positive feedback loop (a “virtually spin cycle” in the terminology of Watanabe, 1995): public R&D (together with other incentives) stimulates industry R&D, and both increase the “technology knowledge stock”\textsuperscript{11} of a particu-

\textsuperscript{10} We recognize the importance of basic R&D as laying the groundwork, typically in form of new scientific knowledge, for applied RD&D and subsequent technological change (cf. Rosenberg, 1990). However, considering the frequently long lead times between the generation of new basic scientific knowledge and first commercial applications as well as the generic nature of scientific knowledge, i.e., it is relevant for more than just a few particular technologies; basic research is not treated separately in our discussion and model.

\textsuperscript{11} This is the sectoral or technology specific equivalent of the knowledge stock introduced in the production function models of the so-called “new growth theory” (e.g., Romer, 1986, and 1990), that can also exhibit increasing returns. Evidently there are likely additional interindustry and cross-national R&D spillover effects (cf. Mansfield, 1985), including
Figure 3: Positive feedback model of RD&D of Japanese photovoltaic development: Major relationships, feedbacks and model parameters estimated from empirical data over the period 1976 to 1990. Source: Watanabe, 1995.
applications\textsuperscript{13}) is not supported by the data.\textsuperscript{14}

Functionally, total RD&D costs and technology costs again exhibit a classical learning curve relationship as shown in Figure 4. (The fact that the resulting learning curve parameter is with 54 percent per doubling higher than that given in Figure 2 above [36 percent per doubling] is self-evident: with falling costs simply more capacity can be installed per unit expenditure.)

This simplifies our basic model considerably as both R&D and investments taken together can be modeled by a single learning curve,\textsuperscript{15} whose actual value is however subject to uncertainty. This constitutes the essence of our simple model of endogenized technological change integrating uncertainty, R&D, and technological learning.

3 The Model

Our optimization model of technology choice is conceptually simple. (For a mathematical description and parameter values see the Mathematical Appendix.)

We suppose one primary resource, whose extraction costs increase over time as a function of resource depletion, while being sufficiently large for not resulting in absolute resource scarcity over the entire simulation horizon (set rather extremely at 200 years). The economy demands one homogeneous good, the demand for which increases over time. Three technologies are in principle available to perform the transformation from primary resource to the good demanded: “Existing,” “Incremental,” and “Revolutionary.”

The “Existing” technology is assumed to be an entirely mature one, i.e. its characteristics (costs and resource conversion efficiency) do not change over time. The “Incremental” technology represents its incremental improvement counterpart with a slight efficiency advantage, but with currently higher (by a factor 2) costs. The “Incremental” technology has potential for technological learning; the mean learning rate assumed is set at 10 percent (for

\textsuperscript{13}There can be quite an overlap between these two types of investments. Consider for example the case of PVs: their use in remote locations constitutes both an important demonstration effort, but in many cases may constitute already a commercial investment as well. This is an additional reason of not separating artificially R&D, from demonstration and subsequent early commercial investments.

\textsuperscript{14}For further evidence see also Mori \textit{et al.}, 1992; and Baba \textit{et al.}, 1995.

\textsuperscript{15}Technically this is done simply by increasing the intercept of the learning curve referring to investments alone through a fixed R&D component percentage.
intervening cumulative investments. The probabilistic characteristics of these random values can be derived from the uncertainty distribution functions of the corresponding learning rates. In our model we are using a simultaneous approximation of these random future cost values by $N$ sample functions of the learning rate, where $N$ is the sample size (see the Mathematical Appendix for further details). For this simultaneous sampling of parameter values, the non-convex and non-smooth optimization problem is solved by applying a combination of a simple global search procedure, a modified Nelder-Mead algorithm, and a BFGS quasi-Newton minimization. The solution path of the optimal technology strategy for our problem with $N$ approaching infinity converges to an optimal solution of the original stochastic problem.

For each sample $N$ we integrate the expected costs into the objective function that consists of three parts. Part 1) corresponds to the expected value for a deterministic formulation. Part 2) in the objective function represents the risk (costs) of having overestimated the technological learning rate, i.e., realized investment costs are higher than expected. The additive term is assumed to be quadratic, i.e. the costs added to the objective function grow quadratically with the deviation of costs from sample $N$ to the mean expected value. Part 3) is its benefit counterpart, i.e. when costs turn out to be lower than the expected (mean) value due to learning rates that are higher than expected. This part added to the objective function is assumed as a linear term.

In our approach, “risk” and “benefits” are non-symmetric and cannot be expressed simply in terms of mean and variance of corresponding economic gain and losses. This reflects our interpretation of reality characterized by asymmetry of the costs associated with under- or overestimating future costs and hence one’s future competitive position. Underestimating costs is penalized more heavily in competitive markets than overestimation. (Though in our stylized model we only have a single decision agent that however, does not operate with perfect foresight.)\textsuperscript{19} Cost underestimation risks the very survival on the market, whereas cost overestimation yields “merely” lower profits than expected. In other words, our model (perhaps conservatively) values survival higher than profitability.

The model is solved for a sufficiently large sample $N$, where the size of

\textsuperscript{19}We are currently working on an extension of the model with multiple agents that can have different valuations of risks and benefits associated with making a wrong “bet” on future learning rates.
Figure 5: Share (in percent) of three technologies in new capacity additions, "Existing" (dotted lines), "Incremental" (dashed lines), and "Revolutionary" (solid lines). Note that for clarity of exposition only growing shares are reported (and the symmetrical declining shares of technologies being substituted are omitted). The simulation runs shown include:
0: static technologies
1: exogenous improvements in "Incremental" technology only
2: learning of "Incremental" technology only
3: uncertain learning of "Incremental" technology only
4: learning of "Incremental" and "Revolutionary" technology
5: uncertain learning of "Incremental" and "Revolutionary" technology (retained as standard base case BC30 in the discussion below).

For a discussion see text.
Figure 6: Market shares (in percent) of the three technologies in total installed capacity under uncertain technological learning with base case parameter specifications (simulation run 5 of Figure 5 above). Note in particular the smooth S-shaped diffusion patterns.

ity) of each of the three technologies. The result is a pattern of technological evolution characterized by a “sequence of replacements” (Montroll, 1978) of older by newer technologies. This technological structural change is consistent with the diffusion patterns observed historically (cf. Nakićenović, 1997) and formulated by diffusion theory (cf. Rogers, 1983). Technologies enter into small niche markets slowly, but with declining costs (through learning) diffuse more rapidly and widely until markets are saturated and technological improvement possibilities (learning potentials) become exhausted. The result, graphically, is the familiar S-shaped curve pattern.

5 Sensitivity

In the simulations reported thus far we have used uncertainty distributions only around the base case parameter values of the learning rate while assuming all other salient model parameters and input variable as perfectly known. We now report several sensitivity analyses that relax successively these simplifying assumptions. We have explored the model’s sensitivity in the following domains:
Figure 7: Time (year) by when the “Revolutionary” technology reaches economic break-even with the “Existing” one as a function of initial start-up costs (in 10,000 US$ per kW) and learning rates (percent cost reduction per doubling of cumulative installed capacity). The vertical axis represents time. Low values indicate the technology becomes rapidly competitive (right-hand side, lower corner), high values (left- and right-hand side upper corners) indicate it never would become competitive. Note in particular the non-linear domain of the parameter space, where even small variations in parameter values result in quite different model outcomes. Our model achieves optimal investment solutions by sampling stochastically drawn samples in this parameter space around the mean value of the learning rate adopted.
esting insight from this sensitivity analysis was obtained when combining high discount rates (7 percent) with uncertainty of technological learning. In this simulation experiment, the “Revolutionary” technology, which invariably appeared as a robust technological diversification strategy in all earlier simulations (albeit with different timing and market penetration profiles) did not make it to the market. In other words, high intertemporal discounting combined with high technological uncertainty favors “no change” technology strategies.

5.4 Uncertainty in demand

We also have explored the sensitivity of the model to uncertainties in demand. Because growth in demand is the result of complex interacting demographic, economic, and lifestyle forces we can expect its future evolution to be highly uncertain. Perhaps demand is even more uncertain than technological parameters. Hence the interest to explore its implications on technology RD&D strategies.

For the demand uncertainty analysis we adopt a somewhat different procedure. Instead of sampling within one singular uncertainty distribution around the mean expected value of a 13-fold increase between 1990 and the year 2100, we divide the uncertainty distribution into four subsamples (see Figure 8) and perform the stochastic sampling on basis of these subsamples. We do not assign relative probabilities to these four samples as our interest lies in examining different technology strategies that emerge from four distinct expectational domains of future demand. As previously, probabilities are assigned to draws within each of the four subsamples.

As a result we obtain four distinct solutions (technology trajectories) corresponding to alternative technology strategies in face of demand uncertainty. These are reported in Figure 9 for the “Revolutionary” technology. For comparison we also show simulations with uncertain technology learning rates (around mean values of 30 and 40 percent respectively) and a simulation run with an uncertain emission tax (cf. the discussion in the next Section below).

Figure 9 illustrates the wide variation in future diffusion pathways of the “Revolutionary” technology as a function of differences in rates of technological learning, demand, and environmental limits. Obviously, if the potential for technological learning is higher, then new technologies penetrate the market earlier (cf. the difference between the base case scenarios BC30 and BC40 in Figure 9). This is also the case if one is uncertain whether environmental
Figure 9: Shares in new capacity additions (in percent) of a “Revolutionary” technology in three different scenario classes:
solid lines: base case and sensitivity run (stochastic uncertainty with mean learning rate of 30 and 40 percent respectively) denoted as BC30 and BC40;
dashed lines: base case with additional uncertainty of demand for four domains of demand uncertainty denoted as A, B, C, and D (A and B represent different degrees of realized demand being lower than expected, C and D indicate domains where demand could turn out higher than expected);
dotted line: base case (BC30) with an uncertain environmental constraint (emission tax), denoted as BC30+Tax. The time axis shows the (positive or negative) diffusion lag (in years) compared to the base case (BC30) simulation.
Figure 10: Results from Figure 9 but shown as new capacity additions (GW) of a “Revolutionary” technology in three different scenario classes (cf. Figure 9 above for a more detailed definition). The time axis shows the (positive or negative) diffusion lag (in years) compared to the base case (BC30) simulation. Solid lines: base case (uncertain learning rates with mean of 30 and 40 percent respectively) denoted BC30 and BC40; Dashed lines: base case with additional uncertainty of demand (A and B represent simulations in which realized demand could turn out lower than expected, in C and D demand could turn out much higher); Dotted line: base case (BC30) with uncertain emissions tax (BC30+Tax).
as optimal strategy vis à vis future contingencies: “get prepared as early as possible for potential surprises that might strike later.”

We conclude this overview of our model runs by pointing out a final potential “surprise” emerging from our model runs. Allowing for technological learning in an endogenous model of technological change could result in pronounced discontinuities of future emission levels. These in fact might drop substantially, not through an exogenous “shock” such as taxation or emission limits, but through the endogenous dynamics of technological change (cf. Figure 11). Such a view is obviously in stark contrast to the typical “business as usual” emission trajectories, which embrace either a static or incrementalist technological change perspective. Our model results strongly suggest that this divergence in future emission pathways might be not only an issue of uncertainty of the future per se (e.g. of resource availability), but also how technological change is represented in models: exogenous, or endogenous.

6 Conclusion

We have developed a model of endogenous technological change, which is driven by expectations of uncertain returns from investments into research, development, demonstration, and commercialization of new technologies. Such technologies are initially unattractive, but they offer (uncertain) potential for future improvements. Lower costs, once realized, allow widespread adoption, i.e. technology diffusion. As in the real world, investments result in (uncertain) technological learning and are a main driver of technological change.

Our model represents technological change as resulting from the (rational) strategies of economic agents that know that technological change does not come as a free good. Rather, improved technologies require dedicated efforts and expenditures, and agents act accordingly. Albeit they remain uncertain about the ultimate outcome of their strategies (i.e. there is a difference between “technological expectations” and the ultimately realized technological learning). In this sense, technological change arises out of the “bounded” economic rationality of pursuing technological R&D and invest-

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23 Of course we can also imagine endogenous technological change trajectories leading to higher emissions rather than lower ones—for example, energy-intensive hypersonic or space travel.
ments in anticipation of future returns in form of performance improvements, cost reductions, etc. that are also main drivers of technology diffusion. As in the real world, uncertainty in outcomes of (returns to) of R&D and investment efforts is a key feature governing technological evolution.

At the analytical level, we were able to demonstrate a model formulation involving simultaneously increasing returns and uncertainty within an intertemporal optimization framework. The most important result is the demonstration of an entirely endogenous mechanism of technological change. In other words, we could show that the non-convex, non-smooth, stochastic optimization problem resulting from stochasticity (uncertainty) and increasing returns (learning) combined, is solvable. Moreover, the patterns of technological change and diffusion exhibited by the model are consistent with those observed historically and in the diffusion literature. As such, our model responds to the frequent (and justified) critique of diffusion studies and models as being phenomenological, lacking a clear endogenous causality mechanism.

In model runs with plausible patterns of uncertainty and technological learning, technologies that are economically unattractive today (e.g. a factor 40 higher costs) nonetheless diffuse into the market within 4-5 decades. Such diffusion is economically optimal, but requires upfront investments into R&D, demonstration (niche markets), and gradually into expanding commercial investments, all of which lead to pervasive diffusion. These upfront investments initiate a process of technological improvements and cost reductions (learning) that is further sustained during subsequent pervasive diffusion.

Our model results also show, that investments into technological learning (RD&D) constitutes an optimal contingency strategy vis-à-vis uncertainty in future demand and the possible emergence of environmental regulations.

After demonstrating the feasibility of a model of endogenous technological change, much remains to be done on both the conceptual and modeling levels. Clearly, the highly stylized structure of the model must be expanded to, at least rudimentarily, resemble the complexity of existing technological systems. This constitutes a prerequisite also to study in more detail the critical issue of technological interdependence, i.e. technological change in one domain (e.g. hydrogen cars) is insufficient if not accompanied by corresponding changes in other technologies (e.g. hydrogen production, transport, and distribution infrastructures). The complex issues of spillovers and learning externalities—such as advances in general scientific knowledge or the possibility of “free riding” on someone else’s learning efforts—also have not been
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References


Objective function.

The objective function is the sum of three components

\[
E \left\{ \int_{1990}^{2200} c_i^l (\tau; \omega) Y_i (\tau) d\tau \right\} + \int_{1990}^{2200} \delta(\tau) \left[ c^l (\tau) R(\tau) + c_i^{OM} X_i (\tau) \right] d\tau + \\
\rho \int_{1990}^{2200} \delta(\tau) E_{\max} \left\{ 0, \left[ Ec_i^l (\tau; \omega) - c_i^l (\tau; \omega) \right]^2 Y_i (\tau) \right\} d\tau - \\
\int_{1990}^{2200} \delta(\tau) E_{\min} \left\{ 0, \left[ Ec_i^l (\tau; \omega) - c_i^l (\tau; \omega) \right] Y_i (\tau) \right\} d\tau \rightarrow \min
\]

where \( \delta(\tau) \) is discount factor for time \( \tau \), \( c_i^{OM} \) represents specific O+M cost of technology \( i \) (assumed to be constant over time) and \( E \) is stands for expectation, with \( \omega \) being an element from a probability space. Part two represents the risk associated with overestimating learning rates with its associated risk factor \( \rho \); part three represents the benefits in case of underestimating the learning rate. As shown above, we apply a quadratic formulation for the risk term and a linear one for the benefit term. In the deterministic formulation parts two and three of the objective function do not appear.

In the model runs defined above, the objective function is substituted by a discrete time formulation. The resulting stochastic optimization problem is solved on the basis of simultaneous approximation of the random function by \( N \) sample functions with sufficiently large \( N \) (see Messner et al., 1996).

Carbon tax

Carbon taxes are introduced in the following way. We assume that the establishment of the tax is uncertain with a given occurrence probability of 0.33. The introduction time (in case the tax would be established) is also unknown with an expected cumulative distribution function that goes from 0 in 1990 to 50% in 2050 reaching 99% by 2100. In the model runs a Weibull distribution around a mean tax value of 50 \$/tC and probability of 99 percent of the tax being lower than 125 \$/tC was assumed. The carbon tax is added to the objective function

\[
p^{\text{tax}} = \int_{1990}^{2200} \rho E_{\max} \left\{ 0, \left[ Ec^C (\omega) - c^C (\omega) \right]^2 \frac{\mu_i}{\eta_i} X_i (\tau) \right\} d\tau - \\
E_{\min} \left\{ 0, \left[ Ec^C (\omega) - c^C (\omega) \right] \frac{\mu_i}{\eta_i} X_i (\tau) \right\}
\]

where \( p^{\text{tax}} \) is the probability that the tax will be established at all. \( \rho' \) is the probability that, if established, the tax will be introduced before time \( t \). \( c^C \) is the uncertain carbon tax value.