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Interdisciplinary Institute for Innovation

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What cost for photovoltaic modules in 2020? Lessons from experience curve models[1]

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Abstract

Except in few locations, photovoltaic generated electricity remains considerably more expensive than conventional sources. It is however expected that innovation and learning-by-doing will lead to drastic cuts in production cost in the near future. The goal of this paper is to predict the cost of PV modules out to 2020 using experience curve models, and to draw implications about the cost of PV electricity. Using annual data on photovoltaic module prices, cumulative production, R&D knowledge stock and input prices for silicon and silver over the period 1990 – 2011, we identify a experience curve model which minimizes the difference between predicted and actual module prices. This model predicts a 67% decrease of module price from 2011 to 2020. This rate implies that the cost of PV generated electricity will reach that of conventional electricity by 2020 in the sunniest countries with annual solar irradiation of 2000 kWh/year or more, such as California, Italy, and Spain.

Key words: Learning curve; solar photovoltaic energy; cost prediction

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1 Introduction

Experience curves, also called learning curves, are widely used to predict cost paths in the mid- to long-term. In its simplest form, an experience curve relates production costs to the accumulation of experience (often measured by cumulative production). Experience curves are based on the theory of learning-by-doing which asserts that "technical change in general can be ascribed to experience, that it is the very activity of production which gives rise to problems for which favourable responses are selected over time" (Arrow, 1962). Strong empirical support has been demonstrated through its application across various industries[i].

In the solar photovoltaic (PV) industry, experience curves are of particular importance in policy discussions surrounding the role of solar in the transition towards low carbon energy systems. PV technology is not yet competitive against conventional energy sources. It is however expected that, given sufficient support in the short-run, the industry will experience important cost reductions through learning-by-doing which will lead to important gains in the future. In addition to the public goods nature of learning and existence of learning spillovers[ii], this provides the rationale for public policies to support the deployment of PV installation.

In this policy context, quantitative evaluation using experience curves can inform a number of important questions. For example, what return, in terms of the magnitude of the cost decrease, can one expect in the future by supporting the development of the market in the short-run? What is the optimal pace at which public subsidies should be reduced? Analysis can help to prevent repeating mistakes from the recent past. For instance, over-pessimistic anticipation of cost reductions led to an uncontrolled PV market boom in Spain in 2008 and in France in 2010, triggering subsequent sharp policy revisions (a cap on installations in Spain and a three-month moratorium together with a drastic cut in the feed-on tariff level in France).

This stop-and-go policy was devastating, resulting in dozens of bankruptcies and thousands of job losses in the local PV industry. Reliable cost prediction is therefore crucial to the sustainable development of this industry.

In this paper, we seek to predict the cost of PV modules production out to 2020 using experience curves, and thereby the cost of PV generated electricity. As mentioned, experience curves in their basic form are derived by regressing the module price (a proxy for the cost) on experience measured by cumulative production. In the recent literature, additional explanatory variables have been included, such as input price, scale, or research and development (Isoard and Soaria, 2001, Kobos et al., 2006, Yu et al., 2011). However, little attention has been paid thus far on the influence of adding these explanatory variables on the predictive power of the model. This paper aims to fill this gap, by explicitly addressing methodological issues that influence the identifying and selecting of the most reliable experience curve model.

This paper uses annual world average data on module price, cumulative capacity, plant size, silicon and silver price, and the R&D knowledge stock from 1990 to 2011, to find a specification that gives the best predictive power – i.e. that minimizes the difference between predicted and realized module prices. The model is then used to make out-of-sample predictions out to 2020.

Possible additional variables are identified through surveying the literature on experience curves for PV modules. We restrict the analysis to modules because they are standard products for which price information is readily available (world average prices expressed in dollar per Watt-peak for standard conditions). Alternative measures of PV costs were considered but deemed unsuitable for the estimation of a global experience curve[iii] on PV technology (and implications for PV generated electricity). For example, other components of PV systems like inverter, battery, and wires are not specific to the PV industry. Other observable factors that influence output such as installation costs and sunlight availability are dependent on local conditions.

The majority of existing studies on PV modules on a global scale use experience as the only explanatory variable, with an average learning rate of 20.9% (see the references below). Three studies include other variables: R&D, scale, silicon price, or/and silver price. Our contribution is to carry out a systematic analysis with respect to the inclusion of such variables, to derive a combination with the best predictive power.

This analysis shows that supplementing experience with silicon price series best predicts module costs. Based on this model, a 67% cost decrease is predicted between 2011 to 2020, 75% of this evolution being attributed to experience, and 25% to the fall in silicon price.

The remainder of this paper is structured as follows: The next section presents the experience curve model and a critical survey of the literature applied to PV modules. We perform an out of sample evaluation to choose the best specification of the model in section three. Section four presents scenarios for module cost until 2020 based on the best specification, and section five the implications for PV electricity's competitiveness. Section six concludes.

2 Literature review

Experience curves are classical econometric models in which the key explanatory variable is experience, as measured by cumulative production or cumulative installed capacity. The simplest specification is defined by:

$$P_t = P_0 \, Y_t^{-E} \qquad (1)$$

where P_t is the price of one unit of output at time *t*. This price is a proxy for cost. P_0 is the price of the first unit, and Y_t is cumulative output at *t*. E captures the experience parameter. A related indicator is the learning rate giving the percentage of change in cost corresponding to a doubling of experience:

$$\text{Learning rate} = 1 - 2^{-E}$$

A learning rate of 0.1 means, for instance, that unit cost decreases by 10% for each doubling of experience. To estimate E econometrically, the following specification can be derived from (1):

$$\log(P_t) = \log(P_{0)} - E \log(Y_t) + \varepsilon_t$$

with ε_t, an i.i.d. error term.

We find 17 studies that estimate one-variable equations with module price as the dependent variable (see Table 1). They differ in terms of time frame used for the estimation, geographical scale, and data source. The average learning rate is 20.2%. The standard error for studies on a global scale is 3.2%, and 7.6% for experience curves estimated at the country level. We explain this difference below by the existence of knowledge spillovers.

Table 1 Review of experience curves of PV modules with experience as only explanatory variable

Study	Geographical scale	Time frame	Learning rate	Data Source
Maycock & Wakefield (1975)	Global	1965-1973	20.0%	n.a.
Tsuchiya (1992)	Japan	1979-1988	19.0%	n.a.
Williams and Terzian (1993)	Global	1976-1992	18.4%	Strategies Unlimited
Cody and Tiedje (1997)	US	1976-1988	22.0%	Maycock
Tsuchiya (1999)	Japan	1979-1998	17.6%	n.a.
IEA (2000)	Global	1976-1984	16.0%	EU-Atlas and Nitsch (1998)
		1987-1996	21.0%	
Harmon (2000)	Global	1968-1998	20.2%	Maycock
Wiliams (2002)	Global	1976-2000	20.0%	Strategies Unlimited
Parente et al. (2002)	Global	1981-2000	22.8%	Maycock
		1981-1990	20.2%	
		1991-2000	22.6%	
Poponi (2003)	Global	1976-2002	25.0%	Maycock
		1989-2002	19.5%	
Schaeffer (2004)	Global	1976-2001	20.0%	Strategies Unlimited
		1987-2001	23.0%	
	Germany	1992-2001	10.0%	Photex database
Papineau (2004)	Germany	1992-2000	15.0%	Extool Project, IEA
	Switzerland	1992-2000	10.0%	
	US	1992-2001	32.0%	
	US	1992-2001	20.0%	US DOE
Nemet (2006)	Global	1978-2001	26.0%	Maycock
		1976-2001	17.0%	Strategies Unlimited
Van Sark (2006)	Global	1976-2001	20.6%	Strategies Unlimited
		1981-1990	16.6%	
		1991-2000	29.6%	
Swanson (2006)	Global	1979-2005	19.0%	Strategies Unlimited & other
Van Sark (2008)	Global	1976-2006	20.6%	Strategies Unlimited & other
Breyer et al. (2010)	Global	1976-2003	22.8%	Strategies Unlimited & other
		1976-2010	19.3%	

Total cost may also be driven down by factors other than experience (Hall and Howell, 1985) that are omitted in the base model:

- Other forms of learning, including learning-by-searching (brought by R&D), learning-by-using (through feed-backs from users which helps optimising the product), and learning-by-interacting (transfer of knowledge between users, producers, research institutes and policy makers due to knowledge networks) (Kamp, 2004).

- Knowledge spillovers, that is, the flow of knowledge that has benefits outside the organisation where it has been created, but with no automatic market compensation. Spillovers are more important between firms that are geographically or technologically close. For experience curves at the firm scale, they induce a cost reduction that is not generated by the firm's own experience, thus altering the experience parameter. However, for global experience curves based on world average cost, spillovers are included in the global experience effect. It explains the difference previously noted in Table 1 between country-level and world-level studies.
- Scale effect, which is the unit cost variation corresponding to an increase in production scale at the plant level.
- Product standardisation, reducing transaction costs in the industry.

To account for some of these factors, in more recent analysis, new explanatory variables such as input price, R&D, or scale effect have been included in three studies, leading to more complex experience curves (Table 2). Kobos et al. (2006) find that R&D through learning-by-searching has a significant positive effect. Isoard and Soria (2001) find constant return to scale. However, allowing for a flexible value of the parameter, they find decreasing return to scale before 1994. With more recent data, Yu et al. (2011) find increasing return to scale. These contradicting results are inconsistent with the constant parameters hypothesis. However, the variability of the scale parameter may be due to multicollinearity increasing the variance of the estimator. Yu et al. (2011) find a strong positive effect of silicon price on module price. They also find a slight negative effect of silver price, explaining it by a substitution effect with other inputs.

The average learning-by-doing rate found by experience curves with several explanatory variables in Table 2 is 13.7%, markedly lower than learning rates found in models with experience only (20.9% on a global scale). This suggests that the experience parameter is seriously biased when it is the only explanatory variable as it captures the influence of other drivers.

The objective of this paper is not, however, to produce unbiased estimates of the learning rate. Our focus is on identifying the specification with the best predictive power. In this respect, the addition of explanatory variables has two opposite effects. On the one hand, it limits the omitted variable bias, which increases the predictive power of the model. Yet on the other hand, it can create multicollinearity if additional variables are highly correlated to the other explanatory variables, thus increasing the variance of the estimator and decreasing the model's predictive power. Whether or not to include an additional variable is thus an empirical question. In the next section, we develop and implement an empirical strategy to select the set of variables that gives the best predict power.

Table 2 Review of multifactor experience curves for PV modules

Study	Time scale	**Learning-by-doing**	**Learning-by-searching (R&D)**	**Return to scale***	**Input price***	
					Silicon	Silver
Isoard and Soaria (2001)	1976-1994	9.2%	-	1	-	-
Kobos et al. (2006)	1975-2000	18.4%	14.3%	-	-	-
Yu et al. (2011)	1976-2006	13.5%	-	1.066	0.285	-0.135

Note: The log-log specification implies that the estimated coefficients reported in the table are elasticities.

3 Selection of the specification with the highest predictive power

3.1 Methodology

Our methodological approach empirically evaluates the predictive power of 33 possible specifications with different sets of explanatory variables. All include an experience variable. We test two proxies: one half of the specifications includes cumulative capacity; the others include cumulative capacity with a one year lag, to account for the time it takes for the learning process to take place. Apart from the experience variable, each specification is a particular combination of four variables identified in the literature: R&D, scale, silicon price, and silver price.[iv] The combinations are listed in Table 3.

Table 3: Sets of additional variables in specifications tested

1) No additional variable	9) Ar and Scale
2) Si (Silicon)	10) Ar and R&D
3) Ar (Silver)	11) Scale and R&D
4) Scale	12) Si, Ar, and Scale
5) R&D	13) Si, Ar, and R&D
6) Si and Ar	14) Si, Scale, and R&D
7) Si and Scale	15) Ar, Scale, and RD
8) Si and R&D	16) All (Si, Ar, Scale, and R&D)

The strategy then involves making predictions and comparing the predicted price with the actual value observed in the data, as we now explain by using an example. Using data from 1990 to 2010, the first step involves estimating the specification, indexed by *i,* on a ten-year period, for instance 1990 to 1999. The estimates are then used to predict the annual module prices from the subsequent year (2000 in this case) to 2011, the last year for which we have historical values. The predictions are based on historical data for the explanatory variables. Let $\hat{P}_{i,t}$ denote the predicted price and $P_{i,t}$ the actual value where *i* is the specification's index and *t,* the time horizon (1 for the prediction in 2000, 2 for 2011 in the above example). The error is given by:

$$\left|\frac{\hat{P}_{i,t} - P_{i,t}}{P_{i,t}}\right|$$

We consider the error relative to the price by taking the percentage error, because price decreases quickly. We also consider the absolute value of these percentage errors, since the direction of the error can be negative or positive.

This procedure is replicated for all possible ten-years periods: from 1991-2000, to 2001 to 2010. The final step is to compute the Mean Absolute Percentage Error (MAPE) of specification *i* at time horizon *t* defined by:

$$MAPE_{i,t} = \frac{1}{n_t} * \sum_{i=1}^{n_t} \left|\frac{\hat{P}_{i,t} - P_{i,t}}{P_{i,t}}\right| \qquad (2)$$

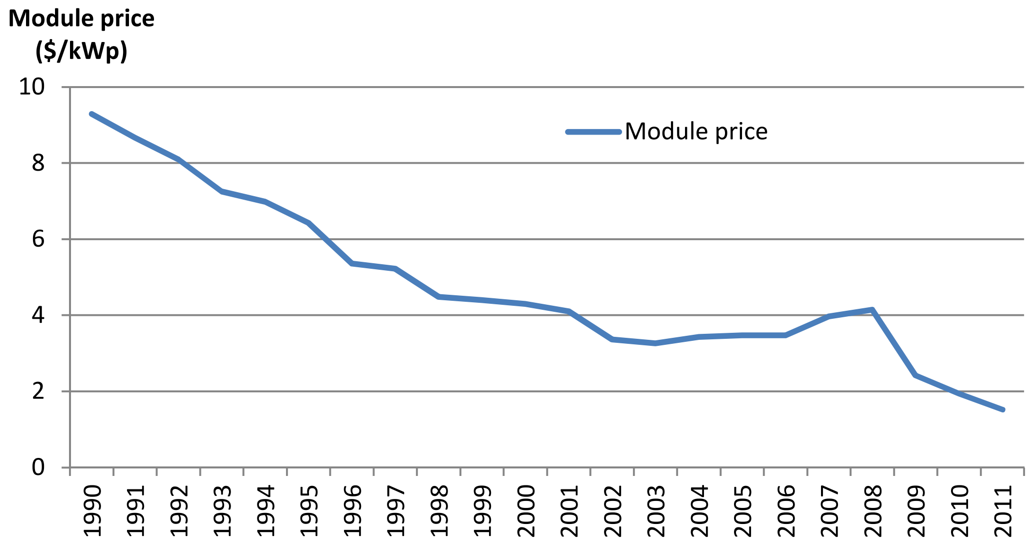
where n_t is the number of estimations of the specification at this time horizon. This methodology provides us with the MAPE of the predictions for time horizons between 1 and 11 years for each of the 16 specifications.

3.2 Data

The dataset consists of world average annual values of module price, cumulative capacity, plant size, silicon price, and R&D knowledge stock from 1990 to 2011, except R&D for which the data stops in 2007. Data sources are listed in annex 1. The R&D knowledge stock has been measured using the cumulative number of patent families as proxy for innovation, according to the methodology developed by Dechezleprêtre et al. (2011). A patent family is the set of patents granted in different countries for the same innovation. Therefore one patent family represents one innovation. We use an annual depreciation rate of 10% to account for technology obsolescence. The patent data is obtained from the European Patent Office. (http://www.epo.org/)

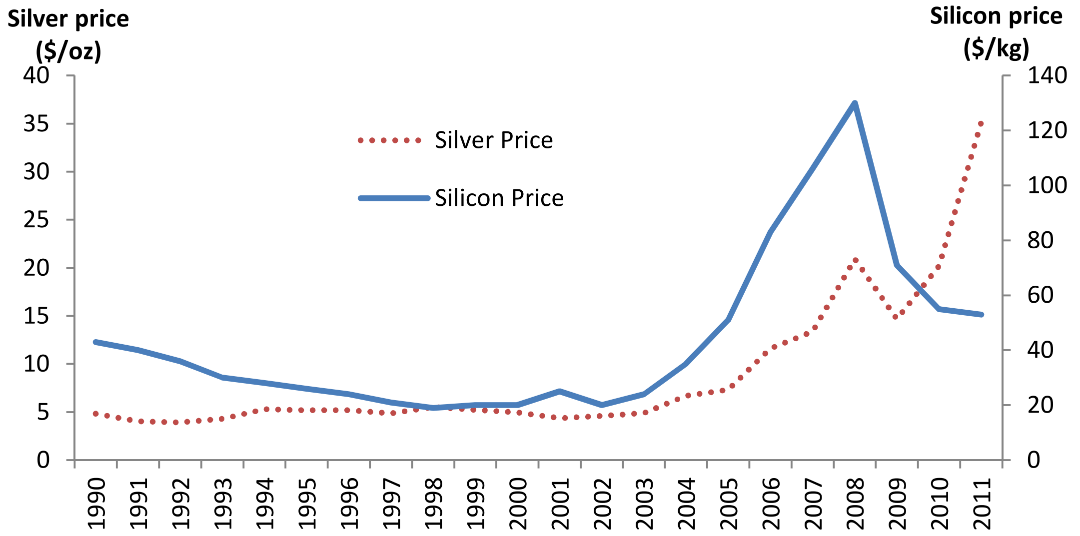
In Figure 1, we show the evolution of module price which in general declines during the twelve year sample period, except from the slight reversal of the trend between 2004 and 2008. The latter corresponds to the period with a global shortage in silicon supply, pushing up silicon prices which peaked in 2008 (Figure 2). Silver price (Figure 3) also started to rise in 2004, due to growing investor's interest in silver which modified the supply/demand balance. Other variables - cumulative capacity, scale, and R&D - increased steadily over time, with the size of the industry.

Figure 1 Evolution of module price from 1990 to 2011



Source: see Annex 1

Figure 2 Evolution of silicon and silver price from 1990 to 2011



Source: see Annex 1

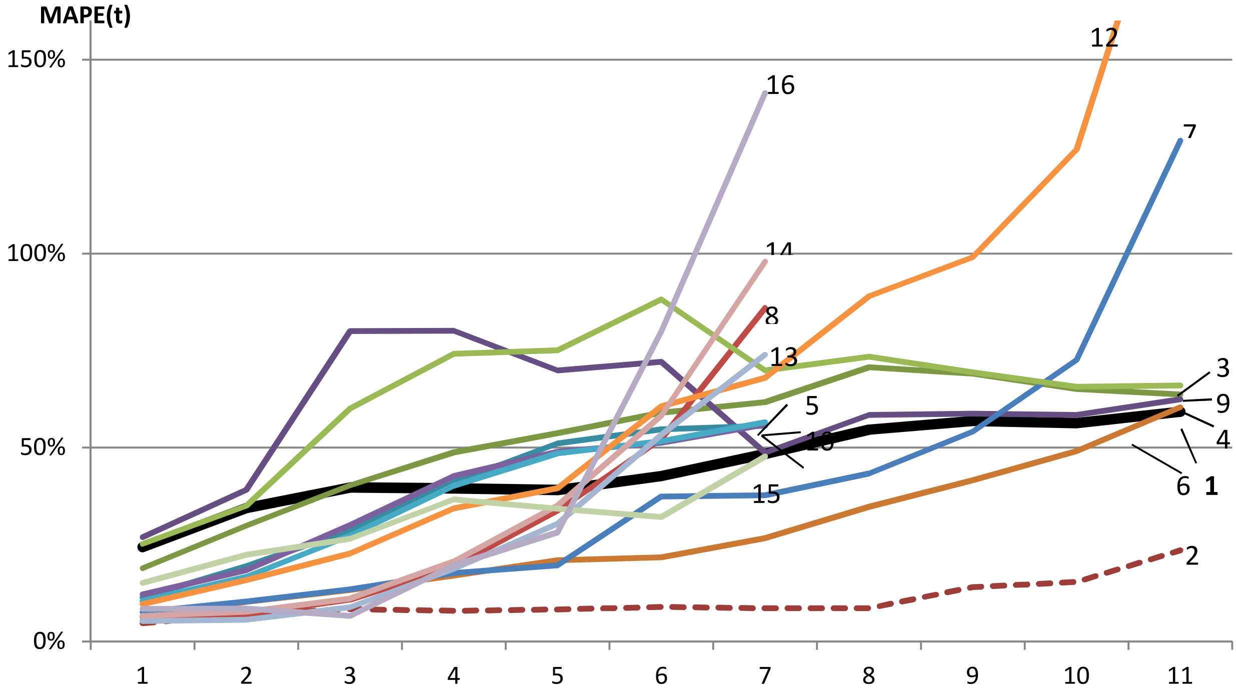
3.3 Results

Of the 32 estimations conducted, only results for the MAPE are reported in this subsection in the interest of space.[v] Figure 3 plots the MAPE over time for each of the 16 specifications, where cumulative capacity with one year lag is used as proxy for experience. These specifications perform better than those using cumulative capacity with no lag: the average MAPE is 41.6% with the lag and 44% without (see Annex 2).

The numbers marked on each line indicate the specification listed in Table 3. The thick and dark curve represents the MAPE for the classic specification with experience. It shows that the best set of explanatory variables is number 2 (doted curve) with experience and silicon price. It performs better than the usual specification with experience alone, and the addition of any other explanatory variable decreases the predictive power of the model. We will therefore use this specification for the prediction beyond 2011.

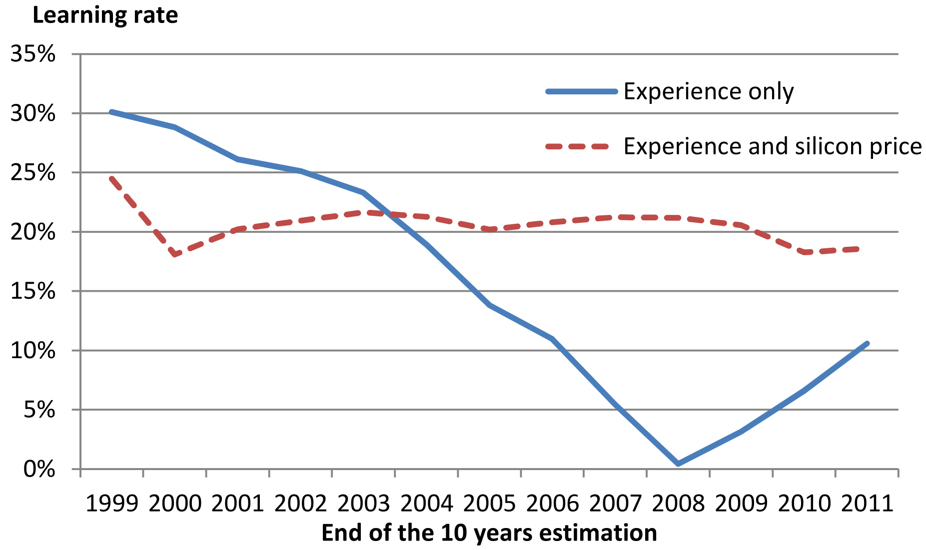
This result illustrates that adding explanatory variables does not necessarily improve predictive power. It can be interpreted in terms of the trade-off between omitted variable bias and multicollinearity. The inclusion of silicon price reduces the omitted variable bias. Figure 4 showing the learning rate of experience curves with and without silicon price shows that the bias corresponding to the omission of silicon price is important and temporally not stable due to the silicon shortage between 2004 and 2009. Moreover, there is limited risk of loss of accuracy due to multicollinearity,[vi] because the correlation between silicon price and experience is low (ρ=0.46). On the contrary, the introduction of scale or R&D reduces the accuracy of the model, because they are highly correlated[vii] to experience (ρ>0.98). Yet the bias resulting from their omission does not affect the predictions' accuracy much: because their relation with experience is stable, the effect of this omitted variable bias in the predictions accounts for the real effect of the omitted variable. Silver price is less correlated to experience (ρ=0.78)[viii], but it has only a small effect on module price, hence should be left out.

Figure 3 Comparison of MAPE(t) for each model, MAPE(t) being the mean absolute percentage error according to the time horizon t



Note: The specifications including R&D (5,8,10,11,13,14,15,16) end after a time horizon of 7 years because we do not have data for R&D after 2007, so no long term evaluation could be done.

Figure 4 Learning rates according to the end of the 10 years estimations, for two specifications: experience only and experience and silicon price.



Note: The learning rate is temporally stable when silicon is included in the specification. But with experience only, the learning rate is not stable. The difference corresponds to the omitted variable bias due to the omission of silicon price in the model.

Table 4 shows the regression results for the selected specification that will be used to make module price predictions below. The estimation period is from 1990 to 2011. The experience parameter of -0.338 corresponds to a learning rate of 20.1%.

Table 4 Results of the regression of log(module price) on log(lagged cumulative capacity) and log(silicon price) on 1990/2011

LogPrice	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
LogExp	-0.338	0.010	-34.030	0.000	-0.359	-0.317
LogSilicon	0.385	0.027	14.300	0.000	0.328	0.441
Constant	2.490	0.073	33.920	0.000	2.336	2.644

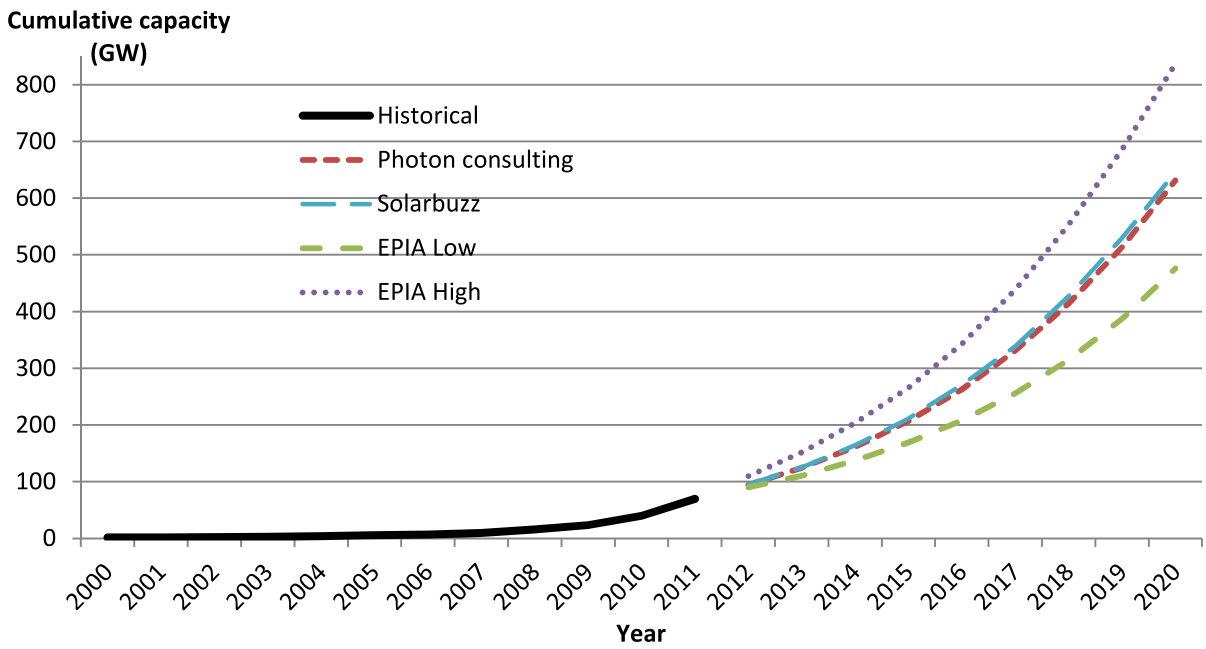
4 Prediction of module price beyond 2011

The best specification includes two independent variables: lagged cumulative capacity (one year) and silicon price. As a next step, we need to obtain plausible projections of the value of these two explanatory variables until 2020,in order to use this model to predict module prices after 2011.

4.1 Cumulative capacity scenarios

Figure 5 shows the cumulative capacity scenarios made in 2012 by Photon Consulting[ix] and Solarbuzz[x], the two leading market research companies in the PV sector, and by the European Photovoltaic Industry Association (EPIA)[xi][xii]. In the following, we consider the two extreme scenarios, which correspond to Compound Annual Growth Rates (CAGRs) of the market from 15% to 23% (EPIA low and high scenarios respectively) between 2011 and 2020. These CAGRs are much lower than that observed between 2000 and 2011 (55%) because lower incentive policies are expected in Europe, the main market.

Figure 5 Cumulative capacity forecast until 2020

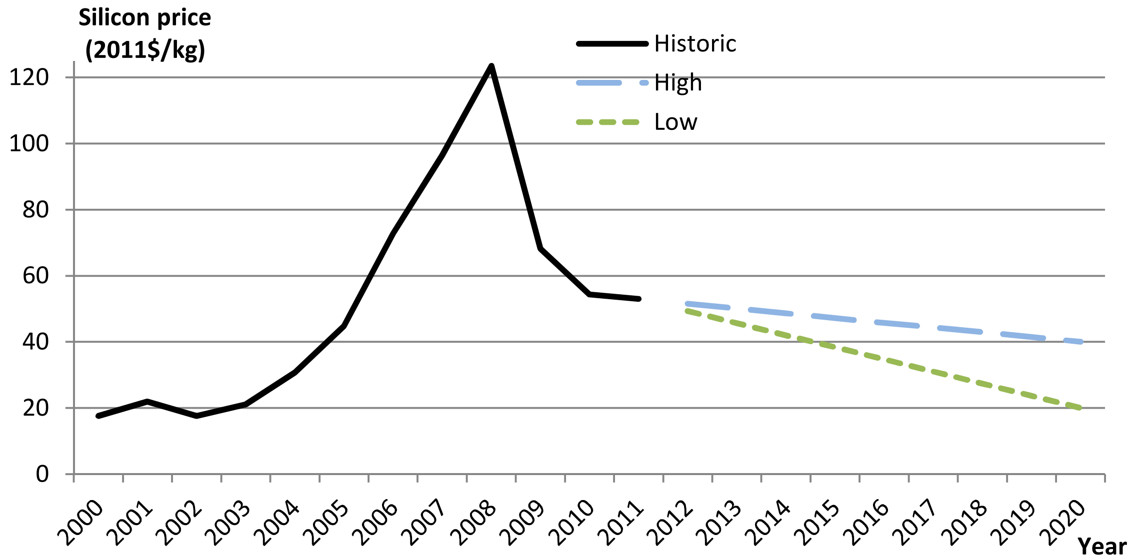


Source: Photon consulting (2012), Solarbuzz (2012), EPIA (2012)

4.2 Silicon price scenarios

We build two scenarios of silicon price evolution until 2020, as shown in Figure 6. The first assume a linear decrease from 53$/kg in 2011 to 20 $/kg in 2020, corresponding to the lower-bound price predictions found across market forecasts from 2012[xiii]. In the second scenario, the price decreases less, to 40 $/kg[xiv]. Linearity is assumed (constant decrease of silicon price) because, based on the announcement of new production capacity, the current oversupply of polysilicon is expected to last in the long-term.

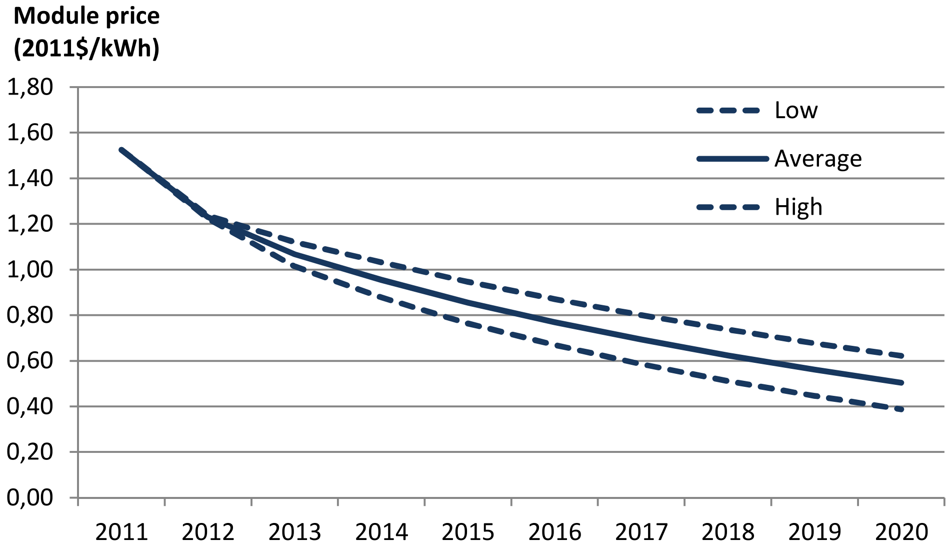
Figure 6 Silicon price forecast until 2020



4.3 Module price prediction until 2020

We now proceed to forecast the evolution of module price, and the results are presented in Figure 7. The low scenario for module price corresponds to the high scenario for PV industry development, and the low scenario of the silicon price path. Conversely, the high scenario for module price corresponds to the low development of the industry and the high scenario for silicon price. On average, we find a 67% decrease of module price from 1.52 $/Wp in 2011 to 0.50$/Wp in 2020. The increase in cumulative capacity is responsible for 75% of this reduction, and the silicon price decrease for 25%.

Figure 7 Module price predictions until 2020



5 Impact on the cost of photovoltaic electricity

In this section, we translate the module price predictions out to 2020 in Section 6 to PV electricity price predictions. We rely on the standard measure of the cost of electricity, the Levelised Cost Of Electricity (LCOE), which is the average cost of generating electricity over the lifetime of the system:

$$LCOE = \frac{Net\ Present\ Value\ (cost\ of\ the\ PV\ system\ over\ the\ lifetime)}{Net\ Present\ Value\ (electricity\ generated\ over\ the\ lifetime)}$$

Module price accounts for 40% of the total price of an average system in 2011[xv]. We thus need to make assumptions about the cost of other components, the type of system, parameters influencing the quantity of electricity produced such as sunlight availability and lifetime of the system, as well as the discount rate.

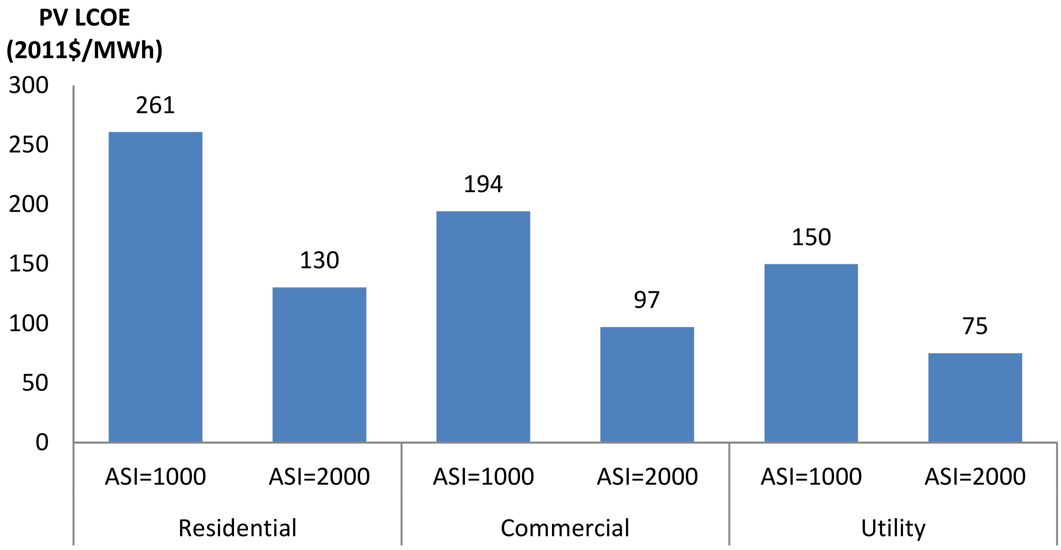
PV systems can be residential, commercial, or industrial (utility). Due to economies of scale, the LCOE is cheaper and modules account for a higher share of total cost for bigger systems. Typically inverters are replaced once during the systems' lifetime. This accounts for most of the operation and maintenance cost. The lifetime of the system itself has an influence on the LCOE.

Sunlight availability, measured by the Annual Solar Irradiation (ASI), has important influence on LCOE. For example, the North of Germany or Alaska has an ASI of 1000 kWh/year, while the south of Spain, Italy, or California has an ASI of 2000 kWh/year. The discount rate is also an important determinant, since 95% of the cost of a PV system over its lifetime is capital expenditure (CAPEX). As Branker et al. (2011) noted in a survey of studies of PV LCOE, the assumptions regarding the discount rate are often not made explicit, although they typically lie between 5% and 10% in most studies. We use 6.8%, which is the rate used by the IEA (2012) to compute LCOEs.

We computed the LCOE for three types of PV systems: residential, commercial, and utility. Two ASI levels are considered, 1000 kWh/year and 2000 kWh/year, corresponding respectively to the north of Germany, and to the sunniest areas such as California or south of Spain[xvi]. The lifetime of the systems is assumed to increase from 25 years in 2011 to 35 years in 2020. The other underlying assumptions are listed in Annex 3.

Figure 8 shows the predicted LCOE in 2020. The differences in the results illustrate the importance of the geographic location, and the type of PV system on the cost of PV electricity. These results are in line with those of Bosetti et al. (2012) who predict a LCOE between 75 and 145 $/MWh for 2030 with an expert elicitation survey, with the most likely scenario being 108$/MWh, not differentiating the location or the type of system.

Figure 8 PV LCOE prediction for 2020 with a 6.8% discount rate (source: Author)



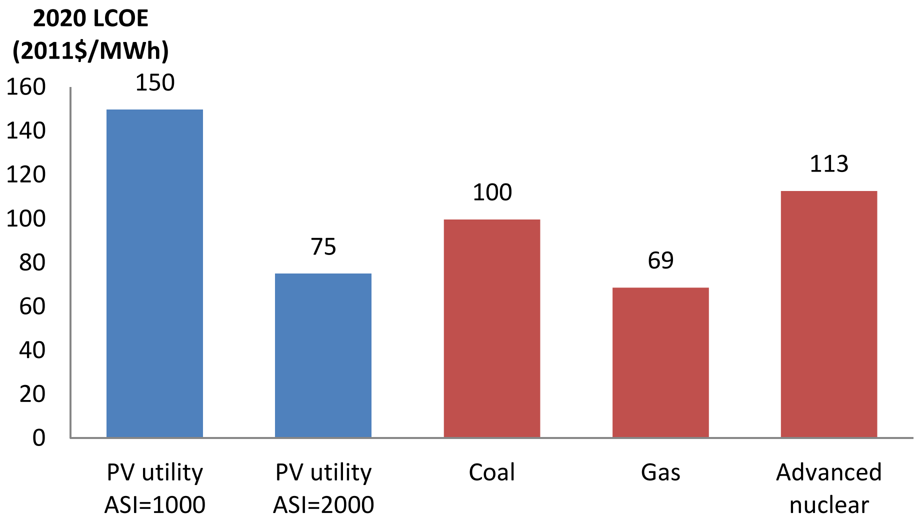
Note: ASI: Annual Solar Irradiation, 1000 kWh/year corresponds to the north of Germany or Alaska, and 2000 to the south of Spain, Italy, or California. Hypothesis used for the computation of the LCOE are explained in Annex 3.

Figure 9 compares predictions of LCOEs in 2020 for conventional electricity sources and a PV utility system for two locations: with solar annual irradiation of 1000kWh/year, and 2000kWh/year. The results suggest that the average cost of electricity generated with PV technology will match the cost of conventional technologies in 2020 in the sunniest places.

Note that these results may or may not underestimate the actual cost of PV electricity as the LCOE abstracts the costs involved in system transitions. For example, large scale renewables penetration into the electricity system involves costs associated with issues of intermittent supply, back-up capacity, storage capacity, grid extension and so forth. These costs are highly uncertain, and depend on many assumptions including the carbon costs trajectory and the counterfactuals assumed.

Moreover, the LCOE does not take into account the country specific load profile. Joskow (2011) notes that, since the wholesale price of electricity varies throughout the day, different load profiles with different base- and marginal- technologies give different market values for the electricity produced. This can have either a negative or a positive impact depending on the synchronisation of the production and demand profiles.

Figure 9 Comparison of the LCOE of different electricity sources



Note: ASI stands for Annual Solar Irradiation. 1000 kWh/year corresponds to the north of Germany or Alaska, and 2000 to the south of Spain, Italy, or California. The discount rate is 6.8%. Additional hypothesis used for the computation of the PV LCOE are explained in annex 3. Source: Author and EIA, 2012.

6 Conclusion

The objective of this paper is to find the best model to predict module price and to use it to forecast module price and photovoltaic (PV) electricity cost out to 2020. The selection of the best set of combination of explanatory variables is based on an out-of-the sample evaluation of the predictive power.

We find that the most accurate combination of explanatory variables include both experience (measured by cumulative capacity with a one year lag) and silicon price. Based on this model and scenarios for the future evolution of the explanatory variables - cumulative capacity and silicon price - we are able to predict module price out to 2020. A 67% decrease of module price is predicted between 2011 and 2020. The increase in cumulative capacity is responsible for 75% of this evolution and silicon price decrease is responsible for 25% of module price reduction.

The results are then used to derive the Levelised Cost of PV Electricity in 2020. Our findings show that PV can reach conventional technologies' LCOE in the sunniest areas with an annual solar irradiation of 2000 kWh/year or more, such as California, Italy, or Spain. Note that these estimates are rather optimistic as the LCOE does not properly take into account additional cost of integrating intermittent sources into the grid.

Annex 1: Data sources

We use multiple data sources which are listed below.

(1) Cumulative output and Average prices:

- 1990-2001: Report PM-52, Five-Year Market Forecast 2002-2007, Strategies Unlimited, 2003 (Through Yu, 2008).
- 2002-2005: Swanson, Progress in Photovoltaics, 2006 (Through Yu, 2008).
- 2006: Photon International magazine (Through Yu, 2008).
- 2007 to 2011: Photon consulting annual reports

(2) Plant size:

- 1990-2001: Nemet (2007), Policy and Innovation in Low-Carbon Energy Technologies Chart 4,
- Page 170: (Yu (2008 obtained these data from Nemet's plant size figure.)
- 2002-2003: Photon International magazine, 7-2003, Page 42.
- 2004-2005: Photon International magazine, 1-2005, Page 42.
- 2006: Photon International magazine, 4-2006, Page 42.
- 2007-2009: Photon international magazine, cell and module production survey 2007, 2008, 2009, 2010, and 2011. A proxy has been constructed by the average production of the 15 biggest firms.

(3) Silver price:

- 1990-20011, Silver Institute website, http://www.silverinstitute.org/site/silver-price/

(4) Silicon price:

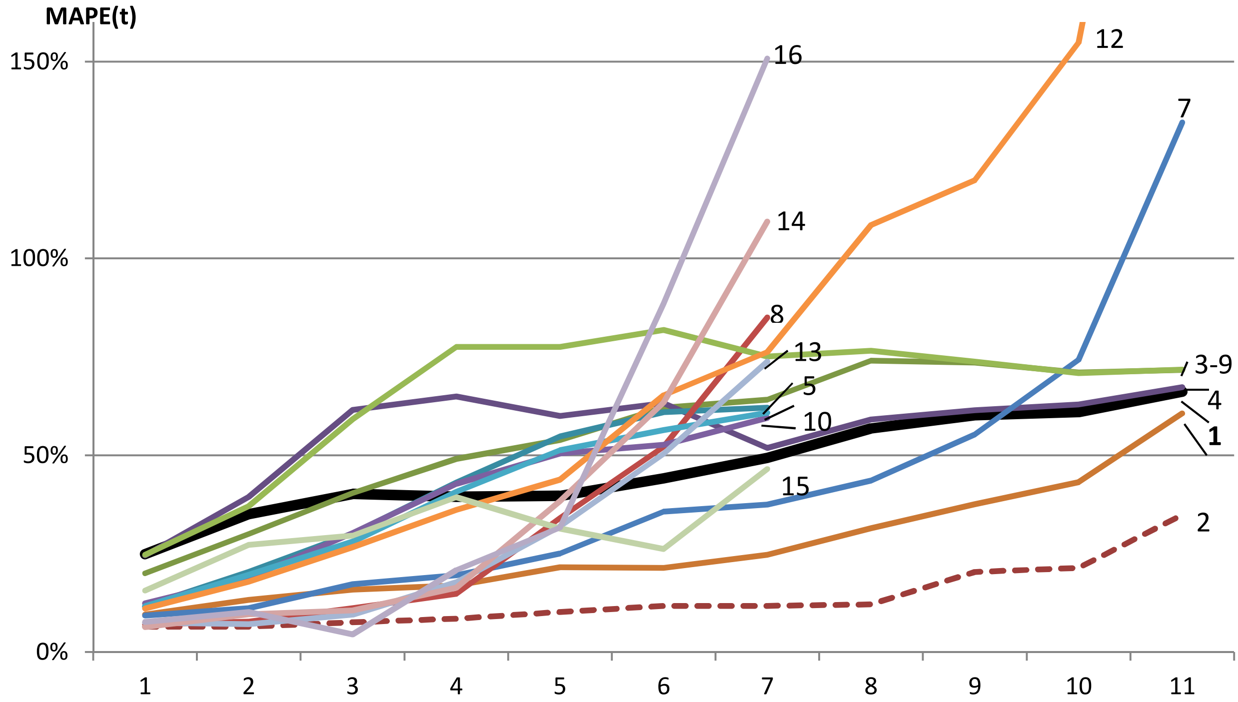
- 1990-2002: Nemet (2007), (Through Yu, 2008)
- 2003: Photon International magazine, 4-2006, Page 30.
- 2004: Photon International magazine, 9-2006, Page 139.
- 2005-2006: Photon International magazine, 12-2007, Page 115.

- 2007-2011: Photon Consulting annual reports

(5) R&D knowledge stock

- 1990-2007: Author. The R&D knowledge stock has been computed with the number of patent families as proxy for innovation according to the methodology developed by Dechezleprêtre et al. (2011). A patent family is the set of patents granted in different countries for the same innovation. Therefore one patent family represent one innovation. We use an annual depreciation rate of 10% to account for technology obsolescence, but no lag since we use patent and not R&D expenditure. The patent data set comes from the European Patent Office website (http://www.epo.org/)

Annex 2 MAPE of the specifications with cumulative capacity as proxy for experience



Note: The specifications including R&D (5,8,10,11,13,14,15,16) end after a time horizon of 7 years because we do not have data for R&D after 2007, so no long-term evaluation could be conducted.

Annex 3: Assumptions for the LCOE simulation:

Each year, the quantity of electricity produced is equal to PR * ASI where PR is the Performance Ratio of the installation (the ratio of the actual and theoretically possible energy output) and ASI is the Annual Solar Irradiation (the sum of the quantity of solar energy reaching the installation over a year).

Performance ratio = 0.75

Lifetime: from 25 years in 2011 to 35 in 2020

Operation and maintenance costs: 6% of system cost

The module accounts for around 30% of the price of a residential system, 40% of a commercial system, and 60% of the cost of a utility plant.

Price evolution of components is derived by extrapolating the projections made by Photon Consulting in 2012.

References

Arrow, K.J., 1962. The economic implications of learning by doing, *The Review of Economic Studies,* Vol. 29, No. 3 (Jun., 1962), pp. 155-173

Bosetti, Valentina, Catenacci, Michela, Fiorese, Giulia and Verdolini, Elena, The Future Prospect of PV and CSP Solar Technologies: An Expert Elicitation Survey (February 14, 2012). FEEM Working Paper No. 1.2012.

Branker, K., Pathaka, M.J.M., Pearce, J.M., 2011. A review of photovoltaic levelized cost of electricity. Renewable and sustainable energy review 15 (2011) 4470-4482

Breyer, Ch., Birkner, Ch., Kersten, F., Gerlach, A., Stryi-Hipp, G., Goldschmidt, J.Ch., Montoro, D.F., Riede, M., 2010. Research and Development Investments in PV – A limitationing Factor for a fast PV Diffusion?

Cody G.D. and Tiedje T., 1997, A learning curve approach to projecting cost and performance for photovoltaic technologies, Proceedings of the First Conference on Future Generation Photovoltaic Technologies, Denver, CO, USA.

De La Tour, A., Glachant, M., and Ménière, Y., (2011), ·Innovation and international technology transfer: The case of the Chinese photovoltaic industry, *Energy Policy* Volume 39, Issue 2, February 2011, Pages 761-770

Dechezleprêtre, A. , Glachant, M., Haščič, I., Johnstone, N., and Ménière, Y., 2011. Invention and Transfer of Climate Change Mitigation Technologies: A Global Analysis. *Review of Environmental Economics and Policy* 2011.

Dutton, J., Thomas, A., 1984. Treating progress functions as a managerial opportunity. The Academy of Management Review 9 (2), 235–247.

EPIA (2011), Solar Photovoltaics competing in the energy sector − On the road to competitiveness, 8th European PV Industry Summit, during the 26th EU PVSEC, September 2011.

Ferioli, F., Schoots, K., and van der Zwaan, B.C.C, 2009. Use and limitationations of learning curves for energy technology policy: a component-learning hypothesis, Energy Policy 37 (2009), pp. 2525–2535.

Flint, A. (2009), Learning Spillovers in the PV Cell Industry, thesis work.

Hall, G. and Howell, S., 1985. The Experience Curve from the Economist's Perspective, *Strategic Management Journal*, Vol. 6, p. 197.

IEA and NEA, 2010. Projected cost of generating electricity. International Energy. Agency and OECD Nuclear Energy Agency, 2010.

EPIA, 2012. Global market outlook for photovoltaics until 2016. European Photovoltaic Association, May 2012.

Isoard, S., Soria, A,, 2001. Technical change dynamics: evidence from the emerging renewable energy technologies, *Energy Economics*, 23 Ž2001. 619_636

IEA (2010), Technology Roadmap – Photovoltaic Solar Energy

Joskow, P., 2011. Comparing the Costs of Intermittent and Dispatchable Electricity Generating Technologies. *American Economic Review*; May2011, Vol. 101 Issue 3, p238-241

Kamp, L.M., Ruud E. H. M. Smits and Cornelis D. Andriesse (2004), Notions on learning applied to wind turbine development in the Netherlands and Denmark, *Energy Policy*, Volume 32, Issue 14, September 2004, Pages 1625-1637

Kobos, P.H., Erickson, J.D., and Drennen, T.E, 2006, Technological learning and renewable energy costs: implications for US renewable energy policy, *Energy Policy*, Volume 34, Pages 1645-1658

Köhler, J., Grubb, M., Popp, D., Edenhofer, O. , 2006. The Transition to Endogenous Technical Change in Climate-Economy Models: A Technical Overview to the Innovation Modeling Comparison Project, *the Energy Journal*

MacDonald and Schrattenholzer (2001), Learning rates for energy technologies, *Energy Policy* Volume 29, Issue 4, March 2001, Pages 255-261

Maycock, P.D., Wakefield, G.F., 1975: Business analysis of solar photovoltaic conversion, The Conference Record of the 11th IEEE Photovoltaic Specialists Conference, pg. 252, IEEE, New York, USA

Nemet G.F., 2006. Interim monitoring of cost dynamics for publicly supported energy technologies, *Energy Policy*, Vol.37, Issue 3, 825-835

OECD, 2009. Patent Statistics Manual

Papineau, M., 2004. An Economic Perspective on Experience Curves and Dynamic Economics in Renewable Energy Technologies, *Energy Policy*, 34(4): 422-432.

Parente, V., 2002. Comments on Experience Curves for PV Modules, *Progress in photovoltaics: research and applications*; 10:571–574 (DOI: 10.1002/pip.458)

Photon Consulting (2012): Solar Annual 2012:"The next wave"

Poponi, D., 2003. Analysis of diffusion paths for photovoltaic technology based on experience curves. Solar Energy 74, 331–340.

Popp, D. (2004), ENTICE: endogenous technological change in the DICE model of global warming, *Journal of Environmental Economics and Management*, Volume 48, Issue 1, July 2004, Pages 742-768

Schaeffer G.J., Seebregts A.J., Beurskens L.W.M., Moor H.H.C., Alsema E.A, Sark W. Durstewicz M., Perrin M., Boulanger P., Laukamp H. and Zuccaro C., 2004, Learning from the Sun; Analysis of the use of experience curves for energy policy purposes: The case of photovoltaic power, Final report of the Photex project, DEGO: ECN-C--04-035.

Strategies-Unlimited, 2003. Photovoltaic five-year market forecast, 2002-2007. Technical Report PM-52, Strategies Unlimited, March 2003.

Sun & Wind Energy. 2011. Z Oversupply ahead, The Solar Silicon Conference, Berlin, Sun & Wind Energy, May 2011.

Swanson, R.M., 2006. A vision for crystalline silicon photovoltaics. *Progress in Photovoltaics: Research and Applications* 2006; 14: 443–453.

Tsuchiya, H., 1992. Photovoltaic cost analysis based on the learning curve, Report, Research Institute for Systems Technology, Tokyo.iya

Tsuchiya, H., 1999. Learning curve cost analysis for model building of renewable energy in Japan. In: Wene C-O, Voss A, Fried T, editors. Proceedings IEA Workshop on Experience Curve for Policy Making—the Case of Energy Technologies, 10–11 May 1999, Stuttgart, Germany. Germany: Forschungsbericht 67, Institute fSur Energiewirtschaft und Rationelle Energieanwendung, UniversitSat Stuttgart; 1999. p. 67–76.

US DOE, 2010 $1/W Systems: A Grand Challenge for Electricity from Solar.

Van Sark, W.G.J.H.M., 2008, Introducing errors in progress ratios determined from experience curves, Technological Forecasting and Social Change Volume 75, Issue 3, March 2008, Pages 405-415

Van Sark, W. G. J. H. M., Alsema, E. A., Junginger, H. M., de Moor, H. H. C., Schaeffer, G. J., 2008. Accuracy of Progress Ratios Determined From Experience Curves: The Case of Crystalline Silicon Photovoltaic Module Technology Development, *Progress in photovoltaics: research and applications;* 16:441–453

Williams, R.H., Terzian, G., 1993. A benefit/cost analysis of accelerated development of photovoltaic technology. PU/CEES Report No. 281, Princeton University, Princeton, NJ.

Yu, C.F., 2008. How to incorporate input price changes and scale effects into the learning curve? A PV case study. Thesis at the Utrecht University Copernicus Institute

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, *Renewable and Sustainable Energy Reviews* 15 (2011) 324–337

F. Ferioli, K. Schoots, B.C.C. van der Zwaan, Use and limitations of learning curves for energy technology policy: A component-learning hypothesis, Energy Policy, Volume 37, Issue 7, July 2009, Pages 2525-2535.

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[i] See for example Dutton and Thomas (1984) who study the results of 108 experience curves in 22 industrial sectors

[ii] Note that public policies are justified because a share of these cost reductions are external in the sense that they do not benefit only the companies which install these capacities due to learning spillovers (Flint, 2009). As a result the private return of installing PV panels is less than their social return.

[iii] To overcome this issue, Ferioli et al. (2009) propose to consider overall costs as the sum of cost dynamics for individual subsystems.

[iv] Other input prices such as flat glass price and synthetic rubber price, but found never significant.

[v] Results for the other estimations are available upon request.

[vi] The Variance Inflation Factor (VIF) of the regression from 1990 to 2011 with experience and silicon price is 1.64. Since 10 is the maximum acceptable with a 0.1 tolerance value, this does not show multicollinearity.

[vii] The VIF are 159 for experience and scale, and 30.9 for experience and R&D, the regression with R&D ending in 2007. This shows important multicollinearity.

[viii] The VIF for silver price is 5.95.

[ix] Photon Consulting annual report 2012, p.149, prediction until 2015. Predictions from 2016 to 2020 have been made using the same trend in the CAGR.

[x] Solarbuzz, Marketbuzz 2012 (annual market report), p.254, prediction until 2016. Predictions from 2017 to 2020 have been made using the same trend in the CAGR.

[xi] EPIA (Global market outlook for photovoltaic until 2016), EPIA, May 2012. Predictions from 2017 to 2020 have been made following the same trend in the CAGR.

[xii] The International Energy Agency predicted a lower cumulative capacity of 210 GW in its roadmap in 2010. However, this scenario is two years older than those from the EPIA, and the prediction for 2010 have already shown an important underestimation of 30% (27 instead of 40 GW). Therefore we do not consider this scenario.

[xiii] Source: Sun & Wind Energy, 2011

[xiv] Source: http://www.pv-magazine.com/news/details/beitrag/report-finds-silicon-market-recovering-on-the-back-of-solar-demand_100003385/

[xv] Source: Photon Consulting (2012), p. 84

[xvi] Source : http://solargis.info/