Learning Curve Analysis for Energy Technologies: Theoretical and Econometric Issues*

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Abstract

In bottom-up energy models endogenous technical change is introduced by implementing so-called energy technology learning rates, which specify the quantitative relationship between the cumulative experience of the technology and cost reductions. The main purpose of this paper is to survey and critically analyze the choice of modeling and estimation strategies in learning curve analyses of power generation costs. We identify and discuss a number of theoretical and econometric issues involved in the estimation of learning curves. These include, for instance, the presence of omitted variable bias and simultaneity. We illustrate the importance of these issues by employing panel data for wind power installations in four European countries, which are used to compare the results from different learning curve model specifications. The results illustrate that the empirical estimates of learning rates may differ significantly depending on the choice of model specification and econometric approach. The paper ends by outlining a number of recommendations for energy model analysts, who need to select appropriate energy technology learning rates from the empirical literature, or who choose to perform the empirical work themselves.

Key words: learning curve; learning rate; energy technology; wind power; econometrics.

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1. Introduction

The introduction of learning curves for different energy technologies in many bottom-up energy system models has become common.[1] The basic idea is that investments in new technologies are more expensive than those in old technologies, but the costs of the former can be assumed to decrease with increases in their market share so that at some point they will be a more attractive choice than the old technology, which is more mature and experiences less cost reductions (Grübler et al., 2002). Cost reductions are a result of learning-by-doing, i.e., performance improves as capacity and production expand. Learning curves are used to empirically quantify the impact of learning on the cost of a given technology, and specifies thus, for instance, the investment cost as a function of cumulative capacity. In this way one obtains an endogenous representation of technical change.

The introduction of learning in energy models may have important implications for the timing and the cost of environmental policies. High learning rates for new versus old technologies support early, upfront investment in new technologies to reap the economic benefits of technological learning, and they also imply that the gross costs of climate policy may be comparatively low (e.g., Gritsevskyi and Nakicenovic, 2000). Naturally, in the long-run differences in learning rates across technologies will also influence the mix of technologies in use. For instance, bottom-up models of the power generation sector typically assume that learning rates for wind and solar power are higher than the corresponding rates for, say, coal and nuclear power. This means that – given the implementation of appropriate technology support policies – the generation share of the former can increase substantially over time even if their current costs are high (e.g., Messner, 1997).

The above suggests that if energy models are to generate meaningful results, reliable estimates of the learning rates are needed. However, it is probably fair to conclude that previous empirical studies of learning rates provide few uniform conclusions about the size of these rates. For instance, McDonald and Schrattenholzer (2001) show that the learning rate for wind turbines range between 8 and 18 percent depending on study, and similar differences exist for other technologies.[2] Given this, the recent research on moving away from deterministic learning estimates to the introduction of uncertainties in the distribution of future costs is therefore welcome (e.g., Gritsevskyi and Nakicenovic, 2000). However, in spite of this there exists a need to provide reliable mean estimates of learning rates.

[1] See, for instance, Messner (1997), Mattsson and Wene (1997), Kouvaritakis et al. (2000), and Barreto and Kypreos (2003).

[2] See also Ibenholt (2002), who analyze the causes of variation in learning rate estimates for wind power technology.

The main purpose of this paper is to survey and critically analyze the choice of modeling and estimation strategies in learning curve analyses of power generation costs. We hypothesize that differences in learning rates for a given technology are not only due to differing data sets, but may arise also as a result of different model specifications and econometric techniques. This point is illustrated by comparing the results from different model specifications using the same panel data set of wind power investment costs across four European countries over the time period 1986-2000. We conclude that the estimation of learning curves involves a number of important econometric and theoretical issues that have rarely been acknowledged in previous work.

The paper proceeds as follows. In section 2 we introduce the theoretical and econometric topics to be addressed in this paper. Section 3 presents the data to be used in the empirical part of the paper and outlines some important model estimation issues, while section 4 presents and discusses the empirical results from different learning curve estimations for the European wind power sector. Finally, section 5 provides some final remarks and implications.

2. The Economics and the Econometrics of Learning Curves

2.1. The Traditional Learning Curve Specification and Econometric Problems

The most commonly used specification of the learning curve relates the cost of the technology to the cumulative capacity. For our wind power case the learning curve can be written as:

$$C_{nt} = \delta_0 CC_{nt}^{\delta_L} \tag{1}$$

where CC_{nt} is the chosen level of total installed wind power capacity in country n (n = 1,....N) for a given year t (t = 1,....T) (used here as a proxy for learning),[3] C_{nt} represents the real engineering unit cost (per kW) of installing a windmill, i.e., all investment cost items, such as grid connection, foundations, and the cost of the turbine, and δ_0 is the corresponding cost at unit cumulative capacity. By taking the logarithm of equation (1) one obtains a linear model, which one can estimate econometrically and in this way obtain an estimate of δ_L. We obtain:

[3] We assume here (fairly realistically) that the installed capacity equals the cumulative capacity (i.e., no windmills have been shut down during the time period under study).

$$\ln C_{nt} = \ln \delta_0 + \delta_L \ln CC_{nt} + \varepsilon_{nt} \quad (2)$$

where ε_{nt} is an additive disturbance term which is assumed to have a zero mean, constant variance, and to be independent and normally distributed. The learning-by-doing rate is then defined as $1-2^{\delta_L}$, and it shows the percentage change in cost due to a doubling of cumulative capacity. A learning rate of 14 % implies thus that the cost is reduced to 86 % of its previous level after a doubling of cumulative capacity.

Recently researchers have extended this simple formulation by incorporating also, for instance, cumulative R&D expenses directed towards wind power (e.g., Kouvaritakis et al., 2000) or an R&D based knowledge stock (e.g., Klaassen et al., 2003; Barreto and Kypreos, 2003) as additional explanatory variables. These latter specifications are commonly known as two-factor learning curves, and they produce also an estimate of the so-called learning-by-searching rate, which shows the impact on costs of a doubling in the R&D based variable. Incorporating such R&D based measures into bottom-up energy models permits an analysis of the optimal allocation of R&D funds among competing technologies. The two-factor learning curve equation can thus be written as:

$$\ln C_{nt} = \ln \delta_0 + \delta_L \ln CC_{nt} + \delta_K \ln K_{nt} \quad (3)$$

where K_{nt} is the R&D based knowledge stock (which is defined in section 2.2). In this paper we highlight three different issues that deserve attention when estimating learning curves using econometric techniques.[4] The *first* issue deals with the choice of data set and definitions. Even though one relies on one specific data set there exists a need to check for the effect of removing single observations, especially outliers that may greatly influence the learning rate estimate. It may also be the case that the learning rate varies over different time periods (e.g., Claeson Colpier and Cornland, 2002). In the empirical section we drop a few early observations and investigate how this affects the estimates of the learning rate. We also consider the impact of using different variable definitions. As has already been noted learning-by-searching can be captured by implementing different R&D based variables.

[4] We do not attempt here to provide an entirely comprehensive analysis of all possible econometric issues involved in the estimation of learning curves. For instance, we neither discuss the problem of multicollinearity (i.e., the presence of linear relationships among explanatory variables), and nor autocorrelation (i.e., the situation in which the successive values of the disturbance term are dependent).

Similarly, as a proxy for learning-by-doing one can also use cumulative production or other activity variables (in replacement of cumulative capacity).

The *second* issue recognizes that the model specified in equation (1) assumes that the cumulative wind capacity is an exogenous (independent) variable. A windmill is not built because it is cheap and efficient, but rather it becomes cheap because it is built and operated. However, one principal reason for why wind generators invest in new capacity is because learning activities and R&D measures have brought down the costs of generating wind electricity. This suggests that both innovation and diffusion ought to be viewed as being endogenous, i.e., they are simultaneously determined and should not be analyzed in isolation. Technically endogeneity implies that within the learning equation in (2) the regressor CC_{nt} and the disturbance term ε_{nt} are positively correlated. This means that estimation by ordinary least squares (OLS) would yield biased and inconsistent estimates of δ_L and thus of the learning-by-doing rate (e.g., Greene, 1993). In order to choose between a model specification that permits simultaneity and one that does not, one can employ the so-called Hausman specification test (Hausman, 1978). If this test suggests that we cannot reject the null hypothesis that $\ln CC_{nt}$ is an exogenous variable in the learning equation, we can use instrumental variable techniques to correct for endogeneity. Specifically, we can regress $\ln CC_{nt}$ on a set of variables considered exogenous to $\ln CC_{nt}$, and then employ the fitted values from this first regression as instruments in place of $\ln CC_{nt}$ in equations (2) and (3). In this paper we compare the results obtained by acknowledging endogeneity to those where simple OLS estimation procedures have been used.[5]

Our *third* econometric issue concerns the presence of so-called omitted variable bias. From econometric theory we learn that if an independent variable whose true regression coefficient is nonzero is excluded from the model, the estimated values of all the regression coefficients will be biased unless the excluded variable is uncorrelated with every included variable (Berndt, 1991). In the case of the learning curve model this could be a real problem since costs clearly are influenced by other variables than cumulative capacity, most notably input prices and scale effects.[6] In order to illustrate the potential importance of this problem, it is useful to see how one can integrate the learning curve into a coherent microeconomic

[5] See also Klaassen and Söderholm (2003) who employ the same data set as that employed here and develop a simultaneous diffusion-innovation model for European wind power.

[6] In many learning curve studies model performance is only evaluated by checking the *t*-statistics for each coefficient and the values of the *R*-square measures. Still, even if R-square is close to one (1) and all coefficients are statistically significant, omitted variable bias may still pose a problem.

framework. In the next section we therefore integrate the learning curve model in equation (3) with the Cobb-Douglas cost function. This permits us to identify under what conditions the traditional learning curve is consistent with neoclassical cost theory, and also to analyze the impact of leaving out important explanatory variables in the learning model.

2.2. Deriving the Learning Curve from a Cobb-Douglas Cost Function

We here follow Berndt (1991) and Isoard and Soria (2001), and derive the learning curve model from a Cobb-Douglas cost function. This means that for our purposes the current unit cost of wind power capacity in country *n* during time period *t*, C_{nt}^{C}, is specified as:

$$C_{nt}^{C} = \frac{1}{Q_{nt}}\left(kQ_{nt}^{1/r} \prod_{i=1}^{N} P_{nti}^{\delta_i/r} \right) = kQ_{nt}^{[(1-r)/r]} \prod_{i=1}^{N} P_{nti}^{\delta_i/r} \tag{4}$$

where

$$k = r\left[A_{nt} \prod_{i=1}^{N} \delta_i^{\delta_i} \right]^{-\frac{1}{r}}$$

and where Q_{nt} is the level of wind-generated electricity output, P_{nti} are the prices (*i* = 1,…,*M*), of the inputs required to produce and operate wind turbines, and *r* is the returns-to-scale parameter which in turn equals the sum of the exponents so that:

$$r = \sum_{i=1}^{N} \delta_i \tag{5}$$

The constraint in equation (5) ensures that the cost function is homogenous of degree one in input prices. That is, for a given output level, the unit cost doubles if all input prices double. Finally, A_{nt} reflect advances in the state of knowledge.

Following the learning curve literature we can now assume that the state of knowledge in country *i* at time period *t* depends on learning-by-doing effects as expressed by the cumulative installed capacity of windmills up to time period *t*, CC_{nt}. However, we also build on Klaassen et al. (2003) and extend this traditional learning curve concept by considering cumulative R&D expenses on wind energy in the model. Specifically, we acknowledge that R&D support adds to what might be referred to as the R&D-based 'knowledge stock', and this we define as:

$$K_{nt} = (1-\gamma)K_{n(t-1)} + RD_{n(t-x)} \tag{6}$$

where K_{nt} is the R&D-based knowledge stock in country *n* and time period *t*, RD_t are the annual R&D expenditures, *x* is the number of years it takes before R&D expenditures add to the knowledge stock, and γ is the annual depreciation rate of the knowledge stock ($0 \leq \gamma \leq 1$). Thus, this formulation takes into account that: (a) the R&D support does not have an instantaneous effect on innovation, but will only lead to tangible results after some year's time; and (b) knowledge depreciates in the sense that the effect of past R&D expenses gradually becomes outdated (Griliches, 1995). By drawing on this extended learning curve concept we can now define the state of knowledge as:

$$A_{nt} = CC_{nt}^{-\delta_L} K_{nt}^{-\delta_K} \tag{7}$$

where δ_L is the traditional learning-by-doing elasticity, and where we refer to δ_K as the learning-by-searching elasticity. Substituting equation (7) into equation (4) yields a modified version of the Cobb-Douglas cost function:

$$C_{nt}^{C} = k' CC_{nt}^{\delta_L/r} K_{nt}^{\delta_K/r} Q_{nt}^{[(1-r)/r]} \prod_{i=1}^{N} P_{nti}^{\delta_i/r} \tag{8}$$

where

$$k' = r\left[\prod_{i=1}^{N} \delta_i^{\delta_i}\right]^{-\frac{1}{r}}$$

This indicates that there are two advantages of specifying a two-factor (rather than a single-factor) learning curve. *First*, R&D support is clearly a policy relevant variable that influences innovation. *Second*, the introduction of R&D expenditures also means that omitted variable bias becomes less of a problem (i.e., the variations in costs that are due to R&D

support are not wrongly attributed to learning-by-doing). Furthermore, the impacts of the three input prices can be captured by the use of the GDP deflator. By assuming that the shares of the inputs in production costs are the same as those used as weights in the computation of the GDP deflator, we can effectively remove the price terms from equation (8) by considering real (rather than current) unit costs of wind power capacity, C_{nt}. We obtain:

$$C_{nt} = k' CC_{nt}^{\delta_L / r} K_{nt}^{\delta_K / r} Q_{nt}^{[(1-r)/r]} \tag{9}$$

where k' is defined as in equation (8). This shows thus that only in the case where the overall impact of the input prices can be assumed to be reflected in the GDP deflator we can remove price observations from the cost function without introducing omitted variable bias in the model. Moreover, by taking natural logarithms and through introducing the following definitions: $\beta_1 = \delta_L / r, \beta_2 = \delta_K / r, \beta_0 = \ln k'$ and $\beta_3 = [(1-r)/r]$, we obtain an econometric specification of the Cobb-Douglas cost function in equation (9):

$$\ln C_{nt} = \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln K_{nt} + \beta_3 \ln Q_{nt} \tag{10}$$

where $\beta_0, \beta_1, \beta_2$ and β_3 are parameters to be estimated. From the parameter estimates one can easily derive the returns-to-scale parameter, *r*, and the two learning curve elasticities, δ_L and δ_K. We have:

$$r = \frac{1}{(1+\beta_3)}, \quad \delta_L = \beta_1 r = \frac{\beta_1}{(1+\beta_3)} \quad \text{and} \quad \delta_K = \beta_2 r = \frac{\beta_2}{(1+\beta_3)} \tag{11}$$

Equation (10) equals the two-factor learning curve specification in equation (3) with one important exception. In equation (10) we incorporate scale effects by including Q_{nt} into the learning curve equation; only in the restrictive case of constant returns to scale (i.e., $r = 1$ and $\beta_3 = 0$), equation (10) collapses to equation (3), and no omitted variable bias in the latter model will be present. If not, however, the leaving out of scale effects will cause bias in the parameter estimates, and one can easily determine the direction if this bias. For instance, in the case of increasing returns to scale (i.e., $r > 1$ and $\beta_3 < 0$), estimation of the learning curve in equation (3) yields a higher estimate of the learning rates than if one includes the output variable (Berndt, 1991). Similarly, if returns to scale are negative the learning rate estimates obtained by estimating equation (2) will be biased downwards. In the empirical section we therefore include current output as an explanatory variable and compare this to model specifications assuming (implicitly) constant returns to scale.

Finally, we also add a fourth independent variable to the learning equation in (10), namely the feed-in price, P_{nt}^{F} (and the corresponding coefficient, β_4). This is the price windmill owners receive for the wind generated and it includes state price support (per kWh). This inclusion captures the following potentially important relationships. *First*, a high feed-in price will induce wind energy generators to use high-cost sites with, for instance, poor wind conditions or expensive grid connections. As a result the average investment cost in country *n* will increase. *Second*, if feed-in prices increase, and the competition with other energy sources thus becomes less intense, innovation activities aimed at reducing costs will be less attractive on the part of the windmill producer.

3. Data and Model Estimation Issues

In this paper we employ pooled annual time series data over four European countries: Denmark (1986-1999), Germany (1990-1999), Spain (1990-1999), and the United Kingdom (1991-2000). Following the above, the data used to estimate learning curve model include: (a) the cumulative capacity of windmills (MW); (b) the feed-in price for electricity produced by windmills (US cents per kWh); (d) windmill investment costs (US$ per kW); (e) public R&D support for wind energy (1000 US$); and wind-generated electricity production (Mtoe). All prices and costs have been deflated to 1998 prices. Data on wind-generated power generation and the cumulative capacity of windmills, respectively, are available from the International Energy Agency's (IEA) annual volume *Electricity Information*.

The investment cost data used here represent averages of various projects (with the exception of the UK 1992 observation, which is only based on one project), and are drawn from ISET (2002), Durstewitz (2000) and Milborrow (2000). The same data sources have been used for collecting feed-in price data. In contrast to most other estimates of windmill investment costs our data cover all investment costs items such as grid connections, foundations, electrical connection and not only the costs of the wind turbine. This is important since the non-turbine part of the investment costs may amount 10 to 40 percent of the total (Rohrig, 2001; Varela, 2001).

Annual wind R&D expenditure data from the IEA (www.iea.org) were used to construct the knowledge stock variable. For this, assumptions are needed on the time lag between R&D expenditures and their addition to the knowledge stock as well as the depreciation rate of the knowledge stock. Klaassen et al. (2003) survey previous studies on these issues, and based on these they suggest a time lag of 2 years and a depreciation rate of 3 percent. These are also the assumptions employed in this paper.

In estimating the learning equation we have to consider how to pool the panel data set. We assume that the learning curve equations have an additive error structure, and we decompose this the error term, ε_{nt}, into two components so that:

$$\varepsilon_{nt} = \lambda_n + \nu_{nt} \qquad (16)$$

where λ_n is the country-specific effects, while ν_{nt} is the remainder stochastic disturbance terms. The country-specific errors may be interpreted as unobserved fundamental differences in windmill investment costs across the four countries. These may include geographic differences such as wind conditions and institutional arrangements related to, for instance, permitting procedures. We assume that these differences are fixed over time for a given country, and we can then eliminate the country-specific components by introducing dummy variables for *N*-1 of the countries. This approach is referred to as the fixed-effects model and it overcomes the bias in the estimation results that can occur in the presence of unobserved country effects that are correlated with the regressors (e.g., Baltagi, 1995). It implies that the parameter estimates will be based purely on the time-series variations in the data sample. The remaining disturbance term, ν_{nt}, is assumed to be normally distributed with zero mean and constant variance.

As was noted above both underlying theory and intuition suggest that investments cost (innovation) could be viewed as being endogenous. We also need to consider the possibility that the feed-in price is endogenous. The feed-in price is likely to be revised downwards as wind power investments costs fall, since it then is less need for policy support. In order to test for endogeneity, we employed the Hausman specification test (Hausman, 1978), and in those cases where the test indicated endogeneity, this problem of simultaneity was solved by the use of instrumental variables. All regressions were performed in the statistical software Limdep, and detailed estimation results are available from the authors on request.

4. Empirical Comparisons of Learning Curve Specifications

The different specifications of the learning curve models to be compared empirically are presented in Table 1. Models I-III all build on the traditional learning curve concept in which investment cost is explained by cumulative capacity, but they differ with respect to variable definitions and use of data sample. In model I a traditional learning curve based on all annual observations is estimated, while in model II we estimate the same equation but after having removed all observations prior to 1992 (a total of 11 observations). It is not entirely clear whether to expect that the learning rates based on the full sample compared to the corresponding estimates for the more recent (and shorter) sample would differ. One reason, though, why we could expect to obtain higher learning rates for the full sample (including the early years) is that as a technology matures the competition on the input factor market becomes stronger and as a result prices fall (e.g., Claeson Colpier and Cornland, 2002). Clearly this is a market power issue and not an innovation impact, but since we do not explicitly acknowledge input prices in our model specifications any observed cost decreases will be attributed to learning (rather than price) impacts. In model III we use a different proxy for learning-by-doing and substitute cumulative capacity (MW) for cumulative wind production ($\ln CQ_{nt}$ measured in MWh).

Table 1 about here

Models IV-VIII are designed to consider various versions of omitted variable bias. First in model IV we extend the traditional learning curve equation (model I) by incorporating also scale effects through the introduction of current wind generation. Models V and VI represent different versions of the two-factor learning curve, where model V uses cumulative R&D expenditures ($\ln RD_{nt}$) while model VI – following Klaassen et al. (2003) – involves the R&D based knowledge stock (thus with time lags and depreciation included) ($\ln K_{nt}$). These models permit thus the estimation of learning-by-searching rates. In models VII and VIII we extend this two-factor learning curve further by adding also scale effects (model VII) and the impact of policy through feed-in prices (model VIII).

In model specifications IX-XII we acknowledge the fact that cumulative capacity and also the feed-in price can be considered endogenous and thus simultaneously determined with investment costs. The Hausman test suggested that for models I, VI and VII we could reject the null hypothesis that $\ln CC_{nt}$ is an exogenous variable. For model VIII only $\ln P_{nt}^{F}$ were found to be endogenously determined. The simultaneity problem was solved using instrumental variables where $\ln CC_{nt}$ and $\ln P_{nt}^{F}$ were regressed on a set of variables considered exogenous. The fitted values of $\ln CC_{nt}$ (models IX-XII) and $\ln P_{nt}^{F}$ (model XII), respectively, were then employed in the different learning equations.

The parameter estimation results for the different learning curve models are presented in Table 2 together with calculated learning-by-doing and – where applicable – learning-by-searching rates. Overall all models display relatively good fits with R^2-values ranging from 0.67 to 0.97. However, the estimated learning-by-doing rates and learning-by-searching rates vary considerably over the different specifications of the learning curve.

Table 2 about here

When comparing models I and II we note that the estimated learning-by-doing rate is substantially higher in the shorter (and more recent) time period. This indicates that the choice of data set has a significant effect on the results, and as was noted above it could be de to the fact that the suppliers of wind turbines and had significant market power during the early diffusion of the technology. Employing an alternative proxy for learning – cumulative wind generation – produces a higher learning-by-doing rate (than in the case where learning is measured through cumulative capacity). Thus, overall the above results indicate that the relatively simplistic traditional learning curve equation is data and definition sensitive and that results from these types of estimations need to be interpreted with some care.

Adding scale effects to the basic learning curve model, as in model III, also significantly affects results. The parameter estimate for $\ln Q_{nt}$ is statistically significant at the one percent level while the estimate for $\ln CC_{nt}$ becomes statistically significant only at the 15-percent level. The negative sign of the coefficient for $\ln Q_{nt}$ implies that wind power developments in the four countries are exhibiting increasing returns to scale. As was noted above, failing to account for this generates a positive bias in the learning rate estimate.

The results of the two-factor learning curve estimations show that the choice of R&D measure marginally affects the learning-by-doing rate (which range from 3.0 to 3.8 percent in models V and VI). With respect to the learning-by-searching rates the model specification including the R&D based knowledge stock, however, produces a more than twice as high estimate than the model including cumulative R&D expenses. Adding additional variables, as in models VII and VIII, also changes the results. Still, the $\ln Q_{nt}$ parameters are statistically insignificant in both model VII and model VIII, indicating that scale economies do not significantly lower costs (and no bias in the results will appear from omitting scale effects). The $\ln P_{nt}^{F}$ parameter in model VIII is statistically significant and positive implying that an increase in the feed-in price will lead to higher (average) investment costs.

In the models where we corrected for endogeneity in $\ln CC_{nt}$, models IX-XI, it is first of all worth noting that the estimated learning-by-doing rates are very stable across specifications (they range from 7.6 to 7.8 percent), but they are substantially higher than those generated by the corresponding models assuming exogeneity in $\ln CC_{nt}$ (i.e., models I, VI and VII). In contrast, the learning-by-searching rates become substantially lower and even negative. In model XII we corrected for the endogeneity of the feed-in price variable. The results from this model are rather close to those obtained in model VIII (with exogenous feed-in prices); the learning-by-doing rates are 3.1 percent and 3.4 percent, respectively, while the learning-by-searching rates are 13.2 and 18.2 percent. It is difficult to conclude what causes these differences in results between model specifications, but is clear that simultaneity should be carefully considered in estimating learning curves.

5. Concluding Remarks

The concept of technological learning has been widely used since its introduction in the economics literature (Arrow, 1962), and it has gained substantial empirical support in many applications. However, while the direction of the impact of learning on costs is undisputed it remains less than clear what the size of this effect is. Still, with the increased use of bottom-up energy models with endogenous learning it is becoming increasingly important for energy scenario analysis to get hold of reliable technology learning rates. In order to estimate learning rates we need to employ econometric methods and in this paper we have discussed and analyzed a number of important – but often neglected – econometric and theoretical issues in the empirical assessment of learning rates. The empirical analysis of learning effects in the European wind power industry illustrates that estimates of learning rates may differ significantly depending on whether one acknowledges these issues in the econometric models.

From the analysis in this paper it is possible to point at some general guidelines for energy analysts who need to select empirical estimates of learning rates from the empirical literature and/or who plan to estimate these themselves. *First*, it is important to perform some type of sensitivity analysis by, for instance, considering (a) the impact of removing some observations from the data sample, and (b) different variable definitions. This also means that if one is to rely on previous empirical learning curve studies, it probably makes most sense to consider the results from several such studies and to make some informed judgment about the mean estimate rather than to rely on the results from one single study.

Second, the problem of omitted variable bias needs to be taken seriously, not only when doing own econometric analyses of learning curves but also in considering other's work. Scale effects should be tested for, and when relying on previous studies any evidence on scale effects should be considered when selecting learning rates. For instance, a learning curve analysis of nuclear power failing to incorporate scale effects would, ceteris paribus, result in a positive bias of the learning rate. That is, by not incorporating the likely positive returns to scale in nuclear power generation a too large part of the cost reductions would be wrongly attributed to learning effects. Similarly, it must also be assessed whether input prices have played an essential role in affecting the cost structure of the specific technology over the time period under study. Moreover, it is equally important to consider the policy impacts on innovation. The learning curve literature recognizes that policy support in the form of investment grants and feed-in tariffs is necessary to encourage technology diffusion and thus learning-by-doing. Still, the measures implemented to bring about diffusion may in themselves affect learning. For instance, fixed feed-in tariffs for wind power (such as those found in Germany and Spain) discourage competition among various renewable energy sources and therefore deter innovation. This notion parallels the so-called Lucas critique as it is outlined in the macroeconomics literature. Lucas (1976) points out that it may be a bad practice for analysts to use an estimated econometric model found suitable for one time period when attempting to predict what will happen in another period but under a different set of policy rules.

Finally, the issue of simultaneity in the technology learning rate estimations addresses the fact that – perhaps most notably – diffusion and innovation are not independent variables. This could (and should) be tested for and remedied through the Hausman test and – if found necessary – through the use of instrumental variable techniques. The issue of simultaneity also raises the more fundamental question of what are the most appropriate causal relationships to consider when analyzing R&D efforts, innovation and technology diffusion. The economics literature on technological change and innovation provide some guidelines but much remains to be done before we can claim to have a more detailed understanding of the technology learning process.

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Table 1: Different Learning Curve Specifications

Model	Estimated Equation	Comments
I:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \varepsilon_{nt}$	*Traditional learning curve (LC)*
II:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \varepsilon_{nt}$	*LC (1992-)*
III:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CQ_{nt} + \varepsilon_{nt}$	*LC with alternative capacity measure*
IV:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln Q_{nt} + \varepsilon_{nt}$	*LC + scale effects*
V:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln RD_{nt} + \varepsilon_{nt}$	*Two-Factor Learning Curve (2FLC)*
VI:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln K_{nt} + \varepsilon_{nt}$	*2FLC with knowledge stock*
VII:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln K_{nt} + \beta_3 \ln Q_{nt} + \varepsilon_{nt}$	*2FLC + scale effects*
VIII:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln K_{nt} + \beta_3 \ln Q_{nt} + \beta_4 \ln P^F_{nt} + \varepsilon_{nt}$	*2FLC + scale effects & feed-in price*
IX:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CChat_{nt} + \varepsilon_{nt}$	*I corrected for endogeneity in CC*
X:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CChat_{nt} + \beta_2 \ln K_{nt} + \varepsilon_{nt}$	*VI corrected for endogeneity in CC*
XI:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CChat_{nt} + \beta_2 \ln K_{nt} + \beta_3 \ln Q_{nt} + \varepsilon_{nt}$	*VII corrected for endogeneity in CC*
XII:	$\ln C_{nt} = \ln \beta_0 + \beta_1 \ln CC_{nt} + \beta_2 \ln K_{nt} + \beta_3 \ln Q_{nt} + \beta_4 \ln Phat^F_{nt} + \varepsilon_{nt}$	*VIII corrected for endogeneity in* P^F

Table 2: Parameter Estimates for the Different Learning Model Specifications

Coefficient (*t*-statistic)	**Model I**	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**	**Model VII**	**Model VIII**	**Model IX**	**Model X**	**Model XI**	**Model XII**
$\beta_0(\text{DK})$:	7.68*** (115.21)	7.97*** (56.96)	7.11*** (246.24)	7.18*** (44.56)	7.87*** (86.88)	8.56*** (35.37)	8.01*** (19.69)	7.91*** (20.75)	7.95*** (286.08)	7.91*** (73.77)	7.84*** (55.72)	7.75*** (23.95)
$\beta_0(\text{DE})$:	7.85*** (108.48)	8.19*** (56.47)	7.22*** (209.48)	7.35*** (44.49)	8.00*** (93.45)	9.11*** (26.62)	8.44*** (16.15)	8.37*** (17.14)	8.13*** (272.05)	8.07*** (52.06)	8.00*** (42.60)	8.25*** (20.01)
$\beta_0(\text{UK})$:	7.81*** (130.02)	8.08*** (72.44)	7.20*** (184.62)	7.29*** (44.11)	8.07*** (75.20)	8.96*** (28.59)	8.32*** (16.82)	8.25*** (17.84)	8.02*** (331.92)	7.97*** (55.42)	7.90*** (44.67)	8.12*** (20.81)
$\beta_0(\text{ES})$:	7.65*** (142.00)	7.94*** (69.37)	7.06*** (169.21)	7.13*** (44.18)	7.73*** (135.02)	8.43*** (29.23)	7.90*** (20.69)	7.83*** (21.93)	7.82*** (368.77)	7.78*** (80.03)	7.72*** (58.86)	7.69*** (25.43)
$\beta_i(\ln CC_{nt})$:	-0.07*** (-7.66)	-0.12*** (-6.16)	–	-0.03* (-1.55)	-0.04*** (-3.13)	-0.06*** (-5.85)	-0.03** (-2.09)	-0.05*** (-2.88)	–	–	–	-0.05*** (-3.72)
$\beta_i(\ln RD_{nt})$:	–	–	–	–	-0.11*** (-2.80)	–	–	–	–	–	–	–
$\beta_i(\ln K_{nt})$:	–	–	–	–	–	-0.26*** (-3.72)	-0.18** (-2.20)	-0.20** (-2.64)	–	0.01 (0.38)	0.02 (0.54)	-0.24*** (-3.66)
$\beta_i(\ln Q_{nt})$:	–	–	–	-0.78*** (-3.34)	–	–	-0.04* (-1.65)	-0.01 (-0.37)	–	–	-0.01 (-0.69)	0.01 (0.50)
$\beta_i(\ln CQ_{nt})$:	–	–	-0.09*** (-10.39)	–	–	–	–	–	–	–	–	–
$\beta_i(\ln P_{nt}^F)$:	–	–	–	–	–	–	–	0.15** (2.57)	–	–	–	–
$\beta_i(\ln CChat_{nt})$:	–	–	–	–	–	–	–	–	-0.12*** (-27.89)	-0.12*** (-20.16)	-0.11*** (-14.26)	–
$\beta_i(\ln Phat_{nt}^F)$:	–	–	–	–	–	–	–	–	–	–	–	0.31*** (4.91)
R^2 (adjusted):	0.67 (0.64)	0.72 (0.67)	0.78 (0.76)	0.75 (0.71)	0.73 (0.69)	0.76 (0.73)	0.78 (0.74)	0.81 (0.77)	0.96 (0.96)	0.96 (0.96)	0.96 (0.96)	0.87 (0.84)
F-statistic:	19.90	17.61	34.89	22.31	20.26	23.93	21.29	21.94	238.32	186.48	153.37	33.09
Observations:	44	33	44	44	44	44	44	44	44	44	44	44
Learning-by-doing rate:	4.96 %	8.25 %	5.84 %	1.77 %	2.97 %	3.80 %	2.33 %	3.11 %	7.76 %	7.85 %	7.62 %	3.32 %
Learning-by-searching rate:	–	–	–	–	7.08 %	16.43 %	11.85 %	13.24 %	–	-0.88 %	-1.30 %	15.41 %

*** Statistically significant at the 1-percent level.

** Statistically significant at the 5-percent level.

* Statistically significant at the 15-percent level.