CHAPTER 2

The experience curve: concept, history, methods, and issues

Atse Louwen[1,2] and Juliana Subtil Lacerda[1]

[1]Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, The Netherlands,
[2]Institute for Renewable Energy, Eurac Research, Bolzano, Italy

Chapter outline

2.1 Introduction

Especially since the Industrial Revolution, impressive technological progress has been made. This progress has resulted in the development of many novel technologies, but there

Technological Learning in the Transition to a Low-Carbon Energy System.
DOI: https://doi.org/10.1016/B978-0-12-818762-3.00002-9

are also abundant examples of technologies that have remained in essence the same (at least performing the same function) but which have seen gradual but strong improvements over time. Examples that come to mind are the airplane and passenger car and, more recently, technologies in the computer industry, such as processors and memory chips. Learning is considered a key driver in these examples of endogenous technological change (Junginger et al., 2010). In this chapter, we introduce the concepts of the learning curve and experience curve, mathematical relationships that describe the technological progress for a technology—measured in unit cost reductions—as a result of increases in cumulative production of this technology. We discuss their origins, definitions, key applications, and finally present some main methodological issues and drawbacks.

2.2 Learning and experience curves

Within the context of technological learning, it is important to distinguish two concepts: (1) learning and (2) experience curves. Both refer in some ways to the same phenomenon that, as producers, gain more *experience* with manufacturing of a product, the costs of production will decrease. However, the exact parameters that the curves describe differ between the two concepts.

The phenomenon of the learning curve was first observed and documented in the 19th century by a German psychologist Hermann Ebbinghaus. He described that learning is an exponential process, meaning that the fastest learning occurs in the beginning and that exponentially more effort is required for subsequent increases in learning (Ebbinghaus, 1885). Ebbinghaus was the first researcher to mathematically document the learning process in an experiment he conducted upon himself. He measured the number of repetitions it took to memorize lists of words and found that those declined in an exponential manner (Ebbinghaus, 1885), as shown in Fig. 2.1.

The first well-documented quantified example of the learning curve in the context of technology costs was published by Wright (1936). When examining the manufacturing of airplanes, Wright stated that the time required (measured in unit labor costs) for each airplane built decreased with a constant percentage every time the cumulative number of airplanes produced doubled. The relation was described by Wright with the equation:

$$F = N^X \tag{2.1}$$

where F is the observed variation in labor costs, N the quantity of airplanes produced. For an 80% reduction in labor costs the exponent X has the value of 0.322. The unit labor costs are then the reciprocal of F. Wright attributed the unit labor cost reductions to a well-known theory that states that as assembly line workers gain more experience, they become more efficient in their work.

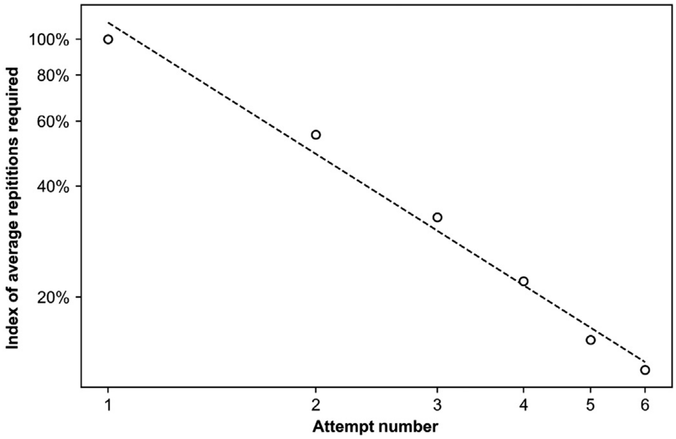

Figure 2.1
Learning curve made from Hermann Ebbinghaus' experiments on the number of repetitions required to memorize certain lists of words. *Data from:* *Ebbinghaus (1885)*.

Wright also examined the relation between quantities of airplanes produced and unit material costs, and observed different mechanisms that led to cost decreases. First, by increasing the production quantity, relative amounts of waste decrease. Second, higher quantities allow for more economical purchasing of materials from external suppliers. By combining the curves for labor and materials, and also including overhead costs, Wright stated that the total airplane costs follow a curve that has a steeper slope in the beginning due to the higher contribution of labor costs and which gradually has a less steep slope, as the proportion of material costs to overall costs increases. He saw the value in this concept and the mathematical representation of the cost decrease resulting from the cumulated production experience to be able to assess the cost developments for very large numbers of production.

2.2.1 The single factor experience curve

After Wright, it took quite some time for this theory to become more mainstream. As discussed in Junginger et al. (2010), it was not until the RAND Corporation revisited the subject to study the possibility of cost reductions in production of war materials that gained more prominence. In the 1960s, the concept was broadened and introduced into the field of economics by Arrow (1962), and it was developed further by the Boston Consulting Group (1970) into the concept of the experience curve. Boston Consulting Group (BCG) expanded Wright's learning curve concept to describe the total cost of products and used it to describe unit cost of a product across a whole industry, rather than within a single company, and called this concept the experience curve to distinguish it from the previous learning curve. BCG included in this theory the combined effects of learning-by-doing, learning-by-researching (more commonly research and development, R&D), scale, and investment. Taking all this into account, the experience curve got the following form:

$$C_{\mathrm{Q}} = C_1 \cdot Q^b \tag{2.2}$$

In this equation, C_{Q} is the cost of the product at cumulative production Q, C_1 is the cost of the first unit ($Q = 1$) produced, and b is the experience parameter. In essence, this is the same formula as posed by Wright, with the distinction that C_{Q} gives the unit cost (not cost reduction) as Q^b is multiplied with C_1, and so

$$\frac{C(n)}{C_1} = \frac{1}{F} \tag{2.3}$$

where F is as in Eq. (2.1). As Wright already showed, this power law shows a straight line when plotted on a double-logarithmic scale. With this in mind the equation can also be expressed as a linear equation by expressing it in a logarithmic form:

$$\log\ C_{\mathrm{Q}} = \log\ C_1 + b \cdot \log\ Q \tag{2.4}$$

The experience curve parameter b thus represents the slope of the linear representation of the experience curve in a double-logarithmic graph. Since the slope of this line indicates the rate at which a technology's cost decreases, two terms have been connected to the experience parameter b: the progress ratio (PR) and the learning rate (LR):

$$PR = 2^b \tag{2.5}$$

$$LR = 1 - 2^b \tag{2.6}$$

For an LR of 20% (PR of 80%), the cost of a product decreases by 20% for every doubling of cumulative production n. Hence, these parameters are a more intuitive expression of the experience parameter b. An example of an experience curve, for solar photovoltaic (PV) modules, is given in Fig. 2.1. Shown in Fig. 2.2 is the raw, empirical data collected, the derived experience curve, and an example of plotting this data on normal, linear scales and on double-logarithmic or log–log scales. For this dataset, an LR of 23.9% was derived, indicating a decline in price of 23.9% for every doubling of cumulative production of PV modules.

2.2.2 Two and multifactor experience curves

As discussed in the previous section, the unit cost reductions observed for a technology, are the result of a combination of learning drivers. In addition, developments in input material prices can also have a large effect on the cost development of a technology. The experience curve as discussed above, which we from now refer to as the one-factor experience curve

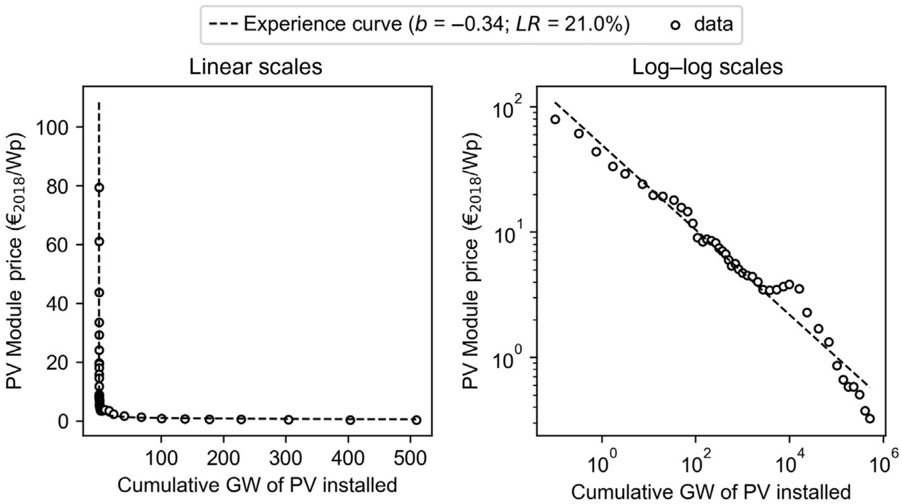

Figure 2.2
Example of experience curves on two different graph scales: normal, linear scales (left), and double-logarithmic or log—log scales (right). *Source: Data from* Louwen et al. (2018).

(OFEC), treats all different drivers and developments essentially as a black box, and thus only describes the observed empirical trend of decreasing unit costs but gives little to no insight in the underlying mechanisms driving these cost reductions. By trying to separate the different drivers of cost reductions, invaluable insight can be obtained on how to influence cost reductions (e.g., from a policy maker's point of view) and how to explain cost developments that seem to deviate from the long-term trend that is given by the OFEC.

To be able to include these considerations in the experience curve concept, several extensions have been made to the OFEC. The first example, we give here, is the extension of the OFEC to include separately the effects of learning-by-doing and learning-by-researching (R&D), in a two-factor experience curve (TFEC). By taking into account R&D expenditures, either directly or using some proxy metric, these drivers can theoretically be separated and measured:

$$C_Q = C_1 Q^b KS^c \tag{2.7}$$

$$\log C_Q = \log C_1 + b \log Q + c \log KS \tag{2.8}$$

$$LR_{LBD} = 1 - 2^b \tag{2.9}$$

$$LR_{LBR} = 1 - 2^c \tag{2.10}$$

Here, we obtain two separate LRs, LR_{LBD}, being the LR for learning-by-doing, or cumulative production, and LR_{LBR} being the LR for learning-by-researching. The latter describes the unit cost reductions of the studied technology, as a function of doubling the R&D effort, in this formula measured by the parameter *KS*, the "knowledge stock." The parameter *KS* takes into account the fact that knowledge gained from R&D expenditures generally does not directly result in cost reductions (there is a certain time lag), and that the knowledge stock depreciates over time when no further research is conducted:

$$KS_t = (1 - \delta)KS_{t-1} + RD_{t-x} \tag{2.11}$$

In this equation, *KS* in year t is based on the *KS* of the previous year, with addition of the R&D expenditures *RD* in year $t - x$, where x is the time lag for implementation of R&D-related learning in technology improvements. The parameter δ describes the depreciation of the knowledge stock, based on the underlying assumption that without further research, the value of knowledge gained from R&D efforts gradually declines, along with its ability to drive down unit costs.

An example of application of the TFEC in the currently developing technology is the study by Kittner et al. (2017), who studied the development of energy storage technology. By taking into account both production volume (as opposed to cumulative production) and "innovation activity," they analyzed the effect of economies of scale and learning-by-researching on declining lithium-ion battery prices and found that this TFEC is better able to describe the observed price trends than an OFEC based on either production volume or cumulative production (Kittner et al., 2017). Further detail on this study is given in Chapter 8.

Further examples of extensions of the OFEC were presented by Yu et al. (2011) for PV technology. Yu et al. analyzed the effect of input prices for silver and silicon, as well as increasing manufacturing scale for PV plants on the cost developments of PV technology. The TFEC was expanded to a multifactor experience curve (MFEC), with different parameters for input prices $(P_1, P_2, \ldots, P_i)$ and multiple learning parameters $(q_1, q_2, \ldots, q_i)$ in the following generalized equation:

$$C_{\text{cum}} = aQ_x^{(1-r)/r}\left(\prod_{i=1}^{m}\left(q_i^{\sigma_i}\right)\right)^{1/r}\left(\prod_{i=1}^{n}\left(P_i^{\delta_i}\right)\right)^{1/r} \tag{2.12}$$

where Q_x is the instantaneous production, δ_i is the elasticity of input prices P_i, and a is defined as $a = r\left(\prod_{i=1}^{n}\delta_i^{\delta_i}\right)^{-(1/r)}$, with r being the returns-of-scale parameter. The first product $\prod_{i=1}^{m}\left(q_i^{\sigma_i}\right)$ in Eq. (1.12) represents the effects of technological changes, for instance as a result of learning-by-doing or learning-by-researching, while the second product $\prod_{i=1}^{n}\left(P_i^{\delta_i}\right)$ represents the effect of prices of inputs, while $Q_x^{(1-r)/r}$ shows the scale effect. The number of input learning variables and input prices is denoted by parameters m and n, respectively.

In addition to the TFEC approach discussed earlier, Kittner et al. also studied a MFEC for lithium technology, incorporating raw material prices in addition to economies-of-scale and innovation activity. Although a high correlation was observed for this MFEC, no significant improvement compared to the TFEC was observed.

2.3 Empirical data collection for experience curves

The value of the experience curve concepts stems for a large part from the use of empirical data, giving us an evidence-based description of technology cost reduction as a function of cumulated production experience. In the following sections, we describe guidelines for data collection and harmonization, experience curve parameter derivation, and assessment of data quality.

2.3.1 Cost versus price data

To be able to derive the experience curve parameters as shown in Eqs. (1.2)−(1.6), at least two datasets are required: the development of unit technology costs over time and the development of cumulative production of this technology over time. Until now in our discussions, both the learning and experience curves refer to the development of production *cost*. However, for most technologies, cost data is not readily available. Hence, most studies of experience curves rather make use of the unit *price* of technologies.

Market prices of technologies depend not only on the production cost and some fixed margin but are also affected by marketing strategy, supply and demand of the product, competitiveness of the market for this product, available subsidies, etc. The Boston Consulting Group (1970) proposed four stages of cost development as a result of pricing policy relative to market and product maturity:

- Development: prices below costs to compete with existing alternatives
- Umbrella: early commercialization leads to price increase above costs
- Shakeout: strong price reductions due to increasing competition
- Stability: costs and prices move parallelly in mature markets

During the development phase a manufacturer introduces a new technology at a price point below that which does not cover production costs (e.g., with a negative margin). With this strategy the manufacturer can compete with incumbent technologies that are already in a further stage of development and can create a market for the new product (forward pricing). When cumulative production increases, unit *production* costs decline rapidly but prices are (kept) stable, until a profit margin becomes viable. This “umbrella” phase shows that the product is commercially viable, and hence should attract competitors to enter the market. The dominant market players can commonly determine the market price for a certain time, until a shakeout occurs where prices decline rapidly in a short period of time. After the shakeout phase the market would reach stability, where both

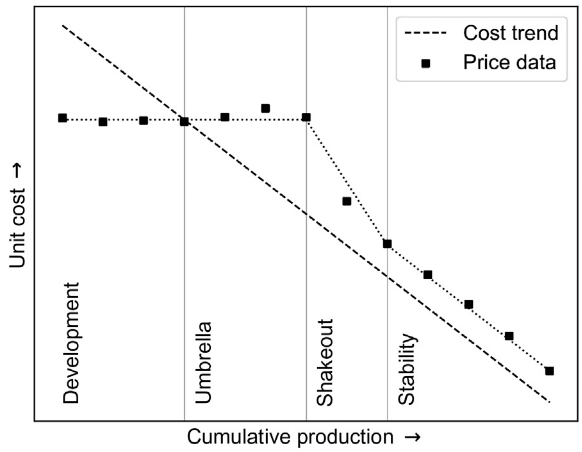

Figure 2.3
Illustration of cost versus price dynamics during the development and introduction of a new technology. *Source: Adapted from Boston Consulting Group (1970); Junginger et al. (2010).*

costs and prices decline at the same stable rate, with constant relative profit margins (Fig. 2.3).

In the context of experience curves, price data is a good proxy for cost only in this final stage of stability, since the slope of cost and price curves should be identical. Experience curves made with data points from early market deployment stages can be highly variable as more data comes in and do not likely reflect the *LR* in a stable, mature market situation. Even in the phase of stability, certain market developments might severely affect the cost versus price dynamics. In particular, when price data is used, a period of at least 10 years' worth of historical data or two orders of magnitude of cumulative output should be available for price trends to be reliably reflective of cost trends (Junginger et al., 2010; Gross et al., 2013).

Although the decision to use price rather than cost data is usually made out of necessity, since cost data is hardly available, there are still reasons to justify the use of price data. When making investment decisions, informed consumers or businesses consider the unit price, total cost of ownership or levelized cost of electricity (LCOE) of a technology, rather than taking into account production costs for the manufacturers. Since experience curves are commonly used to make projections about future investment decisions between a number of competing technologies, it makes sense to consider prices rather than costs. This does mean that when analyzing experience curves, particular care needs to be taken to take into account market dynamics.

2.3.2 Functional unit

When gathering unit cost or price data for experience curve analyses, it is important to determine for which unit this data is being collected. This unit should relate to the function of the product, as it is likely that a manufacturer will try to optimize production so that the economic performance of the products' function will improve. Hence, data should be collected for the unit that best describes the technology's function, for example, the *functional unit*. The technology characteristics determine the functional unit.

For instance, when purchasing solar PV systems, consumers (or commercial installers) often make a comparison between different offered PV systems based on the cost per unit of rated capacity (kW) and use this metric to make an investment decision. Although in the end, the LCOE (EUR/kWh) is most likely the most suitable metric to make an investment decision; the cost in EUR/kW is the most convenient and hence the most likely method in making this decision.

For other technologies or products, for instance hydrogen production by means of electrolysis, costs are often reported per unit of electrolysis stack capacity (EUR/kW), while an end consumer of hydrogen would be more interested in the cost per unit of output product (EUR/kg hydrogen). In the end the application of the experience curve determines the functional unit that is required, but technology characteristics will affect whether this unit is suitable for deriving an experience curve. An example of this issue is found in Chapters 6 and 7, where experience curves for on- and offshore wind are discussed. While earlier studies show reasonable experience curves of unit capacity cost (EUR/kW) versus cumulative production, certain developments in wind technology have led to an increase in the unit capacity cost. One of the reasons behind this is that manufacturers and installers of wind farms seem to optimize this technology to improve LCOE, rather than unit capacity cost (Williams et al., 2017).

Related to the topic of the functional unit is the issue whether it is reasonable to assume that a technology learns as a whole, or as a function of learning in several separate components. Datasets for solar PV-system components (see Chapter 5) indicate that different components have different *LR*s; hence, the overall cost decline of the PV systems is more accurately described by taking into account these separate *LR*s, rather than a single *LR* for the complete systems.

2.3.3 Data harmonization

When collecting data, it is likely that datasets gathered will be consisting of different source datasets, each in its own currency and/or currency year. When deriving an experience curve, it is important to make sure the complete dataset is harmonized to a single currency and currency year. For this harmonization the following steps are necessary: correction for inflation of the currency and conversion to a single currency using exchange rates. We suggest the following approach:

- Correct for inflation using a GDP deflator for the local currency
- Convert the currency to EUR using exchange rate of the given currency year

Other means of inflation correction are those using consumer price indices (CPI) or producer price indices, and additionally, one could argue that the conversion furthermore needs to take into account purchasing power parity. Depending on the technology or product under study, it might be more reasonable to use CPI for inflation correction, especially if the technology is primarily a consumer product. However, for most of the technologies discussed in this book, using the GDP deflator approach is deemed most suitable.

2.3.4 Common issues with data collection

When collecting data for derivation of experience curves, a number of issues often arise. In Table 2.1, an overview is given of common issues, based on the experiences in the REFLEX project (Louwen et al., 2018). In addition, several ways to solve these issues are listed and are discussed next. In Chapters 5−13, wherever applicable, these data collection and quality issues are discussed.

Arguably, the most common issue with data collection is the unavailability of production cost data. Hence, the majority of experience-curve studies are based on price data. In the previous section, we have discussed the implications of this issue. Out of necessity, the solution is to use price data, but another important recommendation is to thoroughly analyze market dynamics and market diffusion stages for the technology under study. Connected to the issue of cost versus price data is one of its implications: that supply and demand dynamics can affect prices significantly. An option would be to use MFECs that account for, for example, supply/demand balance (Gan and Li, 2015), which is also recommended if there is evidence that input material prices affect the price or cost to a substantial degree.

Data that can be used to derive experience curves is often gathered on a country basis. Hence, price data could be very specific for the local market conditions. In addition, when deriving the *LR* based on, for example, local cumulative production data, the value of the *LR* will be very different from that based on global cumulative production data. A trivial solution is to collect more data from different regions in order to form an aggregate dataset that could more closely reflect average global prices. For specific technologies, it might be necessary to adjust the data for purchasing power.

Table 2.1: Overview of possible data gathering issues.

Issue	Resolution
Data is not for cost but for price	Use price data as indicator for costs
Data not available for desired cost unit	Convert data to desired unit if possible Use available data as a proxy
Data is valid for limited geographical scope	Convert currency and adjust for PPP if necessary Combine with other datasets from various geographical scopes
Cumulative production figures not available	Calculate from annual production figures Calculate from annual sales figures
Data is in incorrect currency or currency year	Convert currency and correct for inflation and PPP if necessary
Early cumulative production figures are not clear or available	Restrict the dataset to time horizon for which reasonable cumulative production figures are available
Supply/Demand affecting costs significantly	Correct using multifactor experience curves (if required data is available) Otherwise, decide whether to discard this data, or keep data as is
Lack of empirical (commercial scale) data	Use proxy technologies, use expert estimates

PPP, Purchasing power parity.

Just like technology production costs are often difficult to collect, cumulative *production* data is normally also not readily available. In many cases cumulative *sales* or *installation* data is much more readily available and can serve as an adequate proxy for cumulative production data, as long as there is no clear evidence of large discrepancies between production and sales or installation. A related issue is the availability or accuracy of early cumulative production data for the beginning of the dataset. In this case it might be advisable to restrict the dataset timeframe to a range for which there is sufficient confidence in the accuracy of the data.

One of the most difficult issues when deriving experience curves, especially apparent for very new technologies, is a complete lack of empirical data. A very prominent example of such a technology is carbon capture and storage (CCS). Although there are a (small) number of pilot plants installed worldwide, and there is cost data for some of these pilot plants, the dataset is too limited and there is too much of heterogeneity between the pilot plants to derive an accurate *LR*. Given the importance of CCS in many energy scenarios, it is thus nearly impossible to use experience curves based on empirical data from CCS installations. In this case a possible solution is to make use of proxy technologies that are closely related to the technology under study. Rubin et al. (2007) made use of this approach for CCS, where they used experience curve data for a number of related proxy technologies to derive a nominal *LR* for power plants equipped with CCS systems.

2.4 Estimation of experience curve parameters

2.4.1 Regression method: linear or nonlinear

To be able to estimate the values of the experience curve parameters, the empirical data is to be used to perform a regression fit. Given the expected relation of $y = a{\cdot}x^b$, one of the options would be to perform a nonlinear regression of the raw, harmonized dataset. However, most commonly for this type of relation, a linear regression is performed of a logarithmic transformation of both x and y data. In general, transformation of the input data is recommended when the resulting fit of a nonlinear regression results in nonnormally distributed fit residuals, or when these fit residuals show heteroscedasticity. The choice between the two methods is also related to the assumption of the type of error in the dependent variable. Assuming an additive error in the original power law function, the equation to be fitted becomes

$$C_Q = C_1 \cdot Q^b + \epsilon \tag{2.13}$$

where ϵ is the error term. Given the power law relation and the developments of unit costs from very high initial values to much lower current values, it seems fair to assume that the error term in Eq. (1.13) would be multiplicative, rather than additive, for example:

$$C_{\mathrm{Q}} = C_1 \cdot Q^b \cdot \exp(\epsilon) \tag{2.14}$$

which becomes, after log-transformation, an equation with an additive error:

$$\log C_Q = \log C_1 + b \log Q + \epsilon \tag{2.15}$$

The difference between the two regression methods is exemplified in Fig. 2.4. In this figure it becomes apparent that there is a large difference between the experience curves derived with the two regression procedures. Visually, the linear regression of log-transformed data gives much better results. In Fig. 2.4 (middle and right panels), the fit residuals are plotted against the "measured" cost data. It is apparent that the nonlinear regression shows large heteroscedasticity, when compared to the fit residuals of the log-transform linear regression. This suggests that using the latter method would be recommended.

2.4.2 Determining fit accuracy and experience curve parameter errors

When performing the regression of the empirical experience curve data, it is recommended to present the accuracy of this regression. Commonly, the authors present the accuracy in terms of the coefficient of determination R^2, which shows that in the context of experience curves, the proportion of observed variance in the costs can be attributed to variation in the cumulative production. Although the R^2 value can be considered a good measure to show goodness of fit, it is important to realize that it does not say anything about causality in the

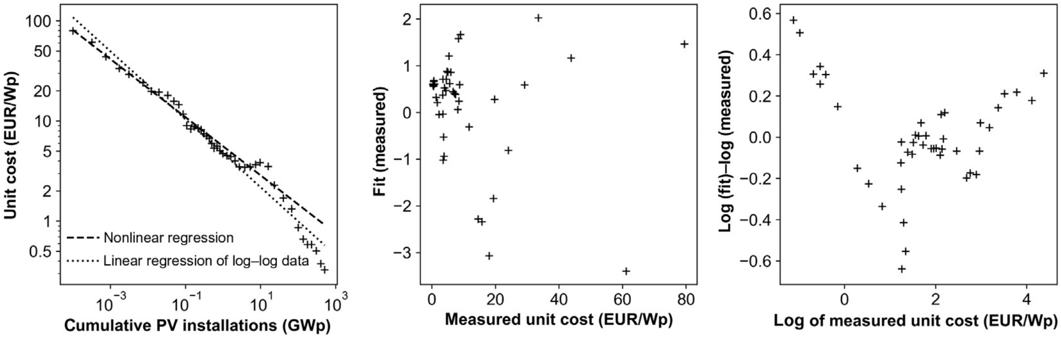

Figure 2.4

Comparison of nonlinear regression of raw data and linear regression of log-transformed data. The example dataset used here is for PV modules. *Data from:* *Fraunhofer ISE (2019)*; *Louwen et al. (2018)*.

observed correlation, if the used dataset is sufficiently large for statistical validity. Furthermore, it does not indicate whether the chosen regression model is the appropriate one, and as Kittner et al. (2017) discuss, it gives no information about omitted-variable bias.

A partial solution to some of these issues, is to furthermore present the P-values of the linear regression. Statistical software commonly gives P-values for the regression coefficients (intercept and slope). These values for the regression coefficients indicate the probability that the null-hypothesis is valid, with the null-hypothesis stating that intercept and slope of the regression are zero. Aside from the P-value for statistical significance, it is also informative to present the errors or the confidence intervals of the fitted regression coefficients, especially for the slope of the regression.

In addition to the P-value for the regression coefficients, it is also useful to present the overall significance of the linear regression. This can be calculated by performing an F-test, and the associated P-value. The F-test compares explained and unexplained variance and tests against the null-hypothesis whether the dataset can be described by a model with only an intercept, and no additional coefficients. A P-value can be attributed to the F-test result, allowing us to reject this null-hypothesis at different levels of significance. It can be said that while the R^2 shows how strong the correlation is between the x and y data, the F-test allows us to judge whether this correlation is statistically significant.

2.5 Applications of experience curves

As discussed in the previous sections, the experience curve is a broadly applied tool, and its validity has been empirically demonstrated for many different technologies (Junginger et al., 2010). The experience curve enables to forecast future changes in the technology costs by assuming that these costs decline as experience with a technology is gained through production and use. A large body of empirical evidence has been already built demonstrating a strong negative correlation between experience and cost for different technologies. The experience curve approach has been used increasingly in economic modeling to endogenize cost developments by accounting for the interrelationship between a technology's cost and its deployment (Löschel, 2002; Gillingham et al., 2008; Della Seta et al., 2012; Wei et al., 2017a,b).

There are many examples of literature of the past decades of experience curves applied to maturing and emerging energy technologies, such as solar PV modules (Bhandari, 2018), wind turbines (Williams et al., 2017), hydropower (Chang et al., 2016a,b), energy storage (Kittner et al., 2017; Schmidt et al., 2017), fuel cells (Wei et al., 2017a,b), and CCS (Riahi et al., 2004).

The experience curve is thriving as a key analytical approach due to its fundamental role in forecasting trajectories of energy system transformation, which is required to tackle challenges such as climate change, energy security, and poverty. By enabling to foresee most likely cost trajectories of different energy technologies, the experience curve facilitates strategy design and policy making as it provides insight into which technological mix is most efficient from economic, environmental, and social points of view. The International Energy Agency (IEA) (200AD) published one of the first comprehensive overviews of experience curves for renewable energy technologies. This assessment only covered a limited set of renewable energy technologies. In 2006 the NEEDS project (Neij et al., 2006) resulted in experience curves for a variety of energy technologies, and also included comparisons with bottom-up engineering estimates. The results of the NEEDS project were updated and extended in 2010 in Junginger et al. (2010), including the addition of demand-side technologies and lessons for policy makers. In this book, we update the results of Junginger et al. with up-to-date datasets, and now include more novel technologies such as energy storage (Chapter 8), electric vehicles (Chapter 9), and heat pumps (Chapter 11). This work is the result of the REFLEX project, where a large set of energy models are coupled and technology costs are modeled using experience curves.

Experience curves can be applied by companies, analyzing the speed at which the manufacturing costs of the products they sell may decline, by energy modelers as a tool to forecast future investment costs, and by policy makers as a tool to design policy measures.

For companies, business digitalization together with electrification and large amounts of data available has made energy a common variable for a range of business decisions almost regardless of the sector. As energy consumption becomes a key cost variable and GHG emissions a fundamental factor for a business reputation, companies are increasingly moving toward forecasting the most economically and environmentally efficient energy sources, giving rise to another application of experience curves in business.

For policy makers, we can identify at least three key applications. First, they can apply experience curves directly as a tool that allows for monitoring and quantification of investments required for technologies to attain a competitive level. Second, experience curves can be used more indirectly, as a means for energy models to estimate future prices of technologies and to forecast the deployment of several competing technologies. Third, experience curves inform climate and energy policy by providing data on the best combination of energy technologies to reduce GHG emissions, on how to increase energy security and on how to reduce energy poverty.

2.5.1 Direct applications of experience curves for policy makers

From a policy maker's point of view, the experience curve can inform policy design at different dimensions such as policy instrument choice (Kivimaa and Kern, 2015), level and type of financial support (Cárdenas Rodríguez et al., 2015), mix of command-and-control and market-based instruments (Jaffe et al., 2005), tackling uncertainty (Guivarch et al., 2017), adaptation to support or regulation needs of a specific technological sector (Malerba, 2005), and efficient pace of phasing out subsidies (Rezai and van der Ploeg, 2016). A key element on policy guidance based on the experience curve relates to the sources of learning. Cost reductions, derived from the experience curve, result from learning gained mainly from three different sources, namely, learning-by-doing (Arrow, 1962), learning-by-using (Chang et al., 2016a,b; Morstyn et al., 2018), and learning-by-interacting.

Learning-by-doing, related to the concept originally developed by Arrow (1962), refers to the cost reductions due to higher efficiency achieved through increasing experience with the production process. Here, deeper knowledge through work specialization and repletion can lead to process improvements such as work pace, waste reduction, and higher labor safety.

Learning-by-using comes from the demand side where efficiency gains come from the users' side, who, by using a technology, can learn how to operate it more efficiently. With the increasing decentralization of energy supply (Kainiemi et al., 2019) and growing role of prosumers (Olkkonen et al., 2017; Masson et al., 2018), learning-by-using is bound to have a stronger impact on the experience curve. Moreover, the spreading number of user groups tends to generate networking effects (Beermann and Tews, 2017; Li et al., 2017) that may strengthen this kind of learning.

Finally, learning-by-interacting is related to the open innovation idea (Bogers et al., 2016) where, along a production chain, actors (from product developers to final users passing by regulators, suppliers, and grid managers) exchange information regarding possible improvements or problems related to the use of a technology (Kreitlein et al., 2015). This information exchange, either formal or informal, opens up further learning opportunities as a broader view of technology performance becomes available to all actors involved. The data collected for experience curve studies show that experience curves are rational and systematic tools that can be used to describe historical developments in cost and performance of technologies. Furthermore, they can be applied to forecast future cost developments. By increasing cumulative production, market prices of a technology are driven down. This means that experience curves are a valuable tool to design policies that aim to increase deployment especially of low-carbon technologies.

The experience curve has been applied to policy making mainly in two areas. First, by looking at the experience curve of a technology (solar PV panels) or even of a technological system (e.g., smart grids), policy makers can forecast future price developments that tend to increase policy performance due to a more efficient design of policy measures as well as the optimization of public funds allocation to guide technology deployment and energy system transformation. For example, price changes, as forecasted by the experience curve, were a key factor to design the change of subsidies to solar energy in Germany and plan the pace of phasing out such incentives whereby controlling for side effects on the industry such as on-job creation and on-international competitiveness (Cherp et al., 2017). In addition, experience curves can serve as an indicator of technological maturity, which helps guide R&D investment both for private and public agents.

Second, experience curves can be applied to estimate the required investments for novel technologies to attain a certain competitive price level. To illustrate this, Fig. 2.5 takes a 20-year step back in history and indicates how technological learning as a result of increasing cumulative production reduced the cost of PV up to 1998. For PV, two levels of competitiveness are shown: socket parity (PV is competitive with the retail price of electricity, for consumers) and grid parity (PV is competitive with electricity spot prices).

The shaded areas of Fig. 2.5 show the total “learning investments” that would be required to reach certain levels of competitiveness. These required investments can be estimated by taking the integral of the experience curve between the current price level and the competitive price level. Taking 1998 as a starting point, and assuming grid parity at a price level of €2.1/Wp (which was roughly the level at which grid parity was achieved in the Netherlands), we can calculate that the total learning investments required are around €13 billion, compared to a total investment in PV modules of €6.52 up to 1998. To achieve grid parity (in this example at €0.37/Wp) would have required a total learning investment of just €925 billion. Current module prices are shown in Fig. 2.5.

The experience curve thus shows the total investments that are required for a technology to reach a competitive price level, but it gives us no information about the timing of reaching this break-even point. This timing depends on technology deployment rates, which policy

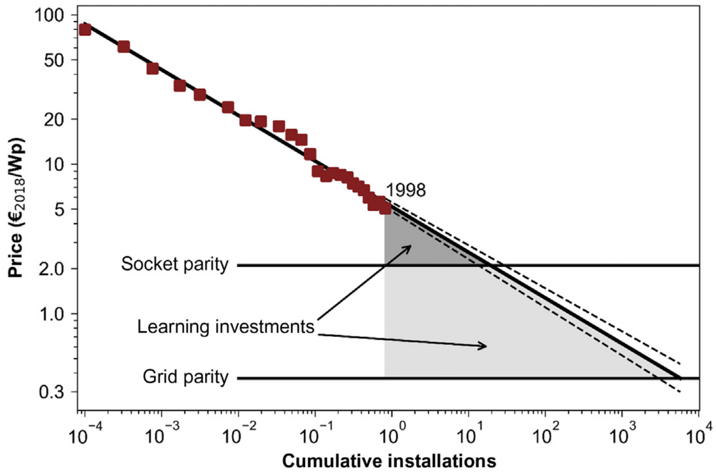

Figure 2.5

Visual example of the calculation of required investment in a technology to reach a certain break-even level of cost competitiveness with an incumbent technology. The dashed lines indicate the 95% confidence interval of the experience curve regression line.

makers can foster through demand pull and technology push incentives. Demand pull focuses on transforming market conditions to incentivize investments in innovation (Dosi and Grazzi, 2009); it is commonly directed toward diffusion improvements and justified by economies of learning obtained through gains of scale and incremental innovations (Nemet, 2009a,b). On the other hand, technology push emphasizes advances in knowledge as the main driver of technological change (Dosi and Grazzi, 2009), directed mostly to early stages of the innovation process; it is typically formulated as public funding of R&D activities (Peters et al., 2012) and performs better for the development of radical innovations (Costantini et al., 2015).

It should be noted that the learning investments only include the direct expenditures toward the technology and thus do not include other societal costs that are not necessarily included in the learning investments as estimated from the experience curve. They are primarily a result of market mechanisms, for example, consumers buying technologies thereby sustaining their markets. In the case of, for instance, government-funded research, development, and demonstration (RD&D), there might be an overlap with learning expenditures, as at least a part of the government funding is used for demonstration projects, and thus used for manufacturing the technology. For technologies very early in their market diffusion, government-funded RD&D might constitute significantly to the ongoing learning investments, but for more mature technologies (such as solar PV and wind), the majority of investments will come from the market. Even in these cases, government funding might be necessary to incentivize deployment.

Thus in order to reach competitiveness, the technology needs to be "driven down the experience curve," requiring that scaling up takes place at the technology domain level. To this end, the classic approach adopted so far by policy makers to foster the deployment of energy technologies in general—but environment-friendly ones in particular—is to adopt a policy mix that combines demand and supply side measures so that all types of learning are benefited. There is consensus that optimal policies to support environmental energy innovation should combine environmental regulation and technology policy (Popp et al., 2010; Acemoglu et al., 2012; Mowery, 2012). Environmental regulation focuses on pricing emissions, seeking to foster diffusion of environment-friendly technologies; whereas technology policy focuses on new technologies through support for knowledge creation. The combined implementation of such policies, addressing both market failures simultaneously, offers several advantages. For example, it enables the use of more precise, detailed, policy instruments, lowering the cost of emission reductions (Fischer et al., 2013). It also favors synergies between policy goals, since public research funding is more effective to foster environment-friendly innovation when accompanied by emission reduction policies (Newell, 2010). In addition, this averts escape routes as the green paradox (emission pricing could avoid increases in energy consumption due to cost-reducing innovations), and environmental rebound, emission pricing tends to stimulate the selection of technologies with least environmental impacts. Also, since emission control policy commonly involves assuring future demand for renewable energy generation, it provides a positive investment stimulus on innovation in this field, reducing uncertainty (Peters et al., 2012) and fossil fuel lock-in (Lehmann and Söderholm, 2017).

2.5.2 Indirect application of experience curves for policy: energy and integrated modeling

In Fig. 2.5 we showed how a single renewable energy technology rides down the experience curve toward a price level that is competitive with an incumbent technology. When thinking of the layout of future energy systems, there are of course many different technologies to consider that compete with each other and fossil fuel alternatives. To be able to analyze possible future energy systems, many research groups have developed energy models in the recent decades. Possibly the most prominent application of these models for policy makers is for the Intergovernmental Panel on Climate Change assessment reports, for which integrated assessment models are used to analyze, among others, how climate targets can be achieved with a mix of renewable and fossil technologies, and what the associated costs are (IPCC, 2014). These models, and many other energy models as well, very commonly use experience curves in some form to be able to model future technology price developments and technology deployment. Especially in endogenous applications, there is a feedback loop in these models between deployment and price of technologies, allowing these models to simulate and optimize future energy system layouts.

Thus by using these modeling results, policy makers gain insight in pathways toward a low-carbon energy system, and the associated costs required for market diffusion of clean but currently noncompetitive technologies. In Chapter 3, we discuss model implementation of experience curves in more detail.

2.6 Main issues and drawbacks of experience curves

As discussed in Section 2.3, a key issue of experience curves is data availability and the relation between cost and price of technologies and its implications for deriving experience curves. Aside from these issues, there are a number of factors that can hamper the applicability or accuracy of price extrapolations from experience curves. In this section, we highlight a number of key issues and drawbacks of experience curves.

2.6.1 Nonconstant learning rates and learning rate uncertainty

Since experience curves are most commonly applied as a tool to make extrapolations on future costs, the value of the *LR* is the key factor that determines how technology costs develop as cumulative production increases. The cost projections are thus extremely sensitive to the chosen *LR* value and its uncertainty. As Nemet (2009a,b) shows, there can be significant variation in the derived *LR* when taking into account datasets of different time periods. In his study of a dataset for PV module prices from 1976 to 2006, Nemet shows that when analyzing all periods in this dataset of 10 years or greater, the value of the derived *LR* can range from 14% to 25% (from 5th to 95th percentile). As a result, when analyzing the break-even year to attain a certain competitive cost level (see also Section 2.5.1), the break-even year ranges from 2017 to 2057 and requires learning investments from US$33 to US$903 billion (both from 5th to 95th percentile).

Aside from this nonconstant behavior of the *LR*, variance in the dataset away from the estimated experience curve trend results in uncertainty of the derived *LR* value. The result is generally an experience curve with relatively low R^2 values and high *LR* errors. When applying the *LR* for cost extrapolations, this *LR* error should be taken into account, for instance by a stochastic model formulation that explicitly calculates the impact of *LR* uncertainty (Junginger et al., 2010).

2.6.2 Technology systems and components

Depending on the technology, the dataset that is collected might represent a technology as an aggregate of components with a single price level. For instance, lithium battery storage system is composed of several components, including the lithium-ion cells, an inverter, and battery management system, and total system costs that can include or exclude installation costs. PV systems comprise PV modules and so-called balance-of-system components, which is shown in Chapter 5, to have different *LR*s. To accurately model and project the total costs of such technology systems, the use a component-based experience curve would be more suitable (Yeh and Rubin, 2012).

Only if a technology system is based on components that all have equal *LR*s based on one single cumulative production value, outcomes of projections will have the same results as those based on one single experience curve. In all other cases, projections might be under- or overestimating the future technology costs.

A similar issue lies in definition of the technology and its system boundaries. Again considering lithium battery storage, we know that lithium batteries exist in many different forms, with different materials, battery layouts, etc. In an ideal situation an experience curve would be based on a clearly defined single-battery technology, but unfortunately, this increases the data requirements substantially.

2.6.3 No explanation for cost reductions and causality

A fundamental issue of experience curves relates to the statistical correlation between cumulative production and observed cost declines. Many authors have argued that the correlation between these two variables offer little explanation of the reasons of the cost declines, as well as the causality between those variables (Yeh and Rubin, 2012). Although the theory on mechanisms of technological progress, such as learning-by-doing, learning-by-searching, and upscaling, is well documented and said to give a realistic representation of how technology costs decline, they are often difficult to separate in experience curve studies. Still, given the often strong correlation between cumulative production volumes and technology cost decline, the representation of this process in a single parameter remains attractive (Junginger et al., 2010). The value of experience-curve studies, however, relies not only on the datasets collected and the derived *LR*s, but equally as much on a thorough examination of the underlying mechanisms of the observed cost decline, as this gives valuable information on (limits to) future prospects of cost development.

2.6.4 Radical innovations

Since the experience curve is based on empirical historical data and is in its simplest form a trend characterized by one parameter that describes its slope, it cannot account for future (or historical) innovations that lead to a step change in technology costs. Substitutions of key materials or other innovations can lead to a drastic change in the technology cost, deviating from the long-term cost trend, and possibly resulting in a change in the observed *LR*. With sufficient data, it is possibly to identify such structural breaks in the experience curve trend, but for future projections, it is difficult to account for such trend breaks when using experience curves. This means that in addition to a thorough examination of historical technology developments (as discussed in the previous section), it is also recommended to make an inventory of possible future innovations of the technology under study.

2.6.5 Technology quality

Another downside to describing technologies with a single parameter, such as the *LR*, is that the quality of the technology is not necessarily taken into account. As discussed in Chapter 6, and by Williams et al. (2017), the unit capacity costs of wind turbines have varied substantially over the past decades. Up to 2005, onshore wind farm costs declined, but between 2005 and 2011, they increased substantially. This rise has been attributed to a variety of factors, but several changes to wind turbine and wind farm quality have contributed to this cost increase. For PV systems, experience curves are mostly also based on unit capacity costs and as such do not take into account variables such as system lifetime or capacity factors. In both cases the issues can be partly solved by analyzing experience curves for LCOE, but as is discussed in Chapter 6, this does not necessarily solve the issue completely. In any case it is important that studies explicitly analyze and discuss the roles of heterogenous quality attributes (Junginger et al., 2010).

References

Acemoglu, D., et al., 2012. The environment and directed technical change. Am. Econ. Rev. 102 (1), 131–166. Available from: https://doi.org/10.1257/aer.102.1.131.

Arrow, K.J., 1962. The economic implications of learning by doing. Rev. Econ. Stud. 29 (3), 155–173.

Beermann, J., Tews, K., 2017. Decentralised laboratories in the German energy transition. Why local renewable energy initiatives must reinvent themselves. J. Cleaner Prod. 169, 125–134. Available from: https://doi.org/10.1016/j.jclepro.2016.08.130.

Bhandari, R., 2018. Riding Through the Experience Curve for Solar Photovoltaics Systems in Germany. Available from: https://doi:10.1109/IESC.2018.8439945.

Bogers, M., et al., 2016. The open innovation research landscape: established perspectives and emerging themes across different levels of analysis. Ind. Innov. 24 (1), 8–40. Available from: https://doi.org/10.1080/13662716.2016.1240068.

Boston Consulting Group, 1970. Perspectives on Experience. Boston Consulting Group.

Cárdenas Rodríguez, M., et al., 2015. Renewable energy policies and private sector investment: evidence from financial microdata. Environ. Res. Econ. 62 (1), 163–188. Available from: https://doi.org/10.1007/s10640-014-9820-x.

Chang, Y.S., Jo, S.J., Jeon, S., 2016a. Using experience curve to project net hydroelectricity generation—in comparison to EIA's projection. SSRN Electr. J. Available from: https://doi.org/10.2139/ssrn.2732485.

Chang, Y.S., et al., 2016b. Is the 2040 projection on net electricity generation by Energy Information Administration too conservative? In comparison to alternate projection using experience curve. SSRN Electr. J. Available from: https://doi.org/10.2139/ssrn.2732488.

Cherp, A., et al., 2017. Comparing electricity transitions: a historical analysis of nuclear, wind and solar power in Germany and Japan. Energy Policy 101, 612–628. Available from: https://doi.org/10.1016/j.enpol.2016.10.044.

Costantini, V., et al., 2015. Demand-pull and technology-push public support for eco-innovation: the case of the biofuels sector. Res. Policy 44 (3), 577–595. Available from: https://doi.org/10.1016/j.respol.2014.12.011.

Della Seta, M., Gryglewicz, S., Kort, P.M., 2012. Optimal investment in learning-curve technologies. J. Econ. Dyn. Control 36 (10), 1462–1476. Available from: https://doi.org/10.1016/j.jedc.2012.03.014.

Dosi, G., Grazzi, M., 2009. On the nature of technologies: knowledge, procedures, artifacts and production inputs. Cambridge J. Econ. 34 (1), 173–184. Available from: https://doi.org/10.1093/cje/bep041.

Ebbinghaus, H., 1885. Über das Gedächtnis: Untersuchungen zur experimentellen Psychologie. Duncker & Humblot, Leipzig, Germany.

Fischer, C., Newell, R.G., Preonas, L., 2013. Environmental and technology policy options in the electricity sector: interactions and outcomes. SSRN Electr. J. Available from: https://doi.org/10.2139/ssrn.2432161.

Fraunhofer ISE, 2019. Photovoltaics Report. Freiburg, Germany: Fraunhofer ISE. Available at: https://www.ise.fraunhofer.de/en/publications/studies/photovoltaics-report.html.

Gan, P.Y., Li, Z., 2015. Quantitative study on long term global solar photovoltaic market. Renew. Sustain. Energy Rev. 46, 88–99. Available from: https://doi.org/10.1016/j.rser.2015.02.041.

Gillingham, K., Newell, R.G., Pizer, W.A., 2008. Modeling endogenous technological change for climate policy analysis. Energy Econ. 30 (6), 2734–2753. Available from: https://doi.org/10.1016/j.eneco.2008.03.001.

Gross, R., et al., 2013. Presenting the Future—An Assessment of Future Costs Estimation Methodologies in the Electricity Generation Sector. UK Energy Research Center, London.

Guivarch, C., Lempert, R., Trutnevyte, E., 2017. Scenario techniques for energy and environmental research: an overview of recent developments to broaden the capacity to deal with complexity and uncertainty. Environ. Modell. Softw. 97, 201–210. Available from: https://doi.org/10.1016/j.envsoft.2017.07.017.

International Energy Agency (IEA), 2000. Experience Curves for Energy Technology Policy. International Energy Agency, Paris.

IPCC, 2014. Zwickel, T., Minx, J.C., Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., et al., (Eds.), Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York.

Jaffe, A.B., Newell, R.G., Stavins, R.N., 2005. A tale of two market failures: technology and environmental policy. Ecol. Econ. 54 (2–3), 164–174. Available from: https://doi.org/10.1016/j.ecolecon.2004.12.027.

Junginger, M., van Sark, W., Faaij, A., 2010. Technological Learning in the Energy Sector: Lessons for Policy, Industry and Science. Edward Elgar Publishing, Cheltenham.

Kainiemi, L., Eloneva, S., Levänen, J., 2019. Transition towards a decentralised energy system: analysing prospects for innovation facilitation and regime destabilisation in Finland. Technol. Anal. Strateg. Manage. 1–13. Available from: https://doi.org/10.1080/09537325.2019.1582765.

Kittner, N., Lill, F., Kammen, D.M., 2017. Energy storage deployment and innovation for the clean energy transition. Nat. Energy 2 (9), 17125. Available from: https://doi.org/10.1038/nenergy.2017.125.

Kivimaa, P., Kern, F., 2015. Creative destruction or mere niche creation? Innovation policy mixes for sustainability transitions. SSRN Electr. J. Available from: https://doi.org/10.2139/ssrn.2743173.

Kreitlein, S., et al., 2015. Green factories Bavaria: a network of distributed learning factories for energy efficient production. Procedia CIRP 32, 58–63. Available from: https://doi.org/10.1016/j.procir.2015.02.219.

Lehmann, P., Söderholm, P., 2017. Can technology-specific deployment policies be cost-effective? The case of renewable energy support schemes. Environ. Res. Econ. 71 (2), 475–505. Available from: https://doi.org/10.1007/s10640-017-0169-9.

Li, Y., et al., 2017. A combined forecasting approach with model self-adjustment for renewable generations and energy loads in smart community. Energy 129, 216–227. Available from: https://doi.org/10.1016/j.energy.2017.04.032.

Löschel, A., 2002. Technological change in economic models of environmental policy: a survey. Ecol. Econ. 43 (2–3), 105–126. Available from: https://doi.org/10.1016/s0921-8009(02)00209-4.

Louwen, A., et al., 2018. Comprehensive Report on Experience Curves. Utrecht, The Netherlands. Deliverable of the project REFLEX. Available on http://reflex-project.eu/.

Malerba, F., 2005. Sectoral systems of innovation: a framework for linking innovation to the knowledge base, structure and dynamics of sectors. Econ. Innov. New Technol. 14 (1–2), 63–82. Available from: https://doi.org/10.1080/1043859042000228688.

Masson, G., et al., 2018. A snapshot of global PV markets—the latest survey results on PV markets and policies from the IEA PVPS programme in 2017. In: 2018 IEEE Seventh World Conference on Photovoltaic Energy Conversion (WCPEC) (A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC). IEEE. Available from: https://doi.org/10.1109/pvsc.2018.8547794.

Morstyn, T., et al., 2018. Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants. Nat. Energy 3 (2), 94−101. Available from: https://doi.org/10.1038/s41560-017-0075-y.

Mowery, D.C., 2012. Defense-related R&D as a model for "grand challenges" technology policies. Res. Policy 41 (10), 1703−1715. Available from: https://doi.org/10.1016/j.respol.2012.03.027.

Neij, L., et al., 2006. Cost Development: An Analysis Based on Experience Curves, Deliverable 3.3—RS1A of the NEEDS Project, co-funded by the European Commission Within the Sixth Framework Programme.

Nemet, G.F., 2009a. Interim monitoring of cost dynamics for publicly supported energy technologies. Energy Policy 37 (3), 825−835. Available from: https://doi.org/10.1016/J.ENPOL.2008.10.031.

Nemet, G.F., 2009b. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. Res. Policy 38 (5), 700−709. Available from: https://doi.org/10.1016/j.respol.2009.01.004.

Newell, R.G., 2010. The role of markets and policies in delivering innovation for climate change mitigation. Oxford Rev. Econ. Policy 26 (2), 253−269. Available from: https://doi.org/10.1093/oxrep/grq009.

Olkkonen, L., Korjonen-Kuusipuro, K., Grönberg, I., 2017. Redefining a stakeholder relation: finnish energy "prosumers" as co-producers. Environ. Innov. Societal Trans. 24, 57−66. Available from: https://doi.org/10.1016/j.eist.2016.10.004.

Peters, M., et al., 2012. The impact of technology-push and demand-pull policies on technical change − does the locus of policies matter? Res. Policy 41 (8), 1296−1308. Available from: https://doi.org/10.1016/j.respol.2012.02.004.

Popp, D., Newell, R.G., Jaffe, A.B., 2010. Energy, the environment, and technological change. In: Handbook of the Economics of Innovation, vol. 2. Elsevier, pp. 873−937. Available from: http://doi.org/10.1016/s0169-7218(10)02005-8.

Rezai, A., van der Ploeg, F., 2016. Second-best renewable subsidies to de-carbonize the economy: commitment and the green paradox. Environ. Res. Econ. 66 (3), 409−434. Available from: https://doi.org/10.1007/s10640-016-0086-3.

Riahi, K., et al., 2004. Technological learning for carbon capture and sequestration technologies. Energy Econ. 26 (4), 539−564. Available from: https://doi.org/10.1016/J.ENECO.2004.04.024.

Rubin, E.S., et al., 2007. Use of experience curves to estimate the future cost of power plants with CO_2 capture. Int. J. Greenhouse Gas Control 1 (2), 188−197. Available from: https://doi.org/10.1016/s1750-5836(07)00016-3.

Schmidt, O., et al., 2017. The future cost of electrical energy storage based on experience rates. Nat. Energy 2 (8). Available from: https://doi.org/10.1038/nenergy.2017.110.

Wei, M., Smith, S.J., Sohn, M.D., 2017a. Experience curve development and cost reduction disaggregation for fuel cell markets in Japan and the US. Appl. Energy 191, 346−357. Available from: https://doi.org/10.1016/j.apenergy.2017.01.056.

Wei, M., Smith, S.J., Sohn, M.D., 2017b. Non-constant learning rates in retrospective experience curve analyses and their correlation to deployment programs. Energy Policy 107, 356−369. Available from: https://doi.org/10.1016/J.ENPOL.2017.04.035.

Williams, E., et al., 2017. Wind power costs expected to decrease due to technological progress. Energy Policy 106, 427−435. Available from: https://doi.org/10.1016/J.ENPOL.2017.03.032.

Wright, T.P., 1936. Factors affecting the cost of airplanes. J. Aeronaut. Sci. 3, 122−128.

Yeh, S., Rubin, E.S., 2012. A review of uncertainties in technology experience curves. Energy Econ. 34 (3), 762−771. Available from: https://doi.org/10.1016/J.ENECO.2011.11.006.

Yu, C.F., Van Sark, W.G.J.H.M., Alsema, E.A., 2011. Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects. Renew. Sustain. Energy Rev. 15 (1), 324−337. Available from: https://doi.org/10.1016/j.rser.2010.09.001.