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Uncertainties in Technology Experience Curves for Integrated Assessment Models

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Abstract

The phenomenon of technological learning has been observed across a wide spectrum of energy and environmental technologies. Quantitative modeling of experience curves has become an increasingly common method of representing endogenous technical change in long-term integrated assessment models used for energy and environmental policy analysis. However, many issues remain to be addressed in the use of experience curves to quantify long-term cost trends of energy technologies. This paper highlights and critically reviews some of the major sources of uncertainty and their implications to model outcomes. It draws on recent empirical literature, as well as on new data characterizing historical cost trends in the early deployment of three environmental technologies especially relevant to energy systems. Our findings indicate the need for a more thorough and systematic examination of the uncertainty of experience curve formulations on the outcomes of energy and environmental policy analyses that extend over many decades.

Keywords: Experience curve, learning curve, learning-by-doing, uncertainties, endogenous technological change, integrated assessment models.

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1. Introduction

Assumptions concerning the nature and rates of technological change are arguably among the most critical for assessments of long-term energy and environmental issues such as global climate change. Large-scale integrated assessment (IA) models used for energy and environmental policy analysis traditionally have employed exogenously specified schedules or rates of improvement in technology performance and/or cost (Kypreos, 1992, Manne and Richels, 1992, Nordhaus, 1994, Prinn et al., 1999). The principal drawback of this method is that technological change is assumed to be autonomous, free, and independent of other policy or economic variables. It has been shown, however, that improvements in technology are neither autonomous nor free, but dependent on factors like investments in research and development (Cohen and Klepper, 1996, Watanabe et al., 2003), capital deepening (Cohen, 1995, Klepper and Simons, 2000), economy-of-scale effects (Sinclair et al., 2000), and the nature and stringency of government regulations (Taylor et al., 2003, Rubin et al., 2004b).

In recent years, as computational barriers have fallen, endogenous models of technical change have gained increased acceptance and use in large-scale IA models, typically in the form of an "experience curve" (also called learning curves). Technology experience curves relate changes in specific investment cost to the cumulative installed capacity of the technology (a surrogate for the combined influence of factors such as those noted above). While this remains an imperfect representation of technical change, it is

nonetheless regarded as an important step toward more realistically representing the dependency of technical change on other factors in IA models.

In this paper we focus on various uncertainties surrounding the use of experience curves in IA models. First we draw on recent literature to identify major sources of uncertainty in current experience curve formulations. We then present new empirical data to characterize the early (pre-commercial) cost trends for environmental technologies important for energy modeling. Finally, we discuss the potential influences and biases of current experience curve formulations on policy-relevant outcomes of IA model analyses, and suggest a path forward for incorporating uncertainties in the future use of experience curves as computational barriers continue to fall.

2. Background

In 1936, the aeronautical engineer Thomas P. Wright published a landmark paper in which he observed that the average direct man-hours required to manufacture a given model of Boeing aircraft dropped systematically with each unit produced (Wright, 1936). Wright captured this phenomenon with an equation representing what he termed a "progress curve":

$$Y = ax^b \qquad \text{(Equation 1)}$$

where Y is the estimated average direct man-hours per unit for the x units; a is the direct man-hours needed to make the first unit; and b $(b<0)$ is a parametric constant. Specifically, Wright demonstrated that man-hour inputs dropped by 20 percent for every

doubling of cumulative output — an 80 percent "progress ratio," where the exponent *b* equaled -0.32.

Wright's work remained relatively obscure until it was revisited a decade later by a group of economists at the then recently founded RAND Corporation (a "think tank" created by the U.S. Air Force in 1946 to develop a complete "science of warfare" during the Cold War era). The RAND economists became vitally interested in the application of Wright's work to the production of war materials—a phenomenon they would eventually call "learning by doing."

Subsequent work by the Boston Consulting Group (1968) applied Wright's equation to the relationship between the average unit price and cumulative industry output of 24 selected products. Since then, this formulation (Equation 1) has been adopted in empirical studies to characterize learning phenomena in a wide range of sectors (Arrow, 1962), including energy technologies (Yelle, 1979, Dutton and Thomas, 1984, Argote and Epple, 1990, IEA/OECD, 2000, McDonald and Schrattenholzer, 2001, Rubin et al., 2004a). When applied to an industry or class product (rather than a specific manufacturing process), Wright's "learning curve" equation is referred to as an "experience curve."

Despite several decades of research, our understanding of the technology innovation process is still rather limited. Various theories have been proposed to explain observed reductions in unit cost as cumulative output increases. Generally, they fall into three categories: (1) costs fall due to changes in production that include process innovations, worker familiarity in the use of tooling, improved management, and economies of scale;

(2) costs fall due to changes in the product itself including product innovations, redesign and standardization; and (3) costs fall due to changes in input prices. While intuitively satisfying, most of these explanations are only qualitatively descriptive and provide little quantification of the direct relationships or contributions of each factor to overall learning. Empirical experience curves thus reflect a combination of factors whose components are not yet well understood or quantified.

Due to the computational complexity of large-scale integrated assessment models, and the non-linear, non-convex nature of the conventional experience curve (Equation 1), it was not until recent years that endogenous technology learning has been incorporated into some of these models (Grubler and Gritsevskii, 1997, Messner, 1997, Weyant and Olavson, 1999, Seebregts et al., 2000, Riahi et al., 2002). Detailed reviews of these developments can be found elsewhere (Grubb et al., 2002b, van der Zwaan and Seebregts, 2004). Here we focus on some of the major uncertainties surrounding the use of experience curves.

3. Uncertainties in Experience Curve Formulations

Today, the log-linear form of the experience curve (Equation 1) remains the most popular equation used to represent the costs improvements of technologies. Dutton and Thomas (1984), for example, surveyed 100 empirical and theoretical studies of progress functions in industrial engineering, economics, and management, and showed that the progress ratios generally fell in the range of 60% to 94% (i.e., learning rates of 6% to 40%). However, studies showing price *increases* were not included in their analysis. For energy-related technologies, McDonald and Schrattenholzer (2002) found a range of

learning rates varying from -14% to 34% with a median value of 16%. Studies of conventional and renewable energy systems similarly have employed the classic experience curve (Equation 1) to calculate a progress ratio (Ostwald and Reisdoft, 1979, Joskow and Rose, 1985, Claeson Colpier, 1999, Neij, 1999, IEA/OECD, 2000, Ibenholt, 2002). Any nonlinearities in the empirical data most often are ignored, and only the "best fit" progress ratio (the value of 2^{-b} in Equation 1) is typically reported. In all energy-related studies, the cumulative installed capacity of a technology is most commonly used as the independent variable, and the reported progress ratio typically applies to the period *after* the technology commercialization stage.

The use of experience curves for forecasting or modeling future trends in energy-related technologies is beset by a number of uncertainties. For example: what is the "correct" progress ratio (or learning rate) applicable for a new energy or environmental technology, or a currently commercial technology? What is the appropriate functional form of the experience curve for the selected technology? Does the learning rate remain constant over time, or does the effect of "learning-by-doing" change over the modeling period? Do costs always decline, or might they also increase, and if so, why or how? While there are still no clear answers to these questions, it is important to recognize these sources of uncertainty and their influence to the results of IA models. Here we attempt to summarize a number of insights and findings from the literature, as well as from our own recent studies of environmental technologies.

3.1 The S-Shaped Learning Curve

Historically, a number of authors have suggested alternative formulations of the learning curve based on empirical observations, especially deviations from log-linearity at the

beginning and tail of the curve. In one of the earliest studies, Carr (1946) argued that the cumulative average curve for airplane production was best represented by an S-shaped curve. This concavity early in the curve also was recognized independently by the Boeing Airplane Company (n.d.) and by the Stanford Research Institute (SRI, 1949b, a). The SRI researchers proposed adding a term, called the "*B*" factor, to the conventional formula (Equation 1) to represent the equivalent units of experience available at the start of a manufacturing program. The SRI studies claimed that the revised formula, $Y = a\,(x+B)^b$, described the empirical production data better than the conventional log-linear function.

In our own studies of experience curves for environmental technologies at coal-fired power plants (Rubin et al., 2004b), we also found that experience curves with initial concavity best fit the data for two widely used technologies—flue gas desulfurization (FGD) systems for sulfur dioxide (SO_2) control, and selective catalytic reduction (SCR) systems for nitrogen oxides (NO_x) control (see Figure 1). In the case of FGD, the low initial learning rates resulted in part from the rapid and widespread deployment of "first-generation" technology in response to environmental regulatory requirements, with little time for learning. This was followed by improvements in succeeding generations of the technology based on factors including continued R&D and experience with the initial (and subsequent) installations.

In addition to studies suggesting concavity at the beginning of some learning curve, many others have challenged the log-linearity hypothesis in the latter part of the curve. Guibert (1945) viewed the progress curve as having a horizontal asymptote that was approached after a large number of aircraft construction units had been produced. A study by the Boeing Airplane Company summarized the cost reduction on the L-15 airplane and

concluded that the slope of the unit cost curve became flat (exhibiting "level-off") with sufficiently large cumulative output. They believed this was probably due to limitations imposed by a given set of tooling. They also found that the level-off point seemed to occur sooner for processes exhibiting steeper learning rates, and for the manufacture of small aircraft compared to large aircraft. Similarly, Asher (1956) analyzed data for nine fighter aircraft models and found that the learning curve began to level off at about 125 units, and that extrapolating to between 100 and 1000 units would result in an estimating error of about 25%.

An extensive survey by Conway and Schultz (1959) studied the existence of learning in four firms manufacturing products with complex as well as simple designs, and cumulative production quantities from fifty to two hundred million units. Their survey found leveling-off, or a decrease in the learning curve slope, when large cumulative production quantities were reached. More recently, Klepper and Graddy (1990) assembled data on the number of firms, outputs, and prices for 46 new products from their initial introduction through the year 1972. They developed both quantitative and qualitative measures characterizing the evolution of new industries, and found that all products appeared to follow a similar general pattern over time, though with considerable quantitative variations. The study found that during both the growth and shakeout stages, the number of firms and total output grew while prices fell. Once the number of firms stabilized, the rates of reduction in price and increase in output leveled off and remained constant over time, typically after 30 to 40 years.

3.2 Cost Increases During Early Commercialization

For many advanced and complex technologies, especially large-scale technologies such as power plants and their environmental control systems, early cost estimates based on laboratory-scale projects and pilot plants are typically lower than the costs subsequently realized for the initial set of full-scale commercial plants. Thus, costs often increase rather than decrease in the early phase of commercial deployment. The reasons for such increases are typically linked to shortfalls in performance and/or reliability that result from insufficient data or experience for scale-up and detailed design, or from new problems that arise during full-scale construction and operation.

Although this phenomenon has been long recognized and often described qualitatively (Merrow et al., 1988), there are relatively few empirical studies that document such trends for energy and environmental technologies. One recent study, however, reported a progress ratio (PR) above 100 percent for an experience curve for natural gas combined cycle (NGCC) systems in the period 1981-1991 (Claeson Colpier and Cornland, 2002). This was followed by subsequent cost declines. Studies of British and Germany wind power (Ibenholt, 2002) and photovoltaic (PV) technologies (Schaeffer, 2003) also found progress ratios above 100 percent at the initial stages of deployment. Though no explanations were provided in the original studies, these rises were likely due to the general observation that the total cost of new technology cannot be reduced as quickly as costs are added through design changes and product performance improvements in the early stages of commercialization (Neij, 1997).

Our own examination of past experience for two large-scale environmental technologies used at fossil fuel power plants — FGD systems for SO_2 control and SCR systems for

NO_x control— also is found to exhibit cost increases during early commercialization. We present this data below, along with observed cost trends for a widely-studied (but not yet widely deployed) technology for CO_2 capture at coal-fired power plants.

3.2.1 Early Commercial Cost Trends for FGD Systems

Under provisions of the Clean Air Act, the U.S. federal government funded research and development on SO_2 removal processes from power plant flue gases starting in the 1960s, including several conceptual design and cost studies. Early cost evaluation for those technologies involved many design assumptions since technical data were limited. Equipment costs were sketchy since most vendors had yet to fabricate and erect the large gas scrubbing devices required for full-scale systems, and very little corrosion data were available to properly select materials of construction for the service involved. In many cases, the "technological optimism" of process developers tended to maximize process potential and minimize problem areas such as corrosion, scaling, solids disposal, sulfite oxidation, mist elimination, gas reheat, operational turndown, and pH control.

Cost estimates in the early 1970s were subject to further uncertainties in scale-up factors based on experimental and prototype installations. Despite some commercial applications on oil-fired power plants in Japan, a basis for more accurately assessing full-scale performance and the costs of FGD installation were not yet established for U.S. coal-fired plants. In the 1970s, the two questions uppermost in the minds of the utility industry regarding FGD systems were system reliability and cost (U.S. EPA, 1974a, b). Cost estimates of the late 1960s proved to be considerably lower than actual costs due to the optimistic view of vendors and analysts that system unknowns would be controlled, and

that inexpensive materials of construction could be utilized (Skopp, 1969, The M. W. Kellogg Company, 1971). However, as time passed, and the results of pilot-plant and early installations became known, the magnitude of cost estimates was scaled up considerably (Spaite, 1972, Battelle, 1973). Figure 2 shows the historical trend of early economic assessments of FGD costs for a typical coal-fired plant. Based on early learning-by-using, costs increased by as much as factor of five as designs were modified to achieve the system reliability and performance needed to comply with regulatory requirements. After a decade of experience and learning, costs finally began to decline in the 1980s.

3.2.2 Early Commercial Cost Trends for SCR Systems

The early economic evaluations of SCR costs at U.S. coal-fired power plant showed a trend similar to FGD systems, although in this case SCR technology was not actually deployed at U.S. coal plants until nearly two decades later. The earliest cost estimates were based on an extrapolation of early Japanese experience with SCR on oil and gas-fired plants (Mobley, 1978). Differences in plant operating conditions and fuel characteristics (such as sulfur and heavy metals content) were recognized, but not factored into these early cost estimates. Subsequent economic studies projected higher costs which included contingencies for lack of experience with high sulfur U.S. coals, and lack of general operating experience with SCR systems (Maxwell et al., 1980, Maxwell and Humphries, 1981, EPRI, 1982).

Figure 3 shows the historical trend in cost estimates for a typical U.S. coal-fired plant. Note the initially optimistic assessments prior to the first commercial SCR installations. Cost estimates for U.S. facilities eventually declined after a decade of Japanese and

German experience, together with U.S. pilot programs, demonstrated increasingly lower capital and operating costs, longer catalyst lifetimes, and lower catalyst prices than had been assumed earlier (the result of learning and competition in both non-U.S. and U.S. markets) (Yeh et al., 2005).

3.2.3 Early Commercial Cost Trends for Amine-Based CO_2 Capture Systems

Environmental technologies that capture CO_2 from power plant flue gases are of growing worldwide interest as a potential climate change abatement measure, and thus are also extremely relevant to integrated assessment models. In contrast to FGD and SCR systems, which were developed largely in response to environmental regulatory requirements, technologies for capturing CO_2 from industrial gas streams (including natural gas, synthesis gas, and flue gas) were developed for commercial applications, mainly in the petroleum and chemical industries. A variety of CO_2 capture systems are in regular use worldwide, with the CO_2 from gas purification processes either vented to the atmosphere or used by other commercial processes.

One of the most common technologies to separate CO_2 from gas streams are amine-based absorption systems. Flue gas scrubbing systems employing monoethanolamine (MEA) is also one of the leading technologies proposed to control greenhouse gas emissions at coal-fired power plants (Rao and Rubin, 2002). The earliest studies of the cost of CO_2 capture at coal-fired power plants (Pappano et al., 1976, Anada and King, 1982) were motivated by the potential use of CO_2 for enhanced oil recovery (EOR) at a time when world oil prices were at their peak (around 1976-1985). It was not until the 1990s that capturing CO_2 at electric power plants (in conjunction with geological storage systems)

gained serious attention as a greenhouse gas mitigation option (e.g., (Smelser et al., 1991, Hendriks, 1994, IEA GHG, 1995).

The main challenge facing amine-based CO_2 capture technology is to reduce the overall cost by lowering both capital and operating expenses, especially the substantial energy requirements associated with sorbent regeneration. Toward this end, the advent of inhibited amine formulations in the post-1980 era has allowed higher sorbent concentrations, significantly reducing the energy penalty associated with this technology (Figure 4). At the same time, the requirements for newer corrosion-resistant materials contributed to higher capital costs relative to early cost estimates (Figure 5). More recent studies (Chapel et al., 1999, DeLallo and Buchanan, 2000, Simbeck and McDonald, 2000, Rao and Rubin, 2002) show a subsequent decline in the estimated capital cost of an MEA capture unit, reflecting further improvements in overall system design. Continued technology advances leading to both capital and O&M cost reductions are anticipated (Rao, 2003).

Note that the cost trend in Figure 5 again shows an initial increase followed by gradual declines. However, unlike the cost trends reported earlier for FGD and SCR systems, no CO_2 capture systems for coal-fired plants at the 500 MW scale (the basis for Figure 5) have yet been built. To date, there have been only a few commercial applications of CO_2 capture at coal-fired units, but at sizes an order of magnitude or two smaller than required for a modern coal-based power plant. Thus, all cost estimates shown here have yet to be validated by actual projects, and the potential for cost *increases* with scale-up cannot be ruled out based on experience with other technologies.

3.3 Interactions of Cost and Performance

The experience curves presented above for SO_2, NO_x and CO_2 control technologies were each based on a constant pollutant removal efficiency in order to characterize the cost of doing the same job at different points in time. However, most of the experience curves used in IA models to characterize cost trends for energy technologies incorporate simultaneous improvements in technology performance. For example, increases in the thermal efficiency of steam turbine generators contributed to the remarkable productive growth and price reductions for electric power since the birth of that industry (Hirsh, 2003). The cost of photovoltaics has fallen more than twenty-fold during the four-decade history of PV, due in part to a nearly three-fold improvement in efficiency (Ramakumar and Bigger, 1993). Similarly, cost reductions for wind energy technology have been due in part to improved efficiency and reliability (Neij, 1999).

For the cases above, efficiency improvements are implicitly embedded in the unit cost data used for an experience curve (e.g., $/kW or $/kWh for an electric power generator). However, IA models with endogenous technical change for energy and environmental technologies typically do not incorporate simultaneous changes in both performance and cost. Rather, performance parameters like thermal efficiency (used to compute fuel requirements) or pollutant removal efficiency (used to compute environmental emissions) often are held constant or improved at rate exogenously specified by modelers while only the unit cost of the technology is determined endogenously. One consequence of such assumptions may be to overestimate the long-term cost of achieving environmental goals like SO_2 or CO_2 reductions. For example, our research on SO_2 removal technologies showed that the average SO_2 removal efficiency of FGD systems increased by 2.6% for

each doubling of cumulative installed capacity over the past several decades (Figure 6). While improved performance of environmental technologies generally comes at a higher initial cost, subsequent cost reductions are such that a high-efficiency SO_2 scrubber today costs much less than a lower-efficiency system a decade ago. Experience curves reflecting such interactions between performance and cost have not yet been developed and incorporated in IA models used for policy analysis.

3.4 Effects of Market Structural Change and Shakeout

Factors related to the marketing of new technologies also influence the shape of a learning curve. Non-linearities in price-based experience curves were regularly observed by the Boston Consulting Group (1968), and attributed in part to structural changes and competition in the marketplace. They hypothesized that at the development stage prices are set below cost to establish an initial market. As sales volume and experience reduce costs, these prices are maintained, gradually converting the negative margin to a positive one. However, if prices do not eventually decline as fast as costs, competitors are attracted to the market. Thus, at some point prices begin to decline faster than costs. Later, a reverse bend in the price curve is reached when the market become mature, and subsequently prices and costs change at the same rate.

In the case of renewable energy technologies like wind and solar energy systems, policy measures such as investment subsidies, production subsidies, tax credits and buy-back rates have been used to provide incentives to stimulate the demand for high-cost technologies. Such policy measures create a price umbrella in which prices decline more slowly than actual costs. After the technologies gain a foot-hold, shakeout begins and the

rate of product innovation tends to slow down following emergence of a dominant design. As noted earlier, the analysis by Claeson-Colpier and Cornland (2002) of the specific investment price for large NGCC power plants found cost increases during 1981-1991, followed by subsequent decreases. The authors characterized the first period as the development and price-umbrella stages, noting that competition in the NGCC market was weak and not many plants were built during that period. Prices also rose as a result of increased technical complexity, the use of new advanced materials, and improvements in thermal efficiency. The subsequent price decreases were attributed mainly to a market shakeout stage as several manufactures competed to gain market share. Price declines also reflected some cost reductions due to improved performance of the NGCC system and a shift towards more standardized and modularized machines. Parente et al. (2002) characterized a similar structural change in the experience curve for photovoltaic modules, noting more rapid cost declines from 1991-2000 compared to the previous decade. The change was attributed to market competition and increasing economies of scale with growing production and use of PV technology.

3.5 Discontinuities and Forgetting

Another uncertainty in the use of experience curves is the potential for organizational "forgetting" in which the knowledge acquired through learning-by-doing may decay or depreciate over time (Argote and Epple, 1990, Argote, 1996, 1999). For example, Argote found that the production of the Lockheed L-1011 TriStar aircraft had a positive progress ratio as production increased from 1972-1975, but a negative progress ratio after a production cut in late 1975, after which costs rose to exceed price. This "forgetting-by-not-doing" was attributed to the loss of knowledge associated with laying off many

experienced workers, leading to a shortage of personnel and parts, and a lack of experienced workers when production later resumed.

Similarly, Sturm (1993) analyzed the operating experience of nuclear power plants from 1981 to 1991 in Eastern and Western Europe, the former Soviet Union, and the United States. He found that while all Western countries reduced their unplanned outages, the former Soviet Union and all countries in Eastern Europe experienced an increase in unplanned outages and a decrease in plant availability. He suggested that this might have resulted from political and economic reorganizations that caused labor turnover, difficulties in obtaining spare parts and maintaining plants, and lack of incentives to provide adequate training programs—another illustration of organizational forgetting.

3.6 Other Factors: Social, Economic and Political Effects

Departures from the conventional (log-linear) experience curve can also arise from changes in regulatory requirements such as environmental, health and safety standards, changes in work rules, and improved design standards. Such changes can increase the total cost of a technology even though the unit costs for wages, materials, and equipment may be static. For example, Cantor and Hewlett (Cantor and Hewlett, 1988) found that despite significant learning-by-doing benefits at the firm/constructor level, new regulations imposed by the Nuclear Regulatory Commission (NRC) contributed to unprecedented increases in construction costs for nuclear power plant from 1979-1988. Similarly, Hewlett (1996) found that real O&M costs for U.S. nuclear power plants escalated at an annual rate of about 11 percent from 1975-1987, primarily because of new safety regulations imposed by the NRC.

In a study of coal-burning power plants, Joskow and Rose (1985) found that the real cost per kilowatt for constructing a power plant in the U.S. declined during the early and mid-1960s, stabilized in the late 1960s, then climbed substantially during the 1970s and 1980s. Their study controlled for scale effects, technological differences, input price changes, major environmental control technologies (scrubbers and cooling towers), and other cross-sectional differences in real costs. The cost increases appeared partially to reflect the increased costs of responding to new environmental, health and safety regulations, as well as to increased construction times and a decline in construction productivity.

Finally, societal factors such as public opposition to a technology also can strongly influence rates of technology diffusion and learning. Perhaps the most well-known example is nuclear power, where public opposition has effectively halted the diffusion of this technology in many countries (e.g., no new plants constructed in the United States since 1978) (U.S. NRC, 2003). Even clean renewable technologies are not immune from this phenomenon: in Norway and elsewhere the siting of new wind energy systems is increasingly being opposed on aesthetic and other grounds.

4. Implications for Modeling and Policy Analysis

While the adoption of experience curves and endogenous technological learning represent important advances in integrated assessment modeling, the factors discussed above introduce uncertainties that can significantly influence the results of energy and environmental policy analyses. In general, models that incorporate induced technological change tend to find accelerated rates of emissions abatement and lower costs of

environmental compliance compared to models that ignore technological change (Grubler and Gritsevskii, 1997, Messner, 1997, Grubler and Messner, 1998, Grubb et al., 2002b, van der Zwaan et al., 2002). However, the sensitivity of policy-related variables to the assumed learning rates can be highly non-linear. Small changes in the assumed technology progress ratio (or learning rate) can change investment patterns considerably, and thus the conditions for long-term competitiveness of new technologies (McDonald and Schrattenholzer, 2002, Barreto and Kypreos, 2004).

For similar reasons, the shape of an experience curve can also significantly influence the outcomes of long-term assessments and policy analyses. A slow initial learning rate for a new technology, characteristic of an S-shaped curve, can discourage the early adoptions and investments needed for long-term growth and innovation relative to competing technologies with more "optimistic" experience curves (such as the prevailing log-linear shape). As a result, some technologies may be "locked-out" of the longer-term picture, affecting the overall cost, technology mix, and other outcomes of interest such as expeditures for R&D (Weyant and Olavson, 1999). The declining rate of improvement at the tail of an S-shaped curve can similarly alter outcomes relative to the conventional log-linear formulation where costs fall indefinitely. In the later case, overestimating cost reductions of mature technologies in the IA models will affect the competitiveness of new competing technologies.

Although computationally more demanding, the use of input *distributions* of learning rates would better represent our limited understanding of the processes underlining technology progress functions. Grubler and Gritsevskii (1997) used a simple optimization model with endogenous technological change, with uncertainty in learning rates

represented by a lognormal distribution function around the mean value. They showed that when the rate of learning is certain (i.e., perfect foresight), the optimal solution is to invest heavily and early in new technology because the resulting cost declines achieved through learning causes the technology to quickly become competitive. Barreto and Klaassen (2004) found similar results. However, when learning rates were uncertain (as in the real world), the optimal solution also became less certain. As a result, there was broader investment in a portfolio of technologies, with slower diffusion and market entry of any particular technology. Messner et al. (1996) also incorporated uncertainties concerning future technology performance and found that it tended to spread risk over a larger number of technologies to cope with uncertainties in the development paths.

Despite the historical evidence, current large-scale IA models typically do not incorporate improvements in environmental performance for new generations of energy or environmental technologies (e.g., an improved CO_2 capture system that removes 99% CO_2 instead of 90%) endogenously. As noted earlier, one consequence of such assumptions may be to overestimate the long-term cost of achieving environmental goals. Nor have IA modelers incorporated the cost *increases* that often occur with initial deployment of a technology, or which can accompany slowdowns in technology diffusion that lead to institutional forgetting, as described earlier.

5. Conclusions and Caveats

The incorporation of induced technological change in large-scale integrated assessment models is an important development that can provide a valuable and more rigorous means of examining a wider range of policy options and the appropriate degree, timing, and distribution of mitigation efforts required to address issues like global climate change.

Nonetheless, the modeling of technological change and innovation is still in its infancy. As elaborated in this paper, there exists a number of key uncertainties surround the use of experience curves to represent technological learning and diffusion.

In the near term, more extensive computer experiments are needed to explore the implications of alternative experience curves formulations, such as an S-shaped curve in lieu of the traditional log-linear curve. Recent empirical evidence suggests this may better approximate the learning behavior of large-scale technologies deployed in response to emission reduction requirements. As computational barriers continue to fall, wider use of *distributions* of learning rates can help explore the sensitivity of model outcomes (and policy implications) to learning rate assumptions. All else being equal, IA models that can utilize input distributions of learning rates will provide greater realism than those employing single values.

Technology cost and performance are two closely coupled parameters which are often treated independently, and specified exogenously, in energy-economic models. Because of their importance in economic and policy analysis, there is a need for improved endogenous modeling methods that account for the interaction of these two factors for key energy and environmental technologies.

This paper does not address other factors that contribute to induced technological change, such as investments in R&D, and spillovers from R&D. Early work by others has begun to explore the effects of these two factors in the context of IA models. In general, this work has found that the incorporation of these two factors, along with learning-by-doing, tends to reduce the costs of environmental policy, accelerate emissions abatement, and

often lead to positive spillover and negative leakage (Watanabe et al., 2000, Grubb et al., 2002a, Watanabe et al., 2003, Barreto and Klaassen, 2004). More detailed models of the learning process that incorporate such effects will no doubt improve the ability of IA models to more accurately represent the policy-related outcomes of technology innovations.

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LIST OF FIGURES

Figure 1. Concave versus log-linear (Equation 1) learning curves fitted to the capital costs of flue gas desulfurization (FGD) and selective catalytic reduction (SCR) systems at *standard* U.S. coal-fired utility plants. The definitions of standard plants are defined in Figures 2 and 3.

Figure 2. Capital and annualized operating and maintenance (O&M) costs of a wet limestone FGD system for a standard new coal-fired power plant. Except where specified, a standard plant is sized 500 MWe, burning 3.5% sulfur coal, and achieve 90% SO_2 removal efficiency. The earliest plants, however, did not achieve the high levels of availability and reliability required for utility operations, leading to more costly designs in later years.

Figure 3. Capital and levelized costs of a SCR system for a standard (500 MWe, burning medium sulfur coal, 80% NO_x removal) new coal-fired power plant. Solid diamond dots are studies based on low-sulfur coal plant, which requires lower SCR capital cost. Empty circles are studies evaluated prior to any commercial SCR installation on a coal-fired utility plant.

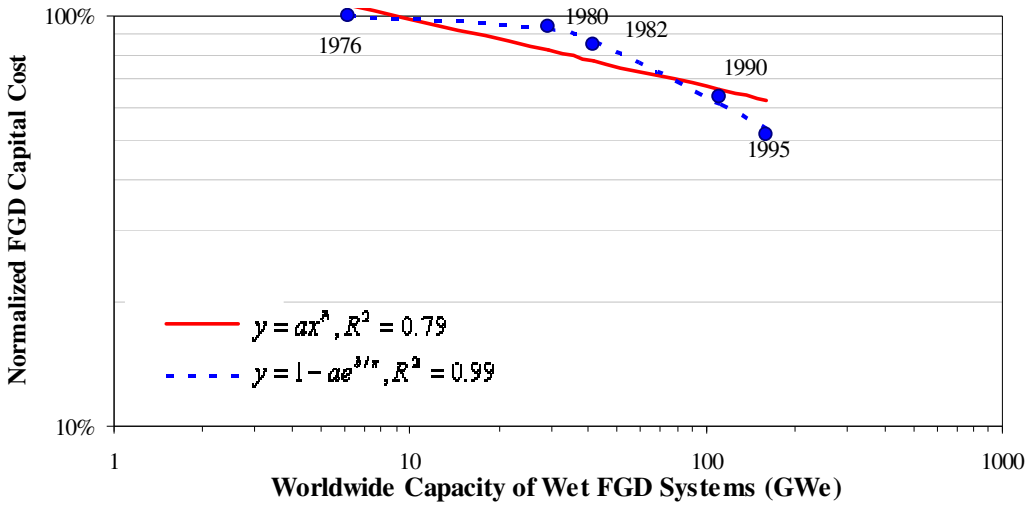
Figure 4. Decreasing trend of the minimum regeneration heat requirement of MEA solvent for CO_2 recovery process.

Figure 5. Estimated capital cost of an amine (MEA) carbon capture system at a standard coal-fired power plant (500 MWe, CO_2 capture efficiency = 90%). The capital cost estimates include the cost of compression (to about 2000 psia) and drying captured CO_2, but do not include the cost of building new power generation plants to supply the energy required for capture plant operation.

Figure 6. Improvements in SO_2 removal efficiency of commercial lime and limestone FGD systems as a function of cumulative installed wet FGD capacity.

FIGURE 1

(a)


100%
10%
Normalized FGD Capital Cost
1976
1980
1982
1990
1995
$y = ax^b, R^2 = 0.79$
$y = 1 - ae^{b/x}, R^2 = 0.99$
1
10
100
1000
Worldwide Capacity of Wet FGD Systems (GWe)

(b)

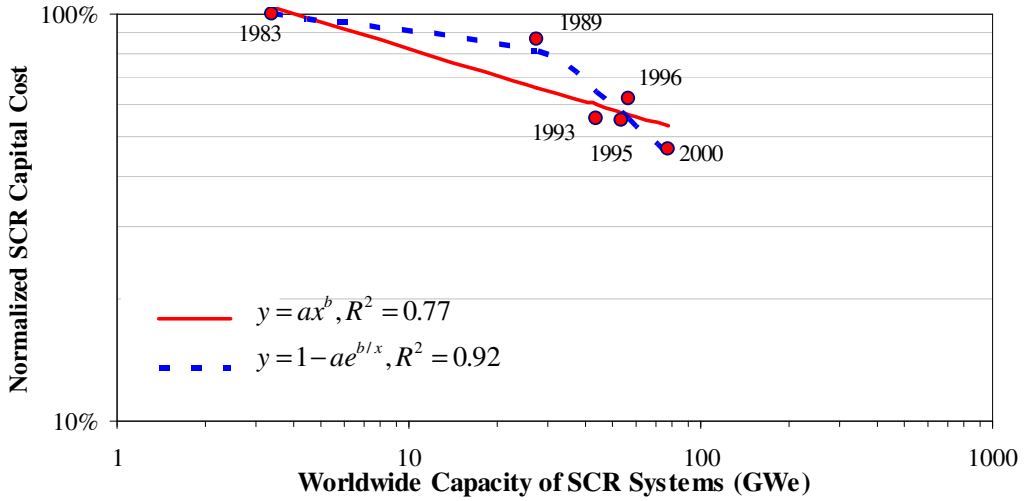
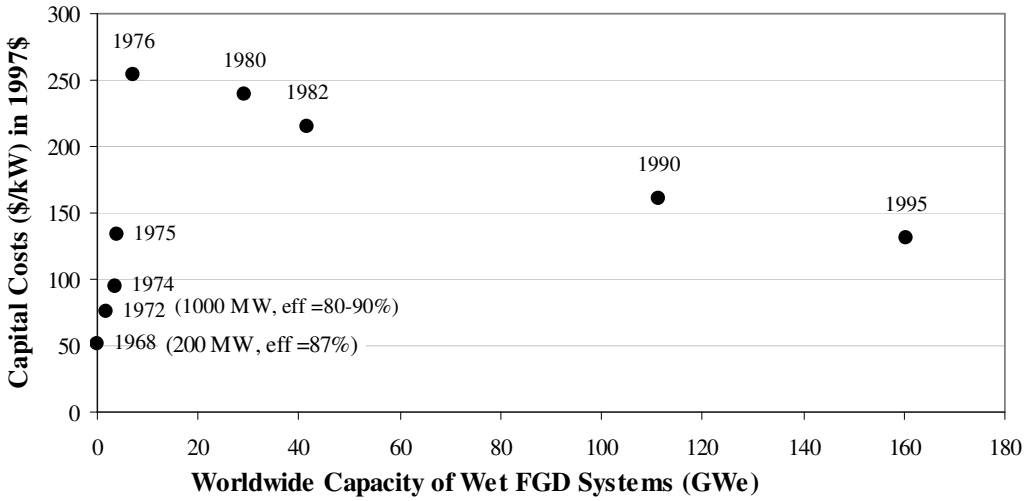

100%
10%
Normalized SCR Capital Cost
1983
1989
1996
1993
1995
2000
$y = ax^b, R^2 = 0.77$
$y = 1 - ae^{b/x}, R^2 = 0.92$
1
10
100
1000
Worldwide Capacity of SCR Systems (GWe)

FIGURE 2

(a)


Capital Costs ($/kW) in 1997$
300
250
200
150
100
50
0
1976
1980
1982
1990
1995
1975
1974
1972 (1000 MW, eff =80-90%)
1968 (200 MW, eff =87%)
0
20
40
60
80
100
120
140
160
180
Worldwide Capacity of Wet FGD Systems (GWe)

(b)

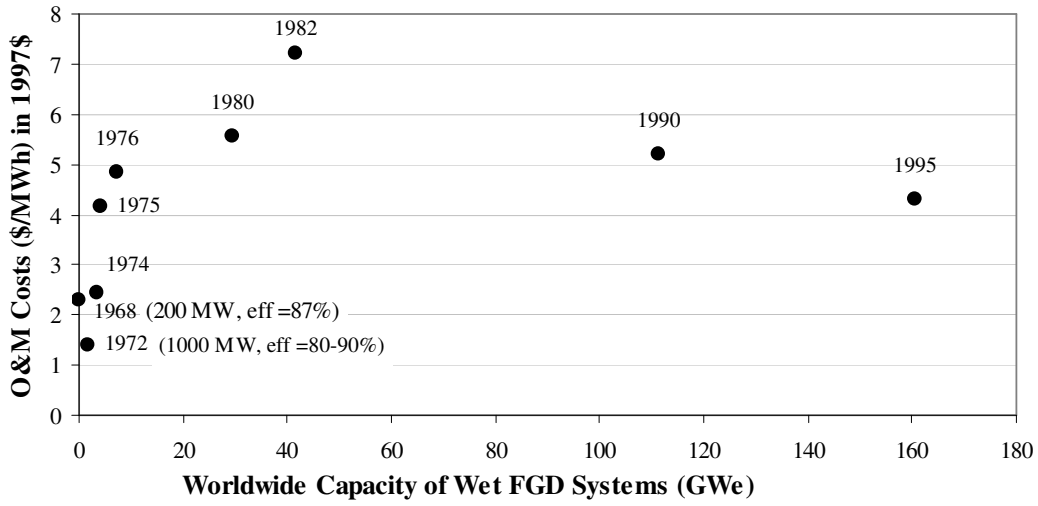
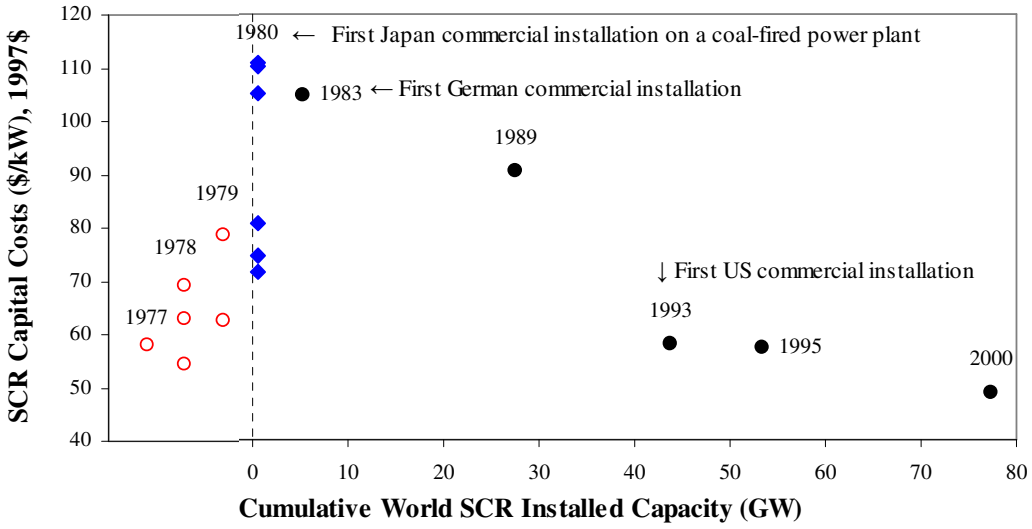

O&M Costs ($/MWh) in 1997$
8
7
6
5
4
3
2
1
0
1982
1980
1990
1976
1995
1975
1974
1968 (200 MW, eff =87%)
1972 (1000 MW, eff =80-90%)
0
20
40
60
80
100
120
140
160
180
Worldwide Capacity of Wet FGD Systems (GWe)

FIGURE 3

(a)


SCR Capital Costs ($/kW), 1997$
120
110
100
90
80
70
60
50
40
1980 ← First Japan commercial installation on a coal-fired power plant
1983 ← First German commercial installation
1989
1979
1978
1977
↓ First US commercial installation
1993
1995
2000
0
10
20
30
40
50
60
70
80
Cumulative World SCR Installed Capacity (GW)

(b)

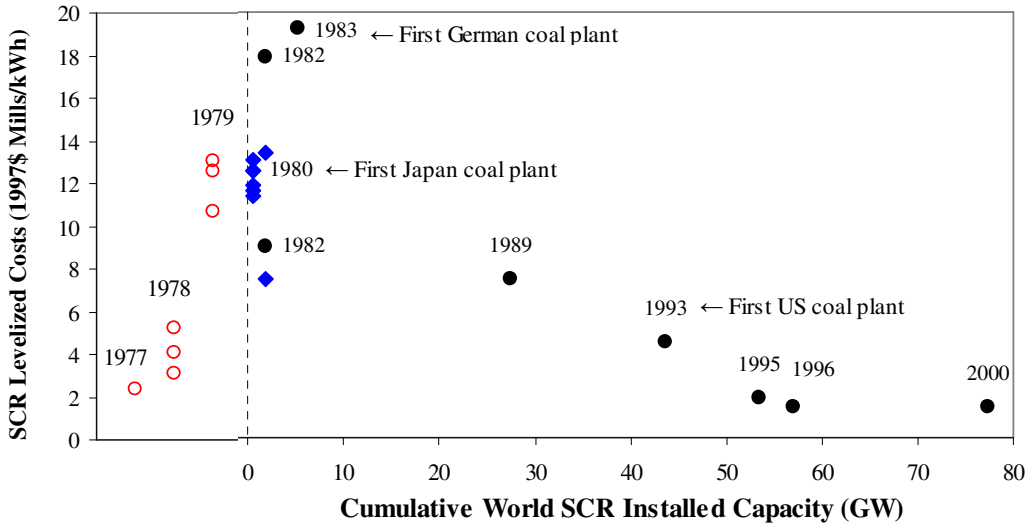

SCR Levelized Costs (1997$ Mills/kWh)
20
18
16
14
12
10
8
6
4
2
0
1983 ← First German coal plant
1982
1979
1980 ← First Japan coal plant
1982
1989
1978
1977
1993 ← First US coal plant
1995
1996
2000
0
10
20
30
40
50
60
70
80
Cumulative World SCR Installed Capacity (GW)

FIGURE 4

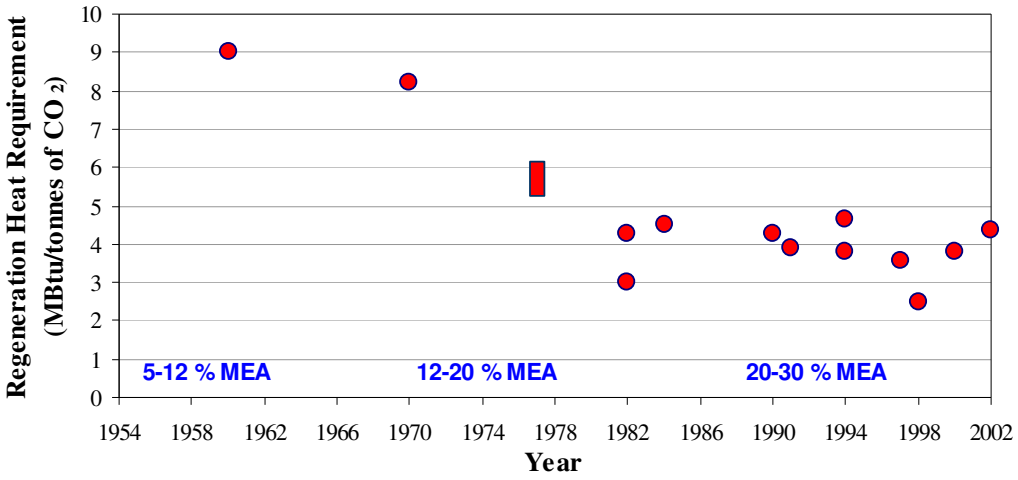

Regeneration Heat Requirement
(MBtu/tonnes of CO 2)
10
9
8
7
6
5
4
3
2
1
0
5-12 % MEA
12-20 % MEA
20-30 % MEA
1954
1958
1962
1966
1970
1974
1978
1982
1986
1990
1994
1998
2002
Year

FIGURE 5

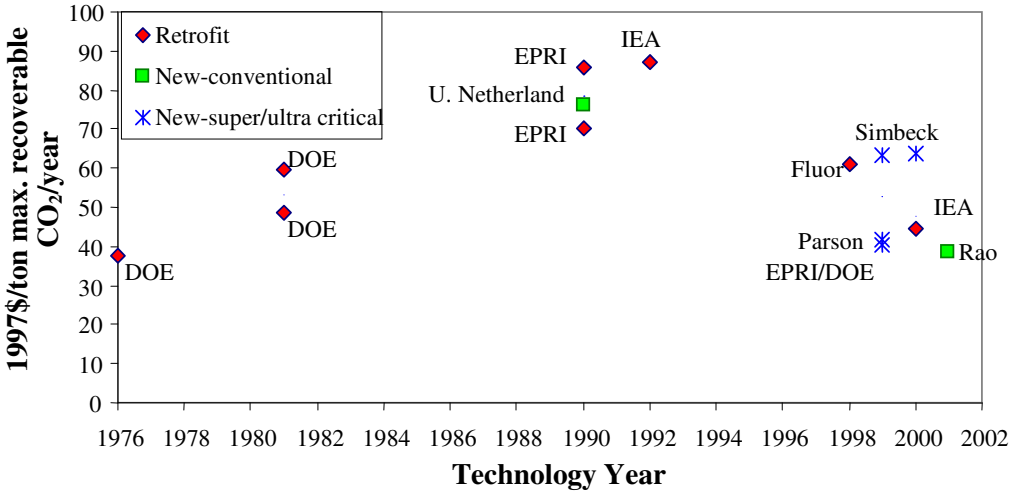
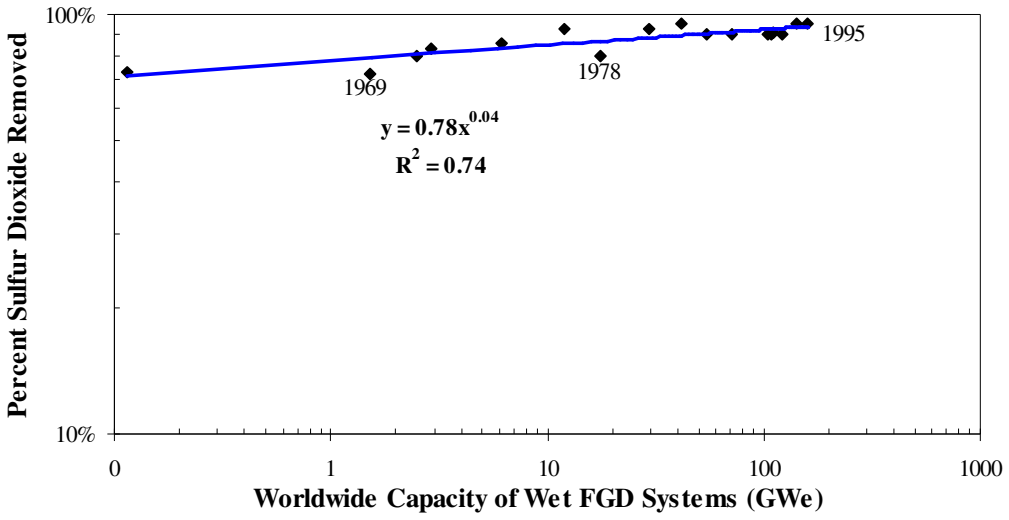

1997$/ton max. recoverable CO2/year
Technology Year
Retrofit
New-conventional
New-super/ultra critical
DOE
DOE
DOE
EPRI
U. Netherland
EPRI
IEA
Fluor
Simbeck
IEA
Parson
EPRI/DOE
Rao
0
10
20
30
40
50
60
70
80
90
100
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002

FIGURE 6


100%
10%
Percent Sulfur Dioxide Removed
1969
1978
1995
y = 0.78x^0.04
R^2 = 0.74
0
1
10
100
1000
Worldwide Capacity of Wet FGD Systems (GWe)