How well does Learning-by-doing Explain Cost Reductions in a Carbon-free Energy Technology?

Gregory F. Nemet

NOVEMBER 2006

CCMP – Climate Change Modelling and Policy

Gregory F. Nemet, *Energy and Resources Group, University of California*

How well does Learning-by-doing Explain Cost Reductions in a Carbon-free Energy Technology?

Summary

The incorporation of experience curves has enhanced the treatment of technological change in models used to evaluate the cost of climate and energy policies. However, the set of activities that experience curves are assumed to capture is much broader than the set that can be characterized by learning-by-doing, the primary connection between experience curves and economic theory. How accurately do experience curves describe observed technological change? This study examines the case of photovoltaics (PV), a potentially important climate stabilization technology with robust technology dynamics. Empirical data are assembled to populate a simple engineering-based model identifying the most important factors affecting the cost of PV over the past three decades. The results indicate that learning from experience only weakly explains change in the most important cost-reducing factors— plant size, module efficiency, and the cost of silicon. They point to other explanatory variables to include in future models. Future work might also evaluate the potential for efficiency gains from policies that rely less on 'riding down the learning curve' and more on creating incentives for firms to make investments in the types of cost-reducing activities quantified in this study.

Address for correspondence:

Gregory F. Nemet
Energy and Resources Group
University of California
310 Barrows Hall 3050
Berkeley CA 94720-3050
USA
E-mail: gnemet@berkeley.edu

1 Technological change and learning curves

The rate and direction of future technological change in energy technologies are important sources of uncertainty in models that assess the costs of stabilizing the climate (Edenhofer et al., 2006).[1] Treatment of technology dynamics in integrated assessment models has become increasingly sophisticated (Grubb et al., 2002) as models have incorporated lessons from the economics of innovation and as increased processing power and improved algorithms have enabled optimization of phenomena, such as increasing returns, which in the past had made computation unwieldy (Messner, 1997). Yet the representation of technological change in large energy-economic model remains highly stylized relative to the state-of-the-art of understanding about the economics of innovation (Nordhaus, 2002). Perhaps one reason for the lag between the research frontier for the economics of innovation and that for the modeling of it has to do with incompatibilities in the methodological approaches of the two fields. On the one hand, research on the economics of innovation has tended to emphasize uncertainty (Freeman and Louca, 2001), cumulativeness (Rosenberg, 1994), and non-ergodicity (Arthur, 2006). The outcomes of this line of inquiry, which dates back to Schumpeter (1934), and even Marx (1867), have often been characterized by richness of description, a case study approach, and arguably, more progress with rigorous empirical observation than with strong theoretical claims. On the other hand, optimization and simulation models require compact quantitative estimation of parameters, with uncertainties that do not become infinite once propagated through the model. One of the few concepts that has bridged the epistemological gap between the economics of innovation and the integrated assessment of climate change is the learning curve (Grübler et al., 1999a).

One of the most important technologies related to the long term assessment of climate policy is photovolatics (PV). The cost of PV has declined by a factor of nearly 100 since the 1950s, more than any other energy technology in that period (Wolf, 1974; McDonald and Schrattenholzer, 2001; Maycock, 2002). Markets for PV are expanding rapidly, recently growing at over 40% per year (Maycock, 2005). Future scenarios that include stabilization of greenhouse-gas (GHG) concentrations assume widespread diffusion of PV. In a review of 34 emissions scenarios, Nakicenovic and Riahi (2002) found a median of 22 terawatts (TW) of PV deployed in 2100 for those scenarios that include GHG stabilization. At present however, PV remains a niche electricity source and in the overwhelming majority of situations does not compete economically with conventional sources, such as coal and gas, or even with other renewable sources, such as wind and biomass. The extent to which the technology improves over the next few decades will determine

---

[1]This paper draws on portions of an earlier one that was published as: Nemet, G. F. (2005) "Beyond the learning curve: factors influencing cost reductions in photovoltaics."Energy Policy (in Press) http://dx.doi.org/10.1016/j.enpol.2005.06.020.

whether PV reaches terawatt scale and makes a meaningful contribution to reducing GHG emissions or remains limited to niche applications.

The learning curve is an important tool for modeling technical change and informing policy decisions related to PV and other energy technologies. For example, it provides a method for evaluating the cost effectiveness of public policies to support new technologies (Duke and Kammen, 1999) and for weighing public technology investment against environmental damage costs (van der Zwaan and Rabl, 2004). Energy supply models now also use learning curves to endogenate improvements in technology. Prior to the 1990s, technological change was typically included either as an exogenous increase in energy conversion efficiency or ignored (Azar and Dowlatabadi, 1999). Studies in the 1990s began to use the learning curve to treat technology dynamically (Williams and Tarzian, 1993; Grübler et al., 1999b) and since then it has become a powerful and widely used model for projecting technological change. Recent work however has cautioned that uncertainties in key parameters may be significant (Wene, 2000), making application of the learning curve to evaluate public policies inappropriate in some cases (Neij et al., 2003). This paper examines some of these concerns. After a review of the advantages and limitations of the learning curve model, the applicability of learning curves to PV is then assessed by constructing a bottom-up cost model and comparing its results to the assumptions behind the learning curve.

1.1 From learning-by-doing to experience curves

Characterizations of technological change have identified patterns in the ways that technologies are invented, improve, and diffuse into society (Schumpeter, 1947). Studies have described the complex nature of the innovation process in which uncertainty is inherent (Freeman, 1994), knowledge flows across sectors are important (Mowery and Rosenberg, 1998), and lags can be long (Rosenberg, 1994). Perhaps because of characteristics such as these, theoretical work on innovation provides only a limited set of methods with which to *predict* changes in technology. The learning curve model offers an exception.

The learning curve originates from observations that workers in manufacturing plants became more efficient as they produced more units (Wright, 1936; Alchian, 1963; Rapping, 1965). The roots of these micro-level observations can be traced back to early economic theories about the importance of the relationship between specialization and trade, which were based in part on individuals developing expertise over time (Smith, 1776). Drawing on the concept of *learning* in psychological theory, Arrow (1962) formalized a model explaining technical change as a function of learning derived from the accumulation of experiences in production. In its original conception, the learning curve referred to the changes in the productivity of labor which

were enabled by the experience of cumulative production within a manufacturing plant. It has since been refined, for example, Bahk and Gort (1993) make the distinction between "labor learning", "capital learning", and "organizational learning." Others developed the *experience curve* to provide a more general formulation of the concept, including not just labor but all manufacturing costs (Conley, 1970) and aggregating entire industries rather than single plants (Dutton and Thomas, 1984). Though different in scope, each of these concepts is based on Arrow's explanation that "learning by doing" provides opportunities for cost reductions and quality improvements. As a result, these concepts are often, and perhaps misleadingly, grouped under the general category of learning curves. An important implication of the experience curve is that increasing accumulated experience in the early stages of a technology is a dominant strategy both for maximizing the profitability of firms and the societal benefits of technology-related public policy (BCG, 1972).

The learning curve model operationalizes the explanatory variable *experience* using a cumulative measure of production or use. Change in cost typically provides a measure of learning and technological improvement, and represents the dependent variable.[2] Learning curve studies have experimented with a variety of functional forms to describe the relationship between cumulative capacity and cost (Yelle, 1979). The log-linear function is most common perhaps for its simplicity and generally high goodness-of-fit to observed data. The central parameter in the learning curve model is the exponent defining the slope of a power function, which appears as a linear function when plotted on a log-log scale. This parameter is known as the learning coefficient (b) and can be used to calculate the progress ratio (PR) and learning ratio (LR) as shown below where C is unit cost and q represents cumulative output.

$$C_t = C_0 \left(\frac{q_t}{q_0} \right)^{-b} \tag{1}$$

$$PR = 2^{-b} \tag{2}$$

$$LR = (1 - PR) \tag{3}$$

Several studies have criticized the learning curve model, especially in its more general form as the experience curve. Dutton and Thomas (1984) surveyed 108 learning curve studies and showed a wide variation in learning rates leading them to question the explanatory power of experience. Argote and Epple (1990) explored this variation further and proposed four alternative hypotheses for the observed technical improvements: economies of

---

[2]Cost is often normalized by an indicator of performance, e.g. \$/watt. Alternative performance measures are also sometimes used such as accident and defect rates.

scale, knowledge spillovers, and two opposing factors, organizational forgetting and employee turnover. Despite such critiques, the application of the learning curve model has persisted without major modifications as a basis for predicting technical change, informing public policy, and guiding firm strategy. Below, the advantages and limitations of using the more general version of the learning curve, the experience curve, for such applications are outlined.

The experience curve provides an appealing model for several reasons. First, availability of the two empirical time series required to build an experience curve—cost and production data—facilitates testing of the model. As a result, a rather large body of empirical studies has emerged to support the model. Compare the simplicity of obtaining cost and production data with the difficulty of quantifying related concepts such as knowledge stocks (Romer, 1990) and inventive output (Hall and Mairesse, 2006). Still, data quality and uncertainty are infrequently explicitly addressed and as shown below can have a large impact on results. Second, earlier studies of the origin of technical improvements, such as in the aircraft industry (Alchian, 1963) and shipbuilding (Rapping, 1965), provide narratives consistent with the theory that firms learn from past experience. Third, studies cite the generally high goodness-of-fit of power functions to empirical data over several years, or even decades, as validation of the model. For example, Fig. 1 shows experience curves for seven technology case studies (Taylor and Nemet, 2006). Fourth, the dynamic aspect of the model—the rate of improvement adjusts to changes in the growth of production—makes the model superior to forecasts that treat change purely as a function of time.[3] Finally, the reduction of the complex process of innovation to a single parameter, the learning rate, facilitates its inclusion in large optimization and simulation models.

The combination of a rich body of empirical literature and the more recent applications of learning curves in predictive models has revealed weaknesses that echo earlier critiques. First, the *timing* of future cost reductions is highly sensitive not only to changes in the market growth rate but also to small changes in the learning rate. Although, an experience curve R^2 value of >0.95 is considered a strong validation of the experience curve model, variation in the underlying data can lead to uncertainty about the timing of cost reductions on the scale of decades. Fig. 2 shows experience curves based on the two most comprehensive world surveys of PV prices (Maycock, 2002; Strategies-Unlimited, 2003). The Maycock survey produces a learning rate of 0.26 while the Strategies Unlimited data gives 0.17.[4] What may appear

---

[3]An example of the opposite, a non-dynamic forecast, is autonomous energy efficiency improvement (AEEI) in which technologies improve at rates exogenously specified by the modeler (Grubb et al., 2002).

[4]Note that the largest differences between the price surveys are in the early stages of commercialization when using experience curves may be least appropriate.
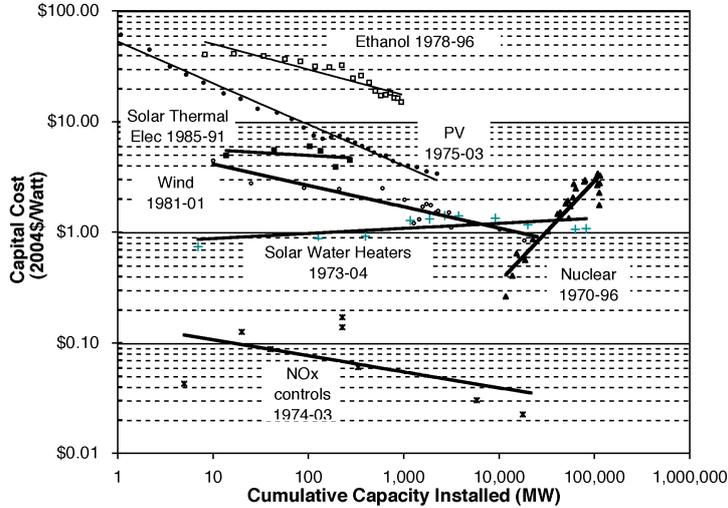
Figure 1: Experience curves for energy technologies. Data: Taylor and Nemet (2006).

as a minor difference has a large effect. For example, assuming a steady industry growth rate of 15% per year, consider how long it will take for PV costs to reach a threshold of $0.30/W, an estimate for competitiveness with conventional alternatives. Just the difference in the choice of data set used produces a crossover point of 2039 for the 0.26 learning rate and 2067 for the 0.17 rate, a difference of 28 years. McDonald and Schrattenholzer (2001) show that the range of learning rates for energy technologies in general is even larger. Neij et al. (2003) find that calculations of the cost effectiveness of public policies are sensitive to such variation. Wene (2000) observes this sensitivity as well and recommends an on-going process of policy evaluation that continuously incorporates recent data.

Second, the experience curve model gives no way to predict discontinuities in the learning rate. In the case of PV, the experience curve switched to a lower trajectory around 1980. As a result, experience curve-based forecasts of PV in the 1970s predicted faster technological progress than actually occurred (Schaeffer et al., 2004). Discontinuities present special difficulties at early stages in the life of a technology. Early on, only a few data points define the experience curve, while at such times decisions about public support may be most critical. Early work in economics is skeptical about the assumption that historically observed rates of learning can be expected to continue in the future. (Arrow, 1962) argued that that learning is subject to "sharply diminishing returns." Looking at studies within single plants, (Hall and Howell, 1985) and (Baloff, 1966) find that learning rates become essentially flat after a relatively short amount of time—approximately 2 years in

6
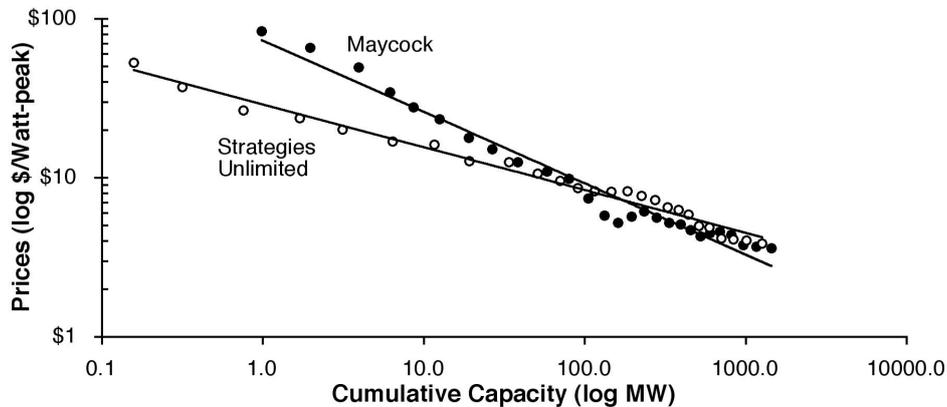
Figure 2: Experience curves for PV modules and sensitivity of learning rate to underlying data. Data: Maycock (2002); Strategies-Unlimited (2003).

these studies. Some have suggested, that as a result, a cubic or logistic function offers a more realistic functional form than a power function (Carlson, 1973).

Third, studies that address uncertainty typically calculate uncertainties in the learning rate using the historical level of variance in the relationship between cost and cumulative capacity. This approach ignores uncertainties and limitations in the progress of the specific technical factors that are important in driving cost-reductions (Wene, 2000). For example, constraints on individual factors, such as theoretical efficiency limits, might affect our confidence in the likelihood of future cost reductions.

Fourth, due to their application in planning and forecasting, emphasis has shifted away from learning curves based on employee productivity and plant-level analysis, toward experience curves aggregating industries and including all components of operating cost. While the statistical relationships generally remain strong, the conceptual story begins to look stretched as one must make assumptions about the extent to which experience is shared across firms. In the strictest interpretation of the learning-by-doing model applied to entire industries, one must assume that each firm benefits from the collective experience of all. The model assumes homogenous knowledge spillovers among firms.

Fifth, the assumption that experience, as represented by cumulative capacity, is the *only* determinant of cost reductions ignores the effect of knowledge acquired from other sources, such as from R&D or from other industries. Earlier, Sheshinski (1967) wrestled with the separation of the impact of two competing factors, investment and output. Others have addressed this limitation by incorporating additional factors such as workforce training (Adler and Clark, 1991), R&D (Buonanno et al., 2003; Miketa and Schrat-

7

tenholzer, 2004), and the interactions between R&D and diffusion (Watanabe et al., 2000). Collinearity among the explanatory variables requires large detailed data sets, the scarcity of which has so far limited widespread application of these more sophisticated models.

Finally, experience curves ignore changes in *quality* beyond the single dimension being analyzed (Thompson, 2001).[5] The dependent variable is limited to cost normalized by a single measure of performance—for example, hours of labor/aircraft, $/watt, or ¢/megabyte. Measures of performance like these ignore changes in quality such as aircraft speed, reliability of power generation, and the compactness of computer memory.

1.2 Methodology

This study seeks to understand the drivers behind technical change in PV by disaggregating historic cost reductions into observable technical factors. The mechanisms linking factors such as cumulative capacity and R&D to technological outcomes, while certainly important, are at present not well understood. Many of the problems mentioned above arise because the experience curve model relies on assumptions about weakly understood phenomena. Rather than making assumptions about the roles that factors like experience, learning, R&D, and spillovers play in reducing costs, a set of observable technical factors are identified whose impact on cost can be directly calculated.

The time period included here begins with the period of nascent commercialization, 1975 and continues to 2001. During this 26-year period, there was a factor of 20 cost reduction in the cost of PV modules. Only PV modules are examined and balance-of-system components such as inverters, storage, and supporting structures are excluded.[6] The focus here is on explaining change in the capital cost of PV modules, rather than on the cost of electricity produced, mainly due to data quality considerations and to be able to exclude influential but exogenous factors such as interest rates. The study is limited to PV modules manufactured from mono-crystalline and poly-crystalline silicon wafers because crystalline silicon has been the overwhelmingly dominant technology for PV over this period. Crystalline silicon PV comprised over 90% of production over this period and its share increased in the second half of the period.[7] While photovoltaic electricity has been produced from a wide variety of other materials, such as cadmium-telluride and copper-indium-diselenide, during the study period these com-

---

[5]Payson (1998) provides an alternative framework that incorporates both changes in quality and cost improvements.

[6]Inverters and other components have similar progress ratios to modules and have exhibited cost decreases by factors of 5 and 10 respectively.

[7]Crystalline silicon makes up close to 100% of the market for applications of >1kW, a definition of the market that includes household-scale and larger power generation and excludes consumer electronics.

peting technologies remained in the development stage were not commercially relevant. The price data used in the study are weighted averages of the two types of silicon crystals. The study uses worldwide data rather than country-level data because over this time period the market for PV became global. Some of the change often attributed to within-country costs is due to the globalization of the industry, rather than learning from that country's experience. Junginger et al. (2005) articulated the need for such an international view and as a result developed a global experience curve for wind power. This study adopts a similarly global view. The scope of this study thus addresses the concerns raised by Schaeffer et al. (2004) regarding the importance of data quality, system boundaries, and sufficient historical time period for assessing experience in energy technologies. Finally, the technological characteristics of PV provide two simplifying aspects that help restrict the influence of potentially confounding factors in the study. First, there has been no significant change in per unit scale in PV panels. PV panels have been sized on the order of one square meter per panel for three decades. Compare this to wind turbines in which the size of individual units has increased by almost two orders of magnitude over the same period (Madsen et al., 2003; Junginger et al., 2005). Second, there are essentially no operation and maintenance costs associated with PV, other than regular cleaning and inverter replacement. This limits the role of "learning by using", which would normally be an important additional factor to consider (Rosenberg, 1982).

The analysis began by identifying factors that changed over time and had some impact on PV costs. Using empirical data, the annual level of these seven factors over the study period, 1975 to 2001 was compiled and a model to quantify the impact of the change in each factor on module cost developed.

2   Description of the cost model

This cost model simulates the effect of changes in each of seven factors on manufacturing cost in each year, t, as follows.

2.1   Cost

Average module cost (C) in $/Watt$_{peak}$ is the dependent variable in the model.[8] The time series for cost uses an average of the two most comprehensive world surveys of PV prices (Maycock, 2002; Strategies-Unlimited, 2003). Using prices as a proxy for costs is a widespread practice whose validity is discussed below. The model uses module cost, rather than cost of

---

[8]All monetary values presented in this study are in U.S. dollars at constant 2002 prices.

energy produced, to avoid the large uncertainties associated with making assumptions about capacity factors, lifetimes, and financing mechanisms.

2.2 Module efficiency

Improvements in the energy efficiency ($\eta = W_{out}/W_{in}$) of modules sold have nearly doubled the rated power output of each square meter (m^2) of PV material produced (Christensen, 1985; Maycock, 1994; Grubb and Vigotti, 1997; Maycock, 2002). The model simulates the impact of efficiency changes on module cost using:

$$\triangle C_{t(\eta)} = C_{t-1} \left(\frac{\eta_{t-1}}{\eta_t} - 1 \right) \tag{4}$$

This simple formulation applies the annual change in efficiency to the previous year's cost, C_{t-1}, to calculate the change in cost due to efficiency, $\triangle C_{t(\eta)}$. As an example, a doubling in efficiency would, ceteris paribus, reduce \$/Watt cost by 50%.

2.3 Plant size

Growth in the expected future demand for PV has led to an increase in the average annual output of PV manufacturing plants of more than two orders of magnitude (Maycock and Stirewalt, 1985; Maycock, 1994; Ghannam et al., 1997; Maycock, 2002; Mitchell et al., 2002). Growing demand has enabled manufacturers to build larger facilities, which exploit economies of scale by absorbing indivisible costs. The effect of increasing plant size (SZ) is estimated using eq. 5. A scaling factor for operating costs is borrowed from the semi-conductor industry ($b = -0.18$)(Gruber, 1996), the industry whose production processes are most similar to those of PV. This value is within the range of assumptions used in studies that calculate future cost savings for large scale PV.[9]

$$\triangle C_{t(SZ)} = C_{t-1} \left(\left(\frac{SZ_t}{SZ_{t-1}} \right)^b - 1 \right) \tag{5}$$

2.4 Yield

Improved cell and module processing techniques have increased yield, the proportion of functioning units available at the end of the manufacturing

---

[9]'Large scale' means >100 MW per plant per year. Other PV scaling factors include the following: $b = -0.07$ (Bruton and Woodock, 1997), $b = -0.09$ (Rohatgi, 2003), $b = -0.12$ (Frantzis et al., 2000), $b = -0.18$ (Maycock, 1997), $b = -0.20$ (Ghannam et al., 1997). It is not surprising that the chosen value lies at the upper end of this range because it is being applied historically, when smaller plant sizes probably were yielding more economies of scale than they would at the levels of 100-500MW/year in these studies.

process (YD) (Little and Nowlan, 1997; Sarti and Einhaus, 2002; Rohatgi, 2003).[10] Because post-wafer yield measures the final stages of the production process, firms incur the entire cost of modules they discard for mechanical or electrical reasons. The trend toward thinner wafers increased the brittleness of cells. This more delicate material increased the possibility of breakage, offsetting some of the gains in yield delivered by automation.

$$\triangle C_{t(\text{YD})} = C_{t-1} \left(\frac{\text{YD}_{t-1}}{\text{YD}_t} - 1 \right) \tag{6}$$

2.5 Poly-crystalline share

Wafers cut from silicon ingots comprised of multiple crystals (poly-crystalline) rather than individual crystals (mono-crystalline) have accounted for an increasing share of world production (Costello and Rappaport, 1980; Maycock, 1994, 2002, 2003; Menanteau, 2000; JPEA, 2002; Goetzberger et al., 2003). Based on comparisons of mono- and poly-crystalline prices (Maycock, 1994, 1997; Bruton and Woodock, 1997; Sarti and Einhaus, 2002), it is assumed that poly-crystalline modules cost 90% that of mono-crystalline modules (PF=0.9). Eq. 7 calculates the cost of poly-crystalline modules (PC) based on average prices of all types of modules. The effect of the growing market share for poly-crystalline modules (PS) on average module cost is obtained in eq. 8 :

$$\text{PC}_t = \text{PF} \frac{C_t}{1 - (1 - \text{PF}) \, \text{PS}_t} \tag{7}$$

$$\triangle C_{t(\text{PS})} = (\text{PS}_t - \text{PS}_{t-1}) (\text{PC}_{t-1} - C_{t-1}) \tag{8}$$

2.6 Silicon cost

The basic material input for producing PV wafers is solar-grade silicon feedstock, the cost of which (SC) fell by nearly a factor of 12 over the study period (Ghosh, 1979; Costello and Rappaport, 1980; Bruton, 2002; Swanson, 2006)(Fig. 3). Changes in the other major materials—glass, ethyl-vinyl acetate (EVA), aluminum and framing materials—are ignored because they are orders of magnitude less costly than silicon.[11] The annual effect of the change due to silicon cost is estimated by calculating the cost of the silicon necessary to produce a watt of PV module, while holding the amount of silicon used (SU) per watt constant:

$$\triangle C_{t(\text{SC})} = (\text{SC}_t \text{SU}_{t-1}) - (\text{SC}_{t-1} \text{SU}_{t-1}) \tag{9}$$

---

[10]Yield improvements in the manufacturing of wafers are captured in the section on silicon consumption below.

[11]Note that in Fig. 3 a log scale is necessary to show the changes in the other materials.
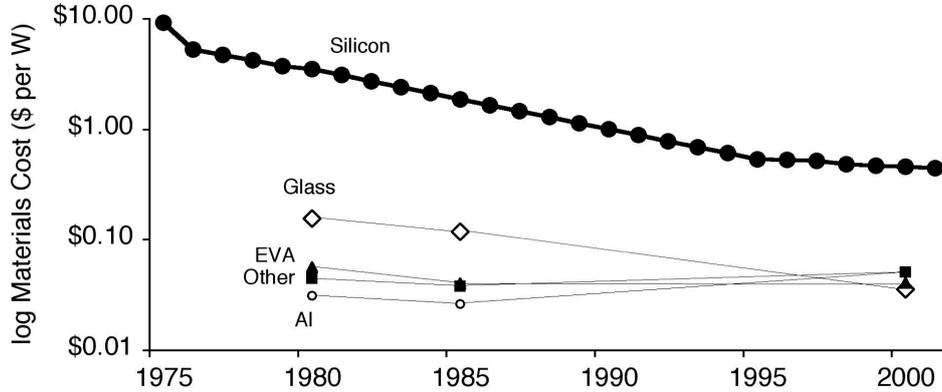
Figure 3: Materials costs for PV modules. Data: Christensen (1985); Maycock (2002).

2.7 Silicon consumption

The amount of silicon used per watt of PV module has fallen by a factor of 1.5 over the period (Maycock, 2002; Woditsch and Koch, 2002; Swanson, 2006). Manufacturers have accomplished this change by reducing the thickness of silicon wafers from 500μm to 250μm and by reducing kerf losses, from the sawing of each wafer, from 250μm to 190μm. The amount of silicon saved each year is calculated and is combined with data on silicon cost to estimate the effect on module cost.

$$\triangle C_{t(\mathrm{SU})} = (\mathrm{SC}_{t-1}\mathrm{SU}_t) - (\mathrm{SC}_{t-1}\mathrm{SU}_{t-1}) \tag{10}$$

2.8 Wafer size

Improved crystal growing methods have increased the cross-sectional area of each wafer (WS) by a factor of four (Christensen, 1985; Symko-Davies et al., 2000; Rohatgi, 2003; Swanson, 2006). Larger wafers facilitate savings in the cell and module assembly processes where there are costs that are fixed per wafer, e.g. forming electrical junctions and testing. Using studies that disaggregate costs, the model assumes that post-wafer processing accounts for 40% of the cost of producing a module in all periods (WP=0.4)(Moore, 1982; Bruton and Woodock, 1997; Maycock, 2002) and that fixed per wafer costs are 10% of cell and module assembly costs (WF=0.1).

$$\triangle C_{t(\mathrm{WS})} = C_{t-1} \left(\frac{\mathrm{WS}_{t-1}}{\mathrm{WS}_t} - 1 \right) \mathrm{WP} \cdot \mathrm{WF} \tag{11}$$

12

Table 1: Summary of model results, 1975-2001

Factor	Change	Effect on module cost ($/W)
Module efficiency	$6.3\% \rightarrow 13.5\%$	-17.97
Plant size	76 kW/yr $\rightarrow$ 14 MW/yr	-13.54
Si cost	300 \$/kg $\rightarrow$ 25 \$/kg	-7.74
Si consumption	30 g/W $\rightarrow$ 18 g/W	-1.06
Yield	$87\% \rightarrow 92\%$	-0.87
Wafer size	37 cm^2 $\rightarrow$ 180 cm^2	-1.16
Poly-crystal	$0\% \rightarrow 50\%$	-0.38
Sum of factors		-42.72
Actual change		-70.36
Residual		-27.63

2.9 Full model

The total change in module cost each year is the sum of the changes in each of the seven factors described above (F).[12]

$$\triangle C_t = \sum \triangle C_{F,t} \tag{12}$$

3 Plant size, efficiency, and silicon dominate

Three factors were most important in explaining cost declines from 1975 to 2001: plant size, cell efficiency, and to a lesser extent, the cost of silicon (Table 1). The other four factors each account for less than 2% of the cost decline. However, these seven factors together explain just over 60% of the change in cost over the period. Such a large residual requires understanding the reasons for this residual before drawing conclusions about the model results. Analysis of the residual shows that the model predicts the actual change in prices much better after 1980 than it does before 1980.

The following sections present results obtained by partitioning the model into two time periods; Period 1: 1975-79 and Period 2: 1980-2001. These periods were chosen for three reasons. First, by 1980 terrestrial applications had become dominant over space-based applications. The emergence of niche markets for navigation, telecommunications, and remote residences

---

[12]Other factors such as labor, automation, and other material inputs were also considered. However, they are excluded from the model because these changes are either very small or are captured as changes in other factors that were included in the model. Similarly, the negative interaction terms among the factors are assumed to be negligible and are excluded from the model.

signaled the start of a viable commercial market. Second, global public R&D spending on PV reached its peak, \$370m, in 1980 (Kammen and Nemet, 2005). The subsequent decline in R&D reflected a less active government role in technology development as the experiences of the 1970s oil crises faded. Third, in 1980, governments such as Japan began subsidizing commercial applications, indicative of the shift from research-oriented to diffusion-oriented technology policies.

3.1   Period 1: 1975-1979

In the first four years of this study, cost declined by a factor of three. Of the factors identified in the model, efficiency, cost of silicon, and plant size accounted for the most change in cost. Three other factors, module size, yield, and silicon consumption, were of less importance but played a role. The share of modules that were poly-crystalline did not change and thus had no effect. These seven factors however fail to explain most of the change in cost over this period, as 54% of the change is unexplained. In the rest of this section, other factors are discussed that may help explain some of this large residual. Understanding the early period of commercialization is important because many technologies tend to attract widespread interest as they emerge from the laboratory and find their first commercial applications. As a result, policy and investment decisions must be made at this early stage when the factors discussed below may be at work.

As a starting point for identifying alternative explanations in this period, it is important to note that there was a dramatic change in the market for PV over these four years. During this period, terrestrial applications overtook space-based satellite applications as the dominant end-use. In 1974, the market share of terrestrial applications was 4%—satellites accounted for the remaining 96% (Moore, 1982). By 1979, the terrestrial market share had grown to 64%. The following sections address the large residual with four possible explanations, each of which is associated with this shift in end use.

3.1.1   Weaker preferences for quality

One reason for the unexplained change in cost is that the shift from space to terrestrial applications led to a reduction in the *quality* of modules. The shift away from space applications rendered certain characteristics non-essential, allowing manufacturers to switch to less costly processes.

First, spatial and weight constraints on rockets required high efficiency panels to maximize watts delivered per m^2. The relaxation of this requirement for terrestrial applications enabled manufacturers to employ two important cost-saving processes (Moore, 1982). Modules could use the entire area of the silicon wafer—even the portions near the edges which tend to suffer from defects and high electrical resistivity. Also, the final assembly
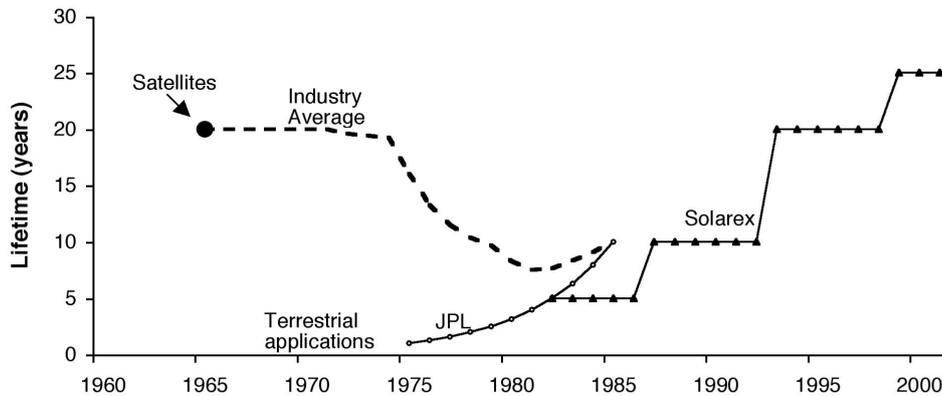
Figure 4: Module lifetime. Data: Moore (1982); Christensen (1985); Wohlgemuth (2003).

process could use a chemical polish to enhance light transmission through the glass cover, rather than the more expensive ground optical finish that was required for satellites.

Second, reliability targets fell. Satellite programs, such as Vanguard and Skylab, needed satellite PV modules that would operate reliably without maintenance, perhaps for twenty years. Terrestrial applications, on the other hand, could be still be useful with much shorter lifetimes. Combining lifetime data (Christensen, 1985; Wohlgemuth, 2003) with the shares of satellite and terrestrial applications shows a decline in average industry module lifetime during the late-1970s (Fig. 4). The transition from 20-year reliability targets in the early and mid-1970s to 5 years in 1980s, allowed the use of cheaper materials and less robust assembly processes that would have enabled less costly manufacturing.

3.1.2 Increasing demand elasticity

Another, and possibly complementary, explanation is that the shift from satellites to terrestrial applications affected prices because of a difference in the demand elasticity of the two types of customers. Price data from the period provide some supporting evidence. In 1974–79, the price per watt of PV modules for satellite use was 2.5 times higher than the price for terrestrial modules (Moore, 1982). The impact of this price difference on *average* PV prices is calculated by taking into account the change in market share mentioned above. The combination of these price and market shifts accounts for $22 of the $28 price decline not explained by the model in this period. Satellite customers, with their hundreds of millions of dollars of related investments, almost certainly had a higher willingness to pay for PV panels, than early terrestrial applications such as telecom repeater sites

15
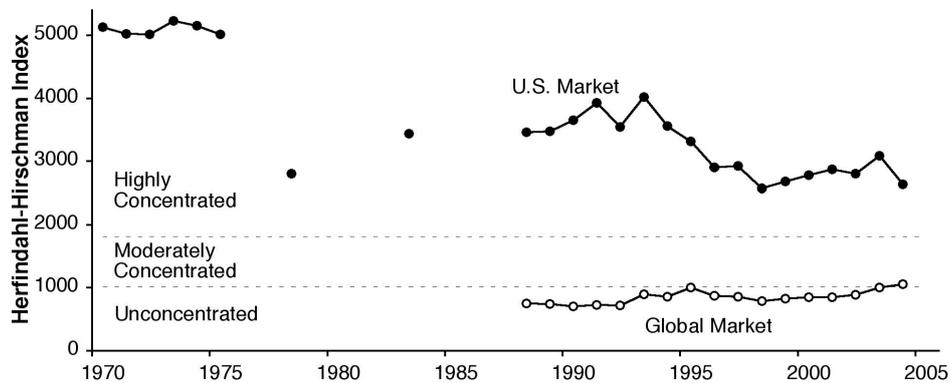
Figure 5: Industry concentration (Herfindahl-Hirschman Index). Data: Wolf (1974); Roessner (1982); Maycock (1984, 1994, 2002, 2005).

or buoys for marine navigation. The difference in quality must account for some of the price difference. But the difference in willingness to pay may also have led to higher differences between cost and price for satellite than for terrestrial applications.

3.1.3 Intensifying competition

Market share data indicate an increase in competition during this period. A decline in industry concentration typically produces an increase in competitiveness, a decline in market power, and lower profit margins. There were only two U.S. firms shipping terrestrial PV from 1970–1975 (Wolf, 1974; Maycock and Stirewalt, 1985). In 1978, about 20 firms were selling modules and the top three firms made up 77% of the industry (Roessner, 1982). By 1983, there were dozens of firms in the industry with the largest three firms accounting for only 50% of the megawatts sold (Maycock, 1984).

The Herfindahl-Hirschman Index (HHI) provides a way of measuring industry concentration (Hirschman, 1945; Herfindahl, 1950). The HHI is calculated by summing the squares of the market shares of all firms in an industry. The maximum possible HHI is 10,000.[13] The data show a trend to a less concentrated U.S. market during Period 1, 1975-1979 (Fig. 5). Concentration in the global market remained stable in the 1990's, the period for which comprehensive worldwide data available. The increase in international trade in PV over the last three decades indicates that the relevant scale of analysis shifted from a national market in the earlier years to an international market today. Thus the most relevant measure of concentration

---

[13]The U.S. Department of Justice uses HHI to assess competitiveness in anti-trust decisions and considers industries with values below 1000 "unconcentrated", 1000 to 1800 "moderately concentrated", and values above 1,800 "highly concentrated" (DOJ, 1997).

would involve not only the trends in the curves themselves but also a shift from the upper domestic curve to the lower global curve.

3.1.4 Standardization

A final explanation for the change in cost is that changes in production methods occurred due to an increase in the number of customers and the types of products they demanded. There was a shift away from a near-monopsony market in the early-1970s when a single customer, the U.S. space program, accounted for almost all sales. In the terrestrial market, in contrast, the U.S. government accounted for only one third of terrestrial PV purchases in 1976 (Costello and Rappaport, 1980). With the rise of the terrestrial industry, a larger set of customers emerged over the course of the decade. One result from this change in the structure of demand was the shift away from producing customized modules, such as the 20kW panels on Skylab, to producing increasingly standard products at much higher volumes.

3.2 Period 2: 1980-2001

In the second period, from 1980 to 2001, PV cost declined by a factor of 7. In contrast to Period 1, the model explains the change in the second period well—just over 5% of the change is unexplained by the model (Table 2). The higher explanatory power of the cost model indicates that the factors mentioned above to explain the residual in Period 1—quality, demand elasticity, competition, and standardization—were either stable or were dynamic but offsetting in Period 2. Two factors stand out as important in Period 2: plant size accounts for 43% of the change in PV cost and efficiency accounts for 30% of the change (Fig. 6). The declining cost of silicon accounts for 12%. Yield, silicon consumption, wafer size, and poly-crystalline share each have impacts of 3% or less.

3.3 Sensitivity of results to data uncertainty

The model is most sensitive to uncertainty in three areas: the change in plant size, the scaling factor, and the change in efficiency.[14] Fig. 7 shows that despite the model's sensitivity to uncertainty in these three areas, the relative importance of the three main factors does not change. Even with the relatively large uncertainty resulting from the choice of the scaling factor, the two orders of magnitude increase in plant size makes it the dominant

---

[14]Uncertainty is calculated based on the full range of estimates obtained. The sensitivity of the model is estimated using opposite ends of ranges to simulate the extremes of large changes and small changes in each factor from 1975-2001. For example, in the case of efficiency, a *small change* is calculated using the upper bound in 1975 and the lower bound in 2001. Similarly, a *large change* consists of the time series using the lower bound in 1975 and the upper bound in 2001.

Table 2: Summary of model results for time period 2: 1980-2001

Factor	Change	Effect on module cost ($/W)
Plant size	125 kW/yr → 14 MW/yr	−9.22
Module efficiency	8.0% → 13.5%	−6.50
Si cost	131 \$/kg → 25 \$/kg	−2.67
Wafer size	48 cm^2 → 180 cm^2	−0.64
Si consumption	28 g/W → 18 g/W	−0.62
Yield	88% → 92%	−0.43
Poly-crystal	0% → 50%	−0.38
Sum of factors		−20.46
Actual change		−21.62
Residual		−1.16
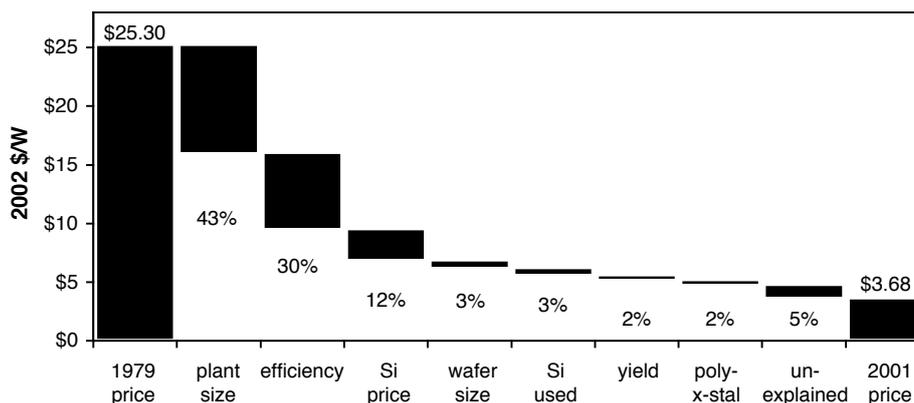
Figure 6: Portion of cost reduction accounted for by each factor, 1980-2001

driver of change in cost. So taking into account the full range of uncertainty in each parameter and conservatively assuming a uniform distribution across the estimates obtained, it can still be concluded that: (1) Module efficiency and plant size were the most important contributors to cost reduction, (2) cost of silicon was moderately important, and (3) the other factors were of minor importance. This finding on the importance of economies of scale fits with other studies estimating the contribution of economies of scale to cost reduction in wind power such as Madsen et al. (2003) who estimated that scale accounted for 60% of reductions in turbine costs.
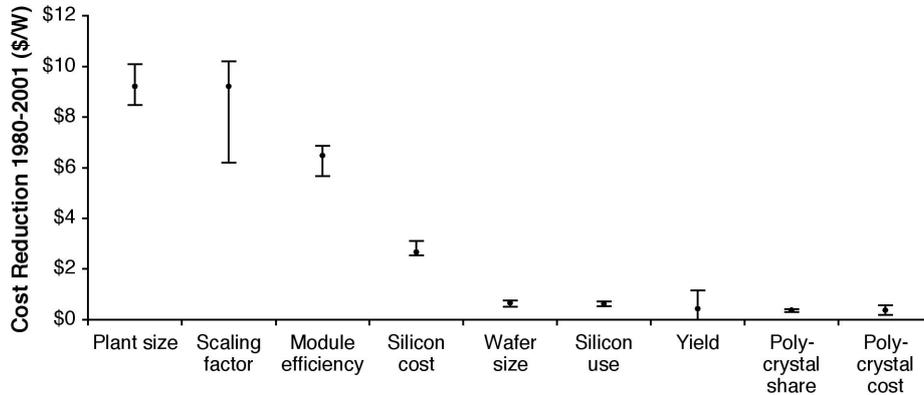
Figure 7: Sensitivity of model results to uncertainty in data and parameters, 1980-2001

4 Limits to the explanatory power of experience

Experience curves are based on the theory that experience creates opportunities for firms to reduce costs and that as a result costs decline in logarithmic proportion to increases in cumulative capacity. Indeed, in the case of PV, cumulative capacity is a strong predictor of cost.[15] However, the mechanistic basis for this apparently strong statistical relationship is rather weak. In this section, the influence of increasing cumulative capacity in driving change in the most important cost-reducing factors is assessed. The results indicate that the most important factors are only weakly explained by cumulative capacity (Table 3). Overall, the "learning" and "experience" aspects of cumulative production do not appear to have been major factors in enabling firms to reduce the cost of PV, which is the assumption underlying the experience curve model.

4.1 Experience and plant size

Growth in expected future demand and the ability to manage investment risk were the main drivers of the change in plant size over the period. Whether experience plays a role in enabling the shift to large facilities depends on whether new manufacturing problems emerge at larger scales and whether experience helps in overcoming these problems. Examples from three PV firms indicate that limited manufacturing experience did not preclude rapid increases in production. Mitsubishi Electric expanded from essentially zero production in 1997 to 12 MW in 2000 and plans to expand to 230 MW in 2006 (Jaeger-Waldau, 2004). While the firm had decades of experience in research and satellite PV applications, its cumulative production was

---

[15]log(CumCapacity) as a predictor of log(C) has an R^2 value of 0.985.

Table 3: Role of learning-by-doing (lbd) in each factor, 1980-2001

Factor	Cost impact	Main drivers of change in each factor
Plant size	43%	Demand and risk management
Efficiency	30%	R&D, some lbd for lab-to-market
Silicon cost	12%	Spillover benefit from IT industry
Wafer size	3%	Strong lbd
Si use	3%	Lbd and technology spillover
Yield	2%	Strong lbd
Poly share	2%	New process, lbd possible
Other factors	5%	Not examined

minimal. It only began substantial manufacturing activity with the opening of its Iida plant and its entry into the Japanese residential PV market in 1998. Similarly, Q-Cells, a German firm, only began producing cells in 2001 with a 12 MW line and increased production to 50 MW in only two years (Maycock, 2005). Sharp is considering construction of a 500 MW/year plant in 2006, which would amount to a ten-fold expansion in the firm's capacity in only 5 years. In the rapid expansions of the past five years, the ability to raise capital and to take on the risk of large investments that enable construction of large manufacturing facilities appear to have played more important roles than learning by experience in enabling cost reductions. These results support the claim of Dutton and Thomas (1984) that "sometimes much of what is attributed to experience is due to scale."

4.2   Experience and module efficiency

Learning-by-doing is only one of several reasons behind the doubling in commercial module efficiency. Data on the highest laboratory cell efficiencies over time shows that of the 16 advances in efficiency since 1980 (Surek, 2003)[16], only six were accomplished by firms that manufacture commercial cells. Most of the improvements were accomplished by universities, none of which would have learned from experience with large-scale production. That government and university R&D programs produced 10 of the 16 breakthroughs in cell efficiency while producing a trivial amount of the industry's cumulative capacity suggests that the effect of learning-by-doing on improving module efficiency is weak. Further, the rapid rise in laboratory cell efficiency from 1983-1990 (Fig. 8) immediately followed the unprecedented $1.5b investment in worldwide PV R&D in the previous 5 years

---

[16]'Advances' are defined as new production of cells that resulted in a cell efficiency higher than any previous laboratory result.
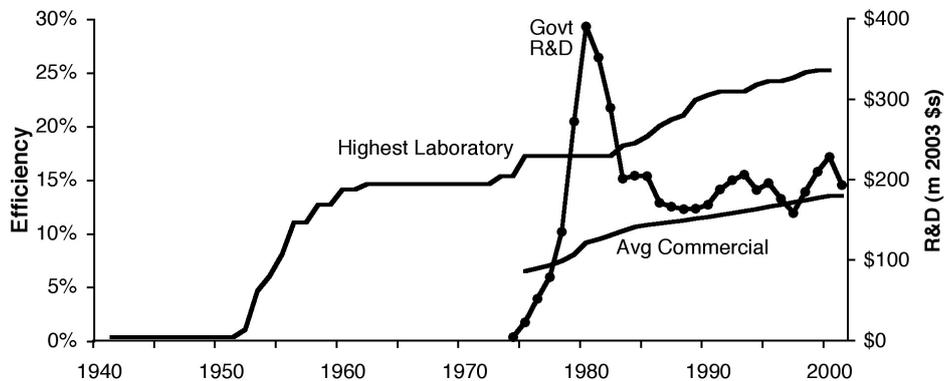
Figure 8: Public R&D and Crystalline PV efficiency (highest laboratory cells and average commercial modules). Data: Christensen (1985); Maycock (1994, 2002); Grubb and Vigotti (1997); Menanteau (2000); Green et al. (2001); Nemet and Kammen (2006).

(IEA, 2005).[17] Experience may help firms generate ideas for incremental efficiency improvements. It may also play a role in facilitating the transition from producing efficient cells of a few watts in a laboratory to producing large modules that can operate reliably under ambient conditions. Still, if the underlying driver of changes in commercial efficiency is incorporating laboratory improvements into commercial manufacturing, then competing hypotheses such as R&D offer more compelling explanations of efficiency improvements than learning-by-doing.

4.3   Silicon cost

Reductions in the cost of purified silicon were a spillover benefit from manufacturing improvements in the microprocessor industry. During the study period, the PV industry accounted for less than 15% of the world market (Menanteau, 2000) for purified silicon. Since the PV industry, until recently, did not purify its own silicon, but instead purchased silicon from producers whose main customers are in the much larger microprocessor industry where purity standards were higher, experience in the PV industry was irrelevant to silicon cost reductions.

4.4   Other factors

Learning-by-doing and experience play more important roles in the following factors. However, these factors together only account for 10% of the overall

---

[17]Although estimating the lags between R&D investments and their effects is difficult (Griliches, 1998).

change in cost.

Yield: Experience would have led to lower defect rates and the utilization of the entire wafer area.

Wafer size: Experience was probably important in enabling growing larger crystals and forming longer conductors from cell edges to electrical junctions.

Silicon consumption: Experience helped improve sawing techniques so that less crystal was lost as saw dust and thinner cells could be produced. The development of wire saws, a spillover technology from the radial tire industry, is less clearly related to experience.

Poly-crystalline share: Casting of rectangular multi-crystalline ingots was a new technology that only partially derives from experience with the Czochralski process for growing individual crystals.

5 Conclusions

Learning derived from experience is only one of several explanations for the cost reductions in PV. Its role in enabling changes in the two most important factors identified in this study—plant size and module efficiency—is small compared to those of expected future demand, risk management, R&D, and knowledge spillovers. This weak relationship suggests careful consideration of the conditions under which one should rely on experience curves to predict technical change. Further, the importance of market dynamics identified in Period 1 advises extra caution when applying experience curves to technologies at early stages, such as might currently be considered for fuel cells, as well as carbon capture and sequestration. Below, the importance of firms' profit margins is discussed as an additional area to consider. The ways in which a bottom-up model such as this one might be used as a complement to experience curves to enhance our understanding of future technical improvements are also described. As an example, this model is applied in a simple scenario exercise to gauge the plausibility of future cost targets.

5.1 Incorporating market structure

The model results for Period 1, 1975–79, indicate that prices are not a reliable proxy for costs. Sensitivity analysis confirms that our price-based experience curve is sensitive to changes in margin. A plausible scenario based on historical data is that margins fell from 30–50% in the early years to near zero at the end of the study period. Such a shift would reduce the learning ratio by 0.03–0.05 and extend the crossover year by 8–15 years.[18]

---

[18]Using assumptions of 15% annual new capacity growth and a target module price of $0.30/Watt.

Empirical data in this case study do not support three assumptions that are commonly made when applying the experience curve model using prices rather than costs: that margins are constant over time, that margins are close to zero with only minor perturbations, and that margins are often negative due to forward pricing. Indeed, earlier work pointed out that firms' recognition of the value of market domination, particularly during incipient commercialization, leads to unstable pricing behavior (BCG, 1972). An implication of the variation in the price–cost margin is that industry structure affects the learning rate. In the case of an industry such as PV that becomes more competitive over time, a price-based experience curve *over*-estimates the rate of technical progress.

One solution would be for future work to obtain real cost data where possible. An alternative would be to use an approach such as that of Irwin and Klenow (1994) in which costs can be derived from prices and market shares using Cournot equilibrium. However, comparisons of competing technologies are best made on the basis of prices, not costs, since prices reflect what a consumer faces in deciding whether and which technology to adopt. A more general approach would be to incorporate market dynamics into predictions of technological change. Industry concentration, market power, and changes in elasticity of demand affect prices. The HHI analysis above shows that concentration is not stable over time, especially if international trade is taken into account. The assumptions of perfect competition and that prices equal marginal cost are too strong in the early stages of the product life-cycle when the technology is improving rapidly, industry structure is unstable, and new types of customers are entering the market.

5.2   Technical factors and uncertainty

These results indicate that the confidence with which we use experience curves to predict technological change might be enhanced with analysis of the underlying technical and market dynamics. This type of approach is suggested by other studies that recommend multiple, complementary methods to inform policy decisions related to energy technology (Neij et al., 2003; Taylor et al., 2003). The combination of disaggregated technical factors and experience curves could inform policy decisions in three ways.

The explicit analysis of technical factors helps identify future barriers that could lead to discontinuities in the slope of the experience curve.[19] Assuming that some of these barriers may be surmountable, it may also help identify critical R&D areas. Identifying barriers might also allow us to predict, or at least gauge the probability of, discontinuities in the experience curve.

---

[19]For example, the theoretical limit on the efficiency of single-junction silicon-based PV modules of approximately $\eta = 0.29$ constrains the cost reductions we can expect in the future from this generation of PV technology.

Additionally, the unraveling of technical factors provides an avenue for the investigation of how influences other than cumulative capacity, such as R&D and knowledge spillovers, contribute to technological change. For example, in the case of PV, firm-level analysis of the drivers behind the doubling in commercial efficiency over the period may enhance our understanding of the roles of R&D, cumulative capacity, and the interaction of the two. This approach would complement econometric investigations of the roles of these factors, such as that of Watanabe et al. (2003).

Finally, a model such as this one allows us to work backwards so that one can identify the level of technical improvement in each factor required for a given cost improvement. For example, if reducing the cost of PV by an additional factor of 10 became a goal, one could ask how large manufacturing plants would need to be to provide adequate economies of scale. With the resulting estimate for plant size, one could then assess whether individual plants are likely to ever reach that scale and the extent to which economies of scale would still exist for facilities that large. This type of analysis provides a basis for assessing the likelihood that such an improvement might occur, which could help estimate uncertainty in the pace of future cost reductions.

5.3   Scenarios of target costs

One might also use such a model to test the plausibility of long-term targets for PV cost reduction. Here, two cost targets are examined using the following assumptions;

- Efficiency improves from 13.5% in 2001 to 25% in 2030 (SEIA, 2004).

- Wafer thickness declines by 25% per decade, its historical rate.

- Scaling factor is -0.13, the mid-range of studies of large scale PV.

- A net increase of one additional manufacturing plant per year.

- No changes to the price of silicon or yield.

We first test the industry's roadmap goal of $1.00/W modules in 2050 (SEIA, 2004). Using the assumptions above, the model indicates that meeting such a goal would imply an industry growth rate of 11% for the next 45 years. At that point, 1.3 TW of PV modules would have been installed at a cost of $1.5 trillion. In 2050, each of 71 PV plants would be manufacturing 1.9 GW of modules annually.[20] In this scenario, 51% of the cost reduction comes from scale and 48% comes from efficiency improvements. These results are roughly similar to projections for large scale PV discussed by Schaeffer et al. (2004) (46% and 31% respectively).

---

[20]A recent National Renewable Energy Laboratory study providing a detailed analysis of a 2.1 to 3.6 GW PV plant describes such a plant as feasible (Keshner and Arya, 2004).
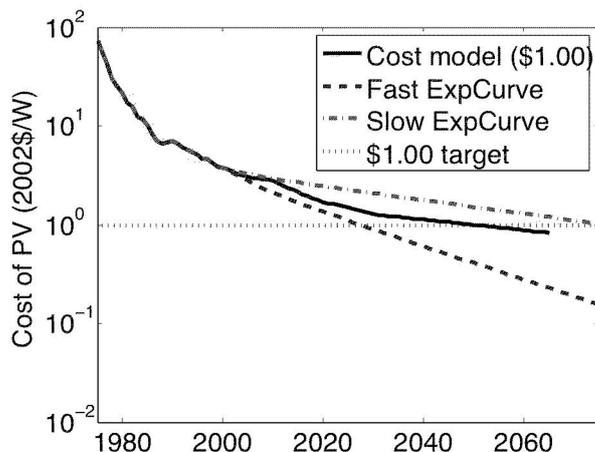
Figure 9: Scenarios comparing cost model, experience curves, and $1.00/W target price.

Others claim that $1.00/W modules would be prohibitively expensive once PV accounts for more than 5 to 10% of electricity generation. At such scale, the costs of electricity transmission and storage required to provide reliable service to an increasingly urbanizing world population would be so large that the cost of PV modules will have to be a minor component of the cost of PV-intensive energy systems. Under this line of reasoning, modules that cost $0.10/W in 2050 might be a goal. The model suggests that this goal is not possible given the assumptions above and an additional constraint that installed PV cannot exceed 30 TW in 2050.[21] In an extremely high-growth scenario in which PV capacity does grow to 30 TW in 2050, this model predicts that module costs would only fall to $0.63/Watt. Projected efficiency improvements, thinner wafers, and economies of scale are insufficient to bring the cost of crystalline PV to $0.10/W. If such a cost target is indeed required then other types of cost reductions, such as switching to other materials like thin-films and organics, will be necessary. Such a change would probably represent a shift to a new technological paradigm (Dosi, 1982) and might be best understood using a model of overlapping technological generations (Irwin and Klenow, 1994), rather than a single learning curve.

A similar scenario using experience curves provides a different outcome. A simple extension of the historical (1975-2001) learning rate, 0.23, using an assumption of 11% growth, would deliver $1.00/W modules in 2027 and $0.10/W in 2086 (Fig. 9). However, choosing which time period to use for calculating the learning rate expected in the future substantially affects the

---

[21]30 TW is a high end estimate for total world energy demand in 2050.
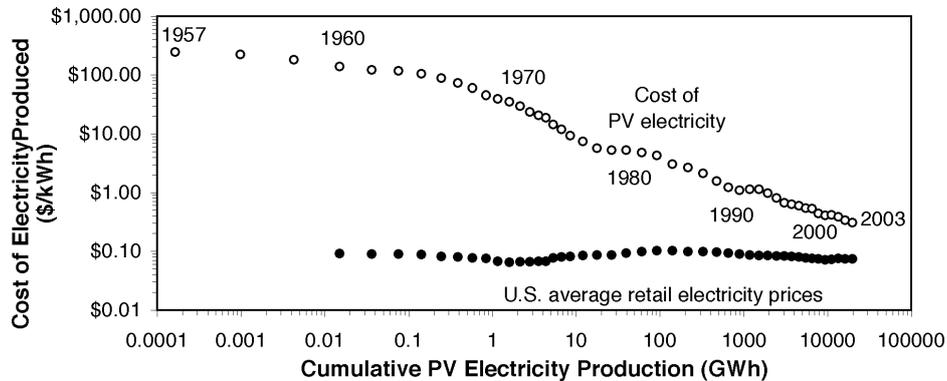
Figure 10: U.S. electricity prices and levelized cost of electricity produced from PV modules. Data: module and BOS prices (Wolf, 1974; Maycock, 2002; Strategies-Unlimited, 2003), lifetime (see Fig. 4), interest rates (Census, 2005), retail electricity prices (EIA, 2004).

outcome. For example, a more conservative learning rate, 0.10, that might be projected using more recent trends, would delay $1.00/W modules from 2027 until 2076. The experience curve does not necessarily produce a faster or slower result than the technical factors model. It does however produce radically different outcomes as a result of apparently inconsequential choices, such as the period over which the learning rate is calculated.

Finally, future work on PV might be expanded to consider not only capital cost but the cost of PV electricity produced. In assessing experience in wind power, Dannemand Andersen (2004) concluded that the cost of electricity is a more comprehensive measure of technological improvement than capital cost because technological competitiveness is ultimately based on decisions concerning electricity cost. Such an approach requires additional data that may be much more difficult to obtain. It also requires including factors such as interest rates whose level is exogenously determined but which are influential as they have varied by a factor of three over this study period. Using data on module and balance of system prices, system lifetimes, capacity factors, and interest rates, an experience curve for PV electricity is plotted in Fig. 10 and is compared to its primary technological competitor, retail electricity rates. Further work might consider what additional dynamics might need to be included to explain change in the cost of electricity curve, for example, the role of learning by doing among system installers.

5.4 Implications for modeling and policy

The inclusion of experience curves in models that optimize and simulate the costs of climate policy has enhanced their realism. Given the vast set

26

of results showing that energy technologies improve over time, incorporating experience curves represents a substantial improvement over omitting them and implicitly assuming a learning rate of zero. But the results of this study indicate that, at least for the case of PV, a broader set of influences than experience alone contributed to the rapid cost reductions in the past; one implication is that experience curves *over*-estimate the technical improvements that should be expected to accrue from deployment alone. As a result, these findings support the efforts by modelers to explore ways of incorporating explanatory variables other than cumulative capacity. Future models will need to take into account the effects of factors such as public and private R&D, knowledge spillovers, technological opportunity, and market dynamics to more realistically inform decisions about large investments in future energy technologies.

If innovation is central to making the cost of climate policy affordable and market failures require government support for innovation, then these results suggest that an efficient policy is unlikely to be one that simply relies on 'riding down the learning curve.' Future work might examine the benefits of a shift in focus toward the design of a set of policy instruments that create incentives for firms to make investments in cost-reducing activities, while acknowledging that payoffs are inherently uncertain and may take several years to be realized.

Acknowledgements

References

Paul S. Adler and Kim B. Clark. Behind the learning curve: A sketch of the learning process. *Management Science*, 37(3):267–281, 1991.

Armen Alchian. Reliability of progress curves in airframe production. *Econometrica*, 31(4):679–693, 1963.

Linda Argote and Dennis Epple. Learning curves in manufacturing. *Science*, 247(4945):920–924, 1990.

Kenneth Arrow. The economic implications of learning by doing. *The Review of Economic Studies*, 29(3):155–173, 1962.

W. Brian Arthur. Out-of-equilibrium economics and agent-based modeling. In K. Judd and L. Tesfatsion, editors, *Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics*. Elsevier/North-Holland, 2006.

Christian Azar and Hadi Dowlatabadi. A review of technical change in assessment of climate policy. *Annual Review of Energy and the Environment*, 24(1):513–544, 1999.

B. H. Bahk and M. Gort. Decomposing learning by doing in new plants. *Journal of Political Economy*, 101(4):561–583, 1993.

N. Baloff. Learning curve - some controversial issues. *Journal of Industrial Economics*, 14(3):275–282, 1966.

BCG. *Perspectives on Experience*. The Boston Consulting Group, Boston, 1972.

T. M. Bruton. General trends about photovoltaics based on crystalline silicon. *Solar Energy Materials and Solar Cells*, 72(1-4):3–10, 2002.

T. M. Bruton and J. M. Woodock. Multi-megawatt upscaling of silicon and thin film solar cell and module manufacturing (MUSIC FM). Technical Report CT94 0008, European Commission Project RENA, 1997.

Paolo Buonanno, Carlo Carraro, and Marzio Galeotti. Endogenous induced technical change and the costs of kyoto. *Resource and Energy Economics*, 25(1):11–34, 2003.

John G. Carlson. Cubic learning curves: Precision tool for labor estimating. *Manufacturing Engineering and Management*, 71(5):22–25, 1973.

Census. *U.S. Census Bureau: Statistical Abstract of the United States*. US Government Printing Office, Washington, DC, 2005.

Elmer Christensen. *Electricity from photovoltaic solar cells: Flat-Plate Solar Array Project of the U.S. Department of Energy's National Photovoltaics Program, 10 years of progress. JPL publication: 400-279*. Prepared by the Jet Propulsion Laboratory for the U.S. Dept. of Energy through an agreement with the National Aeronautics and Space Administration, Pasadena, CA, 1985.

Patrick Conley. Experience curves as a planning tool. *IEEE Spectrum*, 7(6): 63–68, 1970.

Dennis Costello and Paul Rappaport. The technological and economic development of photovoltaics. *Annual Review of Energy*, 5(1):335–356, 1980.

Per Dannemand Andersen. Sources of experience: theoretical considerations and empirical observations from danish wind energy technology. *International Journal of Energy Technology and Policy*, 2(1/2):33–51, 2004.

DOJ. Horizontal merger guidelines. Guidelines document, U.S. Department of Justice and the Federal Trade Commission, April 8 1997.

Giovanni Dosi. Technological paradigms and technological trajectories : A suggested interpretation of the determinants and directions of technical change. *Research Policy*, 11(3):147–162, 1982.

R.D. Duke and D.M. Kammen. The economics of energy market transformation initiatives. *The Energy Journal*, 20(4):15–64, 1999.

John M. Dutton and Annie Thomas. Treating progress functions as a managerial opportunity. *Academy of Management Review*, 9(2):235–247, 1984.

Ottmar Edenhofer, Kai Lessmann, Claudia Kemfert, Michael Grubb, and Jonathan Köhler. Induced technological change—exploring its implications for the economics of atmospheric stabilization: Synthesis report from the innovation modeling comparison project. *The Energy Journal*, 27(Special Issue on Endogenous Technological Change and the Economics of Atmospheric Stabilisation):57–108, 2006.

EIA. Annual energy review 2003: Table 8.10 average retail prices of electricity, 1960-2003. Report, Energy Information Administration, 2004.

L. Frantzis, E. Jones, C. Lee, M. Wood, and P. Wormser. Opportunities for cost reductions in photovoltaic modules. In *16th European Photovoltaic Solar Energy Conference*, pages 2100–2103, Glasgow, 2000.

Chris Freeman. The economics of technical change. *Cambridge Journal of Economics*, 18(5):463–514, 1994.

Chris Freeman and Francisco Louca. *As time goes by: from the industrial revolutions to the information revolution*. Oxford University Press, Oxford, 2001.

M. Ghannam, S. Sivoththaman, J. Poortmans, J. Szlufcik, J. Nijs, R. Mertens, and R. Van Overstraeten. Trends in industrial silicon solar cell processes. *Solar Energy*, 59(1-3):101–110, 1997.

Amal K. Ghosh. Solar cells: Present and future technology and cost. In R.F. Meyer, editor, *Long Term Energy Resources*, volume II, pages 761–771, Montreal, 1979. Pitman.

Adolf Goetzberger, Christopher Hebling, and Hans-Werner Schock. Photovoltaic materials, history, status and outlook. *Materials Science and Engineering*, R 40:1–46, 2003.

M. A. Green, J. Zhao, A. Wang, and S. R. Wenham. Progress and outlook for high-efficiency crystalline silicon solar cells. *Solar Energy Materials and Solar Cells*, 65(1-4):9–16, 2001.

Zvi Griliches. *R&D and productivity: the econometric evidence.* University of Chicago Press, Chicago, 1998.

Michael Grubb and Roberto Vigotti. *Renewable Energy Strategies for Europe, Volume II.* Earthscan, London, 1997.

Michael Grubb, Jonathan Köhler, and Dennis Anderson. Induced technical change in energy and environmental modeling: Analytic approaches and policy implications. *Annual Review of Energy and the Environment*, 27: 271–308, 2002.

Harald Gruber. Trade policy and learning by doing: the case of semiconductors. *Research Policy*, 25:723–739, 1996.

A. Grübler, N. Nakicenovic, and D. G. Victor. Modeling technological change: Implications for the global environment. *Annual Review of Energy and the Environment*, 24:545–569, 1999a. Review.

Arnulf Grübler, Nebojsa Nakicenovic, and David G. Victor. Dynamics of energy technologies and global change. *Energy Policy*, 27:247–280, 1999b.

Bronwyn Hall and Jacques Mairesse. Empirical studies of innovation in the knowledge-driven economy. *Economics of Innovation and New Technology*, 15:289–299, 2006.

G. Hall and S. Howell. The experience curve from the economist's perspective. *Strategic Management Journal*, 6(3):197–212, 1985.

O.C. Herfindahl. *Concentration in the US Steel Industry.* PhD thesis, Columbia University, 1950.

Albert O. Hirschman. *National power and the structure of foreign trade.* University of California press, Berkeley and Los Angeles, 1945.

IEA. International energy agency, energy technology R&D statistics, 2005.

Douglas A. Irwin and Peter J. Klenow. Learning-by-doing spillovers in the semiconductor industry. *Journal of Political Economy*, 102(6):1200–1227, 1994.

Arnulf Jaeger-Waldau. PV status report 2004: Research, solar cell production and market implementation of photovoltaics. Technical Report EUR 21390 EN, European Commission, DG JRC, Institute for Environment and Sustainability, Renewable Energies Unit, October 2004.

JPEA. Shipping statistics of PV cells and modules, FY2001. Newsletter No. 02-03, Japanese Photovoltaic Energy Association (JPEA), July 2002.

M. Junginger, A. Faaij, and W.C. Turkenburg. Global experience curves for wind farms. *Energy Policy*, 33:133–150, 2005.

Daniel M. Kammen and Gregory F. Nemet. Reversing the incredible shrinking U.S. energy R&D budget. *Issues in Science and Technology*, 22(1): 84–88, 2005.

M.S. Keshner and R. Arya. Study of the potential cost reductions resulting from super-large-scale manufacturing of PV modules. Subcontractor Report NREL/SR-520-36846, National Renewable Energy Laboratory, October 2004.

Roger G. Little and Michael J. Nowlan. Crystalline silicon photovoltaics: the hurdle for thin films. *Progress in Photovoltaics: Research and Applications*, 5(5):309–315, 1997.

Erik Strojer Madsen, Camilla Jensen, and Jorgen Drud Hansen. Scale in technology and learning by doing in the windmill industry. *Journal for International Business and Entrepreneurship Development*, 1(2), 2003.

Karl Marx. *Capital*. Harmondsworth, Middlesex, England, 1867.

Paul D. Maycock. The world photovoltaic market. Report, PV Energy Systems, January 2002.

Paul D. Maycock. PV market update. *Renewable Energy World*, 6(4):84–101, 2003.

Paul D. Maycock. PV news. Report, PV Energy Systems, 2005.

Paul D. Maycock. U.S.-Japanese competition for the world photovoltaic market. In Charles K. Ebinger and Ronald A. Morse, editors, *U.S.-Japanese Energy Relations: Cooperation and Competition*, pages 207–217. Westview Press, London, 1984.

Paul D. Maycock. International photovoltaic markets, developments, and trends forecast to 2010. In *Conference Record of the twenty-fourth IEEE Photovoltaic Specialists Conference*, volume 1, pages 694–699. IEEE, 1994.

Paul D. Maycock. Cost reduction in PV manufacturing: Impact on grid-connected and building-integrated markets. *Solar Energy Materials and Solar Cells*, 47:37–45, 1997.

Paul D. Maycock and Edward N. Stirewalt. *A Guide to the Photovoltaic Revolution.* Rodale Press, Emmaus, PA, 1985.

Alan McDonald and Leo Schrattenholzer. Learning rates for energy technologies. *Energy Policy*, 29:255–261, 2001.

Philippe Menanteau. Learning from variety and competition between technological options for generating photovoltaic electricity. *Technological Forecasting and Social Change*, 63(1):63–80, 2000.

Sabine Messner. Endogenized technological learning in an energy systems model. *Journal of Evolutionary Economics*, 7(3):291–313, 1997.

Asami Miketa and Leo Schrattenholzer. Experiments with a methodology to model the role of R&D expenditures in energy technology learning processes; first results. *Energy Policy*, 32:1679–1692, 2004.

Richard L. Mitchell, C. Edwin Witt, Richard King, and Douglas Ruby. PVMaT advances in the photovoltaic industry and the focus of future PV manufacturing R&D. In *Conference Record of the 29th IEEE Photovoltaic Specialists Conference*, pages 1444–1447, 2002.

Robert M. Moore. Czochralski silicon solar cell modules: Present cost and future prospects. *Solar Cells*, 5:313–329, 1982.

David C. Mowery and Nathan Rosenberg. *Paths of Innovation: Technological Change in 20th-Century America.* Cambridge University Press, Cambridge, 1998.

Nebojsa Nakicenovic and Keywan Riahi. An assessment of technological change across selected energy scenarios. Research Report RR-02-005, IIASA, May 2002.

Lena Neij, Per Dannemand Andersen, and Michael Durstewitz. The use of experience curves for assessing energy policy programs. In *Proceedings of the EU/IEA Workshop on Experience Curves: A tool for energy policy analysis and design*, Paris, 2003.

Gregory F. Nemet and Daniel M. Kammen. U.S. energy research and development: Declining investment, increasing need, and the feasibility of expansion. *Energy Policy*, (in press), 2006.

William D. Nordhaus. Modeling induced innovation in climate change policy. In Arnulf Grubler, Nebojsa Nakicenovic, and William D. Nordhaus,

editors, *Technological change and the environment*, pages 182–209. Resources for the Future, International Institute for Applied Systems Analysis, Washington, DC, 2002.

Steven Payson. Quality improvement versus cost reduction: A broader perspective on evolutionary economic change. *Technology Analysis and Strategic Management*, 10(1):69–88, 1998.

Leonard Rapping. Learning and world war II production functions. *The Review of Economic Statistics*, 47(1):81–86, 1965.

David J. Roessner. Government-industry relationships in technology commercialization: The case of photovoltaics. *Solar Cells*, 5(2):101–134, 1982.

A. Rohatgi. Road to cost-effective crystalline silicon photovoltaics. In *Proceedings of 3rd World Conference on Photovoltaic Energy Conversion*, volume A, pages 829–834, Osaka, Japan, 2003.

Paul M. Romer. Endogenous technological change. *The Journal of Political Economy*, 98(5):S71–S102, 1990.

Nathan Rosenberg. *Inside the Black Box: Technology and Economics*. Cambridge University Press, Cambridge, 1982.

Nathan Rosenberg. *Exploring the Black Box: Technology, Economics, and History*. Cambridge University Press, Cambridge, 1994.

Dominique Sarti and Roland Einhaus. Silicon feedstock for the multicrystalline photovoltaic industry. *Solar Energy Materials and Solar Cells*, 72(1-4):27–40, 2002.

G.J. Schaeffer, A.J. Seebregts, L.W.M. Beurskens, H.H.C. de Moor, E.A. Alsema, W. Sark, M. Durstewicz, M. Perrin, P. Boulanger, H. Laukamp, and C. Zuccaro. Learning from the sun; analysis of the use of experience curves for energy policy purposes: The case of photovoltaic power. final report of the PHOTEX project. Report ECN DEGO: ECN-C–04-035, ECN Renewable Energy in the Built Environment, 2004.

Joseph A. Schumpeter. *The Theory of Economic Development*. Harvard University Press, Cambridge, MA, 1934.

Joseph A. Schumpeter. *Capitalism, socialism, and democracy*. Harper and brothers, New York, London, 2d ed. edition, 1947.

SEIA. Our solar power future: The photovoltaics industry roadmap through 2030 and beyond. Report, Solar Energy Industries Association, September 2004.

Eytan Sheshinski. Tests of the learning by doing hypothesis. *Review of Economics and Statistics*, 49(4):568–578, 1967.

Adam Smith. Chapter 1: Of the division of labor. In *An Inquiry into the Nature and the Causes of the Wealth of Nations*. London, 1776.

Strategies-Unlimited. Photovoltaic five-year market forecast, 2002-2007. Technical Report PM-52, Strategies Unlimited, March 2003.

Thomas Surek. Progress in U.S. photovoltaics: Looking back 30 years and looking ahead 20. In *3rd World Conference on Photovoltaic Energy Conversion*, Osaka, Japan, 2003.

Richard M. Swanson. A vision for crystalline silicon photovoltaics. *Progress in Photovoltaics: Research and Applications*, 14(5):443–453, 2006.

M. Symko-Davies, R.L. Mitchell, C.E. Witt, H.P. Thomas, R. King, and D. Ruby. Decade of PV industry R&D advances in silicon module manufacturing. In *Record of the Twenty-Eighth IEEE Photovoltaic Specialists Conference, 2000. Conference*, pages 1460–1463, Anchorage, AK USA, 2000.

Margaret R. Taylor and Gregory F. Nemet. The interaction between policy and innovation in clean energy technologies. In *USAEE/IAEE/ASSA meetings: Current Issues in Energy Economics and Energy Modeling*, Boston, 2006.

Margaret R. Taylor, Edward S. Rubin, and David A. Hounshell. Effect of government actions on technological innovation for SO_2 control. *Environmental Science and Technology*, 37(20):4527–4534, 2003.

Peter Thompson. How much did the liberty shipbuilders learn? new evidence for an old case study. *Journal of Political Economy*, 109(1):103–137, 2001.

Bob van der Zwaan and Ari Rabl. The learning potential of photovoltaics: Implications for energy policy. *Energy Policy*, 32:1545–1554, 2004.

Chihiro Watanabe, Kouji Wakabayashi, and Toshinori Miyazawa. Industrial dynamism and the creation of a "virtuous cycle" between R&D, market growth and price reduction - the case of photovoltaic power generation (PV) development in Japan. *Technovation*, 20:299–312, 2000.

Chihiro Watanabe, A. Nagamatsu, and C. Griffy-Brown. Behavior of technology in reducing prices of innovative goods—an analysis of the governing factors of variance of PV module prices. *Technovation*, 23:423–436, 2003.

Clas-Otto Wene. Experience curves for technology policy. Technical report, International Energy Agency, 2000.

Robert H. Williams and Gregory Tarzian. A benefit-cost analysis of accelerated development of photovoltaic technology. PU-CEES Report No. 281, The Center for Energy and Environmental Studies - Princeton University, October 1993.

Peter Woditsch and Wolfgang Koch. Solar grade silicon feedstock supply for PV industry. *Solar Energy Materials and Solar Cells*, 72(1-4):11–26, 2002.

John H. Wohlgemuth. Long term photovoltaic reliability. In *NCPV and Solar Program Review Meeting*, pages 179–182, Denver, CO, 2003.

Martin Wolf. Historic development of photovoltaic power generation. In Helmut R. Loesch, editor, *International Conference on Photovoltaic Power Generation*, pages 49–65, Hamburg, Germany, 1974. Deutsche Gesellschaft fuer Luft- und Raumfahrt.

T. P. Wright. Factors affecting the costs of airplanes. *Journal of the Aeronautical Sciences*, 3:122–128, 1936.

Louis E. Yelle. The learning curve: Historical review and comprehensive survey. *Decision Science*, 10:302–328, 1979.

NOTE DI LAVORO DELLA FONDAZIONE ENI ENRICO MATTEI

Fondazione Eni Enrico Mattei Working Paper Series

Our Note di Lavoro are available on the Internet at the following addresses:

http://www.feem.it/Feem/Pub/Publications/WPapers/default.html
http://www.ssrn.com/link/feem.html
http://www.repec.org
http://agecon.lib.umn.edu

NOTE DI LAVORO PUBLISHED IN 2006

CTN	80.2006	*Maria MONTERO*: <u>Inequity Aversion May Increase Inequity</u>
CCMP	81.2006	*Vincent M. OTTO, Andreas LÖSCHEL and John REILLY*: <u>Directed Technical Change and Climate Policy</u>
CSRM	82.2006	*Nicoletta FERRO*: <u>Riding the Waves of Reforms in Corporate Law, an Overview of Recent Improvements in Italian Corporate Codes of Conduct</u>
CTN	83.2006	*Siddhartha BANDYOPADHYAY and Mandar OAK*: <u>Coalition Governments in a Model of Parliamentary Democracy</u>
PRCG	84.2006	*Raphaël SOUBEYRAN*: <u>Valence Advantages and Public Goods Consumption: Does a Disadvantaged Candidate Choose an Extremist Position?</u>
CCMP	85.2006	*Eduardo L. GIMÉNEZ and Miguel RODRÍGUEZ*: <u>Pigou's Dividend versus Ramsey's Dividend in the Double Dividend Literature</u>
CCMP	86.2006	*Andrea BIGANO, Jacqueline M. HAMILTON and Richard S.J. TOL*: <u>The Impact of Climate Change on Domestic and International Tourism: A Simulation Study</u>
KTHC	87.2006	*Fabio SABATINI*: <u>Educational Qualification, Work Status and Entrepreneurship in Italy an Exploratory Analysis</u>
CCMP	88.2006	*Richard S.J. TOL*: <u>The Polluter Pays Principle and Cost-Benefit Analysis of Climate Change: An Application of Fund</u>
CCMP	89.2006	*Philippe TULKENS and Henry TULKENS*: <u>The White House and The Kyoto Protocol: Double Standards on Uncertainties and Their Consequences</u>
SIEV	90.2006	*Andrea M. LEITER and Gerald J. PRUCKNER*: <u>Proportionality of Willingness to Pay to Small Risk Changes – The Impact of Attitudinal Factors in Scope Tests</u>
PRCG	91.2006	*Raphäel SOUBEYRAN*: <u>When Inertia Generates Political Cycles</u>
CCMP	92.2006	*Alireza NAGHAVI*: <u>Can R&D-Inducing Green Tariffs Replace International Environmental Regulations?</u>
CCMP	93.2006	*Xavier PAUTREL*: <u>Reconsidering The Impact of Environment on Long-Run Growth When Pollution Influences Health and Agents Have Finite-Lifetime</u>
CCMP	94.2006	*Corrado Di MARIA and Edwin van der WERF*: <u>Carbon Leakage Revisited: Unilateral Climate Policy with Directed Technical Change</u>
CCMP	95.2006	*Paulo A.L.D. NUNES and Chiara M. TRAVISI*: <u>Comparing Tax and Tax Reallocations Payments in Financing Rail Noise Abatement Programs: Results from a CE valuation study in Italy</u>
CCMP	96.2006	*Timo KUOSMANEN and Mika KORTELAINEN*: <u>Valuing Environmental Factors in Cost-Benefit Analysis Using Data Envelopment Analysis</u>
KTHC	97.2006	*Dermot LEAHY and Alireza NAGHAVI*: <u>Intellectual Property Rights and Entry into a Foreign Market: FDI vs. Joint Ventures</u>
CCMP	98.2006	*Inmaculada MARTÍNEZ-ZARZOSO, Aurelia BENGOCHEA-MORANCHO and Rafael MORALES LAGE:* <u>The Impact of Population on CO2 Emissions: Evidence from European Countries</u>
PRCG	99.2006	*Alberto CAVALIERE and Simona SCABROSETTI*: <u>Privatization and Efficiency: From Principals and Agents to Political Economy</u>
NRM	100.2006	*Khaled ABU-ZEID and Sameh AFIFI*: <u>Multi-Sectoral Uses of Water & Approaches to DSS in Water Management in the NOSTRUM Partner Countries of the Mediterranean</u>
NRM	101.2006	*Carlo GIUPPONI, Jaroslav MYSIAK and Jacopo CRIMI*: <u>Participatory Approach in Decision Making Processes for Water Resources Management in the Mediterranean Basin</u>
CCMP	102.2006	*Kerstin RONNEBERGER, Maria BERRITTELLA, Francesco BOSELLO and Richard S.J. TOL*: <u>Klum@Gtap: Introducing Biophysical Aspects of Land-Use Decisions Into a General Equilibrium Model A Coupling Experiment</u>
KTHC	103.2006	*Avner BEN-NER, Brian P. McCALL, Massoud STEPHANE, and Hua WANG*: <u>Identity and Self-Other Differentiation in Work and Giving Behaviors: Experimental Evidence</u>
SIEV	104.2006	*Aline CHIABAI and Paulo A.L.D. NUNES*: <u>Economic Valuation of Oceanographic Forecasting Services: A Cost-Benefit Exercise</u>
NRM	105.2006	*Paola MINOIA and Anna BRUSAROSCO*: <u>Water Infrastructures Facing Sustainable Development Challenges: Integrated Evaluation of Impacts of Dams on Regional Development in Morocco</u>
PRCG	106.2006	*Carmine GUERRIERO*: <u>Endogenous Price Mechanisms, Capture and Accountability Rules: Theory and Evidence</u>
CCMP	107.2006	*Richard S.J. TOL, Stephen W. PACALA and Robert SOCOLOW*: <u>Understanding Long-Term Energy Use and Carbon Dioxide Emissions in the Usa</u>
NRM	108.2006	*Carles MANERA and Jaume GARAU TABERNER*: <u>The Recent Evolution and Impact of Tourism in the Mediterranean: The Case of Island Regions, 1990-2002</u>
PRCG	109.2006	*Carmine GUERRIERO*: <u>Dependent Controllers and Regulation Policies: Theory and Evidence</u>
KTHC	110.2006	*John FOOT* (lxxx): <u>Mapping Diversity in Milan. Historical Approaches to Urban Immigration</u>
KTHC	111.2006	*Donatella CALABI*: <u>Foreigners and the City: An Historiographical Exploration for the Early Modern Period</u>
IEM	112.2006	*Andrea BIGANO, Francesco BOSELLO and Giuseppe MARANO*: <u>Energy Demand and Temperature: A Dynamic Panel Analysis</u>
SIEV	113.2006	*Anna ALBERINI, Stefania TONIN, Margherita TURVANI and Aline CHIABAI*: Paying for Permanence: <u>Public Preferences for Contaminated Site Cleanup</u>
CCMP	114.2006	*Vivekananda MUKHERJEE and Dirk T.G. RÜBBELKE*: <u>Global Climate Change, Technology Transfer and Trade with Complete Specialization</u>
NRM	115.2006	*Clive LIPCHIN*: <u>A Future for the Dead Sea Basin: Water Culture among Israelis, Palestinians and Jordanians</u>
CCMP	116.2006	*Barbara BUCHNER, Carlo CARRARO and A. Denny ELLERMAN*: <u>The Allocation of European Union Allowances: Lessons, Unifying Themes and General Principles</u>
CCMP	117.2006	*Richard S.J. TOL*: <u>Carbon Dioxide Emission Scenarios for the Usa</u>