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Abstract

Preferential feed-in tariffs (FITs) for solar generated electricity increases the demand for solar photovoltaic systems. They can thus induce price to increase, creating the potential for PV systems producers to collect rents. This paper analyses the interactions between feed-in tariffs, silicon prices and module prices, using weekly price data and FIT values in Germany, Italy, Spain, and France from January 2005 to May 2012. Relying methodologically on the Granger causality tests applied to vector autoregressive models, we show that since the end of the period of silicon shortage in 2009, module price variations cause changes in FITs, and not the reverse. This is good news as it suggests that the regulators have been able to prevent FITs to inflate module prices.

Key words: solar photovoltaic energy, feed-in tariffs, photovoltaic panel price

JEL codes: Q40, Q48

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1 Introduction

Preferential feed-in tariffs (FITs, hereafter) for solar generated electricity are the most common policy tools to stimulate the installation of solar photovoltaic (PV) generation capacities, particularly in Europe and Japan, but also in a growing number of emerging economies such as China and India[2]. This mechanism works by setting guaranteed prices at which grid operators is obliged to buy electricity from solar energy sources. Solar PV generated power is offered a higher price relative to other sources, reflecting higher costs. The mark-up can be substantial, even compared with other renewable energy sources like wind. For example, the FIT in Germany for rooftop mounted PV installations was about 24 €-ct/kWh in 2012, compared to less than 9 €-ct for onshore wind. This price premium is financed by the consumers' electricity bill.

A direct consequence of FITs is to stimulate the demand for PV systems and services. The economic law of supply and demand then predict that this will increase prices in these upstream markets, at least in the short-run. The price impacts are more complicated in the long-run because increased installation capacity can generate learning-by-doing effects and lead to cost reductions and hence lower prices. In the absence of fierce competition, FITs can then generate rents for PV systems producers and/or for the companies installing those systems. Obviously, the regulators in charge of setting the level of the tariffs seek to avoid such windfall profits by keeping FITs as close as possible to the cost of solar-generated

[2] A notable exception is the US in which 29 states have opted instead for the use of Renewable Portfolio Standards (RPS). RPS are mandates requiring each utility to have a minimum percentage of power that is sold or produced by renewable energy sources. That is, the PRS is a quantity instrument in contrast to the FIT which is a price instrument.

electricity, but this is not an easy task as they are not perfectly informed about production and installation costs.

This paper seeks to contribute towards understanding the impact of FITs on the PV price dynamics. We focus on the interactions between the FITs and two upstream markets: the market of PV panels and the market of polysilicon. Using time series of FITs, panel and polysilicon prices, our main aim is to test whether FITs influence panel prices or vice versa. The latter would imply the regulators adjust the level of FITs in order to reduce rents. The analysis takes into account the role of polysilicon price, the main material input for panels production – previous analysis on the period of polysilicon shortage before 2009 showed that its price significantly influences the panel price, and consequently on the PV experience curves (de la Tour et al., 2013).

The panel data used for this analysis consists of weekly polysilicon and module spot price, and FITs values in Germany, Italy, France and Spain from January 2005 to May 2012. To focus on market effects, we control for underlying long-term cost drivers, as measured by the experience effect. Methodologically, we use vector autoregressive variable (VAR) models and Granger causality tests to find the direction of the causality between the variables. We also study variations of module price around a FIT decrease with polynomial growth models.

Evidence on how FITs influence panel price is critical information for policy makers for several reasons. To begin with, the problem is of significant economic importance as panel prices represent about forty percent of the overall cost of PV electricity generation. The fact that FITs potentially induce a transfer from the electricity consumers who finance the FITs to panel producers becomes extremely sensitive in several industrialized countries as the bulk of world PV panels production is located in China. High rents can also induce market overheating which is costly and often followed by drastic production cuts, which harm the industry's long-term development as illustrated by the French or Spanish cases. Last, the potential increase of panel prices reduces the effectiveness of FITs as it increases the overall cost of PV systems.

Panel prices reflect production costs, plus margin. Cost are driven by technical factors, such as scale effect, R&D, learning-by-doing brought by the accumulation of experience. In contrast, the profit margin component - the difference between price and cost - are more driven by market based elements, such as competition, demand and supply balance and strategic behaviours. A substantial amount of literature focuses on the analysis and prediction of the cost of solar PV modules and systems using several methodologies: econometric estimation of learning curves (Yu et al., 2011; Poponi, 2003), expert elicitation surveys (Bosetti et al., 2012), and engineering studies (Nemet, 2006; Branker et al., 2011).

To the best of our knowledge, there are no academic work to date on pricing issues, and more specifically on the interactions between FITs and panel prices. These market effects issues are, however, often mentioned in the grey literature. Hayward and Graham (2011) suggest that second to the experience effect, market forces such as demand/supply imbalance or input price are responsible for recent deviation in module price from the historical trend.

This paper provides descriptive statistics which show that the evolutions of FITs and module price are strongly correlated. Moreover, the econometric analysis shows that since 2009, the direction of causality is from panel price to FITs and not the reverse. This result suggests that regulators were able to adjust tariffs levels according to the module price, thereby limiting the rents collected by panel manufacturers. This result is in line with the prevailing fierce competition observed in the module manufacturing market which has helped bridge the gap between cost and price. We also examine the very short-term effects of changes in FIT levels, and show that module prices tend to increase before FITs decrease, indicating that firms' anticipate policy changes and this influences their pricing strategies. However, this effect is temporary.

The remaining of the paper is structured as follows. Section two introduces the analytical framework and the hypothesis that are tested later on. The dataset is presented in Section 3 together with a first correlation analysis. Section 4 aims at finding the direction of the causality to test the hypotheses set out by the analytical framework. In Section 5, we analyse the influence of past and future FIT changes on module prices using polynomial growth models. Section 6 concludes.

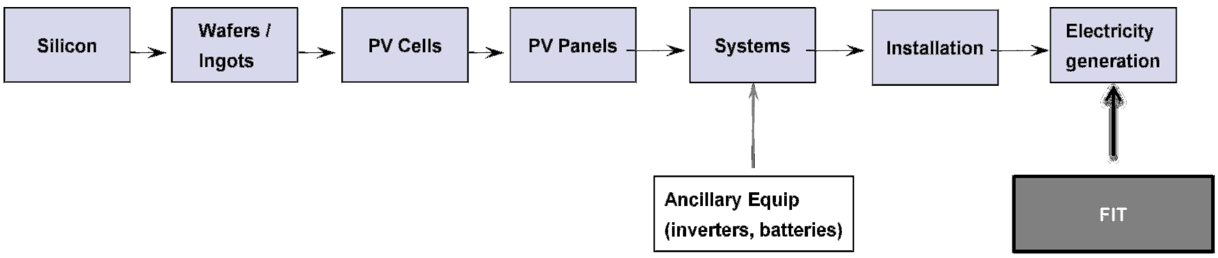
2 Background and tested assumptions

Before introducing a simple framework used to formulate hypothesis about the influence of FITs and silicon price on module price, it is worth describing briefly the crystalline PV production chain. Panel production from silicon involves several steps. The silicon is crystallised, forming ingots which are sliced into wafers. The wafers are processes and assembled by pairs into cells, which are soldered and encapsulated to build modules. Then the deployment of the PV system requires combining the modules with complementary equipment (such as batteries and inverters) into integrated systems which, once installed, can generate power. In 2006, modules on average accounted for 40% of the cost of installed PV systems globally.

The upstream production of polysilicon is a key step in the PV chain, given silicon is the main material input and accounts for 20% of the module costs. This stage also accounts for the largest share of the energy use in PV production. Other material inputs – glass, aluminium and silver - account for a small part of the manufacturing cost and/or have stable prices. Polysilicon is a commodity: Once silicon exceeds the minimum purity level of 999.999%, this leaves little room for product differentiation. Firms instead compete on price. The intensity of competition is, however, strongly influenced by production capacity, which is constrained since it takes two years to build a production plant. To illustrate this point, silicon shortage gave considerable market power to silicon producers during this pre-2009 period, leading to a dramatic price increase. Since the price peak, overcapacity has prevailed and prices declined as a consequence. We come back on the evolution of the silicon market below.

To a large extent, crystalline PV panels are also commodities, but its supply is capacity constrained to a lesser extent. Rather, supply is a function of the experience effect which steadily reduces cost through accumulation of experience. The price of silicon is also a potential driver; this hypothesis will be tested below.

Figure 1: Crystalline photovoltaic production chain



Source: de la Tour et al. (2011)

We formulate four assumptions – represented in Figure 2 - which will be tested in the rest of the paper:

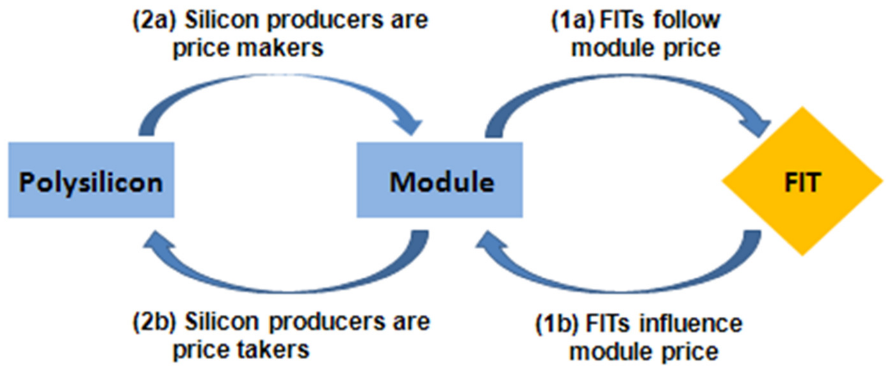
Hypothesis 1a: FITs follow module price, reducing rents in the downstream segments of the industry, i.e. PV systems installation and electricity production.

Hypothesis 1b: FITs influence module price, a higher FIT leading to increasing module prices and creating rents in the cell and module production segments. The causality is the reverse of Hypothesis 1a.

Hypothesis 2a: Silicon producers are price setters. They can pass through silicon price increase to module prices. This implies that silicon prices should be used as an exogenous variable in models predicting module price.

Hypothesis 2b: Silicon producers are price takers. Since module production is the main market for silicon (87% in 2011, SolarBuzz 2012), a module price variation changes the demand for silicon, thus impacting its price.

Figure 2: Our four hypotheses



3 Descriptive statistics

The hypotheses formulated in the preceding section are tested with a dataset of weekly silicon and module spot prices from PV Insight[3], and FITs values in Germany, Italy, France, and Spain (various sources, listed in Annex 1). The time series start in January 2005 and end in May 2012.

As Table 1 indicates, silicon and module price have been very unstable during the period considered, with a standard deviation of 75% of the mean for silicon price, and 38% for module price. This is illustrated by Figure 3 representing silicon and module price evolutions during our sample period. Silicon price increased markedly from 56 \$/kg in 2005 to 396 \$/kg in 2008. This corresponds to a period of global silicon shortage from 2005 to 2009. Meanwhile, module prices also increased from 2.55 \$/Wp in 2005 to 3.56 \$/Wp in 2008.

[3] http://pvinsights.com/

From July 2009 on, prices are much more stable, with silicon prices returning to January 2005 levels, indicating the end of the silicon shortage.

Silicon and module price are highly synchronised (the correlation coefficient is 0.91). At the same time, the rate of price increase is considerably lower for modules (40%) compared to silicon (607%). Two facts explain this observation: First, silicon price represents only 20% of a module's total cost[4]. Second, silicon is sold by and large through long-term contracts (about 80%, Photon Consulting 2012), thus the average purchase price did not rise in the same proportions as the spot price (143%, from 51$/kg to 124$/kg , Photon Consulting 2012).

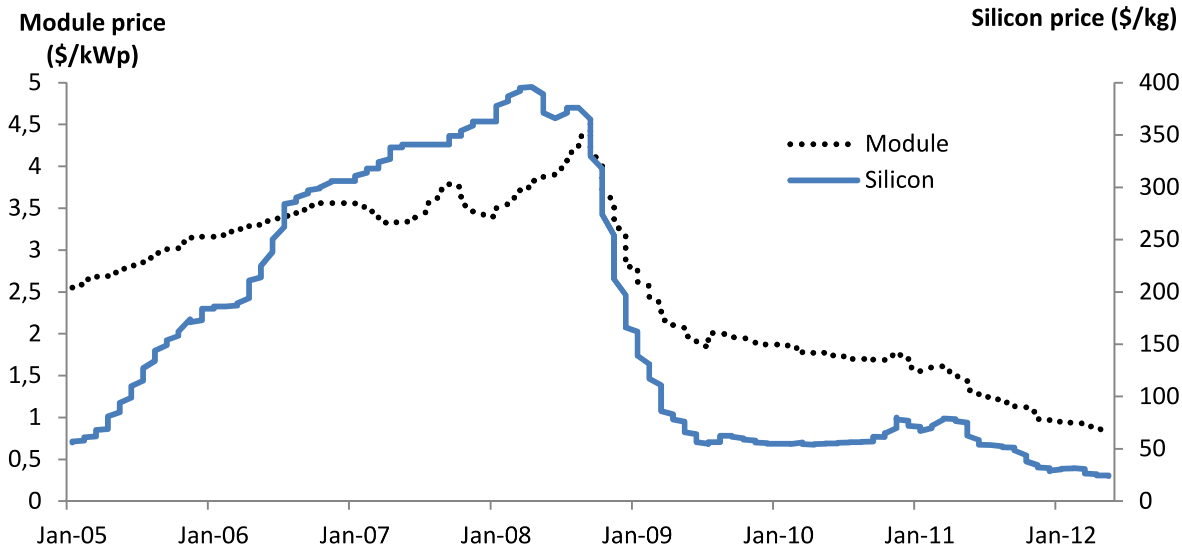
The high correlation between silicon and module price, however, does not provide indication of the direction of the causality between the two variables; that is, which of the two hypotheses - 2a and 2b - holds true.

Table 1 Summary statistics of module and silicon price data (Data source: PV Insight)

Variable	Obs	Mean	Std. Dev.	Min	Max
silicon	387	168	127	24.1	396
module	387	2.57	0.98	0.84	4.60

[4] Source: Photon consulting annual report 2012, p. 154.

Figure 3 Silicon and PV modules spot price evolution from January 2005 to May 2012



Turning next to feed-in tariffs, we collected weekly values of FITs in Germany, Italy, Spain, and France from January 2005 to May 2012. Other countries are not considered because they implemented alternative PV technology development policies (RPS, investment subsidies, etc.) such as in Japan or the US, or they do not account for a significant share of the global market. The four countries included in the study covers more than 60% of the global market over the sample period.

Among the four countries studied, different tariffs are set for different types of PV sytems (ground based, commercial, residential, etc.). We therefore calculate the average value weighted by the market share of each type in any given period. On the period considered, there have been 11 changes to FIT levels in Germany, 14 in Italy, 6 in Spain, and 9 in France.

Figure 4 shows the evolution of the average FIT for Germany, Italy, France, and Spain. It indicates that the German and Italian FITs have been decreasing steadily, while more chaotic variation was observed in the Spanish and French markets. Table 3 shows the correlation of module price with the average FIT in the four countries studied. It indicates that the German and Italian FITs are not only more stable than the Spanish and French ones, but also more correlated to module prices. But once again, this gives no information about the direction of the causality, which is investigated in next section.

Figure 4 Average FIT evolution in the main countries

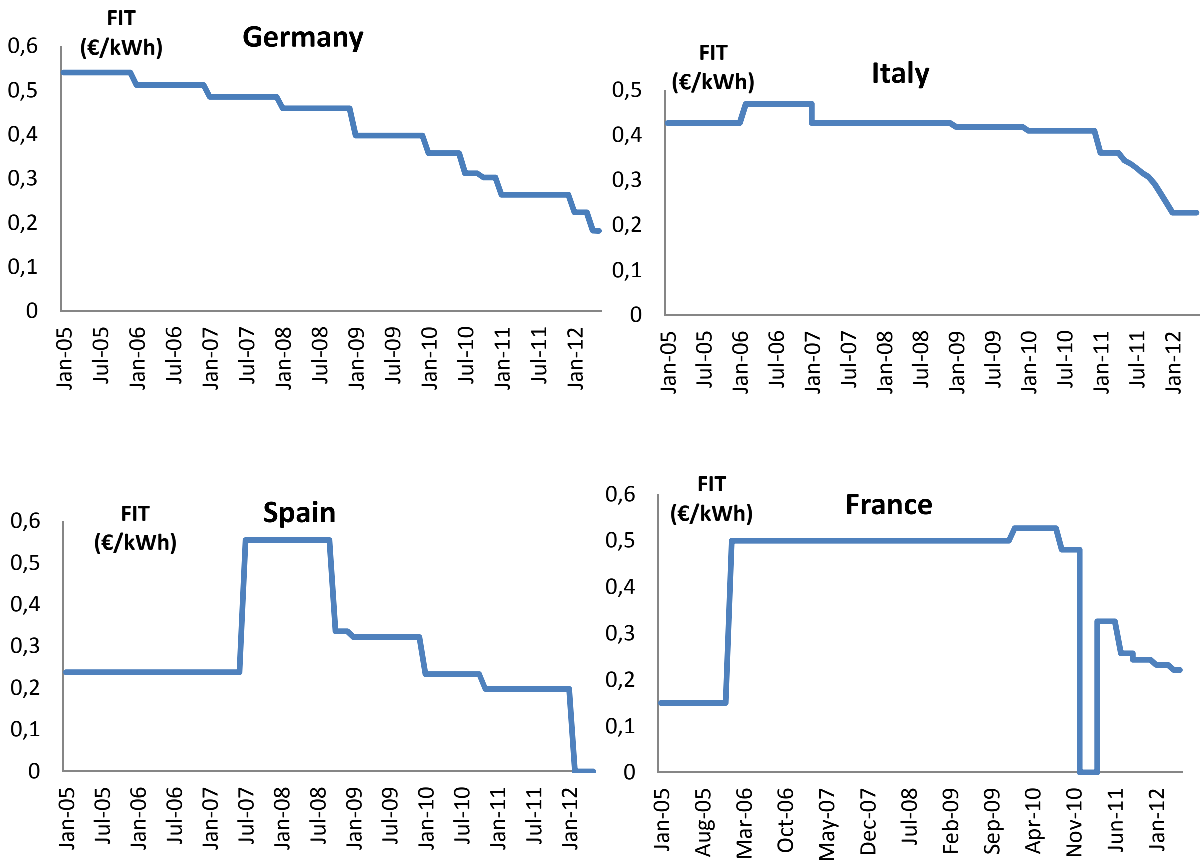


Table 2 Correlation table of module price and countries FITs

	German FIT	Italian FIT	Spanish FIT	French FIT
Module price	0.86	0.76	0.67	0.39

How does the evolution of panel prices compare to that of the FITs implemented in the various countries? The comparison is not straightforward as the two variables are not expressed in the same unit: FITs correspond to the price of a quantity of electricity (in \$/kWh), while module prices corresponds to the price of a production capacity (in \$/kWp[5]). To allow comparison, we convert the module price into the net present value of the electricity generated over its lifetime by a module of a standard capacity of 1kWp and sold at this FIT. The net present value of the electricity generated by the module in country *i* is given by the usual formula:

$$NPV_{i,t} = FIT_{i,t}\left(\sum_{a=1}^{T}\frac{PR * ASI_i}{(1+r)^{a-1}}\right) \quad (1)$$

where $FIT_{i,t}$ is the feed-in tariff in country *i* at time *t*. *T* is the lifetime of the PV system, *r* is the discount rate. The product $PR * ASI_i$ is the electricity produced each year in country *i* by the PV system, with PR, the Performance Ratio of the installation (the ratio of the actual and theoretically possible energy output) and, *ASI,* the Annual Solar Irradiation (the sum of the quantity of solar energy reaching the installation over a year) which is country-specific.

[5] Watt-peak (Wp) is a measure of the nominal power of a photovoltaic device under laboratory illumination conditions.

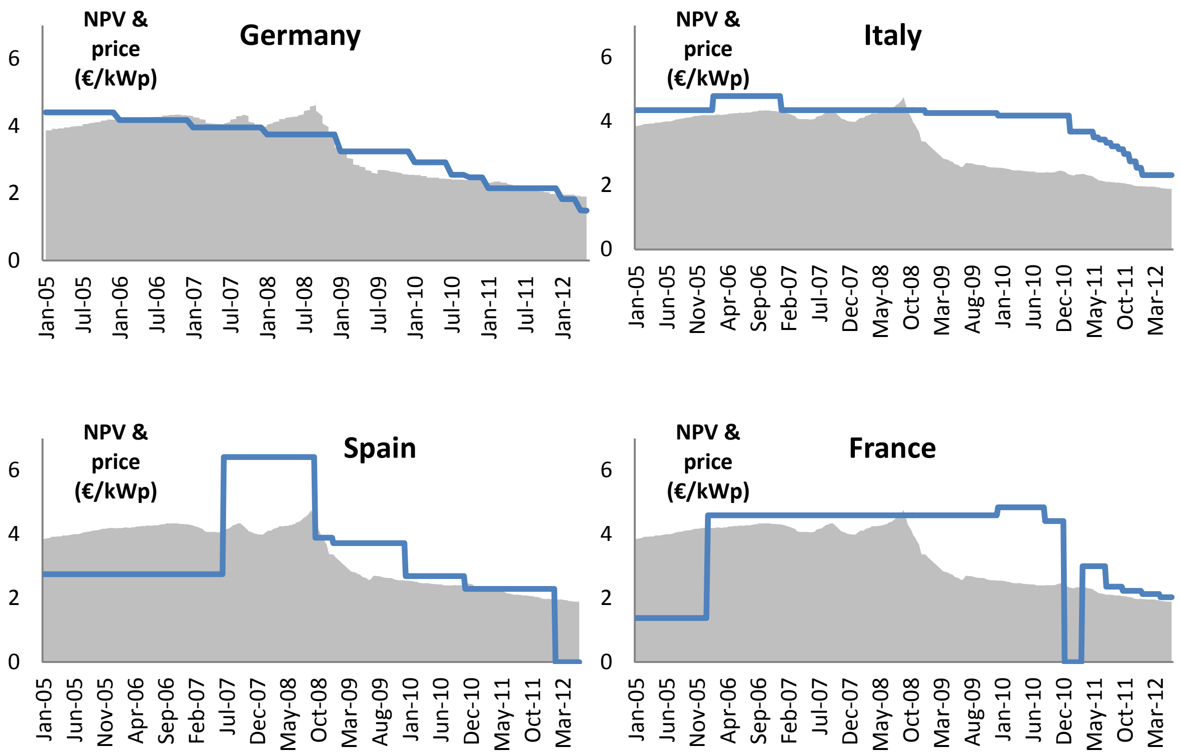
We take the following values for the different parameters: a discount rate of 10%, a lifetime of 25 years, and a performance ratio of 0.75. The ASI is assumed to be 1200 kWh/kWp/year for Germany, 1500 for Italy, 1700 for Spain, and 1350 for France[6].

The net present value of electricity given by Equation (1) needs to be compared to the price of the whole PV system, of which in 2011 the panel price accounted for around 40% (Photon Consulting, 2012). To obtain the price of a PV system, we add to the module price, the price of other components such as the inverter, wire and mounting system. Weekly values of the prices of other components are computed using the annual price trends obtained from Photon international (2012).

For each country, Figure 5 compares the cost of a PV system (the shaded area) with the net present values of the electricity produced by a PV system sold at the national FIT. It shows that the German FIT follows PV system price the most closely. In contrast, important divergences can be observed between the FIT and module price in 2007/2008 in Spain and in 2009/2010 in France, following the uncontrolled developments of the PV market and the subsequent sharp FIT cuts. The significant gap in 2010/2011 in Italy can also be explained by the fast market growth during this period, which multiplied by 13 in two years, from 720 MW in 2009 to 9300 MW in 2011 according to the EPIA (2012). Note that additional incentive policies such as tax rebates are not taken into account here but act to further increase the attractiveness of PV systems.

[6] Source : solarGIS website http://solargis.info/

Figure 5 Comparison of PV systems price (shaded area) with the value of the FIT corresponding to all the electricity produced by a PV system over its lifetime (line)



4 Econometric methodology

In this section, we further analyse the interdependencies by disentangling the causal relationships. We test the hypotheses represented in Figure 2: (1a) Do FITs follow module price closely? (1b) Do FITs cause module price by driving the demand? (2a) Are silicon producer price makers? Or (2b) price takers?

As we make no assumption about the direction of the causal relationships for now, all the variables are endogenous in an econometric sense. The only equations that can be estimated are then one variable written as a function of its own lagged values and the lagged values of all the other variables. Those equations make up a vector-autoregressive (VAR) model. Furthermore, "real" causality cannot be identified with econometric tools. Therefore we adopt the definition of Granger (Granger, 1969): x “granger causes” y if the prediction of the current value of y is enhanced by the knowledge of past values of x. In the following sections, as “causes” we mean “granger causes”. Granger developed a methodology based on VAR models to test for this causality. We use this test to identify causality among the variables.

As mentioned before, the module price is made of a cost and a margin. The former is influenced by long-term drivers, in particular learning-by-doing improvements that need to be controlled for, in order to focus on market effects. We do so by adopting the learning curve theory which predicts that learning-by-doing decreases price through the accumulation of experience measured by cumulative production, according to the following formula:

$$module_t = module_{t_0} * \left(\frac{cum\_prod_t}{cum\_prod_{t_0}}\right)^{-E} \qquad (2)$$

Here, $module_t$ is module price at time *t*. cum_prod_t is the cumulative PV module production at the same date[7]. t_o is an arbitrarily chosen reference date. E is the experience parameter, measuring the intensity of the learning-by-doing process. Equation (2) is usually estimated econometrically. In this paper, we use an experience parameter of 0.338, corresponding to a learning rate[8] of 20.1%, which has been estimated in the study by de la Tour et al. (2013) who used the same data.

[7] Since the learning effect is a slow process which cannot be affected to the production of a particular week or even month, we create a proxy for weekly cumulative production following the yearly production trend obtained from Photon Consulting (2012).

[8] A learning rate of 20.1 means that unit cost decreases by 20.1% for each doubling of cumulative production.

Using data on cumulative production[9], we are able to predict the value of $module_{t_0}$, which is the module price equivalent to $module_t$ if no learning would have happened since t_0. We denote $module_t^0$, the corresponding predicted value.

We also create a variable FIT, the average of countries' FITs, weighted by the size of the national electricity markets:

$$FIT_t = \sum_i FIT_{i,t} * elec_{i,t} \tag{3}$$

where $elec_{i,t}$ is the size of the electricity market of country *i* at time *t*.

Then we apply the VAR model to the first order derivative of the logarithm of module price, silicon price, and FIT with a lag equal to l. This gives:

$$D.Y_t \; = \; \sum_{j=1}^{l} \gamma_j \, D.Y_{t-j} + \mathrm{E}_{i,t} \tag{4}$$

In this equation, $D.Y_t$ is the vector of the first order derivatives of the three price variables which are logged: $\ln(module_t^0)$, $\ln(silicon_t)$, and $\ln(FIT_t)$. γ_j is the vector of parameters to be estimated and E_i is the vector of error terms, assumed to be independent and identically distributed.

The estimation is done by running a separate regression for each variable, regressing it on lags of itself and all other variables, using ordinary least squares (OLS). A Dickey-Fuller test for unit root shows that the time series are not stationary, even when a trend is allowed, but they are first-order stationary. This explains why we apply the VAR model to the first-order derivatives of the variables. A Clemonte-Montañés-Reyes test for unit root, allowing for one or two breaks in the time series, points out a break in the fourth week of September for

[9] Photon consulting annual reports

$\ln(silicon_t)$ (see Annex 2). We therefore run the regressions of the VAR models on two periods: before and after 24/09/2009. The first period corresponds to the silicon shortage, while the second period starts after this event. The optimal lags are found by maximizing the AIC information criterion; 2 weeks during the silicon shortage, and 3 weeks after.

5 Results

The model (4) is estimated during and after the silicon shortage. The regression coefficients are all significant at the standard significance levels. Tables 4 and 5 show the results of Granger causality tests applied to the estimations of the model during the silicon shortage between January 2005 and July 2009 (Table 4) and after the shortage (Table 5). The grey boxes correspond to the cases where the null hypothesis - that the excluded variable does not cause the dependant variable - is rejected at a 0.05 significance level.

Consider first, the causality between silicon and module price. There is a switch at the end of the silicon shortage period. During the silicon shortage period, silicon price causes module price (hypothesis 2b), while after the end of the shortage, the opposite holds (hypothesis 2a). These results are completely in line with economic theory which predict that, in commodity markets, producers have market power only in case of under capacity of production. The shift in market power from silicon producers to module manufacturers can also be due to the PV industry becoming a more and more important market for silicon, overtaking the semi-conductor industry since 2007 (SolarBuzz 2012).

Results on the causality between module price and FITs are more ambiguous. During the first period, the Granger test does not yield any conclusion regarding causal relationships, at least at the 5% or even the 10% significance level. After July 2009, FIT still does not cause module price, but the test indicates that silicon price causes FITs. As module price causes silicon price, we can conclude that the module price indirectly causes FITs (hypothesis 1a). This can be interpreted as a consequence of the fierce competition prevailing in the cell and module market, keeping prices close to production costs, preventing producers from collecting rent from attractive FITs.

Looking at Figure 4 helps understand why module price causes FITs after 2009 but not before. Before 2009, FITs were very stable, modified only once a year in Germany, and even less frequently in other countries. Their level was set well in advance, sometimes years ahead[10]. FITs were thus very rigid, explaining why they couldn't follow module price closely. After 2009, however, FITs became much more flexible with intra-year adjustments, sometimes unscheduled, to follow module price more closely. Moreover, volume responsive systems have been implemented including the FIT corridor in Germany in 2009 and in France in 2011, further enhancing the flexibility. The fact that FITs track module price more closely in the recent years should then be interpreted as a consequence of a modification of the FITs schemes.

Table 3 Granger causality test results for the period of the silicon shortage

Dependent variable	Excluded	chi2	df	Prob > chi2
$\ln(module_t^0)$	$\ln(silicon_t)$	22.48	2	0.000

[10] This was adapted to the steady and predictable price decrease triggered by the experience effect before the silicon shortage.

	$\ln(FIT_t)$	0.120	2	0.942
	ALL	22.76	4	0.000
$\ln(silicon_t)$	$\ln(module_t^0)$	1.373	2	0.503
	$\ln(FIT_t)$	0.078	2	0.962
	ALL	1.468	4	0.832
$\ln(FIT_t)$	$\ln(module_t^0)$	0.724	2	0.696
	$\ln(silicon_t)$	4.288	2	0.117
	ALL	7.046	4	0.133

Table 4 Granger causality test results for the period after the silicon shortage

Dependent variable	Excluded	chi2	df	Prob > chi2
$\ln(module_t^0)$	$\ln(silicon_t)$	3.090	3	0.378
	$\ln(FIT_t)$	2.722	3	0.436
	ALL	7.006	6	0.320
$\ln(silicon_t)$	$\ln(module_t^0)$	17.47	3	0.001
	$\ln(FIT_t)$	0.567	3	0.904
	ALL	18.69	6	0.005
$\ln(FIT_t)$	$\ln(module_t^0)$	1.518	3	0.678
	$\ln(silicon_t)$	19.73	3	0.000
	ALL	21.50	6	0.001

6 Anticipations of feed-in tariffs change

VAR models use past values as explanatory variables, while FITs are announced, and therefore anticipated, months or even years ahead. This section further investigates the FITs' effect on module price, by analysing the effect of *future* FIT changes on module price. Our approach examines the variation of module price before a FIT decrease (which occurred 24 times during the period considered). A simple theoretical reasoning suggests that firms would anticipate a decrease of FIT by purchasing more modules before the change to benefit from the higher FIT, which eventually increases price. Anecdotal evidence supports this assumption. For instance, the observation of monthly PV installation levels and the FIT evolution in Germany depicted in Figure 6 clearly indicates that peaks of installation, measured by the number of connections to the grid, arise in the months before the FIT decreases.

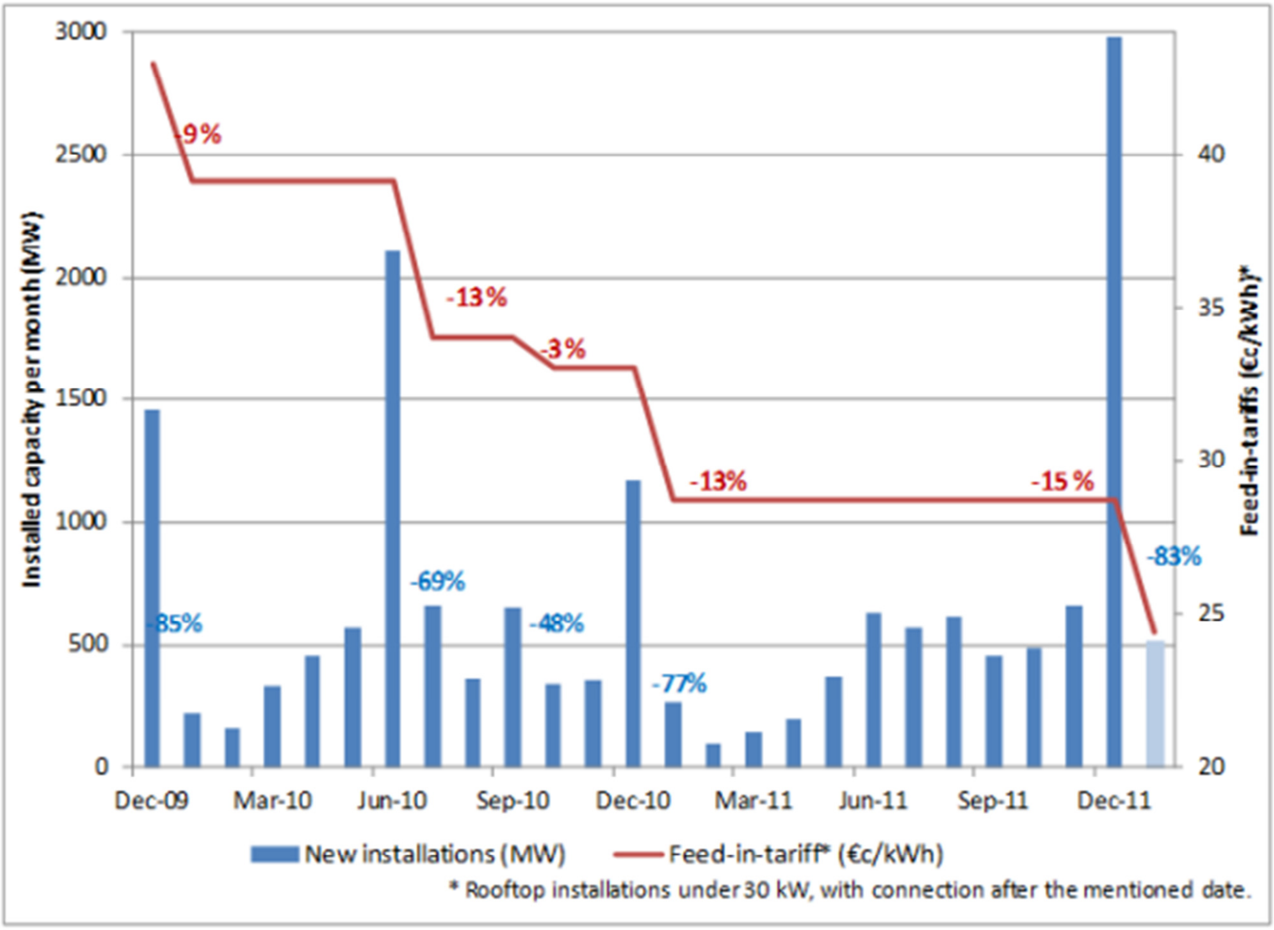
While Figure 6 describes the impact of anticipations on quantities, what about the impact on module prices? To answer this question, we build a difference-in-difference indicator to measure short-term price variations: the variable $deviation_t$ is the deviation of the first order derivative[11] of module price compared to a business as usual (BAU) scenario at date *t*:

$$deviation_t \equiv D.module_t - D.module_t^{BAU} \qquad (5)$$

If $deviation_t$ is positive, this indicates that the increase in module price in week *t* exceeds the BAU scenario prediction.

[11] We use its first-order derivative because, contrary to $module_t$, the derivative is stationary.

Figure 6 Impact of the feed-in tariff reductions on monthly capacity addition in Germany



Source: Enerdata, from German Ministry for Environment, SolarWirtshaft

We rely on results from Section 4.4 to calculate the BAU price. They say that module pricing obeys to different rules during and after the silicon shortage. During the silicon shortage, the price is driven by the silicon price. We thus assume the following relationship:

(6)

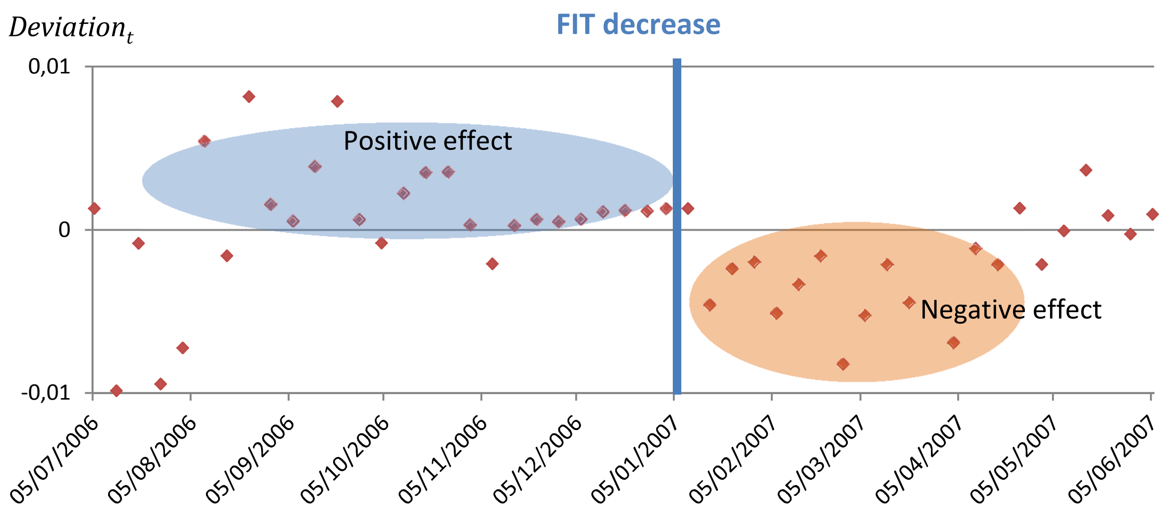
The length of the lag of silicon price used is two weeks as found optimal in Section 4.4. After the silicon shortage, the BAU price is assumed constant:

(7)

Regression results of (6) and (7) are presented in the Appendix.

Using the indicator , we indeed observe a positive effect during the few months before a FIT decrease, and a negative one afterwards. This is illustrated in Figure 7, showing the evolution of the variable over a 1 year-period around a FIT decrease which occurred simultaneously in Germany and Italy on January 1st 2007.

Figure 7: Deviation of module price compared to a business as usual scenario before and after a FIT decrease in January 2007.



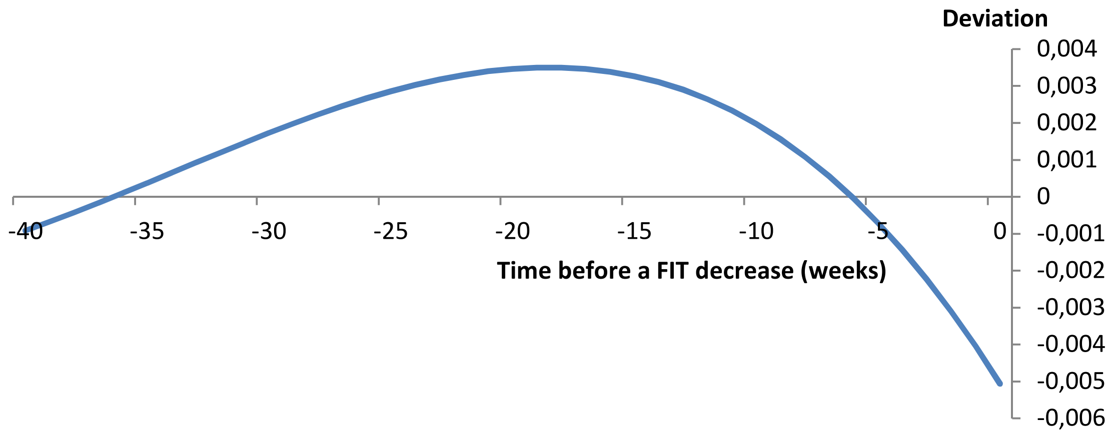
In order to gain further understanding of the dynamic effect of a FIT decrease on module prices, we now estimate a polynomial growth model. This explains the deviation of module price by a polynomial function of the time before the following FIT decrease. The regression equation is:

$$deviation_t = \sum_{x=1}^{3} b_x(before_t)^x + \epsilon_t \quad (8)$$

where $before_t$ is the number of weeks before the following FIT decrease. ϵ_t is the usual i.i.d error term. The observation of Figure 7 suggests that polynomial models should preferably be at least quadratic, or degree 3.

Regression results are given in Annex 4. We use them to predict the value of $deviation_t$ before a FIT decrease (Figure 8). Predictions cover a 40 weeks period. As expected, the graph shows a positive deviation before FIT decreases. However, the impact becomes negative 5 weeks before.

Figure 6 Simulation of the deviation of the first order derivate of module price from a business as usual scenario before a FIT decrease



These results are easy to interpret: In order to be able to connect the PV installation before the FIT decreases, firms installing PV systems need to buy the modules a few weeks before for small projects, or a few months for big installations. This boosts module demand during the months before the FIT cuts, and therefore increases the module price. A few weeks before the decreases, firms lose this incentive since there is not enough time to complete the installation and connect it to the grid before the FIT changes. This lowers the demand, decreasing the module price, which encourages firms to wait to benefit from this reduction, eventually decreasing price even more. Our results indicates that this happens five weeks before the decrease.

7 Conclusion

This paper aimed to analyse the influence of feed-in tariffs and silicon prices on module prices. We rely on a database of silicon and module weekly spot price, and FIT values in Germany, Italy, Spain, and France from January 2005 to May 2012. We find the direction of causality relations using Granger causality tests on vector-autoregressive (VAR) models.

Granger causality tests show that since the end of the period of silicon shortage in 2009, module price variations cause changes in FITs, and not vice versa. This is good news as it suggests that regulators have been able to prevent FITs to inflate module prices, limiting the creation of rents in the PV panel industry. This can be explained by the fierce competition prevailing on the module market, keeping module price close to production cost whatever the FITs level.

Nevertheless, polynomial growth models show FIT short-term effects on module price. In the months before the FIT decreases, the module price increases. The interpretation is straightforward: a higher demand triggered by market anticipation, accelerate installations before the FIT level decreases. This inflation is temporary, however.

The analysis also suggests that the silicon price was driving module price only during the silicon shortage, suggesting that silicon producers had market power. This is in line with the observation of production under capacity and a low contestability of the silicon market before 2009. After the end of the shortage period, they lost their market power and we find that module prices now drive silicon prices. This can be explained by an increasing competition with new players entering the market, including many Chinese corporations such as LDK Solar, which directed the situation from shortage to excess production.

This study shows that price formation in the PV industry is very complex, and difficult to predict. It follows that FIT mechanisms should be sufficiently flexible to avoid important gaps in PV electricity cost when price evolution has not been anticipated correctly. So far, flexibility has been allowed by several means: a) implementing unscheduled modifications, b) increasing the frequency of FITs change, and c) making changes dependent on previous PV installation through volume responsive mechanisms. Unscheduled FIT changes are certainly not a good solution since they increase the uncertainty in the PV industry. More frequent FIT changes allow a faster adaptation to module price. Moreover, a higher frequency implies lower size, reducing the magnitude of the price distortions around FIT changes. The volume responsive aspect enables fast responses to the market, and the transparent process gives visibility to investors.

Annex

A1 Sources for FIT value*s*

International Energy Agency (http://www.iea.org)

Solar Feed In Tariff website (http://www.solarfeedintariff.net)

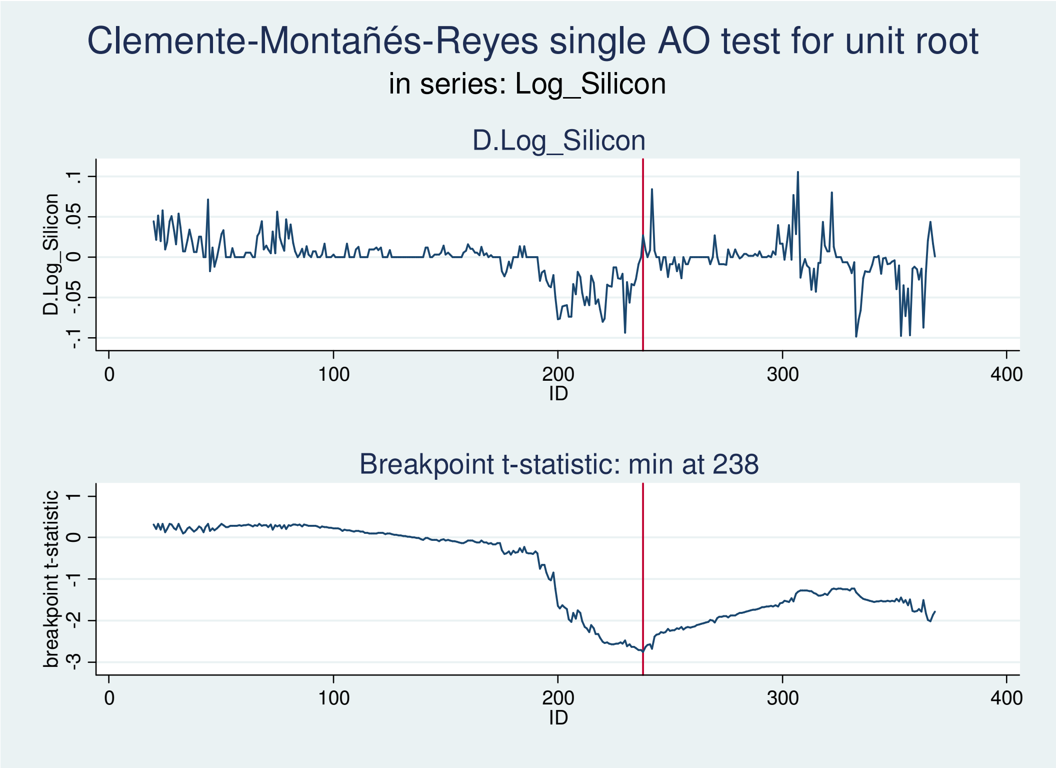
PV Magazine (http://www.pv-magazine.com/)

RES LEGAL website (http://www.res-legal.de/)

Solarenergie-Förderverein Deutschland

(http://www.sfv.de/druckver/lokal/mails/sj/verguetu.htm)

A2 Clemonte-Montañés-Reyes test for unit root applied to log (silicon price)



The 238th value of the time series correspond to 22/07/2009

A3 Regression results of the BAU model (Equations 6 and 7)

	Before	**After**
Dependent variable	$\text{D.}\ln(module_t\ )$	$\text{D.}\ln(module_t\ )$
$\text{LD.}\ln(silicon_t)$	0.2160*** (0.041)	-
$\text{L2D.}\ln(silicon_t)$	0.0935** (0.041)	-
Constant	0.0006 (0.001)	-0.0022** (0.001)
Observations	234	150
R-squared	0.3746	0.0000
Adj. R-squared	0.3692	0.0000

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Regression performed during the silicon shortage. L stands for the operator for Lag, F for Forward lag, and D for first order derivative.

A4 Regression results of the polynomial growth model (8)

Dependent variable	$deviation_t$
$before_t$	0.001057984*** (0.000)
$(before_t)^2$	-0.000039290*** (0.000)
$(before_t)^3$	0.000000386* (0.000)
Constant	-0.005062572*** (0.001)
Observations	380
R-squared	0.0651
Adj. R-squared	0.0576

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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