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Interpreting interim deviations from cost projections for publicly-supported energy technologies

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Abstract

Widespread public funding of nascent energy technologies, combined with recent increases in the costs of those that have been most heavily supported, has raised the stakes of a policy dilemma: should policy makers sustain these programs anticipating that recent cost increases are temporary disturbances or should they eliminate them to avoid risking billions of dollars of public funds on technological dead ends? This paper uses experience curves for photovoltaics (PV) and wind to (1) estimate the range of possible policy outcomes and (2) introduce new ways of assessing near term cost dynamics. For both technology cases, the costs of the subsidies required to reach cost targets are highly sensitive to the choice of the historical time series used. The variation in the discounted social cost of subsidies exceeds an order of magnitude. Vigilance is required to avoid the very expensive outcomes contained within these distributions of social costs. Two measures of the significance of recent deviations are introduced. Both indicate that wind costs are within the expected range of prior forecasts but that PV costs are not. The magnitude of the public funds involved in these programs heightens the need for better analytical tools with which to monitor and evaluate cost dynamics.

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1 Introduction

Policy makers are increasingly being challenged to make decisions about whether, when, and how much to subsidize socially beneficial energy technologies. The costs and benefits of these programs depend heavily on the extent to which technologies improve over time. Experience curves provide a way for policy makers to incorporate technology dynamics into decisions that involve the future costs of technologies. They are now used widely to inform decisions that involve billions, and even trillions, of dollars in public funding. The general notion that learning from experience leads to costs reductions and performance improvements is well supported by a large array of empirical studies across a variety of technologies. But the appropriateness of using experience curves to guide policy is less uniformly acknowledged. Despite caveats in previous work, the cost projections that result from experience curves are typically used without characterizing uncertainty in those estimates This study examines two questions: How sensitive are policy decisions to this uncertainty? and does characterization of uncertainty allow interpretation of the significance of apparent deviations from projections?

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

The following section discusses the reasons for using experience curves, their prevalence, and the way that experience curve-derived cost projections are used in policy decisions. In Section 3 a highly stylized model is described for calculating the cost of a subsidy program. Section 4 presents the range of values that result from applying the model to two case studies, photovoltaics (PV) and wind power. Section 5 introduces two approaches to compare recent deviations to historical ex ante predictions. Finally, in Section 6 the implications of applying the results of this type of model to policy decisions are discussed.

2 Using experience curves for technology policy

Despite ample evidence of technological learning, the weak reliability of experience curve projections makes their application to inform policy decisions subject to strong caveats.

2.1 A wide array of technologies demonstrate "learning"

Experience curves have been assembled for a wide range of technologies. While there is wide variation in the observed rates of "learning", studies do provide evidence that costs, almost always, decline as cumulative production increases (Wright, 1936; Alchian, 1963; Rapping, 1965; Dutton and Thomas, 1984). The roots of these micro-level observations can be traced back to early economic theories about the importance of the relationship between specialization and trade, which were based in part on individuals developing expertise over time (Smith, 1776). The notion of the *experience curve* varies from the more specific formulation behind the learning curve in that it aggregates from individuals to entire industries, and from labor costs to all manufacturing costs.[2]

Experience curves have been assembled for a wide variety of energy technologies. For useful studies and surveys see Wene (2000); McDonald and

[2]The technological "learning" used in the literature on experience curves refers to a broad set of improvements in the cost and performance of technologies, not strictly to the more precise notion of learning by doing, e.g. (Arrow, 1962).

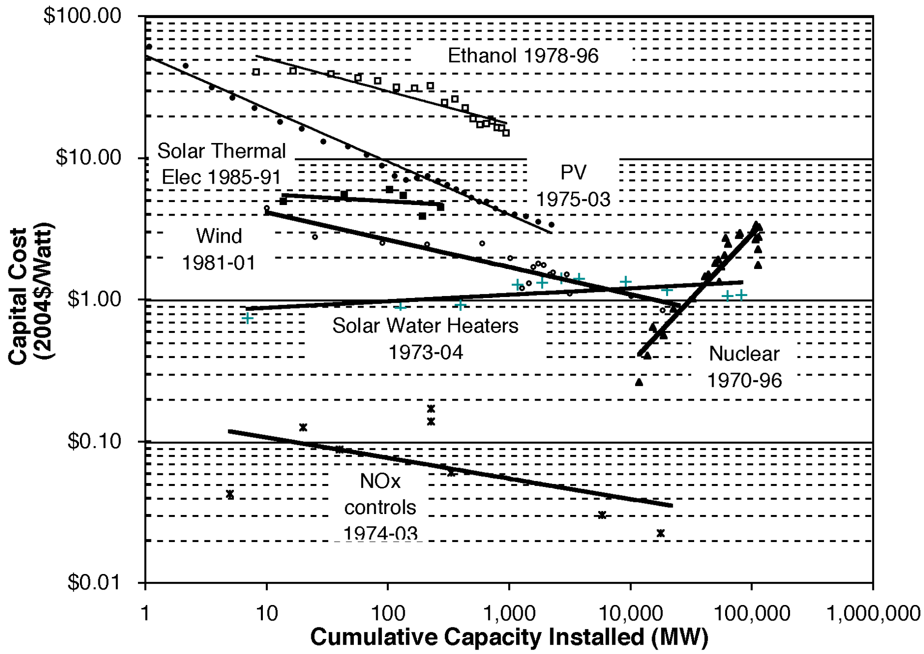

Figure 1: Experience curves for energy technologies. Data: Nemet (2007).

Schrattenholzer (2001); Junginger et al. (2005); Albrecht (2007); Hultman and Koomey (2007); Neij (2008). Fig. 1 shows learning rates for a variety of energy-related technologies.[3] The rates vary, but, with the exception of nuclear power and solar hot water heaters, costs do appear to decline with cumulative capacity. The dispersion in learning rates included in these studies is attributable two two factors: differences in how fast technologies "learn" and to omitted variable bias; exogenous technical improvements, changes in quality, and the price of input materials, all affect costs over time, and are not included in the cumulative capacity variable on the horizontal axis (Nemet, 2006). Still, perhaps because of a dearth of better tools, the experience curve persists as powerful tool for guiding policy decisions about the costs of future energy technologies.

[3]The data for ethanol are in units of dollars per gallon, rather than dollars per Watt. For insight into why the cost of nuclear power increased, see Hultman et al. (2007).

2.2 Experience curves used to inform policy decisions

Experience curves are now used widely to inform decisions that involve billions of dollars in public funds. They have been used both directly—as graphical exhibits to inform debates—and indirectly, as inputs to energy-economic models that simulate the cost of achieving environmental goals. Much of the early work to translate the insights from experience curve studies to energy policy decisions is included in a study for the International Energy Agency (Wene, 2000). Other studies have used the tool directly to make claims about policy implications (Duke and Kammen, 1999; van der Zwaan and Rabl, 2004).

Energy-economic models that minimize the cost of energy supply now also include experience curve relationships to include technology dynamics. Model comparison studies have found that models' estimates of the social costs of policy are sensitive to how technological change is characterized (Edenhofer et al., 2006). Working Group III of the Intergovernmental Panel on Climate Change (IPCC) used results from a variety of energy-economic models to estimate the magnitude of economically available greenhouse gas emissions in its Fourth Assessment Report (IPCC, 2007). The results of this assessment are widely used to inform national climate change policies, as well as the architecture for the next international climate policy regime. In the 17 models they review, some form of experience curve is used to characterize technological change in at least ten of those models.[4] Another influential report in 2006, the Stern Review on the economics of climate change (Stern, 2006), relied heavily on experience curves to model technological change. This report has been central to the formation of climate policy in the U.K. and has played a role in debates in the U.S. as well, at both the federal level and in California. The International Energy Agency relies on experience curves in its assessment of the least cost method for meeting greenhouse gas reduction targets and energy demand for 2050 (IEA, 2008). Note that the "learning investments" that result from the analyses in this report are estimated in a range of 5–8 *trillion* dollars. Debates about subsidies and production requirements for ethanol also use historical experience curves as a justification for public support of the production of biofuels (Goldemberg et al., 2004).

At the state level, experience curves have provided one of the most influential justifications for a three billion dollar subsidy program for photovoltaics (PV) (Peevey and Malcolm, 2006). Experience curves have also been used in economic models of the cost of meeting California's ambitious

[4] See Table 11.15 in IPCC (2007).

greenhouse gas reduction targets (Nunez, 2006). Finally, debates related to decisions by the 24 states that have passed renewable portfolio standards include discussions of how mandatory renewables deployment will bring down the cost of renewables (Sher, 2002; CPUC, 2003).

2.3 Characterizing unacknowledged uncertainty

This study addresses a basic discrepancy between the way that experience curves are used in policy debates and the strong caveats that have emerged from recent literature. A primary concern is the issue of unacknowledged uncertainty.[5] In each of the circumstances mentioned above, experience curves are used because optimal technology policy decisions depend heavily on future rates of technological change (Popp, 2006; Sue Wing, 2006). And for those studies that use experience curves to represent technological change, assumptions about learning rates are important (Rubin et al., 2004; Kahouli-Brahmi, 2008).

Although studies have cautioned that policy makers must contend with discontinuities and uncertainties in future learning rates, few do; the cost projections that result from experience curves are typically estimated without acknowledging uncertainty. Yet a wide array of studies now have pointed to serious reservations about using experience curve projections to inform policy decisions. Wene (2000) emphasized the ways that experience curves could be used to design subsidy programs, but cautioned about the key uncertainties in parameters because "small changes in progress ratios will change learning investments considerably." Concerned about the scale of this uncertainty problem, Neij et al. (2003) "do not recommend the use of experience curves to analyze the cost effectiveness of policy measures" and recommend instead using multiple methods. More recently, Neij (2008) compared experience curve projections to those based on bottom up models, as well as expert predictions, and found that they "agree in most cases." However, in some cases large uncertainties that emerge from the bottom up analyses are "not revealed" by experience curve studies. Rubin et al. (2005) indicate that early prototypes often underestimate costs of commercially viable applications so that costs rise. Koomey and Hultman (2007) have documented a more persistent form of this cost inflation effect for nuclear reactors. Addressing PV specifically, Borenstein (2008) argues that experience curve based analyses do not justify government programs because they conflate multiple effects and ignore appropriability concerns.

[5] This issue is analogous to that examined in the discourse over climate change mitigation (Schenk and Lensink, 2007).

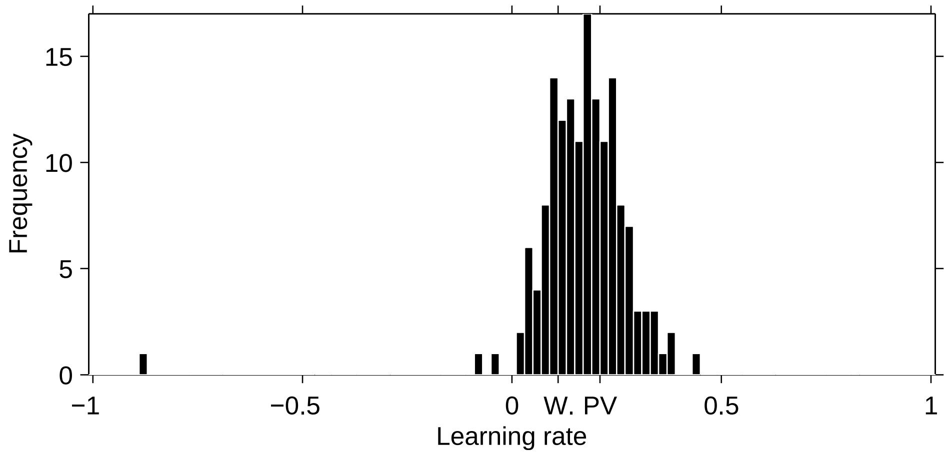

Figure 2: Frequency distribution of learning rates calculated in 156 learning curve studies. Median learning rates for wind and PV obtained in this study indicated by 'W.' and 'PV.' Data from: Dutton and Thomas (1984); McDonald and Schrattenholzer (2001); Nemet (2007).

Empirical observations of technology cost dynamics support the notion that variation in learning rates is substantial. 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. Fig. 2 combines their learning rate data with those of a survey of energy technology learning rates by McDonald and Schrattenholzer (2001), as well as those for the experience curves shown in Fig. 1 to display a distribution of 156 learning rates. The learning rate for PV, 0.23, lies at the 66th percentile of the distribution and that for wind, 0.12 lies at the 17th percentile of the distribution.

This paper addresses three sources of uncertainty in projecting experience curves. First, there is the typical dispersion in learning rates caused by imperfect correlations between cumulative capacity and cost. Sark (2008) explores the effects of this 'r-squared' variation to calculate an error around the learning rate. This paper addresses this type of uncertainty in Section 5. A second source has to do with whether historically observed rates of learning can be expected to continue in the future. Even in his seminal work on learning-by-doing Arrow (1962) argued that that learning is subject to "sharply diminishing returns." Looking at studies within single manufacturing facilities, Baloff (1966) and Hall and Howell (1985) find that learning rates become essentially flat after a relatively short amount of time—approximately 2 years in these studies. As a result, some have suggested that a cubic or logistic function offers a more realistic functional form than a power function (Carlson, 1973). This study addresses this source of uncertainty by recalculating the learning rate continuously over time. A third source of uncertainty derives from the choice of historical time period used to calculate learning rates (Nemet, 2006). The timing issue captures variation in the source data, as well as changes in the slope over time. This paper explores this variation in the next section.

This study assesses the extent to which the sources of uncertainty affect policy decisions. As such the focus is not on how uncertainty affects learning rates themselves but on the non-linear affects that emerge as they propagate through policy models. Studies that focus on the source of uncertainty typically underemphasize the ramifications of an apparently small variation in learning rates. One notable exception is a study by Alberth and Hope (2007), who found that optimal climate change abatement efforts are made more uncertain by the inclusion of assumed distributions in learning rates. Uyterlinde et al. (2007) also show the sensitivity of outcomes by using multiple learning rates, albeit across a narrower range of values than is assessed here.

2.4 The cases: PV and wind power

This uncertainty is examined for the cases of two energy technologies, the future deployments of which are intimately tied to government actions: photovoltaics and wind power. These are appealing cases to examine for several reasons. First, experience curves have been used to justify public support for these technologies. Both technologies address environmental externalities, such as climate change and local air pollution, so the private value of each depends heavily on the government's assignment of prices, in the form of subsidies and pollution regulations. As a result, experience curves have been used frequently as justification for subsidizing each. Second, sales for both have been growing rapidly, at greater than 30% per year, so subsidies to promote them now involve large allocations of public funds, on the order of billions. Third, technically, the costs of both technologies have been dynamic over multiple decades, with strong trends in cost reduction over time. Fourth, both have seen improvement within a single technological generation. So unlike the overlapping curves observed in other technologies with novel architectures, such as semiconductors, slopes are expected to be smooth for each (Irwin and Klenow, 1994). Finally, these technologies are important; because the availability of the resource to deploy them is incred-

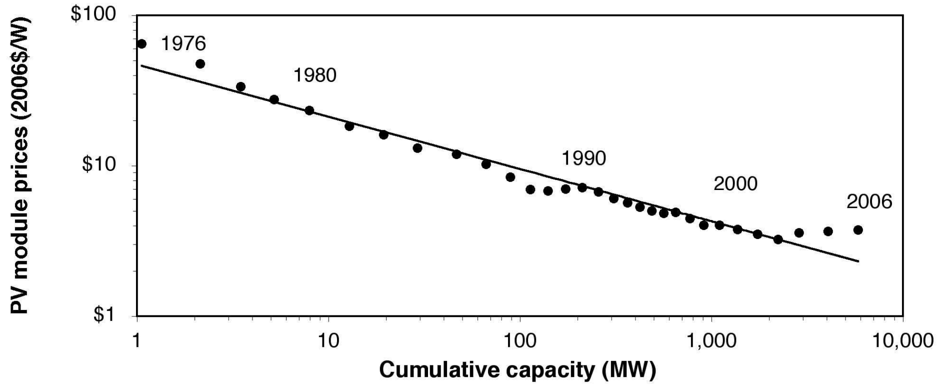

Figure 3: Experience curve for PV modules (1976–2006). Data from Nemet (2007).

ibly large, their future deployment could be massive or niche depending on the extent of future cost reductions. Price and production data for the past three decades are used for each technology. The experience curves for each are shown in Fig. 3 for PV from 1976 to 2006 and in Fig. 4 for wind from 1981 to 2006.

3 Approach: a stylized subsidy cost model

The approach presented here involves developing a simple and transparent model of the costs of subsidizing technologies until they are competitive with alternatives. While this model is a stylized representation of the more detailed analytical models used to inform policy decisions, it retains the core methodology developed by Williams and Terzian (1993), Duke and Kammen (1999), and van der Zwaan and Rabl (2003). The tradeoff made in the attempt to construct a model in the simplest terms possible is that it characterizes neither the richness of technological detail nor the macro-economic impacts in the energy economic and computable general equilibrium models used to inform policies. The advantage of this simple form is that it employs a minimal set of assumptions. Since each of the additional assumptions about parameters made in these more detailed models involve their own uncertainty, this highly stylized form provides a *lower bound* on the uncertainty in the outcomes. The resulting cost model works as follows:

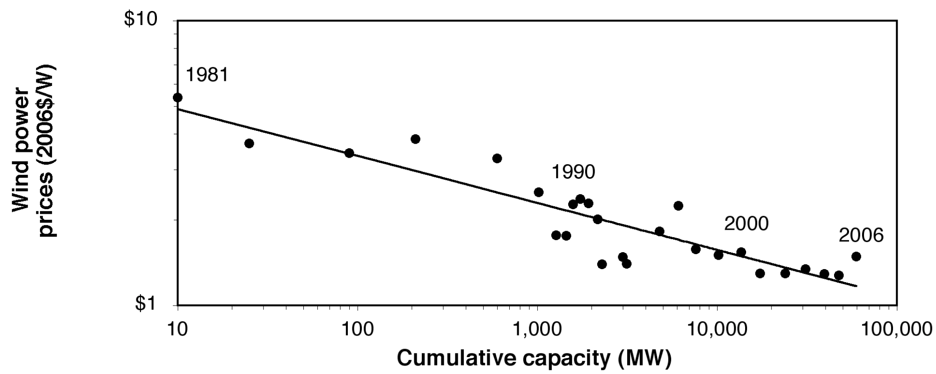

Figure 4: Experience curve for capital cost of wind turbines (1981–2006). Data from Nemet (2007).

3.1 Calculating learning rates

Learning rates are calculated by fitting a power function to the data set of annual levels of cumulative capacity (which is denoted as E for experience) and price, P in each year. Following Epple et al. (1991), cumulative capacity is lagged one year to account for the time it takes to incorporate new techniques obtained as a result of learning from experience. The power function takes the form:

$$P_n = P_m \left(\frac{E_{n-1}}{E_m} \right)^b \tag{1}$$

where P_n is the new price at year, n and P_m is the initial price at year m, that is where cumulative capacity is E_m. The learning coefficient, b is calculated using:

$$b = \frac{\log P_n - \log P_m}{\log E_{n-1}} \tag{2}$$

This equation allows calculation of the "progress ratio", $PR = 2^b$ and the "learning rate", $LR = 1 - PR$. The model then uses equations 1 and 2 to calculate LR for the data for every combination of beginning years t_m and end years, t_n for which $t_n - t_m \geq 9$.

3.2 Year to reach target level

At this point the analysis becomes prospective; the last year of available data, 2006, is used as the base year, t_o. The model compares the cost of the 'learning' technology (PV or wind) to an alternative technology, α. The learning technology becomes competitive with the alternative technology when its price, P reaches that of the alternative technology, that is when $P = P_\alpha$. First, the cumulative manufacturing experience needed E_α for $P = P_\alpha$ is calculated using:

$$E_\alpha = E_o \left(\frac{P_\alpha}{P_o} \right)^{\frac{1}{b}} \tag{3}$$

where P_o is the price of the learning technology in the base year and E_o is the cumulative manufacturing experience in the base year.

Next, the year at which capacity E_α is reached, t_α is calculated using:

$$t_\alpha = \frac{\log E_\alpha - logE_o}{\log(1+g)} \tag{4}$$

where g is the assumed annual growth rate of cumulative capacity of the learning technology. This paper assumes a long term value for g of 0.15.

3.3 Cost of subsidy program

Next, the cost of the subsidies required to "buy-down" the price of the learning technology until it is equal to P_α is calculated. First, the price of the learning technology in each year from t_o until t_α is calculated using:

$$P_t = P_o\,(1+g)^{(t \cdot b)} \tag{5}$$

The annual production of the learning technology M_t is calculated using:

$$M_t = M_o(1+g)^t \tag{6}$$

where M_o is annual production in the base year. The total present value cost of the subsidy program, S is:

$$S = \sum_{t=0}^{t_\alpha} M_t(P_t - P_\alpha)(1+\delta)^{t_o - t} \tag{7}$$

where δ is the assumed discount rate, 0.05. This simple model is applied to the price and production data for PV and wind power.

4 How large is the dispersion in subsidy costs?

This model is used to simulate the cost of a subsidy program, calculating the dispersion in estimates that arises from the variation described above. This section describes three policy-relevant outcomes: (1) the learning rate, (2) the year at which the cost of a subsidized technology approaches a target level, and (3) the discounted cost of government payments needed to achieve that level. This section shows the results first for PV and then for wind.

4.1 Photovoltaics

The data displayed in Fig. 3 is used, for which $r^2 = 0.96$, to calculate learning rates for all possible time periods.

4.1.1 Learning rates over time

Equations 1 and 2 are used to estimate the learning rate (LR) for PV in each of the 253 time periods of 10 years or greater between 1976 and 2006. Fig. 5 plots these learning rates by the year at which each time series ends. For example, the values shown for 1995 include all eleven time series that end in 1995. This set of values indicates the range of learning rates that would have been available to an analyst using experience curves to project costs in 1995. The data begin in 1985 because that is the first year for which 10 years of historical data (1976–1985) are available. The data reveal two features about the trend in calculated learning rates. First, there is a negative time trend; the mean of the learning rate values has decreased over time, by approximately 0.005 per year. Second, the dispersion in learning rate values around the annual mean has increased over time.

The upper panel of Fig. 6 shows the distribution of learning rates for all 253 periods (black columns). The white columns show the distribution of rates using only those series that end in 2006. The latter is the data set one would expect a contemporary planner to use. Table 1 shows the descriptive statistics for the distribution of all 253 time series and for the subset of 22 series that end in 2006. The median of the distribution of learning rates from all 253 time series ($LR = 0.21$) is substantially higher than the median of the series ending in 2006 ($LR = 0.15$), although this difference is not significantly different.

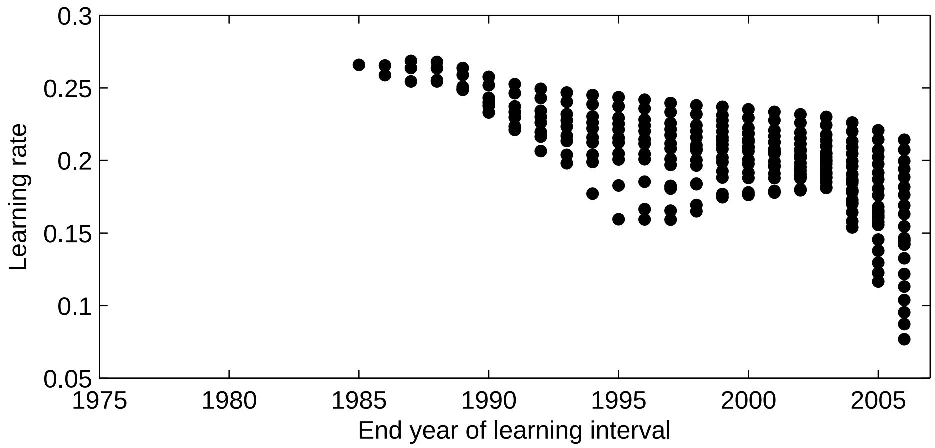

Figure 5: Learning rates for PV (1976–2006) calculated for all periods ≥ 10 years (n=253).

Table 1: Descriptive statistics for distributions of experience curve results for PV.

	Learning rate	Breakeven year	Cost to breakeven ($b)
For all time series (n=253)			
5th %ile	0.25	2028	38
Median	0.21	2034	62
95th %ile	0.14	2049	175
σ	0.03	8	229
For time series ending 2006 (n=22)			
5th %ile	0.21	2034	59
Median	0.15	2048	163
95th %ile	0.08	2082	2172
σ	0.04	15	713

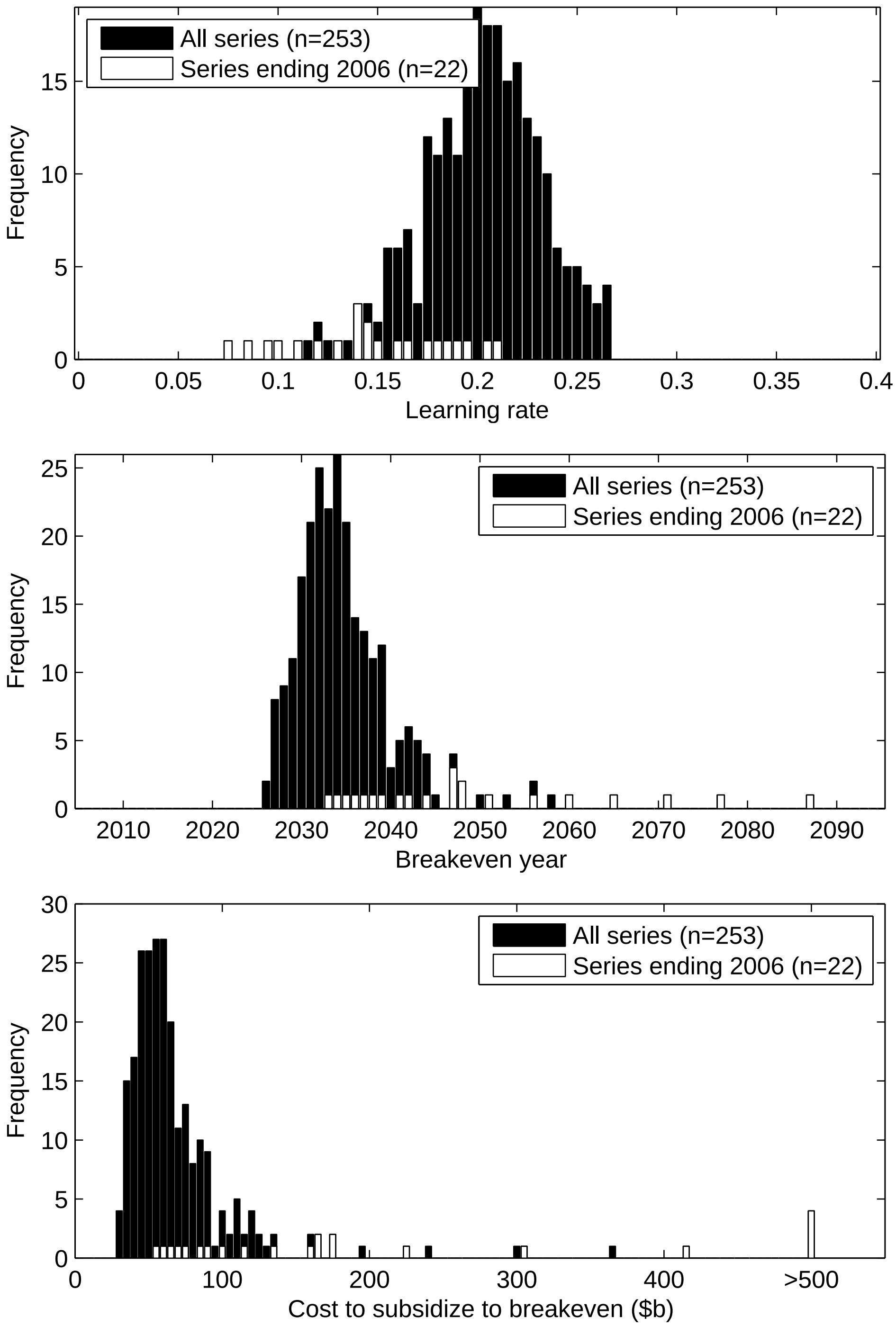

Figure 6: Upper: Calculated learning rates for PV; Middle: Year at which price of PV equals that of competing technology; Lower: Present value of cost to subsidize PV until it equals cost of competing technology. The black columns include values for all 253 time series from 1976–2006. The white columns include only those time series that end in 2006.

4.1.2 Crossover year

Equations 3 and 4 are used to estimate the year at which a subsidized technology will equal the cost of the competing technology, α. The target cost for PV modules used in this example is $P_\alpha = \$1$/per watt (SEIA, 2004). The middle panel of Fig. 6 shows distributions of the estimated years at which the price of PV will equal that of this competing technology. Descriptive statistics for these distributions are shown in Table 1 for all time series and for all series that end in 2006. The median crossover year for all series, $t_\alpha = 2034$ occurs 14 years earlier than the estimates using only data through 2006 $t_\alpha = 2048$. Note that the dispersion has also increased with the more recent data set.

4.1.3 Cost of a subsidy program

The present value of the cost of the program to subsidize PV until its cost equals that of the competing technology is calculated using equations 5, 6, and 7. The lower panel of Fig. 6 shows the distributions for the total cost of a subsidy program, S. Descriptive statistics for these distributions are shown in Table 1. The median cost to subsidize PV is \$62b when using all time series and \$163b when using only the time series that end in 2006. Note that a difference in median learning rate of 40% leads to a difference in median program costs of between a factor of two and three. The dispersion in costs has also become large; the range from the fifth percentile to the 95th percentile spans an order of magnitude. Further, notice that costs around the 95th percentile become very large, rising to the tens of trillions. Slow learning has non-linear effects on cost and leads to very expensive subsidy programs—even when these future costs are discounted to present values.

4.2 Wind power

Similarly, this analysis is run on the wind power data. The data displayed in Fig. 4, for which $r^2 = 0.82$, is used to calculate learning rates for varying time periods.

4.2.1 Calculate learning rates for varying periods

Fig. 7 shows the trend in learning rates for wind power over time. The figure shows a negative time trend in learning rates as was observed with PV, albeit at about half the rate of decline, about 0.0025 per year. In this case the dispersion in values *decreases* over time.

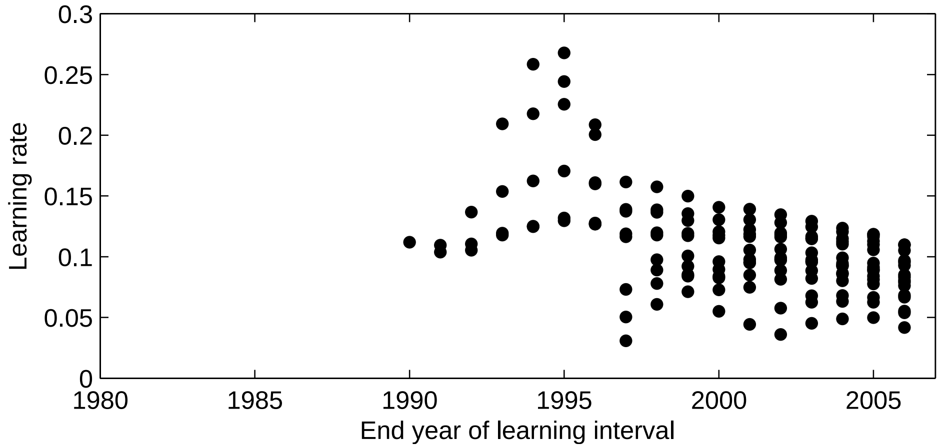

Figure 7: Learning rates for wind power (1981-2006) calculated for all periods $\geq$ 10 years (n=153).

The upper panel of Fig. 8 shows the distribution of learning rates for all 153 periods (black columns). The white columns show the distribution of rates using only those 17 series that end in 2006. Table 2 shows the descriptive statistics for all 152 time series and for the subset of 17 series that end in 2006.

4.2.2 Crossover year

The target cost for wind power turbines, P_α is \$700/kW (IEA, 2008). The middle panel of Fig. 8 shows distributions of the estimated years at which the price of wind will equal that of the competing technology. The median crossover year for all series, $t_\alpha = 2021$ is five years less than the estimates using only data through 2006 $t_\alpha = 2026$, not a significant difference.

4.2.3 Cost of a subsidy program

The median cost to subsidize wind is \$138b when using all time series and \$234b when using only those time series that end in 2006 (see lower panel of Fig. 8 and Table 2). Similarly to PV, the range of cost values across the middle 90 percentiles is large—over an order of magnitude in both sets of time periods. Here too, the possibility of the return of the slowest learning rates experienced in the past produces very expensive subsidy programs, well into the trillions of dollars.

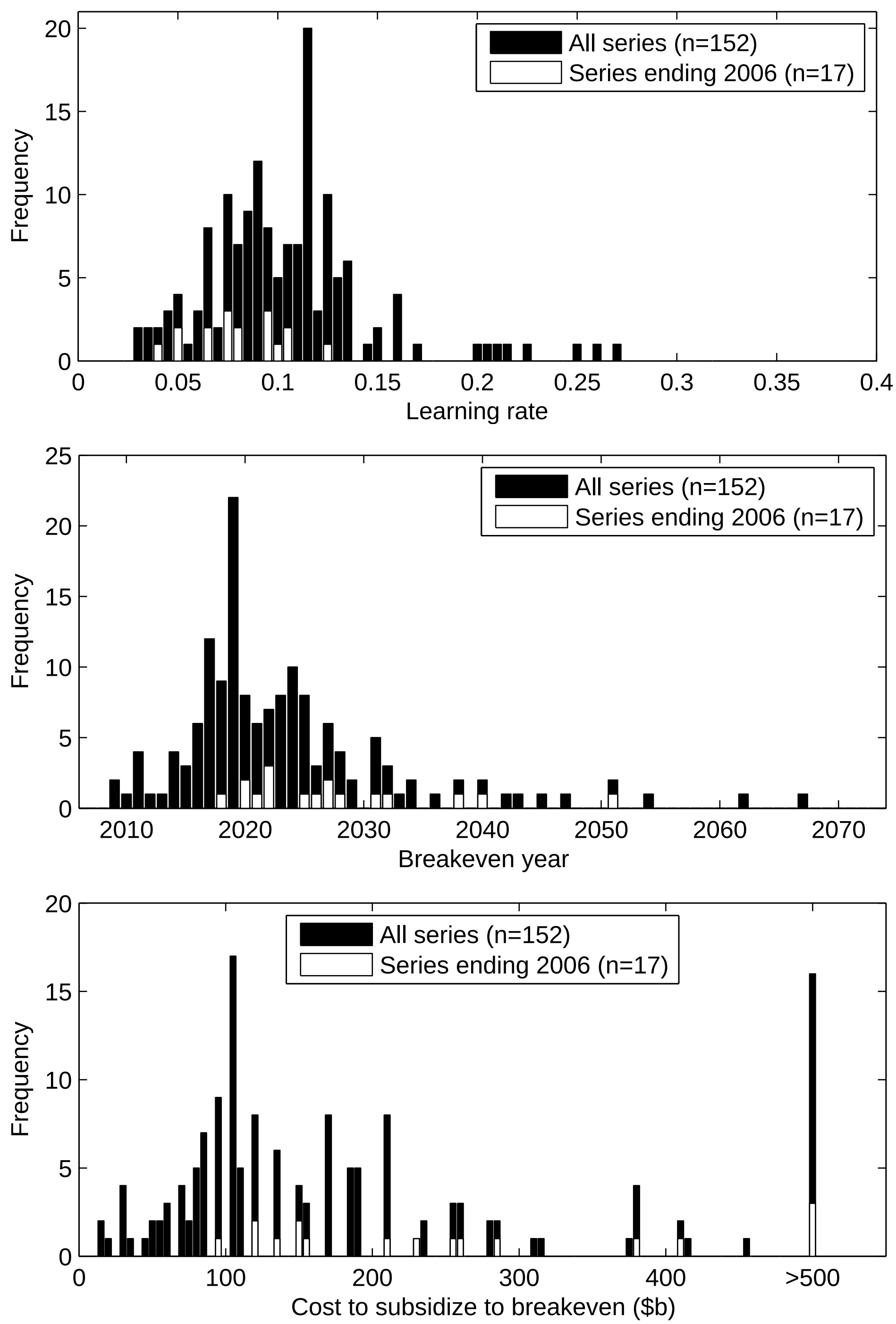

Figure 8: Upper: Calculated learning rates for wind; Middle: Year at which price of wind equals that of competing technology; Lower: Present value of cost to subsidize wind until it equals cost of competing technology. The black columns include values for all 152 time series from 1981–2006. The white columns include only those time series that end in 2006.

Table 2: Descriptive statistics for distributions of experience curve results for wind.

	Learning rate	Breakeven year	Cost to breakeven ($b)
For all time series (n=152)			
5th %ile	0.20	2012	39
Median	0.10	2021	138
95th %ile	0.05	2043	1121
σ	0.04	8	952
For time series ending 2006 (n=17)			
5th %ile	0.12	2019	105
Median	0.08	2026	234
95th %ile	0.04	2047	1783
σ	0.02	9	528

4.3 Summary of results

In the case of PV, an apparently high r^2 value of $> 95\%$ contains variation that leads to substantial learning rate variation depending on the time period chosen. The resulting dispersion in learning rates leads to ranges of subsidy cost estimates that are not only large, but asymmetric around the mean. Slow learning is possible, even within highly correlated data sets with above average learning rates. This outcome leads to very expensive subsidy programs in order to reach target levels.

5 Assessing the significance of recent deviations

The possibility of very expensive subsidy programs makes early identification of such a scenario important. This section briefly explores whether the types of analysis above provide a means with which to conduct interim monitoring of cost dynamics. These exploratory approaches are intended to fit under the rubric of "outcome indicators" suggested by Neij and Astrand (2006). Working specifically on government energy technology development programs, they emphasized the need for "continuous evaluation" of policy outcomes. This study looks for insight on early identification by employing two methods of addressing the question: *do recently observed costs represent* *a significant deviation from the historical trend or does historical variation explain them?* First, recent costs are compared to the confidence interval for the power function resulting from the dispersion in past observations. Second, these costs are compared to the set of all possible experience curve forecasts made over time.

5.1 Confidence interval for observations around power function

The first method uses straightforward statistics examining whether recent variation fits within the confidence interval for observations around the power function. This variation is caused by imperfect fit of the power function to the experience curve data (Sark, 2008). Here a confidence interval is constructed for the PV data through 2003. This range is compared to the most recent three years of data, 2004, 2005, and 2006, to determine whether they fit within the range defined by projecting the experience curve for three years. For the case of wind, apparent deviation began one year later, so 2005 and 2006 are compared to the interval defined by cost trends in the prior years.

The data for PV from 1976-2003 have $r^2 = 0.98$ and $LR = 0.22$. The variation around the experience curve power function using least squares yields a 95% CI around the LR of 0.22±0.01. Projecting the experience curve to the capacity reached in 2006 (E_{2006}), yields a 95% confidence interval of expected costs in 2006 of \$1.58–\$2.51. The actual value for 2006, \$3.74, lies outside this range (Fig. 9).

For wind power, the data from 1981–2004 have $r^2 = 0.75$ and $LR = 0.11$. The variation around the experience curve power function yields a 95% CI around the LR of 0.11±0.03. Projecting the experience curve to the capacity reached in 2006 (E_{2006}), yields a 95% confidence interval of expected costs in 2006 of \$1.65–\$0.76. The actual value for 2006, \$1.49, lies inside this range. But note that this range is substantially larger than that for PV.

When error around the experience curve derived from least squares variation in the data is used to project future costs, recently observed PV costs are outside this range while wind costs are inside it.

5.2 Range of historical projections for recent prices

Next, an approach is developed that assumes the perspective of a policy analyst making ex ante forecasts each year, incorporating new data as it becomes available. This approach assesses whether recent observations could

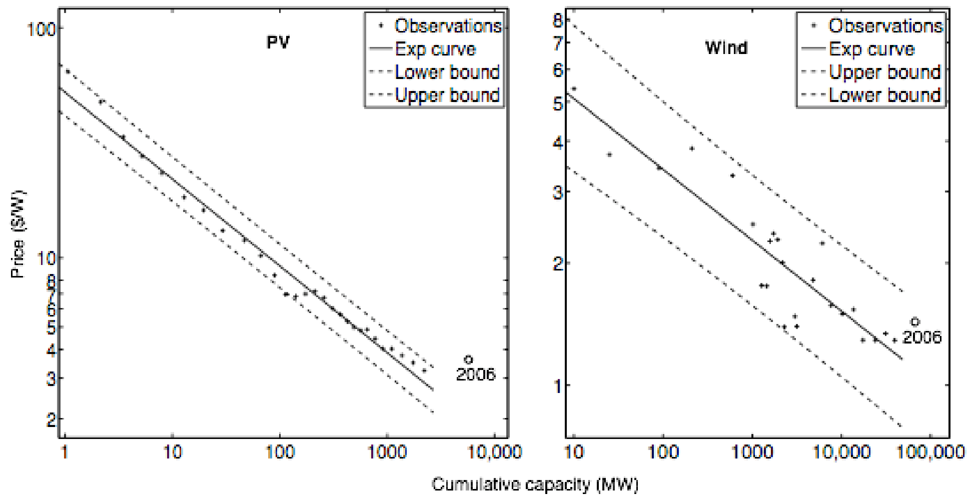

Figure 9: Observations, experience curves, and 95% confidence intervals based on dispersion in historical data. Left panel: PV 1976-2003. Right panel: Wind 1981–2004.

have been predicted by the set of all possible historical forecasts. This section uses eq. 1 and, forecasting for each year, t, calculates the expected price at the cumulative capacity that was actually reached in 2006, E_{2006}:

$$P_{2006} = P_m(E_{2006})^{b_i} \tag{8}$$

A price, P_{2006} is projected using the set of learning factors b_i, calculated from all the time series that were available at year t (eq. 2).

To illustrate, Fig. 10 shows the predictions, over time, of the price of PV for the cumulative capacity that was reached in 2006, E_{2006}. The first result is that none of the 232 possible projections for 2006 would have predicted a level at or above the actual 2006 price. Next this method is used to project prices for the cumulative capacities reached in all years from 1986–2006. In Fig. 11, the range in gray represents the full range of forecasts for the capacity that was reached in each year. For example, the gray range for 2006 includes all of the 232 data points portrayed in Fig. 10. Actual prices in each year are shown as a line with white circles. The second result is that, other than two individual occurrences, the only time the actual prices have consistently fallen outside the range of all possible learning rate derived price forecasts was in 2004–06.

Similarly, Fig. 12 shows the predictions, over time, for the price of wind power for the cumulative capacity that was reached in 2006, E_{2006}. In

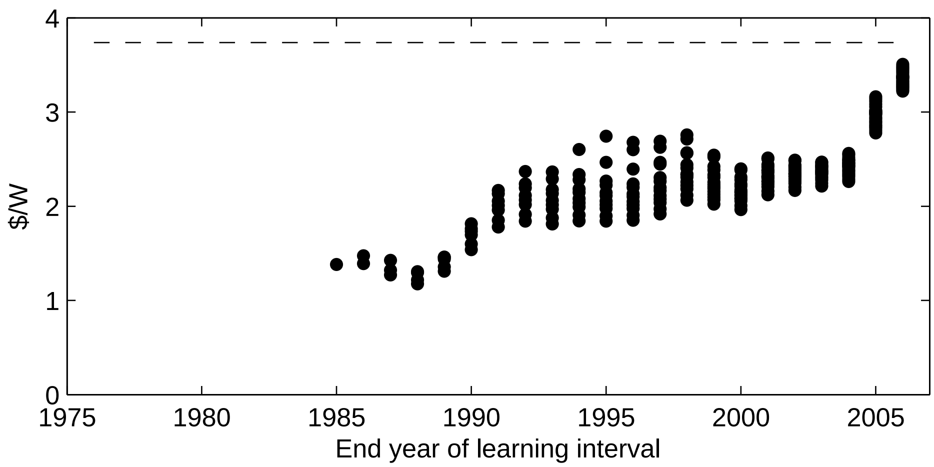

Figure 10: PV: trend in predictions of prices for the capacity levels reached in 2006. Dashed line shows actual value in 2006.

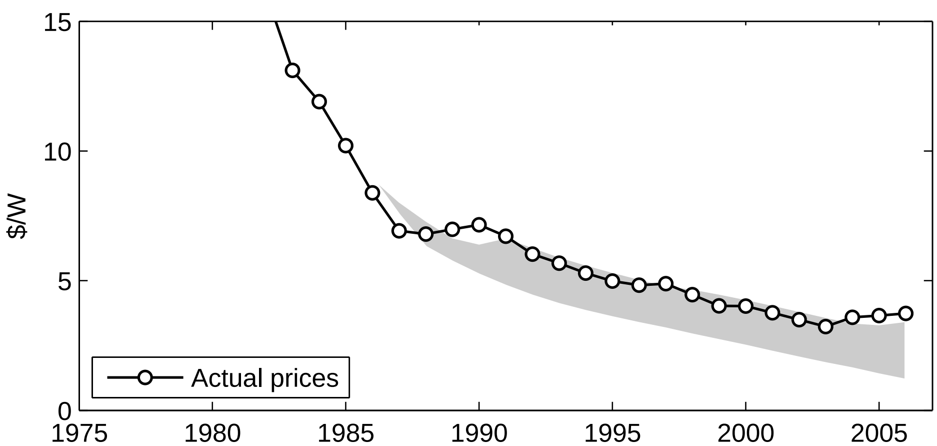

Figure 11: PV: gray shows the range of all forecasts for the price of PV at the cumulative capacity reached in each year. Actual prices are shown as a line with white circles.

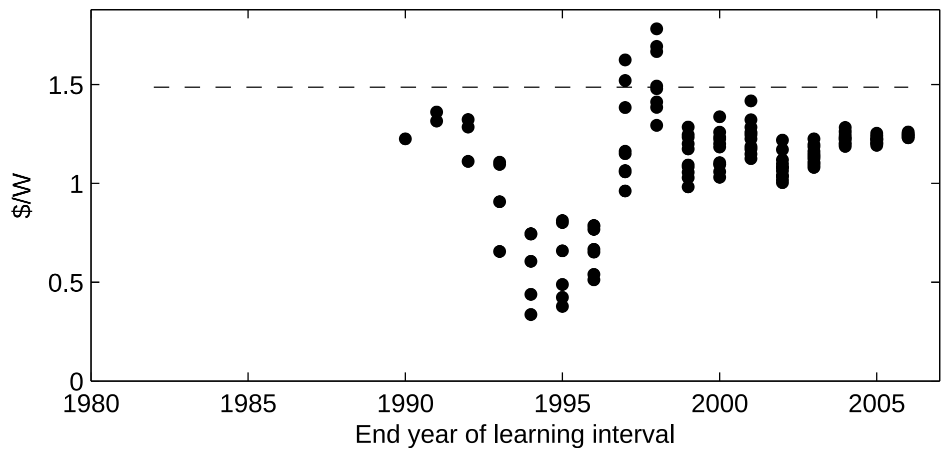

Figure 12: Wind: trend in predictions of prices for the cumulative capacity levels reached in 2006. Dashed line shows actual value in 2006.

contrast to PV, some projections for wind power prices would have been quite close to the actual 2006 price level, with several even overestimating the actual price. As with PV, this method is applied to predict all years from 1991–2006 in Fig. 13. In the case of wind, recent prices do fit within the range defined by all previous forecasts. Similarly to PV, historical wind power prices have always stayed within the range, except for one year, 1997.

The outcome of this analysis concurs with that of the confidence interval analysis: the recent deviations in PV fall outside the range of historical precedent, while those of wind remain within. While further analysis is certainly needed to characterize the sources and persistence of these deviations, these methods may be useful as a preliminary screen to identify that near term deviations merit further investigation.

6 Discussion

The results of the analyses in this paper indicate (1) a need for policy makers to more explicitly consider uncertainty in cost projections and (2) the importance of the development of better tools to identify the significance of near term deviations from projections. This study assessed two technology case studies and provided evidence that expected costs to subsidize technologies until they are competitive with alternatives span a large range—beyond an order of magnitude. Note that this range was a observed for a technology,

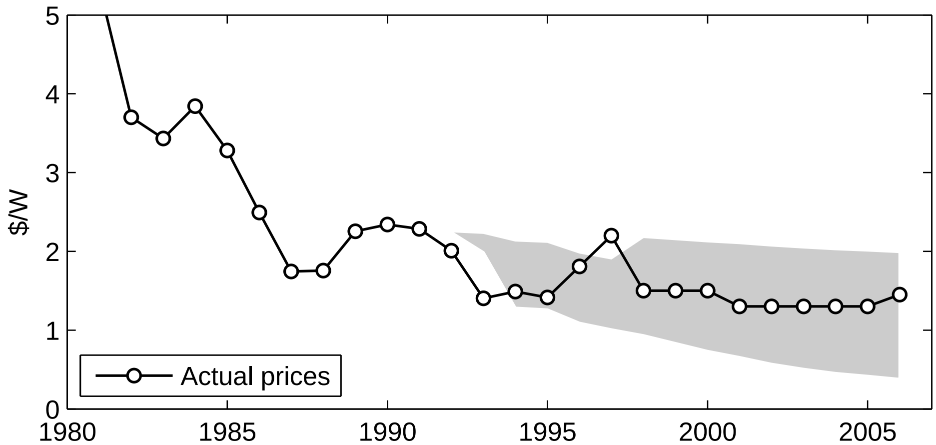

Figure 13: Wind: gray shows the range of all forecasts for the price of wind at the cumulative capacity reached in each year. Actual prices are shown as a line with white circles.

PV, for which goodness of fit of logged prices to logged cumulative capacity was over 0.95. Dispersion in cost projections for wind power was even larger. These results suggest that projected subsidy costs are highly sensitive to timing of the data used: both *when* the forecast was made, and the *duration* of the historical data set used. The high dispersion in costs—and especially the skewness of the distribution toward high values—emphasizes the importance of interim monitoring of technological improvement.

To this end, two methods were employed to assess technology cost development in the near term. Ranges of projected values were estimated using (1) confidence intervals around the power function and (2) a moving range of forecasts based on all possible historical time series. Recent prices were then determined as falling within or outside of these ranges, since in both cases recent costs appear to have deviated from experience curve projections. For PV, recent prices fall outside the full range of projections using both methods. For wind recent prices remained within the range of projections under both methods.

6.1 Policy implications

This analysis points to two normative conclusions for policy makers. First, if policy makers are to rely on future cost projections derived from experience curves, they need to be explicit about the reliability of predictions.

Policy decisions should be made acknowledging the observed variation in rates of technological improvement over time. Policy makers would do well to consider learning as a stochastic process (Gritsevskyi and Nakicenovic, 2000), perhaps similar to the way that the outcomes of R&D investments are inherently uncertain, despite improvements in understanding about R&D productivity (Baker and Adu-Bonnah, 2008).

Second, devising ex ante methods to identify the significance of near-term deviations in technology cost and performance trends is essential. How should policy makers respond to situations such as those for PV (Fig. 3) and wind (Fig. 4) in which recent prices appear to be deviating from the experience curve path? Are these short term deviations driven by supply bottlenecks, or are they representations of the lower limits on cost? Deviations make policy difficult; policy makers need to be vigilant against encountering the extremely expensive outcomes found in Sec.4. For example, debate over subsidies amounting to several billions dollars in the 2007 Independence and Security Act in the U.S. EIA suggests that programs involving hundreds of billions will be subject to scrutiny (Schnapp, 2008). But the substantial social value these technologies have the potential to deliver at widespread deployment implies that policy makers may also need to defend technology support against competing social priorities when deviations are actually short term aberrations. How can near term data be used to assess confidence in longer term projections?[6] The methods developed in Sec. 5 suggest some avenues for analysis; ultimately, better tools will be required.

6.2 The need for new analytical tools

An ongoing deficiency in government support for technology improvement arises from the lack of analytical tools with which to add insight on future costs. Much is at stake, both in terms of the public's financial resources used to fund these programs and the environmental impacts these programs are designed to mediate. These decisions are too important—and mistakes too expensive—to rely on simple heuristics that mask large uncertainties, which are easily ignored. Promising developments exist. An important analytical improvement has certainly been the inclusion of explicit treatment of learning uncertainty in modeling (Alberth and Hope, 2007; Rubin et al., 2007; Uyterlinde et al., 2007). Estimating technology costs through the summation of 'bottom-up' characterization of technology dynamics in individual components provides an appealing alternative, in that sources of uncertainty

[6] In many ways, this challenge is similar to debates about indicators of climate change (Rahmstorf et al., 2007; Pielke, 2008).

can be identified more precisely (Keshner and Arya, 2004). Comparisons of such bottom-up models with experience curves and expert opinion provides a method that is more robust to bias within any single method (Neij, 2008). An alternative use of bottom-up methods is to integrate them with expert elicitation into a single model that represents both incremental and non-incremental technical change (Nemet and Baker, 2008). Improving the accuracy and precision of models such as these is an important research endeavor. Still, one should not lose sight of the goal of the ambitious plans to devote public resources to the improvement of societally beneficial energy technologies. Ultimately, the insights from these models need to be built in to the design of programs that create strong and persistent incentives for private sector investments in cost-reducing activities.

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References

Alberth, S., Hope, C., 2007. Climate modelling with endogenous technical change: Stochastic learning and optimal greenhouse gas abatement in the PAGE2002 model. Energy Policy 35 (3), 1795–1807.

Albrecht, J., 2007. The future role of photovoltaics: A learning curve versus portfolio perspective. Energy Policy 35 (4), 2296–2304.

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

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

Arthur, W. B., 2006. Out-of-equilibrium economics and agent-based modeling. In: Judd, K., Tesfatsion, L. (Eds.), Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics. Elsevier/North-Holland, pp. 1551–1564.

Baker, E., Adu-Bonnah, K., 2008. Investment in risky R&D programs in the face of climate uncertainty. Energy Economics 30 (2), 465–486.

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

Borenstein, S., 2008. The market value and cost of solar photovoltaic electricity production. Working Paper CSEM WP-176, University of California Energy Institute's Center for the Study of Energy Markets.

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

CPUC, 2003. Decision 03-06-071, order initiating implementation of the Senate Bill 1078 Renewable Portfolio Standard Program.

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

Dutton, J. M., Thomas, A., 1984. Treating progress functions as a managerial opportunity. Academy of Management Review 9 (2), 235–247.

Edenhofer, O., Lessmann, K., Kemfert, C., Grubb, M., Köhler, J., 2006. Induced technological change—exploring its implications for the economics of atmospheric stabilization: Synthesis report from the Innovation Modeling Comparison Project. The Energy Journal 27 (Special Issue on Endogenous Technological Change and the Economics of Atmospheric Stabilisation), 57–108.

Epple, D., Argote, L., Devadas, R., 1991. Organizational learning curves: A method for investigating intra-plant transfer of knowledge acquired through learning by doing. Organization Science 2 (1, Special Issue: Organizational Learning: Papers in Honor of (and by) James G. March), 58–70.

Freeman, C., Louca, F., 2001. As time goes by: from the industrial revolutions to the information revolution. Oxford University Press, Oxford.

Goldemberg, J., Coelho, S. T., Lucon, O., 2004. How adequate policies can push renewables. Energy Policy 32 (9), 1141–1146.

Gritsevskyi, A., Nakicenovic, N., 2000. Modeling uncertainty of induced technological change. Energy Policy 28 (13), 907–921.

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

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

Hultman, N. E., Koomey, J. G., 2007. The risk of surprise in energy technology costs. Environmental Research Letters 2 (3), 034002.

Hultman, N. E., Koomey, J. G., Kammen, D. M., 2007. Viewpoint: What history can teach us about the future costs of U.S. nuclear power? Environmental Science and Technology 41 (9), 2088–2093.

IEA, 2008. Energy Technology Perspectives: Scenarios and Strategies to 2050. International Energy Agency, Paris.

IPCC, 2007. Climate change 2007: Mitigation. Contribution of Working group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Irwin, D. A., Klenow, P. J., 1994. Learning-by-doing spillovers in the semiconductor industry. Journal of Political Economy 102 (6), 1200–1227.

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

Kahouli-Brahmi, S., 2008. Technological learning in energy-environment-economy modelling: A survey. Energy Policy 36 (1), 138–162.

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

Koomey, J., Hultman, N. E., 2007. A reactor-level analysis of busbar costs for U.S. nuclear plants, 1970-2005. Energy Policy 35 (11), 5630–5642.

Marx, K., 1867. Capital. Harmondsworth, Middlesex, England.

McDonald, A., Schrattenholzer, L., 2001. Learning rates for energy technologies. Energy Policy 29, 255–261.

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

Neij, L., 2008. Cost development of future technologies for power generation–a study based on experience curves and complementary bottom-up assessments. Energy Policy 36 (6), 2200–2211.

Neij, L., Andersen, P. D., Durstewitz, M., 2003. The use of experience curves for assessing energy policy programs. In: Proceedings of the EU/IEA Workshop on Experience Curves: A tool for energy policy analysis and design. Paris.

Neij, L., Astrand, K., 2006. Outcome indicators for the evaluation of energy policy instruments and technical change. Energy Policy 34 (17), 2662–2676.

Nemet, G. F., 2006. Beyond the learning curve: factors influencing cost reductions in photovoltaics. Energy Policy 34 (17), 3218–3232.

Nemet, G. F., 2007. Policy and innovation in low-carbon energy technologies. Dissertation, University of California.

Nemet, G. F., Baker, E., 2008. Demand Subsidies versus R&D: Comparing the Uncertain Impacts of Policy on a Pre-Commercial Low-Carbon Energy Technology. SSRN.

Nordhaus, W. D., 2002. Modeling induced innovation in climate change policy. In: Grubler, A., Nakicenovic, N., Nordhaus, W. D. (Eds.), Technological change and the environment. Resources for the Future, International Institute for Applied Systems Analysis, Washington, DC, pp. 182–209.

Nunez, F., September 27 2006. Assembly Bill 32: the California Global Warming Solutions Act of 2006.

Peevey, M. R., Malcolm, K., 13 December 2006. Interim order adopting policies and funding for the California Solar Initiative.

Pielke, R. A., 2008. Climate predictions and observations. Nature Geosci 1 (4), 206–206.

Popp, D., 2006. ENTICE-BR: The effects of backstop technology R&D on climate policy models. Energy Economics 28 (2), 188–222.

Rahmstorf, S., Cazenave, A., Church, J. A., Hansen, J. E., Keeling, R. F., Parker, D. E., Somerville, R. C. J., 2007. Recent climate observations compared to projections. Science 316 (5825), 709.

Rapping, L., 1965. Learning and World War II production functions. The Review of Economic Statistics 47 (1), 81–86.

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

Rubin, E. S., Antes, M., Yeh, S., Berkenpas, M., August 1 2005. Estimating future trends in the cost of CO2 capture technologies. Report, International Energy Agency Greenhouse Gas R&D Programme (IEA GHG).

Rubin, E. S., Taylor, M. R., Yeh, S., Hounshell, D. A., 2004. Learning curves for environmental technology and their importance for climate policy analysis. Energy 29 (9-10), 1551–1559.

Rubin, E. S., Yeh, S., Antes, M., Berkenpas, M., Davison, J., 2007. Use of experience curves to estimate the future cost of power plants with CO2 capture. International Journal of Greenhouse Gas Control 1 (2), 188–197.

Sark, W. G. J. H. M. v., 2008. Introducing errors in progress ratios determined from experience curves. Technological Forecasting and Social Change 75 (3), 405–415.

Schenk, N., Lensink, S., 2007. Communicating uncertainty in the IPCC's greenhouse gas emissions scenarios. Climatic Change 82 (3), 293–308.

Schnapp, R., April 2008. Federal financial interventions and subsidies in energy markets 2007. Report R/CNEAF/2008-01, Energy Information Administration: Office of Coal, Nuclear, Electric, and Alternate Fuels.

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

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

Sher, B., September 27 2002. Senate Bill 1078: The Renewables Portfolio Standard of California - chapter 516, statutes of 2002.

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

Stern, N., 2006. Stern Review on the economics of climate change. Cambridge University Press, Cambridge, UK.

Sue Wing, I., 2006. Representing induced technological change in models for climate policy analysis. Energy Economics 28 (5-6), 539–562.

Uyterlinde, M. A., Junginger, M., de Vries, H. J., Faaij, A. P. C., Turkenburg, W. C., 2007. Implications of technological learning on the prospects for renewable energy technologies in europe. Energy Policy 35 (8), 4072–4087.

van der Zwaan, B., Rabl, A., 2003. Prospects for PV: A learning curve analysis. Solar Energy 74, 19–31.

van der Zwaan, B., Rabl, A., 2004. The learning potential of photovoltaics: Implications for energy policy. Energy Policy 32, 1545–1554.

Wene, C.-O., 2000. Experience curves for technology policy. Report, International Energy Agency.

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

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