Spanish photovoltaic learning curve

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Abstract
Learning by doing, or learning through market experience, reduces costs for energy production technologies. This phenomenon is modelled by using experience curves which reflect the changes in the cost of the technology as it becomes increasingly used. This article calculates the Spanish photovoltaic (PV) learning curve over the period 2001–12 by using cost data from the PV sector itself (installers, distributors and even engineers) and determines the accuracy of the obtained progress ratio by using both the coefficient of determination \( R^2 \) and also the error \( \sigma_{PR} \), which is directly determined from fitting the data. The results show a curve with a strong structural change in the speed of cost reduction in October 2009.

Keywords: learning curve; renewable energy policy; feed in tariff; Spanish photovoltaic learning rate

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1 INTRODUCTION
Experience curves have been widely used in the literature as a method for cost forecasting in new technologies. Photovoltaic technologies have been using this methodology in recent years not only in order to estimate future costs, but also as a key driving force for incorporating endogenous technological change into large-scale energy–environment–economy models [1].

Those models gave fundamental insights and analysis of the energy mix under different scenarios and also gave an overview of the effectiveness of environmental policies. Although the methodology is widely accepted, it is important to mention the intrinsic difficulty involved in the calculation methodology by non-linear systems, as well as the problem of non-convexity of the system.

Initially, most academics were studying the learning curve as a global trend in the market, as modules are marketed internationally, by using either total shipments or total production from the sector. Later when different countries started to publish the Feed in Tariffs (hereinafter FIT) policies, there was a shift to either cumulative capacity or gross electricity production as the studies were focusing on modelling the evolution of the energy mix.

The study of local learning rates (hereinafter LR) is rather recent. For example, looking into the relevant literature we can find the calculations for Germany, the Netherlands or the USA over different time periods, for the complete system so System LR (modules, inverters, wiring, labour cost and project and administrative cost) or for individual components such as modules, inverters or BOS (BOS: balance of system: a name given to the system without the panels) obtaining a partial LR (BOS LR, modules LR or inverter LR).

After 10 years of solar PV promotion in Spain it is interesting to look at the Spanish figures, in terms of cost of the installations for end purchasers together with the achieved cumulative capacity and calculate a sector experience curve during this period of time. This figure will give us an evaluation of the cost-effectiveness of the policy measures over the time and it will also be a base for calculating the social benefit obtained with the application of FIT policies; the most widely used subsidy when promoting photovoltaic installations.

This article collects the installation system costs from the period 2001 to 2012 for calculating the Spanish learning curve and its LR and determines the accuracy of the obtained rates by using both the coefficient of determination \( R^2 \) and the error \( \sigma_{PR} \) in compiling the data.

The aim of this article is to find the local LR of the Spanish photovoltaic market in order to include the figure in larger forecasting models, as for example, in a model able to compute the social welfare of the implementation of an FIT policy for small installations, or even for the introduction of net metering policies for small roof-top household installations in the Spanish market. A net metering policy will allow customers to use the production of the photovoltaic installation while there is demand in the household while electricity that is not used will be fed into the grid. Fed electricity represents a credit for the customer that can be used in the next billing period.

This article is organized as follows: Section 2 presents a literature review of the concept of learning by doing over time, and its

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later application to the photovoltaic industry. Section 3 shows the theoretical aspects of the experience curve and calculation of the accuracy of the model. In Section 4 the results and discussion of the calculation are shown and in Section 5 the article finishes with some conclusions and by suggesting additions to the research.

2 LITERATURE REVIEW

Learning by doing is studied in the academic literature mainly related to dynamics technology evolution. Its genesis was in the 1930s when from empirical observations it was realized that workers and manufacturing plants become more efficient as they were producing increasing amounts of units. Wright in 1936 derived the concept of ‘learning by doing’ from these observations. Later on Arrow [2] formalized the model by explaining how technological change as a function of learning originated within the process of manufacturing; the concept was close to a labour productivity rate located in a manufacturing plant.

The Boston Consulting Group used the concept in the 1960s in their consulting activities with their customer’s competitive strategies and identified the drivers of the experience curve (as described in [3]): labour learning, managerial learning, process improvement, product standardization and economies of scale, although identified by them, they never deconstructed these effects to analyse their individual roles on the global curve.

Over time the concept was broadened by deconstructing the effects of the components [4] and it was also amplified by adding up all the manufacturing industries for a specific sector or technology rather than a specific manufacturing site [5]. It was therefore understood that the experience curve was describing the reductions in all relevant costs of the manufacturing process: labour, research and development, commercial department and marketing when the level of production was increasing. These cost reductions could be explained by several factors, such as process innovation, innovation in raw materials or manufacturing technology, economies of scale and re-designing of products. Learning curves were used at this stage for management and planning production processes within the manufacturing industry and also to forecast technology cost reductions.

When calculating experience curves from the sectorial perspective, the manufacturing companies were not willing to share the cost data information and so the experience curves were calculated by using the average selling prices. This approach can be found in Poponi [6] and Alberth [7]. The relationship between prices and shipments is also used by Williams [8], Neij [9] and Harmon [10]. Although used with in the literature, we believe that the concept of learning by doing is rather appropriate with cost data instead of price data. We understand the difficulties involved in finding the appropriate data sets, as reflected in the articles by these authors.

Also very interesting is the approach described in the Results of Photex Project [11] where the concept of learning by doing is considered to include learning by doing, which refers to the manufacturing process, learning by searching, which takes into account the investment in R&D, learning by using, which introduces the concept of the diffusion parameter, learning by interacting, that accounts for the transfer of knowledge between users, producers, research institutes and policy-makers.

In recent decades the experience curve concept has been used for macroeconomic predictions in energy modelling; as for example Bandhari and Stadler [12] analyses the experience curve of the German market based on the data series 1994–2006 and forecast the ‘Grid parity Year’: the time point in the future when the fossil fuel produced electricity price will be equal to the renewable one. These types of studies allow policy-makers to create horizons for the promotion of photovoltaic with a quantitative value of the selected policies in the form of benefit cost or breakeven analysis. The study of the learning curve allows us to assess whether public support for new technologies is justified by the future benefits derived from renewable technologies [13].

The calculation of the LR is based on the empirical data extracted from the company or from the sector when studying a global rate over a period of time and it is formulated as follows:

\[ C_x = C_0 x^{-\beta} \]  

where \( C_x \) is the cost required to produce up to the \( x \)th unit and \( x \) the cumulative production, \( C_0 \) the cost required for producing the first unit and \( \beta \) the elasticity of unit cost with respect to cumulative production volume and therefore the learning parameter.

Following the work of Papineau [14] some other authors performed their learning curve studies using other magnitudes for the variable \( x \) such as: accumulated installed capacity, the accumulated amount of net-generating capacity of the technology, as found in refs [9, 12, 15–18]; accumulated electricity production, the accumulated amount of gross electricity produced by the technology as found in refs [19, 20] or cumulative shipments, annual data on total industry shipments were accumulated through to the end of each observation year, used by Poponi and Bandhari and Stadler [6, 21] as a specific case for the Dutch market.

The earliest applications of the use of PV learning curves in the photovoltaic sector can be found in the article of Williams and Terzian [8] where a cost/benefit analysis of the implementation of photovoltaic was performed, later on we can find in Neij [9] a first calculation of the photovoltaic global LR by using the experience curve in the context of analysing the diffusion pattern of the photovoltaic implementation using as a variable \( x \) the cumulative installed capacity.

Studies of photovoltaic experience curves shifted from manufacturing to policy-makers: the methodology is used nowadays to predict future PV cost trends that will be incorporated in climate change/CO₂ abatement models. It is also used in the analysis of the economic implications of photovoltaic promotion policies by connecting future cost developments with current investments as the photovoltaic cost evolution will depend on early implementation of these measures. Its original usage also remains as described by Nemet [22]: a powerful tool that can play its role as a guide for firm strategy and prediction.
of technical changes. Clarke and Tiedje [23] later on will include R&D, spillover effects and economies of scale and furthermore Poponi [6] will include in the concept many other factors as increasing skills of labour force, and design and construction innovations. All these effects will be crucial in order to achieve a breakeven price for PV technology so that photovoltaic can be competitive without any incentives.

Most of the empirical studies in photovoltaic LR s have been calculated for the industry as a whole, in that line Harmon [10] with a time horizon from 1968 to 1998 and a rate of 20.2%, Parente et al. [24] working in the period 1981–2000 and a rate of 22.8% and Poponi [6] for the period 1976–2002 with a rate of 25% and a 19.5% while using the period 1989–2002. All of them find that long periods of time are required for accurate study and understanding of the effects of the learning process for any technology. In view of this, Poponi [6] indicates that several doublings of cumulative production are usually needed to correctly discern any specific pattern.

Besides these global rates it is also very important to consider LR studies for single countries or regions, in this field we can find the calculations of Schaeffer et al. [11] with rates for European market of 26%, while in the same period of time Germany and the Netherlands had a 10% rate. According to Schaeffer this can be explained as differences in national PV deployment programmes and installation costs which will made that the number of doublings in installations are higher in a geographical location rather than in other locations or even rather than the global one.

Wand and Leuthold [17] shows that the majority of the global experience curves show LR s between 18 and 25%, while in contrast LR s for single countries vary between 10 and 47%.

The studies based on the empirical learning effects, past evolution of the cost (or average selling price) will show the experience curve as a global learning effect as modules are marketed globally. The system is also consistent with inverters. Wiring and installation cost may vary from country to country as national building and electrical codes may apply and therefore different cost implications can be found. Thus, in Maycock and Wakefield [15] we can find a rate of 22% for the USA market, while Schaeffer et al. [11] calculates a rate of 26% for the German's one.

Most of the authors agree on breaking down the experience curve into two separate ones as the system has two components, PV panels on one side and BOS (the rest of the components) on the other side. It is an interesting approach that we can find in ref. [25] where the differentiation between BOS LR and PV LR is encouraged as learning rates based on modules alone are not representative of PV system learning, and system level cost reductions cannot be easily attributed to any individual component. Schaeffer et al. [11] identifies that Germany has a 10% LR for the modules, while it is 22% for the BOS, while the Netherlands shows the same rate for the panels and a rate of 19% for BOS. The total learning curve will be an aggregate of both sub-learning curves.

According to Schaeffer et al. [11] and Wand and Leuthold [17] this can be explained by differences in national PV deployment programmes and the associated installations numbers. It can be observed clearly in countries with a strong growth in installations such as Germany and the Netherlands. We can also consider as an explanation of the differences due to the regulation of the electrical connection or administrative-related regulations, and its cost implications.

3 THEORETICAL CONSIDERATIONS

The aim of this article is calculating the Spanish learning curve and determining the accuracy of the obtained progress ratio (hereinafter PR).

3.1 Learning curve

As described earlier on, in this article the experience curve definition as indicated by Equation (1) will be used. In the calculation of the curve for the Spanish market $C_x$ is the installation cost required for the xth installation performed and x represent the cumulative installed capacity. $C_0$ represents the cost required for installing the first unit and $\beta$ is the learning parameter.

PR and LR are calculated by using equations (2) and (3) and comparing the two periods of time: period $t_1$ with $C_0$ the cost of installation (starting cost of the period of time) and $x_1$ the installed capacity and period $t_2$ with $C_0$ the cost of installation (as it is again referred to the initial one) and $x_2$ the installed capacity. LR reflects the relative cost reduction with each doubling of cumulative production. Mathematically:

$$PR = \frac{C_0 x_2^{-\beta}}{C_0 x_1^{-\beta}} = 2^{-\beta} \quad x_2 = 2x_1$$

$$LR = (1 - PR)$$

The error in the PR estimation ($\sigma_{PR}$) can be calculated following Sark et al. [16, 21] as

$$\sigma_{PR} = \left(\frac{d (2^{-\beta})}{d\beta}\right) \sigma_\beta = \ln 2 \cdot 2^\beta \sigma_\beta = \ln 2 \cdot PR \cdot \sigma_\beta$$

where $\sigma_\beta$ is the error in $\beta$ resulting for the estimation.

The representation of the curve is a double logarithmic scale, with a continuous decrease of the cost, as cumulative production is doubling. The speed of cost reduction is therefore reducing over time, as technology approaches its maturity and the markets are exhausted [20].

3.2 Accuracy of the progress ratio

We can generalize the experience curve formulation as

$$y = f (x, C_0, \beta)$$

where $y$ is the dependent variable (our cost) and $x$ the independent one (cumulative capacity in our data set). Function is homogeneous of $\beta$ degree and continuous.
To test the accuracy of the fit it will be used the coefficient of determination $R^2$, also known as goodness-of-fit parameter, defined as the ratio of regression sum of squares to the total sum of squares:

$$R^2 = \frac{\sum_i [f(x_i; C_0, \beta) - \bar y_i]^2}{\sum_i [y_i - \bar y_i]^2}$$

$R^2$ varies between 0 and 1 and denotes the strength of the association between both terms on Equation (5). Fitted data with $R^2 > 0.8$ are considered strongly correlated.

In line with Parente et al. [24] the possibility of finding structural breaks will also be reviewed over the analysed period of time, by using the Chow structural break test, which checks the statistical relevance of the changes to verify if the new sets of curves represent a better adjustment.

4 RESULTS AND DISCUSSION

For the construction of the Spanish learning curve in the period 2001–12 the data set is the average monthly cost prices of PV installations (€/Wp) as a function of the cumulative monthly installations (kWp/month).

Following Poponi [6] experience curves can be developed for both cost and prices and, especially in competitive and stable markets (with a stable return on equity for the producer) the ratio between cost and price is fixed. Consequently, the cost experience curve and the prices experience curve are two parallel lines with the same PR [19]. Although that relationship can be found between both parameters and the calculation of the experience curve using price data has been reported in many articles, in this article the estimation will be performed using data cost of the installations (€/Wp) as a function of the cumulative monthly installations (kWp/month).

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On the other side, the calculation is performed by using an independent variable $x$ and the cumulative installations instead of cumulative production so that the reductions of the total cost of the installations can be better explained in function of the cumulative installed capacity in line with the methodology followed in refs [9, 12, 15–18].

A non-linear regression is run using the data for the period 2001–12; Gretl program estimates the equation for the curve as follows (standard error in parenthesis):

$$-0.126968 \quad C_t = 9.971 \times 10^{-0.00349} \quad (6)$$

A PR of 91.57% implies a cost reduction of 8.43% every time capacity installed doubles (Table 1).

Figure 1 illustrates the estimated curve against the observed one. There are some relevant facts in Figure 1 that should be pointed out. First of all in the spring and summer of 2008 we can also find a variation of the slope of the curve; this situation was also reported by Bazilian et al. [26] in that period prices globally increased almost a 30% due to a shortage on both cell and module production, this was amplified by the Spanish market where 3000 MW were installed over a short period of 8 months. This strong unforeseen demand from Spain had an important influence over prices Europe wide. The expected change of regulation was the reason behind this sharp increase in the accumulated capacity in such a short period of time. In September 2007 the Spanish government announced that 80% of the estimated capacity had been met and therefore gave just a year to complete existing projects. New regulations were to replace the existing ones but there was no indication as to what form these new regulations might take. This lack of information about the future prospect together with the economic situation of the country and a construction sector going through difficulties resulted in a huge increase of projects that were planned and executed within very short period of time. Some of these projects were completed on the roofs industrial buildings that were built specifically to access a higher FIT tariff.

Secondly, it is interesting to point out that after the September 2008 structural break the curve is no longer an exponential one, but rather latter on it has become an inverse linear one. Mathematically, a linear dependency rather than an exponential one improves the fit of the estimation.

Considering the September 2008 structural break and performing a separate analysis by breaking the previous curve into two periods, corresponding to January 2001–September 2008 and October 2008–December 2012 and running again the estimation, the estimated curves for each of these periods are given in Table 2 (again standard errors in parenthesis).

For the period October 2008 to December 2012 the LR fell to its lower figure in the period: 0.16%; however, the empirical data show a reduction from a starting value of 4.93 €/W to a 1.47 €/W figure by the end of the period, how can we explain these empirical findings? The methodology for calculating both PR and LR assumes that installed capacity doubles itself over the studied period; however, in this period between the initial and final capacity there is merely a ratio of 1.45 which clearly shows that the accumulated installations did not achieve even a doubling as LR figures are calculated per doublings in the case of having cap amounts for policy reasons, we will not be able to see the cost reductions reflected on the LR figures.

It is also important to consider the legislation that was in place at that moment, RD1578 established a cap figure of 500 MW for the total amount of installations to be connected each year. This cap figure will affect the amount of installations connected every year and therefore the market is no longer working.

| Table 1. Result for the period January 2001–December 2012. |
|-----------------|----------|------|------|------|
| $R^2$            | PR (PR)  | LR  | $a_{PR}$ |
| 0.845776        | 91.57%  | 8.43%  | 0.22% |

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under the same conditions as before, an exponential growth will never be achieved again under a cap promotion policy.

Graphically, new estimation is represented in Figure 2. In order to check for the presence of structural change the Chow structural break test is performed. The null hypothesis assumes the irrelevance of 2008 break. The result rejects the null hypothesis and shows that the proposed structural break is highly significant. For simplicity results are shown in Table 3.

5 CONCLUSIONS

Learning curves are powerful tools for estimating future cost reductions by simple extrapolation. They can also be employed to calculate the amount of investment needed to bring down the price of a particular industry or product. We have applied this methodology to the case of photovoltaic installation cost for the Spanish market in order to determine the evolution over the time.

The Spanish case shows values in line with the values that can be found in other countries for which the curve has been calculated and also some structural changes at different periods of time. Those changes on the LR were due to deep changes in the regulation framework of the market (or even uncertainties associated with particular moments) rather than to real cost abatements (see for example the period previous to September 2008).

The introduction of RD436 in 2004 was the initial stage for photovoltaic growth in installed capacity and it was also the key driver on its cost reductions and commercial viability.

It may be argued that the strong reduction from 2001 to 2005 was due to economies of scale rather than to learning improvements, in the particular case of Spain those early reductions in cost were mainly due to the increasing size of the installations; but we should not forget that panels are marketed globally and thus the incremental capacity globally which drove down prices also applied to the Spanish market reductions.

The period of time from 2004 to September 2008 shows an exponential growth in the installed capacity and a high decreasing end-user cost figure. The policy helped the deployment of the technology and even further reductions in costs. The period between September 2007 and September 2008 is marked as a volatile time for installation prices, component costs were increasing, which breaks the cost reduction trend. It was a period where an unexpected demand drove to a shortage in crystalline cells, and therefore an increase in panel costs. The BOS cost

Table 2. Results for the period January 2001–September 2008 and the period October 2009–December 2012.

|       | January 2001–September 2009 | October 2009–December 2012 |
|-------|-----------------------------|-----------------------------|
| \( R^2 \) | PR | \( \sigma_{PR} \) | \( R^2 \) | PR | \( \sigma_{PR} \) |
| 0.749313 | 92.87% | 7.13% | 0.26% | 0.867154 | 99.84% | 0.16% | 0.01% |

![Figure 1. Estimated vs. calculated learning curve.](https://example.com/figure1)

![Table 2. Results for the period January 2001–September 2008 and the period October 2009–December 2012.](https://example.com/table2)
remained quite the same throughout this time, or was even
reduced due to the increasing effect of the panel cost over the
total price of the installations, which in most of the cases was
already fixed by the buyer in a previous purchase agreement.

After September 2008 there is a gradual return to a decreasing
value in both the panel cost and the BOS cost. RD1578 in place
from September 2008 stated a cap amount of 500 MW and so
the learning curve structurally changed and became a linear one.
Over the period 2008–12 still further reductions in cost were
achieved but due to the methodology used in the calculation of
LR the reductions are no longer properly accounted for. For
periods of time where the maximum installed capacity is driven
by political reasons by establishing cap amounts we shall use an
alternative way of calculating LR figures. We can see this situ-
ation over the period 2008–12 in the Spanish market which
reveals one of the limitations of forecasting future scenarios by
using learning curves, as they are not able to predict discontinu-
isities in learning that may be due to market structural changes or
even in the Spanish case to deep legislation changes.

However, the calculation of the learning curve is relevant as it
shows the experience path of the sector and the economics
implications of government investments. The understanding of
the foundations of the process will also help in developing any
future promotion policies for the same technology or for other
types of RES. It is important to estimate future cost trends for
any RES technology while deciding the level of remuneration of
future promotion policies to avoid windfall profits so that the
knowledge of the specific country and/or sector figures is funda-
mental for policy-makers.

Some future additions to the article would be to calculate the
learning curve, by using the log–log formulation, rather than
the exponential one, and comparing the values and accuracy of
the curve. Another addition would be the calculation of the
learning curves for the subsystems it contains, modules and
BOS. This will eliminate the effect of the global module price
trend from the global Spanish LR. BOS learning is mostly attrib-
uted to local cumulative experience on system design, planning
and execution. The analysis and calculation of the Spanish BOS
rate will show in more depth the Spanish evolution and LR of
the photovoltaic local sector.

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