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A critical assessment of learning curves for solar and wind power technologies

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Abstract

The learning curve concept, which relates historically observed reductions in the cost of a technology to the number of units produced or the capacity cumulatively installed, has been widely adopted to analyse the technological progress of renewable resources, such as solar PV and wind power, and to predict their future penetration. The observed relationship has often been used as an input to energy system models and a justification for public spending on R&D and enhancing the scale of the technology. Learning curves have a place in research, but in this paper we argue that analysts often apply the concept, or make related assumptions, uncritically in their analysis of the technology. We make three observations. First, cost reduction can be driven by factors not correlated with current output, implying other factors as drivers of long-term learning effects. Second, despite the empirical observations, the theoretical foundation for learning curves is insufficiently established. The concept relies on historical development of the technology, that is, the result will be accurate if the future holds a path-dependent trajectory, whereas in reality there is a possibility of future breakthroughs as well as technological stalemates. Third, an observable cost reduction of a component in a given generation technology does not necessarily correspond with the trend in the total cost of deploying that technology. For example, module costs currently constitute a much smaller share of the total cost of solar PV compared with a few years ago. If the module's rate of cost decrease is applied to the total cost of solar PV, it is highly likely to result in an incorrect prediction of future diffusion. As an empirical tool to evaluate learning-by-doing, learning curves were originally introduced for study of manufacturing industry and the jump to analysis of country-level technological change in renewable energy is an extension that requires careful consideration.

Keywords: Learning curve; Learning rate; Energy technology; Wind power; Solar power.
JEL classification: E61, O32, Q2, Q58.

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1. Introduction

Learning curve has been extensively used in the academic literature to explain the historically observed cost reduction of a technology in terms of factors such as the number of units produced or the capacity cumulatively installed. Although the learning curve concept has been known for almost a century, the pressing need to decarbonize the economy with the aim of fighting climate change has resulted in enhancing our understanding of improvements in energy and environment technologies gaining the highest importance. There is increasing interest in how a rapid reduction in the cost of renewable energy will affect the diffusion of these power sources (Nordhaus, 2014).

Learning curves appear in numerous research papers and the relationship between a technology's cost reductions and cumulative installed capacity are often used as a justification for public spending on R&D and enhancing their scale (Wright, 1936; Henderson, 1968; Arrow, 1962; Bhandari and Stadler, 2009; Philibert and Frankl, 2011; Lindman and Söderholm, 2012; Odam and de Vries, 2020). However, extending the principle of the learning curve from manufacturing and production activities to global technological change is a substantial step that requires attention because of the implications that the concept has for policies that promote environmentally friendly technologies (Jamasb and Köhler, 2008).

Although the learning curve concept is used in hundreds of studies, there are surprisingly few critical papers written on the subject. While the way in which the specifications for learning curve models are formulated and the related assumptions made are crucial for estimation of learning rates, these specifications and assumptions have rarely received formal treatment in the literature. This paper in no way seeks to falsify the concept of the learning curve, but instead invites caution in its application. Clearly the price of low-carbon technologies has fallen over time and installed capacity has gone up. Our arguments are solely concerned with the observational validity of learning curves, and their usefulness and limitations when assessing the future of wind and solar power. Our contribution is a thorough investigation of the limitations of learning curves, covering both conceptual and econometric issues.

More specifically, the purpose of this paper is to assess the analytical and statistical basis of learning curves. The basic messages are simple. Despite their popularity and wide applicability, there are important conceptual and practical limitations to the use of learning curves. Putting minor issues to one side, learning curve studies utilize historical data and hence give a picture of how it was, but not necessarily how it will be. It is, therefore, essential to analyse the pros and cons of employing learning curves in technology and policy evaluation. Based on the above, this paper therefore adds to the existing literature in the following ways: it (1) highlights several issues with the popular learning curve, (2) suggests some remedies, and (3) assesses the development of the learning curve literature.

Although empirical observations of the existence of a learning curve are strong, the theoretical foundation is less well established. While learning curves forecast the correlation between cumulative experience/production and falling costs, the detail of the causal links is more ambiguous. While the literature from a business perspective comprehensively relates higher returns to increases in scale, the question is more open on the technology level.

A few researchers, such as Jamasb and Köhler (2008), have contributed with a broad critical assessment of learning curve applications. Nordhaus (2014) emphasizes that a statistical identification problem is present when one tries to separate learning from exogenous technological change, which creates upward biases in learning estimations. Furthermore, Nordhaus showed that erroneous estimates of the total marginal cost of output will introduce bias in optimization models, which leads to policy problems. Odam and de Vries (2020) highlight potential problems with learning curve estimation, concluding that learning curves should be interpreted with prudence. Söderholm and Sundqvist (2007), as a noteworthy exception, discuss econometric aspects of learning curves and potential problems with the impact of scale effects.

The learning curve and related concepts sometimes have been referred to by other names in the literature such as improvement curve, progress curve and experience curve. In this article we use the term learning curve. Interchangeability between the terms learning curve and experience curve has appeared over the last century, but learning curve has become dominant in the literature.[1]

The paper is organized as follows. Section 2 introduces the learning curve and the historic thinking around it. Section 3 considers the issues surrounding the learning curve, while Section 4 discusses these identified issues. Section 5 presents the conclusions and policy implications.

2. The learning curve

As a phenomenon, learning curves are well documented in the research literature, with input from several groups of technology (Yelle, 1979). Learning curves emerged in a microeconomic context as an empirical method for evaluating how learning affected technological change. Technological change was measured as an improvement in cost (or an input factor) due to learning (see, for example, Yelle, 1979; Wright, 1936; Henderson, 1968; Arrow, 1962; Bhandari and Stadler, 2009).

The earliest paper mentioning a concept like learning curves is about experience curves for telegraph operators (William and Harter, 1899). Learning curves have been used in studies of aircraft (Wright, 1936), shipbuilding (Rapping, 1965) and several other manufacturing and service sectors. In the 1970s and 1980s, learning curves were adopted in business management, strategy, and organisational research (BCG, 1970; Argot and Epple, 1990). The learning curve concept has been extended to production processes, as for example by Jaber and Guiffrida, (2008), and Hatch and Mowery (1998) for semiconductors. Learning and experience curves have been utilized to research renewable energy (e.g. Bhandari and Stadler, 2009; Lindman and Söderholm, 2012). Many of these learning curve studies discuss how costs have been reduced over time and, to a lesser extent, how the costs have been reduced (e.g. Neij, 1997).

Originally learning curves referred to a rather narrow field, namely work study and cost control, and usually focused solely on labour costs. Experience curves, in contrast, described the fall in cost that supposedly occurs over the total life of a product (Hall and Howell, 1985). Learning and experience curves should consequently differ according to the costs they cover, the production output range and the causes of cost reduction. Since the trend line found by Wright (1936) showed the relationship between unit cost and cumulative production, learning was assumed to be the main driver. The argument was that skills improved through learning. Later it was discovered that the learning was persistent even when the labour force had rapid turnover. Conway and Schultz (1959) discarded learning as an important contributor to falling manufacturing cost and for a time the learning curve was called the manufacturing progress function. Subsequently the function was named the experience curve to better reflect the association with technological change (Goddard, 1982). As time has passed, experience curve and learning curve have been used more interchangeably.

The basic idea is that when a new product is introduced the cost per unit at a production facility is initially high, but decreases over time as cumulative production increases. The reduction seems to be rather orderly as the log of the current average cost per unit versus the log of the cumulative output exhibits a linear declining trend. Hence, the learning curve shape is linear on log-log axes (Hall and Howell, 1985). Learning and experience curves partly reveal the marginal innovations that transpire in a technology or, alternatively, are the product of increasing productivity induced by experience, experimentation, implementation, and R&D during the production process (Rao and Kishore, 2010; Rubin et al., 2015).

There have been several hypothesizes about how the cost of a technology decreases over time. Theodore Wright in 1936 thought that cost decreases as a power law of cumulative production. An alternative hypothesis was seen in Moore's law (Moore, 1965; 1975) which, at least for computers,

[1] A comparison of the use of these expressions via Google Ngram shows that from being used roughly the same number of times after World War II, use of the expression learning curve has increased tenfold compared to experience curve.

states that technology improves exponentially over time. Other variants have been seen in Goddard (1982), Sinclair et al. (2000), and Nordhaus (2007; 2014). Nagy et al., (2013) identified six major learning curve forms:

- *Moore:* $\log y_t = at + b + n(t)$
- *Wright:* $\log y_t = a \log x_t + b + n(t)$
- *Lagged Wright:* $\log y_t = a \log (x_t – q_t) + b + n(t)$
- *Goddard:* $\log y_t = a \log q_t + b + n(t)$
- *SKC:* $\log y_t = a \log q_t + c \log (x_t – q_t) + b + n(t)$
- *Nordhaus:* $\log y_t = at + c \log x_t + b + n(t)$

In these specifications the dependent variable y_t is the inflation-adjusted unit cost of the technology. The independent variables are the time t (measured in years), the annual production *qt*, and the cumulative production $x_t = \sum_{i=1}^{t} q_i$ *xt~Pt i~1 qi* . The noise term $n(t)$, the constants *a*, *b,* and *c*, and the predictor variables differ for each hypothesis. It should be noted that these methods forecast slightly different things: Moore's law forecasts the cost at a given time, Wright's law at a given cumulative production, and Goddard's law at a given annual production. However, when tested by Nagy et al., (2013) they render somewhat similar results.

The classic learning curve model is not the only model that describes the relationship between cumulative unit numbers and production cost/time (Yelle, 1979). Several geometric forms of the learning curve model have been suggested since the Wright (1936) paper. Some of the geometric models are: (1) the log-linear model, (2) the plateau model, (3) the Stanford-B model, (4) the DeJong model, and (5) the S-model (i.e. cubic L-C). For example, Garg and Milliman (1961) found that Wright's log-linear model did not describe progress at Boeing, but rather the Stanford-B model fitted the manufacturing process for the Boeing 707.

The basic and commonly utilized form of learning curve specification relates the cost of the technology to the its cumulative capacity that is installed. The learning curve can (in the wind and solar case) be approximated by the cumulative installed capacity (in megawatts [MW]) or production (in megawatt hours [MWh]) up to period *t*, (Junginger et al., 2010). Following Neij (1997), learning curves show cost reductions of a constant percentage for each doubling of cumulative capacity:

$$Cn_t = \delta_0 CC_{nt}^{-L} \tag{1}$$

where C_{nt} represents the real engineering cost per unit (kilowatt [kW]), that is, all investment costs, and δ_0 is the cost fo the first unit produced. CC_{nt} represents the volume of total capacity installed in country n (n = 1, …, N) for a given year t (t=1, …, T), and L is the so-called learning-by-doing elasticity, which shows the percentage change in cost as a result of one percentage point rise in cumulative capacity. The logarithm of Eq. (1) is taken to obtain a linear model that can be estimated econometrically:

$$\ln Cn_t = \ln \delta_0 + L \ln CC_{nt} \tag{2}$$

A learning-by-doing rate can be calculated, which is then defined as 1−2L, showing the percentage change (often falling) in cost for each doubling of cumulative capacity.[2] The interpretation of computed learning-by-doing rate is simple. For example, if the rate of learning-by-doing is 0.30 it indicates that a

[2] When estimating a learning curve, an assumed relationship exists in the form of c(Y) = aY-b, where c is the unit of production cost and Y is the cumulative output. The reduction in unit production cost will be due to increases in the aggregate output; it is usually stated in terms of the 'learning rate' – revealing by what percentage the cost decreases when production is doubled. For example, suppose that $C_{nt} = \delta_0 CC_{nt}$−L changes from C_0 to C´; then if output doubles, we have C´/C_0= 2-L. Hence, the percentage change can be calculated and is LC = (1- C´/C_0)*100 = (1-2-L) *100.

doubling of the cumulative capacity leads to a cost reduction of 30 percent. The cost reductions in the learning curve refer to total costs and changes in production (process innovations, learning effects, and scaling effects), product (product innovations, product redesign, and product standardization), and input prices.

In the literature there is a ‘rule of thumb’ that assumes the progress ratio to be 80 per cent, which hence gives a 20 per cent reduction in unit cost per doubling of output. Dutton and Thomas (1984) studied 108 cases and found a progress ratio range of 55 to 86 per cent and the centre of the distribution to be 80 to 82 per cent. Using such a rule of thumb for long-run modelling is of course problematic since the cost of a technology then approaches zero rather rapidly and become absurdly inexpensive. To some extent certain technologies do approach zero cost. For example, over 40 years the cost of one megabyte of storage space in a computer has approached zero, but if we look at the cost of a car the price does not approach zero (with full awareness that it is an apples with oranges comparison). Some studies use a ‘floor price’ as a remedy to rapid learning rates that, in essence, have an exponential cost decrease (Köhler, 2006). Usually, it is assumed that the learning rate is not linear, but rather smooth and dynamic where the learning rate is faster at the beginning and then flattens out.

3. Challenges in using learning curves

3.1 What does the past say about the future?

Although learning curves are used to predict technological change, they are essentially rooted in the historical development of the technology. Therefore, the result will be accurate if the future holds a path-dependent trajectory, but it does not allow the data to be a random walk. Future breakthroughs and technological stalemates are also not allowed for the prediction to be accurate. An extreme stalemate is characterised by the earliest computer program, which was said to be written by Ada Lovelace, the daughter of Lord Byron, over a hundred years before the first computer-like device. In technology we might see periods of rapid development due to breakthroughs that enable the use of previously useless inventions to be added to a technology. Technologies often develop in stages with different rates of growth. Therefore, from a theoretical point of view, future technological development can be quite different from previous progress.

Something that has been observed, especially in the older literature, is that the early stages of the learning curve is rather flat, but later the curve on the log-log axes reverts to an S-shape instead of a linear shape (Carr, 1946; Crawford and Strauss, 1947). The learning rate did not increase indefinitely, and some products only saw a two-year decline in costs after which further improvements were negligible. There is a risk that the early phase of a technology’s development experiences a rapid initial improvement, but later phases stagnate.

New technologies are often assumed to be costlier than established ones and a possibility for cost decline exists for the newer technologies. A price reduction for a specific technology can increase market share and hence outcompete rival technologies with lower potential for cost reduction. Cost reductions can come from learning-by-doing (Söderholm and Sundqvist, 2007) but also from policy that creates incentives for invention or innovation, which can accelerate technology diffusion (Fischer and Newell, 2008).

There are complexities in decomposing the cost reduction effects of learning from those of R&D, scale economies, and other factors. (Lindman and Söderholm, 2012; Nordhaus, 2014). A natural problem is that it is hard to quantify technology performance with a single number. An aircraft, for example, could be evaluated using factors such as speed, passenger capacity, reliability, fuel efficiency, and other intangible characteristics. A plane might have a longer lifetime and lower maintenance requirement, but be more expensive. Hence, to make meaningful comparisons a single metric is used. Often such a metric is the inflation-adjusted cost of one ‘unit’. In wind and solar power, this is the installation cost of

1 MW of the technology. This metric allows us to compare other energy generation technologies with wind and solar photovoltaic (PV).

There is also the issue of the absence of reliable and sufficiently detailed data. For example, in many cases the time series are of varying quality because they are created by different sources and this makes it hard to piece together longer series. Furthermore, comparing the technology with its predecessors might not be fruitful. The performance characteristics of today's wind power plants can hardly be compared to plants several decades ago. In a similar way, today's cars with seat belts, airbags, and other safety features cannot be compared with the earliest cars from, for example, the Ford factory. The unit cost approach hence produces a crudeness that increases the difficulty of forecasting the future.

One must also consider where in the development process the technology is. As highlighted by Langniß and Neij (2004), wind power, for example, has matured in the learning process and has gone from local to international. In the early development phase, wind power was highly localised with small experimental windmills built by enthusiasts. The local wind industry has, however, turned international over time; companies are now involved in this industry across all continents.

Estimation of the learning curve can yield a negative rate (Rubin et al., 2015; Samadi, 2018). One reason for negative learning rates is sometimes that important factors have not been considered. Costly regulatory measures have made some technologies more expensive over time. For example, the increased safety requirements placed on nuclear power plants or the cost of desulphurization at coal and natural gas power plants affect the cost of constructing 1 MW of each generation technology (Jamasb and Köhler, 2008). If the technology were built as originally constructed, costs would be lower, but new specifications or requirements are driving the costs.

Lindman and Söderholm (2012) conducted a comprehensive meta-analysis where they looked at learning rates for wind power and found a large variance in the results, which ranged from over 30 per cent to negative numbers. They also warned of the potential for unit roots with consequences for statistical inference. Substantial variability in learning rates has been identified for other electric power generation technologies (see, for example, Rubin et al., 2015; Samadi, 2018). The variance found in learning rates is not new or surprising. The original thinking around learning curves centred on the study of a single manufacturer as opposed to the country-level or international industry that is now being seen for different renewable energy sources. Even the early single-site studies have been the subject of criticism. Hirsch (1952; 1956), for instance, found in a comparative study of seven different machines built by the same manufacturer that they each had individual progress ratios, ranging from 16.5 per cent to 24.8 per cent.

3.2 Prices and decreasing elements of the cost

Any PV system primarily comprises two components, which renders a common cost structure: (1) the module, from which sunlight is converted to electricity, and (2) the balance-of-system costs, which refers to all other items required for the PV system to be operational ranging from mounts, cables, bolts, inverter(s), grid connection to labour and permitting (Elshurafa et al., 2018). As seen in Table 1, the price decrease across the different subparts of solar PV is not uniform.

Table 1: NREL residential PV benchmark summary (USD per watt, direct current, inflation-adjusted), 2010–2017

	2010	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*
Module	2.26	1.89	0.98	0.68	0.65	0.63	0.57	0.31
Inverter	0.41	0.6	0.4	0.38	0.28	0.26	0.19	0.17
Hardware balance-of-system – structural and electrical components	0.49	0.45	0.42	0.46	0.42	0.3	0.33	0.31
Soft costs – installation labour	0.99	0.62	0.59	0.73	0.29	0.3	0.26	0.27
Soft costs – others (permitting, inspection, and interconnection, sales tax, overhead, and net profit)	2.22	2.01	1.54	1.2	1.37	1.31	1.26	1.4
Total	**6.36**	**5.58**	**3.94**	**3.44**	**3.02**	**2.8**	**2.61**	**2.45**

Source: Fu et al., (2017).

Converting the decreases in price shown in Table 1 to per cent, as shown in Table 2, reveals an erratic pattern over time. The price decreases over time, but there seem to be leapfrogging events and decreases in different fields at different times, while there are also times of plateau.

Table 2: Yearly percentage change in price

	2010	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	***2010-2017***
Module	0	-16.4	-48.1	-30.6	-4.4	-3.1	-9.5	-45.6	**-86.3**
Inverter	0.0	46.3	-33.3	-5.0	-26.3	-7.1	-26.9	-10.5	**-58.5**
Hardware balance-of-system – structural and electrical components	0.0	-8.2	-6.7	9.5	-8.7	-28.6	10.0	-6.1	**-36.7**
Soft costs – installation labour	0.0	-37.4	-4.8	23.7	-60.3	3.4	-13.3	3.8	**-72.7**
Soft costs – others (permitting, inspection, and interconnection, sales tax, overhead, and net profit)	0.0	-9.5	-23.4	-22.1	14.2	-4.4	-3.8	11.1	**-36.9**
Total	**0.0**	**-12.3**	**-29.4**	**-12.7**	**-12.2**	**-7.3**	**-6.8**	**-6.1**	**-61.5**

Source: Own calculation based on Fu et al., (2017).

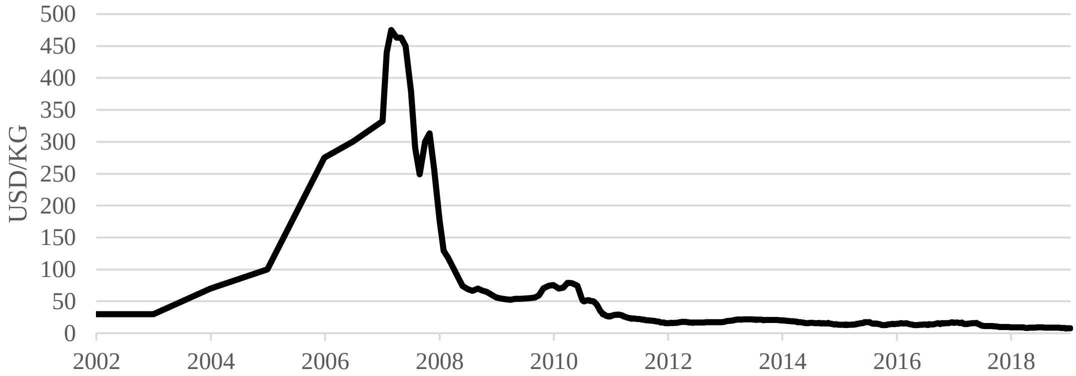
As shown, the cost of solar modules has decreased over time. Table 3 highlights that the module cost as a share of the total installation cost of solar PV has gone down from 36 per cent to 13 per cent. Hence, the decrease in the cost of a solar module matters less over time for the overall cost. For example, in 2017 a 10 per cent decrease in module cost results in only a 1.3 per cent reduction in the cost of the overall installation. Any modeller who applies the module cost's rate of decrease to the total cost of solar PV will inevitably make the wrong prediction about future diffusion.

Table 3: Solar module cost as a proportion of total installation cost

	2010	2011	2012	2013	2014	2015	2016	2017
Module cost out of total cost	0.36	0.34	0.25	0.20	0.22	0.23	0.22	0.13

In the case of both wind and solar PV, previous studies that looked at cost reductions mostly focused on the module price. While this is an important element of the incentive to install new solar panels or wind power plants, the hardware cost is only a small part of the total cost. Furthermore, the hardware cost will be (and historically has been) affected by input prices. In the case of solar power, for instance, the price of polysilicon has varied greatly.

Figure 1: Polysilicon overall average price

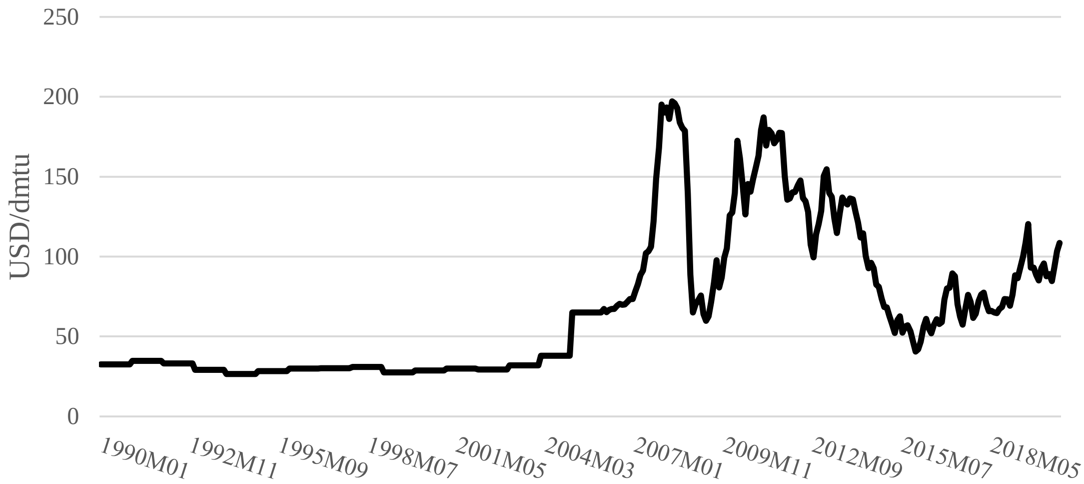


Source: SSPFPSNO Index (BNEF survey spot polysilicon overall average USD price), price on close.

Polysilicon is a major input in a PV cell. Its price has fluctuated over the years, but has trended downwards over the past decade. The polysilicon price can affect all three development stages of solar power: (1) at the invention stage a high price leads to efforts to reduce dependency on the product, (2) at the diffusion stage consumer demand is expected to decline at times of a high price, and (3) at the innovation stage a high price is expected to create the incentive for cost reduction efforts.

In a similar manner, for wind power the price of steel and iron affect the total cost of installation. In terms of material composition, stainless steel and cast iron constitute 72 per cent and 15 per cent of a wind power plant respectively, thus making these elements primary material make-up of the technology (Willburn, 2011). Figure 2 shows the development of the price for iron ore, where prices have clearly fluctuated over time.

Figure 2: Iron ore, CFR spot



Source: World Bank Commodity Price Data (The Pink Sheet).

When conducting a learning curve study, it is important to emphasize that cost reductions can come from multiple sources and not just those relating to manufacturing the product. Cost reductions can be related to improved site selection, tailoring devices to the individual site, cheaper maintenance, and better power management, and hence should also be included in learning curves. Other researchers have emphasized that scaling effects, product standardization, and input prices affect technological learning (Neij, 1997; Yu et al., 2011).

The significance of additional non-manufacturing cost sources can be great and render a year-by-year comparison problematic. For example, economies of scale will affect prices even if there is no technological development. Learning-by-doing is the cost reductions from increased efficiency or technological innovation. Learning-by-doing must be differentiated from scale effects since they are unlikely to share the same cost structure and will affect total cost differently. If a researcher fails to do this when estimating a learning curve, then there will be overestimates of the cost savings in the future and hence the diffusion phase. Economies of scale dilute some costs even if the same product is produced, since overhead costs stay the same even while the number of units goes up. Thus, if we produce more units every year it may look like a price drop due to learning, but this is not necessarily the case.

There is a radical difference over the decades in how wind and solar power units are constructed. For example, early solar panels could have a large human component in their assembly, while more modern panels are assembled by robots. In the case of wind power, the unit or installation size has increased tenfold and so has the number of computer and electronic parts. The learning curve may exhibit discontinuities or disruption if new designs are introduced or the existing designs experience an intermittent production pattern. Such disruptions create learning losses when operators who originally performed a task are no longer needed.

Economies of scale have been known to serve as a barrier to entry and influence costs to consumers. They have thus attracted the attention of economists, dating from the work of Kaldor (1935). Where one producer achieves significant economies of scale it can lead to a monopoly and hence reduced output with higher prices. An incumbent with market power could outcompete new entrants using various pricing strategies. Therefore, in the wind power industry, which is a heavy manufacturing industry that benefits from economies of scale, we should over time expect few new entrants, a small number of large firms, and little competition.

3.3 Econometric considerations

There is a valid critique against the use of single-factor learning curves. While they capture a major driver of cost reduction in new technologies, several scholars have criticized the use of learning curve effects based on a single factor to explain decreases in the cost of PV technologies (Yu et al., 2011; Nemet, 2006; Nicolli et al., 2012). As observed, single-factor learning curve models exhibit shortcomings, but can be improved by incorporating technical change and innovation theory, which expands the model to two- or multi-factor models (Jamasb and Köhler, 2008). Learning models can be extended to include learning-by-researching and incorporated R&D in the technological development process.

Kouvariatakis et al. (2000) introduced two-factor learning curve models and examined the effect of cumulative R&D and cumulative production as determinants of the technology cost reduction. A two-factor learning curve (2FLC) can be derived by augmenting the single-factor learning model. According to Odam and de Vries (2020), the main difference between the single- and two-factor models is that in the former cumulative capacity is implicitly capturing cost reductions from innovation, whilst the cost reductions from innovation in the two-factor model are explicitly captured by including a knowledge stock variable.

In their paper, Söderholm and Sundqvist (2007) identify several econometric issues concerning learning curve models, which we highlight here. The learning rate can differ across time as a new technology can experience a wave of new innovations at the beginning, but after many years the easy opportunities for cost reductions may be exhausted; conversely, technological development can accelerate.

The way which technology learning is operationalised is an important issue. Although cumulative capacity has been used in the literature as the standard indicator of learning-by-doing, this approach is not free from criticism. The cumulative capacity often shows an increasing trend over time, creating the question of whether cumulative capacity encapsulates the specific impact of learning-by-doing activities, or if instead general (exogenously driven) technological development. The same trend problem can occur in any knowledge stock-based variable. To deal with this issue, a time trend can be incorporated in the learning equation. If the learning coefficients still pick up the learning activity impacts and remain statistically significant, once the time trend has been added to the model, it could be argued that the problem has been remedied.

A further issue with estimating the learning models is the additive structure of error term in them. The error term, e_{nt}, can be decomposed into two components as shown in (3):

$$\varepsilon_{nt} = \lambda_n + \upsilon_{nt} \tag{3}$$

where λ_n is the country-specific effects, while υ_{nt} represents the remainder stochastic disturbance term. There can be unobserved country-specific heterogeneity in, for example, solar PV investment costs across countries related to policy and institutional arrangements. It thus needs to be assumed that these differences are fixed in the countries over time and that these country-specific effects can be captured by using a dummy variable for *N-1* of the countries, that is, a fixed-effects model. The fixed-effects model is intended to remedy the estimation bias resulting from correlation between unobserved country effects and regressors (Baltagi, 2008).

Yet another issue is that the model in (3) assumes that the cumulative capacity is an exogenous variable (i.e., not correlated with error term). An installation is not always constructed because it is the most efficient alternative. Learning activities and R&D spending can reduce the cost of generating PV electricity. Hence both innovation and diffusion could be considered as endogenous, they are possibly simultaneously determined and are problematic to analyse separately.

From an econometrics perspective, endogeneity means that in the learning curve model, Equation (1), the explanatory variable CC_{nt} and the disturbance term e_{nt} are correlated. The correlation between them implies that classical Ordinary Least Squares estimation attempts would render biased and inconsistent estimates (Greene, 2003). To remedy this problem the so-called Hausman specification test is often utilized. If the Hausman specification test suggests non-rejection of the null hypothesis, meaning that $lnCC_{nt}$ is an exogenous variable in the learning model, we can adopt instrumental variable approach to correct for endogeneity (Hausman, 1973) – that is, we can regress $lnCC_{nt}$ on a set of variables that are exogenous to $lnCC_{nt}$, and then use the fitted values from this regression as instruments instead of $lnCC_{nt}$ in Equation (2).

If a small model is run with few control variables, then omitted variable bias could be a problem. When an exogenous variable, whose true regression coefficient is non-zero, is omitted from the model, the estimated coefficients will be biased unless there is no correlation between omitted variable and every included variable. In a learning curve model this could be problematic since costs could be expected to be affected by variables other than cumulative capacity, for example a fluctuating silicon price for solar PV. The inclusion of control variables reduces the omitted variable bias, but can create endogeneity issues which is a concern when including R&D variables – that is, when the amount of constructed power plants expands, it then reduces the average cost, which in turn affects future prices, which will drive demand.

4. Discussion

The learning curve has served researchers well and enabled instrumental analytical insights for our understanding of technological change in the renewable energy sector and in general. As mentioned previously, there is a plethora of papers that utilize the learning curve for renewable energy (Yu et al., 2011; Nemet, 2006; Nicolli et al., 2012; Grafström and Lindman, 2017) or that analyse the method in general (Goddard, 1982; Sinclair et al., 2000; Nordhaus, 2007, 2014; Nagy et al., 2013). While the insights presented in this paper do not suggest that learning curves should be abandoned, caution is still advised in its application.

Factors that affect the price of a renewable energy installation (to name a few) are returns to scale, geographical distances (from, for example, grid connection, production hubs and infrastructure), labour cost differences, and institutional factors. Moreover, when studying previous installations, one must also be careful to ensure consistency in the methods used for data collection and the assumptions made about the speed of technological development, the maturity of the industry, and the availability of skilled labour.

There are local components of the cost (for example, ground work, permit accruing processes, territorial planning activities, grid connections etc.) that are nation-specific because of differences in geographical, legal, or economic conditions (Elshurafa et al., 2018). The local components of cost make an aggregated learning curve using general panel data less useful. The level of aggregation can also render different outcomes. For example, an experience curve for PV cells might aggregate over plants, firms, and countries.

It is also important to study the main input prices during the period. In the solar case, we exemplified in Figure 1 that the price of polysilicon, a major input, could vary by several hundred percent over just a few years. For wind power, steel and iron prices are important. As shown in Figure 2, the machinery and technology might be the main cost, but the structure quickly becomes more costly if the iron ore price goes from USD 40 to USD 160 per dry metric tonne (dmtu). Hence, if the calculation produces a negative learning rate, it might not be the case that the learning rate was negative, rather it might just be the case that strong economic growth has driven up the price of natural resources.

The objective of learning curve study is also very important. If the research goal is to see the average learning rate over a long period, then more data is better. However, if the goal is to say something about the future, then the average learning rate in the last ten years should give more insights than the last thirty. Hence, there is an argument for limiting or extending the data depending on what the research goal is. In plainer terms, if one wants to predict the future of a soccer team season, the last ten games are a better predictor than the average over the last ten years.

On a more technical note that is directed more at practitioners, how the learning curve is approached econometrically will affect the results obtained. As shown by Söderholm and Sundqvist (2007), several specific econometric issues exist concerning learning curve models. However, learning curves are also affected by general econometric issues (Baltagi, 2008; Greene, 2003). There are assumptions in learning curve estimates for which not so much empirical evidence exists. For example, the assumptions concerning the prevalence of learning spillovers between countries. There are multiple directions for future applications of learning curve models where issues such as knowledge spillovers between countries (Grafström, 2018) and correlation between seemingly unrelated technologies can be investigated (Grafström, 2019). Also, if there is likelihood of presence of both a national and an international component for the (capital) costs for a renewable energy technology, it is useful to consider national and global learning in combination on the basis that they are co-dependent.

This paper surveys the analytical and statistical basis of learning curves, and reveals conceptual and practical limitations. Although some concerns about the validity of learning curves are raised, it does not argue that learning curves should not be used. An observer might ask, why try to fix something that is not broken? The answer is that even though a compelling concept such as the learning curve may be available, it is nonetheless easy to derive unintended results if the work is not well planned and executed. Also, even if all concerns raised in this paper are remedied, there are surely further issues to consider in any specific case. This paper raises more general problems for the reader to elaborate on further in their own research. Learning curves will, and indeed should, be used in the future when planning for energy scenarios and ways to mitigate climate change. However, the researcher needs to be careful about how the model is best constructed, what variables to include, and what questions the model is supposed to provide answers to.

5. Concluding remarks and implications

With the growing adoption of ambitious decarbonisation objectives across the globe, there is increasing interest in understanding how a rapid reduction in the cost of renewable energy sources such as solar and wind power will affect the diffusion of these generation technologies. The learning curve – a concept that relates historically observed cost reductions to the number of units produced or cumulatively installed capacity – has been widely adopted to analyse the technological progress and adoption of renewable energy technologies. Relying on past empirical observations of the existence of such a relationship, researchers often apply the concept or make associated assumptions uncritically in their technology analysis. While this paper does not falsify the validity of the concept of learning curves, it argues that their application in forecasting the future has limitations, at least at the country level. The learning curve correlation is generally observable across wind and solar power, but our argument is that cost reduction can be driven by factors not correlated with current output, implying that other factors are drivers of long-term learning effects. The continued use of learning curves, however, is a sign of their attractiveness within the economic community and their gradual improvement over time.

The increased use of learning curves for the analysis of technology in relation to decarbonisation policies underlines the need for a critical assessment of these concepts' application. Learning rates for technology development analysis are as important as the discount rate in a cost-benefit analysis. Learning curves are also used as inputs in energy system models. Flawed learning models will inevitably weaken the chances of improving our understanding of the role of technologies in achieving energy transition objectives. The choices made when calculating learning curves will result in different learning rates and lead to different analytical and policy outcomes. Applying the results of a learning curve estimation, when modelling projections can create exaggerated cost reduction effects, might create misleading results.

Learning curves may be utilized for projections, but it is important to make sure that they are in line with the past progress, which is assumed to carry on into the future. A notable problem is that emerging technologies typically progress in several stages. Certain patents can be critical in large development jumps that spur further innovation. Conversely, technologies can also remain stagnant for some periods. When a new technology reaches price parity with older competitors, a rush of diffusion might take place and spur a different kind of innovation. Therefore, from a theoretical perspective, it is entirely possible that the forthcoming advancement paths of technologies will be different from their progress in the past.

As a final word, we must add the usual caveats about making forecasts – as Niels Bohr reputedly said: prediction is very difficult, especially about the future.

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