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Beyond the learning curve: factors influencing cost reductions in photovoltaics

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Abstract

The extent and timing of cost-reducing improvements in low-carbon energy systems are important sources of uncertainty in future levels of greenhouse-gas emissions. Models that assess the costs of climate change mitigation policy, and energy policy in general, rely heavily on learning curves to include technology dynamics. Historically, no energy technology has changed more dramatically than photovoltaics (PV), the cost of which has declined by a factor of nearly 100 since the 1950s. Which changes were most important in accounting for the cost reductions that have occurred over the past three decades? Are these results consistent with the notion that learning from experience drove technical change? In this paper, empirical data are assembled to populate a simple model identifying the most important factors affecting the cost of PV. The results indicate that learning from experience, the theoretical mechanism used to explain learning curves, only weakly explains change in the most important factors—plant size, module efficiency, and the cost of silicon. Ways in which the consideration of a broader set of influences, such as technical barriers, industry structure, and characteristics of demand, might be used to inform energy technology policy are discussed.

Keywords: Photovoltaics; Learning curves; Experience curves

1. Introduction

The cost of photovoltaics (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 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 energy technology. 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,

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1999). Studies in the 1990s began to use the learning curve to treat technology dynamically (Williams and Tarzian, 1993; Grübler et al., 1999) 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. The learning curve model

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 become more efficient as they produce more units (Wright, 1936; Alchian, 1963; Rapping, 1965). 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.[1] 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:

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

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

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

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 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 flows

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

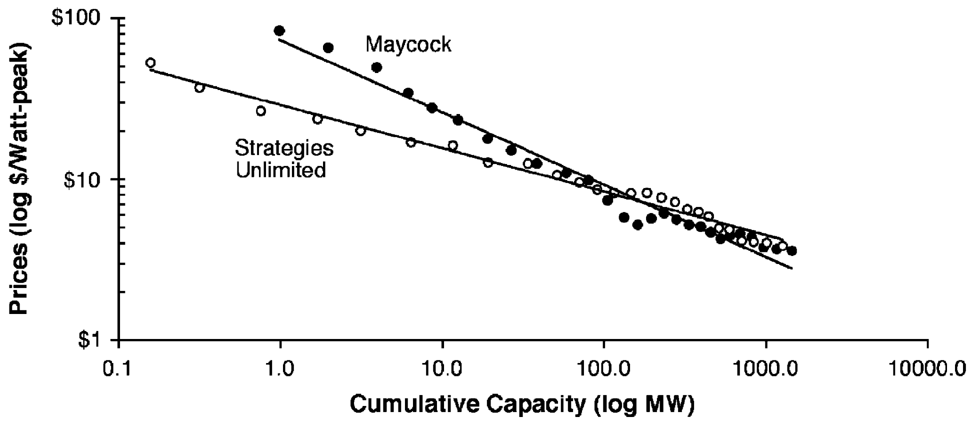

Fig. 1. Experience curves for PV modules and sensitivity of learning rate to underlying data. *Data*: Maycock (2002) and Strategies-Unlimited (2003).

and inventive output. Still, data quality and uncertainty are infrequently explicitly assessed 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. 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.[2] Finally, the reduction of the complex process of innovation to a single parameter, the learning rate, facilitates its inclusion in energy supply and computable general equilibrium 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. 1 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 give 0.17.[3] What may appear 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 very sensitive to such variation. Wene (2000) observes this sensitivity as well and recommends an ongoing 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.

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, to experience curves aggregating industries and

[2] 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).

[3] Note that the largest differences between the price surveys are in the early stages of commercialization when using experience curves may be least appropriate.

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 Schrattenholzer, 2004), and the interactions between R&D and diffusion (Watanabe et al., 2000). The amount of data required for parameter estimation 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).[4] The dependent variable is limited to cost normalized by a single measure of performance—for example, hours of labor/aircraft, \$/W, 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. Approach

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.

This study includes the period from nascent commercialization, 1975, 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.[5] 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.[6] 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 competing technologies remained in the development stage and 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

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

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

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

factors over the study period, 1975–2001, was compiled and a model to quantify the impact of the change in each factor on module cost developed.

2. Cost model methodology

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 $\$/W_{peak}$ is the dependent variable in the model.[7] 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 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, 2002; Grubb and Vigotti, 1997). The model simulates the impact of efficiency changes on module cost using

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

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, $\Delta C_{t(\eta)}$. As an example, a doubling in efficiency would, ceteris paribus, reduce \$/W 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, 2002; Ghannam et al., 1997; 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:[8]

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

2.4. Yield

Improved cell and module processing techniques have increased yield, the proportion of functioning units available at the end of the manufacturing process (YD) (Little and Nowlan, 1997; Sarti and Einhaus, 2002; Rohatgi, 2003).[9] 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:

$$\Delta C_{t(YD)} = C_{t-1}\left(\frac{YD_{t-1}}{YD_t} - 1\right). \tag{6}$$

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

[7] All monetary values presented in this study are in US dollars at constant 2002 prices.

[8] '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 100–500 MW/year in these studies.

[9] Yield improvements in the manufacturing of wafers are captured in Section 2.7.

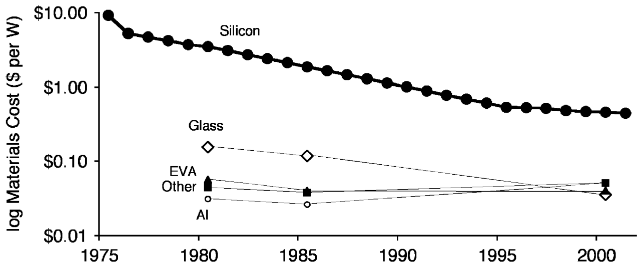

Fig. 2. Materials costs for PV modules. *Data*: Christensen (1985) and Maycock (2002).

obtained in Eq. (8):

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

$$\Delta C_{t(\mathrm{PS})} = (\mathrm{PS}_t - \mathrm{PS}_{t-1})(\mathrm{PC}_{t-1} - C_{t-1}). \tag{8}$$

2.6. Silicon cost

The basic material input for producing PV wafers is solar-grade silicon feedstock, the cost of which (SC) has fallen by nearly a factor of 12 over the study period (Ghosh, 1979; Costello and Rappaport, 1980; Bruton, 2002; Swanson, 2004) (Fig. 2). 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.[10] 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:

$$\Delta C_{t(\mathrm{SC})} = (\mathrm{SC}_t\mathrm{SU}_{t-1}) - (\mathrm{SC}_{t-1}\mathrm{SU}_{t-1}). \tag{9}$$

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, 2004). Manufacturers have accomplished this change by reducing the thickness of silicon wafers from 500 to 250 μm and by reducing kerf losses, from the sawing of each wafer, from 250 to 190 μm. The amount of silicon saved each year is calculated and is combined with data on silicon cost to estimate the effect on module cost:

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

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, 2004). 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):

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

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):[11]

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

Table 1
Summary of model results, 1975–2001

Factor	Change	Effect on module cost ($/W)
Module efficiency	6.3% → 13.5%	−17.97
Plant size	76 kW/yr → 14 MW/yr	−13.54
Si cost	300 $/kg → 25 $/kg	−7.74
Si consumption	30 g/W → 18 g/W	−1.06
Yield	87% → 92%	−0.87
Wafer size	45 cm^2 → 180 cm^2	−0.67
Poly-crystal	0% → 50%	−0.38
Sum of factors		−42.24
Actual change		−70.36
Residual		−28.13

3. Model results: plant size, efficiency, and silicon cost

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 less than 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

[10]Note that in Fig. 2 a log scale is necessary to show the changes in the other materials.

[11]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.

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 signaled the start of a viable commercial market. Second, global public R&D spending on PV reached its peak, \$370m, in 1980 (IEA, 2004). 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 policies.

3.1. Period 1: 1975–79

In the first 4 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. Two other factors, yield and silicon consumption, were of less importance but played a role. Wafer size and poly-crystalline share 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 59% 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 4 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. Shift to lower quality reduces cost

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 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 20 years. Terrestrial applications, on the other hand, could 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. 3). 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. Change in demand elasticity decreases margins

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

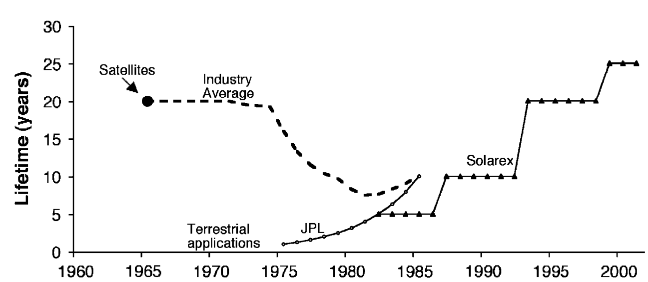

Fig. 3. Module lifetime. *Data*: Moore (1982), Christensen (1985) and Wohlgemuth (2003).

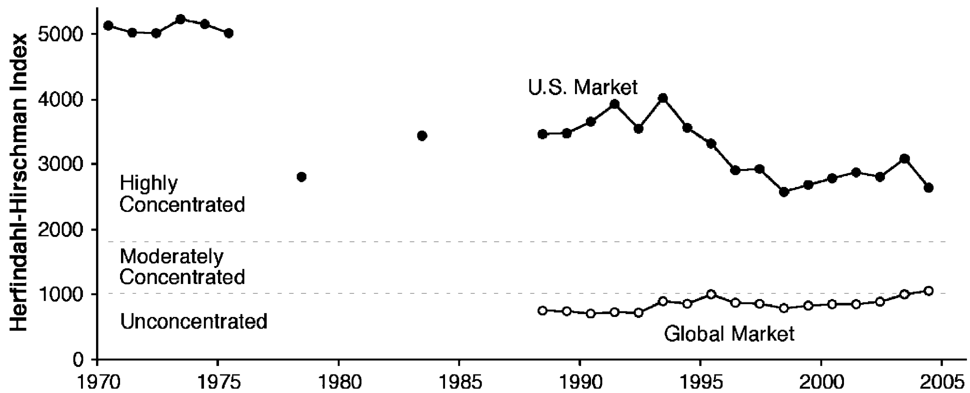

Fig. 4. Industry concentration (Herfindahl–Hirschman Index). *Data*: Wolf (1974), Roessner (1982) and Maycock (1984, 1994, 2002, 2005).

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 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. Increasing 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 US firms shipping terrestrial PV from 1970 to 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. 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.[12] The data show a trend to a less concentrated US market during Period 1, 1975–79 (Fig. 4). Concentration in the global market remained stable in the 1990s, the period for which comprehensive worldwide data are 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 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 US space program, accounted for almost all sales. In the terrestrial market, in contrast, the US 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 20 kW 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. The declining cost of silicon accounts for 12%. Yield, silicon consumption, wafer size, and poly-crystalline share each have impacts of 3% or less.

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

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	45 cm^2 → 180 cm^2	−0.67
Si consumption	28 g/W → 18 g/W	−0.62
Yield	88% → 92%	−0.43
Poly-crystal	0% → 50%	−0.38
Sum of factors		−20.48
Actual change		−21.62
Residual		−1.13

3.3. Sensitivity analysis

The model is most sensitive to uncertainty in three areas: the change in plant size, the scaling factor, and the change in efficiency.[13] Fig. 5 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 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 (a) module efficiency and plant size were the most important contributors to cost reduction, (b) cost of silicon was moderately important, and (c) 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.

4. Roles of experience and learning

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.[14] 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 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 2 years (Maycock, 2005). Sharp is considering construction of a 500 MW/year plant in 2006, which would amount to a 10-fold expansion in the firm's capacity in only 5 years. In the rapid expansions of the past 5 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 much bigger roles than learning by experience in enabling cost reductions. These results support the finding by 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 show that of the 16 advances in efficiency since 1980

[13] 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 to 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.

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

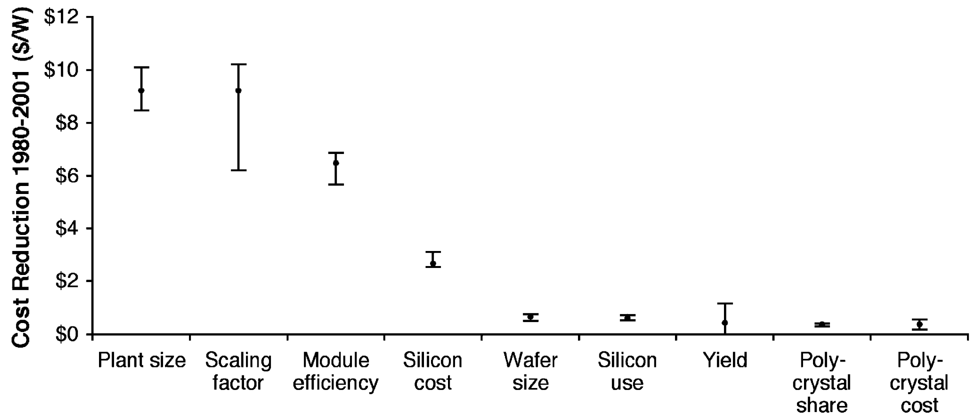

Fig. 5. Sensitivity of model results to uncertainty in data and parameters, 1980–2001.

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

(Surek, 2003),[15] 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 to 1990 (Fig. 6) immediately followed the unprecedented $1.5b investment in worldwide PV R&D in the previous 5 years (IEA, 2004). 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.

[15]'Advances' are defined as new production of cells that resulted in a cell efficiency higher than any previous laboratory result.

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, has never purified its own silicon, but instead has purchased silicon from producers whose main customers are in the much larger microprocessor industry where purity standards are 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 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.

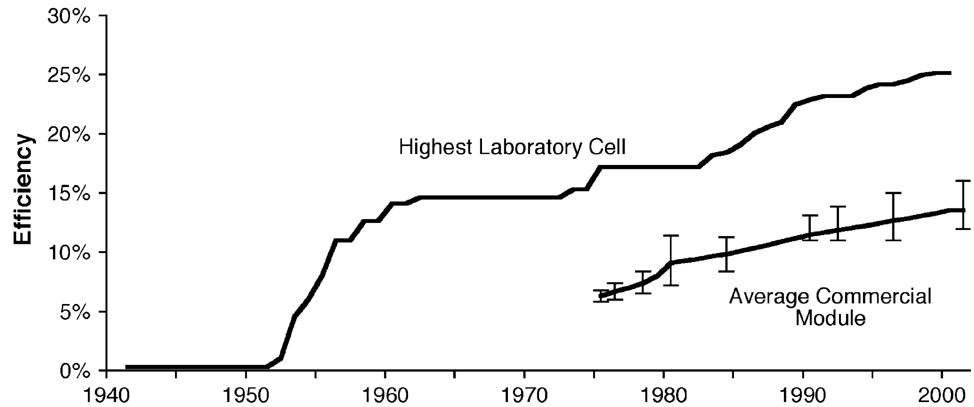

Fig. 6. Crystalline PV efficiency: highest laboratory cells vs. average commercial modules. *Data*: Christensen (1985), Maycock (1994, 2002), Grubb and Vigotti (1997), Menanteau (2000) and Green et al. (2001).

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 we can 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. Addressing market dynamics

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.[16]

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. 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

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

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.[17] 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.

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 how likely it is 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; and
- 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.[18] 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).

Others claim that $1.00/W modules would be prohibitively expensive once PV accounts for more than 5–10% 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.[19] 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/W. 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 technological generations model (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. 7). However, choosing which time period to use for calculating the learning rate expected in the future substantially affects the outcome.

[17] 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.

[18] A recent National Renewable Energy Laboratory study providing a detailed analysis of a 2.1–3.6 GW PV plant describes such a plant as feasible (Keshner and Arya, 2004).

[19] 30 TW is a high end estimate for total world energy demand in 2050.

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. 8 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.

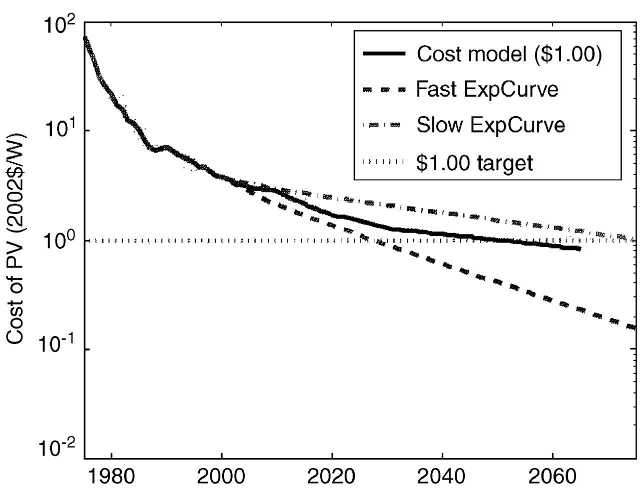

Fig. 7. Scenarios comparing cost model, experience curves, and \$1.00/W target price.

5.4. Summary

Over the coming decades, investments on the order of a trillion dollars will have to be made if PV is to contribute to energy supply at terawatt scale. The magnitude of such a project demands more sophisticated models for estimating the pace and likelihood of future improvements. The evidence presented here indicates that a much broader set of influences than experience alone contributed to the rapid cost reductions in the past. Future models will need to take into account other factors such as R&D, knowledge spillovers, and market dynamics to more realistically inform decisions about large investments in future energy technologies.

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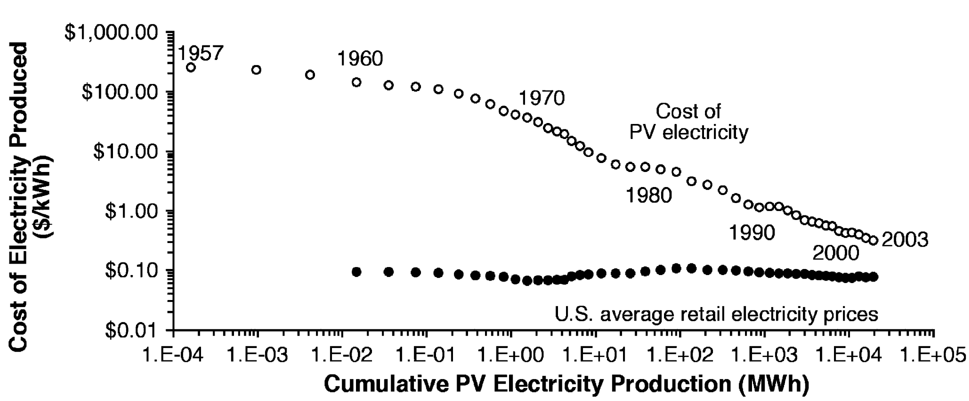

Fig. 8. US electricity prices and levelized cost of electricity produced from PV modules. *Data*: module and BOS prices (Wolf, 1974; Maycock, 2002; Strategies-Unlimited, 2003), lifetime (see Fig. 3), interest rates (Census, 2005), and retail electricity prices (EIA, 2004).

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