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Interim monitoring of cost dynamics for publicly supported energy technologies

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ABSTRACT

The combination of substantial public funding of nascent energy technologies and recent increases in the costs of those that have been most heavily supported has raised questions about whether policy makers should sustain, alter, enhance, or terminate such programs. This paper uses experience curves for photovoltaics (PV) and wind to (1) estimate ranges of costs for these public programs and (2) introduce new ways of evaluating recent cost dynamics. For both technology cases, the estimated costs of the subsidies required to reach targets are sensitive to the choice of time period on which cost projections are based. 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.

1. Introduction

Large programs and deviations from trends in cost reductions are challenging policy makers to make decisions about whether, when, and how much to stimulate the development of energy technologies that have high external benefits. The net benefits of subsidies and other incentives 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 cost 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.

The motivating premise behind this study is that rigorous analysis of the uncertainty involved in making experience curve-based cost projections can inform policy decisions and improve the outcomes of technology subsidy programs. Without better analytical tools, decisions about these programs are vulnerable to political expediency and near-term fiscal constraints. The use of the term interim monitoring here is meant to suggest the evaluation of data available between the time at which programs have begun and when the full benefits of cost reductions are expected to arrive. Because a substantial portion of the benefits of these programs arrive several years hence, monitoring the progress of technology cost reductions in the intermediate term is crucial for decision-making. Possible responses to interim results include: continuation of existing programs, early termination, changes to subsidy levels, and supplementing subsidies with complementary programs that address additional market failures and barriers. This study examines two questions: How sensitive are the social costs of subsidy programs 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

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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. Experience curves provide a way to project future costs conditional on the cumulative quantity of capacity produced. The resulting cost predictions are less deterministic than those generated by temporal-based rates of technological change, but they are also not simply scenarios, internally consistent descriptions of one possible future state of technology; they are conditional predictions.

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 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.[1]

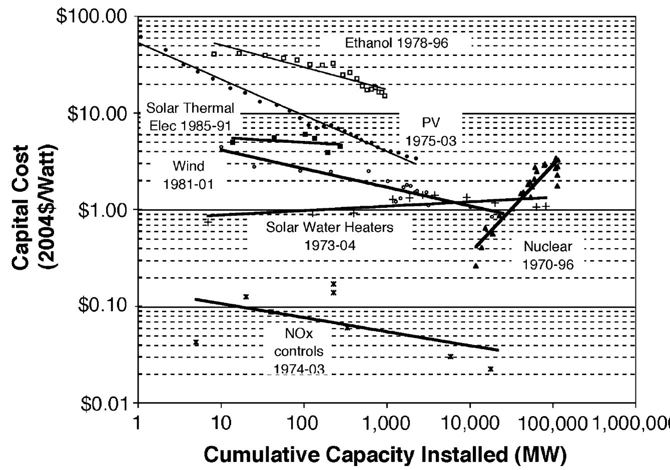

Fig. 1. Experience curves for energy technologies. Data from Nemet (2007).

Experience curves have been assembled for a wide variety of energy technologies. For useful studies and surveys see Wene (2000), McDonald and Schrattenholzer (2001), Junginger et al. (2005), Albrecht (2007), Hultman and Koomey (2007), and Neij (2008). Fig. 1 shows learning rates (LRs) for a variety of energy-related technologies.[2] 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 LRs included in these studies is attributable 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.

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

[1] 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).

[2] 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).

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 10 of those models.[3] 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 UK and has played a role in debates in the US 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 [3–7] 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 PV (Peevey and Malcolm, 2006). Experience curves have also been used in economic models of the cost of meeting California's ambitious 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.[4] 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 LRs are important (Rubin et al., 2004; Kahouli-Brahmi, 2008).

Although studies have cautioned that policy makers must contend with discontinuities and uncertainties in future LRs, 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

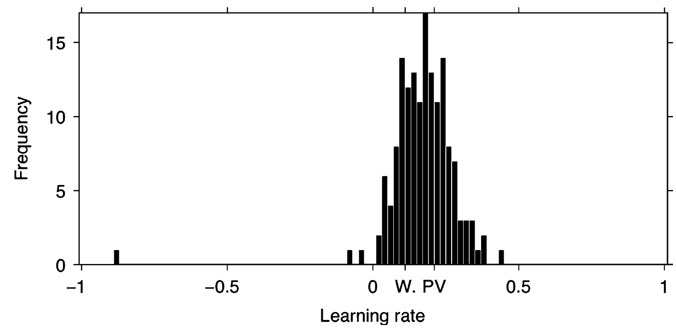

Fig. 2. Frequency distribution of learning rates calculated in 156 learning curve studies. Median learning rates for wind and PV obtained in this study indicated by "W." and "PV." Data from Dutton and Thomas (1984), McDonald and Schrattenholzer (2001), and Nemet (2007).

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.

Empirical observations of technology cost dynamics support the notion that variation in LRs is substantial. Dutton and Thomas (1984) surveyed 108 learning curve studies and showed a wide variation in LRs leading them to question the explanatory power of experience. Fig. 2 combines their LR data with those of a survey of energy technology LRs by McDonald and Schrattenholzer (2001), as well as those for the experience curves shown in Fig. 1 to display a distribution of 156 LRs. The LR 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 LRs caused by imperfect correlations between cumulative capacity and cost.[5] Sark (2008) explores the effects of this "*r*-squared" variation to calculate an error around the LR. Inconsistencies of the system boundaries chosen, e.g. geographic scope, may introduce some of this variation. 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 learning is subject to "sharply diminishing returns." Looking at studies within single manufacturing facilities, Baloff (1966) and Hall and Howell (1985) find that LRs 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 LR continuously over time. A third source of uncertainty derives from the choice of historical time period used to calculate LRs (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 LRs themselves but on the non-linear effects that emerge as they propagate through policy models. Studies that focus on the source of uncertainty typically underemphasize the

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

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

[5] Imperfect here means that the measure of fit, e.g. r^2, when regressing log of cost on log of cumulative capacity is less than one.

ramifications of an apparently small variation in LRs. One notable exception is a study by Alberth and Hope (2007); they found that the level of optimal climate change abatement becomes more uncertain when distributions of LRs, rather than point estimates, are used. Uyterlinde et al. (2007) also show the sensitivity of outcomes by using multiple LRs, 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: PV 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, cost reductions are expected to be continuous for both (Irwin and Klenow, 1994). Finally, these technologies are important; because the availability of the resource to deploy them is incredibly 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 (Gipe, 1995; CEC, 1997; IEA, 2002; Strategies-Unlimited, 2003; AWEA, 2004; Maycock, 2005; Nowak, 2005; Maycock and Bradford, 2007; Nemet, 2007; Wiser and Bolinger, 2007; BEA, 2008).

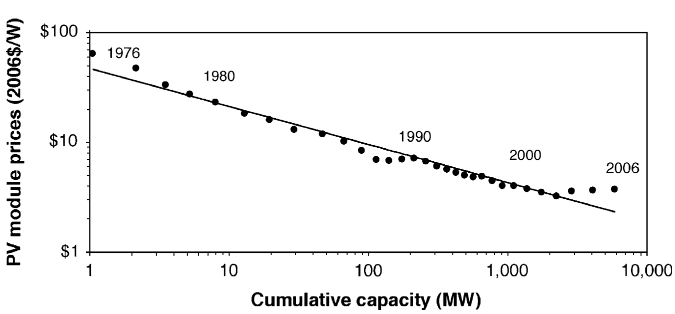

Fig. 3. Experience curve for PV modules (1976–2006). Data from Nemet (2007).

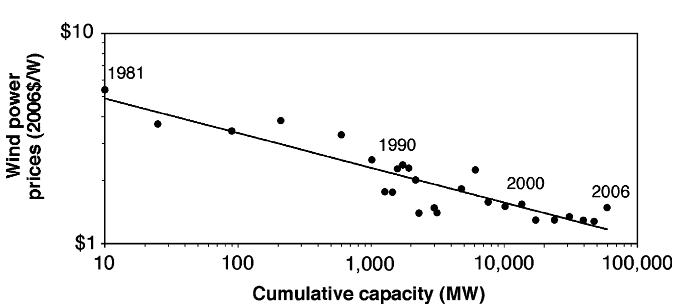

Fig. 4. Experience curve for capital cost of wind turbines (1981–2006). Data from Nemet (2007).

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. For example, measurements based on capital cost ignore changes in operations, such as availability rates. 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.

3.1. Calculating LRs

LRs 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. Using manufacturing cost data, rather than prices, provides clearer identification of technical progress since the former are independent of changes in profit margins due to evolving market structure (Irwin and Klenow, 1994). However, in the case of competing technologies, technology users make adoption decisions based on the purchase prices they face, not the costs to a manufacturer. Because this study is ultimately concerned with estimating the point at which adopters will prefer a new technology to an existing technology, price data are used throughout. 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

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

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. For each set of data, values for b are determined by linearly regressing a vector $\log(P_t)$ on vector $\log(E_{t-1})$ for $t = m$ to n, where b is the coefficient that minimizes the sum of squared differences between the actual data for P_t and the predicted values (Sark, 2008). The model estimates a value for b for every combination of beginning years, t_m and end years, t_n for which $t_n - t_m \geqslant 9$. Estimating b allows calculation of the "progress ratio", $PR = 2^b$ and the "learning rate", $LR = 1 - PR$.

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_0. 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 the price of electricity from that technology reaches that of the existing technology. Since capital costs for PV and wind are the dominant component of their electricity costs, comparisons are made based on capital costs. The learning technology becomes competitive when its price, P reaches a price at which electricity from the learning technology is equal to 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

$$E_\alpha = E_0\left(\frac{P_\alpha}{P_0}\right)^{1/b} \quad (2)$$

where P_0 is the price of the learning technology in the base year and E_0 is the cumulative manufacturing experience in the base year.

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

$$t_\alpha = \frac{\log E_\alpha - \log E_0}{\log(1+g)} \quad (3)$$

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_0 until t_α is calculated using

$$P_t = P_0(1+g)^{(t\cdot b)} \quad (4)$$

The annual production of the learning technology M_t is calculated using

$$M_t = M_0(1+g)^t \quad (5)$$

where M_0 is annual production in the base year. The total present value cost of the subsidy program, S, is

$$S = \sum_{t=0}^{t_\alpha} M_t(P_t - P_\alpha)(1+\delta)^{t_0 - t} \quad (6)$$

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 LR, (2) the year at which the cost of a subsidized technology approaches a target level, and (3) the discounted cost of government subsidies 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 are used, for which $r^2 = 0.96$, to calculate LRs for all possible time periods.

4.1.1. *LRs over time*

Eq. (1) is used to estimate the LR for PV in each of the 253 time periods of 10 years or greater between 1976 and 2006.[6] Fig. 5 plots

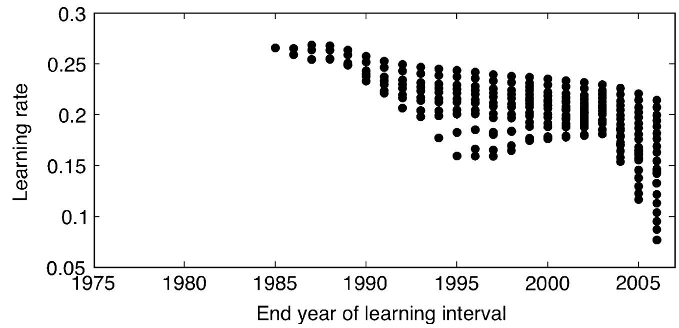

Fig. 5. Learning rates for PV (1976–2006) calculated for all periods $\geqslant$10 years ($n = 253$).

these LRs by the year at which each time series ends. For example, the values shown for 1995 include all 11 time series that end in 1995. This set of values indicates the range of LRs 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 LRs. First, there is a negative time trend; the mean of the LR values has decreased over time, by approximately 0.005 per year. Second, the dispersion in LR values around the annual mean has increased over time. The dispersion includes an oscillation with maxima in 1995 and 2006.

The upper panel of Fig. 6 shows the distribution of LRs 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 LRs 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.

4.1.2. *Crossover year*

Eqs. (2) and (3) 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 $P_\alpha = \$1/\text{W}$ (SEIA, 2004). A 73% subsidy on actual 2006 prices is needed for consumers' costs to equal this target. 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 Eqs. (4)–(6). 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

[6] Each year represents a full year of data, so inclusively there are 31 years of data in the data set ($2006 - 1976 + 1 = 31$). Here, a LR requires >9 years to be valid. So there are $31 - 9 = 22$ periods available that have 1976 as the first year $(2006 - 1977 + 1) - 9 = 21$ periods beginning in 1977, and $(2006 - 1997 + 1) -$

(*footnote continued*)
$9 = 1$ period available beginning in 1997, the last year for which a 10-year time series is available. For PV, the number of time periods from which to calculate LRs is $\sum_{n=1976}^{1997}(2006 - n + 1 - 9) = 253$. Similarly, for wind, $\sum_{n=1981}^{1997}(2006 - n + 1 - 9) = 153$.

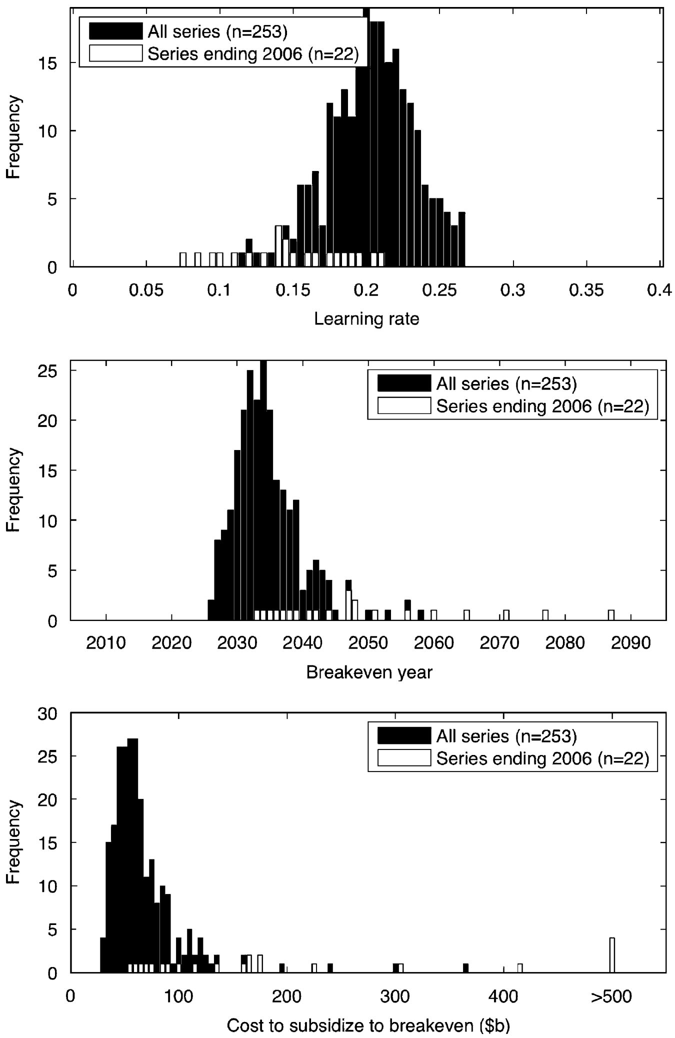

Fig. 6. Upper: calculated learning rates for PV; middle: year at which price of PV equals that of competing technology; lower: present value of cost to subsidize PV until it equals cost of competing technology. The black columns include values for all 253 time series from 1976 to 2006. The white columns include only those time series that end in 2006.

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$)			
5th percentile	0.25	2028	38
Median	0.21	2034	62
95th percentile	0.14	2049	175
σ	0.03	8	229
For time series ending 2006 ($n = 22$)			
5th percentile	0.21	2034	59
Median	0.15	2048	163
95th percentile	0.08	2082	2172
σ	0.04	15	713

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 LR 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 5th 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 $r^2 = 0.82$, are used to calculate LRs for varying time periods.

4.2.1. Calculate LRs for varying periods

Fig. 7 shows the trend in LRs for wind power over time. The figure shows a negative time trend in LRs 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.

The upper panel of Fig. 8 shows the distribution of LRs 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 153 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 $900/kW (IEA, 2008). A 40% subsidy on actual costs would be needed for consumers to see this target. 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, $t_\alpha = 2029$, is six years less than the estimates using only data through 2006 $t_\alpha = 2035$, not a significant difference.

4.2.3. Cost of a subsidy program

The median cost to subsidize wind is $105b when using all time series and $174b 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 LRs experienced in the past produces very expensive subsidy programs, well into the trillions of dollars.

4.3. Summary of results

In the case of PV, an apparently high r^2 value of $>95\%$ contains variation that leads to substantial LR variation depending on the time period chosen. The resulting dispersion in LRs leads to ranges of subsidy cost estimates that are not only large, but asymmetric around the mean. Slow learning is possible, even within highly

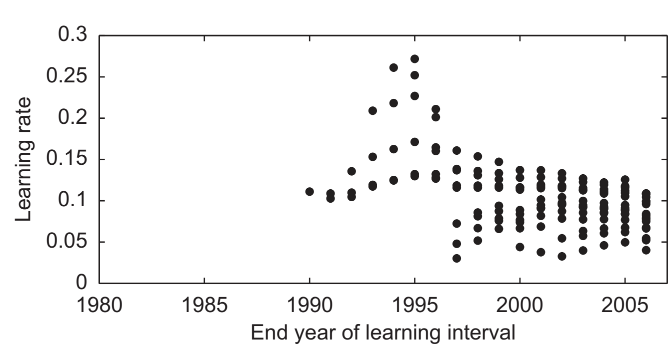

Fig. 7. Learning rates for wind power (1981–2006) calculated for all periods $\geqslant 10$ years ($n = 153$).

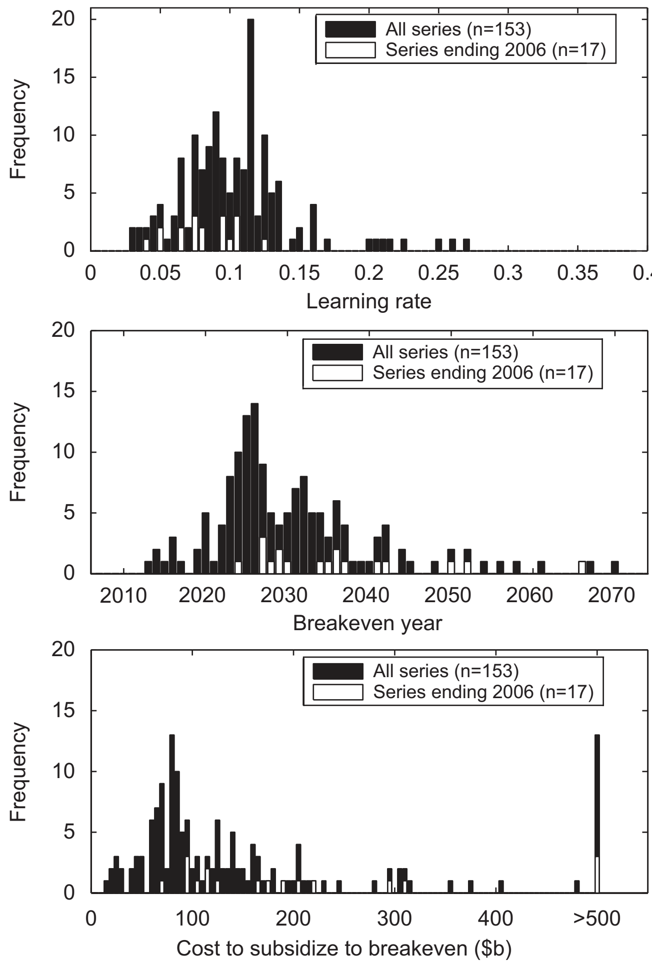

Fig. 8. Upper: calculated learning rates for wind; middle: year at which price of wind equals that of competing technology; lower: present value of cost to subsidize wind until it equals cost of competing technology. The black columns include values for all 153 time series from 1981 to 2006. The white 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 = 153$)			
5th percentile	0.20	2017	33
Median	0.10	2029	105
95th percentile	0.05	2057	903
σ	0.04	11	918
For time series ending 2006 ($n = 17$)			
5th percentile	0.12	2026	82
Median	0.08	2035	174
95th percentile	0.05	2061	1430
σ	0.02	11	438

correlated data sets with above average LRs. 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 to 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 to 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 have been projected 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}:

$$P_{2006} = P_m(E_{2006})^{b_i} \tag{7}$$

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. (1)).

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 231 possible projections for 2006 would have predicted a level at or above the actual 2006

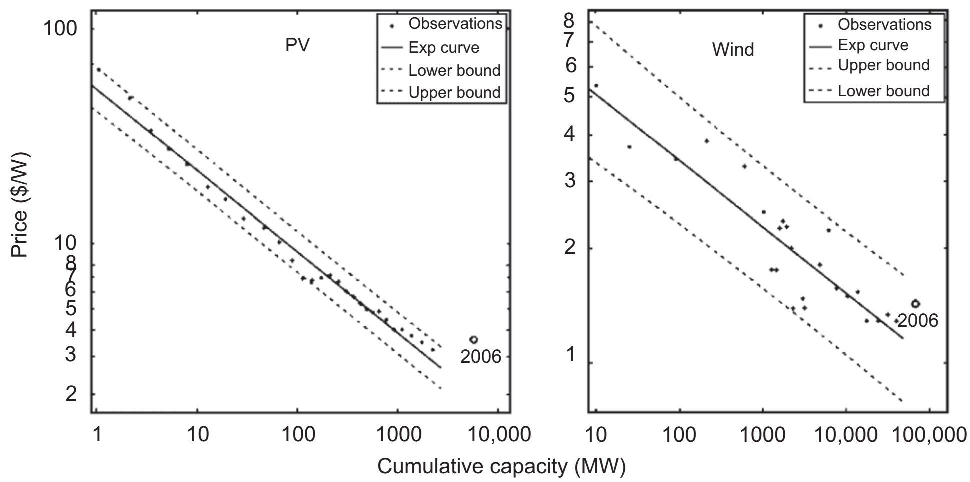

Fig. 9. Observations, experience curves, and 95% confidence intervals based on dispersion in historical data. Left panel: PV 1976–2003. Right panel: Wind 1981–2004.

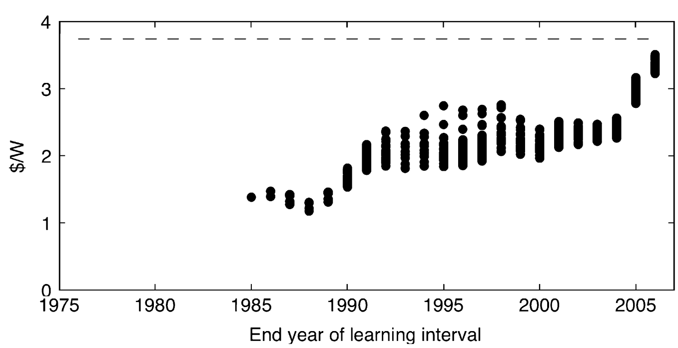

Fig. 10. PV: trend in predictions of prices for the capacity levels reached in 2006. Dashed line shows actual value in 2006.

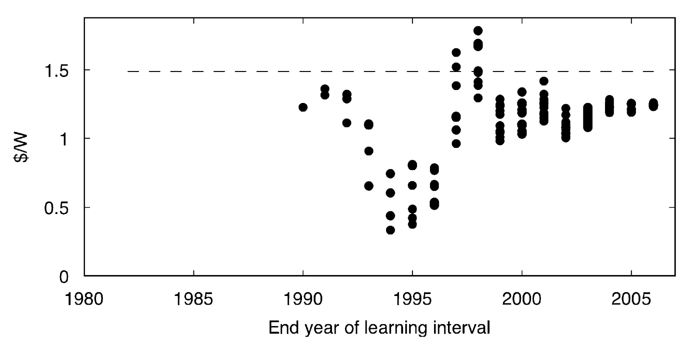

Fig. 12. Wind: trend in predictions of prices for the cumulative capacity levels reached in 2006. Dashed line shows actual value in 2006.

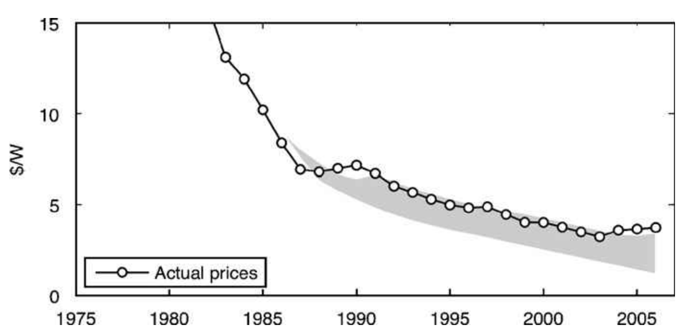

Fig. 11. PV: gray shows the range of all forecasts for the price of PV at the cumulative capacity reached in each year. Actual prices are shown as a line with white circles.

price. Next this method is used to project prices for the cumulative capacities reached in all years from 1986 to 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 231 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 LR derived price forecasts was in 2004–2006.

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 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 to 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.

5.3. Savings from niche markets

Finally, one should also consider that niche markets exist where early adopters have a higher willingness to pay than the cost of the alternative technology (Geels, 2002; Shum and Watanabe, 2007). Accounting for these niche markets will lower subsidy costs because willingness to pay among these consumers is not P_α but P_v where $P_t > P_v > P_\alpha$. Here, the size of the niche markets is based on a fraction, v of the breakeven capacity, so that the size of the niche market, $E_v = v(E_\alpha - E_0)$. The total savings due to niche markets are

$$N = \sum_{t=0}^{t_v} M_t (P_t - P_v)(1+\delta)^{t_0 - t} \tag{8}$$

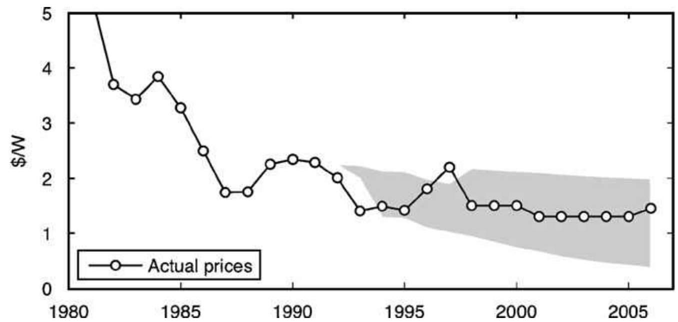

Fig. 13. Wind: gray shows the range of all forecasts for the price of wind at the cumulative capacity reached in each year. Actual prices are shown as a line with white circles.

Table 3
Sensitivity of subsidy program costs to size of niche markets, v.

	PV		Wind	
v:	1%	10%	1%	10%
Program costs with niches, $S-N$ ($b)				
Median	59	46	103	84
95th percentile	159	124	823	649
Savings due to niches, N/S				
Median	4%	25%	2%	21%
95th percentile	9%	29%	9%	28%

where t_v is the year at which niche markets are saturated, $E_t > E_v$. The cost of the subsidy program after accounting for niche markets is $S-N$.

The sensitivity of subsidy costs to niche markets is evaluated by assuming that in niche markets $P_v = (P_t + P_\alpha)/2$, and that reasonable values for the size of niche markets are 1% and 10% of cumulative demand through breakeven. Table 3 shows that for PV, niche markets of 1% and 10% reduced median program costs by 4% and 25%, respectively. Their effect on the most expensive outcomes, the 95th percentile, was larger. Results for wind were similar, albeit with slightly smaller effects.

The existence of niche markets is substantial and they should be accounted for. Empirical analysis of the level of willingness to pay in niche markets, and the size of these markets will add insight into the extent to which they reduce the cost of subsidy programs. Still, the inclusion of niche markets does not change the finding that outcomes at the 95th percentile are far larger than those at the median.

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 observed for a technology, 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. Given the current state of knowledge about what actually causes variation in LRs, policy makers would do well to consider learning as a stochastic process—that is, that some aspects of the process remain unpredictable (Gritsevskyi and Nakicenovic, 2000). In this respect, learning is similar to the outcomes of R&D investments; they are inherently uncertain despite improvements in understanding about R&D productivity (Baker and Adu-Bonnah, 2008). Important further work on this topic involves assessment of whether this uncertainty is likely to diminish over time as more observations are obtained, in a manner suggested by the central limit theorem. It is unclear whether the results in this study so far support such a notion. In Fig. 5 it appears that the dispersion in LRs for PV has increased over time, while in Fig. 7 the dispersion for wind power fits with the notion of decrease. Even if such a convergence were to occur, a practical issue for policy makers is whether it will occur quickly enough to inform decision-making, and whether the cumulative capacity required for convergence is small relative to the size of the world energy demand.

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 Section 4. For example, debate over subsidies amounting to several billions dollars in the 2007 Independence and Security Act in the US 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?[7] The methods developed in Section 5 suggest some avenues for analysis, but ultimately better tools will be required.

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

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 can be identified more precisely (Keshner and Arya, 2004). Comparisons of such bottom-up models with experience curves and expert opinion provide 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). This integration will help account for the introduction of new technological generations, which seems especially likely in the case of PV. Finally, empirically distinguishing local from global learning effects is needed to inform international coordination among government programs (Benthem et al., 2008; Shum and Watanabe, 2008). The role of international coordination is especially important given the uncertainty that arises from multiple independent national programs and modeling results that show strong path dependence in technology learning (Mattsson and Wene, 1997). 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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