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Technical Change in Photovoltaics and the Applicability of the Learning Curve Model

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Abstract

The extent and timing of cost-reducing improvements in low-carbon energy systems are important sources of uncertainty in the future levels of greenhouse-gas emissions. Models that assess the costs of climate change mitigation policy rely heavily on learning curves to incorporate changes in technology. 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 widely held learning-by-doing theory of technological change? We gather empirical data and populate a simple model to identify the most important factors affecting the cost of PV. We find that the learning curve theory only weakly explains change in the most important factors—plant size, module efficiency, and the cost of silicon.

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Gregory F. Nemet

1 Introduction

Models of future greenhouse-gas (GHG) concentrations and surface temperatures are highly sensitive to assumptions about the improvement and deployment of low-carbon energy technologies (Nakicenovic et al. 2000). 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 early 1990s began using the learning curve to endogenate changes in technology based on a power function relationship between cumulative production and cost (Williams and Tarzian 1993, Grübler, Nakicenovic and Victor 1999). In this paper we begin with a discussion of the advantages and limitations of the learning curve theory of technical change. We then test the applicability of the learning curve to photovoltaics (PV) by constructing an engineering-based model and comparing that to the learning curve.

We use the case of PV to test the model for several reasons. The cost of PV has declined by a factor of 100 since the 1950s, more than any other energy technology in the period. Markets for PV are expanding rapidly, recently in excess of 30% per year. Also, long-term emissions scenarios depend heavily on future cost reductions in PV. Nakicenovic and Riahi (2002) reviewed scenarios of emissions levels, and found that the median amount of PV deployed by mid-century in the 34 studies they reviewed is 6 terawatts (TW)[1]. For those scenarios that include stabilization of GHG concentrations, median deployment of PV is 22 TW by 2100. How the technology evolves over the next few decades will determine whether PV reaches terawatt scale and makes a meaningful contribution to reducing GHG emissions or whether it remains limited to niche applications.

Our analysis begins by identifying technical factors which have changed over time and which are likely to have had some impact on PV costs. We then collect empirical data to create an annual time series of each factor for the study period. We build a cost model that simulates the effect of changes in each factor on the manufacturing cost of PV modules. We then discuss how well the learning curve theory explains the most important factors identified in the model.

1.1 The learning curve model

Theories of technological change have identified patterns in the ways that technologies are invented, improve, and diffuse into society (Schumpeter 1947). Studies have pointed out the complex nature of the innovation process in which uncertainty is inherent (Freeman 1994), 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.

[1] For comparison, world electricity capacity in 2004 for all types of generation was approximately 4 TWs.

The learning curve model 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 theory referred to the changes in the productivity of labor as a function of cumulative production within a manufacturing plant. Later, others developed the *experience curve* to provide a more general formulation of the theory, including not just labor but all manufacturing costs (Conley 1970) and aggregating entire industries rather than single plants (Dutton and Thomas 1984) [2]. Though different in scope, each of these concepts is based on Arrow's explanation of technical progress as the result of learning by doing. As a result, they are often, and perhaps misleadingly, grouped under the general category of learning curves. The most basic implication of the learning curve theory is that increasing cumulative output is a dominant strategy for maximizing both the profitability of firms and the societal benefits of technology-related public policy.

The 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[3]. 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, a linear function 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 $Cost$ is unit cost and q represents cumulative output.

$$Cost_t = Cost_0 \left(\frac{q_t}{q_0}\right)^{-b} \tag{1}$$

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

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

Subsequent studies have criticized the learning curve model. 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 hypothesis for the observed technical improvements: economies of scale, knowledge spillovers and two opposing factors, organizational forgetting and employee turnover. Despite these criticisms, the learning curve model has survived without any major modifications as a basis for predicting technical change, informing public policy, and guiding firm strategy. Below, we outline the advantages and limitations in using the model for such applications[4].

1.1.1 Advantages

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

[2]The industry-level aggregation is sometimes also referred to as a "progress curve."

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

[4]We focus our discussion on the more general application of the learning curve theory, the experience curve.

quantifying related concepts such as knowledge flows and inventive output. 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 which treat change purely as a function of time[5]. Finally, the reduction of the complex process of innovation to a single parameter, the learning rate, provides a way to include technological change in models, such as energy supply and greenhouse-gas emissions models.

1.1.2 Limitations

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 to small changes in the learning rate. For example, an experience curve R^2 value of >0.95 is considered impressive and a strong validation of the experience curve model. However, the variance in such a goodness of fit can lead to uncertainty in the timing of cost reductions on the scale of decades. In Figure 1 we plot experience curves based on the two most comprehensive world surveys of PV prices (Maycock 2002, Strategies-Unlimited 2003) [6]. The Maycock survey produces a learning rate of 0.26 while the Strategies Unlimited data gives 0.17. What may appear as a minor difference has a large effect. Assuming a steady industry growth rate of 15% per year [7], we calculate how long it will take for PV costs to reach a threshold of $0.30/W, a mid-range estimate for competitiveness with conventional alternatives. We find that just the difference in the choice of data set used produces a cross-over point of 2039 for the 0.26 learning rate and 2067 for the 0.17 rate, a difference of 28 years[8].

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 we would expect that the experience curve-based forecasts of PV in the 1970s would have predicted much faster technological progress than actually occurred—a retrospective analysis shows that they did (Schaeffer 2004)[9]. 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 which are important in driving cost-reductions. 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 interpre-

[5] 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, Kohler and Anderson 2002).

[6] In our model, we use an average of the two surveys

[7] The historical rates have generally been in the range of 10-30%.

[8] The biggest differences in the two datasets were in the 1970s.

[9] That study also showed significant variation in the learning rate for PV depending on the choice of time period.

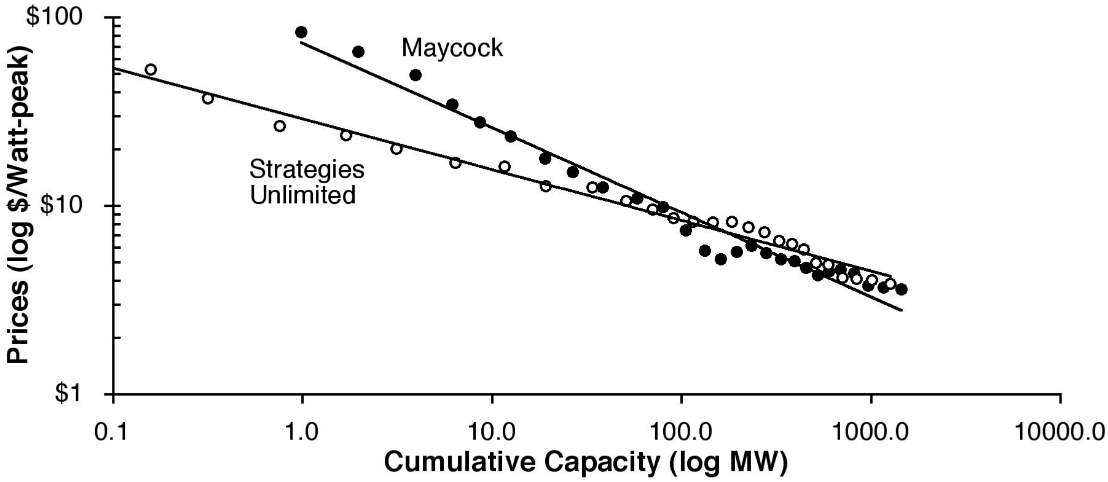

Figure 1: Sensitivity of learning rate to underlying data. Sources: Maycock 2002 and Strategies Unlimited 2003.

tation 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 perfect 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 (Miketa and Schrattenholzer 2004), and the interactions between R&D and diffusion (Watanabe, Nagamatsu and Griffy-Brown 2003). Finally, experience curves ignore changes in *quality* beyond the single dimension being analyzed[10]. The dependent variable is limited to cost normalized by a single measure of performance—for example, hours of labor/aircraft, $/watt, or cent/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 uses an alternative approach to predicting technological change based on a traditional engineering analysis. 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, we look at a set of more specific technical factors whose impact on cost we can directly calculate.

To look at the impact of a more specific set of factors, we use a case study of a single technology, photovoltaics (PV). To isolate the effect of technological change, we look at PV modules and do not include in our analysis balance-of-system components such as inverters, storage, and supporting structures[11]. We also focus on PV modules manufactured from mono-crystalline and poly-crystalline silicon wafers, the technology that has comprised over 90% of production over this period and increasingly dominates the PV industry.

[10]Payson (1998) provides an alternative framework that incorporates both changes in quality and cost improvements.
[11]Inverters and other components have also exhibited cost decreases by factors of 5 and 10 respectively.

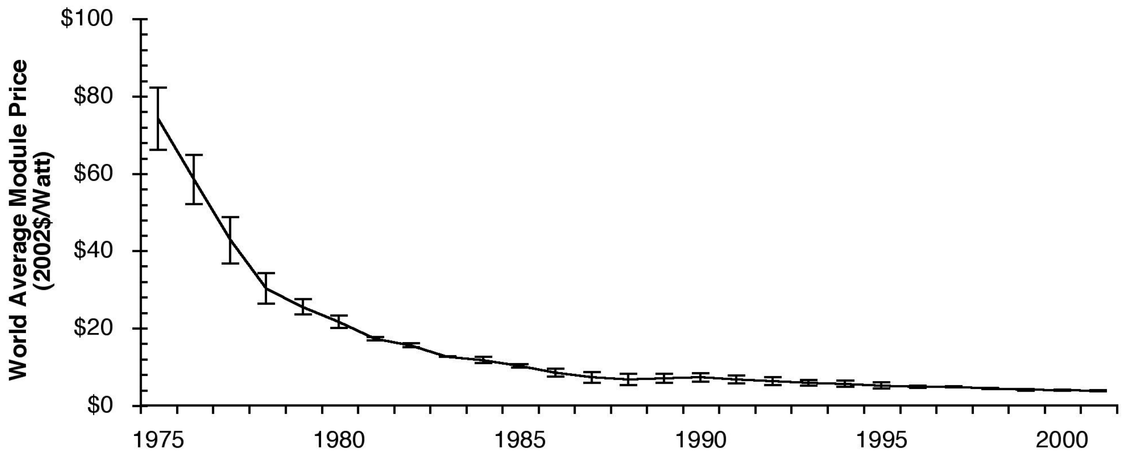

Figure 2: World average prices for photovoltaic modules. Sources: Maycock 2002 and Strategies Unlimited 2003

The cost of PV has declined by a factor of 100 from the 1950s until the present (Wolf 1974). In our study we look at the period from early commercialization, 1975 to the year with the most recently available data, 2001. During this 26-year period, there was a factor of 20 cost reduction (see Figure 2). Practically, this reduction has meant that in the early-1970s nearly the only applications which could afford PV were in the U.S. space program. By 2000, PV was being used as a roofing material in place of asphalt shingles. PV, however, remains a niche product and in the overwhelming majority of situations cannot compete economically with traditional electricity sources such as coal and gas, or even with other renewable energy sources, such as wind. How far PV costs need to come down to be deployed on a large scale is a matter of debate. The range of estimates include those such as the main PV industry trade group, which claims that \$1.00/W_{peak} would be sufficient (SEIA 2004), to those who claim that the associated costs of transmission and storage require PV modules that cost essentially nothing. In either case, widespread diffusion of PV requires significant future cost declines.

We use empirical data to estimate the annual level of seven factors over the study period, 1975 to 2001. We then build a model to quantify the impact of the change in each factor on module cost. Here we outline the steps involved in determining which technical and economic factors were most important.

We begin by identifying candidate factors which have changed over time and which are likely to have had some impact on PV costs. We identify specific factors by breaking the PV module production process into five stages and using prior studies to identify the cost components in each stage. We then collect empirical data to create an annual time series of each factor for the study period. For years in which we do not have actual data for a factor, we use constant growth rates to interpolate the years between data points. In the section below we describe the detail behind our next step, which is to build a simple model that simulates the annual cost impact of changes in each factor. Finally we perform a series of tests on the model. We compare model results for different time periods. We estimate uncertainty in each factor and test the sensitivity of the model to the range of possible values.

2 Cost Model Methodology

We build a cost model that simulates the effect of changes in each factor on manufacturing cost. Below, we outline the methodology for estimating the impact of each factor.

2.1 Cost

Average module cost (in units of 2002\$s/Watt$_{peak}$) is the dependent variable in the model. We build the time series for cost using an average of the two most comprehensive world surveys of PV prices (Maycock 2002, Strategies-Unlimited 2003)[12]. Due to the proprietary nature of cost data, we follow the widespread practice of using prices instead of costs under the assumption that prices provide a reasonable proxy for costs. We discuss later some of the pitfalls of using prices to represent costs. Variation in the price-cost margin and in the surveys themselves are two sources of uncertainty in the model. The analysis focuses on module cost, rather than cost of energy, 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 (Christensen 1985, Maycock 2002, Maycock 1994, Grubb and Vigotti 1997) have nearly doubled the rated power output of each square meter (m^2) of PV material produced. We simulate the impact of efficiency changes on module cost using;

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

This simple formulation applies the annual change in efficiency to the previous year's cost, $Cost_{t-1}$, to calculate the expected change in cost due to efficiency, $\triangle Cost_t$. The relationship above holds because in this study we are defining cost as \$s/W_{out}. W_{out} is proportional to efficiency because $\eta = W_{out}/W_{in}$ and incoming solar radiation is constant. As a result, change in cost is inversely proportional to change in efficiency. For 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 2002, Mitchell, Witt, King and Ruby 2002, Ghannam, Sivoththaman, Poortmans, Szlufcik, Nijs, Mertens and Van Overstraeten 1997, Maycock 1994). Growing demand has enabled manufacturers to build larger facilities and exploit economies of scale. We assume that half of the costs in PV manufacturing are sensitive to scale [cite] and use a scaling factor ($b = -0.35$) from the micro-processor industry[cite]. We estimate the effect of increasing scale using the equation below. We borrow a scaling factor for operating costs from the semi-conductor industry ($b = -0.18$)(Gruber 1996), the industry whose production processes are most similar to that of PV. This value is within the range (b=-0.07 to -0.20) of assumptions used in studies that calculate future cost savings for large scale PV[13]. Other PV scaling factors include the following: b=-0.07 (Bruton and Woodock 1997), b=-0.09 (Rohatgi 2003), b=-0.12 (Frantzis, Jones, Lee, Wood and Wormser 2000), b=-0.18 (Maycock 1997), b=-0.20 (Ghannam et al. 1997)[14].

[12] Country and regional-level surveys also exist and may be accurate as well. However, we avoid using these surveys because over this time period the market for PV became global. As a result some of the change in within-country learning rates is due to the globalization of the industry, rather than learning.

[13] 'Large scale' means >100 MW per plant per year.

[14] It is not surprising that our value lies at the upper end of this range because we are applying it historically, when smaller plant sizes probably were yielding more economies of scale than at the levels of 100-500MW/year in these studies.

$$\triangle Cost_{t(size)} = Cost_{t-1}\left(\left(\frac{Size_t}{Size_{t-1}}\right)^b - 1\right) \tag{5}$$

2.4 Yield

Improved cell and module processing techniques have increased post-wafer *yield*[15] (Little and Nowlan 1997, Sarti and Einhaus 2002, Rohatgi 2003). Because post-wafer yield measures the final stages of the production 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.

$$\triangle Cost_{t(yield)} = Cost_{t-1}\left(\frac{Yield_{t-1}}{Yield_t} - 1\right) \tag{6}$$

2.5 Poly-crystalline share

Throughout the study period, 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 (Maycock 2002, Maycock 1994, Costello and Rappaport 1980, Maycock 2003, Goetzberger, Hebling and Schock 2003, Menanteau 2000, JPEA 2002) [16]. Based on comparisons of mono- and poly-crystalline prices for four years (Maycock 1994, Bruton and Woodock 1997, Maycock 1997, Sarti and Einhaus 2002), we assume that poly-crystalline modules cost 90% that of single crystal modules. The formula below simulates the effect of the growing market share for poly-crystalline designs on average module cost. market share reduces average cost by 0.5%.

$$\triangle Cost_{t(poly)} = (Polyshare_t - Polyshare_{t-1})(Polycost_{t-1} - Cost_{t-1}) \tag{7}$$

$$Polycost_{t-1} = 0.9 \cdot \frac{Cost_{t-1}}{1-(1-0.9)\,Polyshare_{t-1}} \tag{8}$$

2.6 Silicon cost

Solar-grade silicon feedstock is the basic material input for producing PV wafers. Silicon prices ($/kg$_{Si}$) have fallen by nearly a factor of 12 over the study period (Costello and Rappaport 1980, Ghosh 1979, Bruton 2002, Swanson 2004). In Figure 3 we show the change in the cost of silicon and other materials used to manufacture modules. In this study, we ignore changes in the other major materials—glass, ethyl-vinyl acetate (EVA), aluminum and framing materials—because they are orders of magnitude less costly than silicon[17]. We estimate the annual effect of this change by calculating the cost of the silicon necessary to produce a watt of PV module, while holding silicon consumption per watt constant.

$$\triangle Cost_{t(sicost)} = (SiCost_t SiConsum_{t-1}) - (SiCost_{t-1} SiConsum_{t-1}) \tag{9}$$

[15] We capture the yield improvements in the manufacturing of wafers in the section on silicon consumption below.

[16] We are excluding from our analysis thin-film silicon designs. Thin-film peaked at about 20% of world production in the early 1990s but have since declined to below 10% of world production.

[17] Note that in Figure 3 a log scale is necessary to show the changes in the other materials.

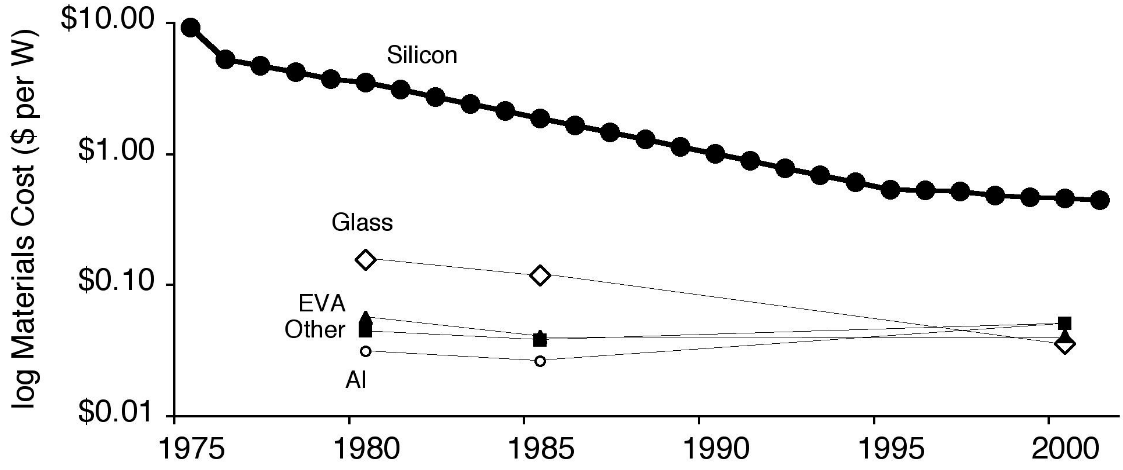

Figure 3: Materials costs for PV Modules. Sources: Christensen 1985 and Maycock 2002

2.7 Silicon consumption

The amount of silicon used per watt (g_{Si}/W) 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 500μm to 250μm and by reducing kerf losses, from the sawing of each wafer, from 250μm to 190μm. We calculate the amount of silicon saved each year and use silicon prices to estimate the effect on module cost.

$$\triangle Cost_{t(siconsum)} = (SiCost_{t-1}SiConsum_t) - (SiCost_{t-1}SiConsum_{t-1}) \tag{10}$$

2.8 Wafer size

Improved crystal growing methods have increased the area of each wafer by a factor of four (Christensen 1985, Symko-Davies, Mitchell, Witt, Thomas, King and Ruby 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, we assume that post-wafer processing accounts for 40% of the cost of producing a module in all periods (Moore 1982, Maycock 2002, Bruton and Woodock 1997) and that fixed per wafer costs are 10% of cell and module assembly.

$$\triangle Cost_{t(wafer)} = Cost_{t-1}\left(\frac{wafer_{t-1}}{wafer_t} - 1\right) \cdot 0.4 \cdot 0.1 \tag{11}$$

2.9 Full model

We define the total change in module cost each year as the sum of the changes in each of the seven components[18].

$$\triangle Cost_t = \triangle Cost_{t(\eta+size+yield+poly+sicost+siconsum+wafer)} \tag{12}$$

[18]We considered other factors such as labor, automation, and other material inputs. However, we exclude them because these changes are either very small or are captured as changes in other factors which we did include in the model.

Table 1: Model Summary 1975-2001

Factor	Change	Effect on Module Cost ($)
Module Efficiency	6.3% → 13.5%	−17.97
Plant size	76 kW/yr → 14 MW/yr	−13.54
Si cost	300 $/kg → 25 $/kg	−7.72
Si Consumption	30 g/W → 18 g/W	−0.98
Yield	80% → 92%	−0.87
Wafer Size	45 cm^2 → 180 cm^2	−0.67
Poly-crystal	0% → 50%	−0.38
Sum of Factors		−42.15
Actual Change		−70.36
Residual		−28.22

3 Model Results

Three factors stand out as particularly important in explaining cost declines from 1975 to 2001: plant size, cell efficiency, and to a lesser extent, the cost of silicon (see 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 that we understand the reasons for this residual before drawing conclusions about the model results. One way to investigate the residual is to analyze how well the model predicts the actual data over time. We observe that the model predicts the actual change in prices much better after 1980 than it does before 1980.

In the following sections, we present results obtained by dividing the model into two time periods; Period 1: 1975-79 and Period 2: 1980-2001. We choose these periods for three reasons. First, by 1980 terrestrial applications had become dominant over space-based applications, signaling the emergence of a 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 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. In the following sections we look at differences in the factors and residual in these two periods and offer hypotheses about explanations.

3.1 Period 1: 1975-1979

In the first four years of this study, costs declined by a factor of three. Of the factors we identify, efficiency, cost of silicon, and plant size accounted for the most change in cost (see Table 2). Three other factors, yield and silicon consumption, were of less importance but played a role. Module size and poly-crystalline share did not change and thus had no effect. These seven factors however fail to explain most of the change over this period, as 59% of the change is unexplained. In the rest of this section, we identify other factors 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

Table 2: Model Results for Time Period 1: 1975-1979

Factor	Change	Effect on Module Cost ($)
Module Efficiency	6.3% → 8.0%	−11.48
Si cost	300 $/kg → 131 $/kg	−5.03
Plant size	76 kW/yr → 125 kW/yr	−4.33
Yield	80% → 82%	−0.44
Si Consumption	30 g/W → 28 g/W	−0.39
Wafer Size	45 cm^2 → 45 cm^2	0.00
Poly-crystal	0% → 0%	0.00
Sum of Factors		−21.67
Actual Change		−48.74
Residual		−27.07

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 application.

3.1.1 Shift to lower quality reduces cost

One reason for the unexplained change in costs is that the shift from space to terrestrial applications led to a reduction in the *quality* of modules. As noted above, the focus in this project on cost/watt$_{peak}$ as the measure of technical change ignores changes in PV modules that are not captured in electrical output, such as reliability and durability. In this case, the shift away from space applications rendered certain characteristics non-essential, allowing manufacturers to switch to less costly processes[19].

The limited size of the payload bays on the rockets that transport satellites to orbit require minimization of the area that a satellite PV panel occupies. Meeting this spatial constraint necessitates 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 which was required to for satellites.

Second, reliability targets fell. The Vanguard satellite program mandated that satellite PV modules operate reliably for 20 years without maintenance. Terrestrial applications, on the other hand, can be still be useful with much shorter lifetimes. A major Jet Propulsion Labs study of PV technology in the 1970s found that the average lifetime for terrestrial PV in the mid-1970's was between 6 months and 2 years (Christensen 1985). They found it rose to 10 years in 1985. Similarly, data from a leading manufacturer show that the warranty period for terrestrial PV prior to the mid-1980s was for 5 years (Wohlgemuth 2003). Subsequently, warranties increased to 10 years in 1987, to 20 years in 1993, and to 25 years in 1999. Combining this reliability data with

[19]For example, the earliest terrestrial modules in the early-1970s were built from reject space cells (Christensen 1985).

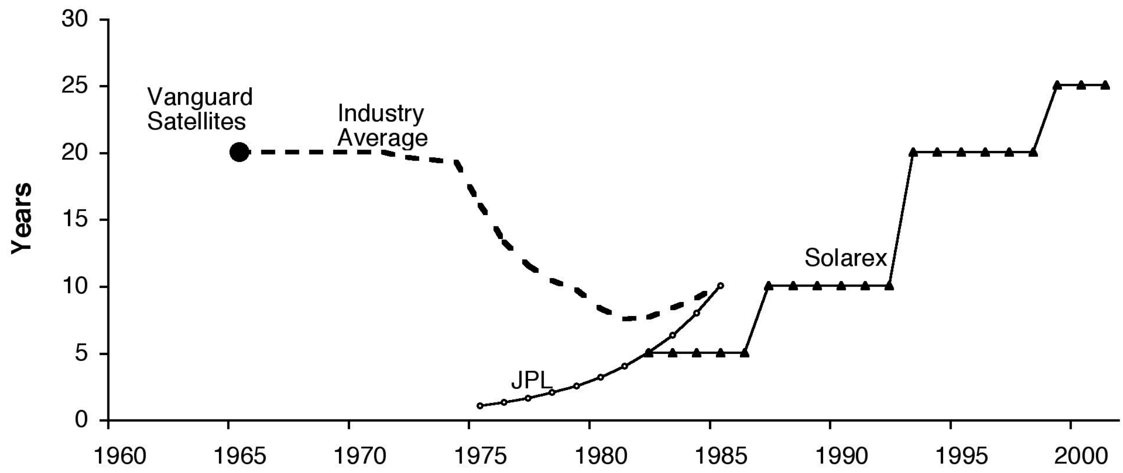

Figure 4: Module Lifetime. Sources: Christensen 1985 and Wohlgemuth 2003

the share of satellite vs. terrestrial applications yields a curve for average industry lifetime that indicates a decline in the 1970s (see Figure 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 led to less costly manufacturing[20].

3.1.2 Change in demand elasticity decreases margins

Another, and possibly complementary, explanation is that the shift from satellites to terrestrial applications affected costs 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, the price per watt of PV modules for satellite use was 2.5 times higher than the price for terrestrial modules (Moore 1982). In 1979, the next year for which price data is available, the satellite price remained higher (by a factor of 2.2) than terrestrial. We calculate the impact of this shift on *average* PV cost 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 not explained by the model in this period.

The shift from satellites to terrestrial applications had a large impact on average cost. However, it is less clear how much of the price difference was due to the changes in quality mentioned above, and how much is due to price discrimination. Satellite customers, with their billions of dollars of related investments, almost certainly had a higher willingness to pay for PV panels, than early terrestrial applications such as telecom power at remote 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 suggest that there was 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 in 1975 (Maycock and Stirewalt 1985). In 1983, there were dozens of firms in the industry with 3 firms accounting for 50% of the megawatts sold. By the late 1990s, 5 firms accounted for half of the MWs sold (Maycock 2002).

[20] By 2000, reliability in terrestrial systems reached 25 years, exceeding that of early satellite systems.

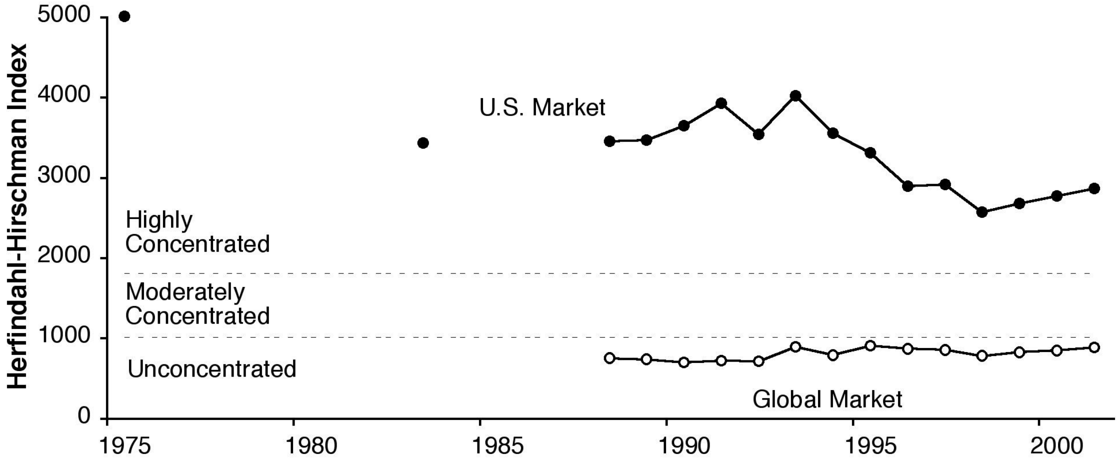

Figure 5: Industry Concentration (Herfindahl-Hirschman Index). Sources: Maycock 1984, 1994, 2002

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[21]. The data show a trend to a less concentrated U.S. market (see Figure 5). Concentration in the global market remained stable in the 1990's, the period for which we have comprehensive data. 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 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 quite well—just over 5% of the change is unexplained by the model (see Table 3). The high explanatory power of the model indicates that the factors mentioned above to explain the residual in Period 1—quality, demand elasticity, competition, standardization— were either stable or dynamic but offsetting in Period 2. Two

[21] 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)

Table 3: Model Results for Time Period 2: 1980-2001

Factor	Change	Effect on Module Cost ($)
Plant size	125 kW/yr $\rightarrow$ 14 MW/yr	-9.22
Module Efficiency	8.0% $\rightarrow$ 13.5%	-6.50
Si cost	131 $/kg $\rightarrow$ 25 $/kg	-2.69
Wafer Size	45 cm^2 $\rightarrow$ 180 cm^2	-0.67
Si Consumption	28 g/W $\rightarrow$ 18 g/W	-0.59
Yield	82% $\rightarrow$ 92%	-0.43
Poly-crystal	0% $\rightarrow$ 50%	-0.38
Sum of Factors		-20.48
Actual Change		-21.62
Residual		-1.14

factors stand out as important in this period. 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% of the change. Yield, silicon consumption, wafer size, and poly-crystalline share each have impacts of 3% or less.

3.3 Sensitivity analysis

Sensitivity analysis points to three important sources of uncertainty in the parameters. However, these results do not change the ranking of each factor if we assign them to three bins based on importance. We assess uncertainty in the seven factors, the dependent variable, and the underlying assumptions. We estimate uncertainty based on ranges of estimates obtained from multiple sources. We then test the sensitivity of the model by using opposite ends of ranges to simulate the extremes of large changes and small changes in each factor from 1975-2001[22].

The model is most sensitive to uncertainty in three parameters: the change in efficiency, the scaling factor, and the change in plant size. Figure 6 indicates that despite the model's sensitivity to uncertainty in these three factors, the relative importance of the factors does not change if grouped in three bins based on contribution to module cost. So taking into account the full range of uncertainty in each parameter, we can still conclude that: (a) Module efficiency and plant size were important contributors to cost reduction, (b) cost of silicon was of moderately important, and (c) the other factors were of minor importance.

4 Roles of Experience and Learning

In this section we discuss whether the results of our model are consistent with the experience curve model. Experience curves are based on the theory that costs decline in logarithmic proportion to increases in cumulative capacity. Indeed, in the case of PV, we find that cumulative capacity is a strong predictor of cost; $log(CumCapacity)$ as a predictor of $log(Cost)$ has an R^2 value of 0.985. However, we explain below the ways in which the mechanistic basis for this strong statistical relationship is rather weak.

[22]For example, in the case of efficiency, we calculate a *small change* by 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.

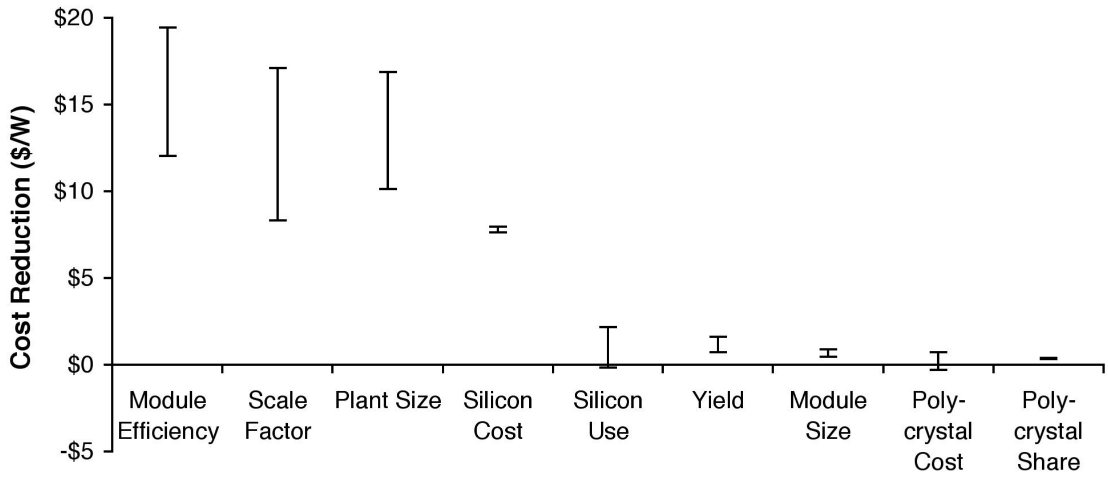

Figure 6: Sensitivity of Model to Uncertainty in Factors

Table 4: Role of learning-by-doing (lbd) in each factor

Factor	Cost impact	Drivers of change in each factor
Plant size	43%	Demand-led, rapid expansion w. no experience
Efficiency	30%	R&D, but lbd for lab→market
Silicon cost	12%	Spillover benefit from IT industry
Wafer size	3%	Strong lbd
Si use	3%	Lbd, spillover for wire-saws
Yield	2%	Strong lbd
Poly share	2%	New process, lbd possible
Other factors	5%	Unknown

Here we assess which factors are most important and how changes in cumulative capacity influence these factors. The most important factors are, at best, weakly explained by cumulative capacity. The learning and experience aspects of cumulative production do not appear to have been major factors in reducing the cost of PV. Future research at the firm and plant level would likely provide more conclusive evidence of this weakness. Still, at the industry level, the role of experience appears far from the dominant driver of technical change, which is the assumption underlying the experience curve model.

Table 4 summarizes the role of cumulative capacity in determining the level of each factor. As the table indicates, three factors—yield, wafer size, and silicon consumption—are strongly influenced by experience and learning in the production of modules. Conversely, changes in poly-crystalline share and the cost of silicon are only distantly related to learning gained from experience. This leaves the two remaining factors, plant size and module efficiency. Both factors appear to be influenced by a combination of experience and knowledge acquired from other sources, such as research and knowledge spillovers.

4.1 Module efficiency

Learning-by-doing is only one of several reasons behind the doubling in commercial module efficiency. Using data on the highest laboratory cell efficiencies over time, we find that of the 16

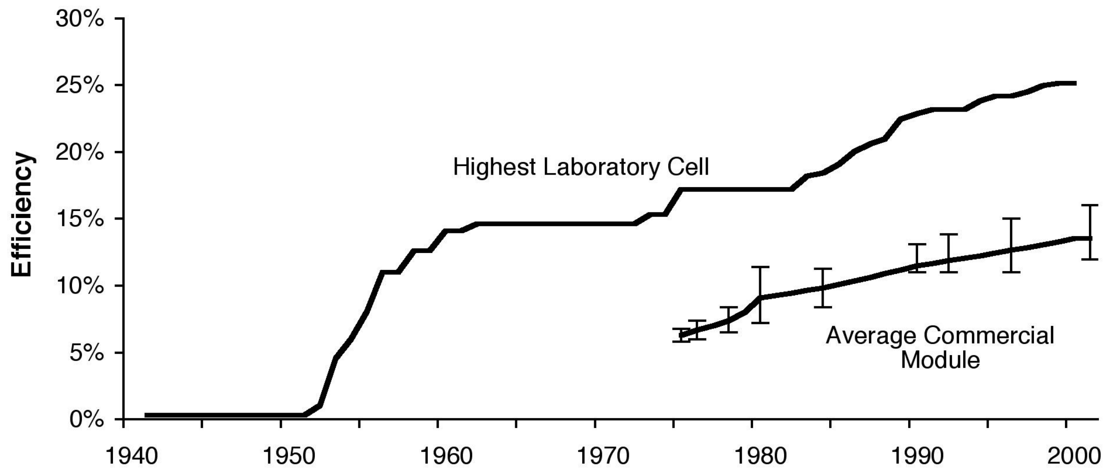

Figure 7: Crystalline PV Efficiency: Highest laboratory Cells vs. Average Commercial Modules. Sources: Christensen 1985; Maycock 1994, 2002; Grubb and Vigotti 1997; Menanteau 2000; Green et al. 2001.

advances in efficiency since 1980[23], only 6 were accomplished by firms that manufacture commercial cells (Surek 2003). 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 (see Figure 7) 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 efficienct 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 commercial efficiency is improvements in the laboratory, then competing hypotheses such as R&D offer more compelling explanations of efficiency improvements than learning-by-doing.

4.2 Scale

Growth in demand and use of knowledge spillovers from other industries 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 deal with these problems. Did experience gained through production enable the expansion of plants to the multi-MW scale? A firm level investigation would enlighten this question. However, examples from two firms suggest that the role of experience in enabling plant expansion is at best an incomplete explanation. First, Mitsubishi expanded from zero production in 1997 to 12 MWs in 2000. They had essentially no experience in the PV industry and became a major producer in less than three years. Second, Sharp plans to open a 500 MW/year plant in 2006, a ten-fold expansion in the firm's capacity in only 5 years. That the firm is locating this new plant adjacent to its micro-processor manufacturing facility suggests that Sharp's experience in this other manufacturing activity is playing a role in their ability to expand their PV plant.

[23] We count as 'advances', production of cells that resulted in a cell efficiency higher than any previous laboratory result.

4.3 Silicon cost

Reductions in the cost of solar-grade silicon were a spillover benefit from manufacturing improvements in the micro-processor industry. Until recently, the PV industry accounted for less than 15% of the market (Menanteau 2000) for purified silicon. Since the PV industry has never purified its own silicon, but has instead purchased silicon from producers whose main customers are in the micro-processor industry, experience in the PV industry was irrelevant to silicon cost reductions.

4.4 Other factors

Learning by doing and experience do appear to have played a role in some of the following factors. However, these factors together only account for 10% of the overall change in cost.

Yield: It is plausible that experience led to lower defect rates and the utilization of the entire wafer area.

Wafer size: Experience was probably important in 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. Whether this method derives from experience with Czochralski process for growing individual crystals is unclear.

5 Conclusions

Learning derived from experience is only one of several explanations of the change in the two most important factors identified in this study—plant size and module efficiency. Its role in causing these two changes appears minor compared to that of R&D and knowledge spillovers. This weak relationship suggests cautious consideration of the conditions under which we can rely on experience curves to predict technical change. Below we point to the importance of firms' profit margins as an additional area to consider. We suggest ways in which an engineering-based model such as this one might be used to enhance our understanding of future technical improvements. As an example we apply our model in a simple scenario exercise to gauge the plausibility of future cost targets.

5.1 Addressing market dynamics

Our results 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. For example, a reasonable scenario based on historical data is that margins fell from 30 to 50% in the early years to near-zero at the end of the study period. We estimate that such a shift would reduce the learning ratio by 0.03 to 0.05 and extend the cross-over year by 8 to 15 years[24].

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. An implication of the variation in the price cost margin and the use of price data as a proxy for cost is that the industry structure affects the learning rate. In the case of an industry which becomes more competitive, a price-based experience curve *over*-estimates the rate of technical progress.

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

One solution would be for future work to obtain real cost or margin data where possible. A disadvantage of using cost data, which is typically difficult to acquire, is that it may shorten the historical time series or require making assumptions to fill in missing years. A second disadvantage is that it may be difficult to obtain a true industry average for cost—cost figures may be disproportionately weighted by firms which are most willing to provide data. Perhaps most important however, is that 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 assumption of perfect competition and that prices equal marginal cost seems least valid in a dynamic situation, such as in this case, in which technology is improving rapidly, industry structure is unstable, and new types of customers are entering the market. A potential disadvantage is that predicting these types of parameters would introduce further uncertainty into predictive models and would require more assumptions. On the other hand, models of change in the diffusion literature might enable us to combine market dynamics with analysis of technical factors, such as those that we assess in this project.

5.2 Incorporating technical factor analysis

Our results indicate that the confidence with which we use experience curves to predict technological change might be enhanced with analysis of the underlying technical dynamics. This approach could improve experience curves 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. For example, the theoretical limit on the efficiency of single-junction silicon-based PV modules of approximately $\eta = 0.29$ limits the cost reductions we can expect in the future. This limit is especially relevant to PV because efficiency accounts for around a quarter of historical cost reductions. Identifying such barriers can help us better predict the practical extent of future cost declines. 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 unravelling 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, firm-level analysis of the drivers behind the doubling in 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, studies which are often limited by data availability and low degrees of freedom.

Finally, an understanding of the underlying factors can help us measure uncertainty in the future rate of technological improvement. A model such as this one allows us to work backwards so that we 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, we could ask how large manufacturing plants would need to be to provide adequate economies of scale. With the resulting estimate for plant size, we 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 estimating how likely it is that such an improvement might occur. We could then propagate that uncertainty through the model to put bounds on our uncertainties in the learning rate. Given the sensitivity of energy supply models to small changes in the learning rate, improving estimates of uncertainty in the learning rate would be an important contribution.

5.3 Scenarios of target costs

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

- Efficiency improves from 13.5% in 2001 to 25% in 2030. We borrow this assumption from the Solar Energy Industry Association's 'roadmap' (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.
- We assume no changes to the price of silicon or yield.

We first test SEIA's roadmap goal of $1.00/W modules in 2050. 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 TWs of PV 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. Such a scale is described as feasible in a recent National Renewable Energy Laboratory study that provides a detailed analysis of a 2.1 to 3.6 GW plant (Keshner and Arya 2004). The model shows that in this scenario, 48% of the cost reduction comes from efficiency improvements and 51% comes from scale.

Others claim that $1.00/W modules would be prohibitively expensive once PV accounts for more than 5 to 10% of electricity generation[25]. 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 part 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[26]. In an extremely high-growth scenario in which PV does grow to 30 TW in 2050, this model predicts that 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 using new materials like dyes and organics, will be necessary.

In contrast, a similar scenario based on an experience curve provides a much 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 (see Figure 8). Choosing which time period to use for calculating the expected future learning rate substantially affects the 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.

[25] This level loosely corresponds to TW-scale PV electricity production.
[26] 30 TW is a high end estimate for total world energy demand in 2050.

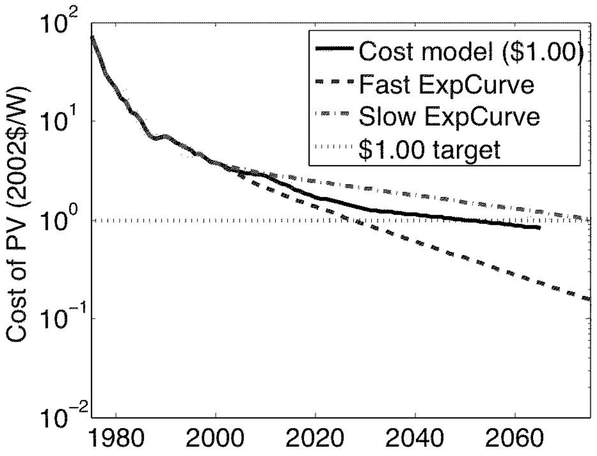

Figure 8: Scenarios using cost model, experience curves, and $1.00/W target price.

5.4 Summary

On the order of a trillion dollars will have to be invested over the coming decades 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 suggests 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 technologies.

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