Modeling Technological Change: Implications for the Global Environment

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Implications for the Global Environment

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■ **Abstract**   Technology largely determines economic development and its impact on the environment; yet technological change is one of the least developed parts of existing global change models. This paper reviews two approaches developed at the International Institute for Applied Systems Analysis, both of which use the concept of technological learning and aid modeling of technological change. The first approach is a micromodel ("bottom-up") of three electricity generation technologies that rigorously endogenizes technological change by incorporating both uncertainty (stochasticity) and learning into the model's decision rules. This model, with its endogenous technological change, allows radical innovations to penetrate the energy market and generates S-shaped patterns of technological diffusion that are observed in the real world. The second approach is a macro ("top-down") model that consists of coupled economic- and technological-system models. Although more stylistic in its representation of endogenous technological change, the macro model can be applied on a worldwide scale and can generate long-term scenarios that are critical for policy analysis. Both the micro- and macro models generate radical departures from currently dominant technological systems ("surprises"), including long-term scenarios with low carbon and sulfur emissions. Our focus is modeling, but for policy, the work underscores the need for huge investments before environmentally superior technologies can compete in the market.

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Introduction

Changes in products, devices, processes and practices—technology (1)—largely determine the development and consequences of industrial society. Historical evidence (1–4) and economic theory (5–8) confirm that advancing technological knowledge is the most important single factor that contributes to long-term productivity and economic growth (9–11). Technology is also central to long-term and chronic environment and development problems now on policy agendas worldwide under the heading of "global change." We focus on energy, the principal cause of atmospheric global changes that include greenhouse warming caused by energy-related emissions of carbon dioxide.

Although technology is central, technological change is typically among the least satisfactory parts of global-change modeling. Each of the factors that determine the wide range in projected emissions of carbon dioxide—the future level of economic activity, energy required for each unit of economic output, and the carbon emitted for each unit of energy consumed (12)—is a function of technology. Indeed, varied technology assumptions largely account for the wide range of published emission estimates for the year 2100, which span 2 gigatons (1 gigaton equals 10^{15} g of elemental carbon) to well above 40 gigatons of carbon (12, 13). Low-emission scenarios envision, for example, massive use of biomass (which, if sustainable, has zero net emissions), wind, solar, or nuclear power (e.g. see the "C" scenarios in 14). High-emission scenarios envision massive use of coal and, in some cases, coal-based synthetic liquid fuels.

Most studies of global change rely on macroeconomic models with simplified representation of the energy system. Although attractive for large-scale and long-term analysis because they are compact, these highly aggregated models are unable to represent how particular technologies are developed and selected. Rather, they typically include aggregate trend parameters that are set exogenously to account for improvements in energy efficiency and other technological changes. Thus, by design, they estimate the future as a marginal and gradual extension of the past. Yet radical shifts in technological regimes and surprises are numerous in the historical record, such as the introduction of steam power in the eighteenth century, the emergence of electricity in the nineteenth century, and the entry of nuclear power in the twentieth century. Typically, the main endogenous mechanism of technological change in macroeconomic energy models has been depletion of resources, which triggers use of new resource-frugal "backstop" technologies (15). Yet exhaustion of energy resources, such as running out of oil, is not evident (16, 17), especially when considering the large potential availability of unconventional oil and gas resources such as oil shale, tar sands, or methane hydrates (18). (For a somewhat contrasting view on the availability of conventional oil resources, see 19.)

Even models in the tradition of systems engineering—in which detailed information on technological costs and performance is used to calculate least cost technological systems—have largely failed to incorporate endogenous technological change. Some ignore changes in costs and performance and thus implicitly

assume that technologies are static, with Malthusian results (20, 21). Most impose those changes exogenously but have no mechanism—other than the intuition of the modeler—to ensure that the assumptions imposed are plausible and internally consistent. Very few systems models have included rudimentary mechanisms of technological change that are endogenous to the model's decision rules, such as uncertainty or technological learning (22–25). Moreover, such models have been criticized because they compute technological systems with reference only to the costs of technologies themselves and do not account for the macroeconomic context, such as prices and the opportunity costs of capital, that also affects patterns and levels of technological investment. A more elaborate discussion is presented elsewhere (26). For further review of the literature on technology and global change, see also Azar & Dowlatabadi (27) in this volume.

We review two modeling innovations developed at the International Institute for Applied Systems Analysis (IIASA) that advance the modeling of technological change. One is a model of technological learning that endogenizes technological choices and simulates microscale technological changes. That approach incorporates learning and uncertainty—which critically affect decisions to develop and deploy technologies in the real world—into model decision rules rather than through exogenous trend parameters. Technological learning can drive down technology costs, and models of cost minimization will take up new technologies once their costs have fallen. The important improvement is that the model knows that learning requires anticipatory investments, hence improved technology does not come for free. The model also recognizes the inherent uncertainties in technological learning by treating learning rates as stochastic. One consequence is a model structure that autonomously generates radical technological changes. The other approach presented here is a stylized application of learning concepts to analysis of global energy systems. It is made possible by coupling a systems engineering model (parameters were established with the help a database of 1600 energy technologies) with a macroeconomic model. The result is a modeling framework that accounts for changing technology systems as well as the macroeconomic context.

Both techniques put choices of individual technologies into the model decision rules, and thus both generate technological change from within. Their essential feature is that they treat technology as dynamic and as endogenous. Technologies are allowed to improve over time, but improvements are strictly contingent on earlier investments, without which technological change does not occur. In both models, technology choice is based on criteria of technical performance (e.g. efficiency and ability to meet a given energy demand) and technology costs. Both models minimize energy systems costs, subject to either stochastic uncertainty or additional exogenous constraints that represent capital shortages and infrastructure bottlenecks that prevent "unlimited" growth of new technologies. Both models represent detailed capital vintage structures and hence are able to represent the additional costs of a premature retirement of capital vintages in case of hasty forced introduction of new technologies. The models also depend on some additional exogenous choices (notably future energy demand) and thus do not completely

solve the vexing problem of how to model fully endogenous technological change, but they indicate promising paths forward.

We argue that progress in technological modeling requires a multitude of highly sophisticated models and methodologies. Although our goal is improved endogenous modeling of technological change, the results have implications for policy. If radically new technologies are to be deployed in competitive markets, massive hedged premarket investment is needed. Most public policy focuses on investing in R&D, but the needed investments to improve technologies through experience (learning) gained in niche markets is equally vital and typically much costlier. The accumulation of experience is necessary to improve technologies and make them commercially viable. Yet care is needed to preserve diversity and avoid excess premature investment in technologies that might fail. To solve the problems of global change requires investments in many radical new technologies because, only an unknown few will ultimately be chosen by commercial markets.
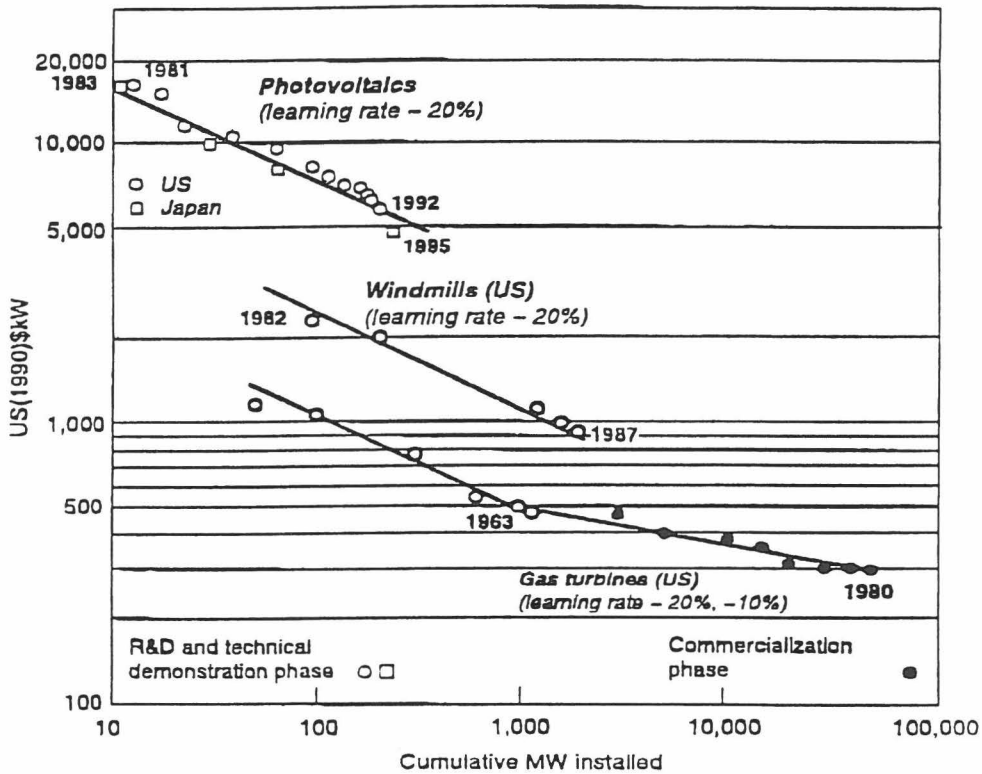
Technological Learning

The innovations in modeling technological change that are presented here depend, in part, on adding to models the process of "technological learning," which is the improvement in cost and performance caused by experience gained by individuals and organizations working with technologies. Typically, new technologies are uncompetitive when introduced (28). Investments into R&D can improve the flexibility, performance, and competitiveness of a new technology to a point where it can be tested in demonstration projects. What we term the "innovation stage" is the span from the idea for a new technology to the point of demonstration. R&D, along with demonstration projects, can yield sufficient improvements in immature technologies that they become competitive in small niche markets in which the new technology has a unique, specialized advantage over existing technologies. Examples include the speed and range of jet airplanes over piston-powered aircraft, and the affordability of solar photovoltaic (PV) power in mountain huts and on lighted road signs where wire connections to the conventional electric grid are too costly. In this "niche market stage" technologies are not (yet) commercially viable for widespread use in the energy system, but they are sold on a commercial basis for specialized applications that allow accumulation of experience that can lower costs further and make the immature technology commercially viable in a wider market. Because of the ambiguity of being both commercial and noncommercial, we treat this stage with a single term—niche markets. A stage of "pervasive diffusion" follows for those technologies that become sufficiently competitive that they are selected in widespread commercial applications. This simple three-phase typology—innovation, niche markets, and diffusion—forms a conceptual framework based on the mechanism at work. In practice, the phases overlap and interact.

A rigorous model of technological change must be able to account for the factors that govern the improvement and selection of technologies that are still in their early stages of development—before demonstration projects and commer-

cial installations—as well as after new technologies become commercially viable. Over the extended periods considered in this paper—five decades and beyond— some of these immature technologies will improve sufficiently so that they will survive in the marketplace. Including these technologies in models is vital because they are most different from the existing dominant technologies, and their widespread use will have a radical impact on global changes. To model these innovative technologies the learning curve concept must be extended upstream to include R&D investments that lead to improved cost and performance during the early, innovation stage. Typically, learning curves have included only improvements that are the result of working with installed technologies. Improvements during both the innovation and niche market stages which are intensive in R&D are usually excluded. In the model presented here both sources of technology improvements R&D as well as learning-by-doing through installing technologies are included. In our view, the result is a technological learning concept that is tractable and conceptually coherent—it offers a means of improving energy models so that they can more accurately reflect both incremental and radical technological change. However, it is not the only possible method for modeling technological change. Other analysts—notably Goulder and colleagues (29–31)—have sought to model the knowledge production process that occurs during R&D as a basis for modeling technological change. At this early period in efforts to model technological change, a multitude of methods is needed.

The "technological learning" phenomenon was first described and quantified for the aircraft industry by Wright (32), who reported that unit labor costs in airframe manufacturing declined significantly with accumulated experience measured by cumulative production (output). Technological learning has since been analyzed empirically for numerous manufacturing and service activities (e.g. shipbuilding, petrochemicals, steam and gas turbines, farming of broiler chickens), and studies have also applied learning concepts to analysis of a wide range of other human activities (e.g. the success rates of new surgical procedures, productivity in kibbutz farming, and reliability of nuclear plant operation) (33). In economics, "learning by doing" and "learning by using" have been highlighted since the early 1960s (34, 35).

Learning phenomena are generally described in the form of learning or experience curves. Unit costs of production typically decline at a decreasing rate as experience is gained, and thus learning curves generally take the form of a power function in which unit costs decrease exponentially as a function of cumulative output. Other proxy measures for experience include installed hardware and cumulative investments. The resulting curve is often plotted on logarithmically scaled axes so that it becomes a straight line. The learning rate—the slope of the line—is the percentage decline in costs per doubling of accumulated experience. This formulation should not be mistaken as indefinitive "linear" progress. Each doubling of output (investments) takes more time (resources), and thus learning curves exhibit decreasing marginal returns and long-term saturation of cost improvements for mature technologies. Learning rates in manufacturing, including

Figure 1 Learning curves for several electricity generation technologies. Shown are gas turbines, which are an "incremental" technology on the cusp of pervasive diffusion and two higher-cost technologies: PVs and advanced windmills. These two most costly technologies are "radical" in that they are competitive only in special niche markets and thus their market share is low, but both hold promise for lower costs with additional investments. Learning rates for all three technologies in their precommercial stage are comparable (~20% per doubling of capacity). (Sources: 36, 84.)

production of energy-related technologies, mainly vary from 10% to 30%. For some technologies, typically in the earliest period of development, learning rates approaching 50% have been observed (36).

Figure 1 shows typical learning curves for three electricity-generating technologies: gas turbines, solar PVs, and wind turbines. Learning curves for technologies that have survived to widespread diffusion, such as gas turbines, typically consist of two segments. The first corresponds with the early stage—from the innovation (adapted from jet aircraft engines) in the 1950s to the middle 1960s when the first demonstration projects had been built and gas turbines entered niche markets. Cost reductions were rapid (~20% per doubling of the small installed capacity of demonstration projects); gas turbines were a truly radical technology—extremely expensive, but promising if substantial risky investments were made. The second segment, from the middle 1960s until 1980, is marked by smaller cost reductions for

each doubling of experience, which is characteristic of expanding niche markets. Learning rates were ~10%. During that period the technology was costlier than its alternatives but became increasingly competitive through continued improvements that were sustained by substantial investments. Overall, the cost per unit of capacity declined by a factor of four as cumulative experience rose three orders of magnitude. Since 1980 gas turbines have been an incremental technology—increasingly applied in commercial markets as one component of the electricity generation system. Today, gas turbines in combined cycle power plants are the preferred technology for most electricity generation applications with natural gas and are in the midst of pervasive diffusion.

The mechanisms for learning by doing are numerous. They include experience gained by individuals in performing repetitive tasks, improvement in the functioning of organizations (e.g. plant management, logistics, and marketing), refinement of design, and economies of scale (37). However, improvements in upstream technologies and other factors are, like learning, also correlated with growing experience and also yield improved costs and performance. The analyst must thus be careful to use the learning concept only when the causal mechanisms of learning are at work. For example, it appears that learning by doing requires continuous experience, not merely the accumulation of output regardless of its time path. Unit costs of the Lockheed L1011 "Tristar" aircraft rose in the late 1970s, when production resumed after a drastic reduction that included large-scale layoffs at production facilities. Experience gained during the early 1970s was lost with the staff turnover; as a result, the planes built in the early 1980s were in real terms more expensive than those built in the early 1970s. Moreover, learning rates are uncertain and vary enormously—from 50% improvement per doubling of output to 10% deterioration (i.e. negative learning, discussed in 33). Learning curves neatly capture the complicated phenomena in simple functions that allow improved modeling, but they do not eliminate the need ultimately to model each causal mechanism of technological change individually nor do they eliminate the need to address the uncertainty that agents face when making investment decisions.

Despite overwhelming empirical evidence and solid theoretical underpinnings, learning phenomena as discussed above have been explicitly introduced into only a few models of intertemporal choice. A first detailed model formulation was suggested by Nordhaus & van der Heyden to assess the potential benefits of enhanced R&D efforts in new energy technology (the fast breeder reactor) (22). Computational limitations at that time precluded the application of the model to a wider portfolio of technologies in the model formulation. A first full-scale operational optimization model incorporating systematic technological learning of energy technologies was first developed at the IIASA (24, 38). But that formulation, which incorporated learning rates for up to a dozen advanced electricity-generating technologies into a linear programming model of the global energy system, was limited. Learning rates were assumed ex ante, and future technology costs in the model depended solely on the amount of intervening investments in installed capacity. The model excluded uncertainty as well as R&D efforts as sources of technological change. The result was that the optimization (with perfect

foresight) identified the most promising technologies and invested in them heavily and early. In the real world, however, learning rates and other parameters are not known perfectly and thus competitive firms invest in portfolios and exercise caution.

A Microlevel Model of Technological Learning

Here we illustrate a model (39) and some key results that reflect our interpretation of the two fundamental sources of technological change: (*a*) investments made by competitive firms into immature technologies in anticipation of improved performance and lower costs, and (*b*) diversification and hedging of those investments because of pervasive uncertainties. The purpose of this new model is to extend the traditional approach to modeling energy technologies, in which technical change is induced only by relative resource and factor endowments and price changes (40–43).

The model is based on technological learning. However, it is inappropriate to build a model of technological change on conventional learning curves, such as in Figure 1. Such curves include only investments that yield installed capacity (including noncommerical demonstration projects). They omit R&D, which also plays a vital role in technological improvement. The cost of PVs produced in Japan, for example, was halved between 1973 and 1976, but this improvement is not evident in Figure 1 because it was before any installation of demonstration units and, thus, the cumulative installed capacity was zero. Two revisions are needed: (*a*) to account for investments in R&D as well as installed capacity and (*b*) to account for uncertainty in the payoff (learning) from such investments.

Expanding learning curves to include R&D requires data that typically have commercial value and thus usually are scarce in the public record. One of the few reliable sources of technology-specific R&D expenditures is Watanabe's analysis of the Japanese Ministry of International Trade and Industry's "sunshine" technology program to promote new energy technologies such as solar PVs (44, updated with personal communication). His data set is unique because it includes private R&D expenditures as well as more readily available data on public R&D. It also includes investments in demonstration projects and niche markets. His data make possible a more comprehensive form of the "learning curve," shown in Figure 2. The independent variable is cumulative expenditure, which includes R&D as well as niche market investments (39). Over the period 1973–1995, a total of 206 billion yen (~US$2.5 billion in 1995 prices and exchange rates) was spent on PVs in Japan. Of that amount, 78% (162 billion yen) was investment in PV electricity-generating capacity, and 22% (44 billion yen) was in R&D proper. The figure confirms that, once a technology reaches the niche market stage, investments in hardware (i.e. installed capacity) dominate, but that R&D remains a significant part of total investments. Moreover, R&D and niche market investments cannot be treated as separate, independent sources of technological improvements. Only when R&D and niche market investments are combined is the result a comprehensive learning curve that spans from innovation through niche markets. [We are
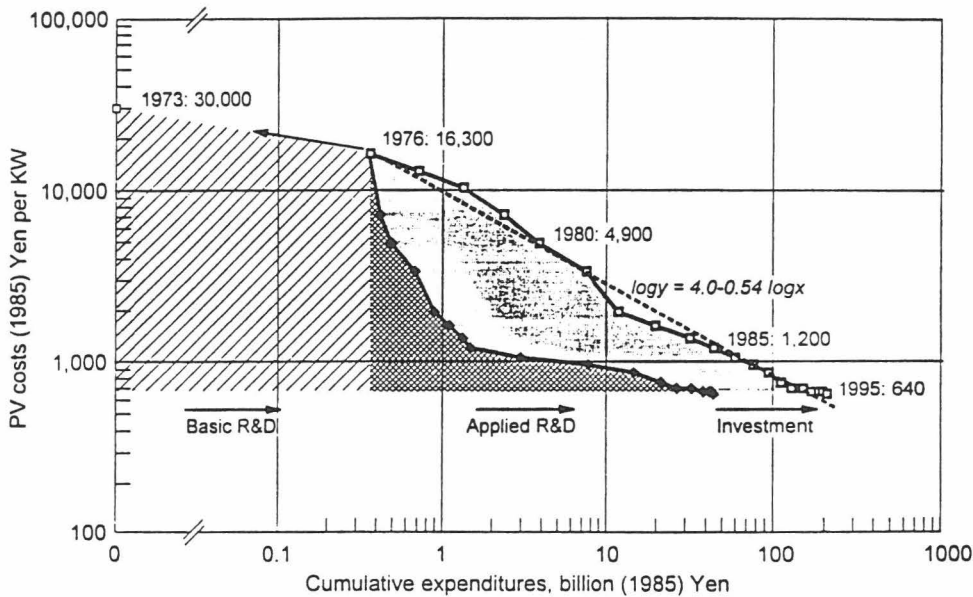
Figure 2 Modified learning curve for PV technologies. The curve shows decline in costs as a function of cumulative investments, including not only cumulative installations from demonstration projects and commercial niche markets but also R&D investments. Conventional learning curves include only commercial installations and ignore other investments. At the early stages, when physical installations are few, R&D is relatively important. The declining costs of PVs correlate well with aggregate R&D investments and are comparable with a classic learning curve pattern with 54% reduction in costs for each doubling of cumulative investment. This formulation allows a single, simple learning curve to be used to model cost reductions from the innovation stage, as well as later commercial stages. (Note that these curves are not directly comparable with Figure 1 because the independent variables and the currency units differ.) Sources: 44 and Watanabe, personal communication.

mindful of the importance of interindustry and cross-national R&D spillover effects (45), including those from purchases of equipment (46), which are excluded from Watanabe's data and our first effort to extend the learning curve concept. Such effects are notoriously difficult to quantify. For more on connections and competition between R&D efforts see 29.]

This extension of the learning-curve concept has two important features. One is that it can be used directly in models that compute relationships between resource allocation and changing costs of technologies. Such relationships are crucial for technological modeling because it is the anticipation of cost improvements that entices competitive agents to invest in immature technologies. Those costs partially determine which technologies markets select for application. This new curve is also conceptually coherent. It includes both of the major sources of technological improvement—investments in R&D and experience gained through technology deployment (installations) in niche markets.

In addition to this new comprehensive learning curve, uncertainty is also built into the model decision rules. The exact links in the chain of relationships—from investments to learning to cost reductions to market application to environmental consequences—are rarely known ex ante. The importance of technological uncertainty has been recognized and explored ever since the earliest days of global environmental modeling (15, 47). Different approaches have been followed for analyzing the impacts of technological uncertainty, including the formulation of alternative scenarios (48, 49), analysis of model sensitivity to input parameters (15, 50, 51), and sensitivity analysis based on elicitation of expert opinion (52). Such approaches allow assessment of the sensitivity of model outcomes to variations in uncertain model input parameters or some exploration of optimal management strategies, such as strategies that emphasize adjustment of policy decisions over time as uncertainties are resolved (53–55). But uncertainty (stochasticity) is not built into the decision framework, and thus the deterministic models are unable to identify investment strategies that are robust or optimal when decision-makers simultaneously and continuously face many uncertain choices. Several stochastic approaches exist, but only a few modeling groups have applied stochastic optimization techniques (e.g. 25, 56).

The combined approach—incorporation of learning and uncertainty—has required the application of models that are mathematically cumbersome involving, simultaneously, stochasticity and recursive formulations. Moreover, the mathematical solutions are nonconvex, which is especially difficult to handle in traditional optimization models and algorithms. Technological learning is a classic example of increasing returns—the more learning takes place, the better a technology's performance, which attracts further investment and learning. However, the rate of learning is uncertain. The IIASA approach is based on a general methodology for handling uncertainty in optimization problems through a stochastic sampling technique described by Ermoliev & Wets (57) and the improved algorithm developed by Ermoliev (personal communication). Our colleagues at IIASA have already applied that stochastic optimization framework in the MESSAGE technological optimization model (58). They have also developed a simple version of the MESSAGE model with learning curves (24). The model presented here merges the two approaches—stochasticity and learning. Similar mathematical and conceptual problems also have been addressed in work on path dependence, in which initial decisions lead to multiplying network effects and increasing returns from the adoption of a particular technological solution (59).

The conceptually simple model represents a rising demand for one homogenous good, electricity, which can be supplied by three hypothetical technology types—"mature," "incremental," and "radical"—that correspond to three prominent electricity technologies available today. The mature technology is in widespread diffusion; its characteristics (costs and resource conversion efficiency) do not change over time. Conventional coal-fired power stations with thermal efficiency of 30% and mean capital costs of US$1000/kW electric power capacity [Kw(e)] are a typical mature technology. The incremental technology has a slight efficiency

advantage over the mature technology, is initially more costly (by a factor of 2), and has a potential mean learning rate assumed at 10% for each doubling of cumulative production capacity. A current example includes advanced coal-fired power stations with fluidized bed boilers and all basic environmental equipment (e.g. precipitators and sulfur and NO_x removal units), with thermal efficiency of 40% and mean initial capital costs of US\$2000/kW(e). The model includes one resource; it corresponds with coal, for which known reserves and resources exceed 200 years and exhibit rising extraction costs as the most accessible and highest-quality reserves are depleted. The radical technology requires few resources and thus offers a substantial efficiency premium, but it is a factor of 40 more costly than the mature technology. However, as is common with radical new technologies, it has high potential for technological learning—a mean learning rate of 30% (per doubling of capacity) is assumed, which is consistent with historical experience. Contemporary examples of radical electric technologies include PV cells, which use an inexhaustible resource (sunlight) but are initially very costly—a starting value of US\$40,000/kW(e) that was characteristic of PV costs in the early 1970s is used in the model simulations.

The model treats the learning rates for the incremental and radical technologies as uncertain, represented by a lognormal distribution function around the mean value. For the radical technology, the variance of the distribution function is three times that of the incremental technology, which reflects the much higher spread of uncertainty associated with truly revolutionary technologies. Each uncertain value is sampled simultaneously; deviations from the expected (mean) value (of the distribution function of unknown learning rates) are added as extra cost or benefit term to an overall objective function; the least-cost solution from numerous draws is the optimal "hedging strategy" for technological investments in our single agent model. (For detail on assumptions and methods, including sensitivity analysis, see 39.)

Figure 3 shows the results—the share of electricity supplied by each technology —for four simulations. If technology is treated as static (no learning), then the more efficient incremental technology replaces the mature technology as resource depletion leads to rising energy prices. The results are typical of optimization models that deploy the concept of a "backstop" technology. A second run, termed "exogenous learning," assumes that the cost of the incremental technology falls at an exogenously determined rate. The result is typical for simple optimization models—a new technology diffuses rapidly and widely at the moment it becomes cheaper than alternatives. Indeed, large-scale technology optimization models, which are widely used to assess the costs of abating various environmental problems, display similar "flip-flop" behavior. Published runs typically do not illustrate such behavior only because additional constraints, such as restrictions on the rate and pattern of technological diffusion, tuned according to the modeler's sense of plausibility, are widely used to make the outputs appear more realistic. Like sausage, the final product is evidently tasty, but the method of producing it is best left shrouded in mystery.
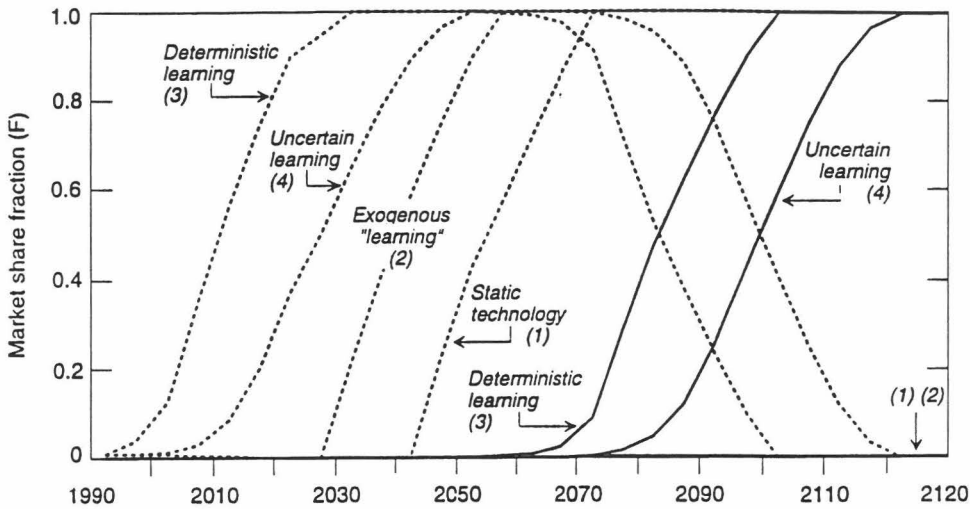
Figure 3 A simple optimization model with endogenous technological change. This fig-
ure shows the fractions of total installed generating capacity supplied by new (incremental
and radical) electricity-generating technologies. These differ in their current costs as well
as possibilities of future cost reductions (learning). Four simulation runs are shown: *(1)*
static-technology costs and performance for all technologies; *(2)* exogenously given cost
improvements for incremental technologies; *(3)* certain (deterministic) learning rates for
incremental and radical technologies; and *(4)* uncertain learning rates for incremental and
radical technologies. Without endogenous learning, the radical technology never earns mar-
ket shares. When the rate of learning is certain (i.e. known with perfect foresight), the
optimal solution is to invest heavily and early in new technologies because the resulting cost
declines through learning render the technology quickly competitive. When learning rates
are uncertain, the optimal solution is more cautious. The (symmetrically declining) market
shares for the existing, mature technology are not shown on this figure to improve clarity.
(Source: 39.)

A third run in Figure 3 shows the effect of adding learning with zero uncer-
tainty—termed "deterministic learning." A fourth run illustrates "uncertain learn-
ing"—it fully incorporates uncertainty (stochasticity) and learning, and thus it
is the full model of endogenous technological change. In both of these runs the
addition of learning leads the radical technology to enter the market. In the de-
terministic case a new technology enters the market earlier and diffuses more
rapidly. But when learning is uncertain, diffusion is more gradual, and market
entry is later; the model hedges its investments because the benefits are uncertain.
Analysis of the historical record shows that technological diffusion, measured by
the share of a market served by a technology, follows an S-shaped pattern charac-
teristic of logistic competition (26). Initially, market share grows slowly; as the
share rises, the rate of diffusion accelerates; diffusion slows again as the point of
saturation is reached (60–64). Only the uncertain-learning run demonstrates this
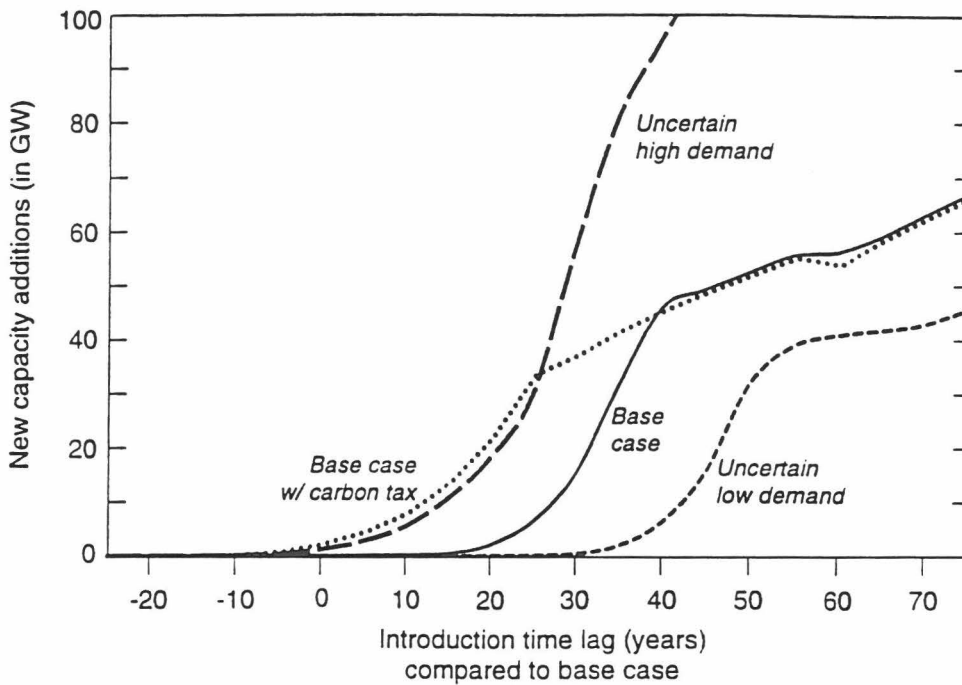
Figure 4 Endogenous technological change with uncertain carbon constraints and uncertain demand. This figure shows new capacity additions for three simulation runs: (*a*) base case with cost improvements caused by uncertain rates of learning (same as run *4* in Figure 3); (*b*) addition of an uncertain carbon constraint (see text); and (*c*) addition of the possibility that demand for electricity will be substantially higher or lower than expected in the base case simulation. Source: reference 39.

S-shaped diffusion pattern. That run is also consistent with the observation that radical technological changes in the energy system (and other large-scale systems in which "inertia" is omnipresent) require many decades (26, 65).

Figure 4 shows the results when an uncertain possibility of a constraint on emissions—represented by a carbon tax—is added to the model. For illustration, the simulation assumes that there is a 1-in-3 chance that some tax would be implemented sometime in the future; if the tax is implemented, the probability of introduction by 2050 is assumed to be 50%, rising to 99% by the year 2100. The level of the tax is also uncertain, represented by an asymmetric (Weibull) distribution around the mean expected value of the tax (US\$50/ton of carbon) to represent the low probability of an extremely high tax. The probability that the tax will exceed US\$125/ton of carbon is <1%. The existence of this uncertain environmental constraint shifts investments into new, less-polluting technologies earlier in time. For comparison, Figure 4 also shows the results if future demand is treated as uncertain—higher or lower—than in the base case runs in Figure 3. These three types of uncertainty shown in Figures 3 and 4—learning,

emissions constraints, and demand—are the most important unknowns for the energy sector. In all three, earlier and larger investments in new technologies are the result when the potential need for technologies with new attributes looms large.

## Technological Choices in the World Energy System

We have shown that it is possible to model the selection among a handful of competing technologies in an isolated market. But at larger scales—the energy system of a whole economy, region, or the planet—models that fully and realistically incorporate endogenous technological change are still impossible. Relationships between the wide array of factors that determine technological choices are poorly understood, and the need to model decision making by thousands of agents and for hundreds of possible technology combinations exceeds available modeling and computational capacity.

We illustrate that a stylized application of the technological learning concept can improve the status quo by focusing on the main application of macro-level modeling: the generation of scenarios and use of varied scenarios to illustrate policy choices. One measure of technological change in such scenarios is the level and rate of decarbonization. The historical record shows a striking and consistent trend of decarbonization, driven by regular radical changes in energy systems. With a rhythmic 70-year period, the major fuel sources have been progressively replaced; by coincidence, each has been progressively lighter in carbon per unit of energy released when burned. Coal, the dominant fuel from 1880 to 1950, contains approximately one hydrogen atom per carbon atom. Today's dominant fuel, oil, contains two hydrogen atoms for every carbon. The hydrogen-to-carbon ratio in natural gas (methane), the major primary fuel whose share is rising most rapidly today, is 4 to 1. More recently also, energy sources that have no direct carbon emissions, such as hydropower and nuclear fission, lighten our carbon diet. Hydrogen-rich fuels release more energy for every carbon atom that is oxidized to CO_2 during combustion.

As shown in Figure 5, the carbon–to–primary-energy ratio for the world has declined at 0.3%/year since 1850. For illustration, Figure 5 also includes the longer and probably more accurate historical record for the United States, with an average 0.25% decarbonization per year since 1800. In some countries decarbonization has been relatively rapid—in France, for example, nuclear power has replaced fossil fuels as the supplier of nearly all electricity. On average, French decarbonization of primary energy was 2.2%/year during the 1970s and 1980s.

Measured as the carbon intensity of the economy, rather than the energy system, the rate of decarbonization has been even more rapid because of structural changes toward less-energy-intensive economic activities, such as the shift from manufacturing to services. In the United States, the specific carbon dioxide emissions per unit value added have declined by almost an order of magnitude during the last 2 centuries, from ~2.5 kg of elemental carbon per US$1 of gross domestic
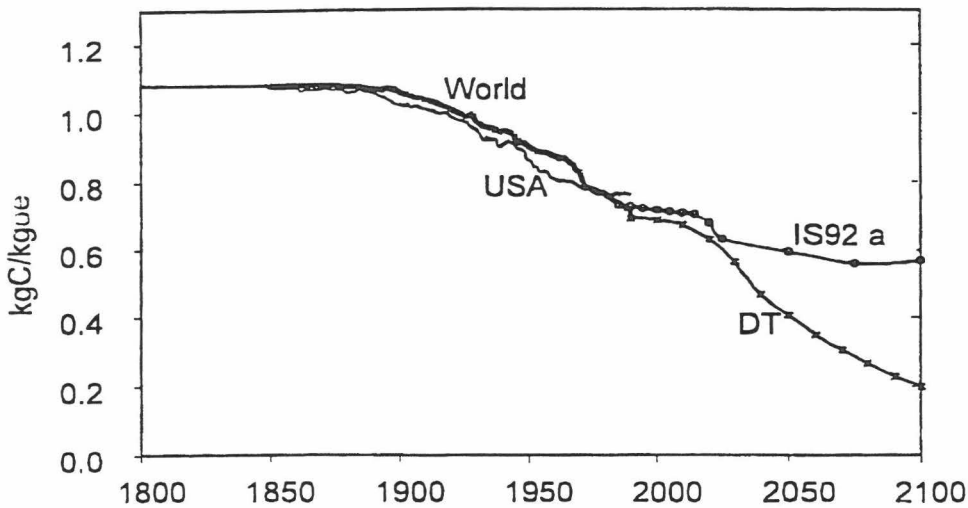
Figure 5   Decarbonization of the energy supply. The ratio of carbon per unit of energy has
steadily declined in the United States and the world. Source: reference 66. Also shown are
the carbon intensity of the Intergovernmental Panel on Climate Change IS92a baseline and
the IIASA Dynamic Technology (DT) projections.

product (at 1990 prices) in 1800 to ~0.3 kg of elemental carbon per US$1 of gross
domestic product in 1990. In other terms, the economic "productivity" of carbon
increased by more than 1% per year during the last 2 centuries. Decarbonization
has not autonomously eliminated carbon from the economy, but it has steadily
softened the economy's impact on the atmosphere. For example, if the fuel mix
of the 1920s powered the American economy today, then annual carbon emis-
sions would be more than 300 million metric tons (24%) higher. For comparison,
those averted American emissions total more than today's annual industrial carbon
emissions from Argentina, Brazil, Canada, and Mexico combined (67).

Do the scenarios generated by global models correspond with historically ob-
served decarbonization? Most scenario analysis begins with a baseline scenario—
often termed "business as usual"—which is the output from a model that includes
no drastic changes in technologies or policies in response to the particular con-
cern that is the subject of the analysis (e.g. greenhouse warming). Those baseline
scenarios are used as the cornerstone for subsequent policy analysis. The baseline
scenario of the Intergovernmental Panel on Climate Change, the most widely ref-
erenced such baseline scenario, known as IS92a, illustrates the generic approach
(see Table 1). Because highly aggregated macroeconomic models generate these
scenarios, radical technological change is absent, and the future is assumed to be
merely the result of compounded marginal changes to today's energy system. Just
as coal was the principal fossil energy source ~50 years ago, in 2100 the world
of IS92a is also principally (47%) powered by coal. Thus, based on the IS92a
scenario, the energy delivered is just as carbon intensive as today. In 1990, every

TABLE 1   Global energy scenarios and technological change[a]

Scenario attributes at year	1990 levels (observed)	Conventional baseline scenarios		MACRO-MESSAGE scenarios (this paper)	
		IPCC IS92a	WEC/IIASA series A2	Baseline	DT
World income (10^{12} 1990 USD, market exchange rates)	20.9				
2050 (% growth)[b]		92 (2.6%)	100 (2.7%)	117 (2.9%)	118 (2.9%)
2100 (% growth)[b]		240 (2.3%)	310 (2.5%)	384 (2.7%)	393 (2.7%)
Final energy intensity (10^6 J/1990 USD)[c]	13.1				
2050		6.8	7.2	5.8	5.7
2100		3.6	3.5	2.5	2.8
Primary energy (10^{18} J)	381				
2050		930	1040	1100	990
2100		1500	1900	1700	1800
Primary energy, share of **coal** and *zero carbon*[d]	**24%**/*22%*				
2050		**37%**/*21%*	**37%**/*27%*	**31%**/*32%*	**4%**/*50%*
2100		**47%**/*30%*	**38%**/*51%*	**42%**/*46%*	**0.4%**/*77%*
Carbon emissions (10^{15} g of C)[e]	6.2				
2050		13	15	16	9.5
2100		20	22	25	8.5

Sulfur emissions (10^{12} g of S)[e]	60				
2050		101	85	170	17
2100		123	160	240	11
Sulfur/carbon ratio (g of S per kg of C)	10				
2050		10	5.7	11	1.8
2100		6.2	7.4	9.6	1.3
Radiative forcing (Wm^{-2})[f]	2.6–1.3 = 1.3[g]				
2050		5.7–2 = 3.7	6–1.5 = 4.5	6.5–2.4 = 4.1	5.6–0.9 = 4.7
2100		8.2–2 = 6.2	9–2.3 = 6.7	10.3–2.9 = 7.4	6.9–0.8 = 6.1

[a]The Intergovernmental Panel on Climate Change (IPCC) IS92a baseline scenario (48) envisions only marginal changes in present technologies. Thus, the future energy system appears similar to that of the present and is heavily based on coal. Using the principles of technological learning applied in the micro-scale model (Figures 3 and 4), the International Institute for Applied Systems Analysis (IIASA) group linked macroeconomic and technological-systems models to allow better incorporation of technological change. Conventional treatment of technology—as a marginal extension of the past—yields a scenario similar to that of IS92: the IIASA-WEC Series A2 scenario. The addition of technological learning yields a dynamic technology (DT) scenario (73), with lower carbon and sulfur emissions even without assumptions about environmental policy constraints. Unlike the conventional baseline scenarios, decarbonization (Figure 5) continues into the future (26).

[b]Average global annual growth rate since 1990.

[c]Intensity of final energy is a measure of the economy's efficiency; it reflects direct improvements in the efficiency with which energy is used to make a given economic output (product or service) as well as structural change (e.g. shifts from energy-intensive manufacturing to service-oriented economy). IPCC values are for "secondary energy," which is comparable in definition of "final energy" in the WEC and IIASA studies (i.e. heat content of energy after conversion and distribution).

[d]These two parameters are indicators of change in technology and the fuel mix. For IPCC, "coal" primary energy is not reported; the values here are for "solid" energy. "Zero carbon" is assumed to be nuclear and renewable energy; in none of the scenarios is carbon "scrubbed" from flue gases.

[e]Carbon and sulfur from industrial processes only, mainly the burning of fossil fuels and biomass for energy and as feedstocks. IPCC reports slightly higher (70×10^{12} g of S) anthropogenic emissions of sulfur.

[f]Increase in radiative forcing since the preindustrial era ($\sim$1765). Cells show net increase in radiative forcing from carbon and other greenhouse gases (including indirect effects such as stratospheric water vapor and ozone) minus the negative forcing from sulfur (direct and indirect effects). Values computed with MAGICC model and added to 1990 forcing levels to yield total increase in forcing.

[g]Values for 1990 used in calculations here; however, note that sulfur forcing is uncertain. IPCC (195, figure 6.19) reports less intense negative sulfur forcing (-0.8 W m^{-2}).

10^6 joules (MJ) of primary energy released 17.4 g of carbon, which decreases slightly in the scenario to 14.1 g of C/MJ of primary energy by 2050. Thereafter, decarbonization in IS92a stagnates and reaches a value of 13.6 g of C/MJ by 2100. Sulfur associated with coal deposits is also burned, fouling the air and acidifying downwind ecosystems. The ratio of sulfur emissions to carbon is thus also high in the world of IS92a.

Improved representation of technological change can yield scenarios that are more consistent with history. Here we illustrate one approach. Collaborators at IIASA have linked a conventional macroeconomic model—an 11-region version of the widely used MACRO model (68)—with MESSAGE (69, 70), a detailed model of regional and global energy systems, with technology parameters based on the IIASA technology database, which contains >1600 technologies (71, 72). (For details of the models see 73; for more on such linkage techniques see 74.) The IIASA approach partially solves the classic top-down and bottom-up dichotomy of energy models. It allows an estimation of the macro-economic losses that result, e.g. when carbon constraints are applied to the economy (a strength of top-down, macroeconomic models), and it also allows calculation of the minimum cost suite of technologies needed to meet given constraints (a strength of bottom-up technological-system models).

The IIASA team first used this coupled model to generate a baseline scenario that mimics the IS92a baseline scenario and then made one revision: the addition of technological learning to yield a "dynamic technology (DT)" scenario (73). As in the micro model discussed above, which endogenized technological learning for a single agent selecting between three technologies, the team divided all technologies considered in the MESSAGE model into three categories—mature (existing), incremental, and radical. The investment cost for existing technologies does not vary; the cost of investing in incremental technologies declines 15% for every doubling of installed capacity; and the cost of radical technologies declines 30% for every doubling. For example, advanced coal power plants (an "incremental technology") decline in cost to US$1200/kW(e), whereas total installed capacity more than doubles. Solar PVs (a "radical" technology) decline in cost from US$5000/kW(e) in 1990 to ~US$500/kW(e) as installed PV capacity rises from practically zero today to ~100 GW by the end of the twenty-first century. [Computational limits required an iterative process that is consistent with the principle of learning but did not confront the mathematical and computational barriers to a model that simultaneously solves all parameters (26, 75, 76).]

The result of these simple adjustments to the representation of technology has little effect on the macroeconomic outputs of the linked model. Because energy costs (per unit of economic output) are lower and investment is higher, the world economy is slightly larger than in the baseline scenario, which already projected even more robust economic growth than in the bullish IS92a scenario. But unlike the baseline and IS92a scenario, the wealthy future of the DT scenario is also relatively clean. Despite declining costs for advanced coal power plants, MESSAGE shifts to even less costly advanced gas plants—that shift is already

evident in today's energy markets—and then to solar and other zero carbon fuels. Until 2060, the share of gas as a transition fuel for electric generation rises in this scenario. Coal and biomass, which supply a growing share of transport fuel (methanol and ethanol) and electricity in the baseline scenario, give way to solar-based energy sources, including hydrogen, and new nuclear power technologies such as inherently safe, modular, high-temperature reactor designs. By 2100, de-centralized (i.e. nongrid) energy generation technologies supply two-thirds of all electricity demand. This category consists of on-site solar PVs (30%), hydrogen cogeneration (25%), and hydrogen fuel cell vehicles that generate household electricity when parked (45%). The hydrogen energy carrier can be generated in many ways—the most efficient emit little carbon and sulfur (e.g. steam reforming of natural gas) or no carbon and sulfur effluents at all (e.g. when splitting water, with solar or nuclear primary energy).

The impact of the different technological selection in the DT scenario on environmental quality is dramatic. Sulfur emissions decline sixfold from 1990 levels by 2100, and world carbon emissions rise only slightly (20%). By 2100, only 4 g of carbon are released per MJ of primary energy supply, which is an average rate of decarbonization of 1.3%/year (threefold the historical value). With the widely used MAGICC climate model (77–80), we estimate the future concentration of carbon dioxide and greenhouse forcing for all the scenarios discussed here. In the baseline scenario, carbon concentrations rise to 800 parts per million by volume (ppmv) from 355 ppmv in 1990. Carbon concentrations also rise in the DT scenario, but more slowly—by 2100 the concentration is only 556 ppmv or approximately equal to the 550 ppmv long-term target for carbon concentrations proposed by European Union policy makers and widely discussed in the preparations for the Kyoto climate change conference in December 1997 (81). That target was widely dismissed as infeasible by mainstream observers, who view the world through an IS92a-like lens. But here we show that plausible representation of technology—unlike the world of IS92a—yields a future in which that target could be met.

It is interesting that greenhouse forcing (and thus global warming) in the DT scenario remains high—only 20% less intense than in the baseline scenario. High sulfur in the baseline scenario masks nearly half the greenhouse forcing from carbon dioxide (caused by the cooling effect from sulfate aerosols), an effect that disappears with drastically declining sulfur emissions and acid rain impacts. The ratio of sulfur (g) to carbon (hg) drops to ∼1—one-tenth that of the baseline scenario—as coal is nearly extinguished from the economy. Low-sulfur oil and natural gas are used as transition fuels to a future hydrogen economy, but those fuels also decline near the end of the scenario. In light of these effects of radical technological change, perhaps policy makers should set long-term targets for global warming based on the problem at hand (radiative forcing) rather than imperfect proxies (carbon concentrations).

Obviously these scenarios, which are summarized in Table 1, depend vitally on the assumptions that drive the models. Our intention here is only to illustrate

a simple but crucial point: plausible improvements to how technology costs and choices are modeled yields dramatically different models and long-term scenarios. Typically, models induce technological change only through resource constraints. Our approach is more consistent with the view that investments into improved technological knowledge are the main driver of long-term productivity growth and technological innovation. Rather than resource depletion, in our view technological changes emerge from demands for new energy services, which create incentives for investments in innovation and niche market application, which lead to learning, declining costs, and then widespread diffusion. These processes yield radical technological changes—shifts in clusters, such as from oil today to a hydrogen economy late next century—over long time scales, which are also characteristic of global change. Similar shifts in technology clusters, primary energy sources, and energy carriers are evident in the historical record (61, 82, 83).

Conclusions

Across a wide range of intellectual and political views one view is shared: In the long run, technology is the factor that most governs growth of the economy, the cost and availability of services such as mobility and food, and the impacts on the environment. Luddites view that as the problem, and enthusiasts embrace technology as the solution. Yet, treatment of technological change in models and scenarios to analyze global environmental changes has been unsatisfactory, and the analysis here suggests some promising avenues forward, with three findings in particular.

First, adding technological change to models can be aided by identifying systematic properties of technologies in the historical record, which include learning curves and characteristic learning rates. However, to make those curves more useful they should be modified to include not only "learning by doing"—which begins in niche markets and continues (for successful technologies) with pervasive diffusion—but also R&D, which is crucial during the earlier stages of technological development. The resulting convenient formulation requires data on public and private investments; additional case studies are urgently needed to gather such comprehensive data for more technologies.

Second, technological change is the consequence of investments that are made for two reasons—expectation that new technologies can be made more competitive, and to hedge against many uncertain risks. It is feasible to solve the nonconvex, stochastic optimization problems associated with a model of such uncertain learning processes. Such a model yields S-shaped patterns of technological dynamics that are consistent with the historical record and diffusion theory. Moreover, the model endogenously generates radical departures from existing technological practices—a zero carbon future without policy constraints on carbon, and even more rapid decarbonization when modest and uncertain carbon constraints are included. Neither outcome is the result of resource constraints, which is the main

mechanism for radical technological change in conventional models that do not incorporate endogenous mechanisms of technological change. We do not contend that the carbon problem will thus autonomously solve itself. But the illustration underscores that new technologies can penetrate the market even if they are initially a factor of 40 (or more) more expensive than the existing dominant technology. The model suggests that a strategy of investing in technological development is rational and optimal when risks must be diversified, especially when there is even a small probability of a significant emissions constraint in the future. If the model included the varied other benefits of diversification and the costs of environmental problems, such as urban smog or regional acidification, that are caused by the same processes that cause carbon emissions, the estimated benefits of diverse investment in new energy systems should grow further.

Third, we have also demonstrated that it is possible to include a stylized representation of technological change in macro-level models of the world's energy system. Most models project patterns of technological change that are gradual—the future, by assumption, is a marginal change from the present. The simple micro-level model developed at IIASA can endogenously generate plausible patterns of technological change that can then be used to inform a more detailed, coupled macroeconomic-systems engineering model of the world's energy system. The coupled model can yield radical technological dynamics, resulting in much lower emissions of carbon and sulfur. This approach still does not fully endogenize technological change at a high level of regional and sectoral detail, but conceptually that is now possible. Computational and mathematical bottlenecks should soon be solvable.

The results suggest that, when confronted with uncertainties—such as whether stringent action to slow global warming or other environmental externalities will be needed—that it is socially rational to diversify technologies. Insofar as societies today increasingly consider the likely need for long-term constraints on carbon, they should focus attention on incentives to diversify the portfolio of especially radical technologies that will be required if it proves necessary to cut carbon emissions sharply in the future. Near-term investments can yield those technologies, with commercially competitive cost and performance, on the time scales (>5 decades) that are relevant for global change. And it is plausible to project a century-long transition to a practically zero carbon emissions that appears to eliminate (today's) fears about energy-related externalities without any extra cost in the long-term. But it remains difficult to assess the probability of such developments.

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LITERATURE CITED

1. Freeman C. 1982. *The Economics of Industrial Innovation.* Cambridge, MA: MIT Press. 250 pp. 2nd ed.
2. Maddison A. 1991. *Dynamic Forces in Capitalist Development: A Long-Run Comparative View.* Oxford, UK: Oxford Univ. Press. 333 pp.
3. Maddison A. 1995. *Monitoring the World Economy 1820–1992.* Paris: Organ. Econ. Coop. Dev. 255 pp.
4. Mokyr J. 1990. *The Lever of Riches: Technological Creativity and Economic Progress.* Oxford, UK: Oxford Univ. Press. 349 pp.
5. Tinbergen J. 1942. Zur Theorie der langfristigen Wirtschaftsentwicklung. *Weltwirtschaftliches Arch.* I:511–49
6. Solow RM. 1957. Technical change and the aggregate production function. *Rev. Econ. Stat.* 39:312–20
7. Griliches Z. 1996. The discovery of the residual: a historical note. *J. Econ. Lit.* 34:1324–30
8. Romer PM. 1990. Endogenous technical change. *J. Polit. Econ.* 98:S71–102
9. Metcalfe S. 1987. Technical change. In *The New Palgrave, A Dictionary of Economics*, ed. J Eatwell, M Milgate, P Newman, 4:617–20. London: Macmillan
10. Abramovitz M. 1993. The search for the sources of growth: areas of ignorance, old and new. *J. Econ. Hist.* 52:217–43
11. Freeman C. 1994. The economics of technical change. *Cambridge J. Econ.* 6:463–574
12. Nakićenović N, Victor N, Morita T. 1998. Emissions scenarios database and review of scenarios. *Mitigation Adapt. Strateg. Glob. Change* 3(2–4):95–120
13. Alcamo J, Bouwman A, Edmonds J, Grübler A, Morita T, Sugandhy A. 1995. An evaluation of the IPCC IS92 emission scenarios. In *Climate Change 1994: Reports of Working Groups I and III of the Intergovernmental Panel on Climate Change*, ed. J Houghton, et al, pp. 251–304. Cambridge, UK: Cambridge Univ. Press
14. Nakićenović N, Grübler A, McDonald A. 1998. *Global Energy Perspectives.* Cambridge, UK: Cambridge Univ. Press. 299 pp.
15. Nordhaus WD. 1973. The allocation of energy resources. In *Brookings Papers on Economic Activity*, ed. AM Okun, GL Perry, 3:529–76. Washington, DC: Brookings Inst.
16. Barnett HJ, Morse C. 1967. *Scarcity and Growth: The Economics of Natural Resource Availability.* Baltimore: Johns Hopkins Univ. Press
17. Rogner H-H. 1997. An assessment of world hydrocarbon resources. *Annu. Rev. Energy Environ.* 22:217–62
18. Nakićenović N, Grübler A, Ishitani H, Johansson T, Marland G, et al. 1997. Energy primer. In *Climate Change 1995: Impacts, Adaptations and Mitigation of Climate Change: Scientific-Technical Analyses*, ed. RT Watson, MC Zinyouera, RH Moss, pp. 75–92. Intergov. Panel Clim. Change, Geneva. Cambridge, UK: Cambridge Univ. Press
19. Campbell CJ. 1997. Depletion patterns show change due for production of conventional oil. *Oil Gas J.* 95(52):33–71
20. Meadows DH, Meadows DL, Randers J, Behrens WW. 1972. *The Limits to Growth: A Report for the Club of Rome's Project on the Predicament of Mankind.* New York: Signet. 205 pp.
21. Meadows DH, Meadows DL, Randers J. 1992. *Beyond the Limits: Global Collapse or a Sustainable Future?* London: Earthscan. 300 pp.
22. Nordhaus WD, van der Heyden L. 1983.

Induced technical change: a programming approach. In *Energy, Productivity, and Economic Growth*, ed. SH Schurr, S Sonenblum, DO Wood, pp. 379–404. Cambridge, MA: Oelgeschlager, Gunn, Hain

23. Messner S, Golodnikov A, Gritsevskii A. 1996. A stochastic version of the dynamic linear programming model MESSAGE III. *Energy* 21:775–84

24. Messner S. 1997. Endogenized technological learning in an energy systems model. *J. Evol. Econ.* 7:291–313; 1995. *Work. Pap. 95–114.* Int. Inst. Appl. Syst. Anal., Laxenburg, Austria

25. Fragnière E, Haurie A. 1995. A stochastic programming model for energy/environment choices under uncertainty. *Int. J. Environ. Pollut.* 6:587–603

26. Grübler A, Nakićenović N, Victor DG. 1999. Dynamics of energy technologies and global change. *Energy Policy* 27:247–80

27. Azar C, Dowlatabadi H. 2000. A review of technical change in assessment of climate policy. *Annu. Rev. Energy Environ.* 24:513–44

28. Rosenberg N. 1994. *Exploring the Black Box: Technology, Economics, and History*, Cambridge, UK: Cambridge Univ. Press. 274 pp.

29. Goulder LH, Mathai K. 1998. *Optimal CO_2 abatement in the presence of induced technological change. Work. Pap. 6494.* Washington, DC: Natl. Bur. Econ. Res.

30. Goulder LH, Schneider S. 1996. *Induced Technical Change, Crowding Out, and the Attractiveness of CO_2 Emissions Abatement.* Work. Pap., Dep. Econ., Stanford Univ. 59 pp.

31. Schneider SH, Goulder LH. 1997. Achieving low-cost emissions targets. *Nature* 239:13–14

32. Wright TP. 1936. Factors affecting the costs of airplanes. *J. Aeronaut. Sci.* 3:122–28

33. Argote L, Epple D. 1990. Learning curves in manufacturing. *Science* 247:920–24

34. Arrow K. 1962. The economic implications of learning by doing. *Rev. Econ. Stud.* 29:920–24

35. Rosenberg N. 1982. *Inside the Black Box: Technology and Economics.* Cambridge, UK: Cambridge Univ. Press. 304 pp.

36. Christiansson L. 1995. *Diffusion and Learning Curves of Renewable Energy Technologies. Work. Pap. 95–126.* Int. Inst. Appl. Syst. Anal., Laxenburg, Austria. 19 pp.

37. Cantley MF, Sahal D. 1980. *Who Learns What? A Conceptual Description of Capability and Learning in Technological Systems. Res. Rep. 80-42.* Int. Inst. Appl. Syst. Anal., Laxenburg, Austria

38. Nakićenović N. 1996. Technological change and learning. In *Climate Change: Integrating Science, Economics and Policy*, ed. N Nakićenović, WD Nordhaus, R Richels, FL Toth, pp. 271–94. CP-96-1. Int. Inst. Appl. Syst. Anal., Laxenburg, Austria

39. Grübler A, Gritsevskii A. 1997. A model of endogenous technological change through uncertain returns on learning (R&D and investments). *Conf. Induc. Technol. Change Environ.* Laxenburg, Austria: Int. Inst. Appl. Syst. Anal.

40. Hayami Y, Ruttan VW. 1985. *Agricultural Development: An International Perspective*, Baltimore: Johns Hopkins Univ. Press. 507 pp. 2nd ed.

41. Binswanger HP. 1978. Induced technical change: evolution of thought. *In Induced Innovation: Technology, Institutions and Development*, ed. HP Binswanger, VW Ruttan, pp. 13–43. Baltimore: Johns Hopkins Univ. Press

42. Jorgenson DW, Fraumeni BM. 1981. Relative prices and technical change. In *Modeling and Measuring Natural Resource Substitution*, ed. E Berndt, B Field, pp. 17–47. Cambridge, MA: MIT Press

43. Ruttan VW. 1996. Induced innovation and Path Dependence: a reassessment with respect to agricultural development and

the environment. *Technol. Forecast. Soc. Change* 53:41–59

44. Watanabe C. 1995. Identification of the role of renewable energy. *Renew. Energy* 6:237–74

45. Mansfield E. 1985. How rapidly does new industrial technology leak out? *J. Ind. Econ.* 34:217–23

46. Org. Econ. Coop. Dev. 1996. *Technology and Industrial Performance: Technology Diffusion, Productivity, Employment and Skills, International Competitiveness.* Paris: OECD

47. Starr C, Rudman R. 1973. Parameters of technological growth. *Science* 182:358–64

48. Pepper W, Leggett J, Swart R, Wasson J, Edmonds J, Mintzer I. 1992. *Emissions Scenarios for the IPCC: An Update.* Work. Group I, Intergov. Panel Clim. Change. Geneva: IPCC

49. Nakićenović N, Grübler A, Jefferson M, McDonald A, Messner S, et al. 1995. *Global Energy Perspectives to 2050 and Beyond.* Laxenburg, Austria: Int. Inst. Appl. Syst., Anal. World Energy Counc. 106 pp.

50. Nordhaus WD. 1979. *The Efficient Use of Energy Resources.* New Haven, CT: Yale Univ. Press. 161 pp.

51. Nordhaus WD, Yohe G. 1983. Future carbon dioxide emissions from fossil fuels. In *Changing Climate*, ed. W Nierenberg, pp. 87–153. Washington, DC: US Natl. Acad. Press

52. Manne A, Richels R. 1994. The cost of stabilizing global CO_2 emissions: a probabilistic analysis based on expert judgement. *Energy J.* 15:31–56

53. Hammitt JK, Lempert RJ, Schlesinger ME. 1992. A sequential-decision strategy for abating climate change. *Nature* 357:315–18

54. Lempert RJ, Schlesinger ME, Bankes SC. 1996. When we don't know the costs or the benefits: adaptive strategies for abating climate change. *Climat. Change* 33:235–74

55. Holling CS. 1978. *Adaptive Environmental Assessment and Management.* New York: Wiley & Sons. 377 pp.

56. Kolstad CD. 1993. Looking vs. leaping: the timing of CO_2 control in the face of uncertainty and learning. In *Costs, Impacts, and Benefits of CO_2 Mitigation*, ed. Y Kaya, N Nakićenović, WD Nordhaus, FL Toth, pp. 63–82, CP-93-2. Laxenburg, Austria: Int. Inst. Appl. Syst. Anal.

57. Ermoliev Y, Wets R. 1988. *Numerical Techniques for Stochastic Optimization.* Berlin: Springer-Verlag. 571 pp.

58. Goldnikov A, Gritsevskii A, Messner S. 1995. *A Stochastic Version of the Dynamic Linear Programming Model MESSAGE III. Work. Pap. 95-94.* Int. Inst. Appl. Syst. Anal., Laxenburg, Austria. 75 pp.

59. Cowan R. 1991. Tortoises and hares: choice among technologies of unknown merit. *Econ. J.* 101:801–14

60. Fisher JC, Pry RH. 1971. A simple substitution model of technological change. *Technol. Forecast. Soc. Change* 3:75–88

61. Marchetti C, Nakićenović N. 1979. *The Dynamics of Energy Systems and the Logistic Substitution Model. Res. Rep. 79-13.* Int. Inst. Appl. Syst. Anal., Laxenburg, Austria

62. Grübler A. 1990. *The Rise and Fall of Infrastructures.* Heidelberg: Physica-Verlag. 305 pp.

63. Grübler A. 1996. Time for a change: on the patterns of diffusion of innovation. *Daedalus* 125:19–42

64. Grübler A. 1998. *Technology and Global Change.* Cambridge, UK: Cambridge Univ. Press. 462 pp.

65. Ha-Duong M, Grubb MJ, Hourcade J-C. 1997. Influence of socioeconomic inertia and uncertainty on optimal CO_2-emission abatement. *Nature* 390:270–73

66. Grübler A, Nakićenović N. 1996. Decarbonizing the global energy system. *Technol. Forecast. Soc. Change* 53:97–110

67. Carbon Dioxide Inf. Anal. Cent. Oak Ridge Natl. Lab., Oak Ridge, TN. http://cdiac.esd.ornl.gov/trends/trends.htm

68. Manne AS, Richels RG. 1992. *Buying Greenhouse Insurance: The Economic Costs of Carbon Dioxide Emission Limits.* Cambridge, MA: MIT Press. 182 pp.

69. Messner S, Strubegger M. 1995. *Model-Based Decision Support in Energy Planning. Work. Pap. 95-119.* Int. Inst. Appl. Syst. Anal., Laxenburg, Austria. 77 pp.

70. Messner S, Strubegger M. 1995. *User's Guide for MESSAGE III. Work. Pap. 95-69.* Int. Inst. Appl. Syst. Anal., Laxenburg, Austria. 755 pp.

71. Schäfer A, Schrattenholzer L, Messner S. 1992. *Inventory of Greenhouse-Gas Mitigation Measures: Examples from IIASA Technology Data Bank. Work. Pap. 92-85.* Int. Inst. Appl. Syst. Anal., Laxenburg, Austria. 66 pp.

72. Messner S, Strubegger M. 1991. *User's Guide to CO2DB: The IIASA CO_2 Technology Data Bank, Version 1.0. Work. Pap. 91-31a.* Int. Inst. Appl. Syst. Anal., Laxenburg, Austria. 57 pp.

73. Nakićenović N, Amann M, Fischer G, eds. 1998. *Global Energy Supply and Demand and Their Environmental Effects. Final Rep. Central Res. Inst. Electr. Power Ind.* Int. Inst. Appl. Syst. Anal., Laxenburg, Austria. 744 pp.

74. Wene C-O. 1995. Energy-economy analysis: linking the macroeconomic and systems engineering approachs. *Energy Int. J.* 21:809–24

75. Nakićenović N, ed. 1998. *Global Energy Supply and Demand and Their Environmental Effects.* Laxenburg, Austria: Int. Inst. Appl. Syst. Anal, 700 pp.

76. Akimoto K. 1997. *MESSAGE Modified Results with Learning Curves.* Work. Pap., Int. Inst. Appl. Syst. Anal., Laxenburg, Austria. 32 pp.

77. Wigley TML. 1991. A simple inverse carbon cycle model. *Glob. Biogeochem. Cycles* 5:373–82

78. Wigley TML. 1993. Balancing the carbon budget: implications for projections of future carbon dioxide concentration. *Tellus B* 45:409–25

79. Wigley TML, Raper SCB. 1987. Thermal expansion of sea water associated with global warming. *Nature* 330:127–31

80. Wigley TML, Raper SCB. 1992. Implications for climate and sea level of revised IPCC emissions scenarios. *Nature* 357:293–300

81. Gov. The Netherlands (on behalf of the Eur. Community), *Implementation of the Berlin Mandate. Climate Change Secretariat. FCCC/AGBM/1997/MISC.1/Add.2.* http://www.unfccc.de/fccc/docs/agbm.htm

82. Grübler A, Nakićenović N. 1991. Long waves, technology diffusion and substitution. *Review* 14:313–42

83. Ausubel JH, Marchetti C. 1996. Elekron: electrical systems in retrospect and prospect. *Daedalus* 125:139–69

84. MacGregor PR, Maslak CE, Stoll HG. 1991. The market outlook for integrated gasification combined cycle technology. *Proc. Int. Exhib. Conf. Power Gener. Ind. Power-Gener.* 7-8:1298–325