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Learning rates for energy technologies

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Abstract

Technological learning, i.e., cost reductions as technology manufacturers accumulate experience, is increasingly being incorporated in models to assess long-term energy strategies and related greenhouse gas emissions. Most of these applications use learning rates based on studies of non-energy technologies, or sparse results from a few energy studies. This report is a step towards a larger empirical basis for choosing learning rates (or learning rate distributions) of energy conversion technologies for energy models. We assemble data on experience accumulation and cost reductions for a number of energy technologies, estimate learning rates for the resulting 26 data sets, analyze their variability, and evaluate their usefulness for applications in long-term energy models. © 2001 Elsevier Science Ltd. All rights reserved.

For many products and services, unit costs decrease with increasing experience. The idealized pattern describing this kind of technological progress in a regular fashion is referred to as a learning curve, progress curve, experience curve, or learning by doing (Dutton and Thomas, 1984; Argote and Epple, 1990; Argote, 1999). In its most common formulation, unit costs decrease by a constant percentage, called the learning rate, for each doubling of experience.

Because experience accumulates with time, unit costs for a given technology thus decrease with time. Early modeling efforts therefore approximated non-linear learning curves by simple time series in an effort to avoid computational and methodological difficulties. Modelers have specified cost reductions over time both for individual energy technologies (Capros and Vouyoukas, 1999; Nakićenović *et al.*, 1998), and for groups (clusters) of similar technologies (Yohe, 1996; IEA-ETSAP, 1999).

When models in which costs decrease only as a function of time are used to compare alternative greenhouse gas (GHG) emission reduction strategies, they generally favor strategies that delay such reductions (Wigley *et al.*, 1996). This is so because the long-term atmospheric concentration of CO_2 depends mainly on cumulative CO_2 emissions (Houghton *et al.*, 1996). Thus, for a given concentration target, it makes no difference whether carbon reductions are early or delayed, and delayed reductions are cheaper. The models therefore tend to recommend delay.

For most products and services, however, it is not the passage of time that leads to cost reductions, but the accumulation of experience. Unlike a fine wine, a technology design that is left on the shelf does not become better the longer it sits unused. Indeed, interruptions in production and use can cause experience to be lost and unit costs to rise, i.e., "forgetting by not doing" in contrast to learning by doing. Therefore, a number of initiatives are underway to incorporate into energy models technological cost reductions, not as functions of time, but as explicit functions of experience, i.e., as learning curves (Messner, 1997; Mattsson, 1997; EIA/DOE, 1999; Goulder and Mathai, 2000; Grübler and Gritsevskii, 2000). Such a formulation introduces in the models both non-linearities and positive feedbacks (the more a technology is used, the greater the incentive for using it more). This drastically increases model complexity and problematic non-convexities, both of which result in large computational requirements. But progress in modeling and computer performance is rapid, and if the new methods are to produce sensible and useful results, good estimates of technological learning rates will be needed as model input.

The importance of good (reliable) learning rate estimates is shown in Fig. 1. Using illustrative, but realistic,

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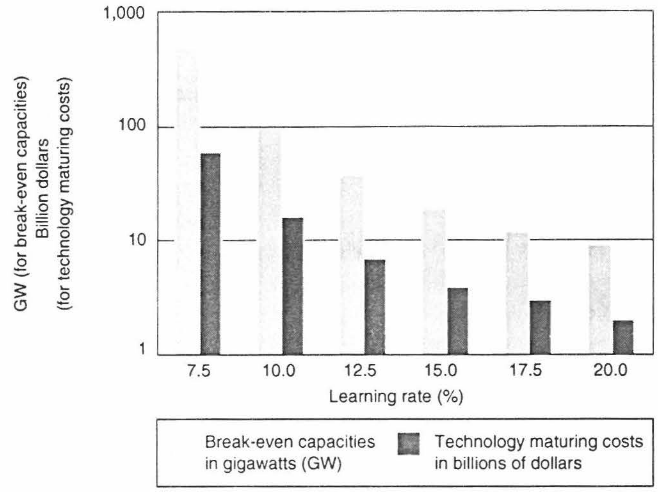

Fig. 1. Sensitivity of break-even capacities and technology maturing costs to learning rate variations.

values, Fig. 1 presents a hypothetical new technology with an initial unit cost of $2000 kW^{-1} and a fixed "competitive cost target" of $1000 kW^{-1}. The left bars represent break-even capacities for a new technology at different assumed learning rates, where the break-even capacity is defined as the capacity additions needed to drive unit costs down to the fixed competitive cost target. The right bars are the technology maturing costs, or the investments — over and above the competitive cost target — needed for the break-even capacity additions. Because the vertical axis of Fig. 1 is logarithmic and the horizontal axis is linear, the figure shows that with decreasing learning rates, technology maturing costs and break-even capacities grow faster than exponentially. For our hypothetical new technology, decreasing the learning rate from 20 to 10% would increase technology maturing costs from $2 billion to $16 billion, and the break-even capacity from 9 to 96 GW.

Such high, non-linear sensitivity to learning rate variations emphasizes the value of, first, reliable learning rate estimates as inputs and, second, stochastic model formulations that can explicitly calculate the impact of remaining learning rate uncertainties on the eventual model results.

As a step in the direction of reliable estimates of energy-related learning rates, and their uncertainties, this paper assembles data for a variety of energy technologies (from natural gas pipelines to sub-components of end-use technologies), estimates the implied learning rates, checks how well the data fit the classic learning curve model, and draws conclusions about incorporating the resulting learning rates in energy models. Table 1 summarizes 26 data sets and their estimated learning rates assuming that cost reductions are a function only of the experience measure specified in the table. Table 1 also gives the correlation coefficients (R^2)[1], the measures of technological improvement used in the different cases, and the measures of experience. For comparison, Table 2 lists additional energy-related learning rates that we have collected or calculated from the literature, but for which the original data sets are not available for our own analysis.

The first important feature of Tables 1 and 2 is the range of the estimated learning rates across the energy technologies. The range from Table 1 is illustrated as a histogram in the left panel of Fig. 2. For comparison, the right panel shows the results of Dutton and Thomas' (1984) compilation of over 100 studies of learning rates (not restricted to energy technologies) at the level of individual manufacturing firms. The ranges of learning rates in both panels of Fig. 2 are comparable, and the median value of 16–17% for energy technologies is not far below the 19–20% median for the manufacturing firms. This suggests that learning rates (and their variations) from studies not restricted to energy technologies are useful starting points for energy modelers until more detailed studies of energy technologies are available.

To shed light on the reliability of the estimated learning rates, Table 1 also shows the correlation coefficients (R^2) for the estimated learning rates, and the second important feature of the table is the range of values for R^2. Values range from very good (0.99 for Harmon's data on solar PV modules) to very bad. Moreover, there can be more variability within a given data set than might be suggested by a high R^2 value. As an example, consider Harmon's data on PV modules as presented in Fig. 3. The left part of the figure fits a learning curve to the data, yielding an estimated learning rate of 20%. The fit looks impressive, and, as just noted, R^2 equals 0.99. But on the right of Fig. 3, we still find considerable variety in the data set. This part of the figure shows all learning rates that can be calculated from any two points in the data set, as follows. Consider first the curve labeled "1968" (the first label in the legend box). This curve describes the learning rates between 1968 and the year described by the value on the horizontal axis. Taken together, the curves on the right of Fig. 3 seem to show more variability within the data than is evident from the estimated learning curve on the left, and indicate how much calculated learning rates depend on the data points that are chosen. Given that the bulk of the calculated learning rates with end points in the last 15 years fall between 18 and 25%, the overall learning rate of 20% shown in Table 1 looks reasonable, but the right-hand side of Fig. 3 suggests an energy modeler might want to incorporate more

[1] The correlation coefficient is a real number between 0 and 1 (inclusively). It expresses the quality of the fit between the learning curve model and the data. The extreme values of 0 and 1 reflect "no correlation" (or no explanatory value of the postulated formula) and "perfect correlation" (complete explanation by the postulated formula), respectively.

Table 1
Estimated energy-related learning rates[a]

Technology	Country/region	Time period	Estimated learning rate (%)	R^2 [b]	Performance measure (dependent variable)	Experience measure (independent variable)	Reference/data source
Oil extraction	North Sea	—	≈ 25	—	sp. labor (man-hrs to construct one ton of platform jacket)	cum. cap. (construction projects)	Blackwood (1997)
Gas pipelines, onshore	US	1984–1997	3.7	0.09	sp. inv. price (\$/mile-inch^2)	cum. cap. (mile-inch^2)	Zhao (1999)
Gas pipelines, offshore	US	1984–1997	24	0.76	sp. inv. price (\$/mile-inch^2)	cum. cap. (mile-inch^2)	Zhao (1999)
DC converters	World	1976–1994	37	0.35	conversion losses (%)	cum. cap. (installed units)	Rabitsch (1999)
Gas turbines	World[c]	1958–1963	22	–	sp. inv. cost (\$/kW)	cum. cap. (MW)	MacGregor *et al.* (1991)
Gas turbines	World[c]	1963–1980	9.9	–	sp. inv. cost (\$/kW)	cum. cap. (MW)	MacGregor *et al.* (1991)
Gas turbines	World[c]	1958–1980	13	0.94	sp. inv. cost (\$/kW)	cum. cap. (MW)	Nakićenović *et al.* (1998); MacGregor *et al.* (1991)
Nuclear power plants	OECD	1975–1993	5.8	0.95	sp. inv. cost (\$/kW)	cum. cap. (MW)	Kouvaritakis *et al.* (2000)
Hydropower plants	OECD	1975–1993	1.4	0.89	sp. inv. cost (\$/kW)	cum. cap. (MW)	Kouvaritakis *et al.* (2000)
Coal power plants	OECD	1975–1993	7.6	0.90	sp. inv. cost (\$/kW)	cum. cap. (MW)	Kouvaritakis *et al.* (2000)
Lignite power plants	OECD	1975–1992	8.6	0.96	sp. inv. cost (\$/kW)	cum. cap. (MW)	Kouvaritakis *et al.* (2000)
GTCC power plants	OECD	1984–1994	34	0.78	sp. inv. cost (\$/kW)	cum. cap. (MW)	Kouvaritakis *et al.* (2000)
GTCC power plants	World	1981–1991	− 11[d]	0.41	sp. inv. price (\$/kW)	cum. cap. (MW)	Claeson (1999)
GTCC power plants	World	1991–1997	26[d]	0.90	sp. inv. price (\$/kW)	cum. cap. (MW)	Claeson (1999)
Wind power plants	OECD	1981–1995	17	0.94	sp. inv. cost (\$/kW)	cum. cap. (MW)	Kouvaritakis *et al.* (2000)
Wind power (electricity)	California	1980–1994	18	0.85	sp. prod. cost (\$/kWh)	cum. prod. (TWh)	CEC (1997); Loiter and Norberg-Bohm (1999)
Wind	Germany	1990–1998	8	0.95	sp. inv. price (\$/kW)	cum. cap. (MW)	Durstewitz (1999)
Wind turbines	Denmark	1982–1997	8	n.a.	sp. inv. price (\$/kW)	cum. cap. (MW)	Neij (1999)
Solar PV modules[e]	World	1968–1998	20	0.99	sp. inv. price (\$/W_{peak})	cum. cap. (MW)	Harmon (2000)
Solar PV panels	US	1959–1974	22	0.94	sp. sale price (\$/W_{peak})	cum. cap. (MW)	Maycock and Wakefield (1975)
Ethanol	Brazil	1979–1995	20	0.89	sp. sale price (\$/boe)	cum. prod. (cubic meters)	Goldemberg (1996)
Model-T ford	US	1909–1918	14	0.96	sale price (\$ per car)	cum. prod. (cars)	Lipman and Sperling (1999); Abernathy and Wayne (1974)
Compact fluorescent lamps, integral-electronic type	US	1992–1998	16	0.66	sp. sale price (\$ per lumen)	cum. prod. (units)	Iwafune (2000)
Air conditioners	Japan	1972–1997	10	0.82	sale price (Yen per unit)	cum. sales (units)	Akisawa (2000)
4-function pocket calculators	US	Early 1970s	30	n. a.	sale price (\$ per unit)	cum. prod. (units)	Maycock and Wakefield (1975)
SONY laser diodes	—	1982–1994	23	0.95	prod. cost (Yen per unit)	cum. prod. (units)	Lipman and Sperling (1999)

[a]Note: sp. = specific; inv. = investment; cum. = cumulative; cap. = capacity; prod. = production.
[b]Two cautions are in order concerning values for R^2. For each line in the table, R^2 expresses the quality of the fit between the data and the estimated learning curve. However, R^2 values in different lines should not be compared because sample sizes are different. Second, R^2 measures the correlation for a straight line fit to the logarithms of the dependent and independent variables. As linear regression minimizes the sum of error squares, this means that relative rather than absolute errors are minimized.
[c]The geographical scope of the data is not reported explicitly. The context suggests it is the whole world.
[d]Note that these learning rates are based on prices, and one explanation of the negative 1981–1991 "learning" rate could be oligopolistic pricing behavior.
[e]Based on preliminary data.

Table 2
Reported energy-related learning rates[a]

Technology	Country/region	Time period	Estimated learning rate (%)	Performance measure (dependent variable)	Experience measure (independent variable)	Reference/data source
Retail gasoline processing	US	1919–1969	20	sp. prod. cost ($/bbl)	cum. prod. (bbl)	Fisher (1974)
Crude oil at the well	US	1869–1971	5	sale price ($/bbl)	cum. prod. (bbl)	Fisher (1974)
Coal for electric utilities	US	1948–1969	25	sale price to utility ($/ton)	cum. prod. (tons)	Fisher (1974)
Electric power production	US	1926–1970	25	sale price ($/kWh)	cum. prod. (kWh)	Fisher (1974)
Solar PV	EU	1985–1995	35	sp. prod. cost (ECU/kWh)	cum. prod. (TWh)	IEA (2000)
Wind power	US	1985–1994	32	sp. prod. cost ($/kWh)	cum. prod. (TWh)	IEA (2000)
Wind power	EU	1980–1995	18	sp. prod. cost ($/kWh)	cum. prod. (TWh)	IEA (2000)
Wind power	Germany	1990–1998	8	sp. inv. price ($/kW)	cum. cap. (MW)	IEA (2000)
Wind power	Denmark	1982–1997	4[b]	sp. inv. price ($/kW)	cum. cap. (MW)	IEA (2000)
Electricity from biomass	EU	1980–1995	15	sp. prod. cost ($/kWh)	cum. prod. (TWh)	IEA (2000)
Supercritical coal	US	n.a.	3	sp. prod. cost ($/kWh)	cum. prod. (TWh)	IEA (2000); Joskow and Rose (1985)
GTCC	EU	n.a.	4	sp. prod. cost ($/kWh)	cum. prod. (TWh)	IEA (2000); Claeson (1999)
Solar PV modules	World	1976–1992	18	sale price ($/$W_{peak}$)	cum. sales (MW)	IEA (2000)
Solar PV modules	EU	1976–1996	21[c]	sale price ($/$W_{peak}$)	cum. sales (MW)	IEA (2000)
Ethanol	Brazil	1978–1995	22[d]	sp. sales price ($/boe)	cum. prod. (cubic meters)	IEA (2000)
Coal power plants	US	1960–1980	1.0–6.4[e]	sp. inv. cost ($/kW)	cum. cap. (units)	Joskow and Rose (1985)

[a]Note: sp. = specific; inv. = investment; cum. = cumulative; cap. = capacity; prod. = production.

[b]Based on Neij (1999). The learning rate of 4% considers only wind turbines equivalent to 55 kW or larger. The 8% learning rate reported in Table 1 for Neij's data includes all Danish wind turbines.

[c]21% is the learning rate for the "stability" stage described in the text. For the "development" and "price umbrella" stages the learning rate is 16%. For the "shakeout" stage it is 47%.

[d]22% is the learning rate for the "stability" stage described in the text. For the "development" and "price umbrella" stages the learning rate is 10%. For the "shakeout" stage it is 53%.

[e]Joskow and Rose estimate a range of learning rates for different utilities, architect-engineering firms, and technology categories, after accounting for inflation, plant size, the inclusion of scrubbers or cooling towers, whether certain structures are indoors or out, and whether a unit is the first on a site.

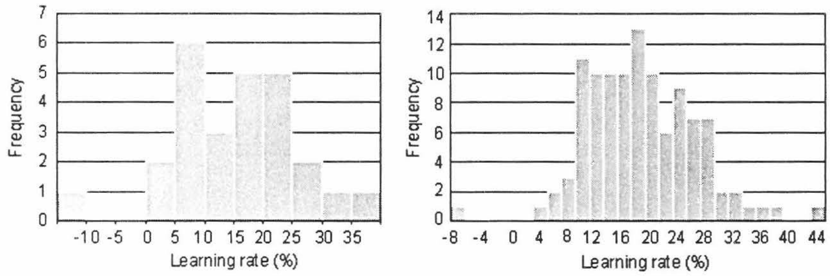

Fig. 2. Distribution of learning rates in Table 1 (left panel) and as observed in 22 field studies (right panel) (Dutton and Thomas, 1984).

uncertainty about this value than suggested simply by the R^2 value of 0.99.

The frequent occurrence of low values for R^2 in Table 1 means that further research is needed to discover missing explanatory factors, some (but not all) of which may be important to include in long-term energy models. As an example of such additional information, consider the one negative "learning" rate in Table 1, –11% for gas turbine combined-cycle (GTCC) power plants from Claeson's 1981–1991 data. Note first that the dependent variable for this data set is the specific investment *price*, not cost. Prices are driven by many factors besides costs, and are for that reason inferior to costs as measures of learning and technological progress. In this case in particular, one

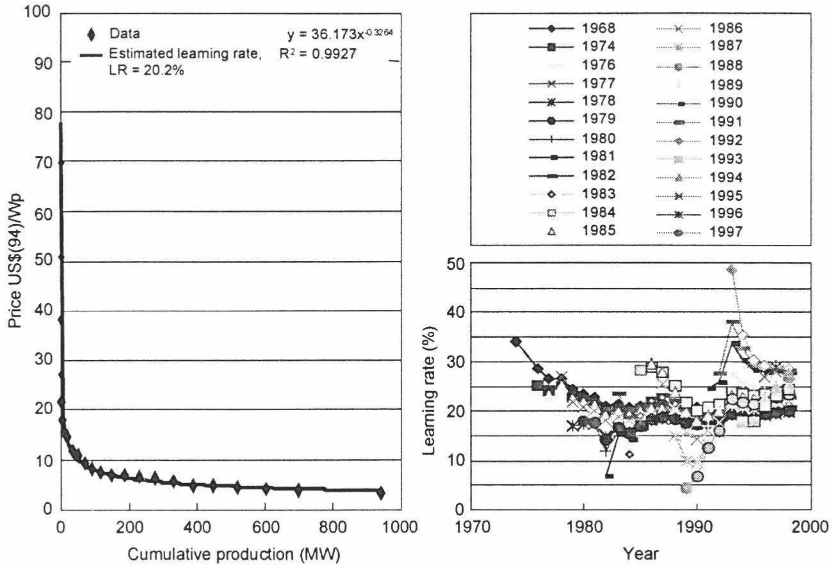

Fig. 3. Learning curve estimated for Harmon's data (2000) on unit prices for solar PV modules (left panel) and variability in learning rates (right panel).

possible explanation of the negative learning rate is short-term oligopolistic pricing behavior (Claeson, 1999). To the extent that such behavior explains the negative learning rate for this data set, the calculated learning rate is largely irrelevant for long-term global energy scenarios in which *costs* rather than prices are the relevant variable. Another explanatory factor is suggested by the negative learning rate shown in the right panel of Fig. 2, which describes the production experience of Lockheed's L-1011 TriStar and provides good evidence of experience depreciation. Experience depreciation is much more relevant to long-term energy scenarios than short-term oligopolistic pricing behavior. It should thus be given higher priority in subsequent research to quantify the missing explanatory factors indicated by low R^2 values in Table 1.

We now turn to the third important feature of Table 1, variations in learning rates among and within data sets for the same technology. Two cases are evident in the table, gas turbines and GTCC power plants. If we neglect the GTCC data set with the negative learning rate (for the reasons discussed in the last paragraph), the trend seems to be that later data imply lower learning rates. Some energy modeling groups therefore use "kinked" (piece-wise linear) learning curves, with successively lower learning rates for technologies at more mature development stages (Kouvaritakis *et al.*, 2000).[2] In an alternative formulation, used by Argote (1999) and others, experience depreciates with time, i.e., experience gained from units built last year results in greater current cost reductions than experience from 10 years ago. This formulation results in the same phenomenon of decreasing learning rates, but in a smooth fashion, not requiring largely arbitrary boundaries between different development stages. Both Argote's and the "kinked" approaches can lead to learning "floors", i.e., non-zero minimums below which unit costs will never fall.

To evaluate and enhance the usefulness of the estimates in Table 1 we need to summarize additional information, provided by the original sources, that might have potentially misleading impacts on learning rate estimates. First, as noted above, prices can be very imperfect measures of costs, and for a number of entries in Table 1, it is price that is the dependent variable. Goldemberg's ethanol data (1996), for example, are in terms of the price paid ethanol producers in Brazil, and a closer look at his original data suggests that these prices have to some extent moved up and down with international oil prices. Thus, some of the variability in Goldemberg's data reflects not variability in ethanol production costs, but volatility in the international oil markets. In this light, estimated learning rate of 20%, as in Table 1, appears more reliable than indicated by the associated R^2 value of 0.89. Neij, who also analyzes prices, finds indications in her data of wind-turbine manufacturers selling below cost to drive out competitors (Neij, 1999). If this is indeed the case, her price data should underestimate costs nearer the beginning of her data set and overestimate costs near the end (presuming less competition after some competitors have left the market). In that case, the learning rate of 8%, estimated from her data in Table 1, would appear to be too low.

[2] We refer here to kinks in learning curves for *costs*. Such kinks reflect postulated decreases in learning rates as technologies mature. This is different from proposed kinks in learning curves for *prices* to reflect changing relationships between cost and price learning rates as markets mature (see discussion of the IEA/BCG model).

The International Energy Agency (IEA) offers a general extended model of relationships between costs and prices based on prior work by the Boston Consulting Group (BCG) (IEA, 2000). The qualitative background of the model is the assumption that costs decrease at a constant learning rate, but price reductions can be divided into four stages. In the first two stages ("development" and "price umbrella"), the learning rate in terms of prices is constant but lower than the constant learning rate for costs. In the "shakeout" stage the learning rate for prices is higher than that for costs. And in the "stability" stage, learning rates for prices and costs are identical. This model is consistent both with Goldemberg's data cited above (see Table 2) and with Neij's data. Her estimated 8% learning rate is close to the 10% the IEA considers typical for the "development" (and "price umbrella") stage. It can also help explain Akisawa's study (2000) of prices for new "heat-pump" air conditioners. He noted particular price volatility around the time the new technology was most aggressively displacing conventional air conditioners. Calculations based only on data from after the period of price volatility yield both a higher learning rate (17%) and higher correlation coefficient (0.94) than the data set as a whole. Postulating that the post-volatility period corresponds to the stability stage of the IEA/BCG model, a learning rate of 17% would be more appropriate in long-term energy models than the 10% shown in Table 1 for the whole data set.

In addition to experience depreciation and short-term pricing behavior, other possible causes of variability or biases in Table 1 include:

- differences in performance measures (e.g., investment costs vs. production costs) or in experience measures (e.g., cumulative capacity or cumulative production),
- definitional differences (are the costs of land acquisition, pollution abatement, and interest during construction treated uniformly for all entries in a data set?),
- varying intensities of research and development (R&D),
- economies of scale,
- and cost variability for such things as land costs, wages, and interest payments that are driven by property, financial, and labor markets.

At this stage we can say something about differences in performance and experience measures and about economies of scale, but not much about the other factors. (An important focus of future research, however, will be the interplay between learning rates and R&D, given the pressure on governments to increase energy R&D expenditures.) Concerning different performance and experience measures, we expect learning rates calculated using production costs and cumulative production to be higher than those using investment costs and cumulative capacity *if* there are concurrent increases in load factors. This is especially true if fuel costs are low — n.b., the variations in learning rates for wind in Tables 1 and 2.[3] Concerning economies of scale, the learning rate in the last row of Table 2 for coal-fired power plants is calculated from a regression that includes a scale term. Thus, it reflects learning after any economies of scale have been taken into account. This is not the case for the other power plant data presented here. They almost certainly include some scale effects, which may partially explain why they yield generally higher learning rates than the last row of Table 2. For long-term energy modeling, however, it is not clear how much effort should be put into trying to distinguish between the two factors. Given the data that are available, model inputs in which learning and scale economies are lumped into a single estimated learning rate may be simpler, as reliable, and therefore more useful than efforts to extract the two separate effects from the empirical data, and then treat them separately in long-term energy models.

The purpose of the analysis presented here was to expand the empirical basis for the choice of learning rates and uncertainty ranges used in long-term energy models. We have presented a first edition of a catalogue of energy-related learning rates intended to quantify the phenomenon of experience-related cost reductions at a level useful to energy modelers. Analyzing the quality of the statistically estimated learning rates we conclude that some of the identified causes of data variability, such as price swings due to marketing strategies, can be considered random and inconsequential for long-term energy models. More work is necessary, however, to properly address other factors, particularly experience depreciation and the impact of R&D investments.

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[3] For wind power IEA's data show higher learning rates when using production costs and experience than when using investment costs and cumulative capacity. This they attribute partly to increasing load factors. They also attribute the difference in learning rates, depicted in Table 2, for the EU and the US partly to faster load factor learning in the US. But this still leaves unexplained the difference between the US learning rate in Table 2 (32%) and the California learning rate in Table 1 (18%).

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