How do solar photovoltaic feed-in tariffs interact with solar panel and silicon prices? An empirical study

This version:7th July, 2014

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Abstract

Preferential feed-in tariffs (FITs) for solar generated electricity increase the demand for solar photovoltaic systems. This can thus induce equipment prices to increase, creating greater potential for PV systems producers to collect rents. There is however a possible countervailing force: public authorities in charge of setting FITs may seek to limit these rents by adjusting tariffs to a level as close as possible to the cost of solar-generated electricity. 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, 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 suggests that the regulators have been successful at preventing FITs from inflating module prices.

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

JEL codes: Q40, Q48

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1 Introduction

The preferential feed-in tariff (FITs, hereafter) scheme for solar generated electricity is the most common policy tool 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.[1] This mechanism works by setting a guaranteed price at which grid operators are 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 (Lang and Mutschler, 2012). 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 predicts that this will increase prices in the market for PV systems, at least in the short-run. In the absence of fierce competition, FITs can then generate rents for PV systems producers and/or for the companies installing those systems. This is problematic from the perspective of expansion of solar energy because higher PV system prices imply higher PV-generated electricity costs, thereby hindering the diffusion of this source of energy. This is also bad news from the perspective of consumers who ultimately pick up the bill.[2]

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

[2] 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.

There is however a possible countervailing force: public authorities in charge of setting the level of FITs may seek to avoid such windfall profits by adjusting FITs to a level as close as possible to the cost of solar-generated electricity. Doing so limits the burden on electricity consumers and bridges the gap between the prices of conventional and PV-generated electricity. Yet getting the FIT level correct is difficult for regulators due to information asymmetry. Specifically, they are imperfectly informed about both production and installation costs.

This paper seeks to contribute towards understanding the interactions between the FITs and the PV price dynamics in two upstream markets: the market of PV panels and the market of polysilicon. Using time series data on FITs, panel prices and polysilicon prices, our main aim is to test whether FITs influence panel and silicon prices or vice versa. If the direction of causality goes from the FITs to PV market prices, this means that market forces dominate the regulators who seek to reduce rents. If the direction is the reverse, this suggests that regulators are successful at adjusting the level of FITs to price evolution and thereby limiting rents in the upstream PV value chain. Our main focus is on the market for PV modules, but the analysis takes the role of polysilicon price into account because previous analysis on the period of polysilicon shortage before 2009 showed that as the main material input for panels production, its price significantly influences panel prices (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 the Granger causality test to find the direction of the causality between the variables. This approach involves using a vector autoregressive

(VAR) framework to test whether past values of one variable can provide statistical information about the current and future values of another variable. We also use polynomial growth models to study the variation of module prices when a decline in the level FITs is observed. These methods allow investigating causalities whereas other strategies tend to identify only correlations. The main limit is that we only look at short-term price effects. In the long run, these short-term effects arguably influence production costs of PV systems, an impact we do not measure in the paper. Another weakness is that we cannot estimate the size of the effects. For instance, assume that a 10% increase of module prices causes an increase in the level of FITs. We are able to establish the validity of this hypothesis, but not the size of the resulting FIT increase. Thus the size of potential rents cannot be quantified. In this example, identifying the causality only says that regulators react in the right direction, but not whether the response is sufficiently strong to prevent rents to rise.

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 have been adjusting tariff levels according to the module price hence limiting the rents collected by panel manufacturers. During the period before 2009, however, no significant effects are found. We discuss below how changes in FIT regime around 2009 could explain this observation. 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.

Providing evidence on how FITs influence panel price is useful for policy makers for several reasons. First, the potential cost of getting FITs wrong (i.e. potential windfall profits) is high, with panel prices typically representing forty percent of the overall cost of PV electricity generation. Second, getting FITs wrong is also politically problematic in many countries because it can imply transferring rents from domestic electricity consumers to foreign panel producers 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. Lastly, the potential increase of panel prices reduces the effectiveness of FITs as it increases the overall cost of PV systems.[3]

An empirical literature has developed on the role and impacts of FITs. Some studies have estimated the impact of FITs on the deployment of solar PV capacities, electricity costs, employment, or innovation (e.g. Leepa and Unfried, 2013, Frondel et al., 2010; Hoppmann et al., 2013). To the best of our knowledge, there are no academic works to date on the interactions between FITs and PV system prices, other than the contribution by Prest (2012) who investigates from a legal point of view how FITs should be adjusted to changes in the markets for PV systems.

Panel and silicon prices reflect the production costs plus profit margins. Costs are driven by technology-specific 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 - is driven by market conditions 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; de la Tour et al., 2013); expert elicitation surveys (Bosetti et al., 2012); and engineering studies (Nemet, 2006;

[3] These are undeniably less hot issues in the short term as PV panel producers are said to sell at a loss for a couple of years because of production overcapacity. But overcapacity cannot but disappear in the future.

Branker et al., 2011). The analysis of pricing issues is far less developed although it is worth mentioning a recent paper by Candelise et al. (2013) who look at both cost and price issues. Contributions in the grey literature also stresses the importance of market forces such as demand/supply imbalance or input price are responsible for recent deviation in module price from the historical trend (Hayward and Graham , Solarbuzz, 2012). None of these studies considers the role of FITs.

The remaining of this paper is structured as follows. Section 2 introduces the analytical framework and the hypotheses to be tested later on. The dataset and preliminary diagnostics are presented in Section 3. Section 4 explores the direction of the causality and tests the hypotheses set out by the analytical framework. Section 5 analyses the influence of past and future FIT changes on module prices using polynomial growth models. Section 6 concludes the paper.

2 Background and tested assumptions

Before introducing a simple framework used to formulate hypotheses about the influence of FITs on silicon price on module price, it is worth describing briefly the crystalline PV production chain. Panel production from silicon involves several steps (see Figure 1, adapted from de la Tour et al., 2011). The silicon is crystallised, forming ingots which are sliced into wafers. The wafers are processed and assembled by pairs into cells, which are soldered and encapsulated to build modules. The deployment of the PV system then requires combining the modules with complementary equipment (such as batteries and inverters) into integrated systems which, once installed, can generate power. The PV module cost is typically between a third and a half of the total capital cost of a PV system (IRENA, 2012).

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 (IRENA, 2012). 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.

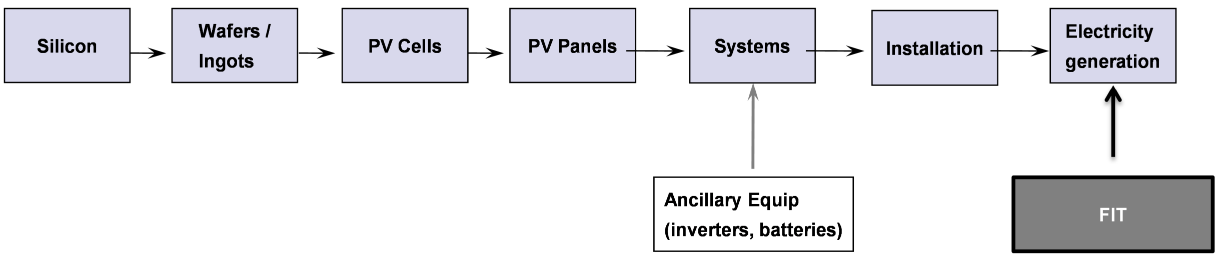
Polysilicon is a commodity, that is, a good which is supplied without qualitative differentiation across the market. Once silicon exceeds the minimum purity level of 99.999%, this leaves little room for product differentiation. In commodity markets, it is well-known from the industrial organization literature that the intensity of competition is strongly influenced by production capacity and that this gives rise to price instability (for instance, see Tirole, 1988). When production capacity is insufficient to cover demand, producers enjoy considerable market power to increase prices above the marginal production cost. Undersupply can persist since it typically takes two years to build a silicon production plant.[4] This occurred before 2009, leading to a dramatic price increase. Since the price peak, overcapacity has prevailed and prices declined as a consequence (Candelise et al., 2013). We will come back to the evolution of the silicon market below.

To a large extent, crystalline PV panels are also commodities with little product differentiation. In the current context of oversupply driven by over-optimistic expectations about the growth of PV markets, economic theory also predicts very low prices (Tirole, 1988). In fact what we observe today are very low prices, probably below the long-term marginal production costs of many manufacturers. This has led major panel producer such as Q-Cells or SunTech Power to bankruptcy in 2012 and 2013 (Sweet, 2013; Hoium, 2013).

[4] In contrast, facilities manufacturing cells and modules can operate in less than a year (de la Tour et al., 2011).

Supply is also a function of the learning effect which steadily reduces costs through the accumulation of experience (Candelise et al., 2013). The price of silicon is another potential driver of PV panel prices; this hypothesis will be tested below.

Figure 1: Crystalline photovoltaic production chain



Source: de la Tour et al. (2011)

In line with the analysis developed in the introduction, we now formulate a set of assumptions which will be tested in the rest of the paper. The first assumption is based on the economic law of supply and demand which predicts that increasing the level of FITs raise module prices, thereby creating rents in the cell and module production segments. Hence,

Hypothesis 1a: FITs positively influence module prices.

However, the direction of causality can also reverse in situations where the regulator reacts to the market price and lowers FITs, in order to minimize windfall profits for manufacturers of PV systems, to limit the burden placed on electricity users and, more generally, to keep the cost of PV electricity as low as possible. Hence:

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

As argued before, the dynamics of module prices have also been affected by evolution in the upstream silicon market as panel production is the main market for silicon (87% in 2011, SolarBuzz 2012). The theory of industrial organization then predicts two possible outcomes. Silicon producers can be *price makers* in the industrial economic sense. That is, they enjoy sufficient market power to pass through a silicon price increase to module price. Alternatively, they can be *price takers*, meaning that they consider the market price as exogenously given in the case where the silicon market is sufficiently competitive. This leads to two exclusive assumptions:

Hypothesis 2a: Silicon prices influence module prices. (Silicon producers make the price in the silicon market.)

Hypothesis 2b: Silicon prices follow module prices. (Silicon producers are price takers.)

3 Preliminary diagnostics

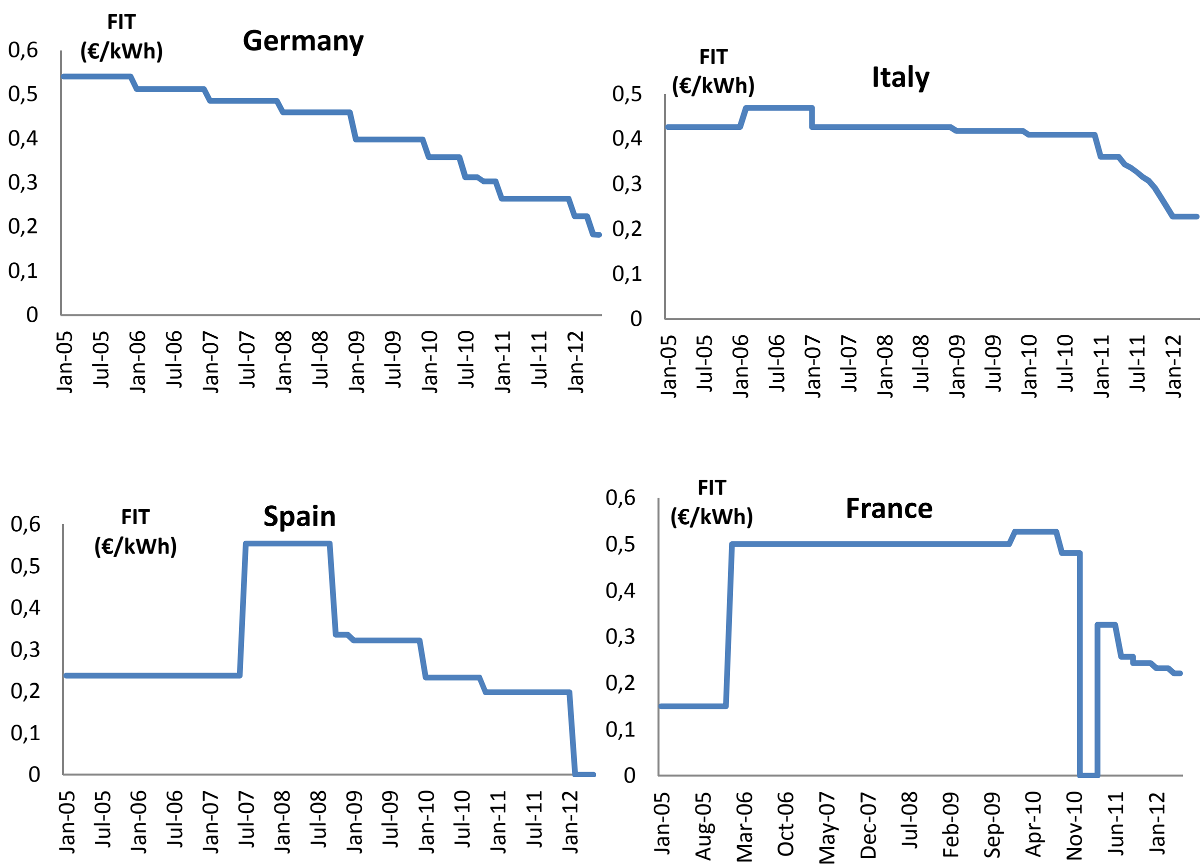
In order to investigate the hypotheses formulated in the previous section, we consider weekly data on silicon and module spot prices provided by PV Insights[5]. Solar PV components are not traded on public exchanges. In order to provide solar PV companies with reliable and concise information on prices, PV Insights make weekly price estimates based on prices for privately traded components which they collect from various contributors. The precise methodology they use is confidential. We rely on weekly data on these estimated spot prices over the period January 2005 to May 2012.

[5] PV Insights is an international solar PV research firm which produces reports, advisory service, and price reports. http://pvinsights.com

The data on Feed-in-Tariffs values for Germany, Italy, France, and Spain have been extracted by the authors from various sources: International Energy Agency (http://www.iea.org), the Solar Feed In Tariff website (http://www.solarfeedintariff.net), PV Magazine (http://www.pv-magazine.com/), RES LEGAL website (http://www.res-legal.de/) and Solarenergie - Förderverein Deutschland (http://www.sfv.de). Other countries such as Japan and United States are not considered in this paper since they implemented alternative PV technology development policies (e.g. renewable portfolio standards or investment subsidies) or do not account for a significant share of the global market. The four European countries considered cover more than 60% of the global market share. A practical problem is that, among countries, different tariffs are set for different types of PV systems (e.g. ground based, commercial and residential). To have a common metrics for measuring the level of FITs in place in each country, we calculate a single FIT value which is equal to the weighted average of a specific type of FIT, weighted by their market share in any given period. Data sources are indicated in Appendix A.

Figure 2 reports the average FITs evolution for Germany, Italy, France, and Spain and shows that the dynamics are different in each country. While German and Italian FITs have been decreasing steadily, more chaotic variation was observed in the Spanish and French markets. 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 2 Average FIT evolution in the main countries

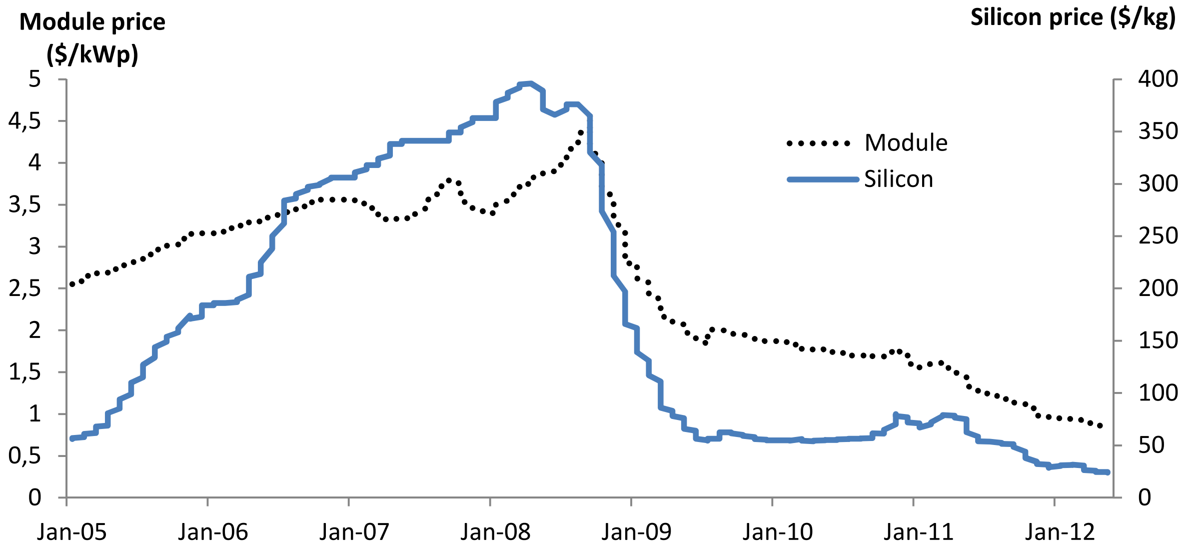


Source: See Annex A

Figure 3 depicts the silicon and PV module's spot price fluctuations from January 2005 to May 2012 and reveals that the price dynamics significantly changed during this period. Silicon prices 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. After the end of 2009, prices appear to be much more stable, with silicon prices returning to January 2005 levels, indicating the end to the shortage period and module prices following almost the same trend.

Silicon and module prices seem to be synchronised throughout the period. However, the rate of price increase is considerably lower for modules (40%) compared to silicon (607%). Two facts can potentially explain this observation: (i) silicon costs represents only 20% of total module cost[6], and (ii) silicon is sold by and large through long-term contracts (about 80%) and thus the average purchase price did not rise in the same proportions as the spot price.

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



Source: PV Insights

In order to have a preliminary intuition about the relationship between FITs and module prices, a good starting point is to understand how the evolution of panel prices compares to that of the FITs implemented in various countries. However, the comparison is not

[6] See Photon Consulting annual report 2012 (p. 154) for more information.

straightforward since the two variables are not expressed in the same unit: whereas FITs are measured in terms of a unit of electricity (\$/kWh), module prices are expressed in terms of production capacity (\$/kWp).[7] To allow for comparison, we convert the FIT into the net present value of the electricity generated over its lifetime by a module of a standard capacity of 1 kWp and sold at this FIT. The net present value of the electricity generated by the module in a country indexed *i* is given by the following expression:

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

where $FIT_{i,t}$ is the feed-in tariff in country *i* at time *t*, *T* is the lifetime of the PV system and *r* is the discount rate. The product $PR \times ASI_i$ is the electricity produced each year in country *i* by the PV system, with PR denoting the Performance Ratio of the installation (the ratio of the actual and theoretically possible energy output) and ASI_i, the country-specific Annual Solar Irradiation (the sum of the quantity of solar energy reaching the installation over a year). 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 (IRENA, 2012). The ASI is assumed to be 1200 kWh/kWp/year for Germany, 1500 for Italy, 1700 for Spain, and 1350 for France. These figures are obtained from the SolarGIS website.[8]

The net present value of electricity given by Equation (1) needs to be compared to the price of the whole PV system, of which the panel price accounted for around 40% in 2011 (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

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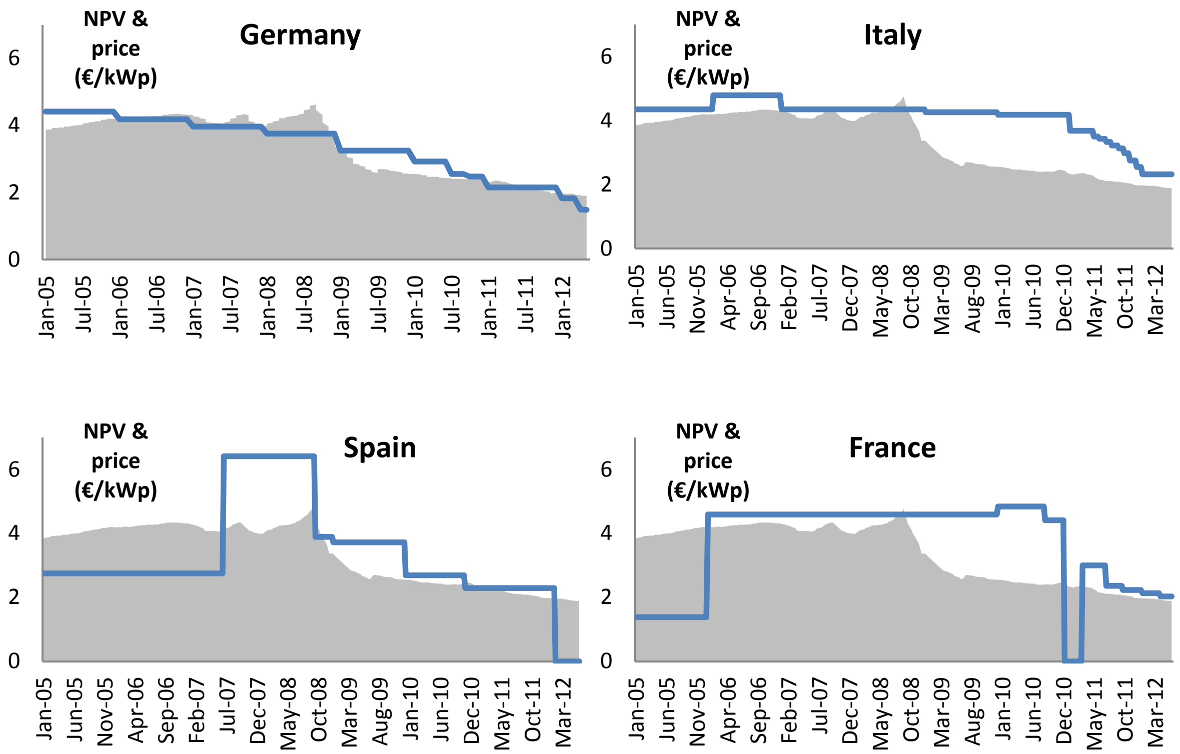
[7] Watt-peak (Wp) is a measure of the nominal power of a photovoltaic device under laboratory illumination conditions.

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

prices of other components are computed using the annual price trends obtained from Photon international (2012).

For each country, Figure 4 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 level. 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).

Figure 4 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 analysis

In this section, we analyse the relationship between prices by using a multivariate econometric approach. More specifically, we test each of the hypotheses given in Section 2 to identify the price dynamics during the period.

4.1 Construction of the time series

Before analysing the interdependencies between prices, one needs to construct consistent time series. This requires solving two problems. First, module and silicon prices are observed at the world level whereas the FITs are country specific. The analysis thus requires constructing a world-level FIT variable averaging the national FITs. We use the average of countries' FITs, weighted by the size of the national electricity markets. Formally, this world-level variable is computed with the following formula:

$$FIT_t = \sum_i FIT_{i,t} * elec_{i,t} \quad (2)$$

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

The second problem is that module prices are known to be influenced by long-term drivers, in particular learning-by-doing improvements. This needs 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:

$$module_t = module_{t_0} * \left(\frac{cum\_prod_t}{cum\_prod_{t_0}}\right)^{-E} \quad (3)$$

Here, $module_t$ is module price at time t, cum_prod_t is the cumulative PV module production at the same date,[9] t_o is an arbitrarily chosen reference date and E is the experience parameter, measuring the intensity of the learning-by-doing process. We use an experience parameter of 0.338, corresponding to a learning rate of 20.1%, which has been estimated in the study by de la Tour et al. (2013) who used the same data.[10] Using data on cumulative production extracted from Photon consulting annual reports, 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. $module_t^0$ denotes the corresponding predicted variable.

4.2 Unit root properties

We now investigate the unit root properties of each series: the silicon price, the deflated module price ($module_t^0$), and the FIT index (FIT_t), both in logarithm and in first log-difference. Testing is necessary as the estimations carried out subsequently require knowing the time series property of the price series (i.e. unit root or stationarity).

To do so we rely on three types of tests, namely the traditional ADF (1981), Schmidt-Phillips (1992, hereafter SS), and KPSS (1992)'s tests. While the first two consider the null hypothesis of unit root, the latter is based on the null of stationarity.

However, in the particular case of the price of silicon, using these tests would not be relevant since that price has experienced periods of relative instability during the shortage period from 2005 to 2009, suggesting potential breaks in its dynamics. Since the seminal

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[9] 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).

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

paper of Perron (1989), researchers have acknowledged the importance of allowing for a structural break in unit root tests. More precisely, Perron has shown that the ability of traditional tests to reject a unit root decreases when the stationary alternative is true and an existing structural break is ignored. Following Perron (1989), two types of approaches are often used. The first assumes exogenous break where break point is known a priori, and the second determines endogenously break points from the data. One widely used endogenous procedures is the minimum test of Zivot and Andrews (1992, hereafter ZA), which selects the point where the t-statistic testing the null of a unit root is the most negative. Given a loss of power from ignoring one break, it is logical to expect a similar loss of power from ignoring two or more breaks in the one-break test. Perron and Vogelsang (1992, hereafter PV) and Lumsdaine and Papell (1997, hereafter LP) contribute in this direction by extending the minimum ZA unit root test to include two structural breaks. One important issue coming from the ZA, PV and LP tests is that they assume no break(s) under the unit root null and derive their critical values accordingly. Thus, the alternative hypothesis would be "structural breaks are present", which includes the possibility of a unit root with break(s). As such, rejecting the null does not necessarily imply rejecting the unit root per se, but would imply rejecting a unit root without breaks. To deal with these issues, we propose using the Lee and Strazicich (2003) endogenous two-breaks LM unit root test, which allows for breaks under both the null and alternative hypotheses.

Results for series in first log-difference are reported in Table 1 and shows that series are integrated all of the same order I(1), meaning that they are stationary in first log-difference.[11] Looking at the LM test of Lee and Strazicich (2003), all series are I(1) without breaks, with the exception that silicon price is I(1) with one structural break. This break most probably

[11] Results for series in logarithm (not reported here) indicate that each serie have unit root.

corresponds to the end of the silicon shortage period. To confirm this fact, we use the structural break test of Bai and Perron (2005) to precisely date-stamp the point break. It reports a break at 5/31/2009.

We therefore split our analysis into two periods corresponding to the break point: the shortage period from 1/05/2005 to 5/31/2009 and the post-shortage period from 6/01/2009 to 5/30/2012, to see whether prices behaviour vary accordingly. Table 1 reports ADF, SS, and KPSS tests for each period and reveals same results than for the whole study period.

Table 1: Unit root test for Silicon price, Module price and FIT index (whole sample: 1/05/2005-5/30/2012)

	Silicon Price	Deflated module Price	FIT index
ADF	-4.674*	-5.300*	-19.983*
SP	-4.212*	-5.108*	-8.881*
KPSS	0.041	0.064	0.198
LM	-5.183*	-5.985*	-8.913*

Notes: ADF and SP tests are based on the null of unit root. KPSS test is based on the null of stationarity. The LM unit root tests assume two breaks under both the null and alternative hypothesis. * denotes rejection of the null hypothesis at 1% significance level.

Table 2. Unit root test for silicon price, deflated module price and FIT index for shortage and post-shortage periods

	Shortage: 1/05/2005-5/31/2009			Post-shortage: 6/01/2009-5/30/2012		
	ADF	SP	KPSS	ADF	SS	KPSS
Silicon price	-4.983*	-3.621*	0.197	-4.547*	-4.619*	0.130
Deflated module price	-6.784*	-3.689*	0.146	-7.129	-4.957*	0.067
FIT index	-15.034*	-14.793*	0.125	-13.114	-13.004*	0.276

Notes: ADF and SP tests are based on the null of unit root. KPSS test is based on the null of stationnarity. * denotes rejection of the null hypothesis at 1% significance level.

4.3 Causality

In this section, we investigate the short-run relationships between silicon price, deflated module price and FIT index for both shortage and post-shortage periods using the well known Granger causality tests (Granger, 1969). Granger has developed a methodology based on vector autoregressive (VAR) models to test for causality between two stationary processes. Consider the following VAR(p) specifications

$$X_t = \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{i=1}^{n} \beta_i X_{t-i} + \mu_{1t} \tag{4}$$

$$Y_t = \sum_{i=1}^{m} \delta_i Y_{t-i} + \sum_{i=1}^{m} \varphi_i X_{t-i} + \mu_{2t} \tag{5}$$

where it is assumed that the disturbances $\mu_{1t} \sim BB(0, \Sigma_{\mu_1})$ and $\mu_{2t} \sim BB(0, \Sigma_{\mu_2})$ are uncorrelated and both variables are I(0) processes. X is said to "Granger causes" Y if past values of X provide statistically significant information about future values of Y beyond what could have been done with past values of Y only. This approach has the advantage of being very easy to apply in many kinds of empirical studies since it can jointly provide results for the two null hypotheses that $\sum \alpha_i$ and $\sum \delta_i$ are both not different from zero.

Our variables all being I(1), we investigate causality between prices of silicon, predicted module ($module_t^0$), and the FIT index (FIT_t) in first log-differences. Given that we have identified one structural break at 5/31/2009, we split our analysis into two episodes and estimate different VAR(2) models for shortage and post-shortage periods respectively.[12] Some bias and size distortion affecting the asymptotic theory of the test can emerge when the sample data is not long enough (i.e. the so-called small sample bias). To deal with this issue,

[12] We use Akaike criterion for lag selection where we find p=2.

we rely on a bootstrap Granger causality approach which allows more precise testing of inferences than the asymptotic method.

Results of the Granger causality tests are reported in Tables 3 and 4. The test clearly indicates that module price causes FITs during post-shortage period (Hypothesis 1b).[13] During the first period, the test does not yield any conclusion regarding causal relationships, at least at the 5% or even the 10% significance level. Turning next to the relationships with silicon prices, the tables show that, during the shortage period, silicon price Granger causes module price in a unidirectional way (Hypothesis 2a). However, the reverse effect appears during the post-shortage period when the module price Granger causes the silicon one (Hypothesis 2b).

How can these results be interpreted? The findings on the silicon price is perfectly in line with economic theory which predicts that, in commodity markets, producers have market power only in cases with production capacity constraints. The shift in market power from silicon producers to module manufacturers can also be due to the PV industry becoming an increasingly dominant buyer in the silicon market, overtaking the semi-conductor industry since 2007 (SolarBuzz 2012).

Looking at Figure 4 helps understand why module prices cause FITs after 2009 but not before. Before 2009, FIT levels 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.[14] FITs were thus very rigid, explaining why they could not follow module price closely. Around 2009, FITs became much more flexible with intra-year adjustments to follow

[13] As suggested by a referee, we also perform as robustness check, the linear dependence test developed by Geweke (1982). Results available upon request to authors confirm those of Granger approach.

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

module prices. Germany revised its Renewable Energy Sources Act (EEG) in 2009 introducing a new responsive FIT scheme. The new scheme set a benchmark FIT for each PV class (e.g., ground-mounted, residential rooftop). But, if annual solar installations are to exceed a certain threshold (e.g., 1,500 MW/year), a FIT higher than the benchmark applies and vice versa if the pace of deployment falls below a certain threshold (Kreycik et al., 2011). In Spain where an uncapped FIT was previously used to support solar electricity generation until 2008, a new legislation (RD 1578/2008) imposed an annual cap on solar PV installations of 500 MW for 2009 and 2010 and a lower cap of 400 MW for 2011 and 2012 (Kreycik et al., 2011). A similar decision was made in France in 2011. The fact that FITs track module price more closely in the recent years should then be interpreted as a consequence of the modifications in FIT-setting mechanisms.

These findings can be viewed as good news as they show that, after an initial period of learning, regulators of the countries covered by the study have been able to adapt the level of the FITs to the evolution of the module markets. Importantly, this does not come from a change in the module markets which occurred simultaneously (an increase of the competition between module manufacturers). This reflects a change in regulators' behaviour which became more responsive to market evolutions.

Table 3: Causality test results (shortage period: 1/05/2005-5/31/2009)

$X \rightarrow Y$	Silicon Price	Module Price	FIT index
Silicon price	-	0.014**	0.577
Module price	0.660	-	0.898
FIT index	0.117	0.974	-

Notes: P-values from Monte Carlo simulation with 10,000 are reported. ** denotes rejection of the null of no causality at 5% significance level.

Table 4: Causality test results (post-shortage: 6/1/2009-5/30/2012)

$X \rightarrow Y$	Silicon Price	Module Price	FIT index
Silicon price	-	0.399	0.721
Module price	0.000*	-	0.054***
FIT index	0:827	0.199	-

Notes: P-values from Monte Carlo simulation with 10,000 are reported. *, ** and *** denote respectively rejection of the null of no causality at 1%, 5% and 10% significance levels.

5 Anticipation of feed-in tariffs change

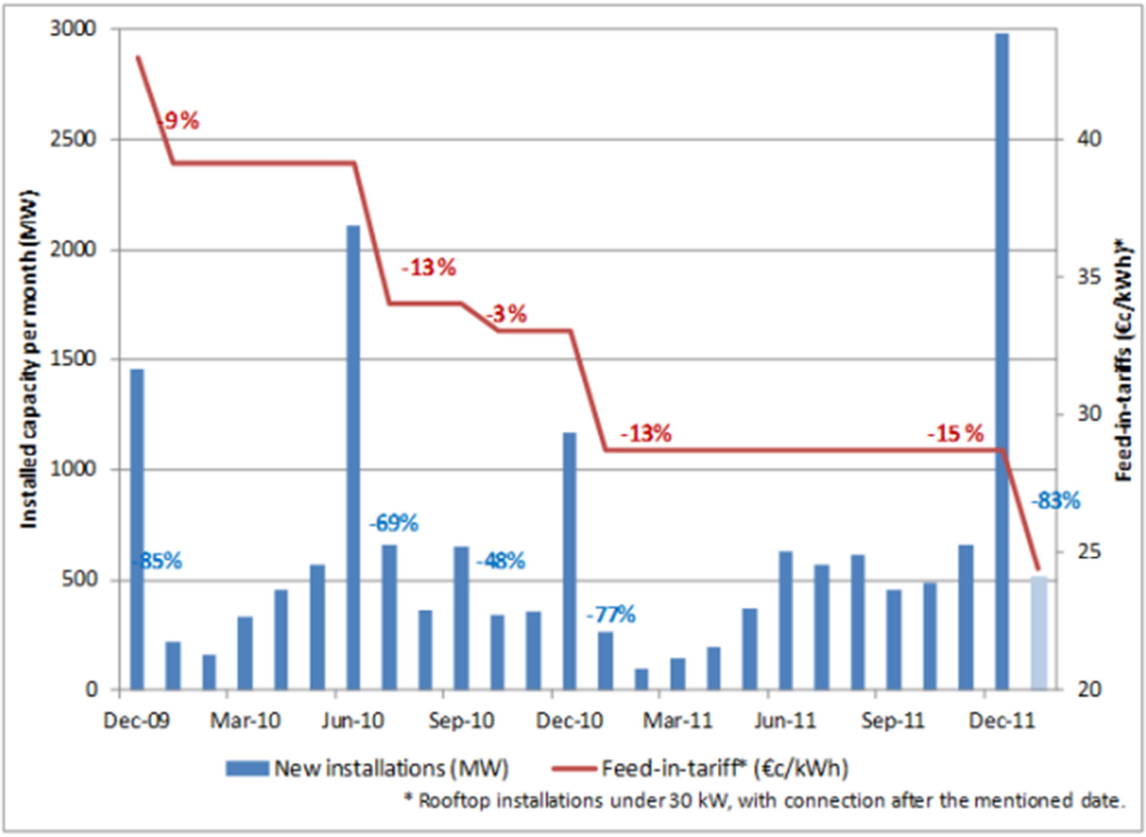
Vector autoregressive models use past (lagged) values as explanatory variables. However, FITs could be announced, and therefore anticipated, months or even years ahead. This section further investigates the FITs' effect on module price, by analysing the effect of *future* FIT changes on module price. Our approach examines the variation of module prices prior to falls in FIT levels (which occurred 24 times in total across all countries studies during the period considered). A simple theoretical reasoning suggests that firms would anticipate a decrease in FITs by purchasing more modules before the change, to benefit from the higher FITs, which would eventually increase price. Anecdotal evidence supports this behaviour indeed occurred. For instance, the observation of monthly PV installation levels and the FIT evolution in Germany depicted in Figure 5 clearly indicate installation peaks, measured by the number of connections to the grid, during the months before drops in FITs. Leepa and Unfried (2013) have thoroughly analysed this pattern in a recent empirical study of the impact of cut-off in feed-in tariffs on photovoltaic capacity.

While Figure 5 describes the impacts of anticipating FIT changes on installed capacity, what about the impacts 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 log-difference of module price, $\Delta lmodule_t$, compared to a business as usual (BAU) scenario at date *t*:

$$deviation_t \equiv \Delta lmodule_t - \Delta lmodule_t{}^{BAU} \tag{6}$$

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

Figure 5 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 5 to calculate the BAU price i.e. that module pricing adheres 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[15]:

$$\Delta lmodule_t{}^{BAU} = A + \sigma_1 \Delta lsilicon_{t-1} + \sigma_2 \Delta lsilicon_{t-2} + \eta_t \qquad (7)$$

where $\eta_t \sim BB(0, \sigma_\eta)$. After the silicon shortage, the BAU price is assumed constant:

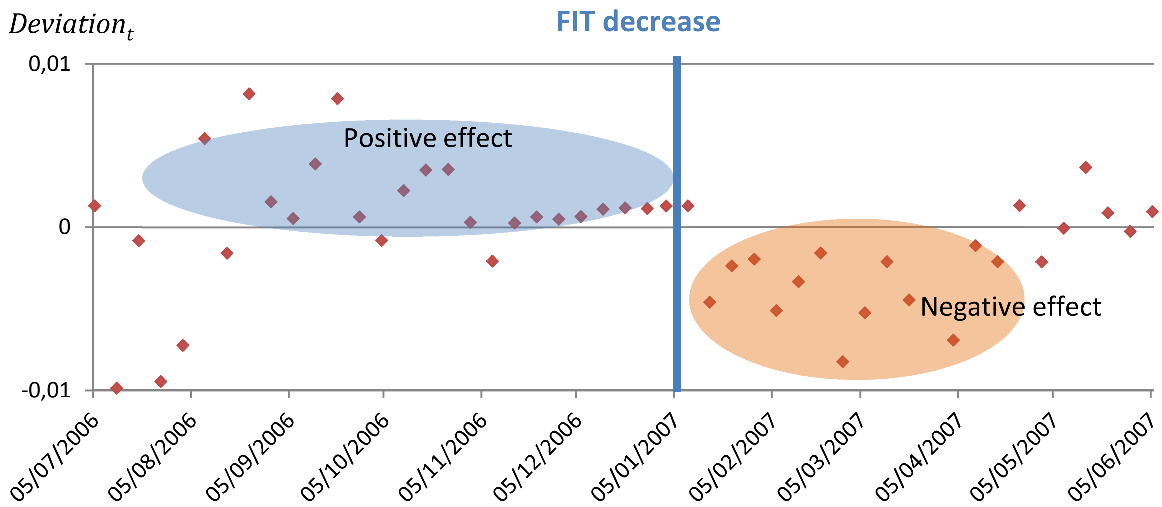
$$\Delta lmodule_t{}^{BAU} = B \qquad (8)$$

Based on the estimations of Equations (7) and (8)[16], we report in Figure 6 the dynamics of $deviation_t$ over a 1 year-period around a particular FIT decrease occurring simultaneously in Germany and Italy on January 1st 2007. We can observe a positive effect during the few months before the decrease, and a negative one afterwards. This pattern suggests there is an announcement effect such that predicted upcoming changes in the level of FITs induce module buyers to anticipate their purchase before the change occurs. This produces a temporary price adjustment around the date of FIT change: the price increases before the change together with the demand, then decreases afterwards.

[15] Previous results from VAR model show that the lag length for silicon price is two weeks.

[16] Results of estimations are presented in Appendix B.

Figure 6: Deviation of module prices 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. The model explains the deviation of module prices by a polynomial function of the time before the following FIT decrease. The regression equation is:

$$deviation_t = \sum_{x=1}^{3} b_x(before_t)^x + v_t \tag{9}$$

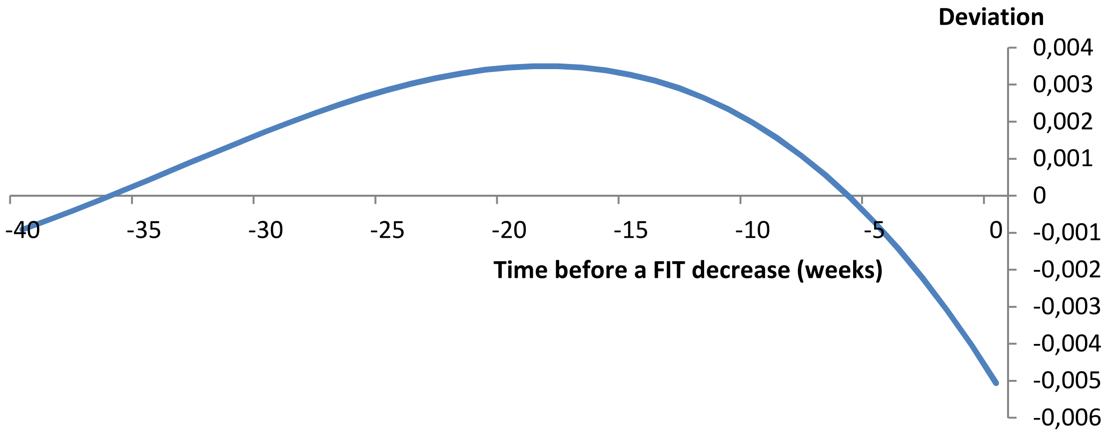
where $before_t$ is the number of weeks before the following FIT decrease and v_t is an i.i.d. error term process.

Predicted $deviation_t$ is computed by Equation (9)[17] over a 40-week period and depicted in Figure 7. As expected, the graph shows a positive deviation before FIT decreases. However, the impact becomes negative 5 weeks before. These results are easy to interpret. In

[17] Results of estimation are relegated in Appendix C.

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 FIT drop, firms lose this incentive since there is not enough time to complete the installation and connect to the grid before change. 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 indicate that this occurs up to five weeks before the decrease.

Figure 7 Simulation of the deviation of the first order derivate of module price from a business as usual scenario before a FIT 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.

These 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 changes in FIT regimes in major markets towards volume responsive systems such as in Germany in 2009, in Spain and in France in 2009 and 2011. In addition, the fierce competition prevailing on the module market has also played a role in keeping module price close to production cost.

Nevertheless, analysis using polynomial growth models shows FIT give rise to inflationary short-term effects on module price. During periods leading up to drops in FIT levels, module prices increases are observed. The interpretation is straightforward: a higher demand is triggered by the market anticipating the FIT drop, and firms rushing to install more PV capacity before the drop. This inflation is temporary, however.

The analysis also suggests that the silicon price drove module price only during the silicon shortage, suggesting that silicon producers held market power. This is in line with the observation that there was under-capacity in silicon production before 2009. After the end of the shortage period, silicon producers lost their market power and we find that module prices began to 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.

As explained in introduction, the existing literature tends to neglect short-term price effects on the market of PV systems, focusing instead on the long-term evolution of costs (arguably driven by learning-by doing and innovation). As we conclude, it is worth questioning the impact of the market-driven mechanisms studied in the present paper on the long-term solar PV cost trajectories. The question amounts to the evaluation of the impacts of potential rents on the long-term cost of PV systems. Giving a definite answer is difficult as there are two schools of thought on the role of rents on innovation. In the Schumpeterian view, rents are necessary to provide innovators with sufficient incentives to devote resources in risky long-term R&D projects. Others claim the opposite thesis that competition, which limits rents, boosts innovation as technological progress is the only solution to escape from a neck-to-neck competition with competitors producing the same standardized products (e.g. Hart, 1983; for a general discussion, see Aghion et al., 2005).

Acknowledgements

Arnaud de la Tour and Matthieu Glachant gratefully acknowledge financial support from the Conseil Français de l’Energie (CFE).

Appendices

A Data sources

We use multiple data sources which are listed below.

1) FIT values

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)

2) Silicon and module prices

PV poly silicon weekly spot price and silicon solar module prices are obtained from PV Insights (http://pvinsights.com)

3) Worldwide cumulative production of PV electricity

Used to deflate module prices. Extracted from Photon consulting annual reports.

B. Regression results of the BAU model (Equations 7 and 8)

	Before	**After**
Dependent variable	D. $\ln(module_t)$	D. $\ln(module_t)$
LD. $\ln(silicon_t)$	0.2160*** (0.041)	-
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.

C Regression results of the polynomial growth model

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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