# What cost for photovoltaic modules in 2020? Lessons from experience curve models

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## 1. Overview

Cost is still the main impediment to photovoltaic industry development and its prediction is thus a critical issue. The purpose of this paper is to find the most accurate predictive models, using experience curves, and to use them to build scenarios for 2020. The evaluation of models' accuracy is based on a review of the literature on the limitations of experience curves and a cross evaluation. The cross evaluation measures the accuracy of actual future predictions contrary most evaluation found in the literature based on in sample evaluations. If cumulative production is the main explanatory variable for experience curves, we show that due to multicollinearity issues, scale and R&D should not be used as additional variables, while silicon price can increases predictions accuracy. Based on two models, with cumulative production, and with cumulative production and silicon price as explanatory variables, scenarios are drawn for module price evolution until 2020.

## 2. Reminder about the experience curve model

Experience curves can have only one explanatory variable, experience, in which case we talk about one factor experience curve (OFEC). Other explanatory variables can be added to create MultiFactor Experience Curves (MFECs). We present the methodology for both types of model.

### 1.1. The One Factor Experience Curve model

Experience, measuring learning by doing, is always included in experience curves; it is even often the only one, in OFECs, according to equation (1). Cumulative production is generally used as a proxy for experience.

$$C_t = C_0 * Cum_t^{-E} \qquad (1)$$

C is the cost of one unit of output at t

$C_0$ is the cost of the first unit

Cum is the cumulative output (or another proxy of experience) at t

E is the experience parameter.

A logarithmic transformation gives the following classical linear regression equation (2), with $\varepsilon_t$ the error term. It is generally estimated with the ordinary least square (OLS). By dropping the error term, we get a deterministic predictive model of cost.

$$\log(C_t) = \log(C_0) - E*\log(Cum_t) + \varepsilon_t \qquad (2)$$

Based on this experience parameter E, two variables have been created to give a practical evaluation of the cost variation corresponding to a doubling of cumulative output: the Progress Ratio (PR) and the learning rate (LR). The LR is the cost decrease corresponding to a doubling of cumulative output.

$$PR = 2^{-E}$$

$$LR = 1 - PR$$

## 1.2.The Multi Factor Experience Curve model

To take them other cost drivers into account, other variables have been added to create MFECs. They are based on Berndt's (1991) work to derive the experience curve equation from a Cobb-Douglas cost function. In particular, considering scale, input price, learning by doing and by searching (without the time index for the sake of clarity):

$$C_t = a\, Q_t^{\,s}\,.Cum_t^{-E}.K_t^{-R}\,.\,\Pi\, p_{i,t}^{\beta i} \qquad (3)$$

a is a constant

$Q^{s}$ stands for the scale effect, Q the output, and s the scale index, or elasticity of the plant size[1]

K is the R&D based knowledge stock, and R is the R&D parameter measuring "learning by searching".

$\Pi\, p_i^{\beta i}$ stands for the effects of the price of inputs i, with $p_i$ the price, and $\beta_i$ the elasticity of input i

As for OFEC, a log-log transformation gives a classical linear regression equation used to estimate the parameters with an OLS regression and obtain a deterministic predictive model.

# 3. Methods

In the literature, the main argument to choose the MFEC over the OFEC is the higher $R^2$ of the MFEC. However, maximizing $R^2$ is not a good selection criterion, since it cannot decrease when additional variables are included; it would always lead to the selection of the model with the highest number of explanatory variables. Moreover, the quite high values of the coefficients standard errors of the MFEC from Yu et al. (2011) (29% of the value of the coefficients on average) cast some doubt concerning its predictive power. In this paper, we adopt a different approach to compare the models, based on an out of the sample cross evaluation, which really evaluate how the models predict future cost.

## 3.1. Models tested

[1] Note that here, s, the scale index, is a constant, leading to a linear function on a log-log scale. Isoard and Soria (2008) suggest a different equation to account for flexible return to scale with a convex or concave shape on a log-log scale.

We want to test models including cumulative capacity, and three other explanatory variables defined in table 1. The models are explained in table 2. Note that R&D is not included because it is not significant.

Table 1 Variables used in the models

| Variable name | Expression |
|---|---|
| LogExperience | log (cumulative capacity) |
| LogSilicon | log (silicon price) |
| LogScale | log (plant size) |
| LogSilver | log (silver price) |

Table 2 Models tested

| | Model | Explanatory variables |
|---|---|---|
| 1 | OFEC | LogCum |
| 2 | &Silicon | LogCum & LogSilicon |
| 3 | &Silicon,Scale | LogCum, LogSilicon, & LogScale |
| 4 | &Silicon,Scale,Silver | LogCum, LogSilicon, LogScale, and LogSilver |

### 3.2. Methodology

The dataset consists in world average annual values of module price, cumulative capacity, plant size, silicon price, silver price, and R&D stock from 1976 to 2006.

To evaluate the predictive power, we perform a cross evaluation, measuring only the accuracy of the predictions made for values out of the sample used to estimate the model. As experience curves are time series, we evaluate the predictions made after the period used to estimate the regression parameters. Those estimations periods are ten years long[2], with the last year rolling from 1985 to 2005. Let T be the time between the estimation and the prediction expressed in years. Low values of T therefore correspond to short term forecast, and high values to long term forecast. For each T, the average accuracy of the prediction is measured by the Mean Absolute Percentage Error (MAPE) of all the predictions made T years ahead according to:

[2] We also perform the same test based on 15 and 20 years regressions showing results consistent with those presented thereafter.

$$MAPE(T) = \frac{100}{n_T} * \sum_{i=1}^{n_T} \left| \frac{\hat{y}_i - y_i}{y_i} \right|$$

Where $\hat{y}_i$ and $y_i$ are respectively the estimation and real value of the $n_T$ predictions

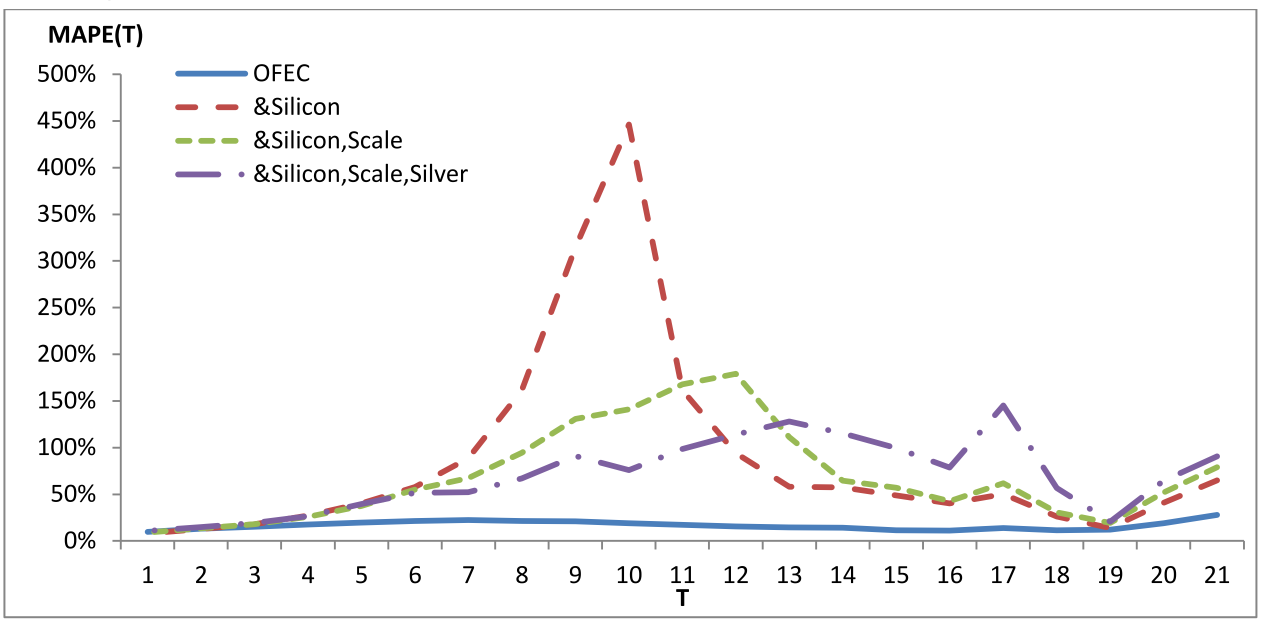
Since the last available year in the data is 2006, for the first estimation of the models from 1976 to 1985, we can evaluate the predictions from T=1 as far as T=21, but for the last estimation of the model, from 1996 to 2005, we can only evaluate the prediction for the following year (T=1). For each T, the MAPE is then the average of $n_T = (21 - T + 1)$ values, each one based on a different 10 years estimation period.

## 4. Results

### 4.1. Best models

Figure 1 shows a comparison of MAPE(T) for each model. On a short term, MFECs perform slightly better than the OFEC. But after 2 years, the OFEC performs better than any other model with additional explanatory variables. This result is strengthened by the fact that on the long term, MFECs also have the disadvantage of requiring more explanatory variables predictions. When the estimating period is longer than ten years, this result holds, although the OFEC performs better after 3 years with 15 years estimating periods, and 4 years with 20 years estimating periods, showing that MFECs require longer estimation periods.

Figure 1 Comparison of MAPE(T) for each model, MAPE(T) being the mean absolute percentage error according to the time T between the estimation and the prediction. Data source: Yu (2008)



Those results confirm that MFECs are better for short term predictions. But surprisingly, it suggests that an OFEC is better for long term predictions, even with accurate predictions of explanatory variables. The limitations of experience curves studied in section 4 suggest that this is due to multicollinearity. By regressing model 4 on the 1976/2006 period, we find a Variance Inflation Factor (VIF) of 28.1 for LogExperience, and 17.0 for LogScale, which is much higher than 10, the maximum acceptable VIF with a 0.1 tolerance. The VIF test shows multicollinearity for those two variables for any combination of explanatory variable, which confirms the multicollinearity for those two variables. Section 4.1. shows that since LogScale and LogR&D are highly correlated with LogExperience and that this correlation is constant over time, there omission in the models creates a bias of remaining parameters that would take their effect on cost into account. Consequently, excluding them wouldn't affect the predictive power of the model. We therefore claim that scale and R&D shouldn't be included in experience curves explaining PV modules cost.

The estimation of model 2 on 1976/2006 gives a VIF of 3.1 for LogSilicon, suggesting that despite its high correlation with LogExperience, this doesn't lead to a multicollinearity issue. We therefore chose to reject models 3 and 4 to keep only silicon price as possible additional variable.

## 4.2. Selection of the best estimating period

The previous evaluation is based on average values of several regressions estimated on different periods. We now go further by taking a look at the influence of the period used the estimate the models. Since the estimating periods might also include data from the last year available (2006), a cross evaluation study as before is not possible to have a quantitative criterion. Therefore, we base our choice on the value of $R^2$. If it was not a good criterion to choose which model to use because it can only increase with the addition of new explanatory variable, it allows discriminating the estimation periods.

### Model 1

Concerning the OFEC, the main issue is the bias of the experience parameter caused by the omission of silicon price. The impressive rise of silicon price starting in 2005 because of the silicon shortage can be considered as an unusual event which introduces a too important downward bias of the experience parameter. This suggests that the OFEC should be estimated before this period. On any period that has been tested, the period 1976/2004 indeed coincides with the highest $R^2$ (0.989) and lowest standard error of the parameters. The model A is then defined as:

**A: OFEC estimated from 1976 to 2004**

Table 3 Result of the OFEC regression from 1976 to 2004

| | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. Interval] | |
|---|---|---|---|---|---|---|
| LogExperience | -0.3238485 | 0.0066287 | -48.86 | 0 | -0.3374493 | -0.3102476 |
| Constant | 3.803175 | 0.0351982 | 108.05 | 0 | 3.730954 | 3.875396 |

Note that the LogExperience coefficient corresponds to a learning rate of 20.1% and a 95% confidence interval of 19.3%-20.9%. This is in line with the average learning rate found in the literature for experience curves based on the same data from Strategies Unlimited (20.8), although in the lower range.

### Model 2

Concerning the MFEC with silicon price, the main issue is the important correlation between silicon price and cumulative capacity in the first twenty years. In the paper, we show that the correlation is very strong for old data, while silicon price and cumulative capacity are not correlated at the end of the period. This suggests that Silicon price should not be used as additional explanatory variable only if the estimation is done on recent data.

For this model, the highest $R^2$ (0.992) and the lowest standard error of the parameters indeed corresponds to the 1990/2006 period. Compared to this model, the addition of Scale or/and LogSilver is not significant at 5%, which confirm that they should not be used in the model. 2006 correspond to the last available data, but estimation with more recent data might improve the quality of the model. The model B is then defined as:

**B: A MFEC with Silicon price as additional variable estimated from 1990 to 2006**

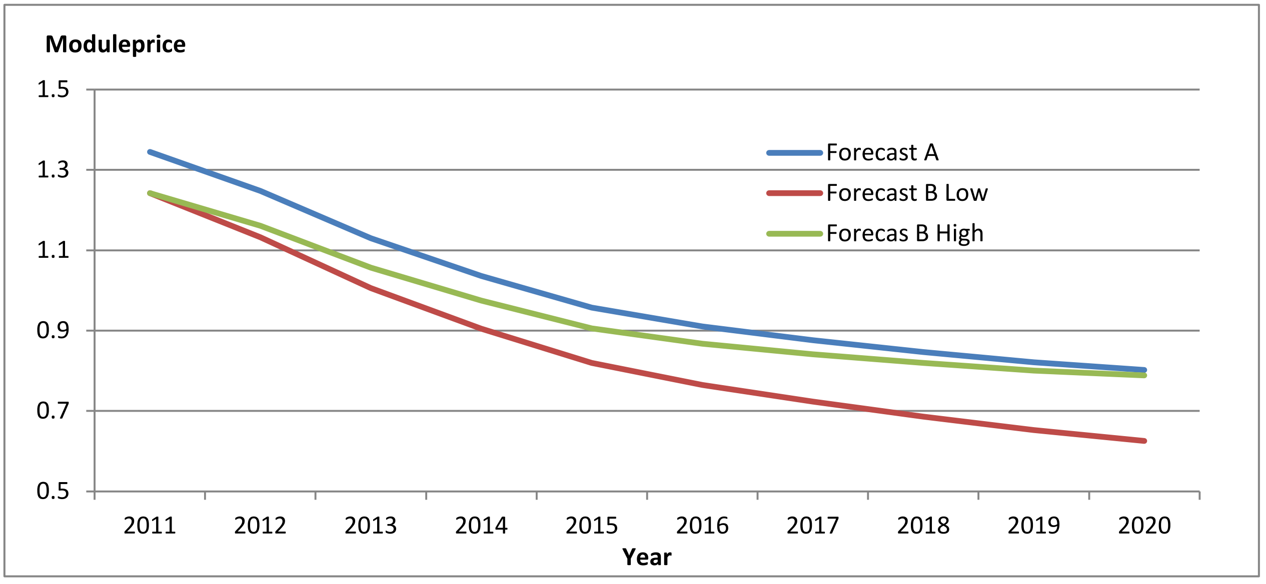
Table 4 Result of the regression with LocCum and LogSilicon as explanatory variables from 1990to 2006

| | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. Interval] | |
|---|---|---|---|---|---|---|
| LogExperience | -0.3330933 | 0.0082307 | -40.47 | 0 | -0.3507464 | -0.3154402 |
| LogSilicon | 0.3341498 | 0.0228515 | 14.62 | 0 | 0.2851383 | 0.3831613 |
| Constant | 2.776797 | 0.0829261 | 33.49 | 0 | 2.598938 | 2.954656 |

## 4.3. Scenarios for 2020

Based on model A and B, we can build prediction of module price evolution until 2020. For this purpose, we need prediction of the explanatory variables. The cumulative capacity prediction comes from EPIA (2011) and consist in a steady grow to 34.5 GW of cumulative installed capacity in 2020. Note that the IEA (2010) predicts a slower growth to 210 GW in 2020, but 2010 values already show an important underestimation of 13 GW (27 GW instead of 40). We build two scenarios of silicon price evolution until 2020. Both scenarios take into account the historic silicon price from 2007 to 2011. The low scenario considers a linear silicon price decrease from 30 $/kg in 2011 to 20 $/kg in 2020, which correspond to the lowest short term production costs prevision in 2011[3], the cost decrease being driven by scale increase, lower electricity cost, and technological improvement. The high scenario considers a linear silicon price increase from 30 $/kg in 2011 to 40 $/kg in 2020 which correspond to the highest predictions found in market forecast[4]. Figure 2 shows the estimations corresponding to the three models. B Low correspond to the model B with the low estimation of silicon price evolution, and model B High the high estimation.

Figure 2 Forecast until 2020 with the model A (OFEC) and model B (MFEC with silicon price) with two scenarios of silicon price decrease (source: Author)




Note that this prediction is consistent with short term predictions made by IHS iSuppli[5] that "from the USD$1.30 seen for the modules today (i.e. 2011), costs per watt will drop to $0.99 by the second quarter of 2012, $0.88 per watt by the second quarter of 2013, and $0.79 per watt by the second quarter of 2014". The learning rate of 20.1% used in model A, which gives predictions already in the higher range of those given by model B, is quite higher than 18%, the

[3] Source: Sun & Wind Energy, 2011

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

[5] Source: http://www.pv-magazine.com/news/details/beitrag/ihs-isuppli--c-si-module-costs-to-fall-below-usd1-per-watt-by-2012_100003392/

one used by the IEA (2010) for its predictions, meaning that it implies faster cost decrease. Added to the fact that the IEA's predictions are based on a lower development of the PV industry, this suggests that PV module price and therefore PV electricity will decrease faster than the IEA(2010) predicted.

As aforementioned, modules lifetime and reliability also have to be taken into account if PV electricity cost should be forecasted.

## 5. Conclusions

A survey of experience curves applied to photovoltaic (PV) modules on a global scale shows that most models so far use cumulative production, as a proxy for experience, as only explanatory variable. Only three studies include additional ones such as R&D, silicon price, or scale.

We compare the predictive power of the models with a cross evaluation. This methodology measure the accuracy of predictions out of the sample used to for the model estimation, therefore really measuring future predictions accuracy.  It is based on a dataset of annual world average values of module price, silicon price, plant size, and R&D knowledge stock. Contrary to what is suggested in the literature, the addition of explanatory variables doesn't improve the accuracy of the predictions.

A survey of the limitations of experience curves and econometric considerations allow us to explain this poor performance of the addition of explanatory variables by their important correlation with cumulative production, leading to multicollinearity. If scale and R&D cannot be used as additional explanatory variables because of this multicollinearity issue, we show that their omission doesn't affect the predictive power of the model since their effect is taken into account in the corresponding omitted variable bias. However, the correlation of silicon price with cumulative production is not constant, and becomes much less important after 1998. Therefore, this variable can be used in the model. It is quite important, since as silicon price has not a stable correlation with cumulative production, if it is excluded from the model, the corresponding omitted variable bias might affect the predictive power of the model. This is especially important for periods when silicon price takes "abnormal" values, such as during the silicon shortage from 2005 to 2009. Therefore, those values shouldn't be used to estimate a model for which silicon price is excluded.

Those insights allow us to recommend the utilisation of two models. The first one explains module cost only by cumulative production, and should be estimated before 2005 to avoid the silicon shortage. The second one includes silicon price as additional explanatory variable, and should be estimated after 1989 to avoid the important correlation of silicon price and cumulative production in old data.

Based on those two models, predictions of cumulative capacity by IEA (2010), and two scenarios of silicon price evolution until 2020 according to the most optimistic and pessimistic prediction of the market, we are able to predict the evolution of module price until 2020. The first model gives an average world module price of 0.8 $/Wp in 2020, while the second model is more optimistic, with 0.79 $/Wp in the worst case concerning silicon price, and 0.63$/Wp in the optimistic case. This shows that module cost evolution is quite dependent on the solar grade silicon market.

Of course those models can still be improved, and in particular, market effects such as market power, overproduction, or incentive policies should be controlled since they influence price independently of cost. Moreover, it should be kept in mind that those predictions don't take module quality into account, which has a great influence on PV electricity price through operation & maintenance cost or lifetime.

Note that we focused on the predictive power of the model, meaning that biased parameters are not considered as an issue as long it doesn't affect the accuracy of the predictions. However, although it might lower the predictive power, MFECs including more parameters bring a more precise analysis of the cost reduction process which can be helpful to design technology policies. Indeed, a technology policy focusing only on market development based on the experience curve with cumulative production as single explanatory variable might fail as other cost drivers such as R&D, scale, or input price wouldn't be taken into account.

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