Economic analysis of the photovoltaic industry : globalisation, price dynamics, and incentive policies

Arnaud Du Fayet de La Tour

École doctorale n° 396 : Economie, Organisation, Sociétés

Doctorat ParisTech

T H È S E

pour obtenir le grade de docteur délivré par

l'École nationale supérieure des mines de Paris

Spécialité " Economie et finance"

présentée et soutenue publiquement par

Arnaud DU FAYET DE LA TOUR

Le 14 décembre 2012

Economic analysis of the photovoltaic industry: globalisation, price dynamics, and incentive policies

Analyse économique de l'industrie photovoltaïque: mondialisation, dynamique des coûts, et politiques publiques

Directeur de thèse : **Matthieu GLACHANT**
Co-encadrement de la thèse : **Yann MENIERE**

Jury

Mme Anna CRETI, Professeur en Sciences Economiques, Université Paris Ouest la Défense	Rapporteur
M. Dominique FINON, Directeur de recherche, CNRS, CIRED	Rapporteur
M. Fréderic LANTZ, Professeur en Sciences Economiques, IFP School	Examinateur
M. Yann MENIERE, Professeur Assistant en Sciences Economiques, MinesParistech	Examinateur
M. Matthieu GLACHANT, Professeur en Sciences Economiques, MinesParistech	Examinateur

T
H
È
S
E

MINES ParisTech
CERNA
60 Boulevard Saint-Michel, 75006 Paris, France

Acknowledgements

Dans le cadre de cette thèse, je souhaite remercier en premier lieux mes deux directeurs de thèse, Matthieu Glachant et Yann Ménière, avec qui j'ai passé de bons moments, en particulier lors de nos déplacements communs. Merci d'avoir cru que l'étudiant qui passait beaucoup de temps sur le toit de l'école des mines et le terrain de basket du jardin du Luxembourg pendant son stage parviendrait à mener à bien le projet de longue haleine que représente une thèse. Merci à Matthieu pour avoir cru en moi au point de ne jamais être satisfait, donc de ne jamais abandonner. Je lui suis vraiment reconnaissant de toujours attendre mieux de ma part, et je sais que j'aurais encore beaucoup à apprendre de lui, en particulier en ce qui concerne la transformation d'idées en exposé clair.

Merci du fond du cœur à Sesaria Ferreira, personne cruciale au Cerna, dont la liste des rôles qu'elle a auprès des doctorants remplirait plus de pages que ce manuscrit de thèse. La version portugaise et surtout humaine du couteau suisse en somme. La vie au Cerna serait beaucoup moins chaleureuse sans les innombrables pots, fruits de sa capacité à transformer n'importe quel évènement en prétexte pour festoyer autour de – au moins - un « poulet frites ».

Je garderai des bons souvenirs de tous les autres thésards, avec qui j'ai eu d'agréables discussions dans la fameuse salle de réunion/cafeteria. Je suis particulièrement content d'avoir « rencontré » Gabrielle alors que nous avions passé trois ans ensemble à l'Agro sans nous connaître.

Un grand merci à mon père qui a passé beaucoup de temps à lire la thèse, et qui est responsable d'un nombre incalculable d'améliorations de l'anglais. Bien sûr, c'est une raison ridicule de remercier ses parents par rapports à tout le reste, mais comme on dit, le reste est en dehors des limites de cette thèse. Je ne vais donc pas remercier toute ma famille et mes amis, mais quand même, sachez que je vous aime.

Merci à toutes les autres personnes qui ont passé du temps à lire des parties de cette thèse pour corriger des erreurs d'anglais ou de français : Louise, Clémentine, Alexandre, Karen, Hannah, et Veronica. Même s'il reste des erreurs, c'est rassurant de savoir que ces pages ont été lues par quelqu'un avant de les figer à jamais dans ce qu'on appelle un pdf.

Preface

This dissertation deals with the photovoltaic industry, however each chapter brings up distinct research themes and can be read separately. They are or are intended to be published separately as well.

The first chapter, "technology transfers to China", is part of a research project for the Agence Française de Développement on technology transfers in in the context of the climate change negotiations. It has been carried out with my two thesis supervisors, Matthieu Glachant, and Yann Ménière. It led to a publication in *energy policy* under the following title: "Innovation and international technology transfer: The case of the Chinese photovoltaic industry". It has been presented at several workshops including the 2010 International Energy Workshop in Stockholm.

The following chapters are part of a research project financed by the Conseil Français de l'Energie. Chapter two has been presented in Toxa at the 5th Atlantic workshop on environmental and energy economics.

Content

Chapter four: Impact of firms' strategies on the optimal feed-in tariff policy 119

Conclusion 157

Introduction

Context

The photovoltaic (PV) market has been growing exponentially over the last decade, more than doubling every two years. PV electricity being until today and in a foreseeable future more expensive to produce than conventional electricity sources, this market is driven by incentive policies. The main one is the feed-in tariff (FIT), administratively setting a price at which electric utilities are obliged to buy electricity produced by renewable energy sources, for a fixed period of time. Besides FITs, other policies contribute to the development of the market, including Renewable Portfolio Standards, mandates requiring each utility to have a minimum percentage of power that is sold or produced by renewable energy sources, tendering schemes, and various investment subsidies. These costly policies were first implemented in industrialised countries, which is where the PV market thus started: Until 2011, 35% of the PV capacity has been installed in Germany (EPIA, 2012), leading the market, followed by Italy, Japan, Spain, and the US.

A side effect of this exponential market growth is the fast cost reduction, as we observe that each time the PV market doubles, the price of PV modules is reduced by 20%. This should lead to further cost reduction provided that the market keeps expanding. This trend was only broken during times of silicon shortage, which started in 2005 when silicon demand driven by the PV market exceeded production capacity. Since the planning and construction of a silicon plant requires several years, the silicon shortage lasted until 2009, with a silicon spot price peak at 396 $/kg in 2008, compared to 56 $/kg in 2005 - driving module price up in the same period.

Polysilicon production overcapacity prevailing since 2009 has lead silicon price back to pre-shortage levels. As a result, module price decreased sharply too, going back to its historical down trend. This created a discrepancy: generous incentive policies, at times when module prices were significantly lower than policymakers expected resulted in high profits and market over-heating to the point where it became too costly to sustain. To cool things down, severe policy adjustments were carried out, such as drastic FIT cuts or moratorium, creating uncertainty and wiping the weakest companies out of the market.

In recent years, globalisation resulted in another important market transformation. Over time, most of the production of cells and modules transferred to China, while demand remained mostly concentrated in Europe. As a consequence, PV modules exports from China to Europe exploded, leading to an increase in polysilicon and manufacturing equipment sales from industrialised countries to China. The aggressive pricing of Chinese firms and the slowing demand in Europe is pushing many firms to bankruptcy. This led to a tense situation today with the US and Europe filing trade cases for illegal price against China. China is seen as a free rider taking profit of the technology developed in industrialised countries at the cost of massive incentive policies.

Research questions and Thesis structure

As explained above, the PV industry went through tremendous changes: in the last ten years, the size of the photovoltaic market was multiplied by 10, module price decreased by 60%, and China's share of cell and module production went from almost nothing to more than half. The purpose of this thesis is to shed light on some of the mechanisms driving these transformations.

The first research question is the following: **How did China acquire the technology required to enter the photovoltaic industry?** We see that China's known competitive advantages came to play in the PV industry as in others: Cheap labour, a strong local supply chain for raw material used to produce modules (glass, Polyvinyl Acetate, aluminium, etc.), cheap energy, etc. Besides, Chinese companies got access to loans at favourable terms and conditions, guaranteed by the government. A more surprising fact is that they managed to acquire and master the technology required to produce cells and modules, and more recently to purify silicon. This became a key issue, as it put tremendous competitive pressure on the traditional players in this segment of the value chain, to the point where some went bankrupt, thus ruining industrialised countries' plans to build a strong domestic industry by stimulating national PV markets. Moreover, this case study gives some insights regarding technology transfers which developing countries ask for in the context of the international negotiations on climate change.

The second research question is: **How fast and how far will cost further decrease?** Will the historical trends observed in the PV industry continue? Will PV eventually become competitive against conventional electricity sources, and when? This hope has justified huge investments in incentive policies. Incidentally, more accurate cost prediction would allow a finer tuning of these policies.

The third and fourth research questions relate to the interdependencies between feed-in tariffs, module price, and silicon price: **How is module price affected by feed-in tariffs and silicon price? How to design feed-in tariffs able to adjust to module price volatility?** Those research questions relate to the efficiency of FITs. Indeed, a better tool to anticipate short term variations in module price, and a better ability to adjust FITs when these anticipations are not accurate enough, would help avoid discrepancies. This is crucial for policymakers since these discrepancies cause market overheating – or recession – calling for drastic and harmful adjustments. Besides, a better anticipation of module price would reduce uncertainty and risk, thus fostering investment in the PV industry.

The fifth and last research question is the following: **What is the influence of firms' strategies on the optimal FIT policy?** The purpose of a FIT policy is to provide the right incentive to drive demand along an optimal path. The issue is to understand how FITs lead companies to decide upon PV installation, depending on the strategy they pursue, and to draw conclusions about the optimal FIT policy. This is important in the context of industry consolidation, evolving from small players pursuing a short term strategy toward bigger players following a long term strategy.

This essay is structured as follows: Each chapter tackles one or two research questions. Chapter one addresses questions around technology transfers to China. Chapter two proposes a model for long term module cost prediction, while chapter three focuses on market drivers, analysing how module price is affected by FITs and silicon price, as well as how FITs can best follow module price. Chapter four also focuses on FITs with a different angle, presenting a model to evaluate the influence of firm's strategies on an optimal FIT policy. While each chapter deals with the PV industry, they bring up distinct research themes and can be read separately.

How did China acquire the technology required to enter the photovoltaic industry?

This question is addressed in the **first chapter**. The issue is not to analyse the competitive advantage of China, but to understand how Chinese firms managed to acquire the technology and knowledge required to produce PV cells and module, and more recently polysilicon. The role of intellectual property rights protection is analysed. We also see if China is able to produce new technologies domestically.

These questions are addressed empirically, by combining both quantitative and qualitative evidence. On the quantitative side, we rely on a dataset comprising 79,642 PV-related patents to analyse innovation and cross country technology transfers in the different segments of the PV industry. To supplement this quantitative analysis, we carried out field interviews with Chinese PV actors. It allows us to understand further details about the economics of the Chinese PV industry, and provides qualitative information about innovation and technology transfers to China.

Chinese firms acquired the technology to produce cells and modules through two main channels: the purchase of manufacturing equipment from historical players of the PV industry - Germany, Japan, and the US - and the recruitment of skilled entrepreneurs from the Chinese

Diaspora who studied or worked abroad. Foreign direct investment played a minor role in the emergence of the Chinese industry, since pioneers were purely Chinese firms.

The trade of intellectual property rights such as licensing has played no role. More generally, the existence of property rights has not prevented the emergence of the Chinese industry. The core technology, being more than 20 years old, was in the public domain. The new patents are protecting only incremental innovation, making it possible to get around them.

The silicon purification technology has also been known for a long time. But mastering it and reaching low cost production, to be competitive on the market, requires advanced know-how protected by trade secrets. In contrast to cell and module segments, the lack of competitive supply of production equipment appears to have been a significant barrier to the development of Chinese firms in the upstream silicon segment. They are now overcoming this barrier thanks to important domestic R&D efforts. However, the low silicon price in 2012 is a threat for many Chinese new entrants, as they still have higher production cost than the incumbents.

As measured by patent statistics, the innovative performance of China denotes a policy-driven effort to catch up in silicon purification rather than the inventive dynamism of local companies. Chinese producers of cells and modules invest less in R&D than their competitors in Japan and Western countries, and consequently file fewer patents that are of lesser value. By contrast, China is making big R&D efforts in the silicon and wafer segments. This is driven by public research institutions, denoting an effort to break the technology barriers preventing firms from entering these segments. China now reaps the benefits of this strategy, accounting for 33% of world silicon production in 2011, but sees many local firms struggling with recent low silicon price.

How fast and how far will photovoltaic module cost further decrease?

We address the question of long term cost prediction in **the second chapter**. The ultimate goal is to predict module cost until 2020. The predictive model we use is based on experience curves, also called learning curves. Based on the learning by doing theory developed by Arrow (1962), they explain cost by experience, measured by cumulative production, or cumulative installed capacity in the case of the PV industry. Additional explanatory variables can been added, such as production scale, research and development (R&D), or input price. Using data on world average annual value of module price, cumulative capacity, plant size, silicon and silver price, and R&D, we select the specification with the best predictive power. That is, the set of explanatory variables which minimises the difference between predicted and realised module price. The model is used to make predictions up to 2020

The most powerful model includes cumulative production (or cumulative capacity) with a one year lag, and silicon price, as explanatory variables. Based on this model, scenarios for module price evolution until 2020 predict a 67% price decrease, from 1.52 $/Wp[1] in 2011 to 0.50 $/Wp in 2020. The increase in cumulative capacity is responsible for 75% of this evolution, corresponding to a learning rate of 19.6%, and silicon price decrease is responsible for 25% of module price reduction.

Using this module price prediction and a simple extrapolation of the price of other components of a PV system, it is possible to predict the competitiveness of PV electricity. Grid parity should be reached by 2013 in Spain, 2015 in Germany, and not before 2018 in California or France where retail price of electricity is low. However, this criterion should be interpreted with caution as it does not take into account the cost of transportation and distribution of PV electricity. Hence it only makes sense for residential systems for which all the electricity is used on-site.

[1] Watt-peak (Wp) is a measure of the nominal power of a photovoltaic solar energy device under Standard Test Conditions.

A comparison against other technologies suggests that PV's levelised cost of electricity (LCOE) will only reach conventional technologies' LCOE in 2020 in the sunniest countries such as California, Italy, or Spain. However, it should be kept in mind that the LCOE is not really appropriate to estimate the economic value of intermittent and non dispatchable technologies such as PV. The reason is that it does not take into account the different production profiles which lead to different market values for the electricity generated. In addition, it does not consider the additional cost of short term integration of intermittent sources into the grid, and storage or back-up capacity required to meet demand in peak periods.

How is module price affected by feed-in tariffs and silicon price? How to design feed-in tariffs able to adapt to module price volatility?

To address these questions, **Chapter three** relies on series of weekly values of module price, FITs in Germany, Italy, Spain, and France, and silicon price from January 2005 to May 2012. The interdependencies between the three variables involved – module price, FIT level, and silicon price – are studied with Granger causality tests applied to vector autoregressive (VAR) models.

It indicates that FITs follow module price more closely in the recent period, especially in Germany. We interpret that as a consequence of a change in their FIT scheme. The frequency of the adjustments increases and flexibility is further improved by volume responsive mechanisms. These two features reduce the deviation of the FITs from module price. This gives important insights as to how to design a FIT able to adapt to module price volatility, which is crucial for policymakers. However, the tests do not show an influence of the FIT level on module price, meaning that FITs are not likely to create a rent in the PV manufacturing activity. A possible explanation is the fierce competition prevailing in this industry. However, polynomial growth models point out short term distortions of module price close to a FIT change caused by firms' anticipation behaviour: before a FIT reduction, module price increases as a consequence of a higher demand, firms rushing to install PV systems before the FIT reduction. A few weeks before the FIT reduction, once it is too late to install a PV system and connect it to the grid before the change, the demand decreases, bringing module price down.

With regards to the influence of silicon price, the Granger causality tests indicate a fundamental change in 2009, at the end of the silicon shortage: during the silicon shortage, silicon producers are price makers, benefiting from market power brought by the capacity constraint. Silicon price thus influences module price. After the shortage, the situation switches to over capacity, preventing silicon producers to benefit from market power and influence price in the PV industry.

What is the influence of firms' strategies on the optimal feed-in tariff policy?

This question is addressed in **chapter four**. To analyse the influence of firm's strategies on the incentive effect of FITs, and therefore their optimal design, we rely on a theoretical model. To get the dynamic effect, the model considers firms installing PV systems over two periods, module price decreasing from period 1 to period 2, according to the quantity installed in period one following the learning by doing theory. A FIT can be implemented in period one, and reduced in period two. Two strategies are modelled: a long term strategy, anticipating FIT modifications and module price variation, and a short term strategy, installing PV systems as long as they are profitable.

The model suggests that firms' strategies should be taken into account when designing a FIT policy. If firms follow a long term strategy, a higher FIT should be implemented initially, with a more important degression rate, to compensate for their expectation of decreasing module price. Another finding is that if firms do not all follow the same strategy, different FITs should be implemented, each addressing firms following a similar strategy. A single FIT is not optimal when firms do not all follow the same strategy.

Chapter One

Technology transfers to China

Abstract

China is the largest photovoltaic (PV) cell producer in the world, with more than half of the worldwide production in 2011, exporting 92 percent of what it produces. The purpose of this chapter is to understand the drivers of this success, with a particular emphasis on the role of technology transfers and innovation. Our analysis combines a review of international patent data at a detailed technology level with field interviews of ten Chinese PV companies. We show that Chinese producers have acquired the technologies and skills necessary to produce PV products through two main channels: the purchasing of manufacturing equipment in a competitive international market and the recruitment of skilled executives from the Chinese diaspora who built pioneer PV firms. The success of these firms in their market is,

however, not reflected in their performance in terms of innovation. Rather, patent data highlight a policy-driven effort to catch up in critical technological areas.

Résumé français

La Chine est devenue en quelques années le premier producteur mondial de panneaux solaires. Elle est à l'origine de plus de la moitié de la production mondiale en 2011 dont une grande majorité exportée vers l'Europe. Le but de ce chapitre est de comprendre les facteurs de ce développement spectaculaire, mais aussi d'en éclairer les limites, en s'attachant particulièrement à l'innovation et aux transferts de technologie. L'analyse proposée s'appuie d'une part sur une base de données de 79.642 brevets liés à l'industrie photovoltaïque, d'autre part sur une enquête de terrain réalisée auprès de professionnels de cette filière en Chine.

Nous montrons que les entreprises chinoises ont acquis la technologie nécessaire pour entrer dans l'industrie solaire photovoltaïque par deux principaux moyens: l'achat de lignes de production « clef en main » sur un marché concurrentiel de fournisseurs d'équipements dans les pays industrialisés, et la disponibilité de cadres qualifiés au sein de la Diaspora chinoise, lesquels ont fondé les premières entreprises du pays. A contrario, les principaux verrous technologiques auxquels sont encore confrontés les industriels chinois concernent des procédés protégés par le secret, pour lesquels il n'existe pas de marchés d'équipements concurrentiels. Dans ce contexte, l'effort d'innovation chinois est principalement mené par l'Etat et vise à rattraper les pays industrialisés dans les segments technologiques en amont de la filière. Leur récente progression dans la purification de silicium montre qu'ils sont en passe d'atteindre leur objectif.

1 Introduction

In 2003, China's market share in cell and module segments was less than 2%. Yet the country became the leader in only a few years, responsible for more than half of worldwide production in 2011. The purpose of this chapter is to analyse how China managed to acquire the technology required for this success.

This is a key issue as it puts tremendous competitive pressure on the traditional players from industrialized countries in the cell and module segments, to the point where numerous companies go bankrupt. It ruins the plans of industrialised countries to build a strong domestic industry based on stimulating national PV markets. This is particularly true for second movers like France, and first movers like Germany and the US are struggling as well.

This case study is also particularly interesting to feed the debate regarding technology transfers in the context of climate change negotiations. On the one hand, it is a successful case of technology transfer that could inspire other countries. By focusing on the role of intellectual property rights (IPR), we analyse which role they play in facilitating or impeding these transfers. On the other hand, it shows that the technology required for the production of PV cells and modules can be transferred without leading to local deployment of PV systems, thus shedding light on new issues.

The purpose of this paper is to understand the drivers and limitations of this Chinese success in mastering a production technology that had initially been developed in industrialized countries. The main questions we will address are: How did Chinese firms manage to acquire production technologies and skills? Which segments of the PV supply chain does it concern? Have IPR impeded this process? Is China now able to produce new technologies domestically?

We address these questions empirically, by combining both quantitative and qualitative evidences. On the quantitative side, we rely on a dataset comprising 79,642 PV-related patents to analyse cross-country innovation and technology transfers in the different segments of the PV industry. To supplement this quantitative analysis, we carry out a series of field interviews with PV actors in China[2]. These interviews allow us to further understand specific details of the economics of the Chinese PV industry, and provide qualitative information concerning the innovation and technology transfers to China.

The theoretical framework of our empirical analysis draws on the economic literature on technology transfer and absorptive capacities (for excellent surveys of this literature, see Keller, 2004 and 2008). Within the Chinese context, our chief purpose is to highlight and explain the mechanisms of technology transfer in each part of the PV value chain. The paper is also related to the available literature on the photovoltaic industry in China. This includes the works of Yanga et al. (2003) and Marigo (2007). We also exploit a substantial body of professional literature published by public organizations (European Commission PV status reports; IEA, 2009; REDP, 2008), industry associations (EPIA, 2012, REN21, 2008) and consulting groups (McKinsey, 2008).

The paper is organized into four sections. In Section 1, we highlight the position of China in the global PV market. We then characterize and explain how technology transfer is occurring from developed countries to China in Section 2. Then, in Section 3, we focus on the innovation process in order to see whether China is now a major innovator. Section 4 presents our conclusions.

2 The global photovoltaic industry

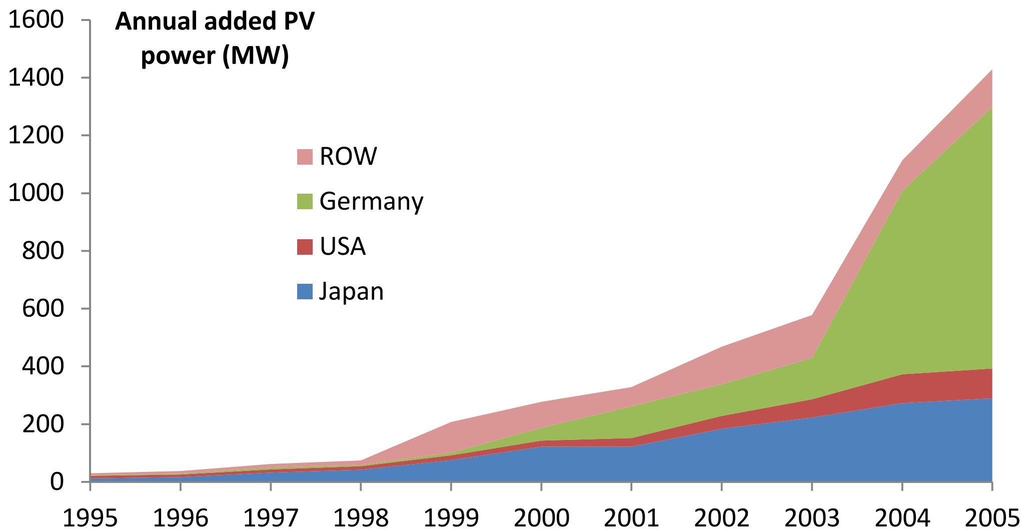
This section yields an economic analysis of the PV sector in order to recast our understanding of the role of China in the rapid development of the PV industry on a global scale.

[2] You can refer to Annex 1 for more information concerning interviewed actors.

2.1 The demand

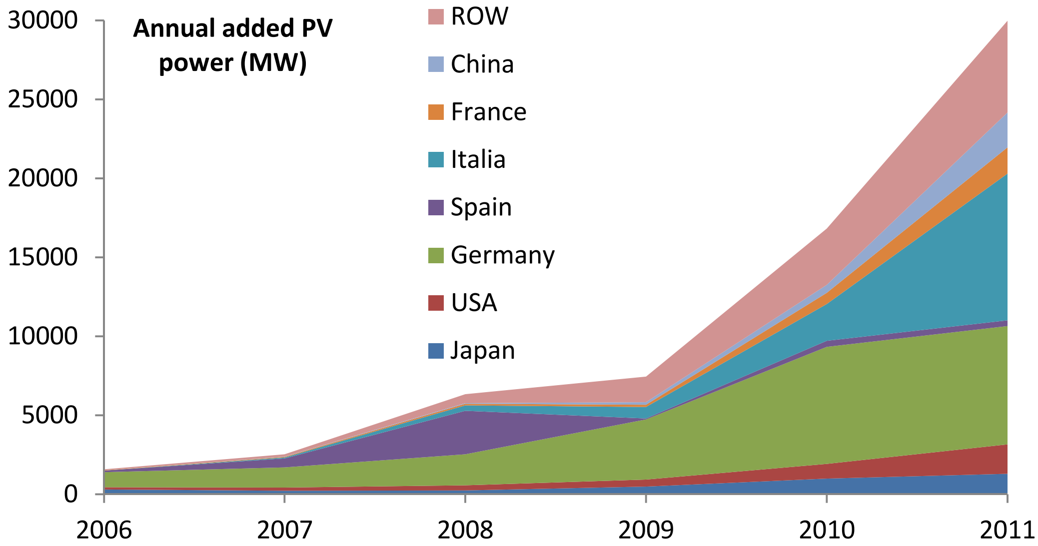
The large-scale deployment of PV generation capacity, and consequently the existence of a mass market for PV modules, is a recent phenomenon. Until the nineties, PV systems have been installed almost exclusively off the grid, for marginal uses (communication devices, satellites, remote habitations) for which PV electricity was competitive compared to other available off-grid electricity sources. As illustrated in Figure 1, the photovoltaic market reached 100 MW in 1999 and grew at a 51% compound annual growth rate (CAGR) from then until 2011. The market is chiefly in industrialized countries, and mainly comprises on-grid installation. In 1995, 33% of PV systems were installed on-grid; by 2011, it had reached 97% (IEA 2011).

Figure 1 Photovoltaic installation per year from 1995 to 2005



Source IEA, 2011

Figure 2 Photovoltaic installation per year from 2006 to 2011



Source IEA, 2011, EPIA (2012)

This fast deployment of on-grid PV systems has been entirely driven by incentive policies initially implemented in a limited number of industrialized countries (mainly Germany, Japan, and the US which are the main historical markets as shows figure 1). PV electricity cannot compete on the power grid because it is more expensive than traditional electricity sources. Therefore, the development of national markets requires economic incentives.

Besides various investment subsidies where the financial burden falls upon taxpayers, the main instruments aimed at stimulating the PV industry are quotas and feed-in tariffs (FITs). Quotas, such as renewable portfolio standards, are mandates requiring each utility to have a minimum percentage of power that is sold or produced by renewable energy sources. FITs consist of setting administratively-fixed guaranteed prices at which electricity suppliers must purchase renewable electricity from producers. That is, they prescribe a price, not a quantity as in the case of quotas. The first FIT leading to a massive development of the PV market has been implemented in 2000 in Germany, under the Erneuerbare Energien Gesetz. Spain also adopted a FIT in 2006 which was so generous that it led to a market boom in the country in 2008 as figure 2 shows. Spanish authorities reacted in 2009 by setting a cap limiting the deployment of PV systems to 500 MW per year. Along with the economic downturn, this policy change explains why the market growth slowed down in 2009.

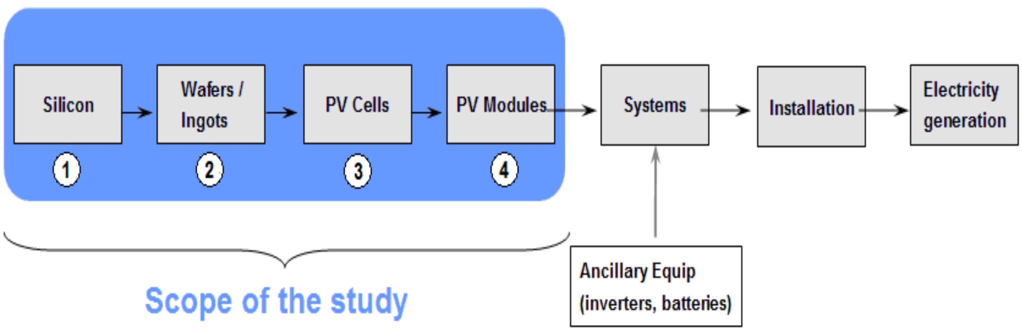
The majority of developed countries have now implemented FITs. A notable exception is the US in which most states have opted instead for the use of renewable portfolio standards.

In contrast, policies promoting solar energy hardly exist in developing countries, or are very recent. Their priority is to find the cheapest source of energy to feed economic development, and therefore PV energy is mostly used in off-grid installations. However, China stands out with a feed-in tariff provided by the China's Renewable Energy Law at a regional level in 2006, and at a national level in 2011. It triggered a fast development with an CAGR of 280% from 2008 to 2011. In 2011, the Chinese PV market represented 7% of the global market, while it was still only 0.6% in 2008.

2.2 The supply

Figure 3 presents the PV supply chain. The industrial production process includes four technical stages that are briefly described in Box 1. Then the deployment of the PV system requires combining the modules with complementary equipment (such as inverters, batteries, mounting systems, etc.) into integrated systems which, once installed, can generate power. As explained in the introduction, we focus our analysis on the first four production stages, Silicon, Wafers/Ingots, PV Cells, and PV Modules. They account for 44% of the average global cost of installed PV systems in 2011 (Photon International 2012).

Figure 3 PV supply chain



Source: Authors

Box 1: The PV production process

The production of PV modules involves four technical steps:

1. Silicon purification from silica (SiO2) found in quartz sand. The ultra-high purity required for the photovoltaic industry (> 99.999% pure) is obtained through heavy and highly energy-consuming chemical processes. The construction of a silicon plant takes about two years.

2. Ingot and wafer manufacturing. An ingot – a cylinder or a brick of silicon – is grown from the pure silicon. It can be a single crystal, leading to monocrystalline cells, or multiple silicon crystals that are smaller leading to polycrystalline cells[3]. Then, using a saw, ingots are sliced into thin layers called wafers. Secondary processes like polishing are involved. New technologies such as sheets or ribbons growing are emerging.

3. Cell production. To form the cell, two differently doped wafers are assembled together to form a so-called p-n junction responsible for the photovoltaic effect, and the top and rear metal contacts are applied. Many treatments or modifications in the process can be applied to increase the efficiency.

4. Module assembling. Cells are soldered together, the electrical junction being done by hand or automatically, and the cells are encapsulated in glass sheets to form a module which will be cooked in a laminating machine.

Table 1 shows the market share of Chinese producers in the different segments. In 2011, China is the world leader in cell production (59.3%), followed by Taiwan (14.7%), Malaysia (6.5%), Japan (5.7%), and Germany (4.8%) (SolarBuzz 2012). China became the leader in 2007 (27%), but this is a recent phenomenon: in 2003, China's market share was only 1.6%, the biggest producers being Japan, Germany, and the US.

[3] The monocrystalline conversion leads to more efficient PV cells, but has large power consumption and is thus more expensive than the polycrystalline process. Dopant impurity atoms such as boron or phosphorus can be added to the molten silicon in precise amounts in order to dope the silicon, thus changing it into n-type or p-type silicon.

An even more recent phenomenon is the vertical integration of China in upstream segments. China's market share in silicon purification grew from 2.3% in 2007 to 33% in 2011, catapulting China to the first place. This fast increase followed the same expansion in the cell and module segments four years earlier. The increase in Chinese polysilicon production has been strongly supported by the Chinese government, as we will see later. The pattern is similar for ingots and wafers: China still represented a minor part of world production in 2007, but has reached 73% in 2011.

Table 1 China market share in different PV industry segments in 2007 and 2011

	China Market share	
Segment	2007	2011
Silicon	3%	33%
Ingot and wafer	<5%	73%
Cells	27%	60%
Module		

Source: Authors calculation from Ruoss, 2007, REDP 2008, and SolarBuzz 2012

It is interesting to relate the timing of China's entry in the PV industry to the economic characteristics of the different segments. Those economic characteristics are presented in Table 2, giving figures for 2011, and 2007 in brackets. We pointed out that China entered first in module and cell manufacturing. They correspond to the most competitive segments as indicate the low Herfindahl-Hirschman Indexes (HHI)[4], even in 2007. They are also the least profitable. China's later entry in silicon and wafer manufacturing after 2007 explains the substantial increase in competition in those segments in 2011.

[4] The HHI is defined as the sum of the squares of the market shares of the largest firms within the industry. The result is proportional to the average market share, weighted by market share. As such, it can range from 0 to 1, moving from a huge number of very small firms to a single monopolistic producer.

Table 2 PV industry segments economic features in 2011 (and 2007 in brackets)

Segment	% cost in a panel	Market concentration (HHI)	Investment cost[a] (millions/USD)	Technological barrier height	% of profit[b]
Silicon	20%	0.059 (0.19)	140	High	43% (41%)
Ingot and wafer	24%	0.028 (0.24)	95	Medium/High	20% (41%)
Cells	24%	0.020 (0.04)	125	Medium/Low	5% (11%)
Module	31%	<0.020 (<0.04)	25	Low	18% (7%)

[a] Investment for a plant with annual production capacity of 1,000 tonnes for silicon purification, and 100MW for the downstream segments.

[b] % of the whole profit along the supply chain in 2007.

Sources: Calculated by the authors with data from SolarBuzz (2012)

China entered the PV industry through the downstream segments where technological barriers to entry are relatively low. The cell and module production technologies are easily accessible because, contrary to upstream segments, turnkey production lines can be bought and run without much prior manufacturing experience. In this context, the relative low price of energy and accessible loans in China has spurred the creation of local firms in the energy and capital intensive cell manufacturing segment. Module assembling is even simpler and is more labour-intensive, which gives Chinese firms another competitive advantage[5]. In contrast, silicon purification requires advanced technologies and very specific know-how to control all the parameters of the chemical reactions, in order to be able to produce silicon at a competitive price. Attracted by the high profits in those segments, China is trying to break those technology locks. We will examine technology issues at length in later sections.

[5] According to Chinese Firms that we interviewed, the labour represents 1-2% of the total cost in China in module production segment in 2009; in developed countries it represents 5-10%.

3 Technology transfers to China

We have seen that China has strong positions in the PV industry, which is a recent pattern especially in more technology-intensive activities located upstream in the production chain. We show in this section how this rapid development of the Chinese PV industry has been made possible by the successful transfer of technologies form industrialized countries during the last decade.

We mean by technology transfers all mechanisms by which a Chinese firm can benefit from a foreign party's knowledge on the design and manufacturing of PV products (Maskus, 2004). The economic literature argues that transfers generally occur through the following channels:

- Licensing: This is the most obvious channel, in which codified technology and the exclusive right to exploit it commercially is sold by one party to another.
- Foreign direct investment: It is the ownership of a productive asset such as factory in a foreign country by a multinational firm. This ownership can be full (subsidiary), or partial (joint venture). As the primary motivation for a firm making a foreign direct investment is to take advantage of some cost or quality advantage on the country based on knowledge asset, this knowledge is expected to be transferred in the subsidiary or the joint venture (Markusen, 1995). The foreign direct investment in a developing country being carried out to benefit of cheap labour, they hire local workforce to which the know-how is then transferred. Licensing contracts may be involved in joint venture.
- Trade in goods and services: Technology can be embedded in goods and services, and thus be transferred when they are exported. For example reverse engineering can allow the importing party to get access to the technology used to produce the goods. Moreover, capital goods such as production lines, fertilizer, software etc. can directly improve productivity by being placed into production processes and thus be a form of technology transfer.
- Movement of personnel: Cross border movements of skilled workers in one multinational firm, or such movements between two firms bring the know-how of the

personnel in the new firm or country. This know-how is a form of disembodied information that can be crucial for the effective transfer of a technology;

We discuss in decreasing order of importance the different channels through which the technology was introduced in China.

3.1 The markets for manufacturing equipment

From purified silicon to solar panels, products along the PV supply chain are very standardized. Market competitiveness mainly derives from the capability to manufacture products that satisfy a standard level of quality at an affordable cost. In this context, successful entry into each of the market segments requires access to state-of-the-art production technology. This in turn requires international markets for production equipment that is competitive.

The number of manufacturing equipment producers registered on ENF website[6] serves as a proxy of competition intensity in the market for PV manufacturing equipment. Table 3 presents each PV industry segment in 2012 with the figure from 2009 in brackets. The first line gives the total number of providers while the second gives only the number of firms which provide turnkey production lines.

There are numerous suppliers in each segment of the supply chain. However, the numbers are significantly higher in the downstream segments. Downstream segments also present more suppliers offering integrated turnkey production lines that make it possible to start production with a minimum level of technical knowledge. This explains the easy entry of Chinese firms in those segments. By contrast, equipment suppliers are scarce in upstream segments. Fewer firms are selling specific equipment, especially in 2009. More importantly, there are no firms selling equipment for polysilicon purification, and only one providing turnkey production lines for ingot production, even in 2012. This is a factor in why Chinese companies had difficulties entering those segments.

[6] http://www.enf.cn/ is an online solar company database.

Table 3 Count of manufacturing equipment providers in the PV industry in 2012 (and 2009)

	Ingot	Wafer	Cell	Module
All firms*	134(70)	361(178)	607(335)	851(234)
Firms providing turnkey production lines	1(1)	15(9)	14(15)	58(26)

* Firms selling specific equipment that are part of the production lines

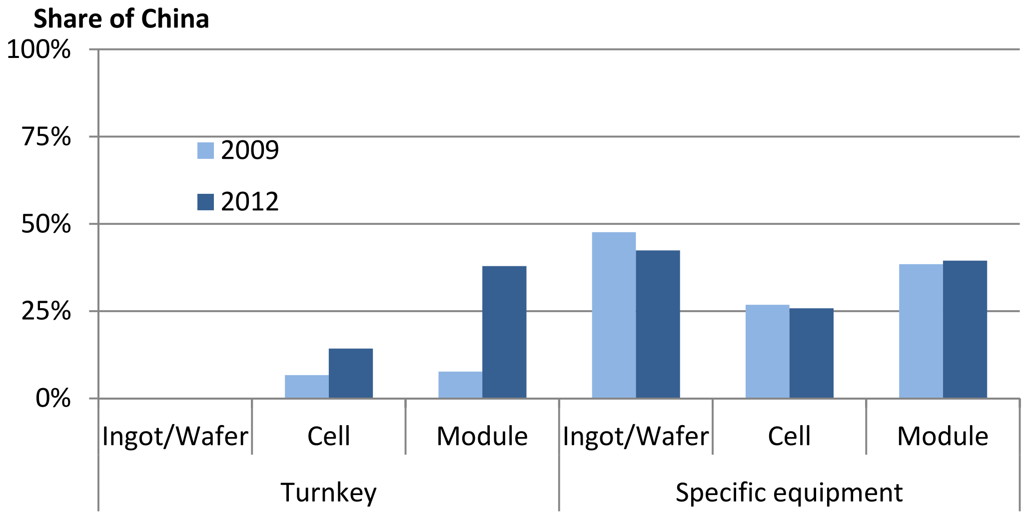
The brackets stand for the 2009 figures

Source: ENF website

Besides the importing of equipment goods, the purchase of manufacturing equipment usually involves the transfer of complementary know-how through training sessions of engineers and technicians operating the production line. This in turn progressively enables PV manufacturers to adapt their production chain to local conditions – for instance, substituting some equipment with a cheaper workforce. Several of our interviewees moreover indicated that large PV manufacturers tend to develop partnerships with equipment suppliers, sharing know-how and feedback to improve the manufacturing process. Although they may include temporary exclusivity clauses, such partnerships make it possible for equipment suppliers to redistribute this know-how to other customers, thereby accelerating the circulation of knowledge across the industry.

Another evidence of the diffusion of technology generated by the international trade of equipment goods is the progressive emergence of equipment goods suppliers that are solely Chinese. This is illustrated in Figure 4, which shows that there existed a significant number of Chinese firms selling specific equipment in 2009, and that in 2012, they have reached an important market share for turnkey production lines in the cell (14%) but especially module (38%) segments. This has important implications as it allows Chinese firms manufacturing PV products to buy cheaper production equipment. They can also do so in the more upstream segments provided that they are able to customize their production line by integrating specific Chinese equipment.

Figure 4 Share of china in the market for manufacturing equipment for each segments[7]



Source: Authors' calculation based on ENF website

3.2 Labour mobility

The circulation of a skilled workforce has been another key factor aiding the emergence of the Chinese PV industry. Recall that a major part of the technology concerns the operation of manufacturing processes, which mainly consists of know-how. In this context, the manufacturing experience of skilled employees is a key asset.

Chinese PV companies have benefited strongly from the arrival of highly skilled executives, who brought capital, professional networks, and technology acquired in foreign companies or universities to China. For instance, the founder and CEO of Suntech, China's largest PV company, had been studying at the University of New South Whales in Australia, and then worked for the Australian company Pacific Solar. In addition, four out of the six members of the Suntech Board studied or worked in the US or in the UK. The CEO of the second largest company, Yingli, also studied abroad. In Trina Solar, half of the 12 person management team have studied or worked abroad: 4 in the US, 2 in Singapore. At Solarfun, the figure is 7 out of 10. On average, 61% of the board members of the three largest Chinese

[7] The number of equipment providers is the only, admittedly rough, indicator available to measure the country market shares as turnover data are seldom available.

PV firms have studied or worked abroad[8]. This highlights the importance of the Chinese Diaspora: 8 million Chinese people live in foreign industrialised countries (source: Overseas Compatriot Affairs Commission, R.O.C).

To a large extent, this prevalence of executives with foreign training results from aggressive recruitment strategies pursued by Chinese firms in a context of scarce skilled labour locally. Suntech has a special program for recruiting foreign Chinese, while Trina Solar has created special "international staffing teams".

The local mobility of Chinese employees has also accelerated knowledge diffusion within China. Although the phenomenon is hard to quantify, representatives of three Chinese companies complained during our interviews about their employees being hired by other companies or creating their own company. Moreover, we also learnt that Chinese firms are developing specific programs to attract middle level management employees. There are even agreements between the 9 biggest Chinese solar firms to prevent hiring each other's skilled employees.

3.3 Foreign direct investment

The economic literature has shown for a long time that investment by a multinational firm in a productive asset such as a factory in a foreign country also induces a transfer of knowledge, since the technology is operated directly in the recipient country.

In 2009, China had attracted about one third of the global foreign direct investment flows in the PV industry. Although massive, this is a rather recent phenomenon, which has not been a decisive factor in the emergence of the Chinese industry. Table 4 presents the top 9 PV manufacturers located in China in 2009. Only three of them feature investment links with foreign companies. Moreover, these firms turn out to be late entrants, whose creation has followed in the footsteps of strictly Chinese pioneer firms.

[8] Information obtained on the companies' website: http://www.suntech-power.com; http://www.trinasolar.com ; http://www.solarfun-power.com.

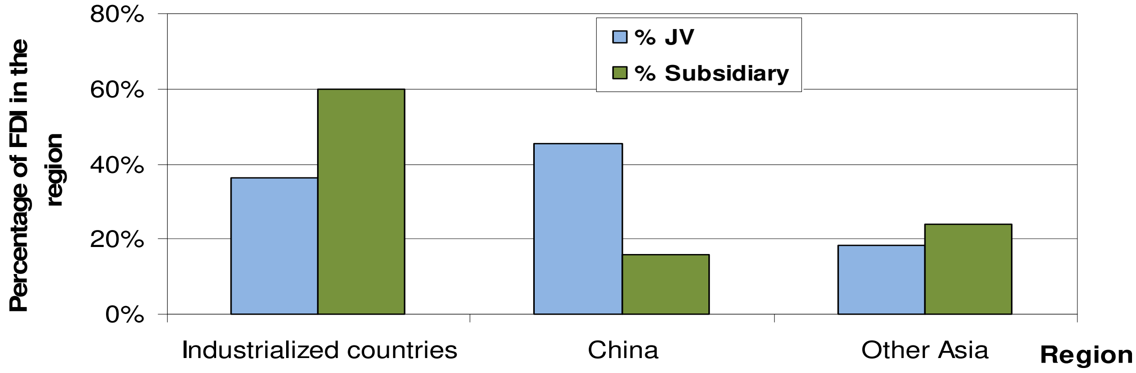
Although it was not decisive for the emergence of Chinese pioneers, incoming foreign direct investment is nevertheless likely to accelerate technology transfers to China. Figure 5 moreover shows that the proportion of joint ventures with respect to fully owned subsidiaries is much more important in China than in other countries. This reflects a general feature of the Chinese economy, where public authorities often force foreign investors to accept joint ownership. Such joint ventures are likely to induce more knowledge spillovers than the creation of mere subsidiaries, because they involve a local partner.

Table 4 Top 9 PV companies in China in 2009

	Output (MWp)	Creation	FDI-Joint Venture links
Suntech	327	2001	None
Yingli	142	1998	None
JingAo	113	2005	Australia
Solarfun	88	2004	None
Sunenergy	78	2004	Australia
Canadian Solar	55	2001	Canada
Ningbo Solar	45	2003	None
Trina Solar	37	1997	None
Jiangsu Junxin	35	-	None

Source European Commission (2008 and 2009)

Figure 5 Regional repartition of the two types of FDI



Source: Authors, European Commission (2005, 2008, 2009)

3.4 Licensing

Another classical market channel of technology diffusion identified in the economic literature – and the most self-evident – is licensing. But it has played no role in our story as licensing is almost inexistent in the PV industry. We are aware of only one case: Germany's Johanna Solar Technology granted a license to the Chinese company Shandong Solar Technology in 2008 to build a production line.

4 Chinese innovation

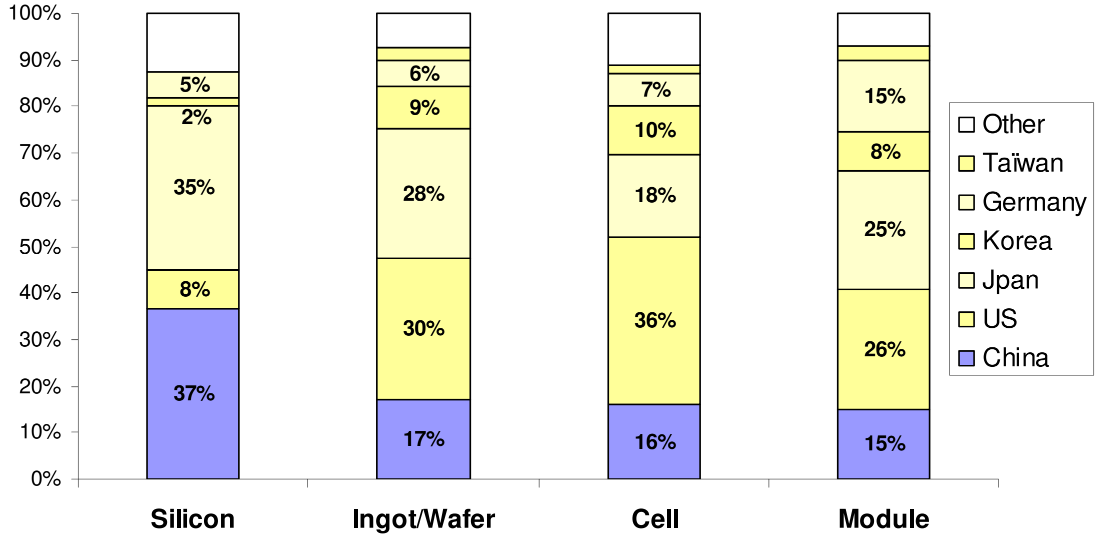
We have just seen that China has mainly acquired foreign technologies to create a domestic PV industry mostly through the international trade of manufacturing equipment and the hiring of top level managers trained in industrialized countries. In this section, we investigate whether China is now able to generate locally new technologies and inventions.

4.1 A study of photovoltaic patents

As a first measure of innovation in the PV industry, we tabulate patent applications. Although patents do not provide a measure of all innovation, they offer a good indication of innovative activity and allow for interesting cross-country comparisons. Data on patents grants with an application date prior 2007 were extracted and filtered from the Espacenet website, a free online service developed by the European Patent Office for searching information on patents and patent applications, available at http://ep.espacenet.com. Using International Patent Classifications combined with key word searches, we created separate patent indicators for each segment of the PV supply chain. More information on our dataset and the methodology used is available in Annex 2.

Figure 6 represents major countries' shares of innovation patented worldwide for each segment of the PV industry in 2006-2007. China's performance is impressive as it ranks third in all segments. But in silicon production it is all the more so, where it leads with 37% of world patents. Comparing these percentages with the 2007 market shares presented above in Table 1 leads again to distinguishing between upstream and downstream segments. China's patenting activity is significantly higher in silicon, ingot, and wafer production than its contribution to world production (respectively, 2.5 and 5%). The reverse is true in downstream segments in which China is the largest producer with a 27% market share whereas it generates around 15% of worldwide inventions. This suggests different roles for innovation in silicon, ingot, and wafer production on the one hand, and cell production and module assembling on the other.

Figure 6 Percentage of world patented innovation by segment and country in 2006-2007



Source: Authors' calculations based on the Espacenet database

4.2 Innovation in cells and modules segments

The important share of China in globally patented innovation has to be put in perspective. Indeed, only 1% of Chinese patents were also filed abroad as compared to 15% for Germany, 26% for Japan, and 7% for the US. Since the foreign extension of patent applications is usually reserved for the most valuable inventions[9], this reinforces the hypothesis that the value of the average Chinese patented invention is quite low. This is in line with the low percentage of revenue that Chinese firms devote to R&D in comparison to western companies, as indicated by Table 5, which gives R&D expenditure for a selection of big PV cell and module manufacturers in 2009. Moreover, the 2008 public budget devoted to R&D in the PV industry in China ranks 12th in the world (with USD 6.30 Million, Mo-Lin and Dan-Wei, 2012).

[9] For further details, see annex 2, Limits of the indicator.

Table 5. R&D expenditure in some major cell and module companies in 2009.

Companies	**Country of origin**	**R&D intensity** (% of 2008 turnover)	**Segments**
Schott Solar	DE+US	5.0%	Cells
Q-cells	DE	2.0%	Cells
SunPower	US + PH	1.7%	Cells+ modules
Solar World	DE	1.4%	Cells
Suntech	CN	0.8%	Cells+ modules
China Sunergy	CN	0.5%	Cells + modules
Solarfun	CN	0.4%	Cells + modules +ingots + wafers
Trina Solar	CN	0.4%	Cells + modules +ingots + wafers

Source: company annual reports

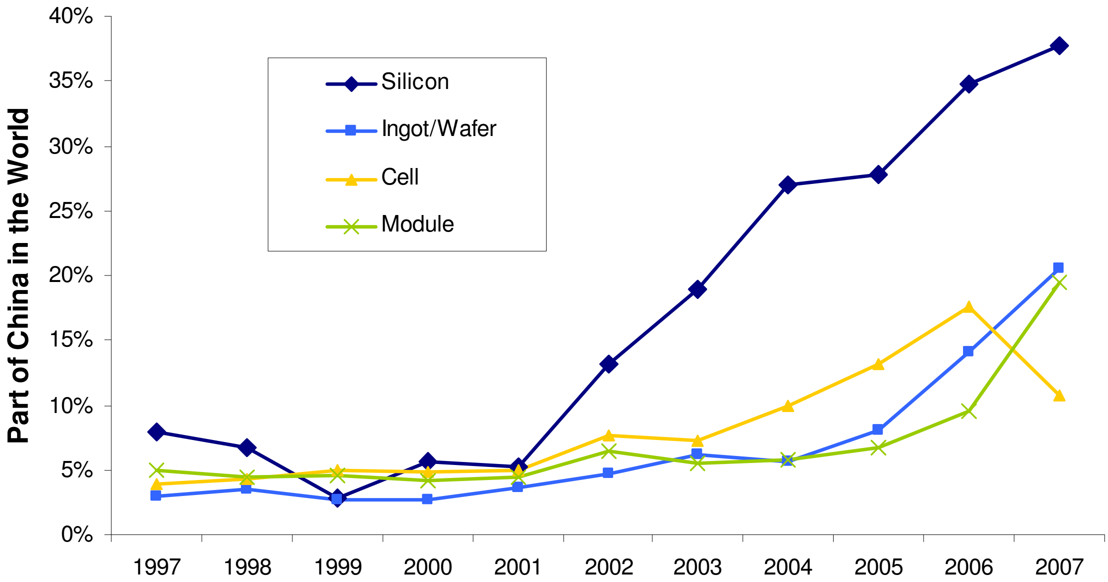
Chinese firms then have a higher propensity to patent than their foreign competitors – they file more patent applications for an equivalent innovation output. Our field investigations in China confirm that local companies patent minor inventions intensively. The reason is not to protect the inventions – critical inventions are usually kept secret – but to send a signal to public authorities. In particular, the allocation of public subsidies by the National Development and Reform Commission (NDRC) is significantly influenced by the quantity of patents.

However, concluding from this low patent value that Chinese firms do not innovate could be misleading. As the interviews suggest, Chinese innovation focuses more on process, which is often not carried out in specific R&D departments but directly on the production lines, and protected by secrecy rather than patenting.

4.3 Innovation in silicon, ingot, and wafer segments

We have seen that China's patenting performance in upstream segments is impressive. This is particularly true for silicon, with 37% of the world's patented inventions as shown by Figure 6. This results from a specific effort initiated in 2002 as figure 7 indicates, showing the evolution of the share of China in world's patenting activity in each segment.

Figure 7 Share of China in world innovation in each segment of the PV industry



Source Authors' calculation based on the Espacenet database

Why is it so? China only accounted for 2.5% of 2007 world production, but the government had voiced its ambition to dramatically raise production capacities in the following years. Domestic production of purified silicon indeed grew at a 192% yearly rate from 2007 to 2011, from 1,100 to almost 80,000 metric tons (REDP, 2008, SolarBuzz, 2012)

The Chinese patenting activity in silicon technology is related to this strategic objective. Besides capital investment in production facilities, the main barrier to entry in the silicon feedstock market is technological. The purification of metallurgical grade silicon into electronical grade silicon is based on the Siemens process – the principles of which have been public information for decades. The key to purifying silicon at reasonable cost, however, is in the efficiency of the silicon purification process, which requires precisely controlling the parameters of all the chemical reactions. Major western and Japanese silicon producers have developed advanced know-how in this domain, which they usually keep secret. In this context, the creation of a competitive branch of the Chinese PV industry in the silicon segment hinges on its domestic R&D effort to develop economically efficient refining processes. These efforts are chiefly funded by public authorities. Private patents represent less than 40% of total Chinese patented innovation, against around 85% in industrialized countries.

To summarize, the Chinese weight in patent applications in silicon purification, far from proving a technological leadership, actually denotes a massive domestic effort to break a technological lock in a strategic segment where the Chinese industry was heavily dependent on a small number of foreign suppliers. In 2011, China is still importing silicon, but is much less dependent on foreign suppliers. However it does not mean that they managed to catch up with incumbents, since except for the two major companies GCL and Dago, new Chinese entrants' production costs exceed 40$/kg, which is above 2011 market price (Morgan Stanley research estimates).

5 Concluding remarks

China has become in just a few years a major player of the global PV industry. In this paper, we explain how this has occurred, and in particular, how Chinese producers got access to the technologies and skills necessary to produce PV systems.

China has acquired the technologies to produce cells and modules through two main channels: the purchase of manufacturing equipment – in particular turnkey production lines – on a competitive international market, and the recruitment of skilled entrepreneurs from the Chinese Diaspora who have managed to build pioneer PV firms, taking advantage of China's comparative advantage of cheap labour, energy, and capital. In contrast, the lack of competitive supply of production equipment appears to have been a significant barrier to the development of Chinese firms in the upstream silicon segment. They are now overcoming this barrier thanks to important R&D efforts. However, the low silicon price in 2012 is a threat for many of those Chinese new entrants still having higher production cost than incumbents.

Foreign Direct Investments, mainly through the establishment of joint-ventures with western partners, are another potential channel for importing technologies. They are very significant in the Chinese PV industry but they are quite recent and they do not involve pioneering Chinese companies. This suggests that they have played a minor role in the emergence of the industry. The trade of intellectual property rights such as licensing has played no role.

More generally, the existence of property rights has not impeded the emergence of the Chinese industry. The core technology, being more than 20 years old, was a public good. The new patents were protecting only incremental innovation; it was thus possible to get round them. Moreover, the high competition prevailing in downstream segments and in the corresponding market of manufacturing equipment prevented the owners of the technologies to get enough market power to stop the entry of new comers.

As measured by patent statistics, the innovative performance of China denotes a policy-driven effort to catch up rather than the inventive dynamism of local companies. Chinese producers of cells and modules invest less in R&D than their competitors in Japan and Western countries, and consequently file fewer patents that are of lesser value. By contrast, the important share of China in world patents in the silicon, ingot and wafer segments is largely accounted for by public research institutions, denoting an effort to break the technology barriers preventing firms from entering those segments. This trend highlights the ability of the Chinese public authorities to intervene selectively when the market fails to generate technology transfers. China now reaps the benefits of this strategy, accounting for 33% of world silicon production in 2011.

Keeping in mind that our analysis is limited to the PV sector in China, it is interesting to recast it in the current policy debate on the promotion of North-South technology transfer. Our results indicate that international trade has been a key factor of PV technology diffusion in China. Chinese firms export their products to industrialized countries, and manufacture them with technology acquired from international equipment goods suppliers. In this respect, low trade barriers and competitive markets for equipment goods seem more important than intellectual property policies. Indeed, our results show that IPR have not been an impediment in the technology transfer process, which is in line with what Barton (2007) or Kirkegaard et al. (2009) observed for solar, biofuel and wind technologies. Competition is sufficient in these sectors to prevent a single company from creating a lock on the technology with patents.

The case of the Chinese PV industry is also interesting with regards to the role of national absorptive capacities. The Chinese PV industry has strongly benefited from the availability of skilled workforce, but also from its local and international mobility. Indeed, the fact that pure Chinese firms have been created before the arrival of foreign direct investors is due to the existence of a highly skilled diaspora; and the diffusion of technical knowledge between Chinese firms has in turn been accelerated by the turnover of their middle management. The Chinese government has been strongly committed to alleviating technology barriers to the entry of Chinese firms in the Silicon segment, with promising results.

Here at the end of this paper, it is also possible to address a more fundamental question: what is the rationale for promoting the transfer of production technologies to the South, from a general interest perspective? The example of the PV sector shows that this transfer does not necessarily induce GHG emissions abatement in emerging economies: China has successfully entered the PV market without deploying panels at home in the first place. In fact, the real justification is that the transfer of technology is necessary in order to transfer production capacities to emerging economies and this relocation can decrease production costs and prices through fiercer competition, as is true in many other industrial sectors. Ultimately, technology transfers reduce the cost of mitigating greenhouse gas emissions. However the price of this static efficiency could be a dynamic inefficiency. The PV industry is technologically intensive as shown by the important R&D efforts from industrialised countries. Since Chinese firms put fewer efforts in R&D, their domination could jeopardise future cost reduction by lowering the global R&D in the PV industry.

From the perspective of industrialized countries, this is disturbing. On the one hand, their companies producing PV cells or modules face tougher competitors and lose market share – see the dozens of companies that filed for bankruptcy in the last years. It also ruined plans of second movers such as France to create a local industry by stimulating the domestic market.

Added to the fact that industrialised countries bore the cost of expensive incentive policies, the transfer of manufacturing capacity to China raises some concerns, as shown by the anti-dumping trade cases in the US in 2011 and in Europe in 2012. But on the other hand, industrialised countries benefit from these cost reductions, as demonstrated by the commercial success of Chinese panels especially in Europe. This provides cheaper PV electricity, helping to reach GHG emissions mitigation targets at a lower price, and participates in stimulating the manufacturing equipment and local installation business.

Annex

Annex 1 List of firms where interviews have been carried out

Firms	Nb Employees	Activity	Creation Year	Turnover (Millions of USD)	2008 cell production	World rank
Suntech	8000	cell+Module	2001	278M	1000	3
TRINA Solar	5200	ingot+wafer+cell+modules	1997	150M	450	11
Solarfun Power	1500	ingot+wafer+cell+modules	2004	576M	200	12
China Sunergy (CEEG)	5000	ingot+wafer+cell+modules	1990	149.5	111	20
Topsolar	800	cell+Module	2002	175	48	38
ST Solar	125	modules	2003	n.a.	25	>50
Universal Solar	120	modules	2003	53	25	>50
Chaori Solar	1100	ingot+wafer+cell+modules	2001	n.a.	22.5	>50
Solar Energy (SSEC)	560	ingot+wafer+cell+modules	2000	n.a.	20	>50

University
Shiaotong University, Institute of Solar Energy

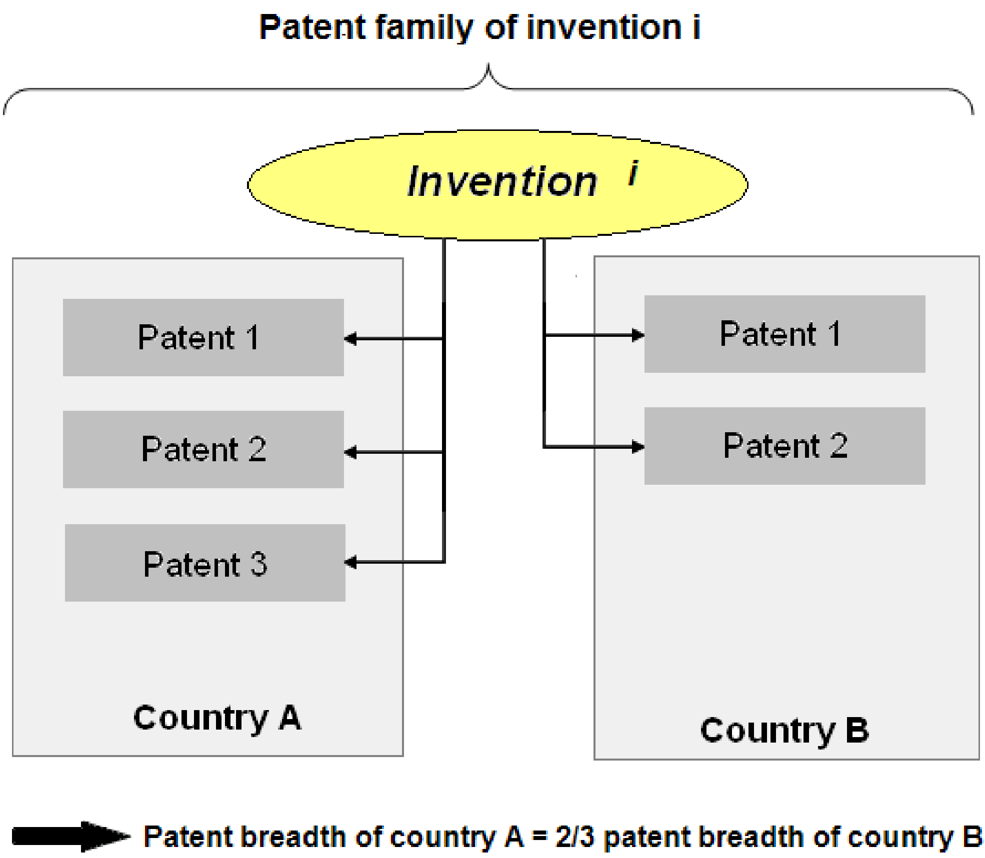
Source: Interviews, ENF website, firms' websites, and PV report 2009

Annex 2 Methodology: The patent as an indicator of the innovation and technology transfer

Innovation cannot be measured directly like other variables. Several indicators have therefore been developed to measure it. One is the measure of the input (R&D expenditure, number of staff in the R&D department), but such information is difficult to find, is aggregated, and only measures the input while the output can be preferable (Dechezleprêtre et al. 2010). Measure of the output can be done by studying the data on patents. This indicator has many advantages as it allows to have disaggregated information by technology, and also gives information about where the innovation is patented, which is necessary to study technology transfer.

As represented in Figure 6, if a person (or firm) innovates, it can decide to patent the invention in one or several countries, which will give him the exclusive right to commercially exploit that invention in those countries. In a single country, one or several patents can be granted to protect the invention according to its importance and the characteristics of the patent office of the country. The heterogeneity of national patent laws makes it difficult to make reliable cross-country comparisons. We deal with this classical problem by counting patent families, i.e. the set of patents granted for the invention in the different countries.

Figure 8 Schema of a patent family



Following the method developed by Dechezleprêtre et al. (2010), the indicator used to measure the quantity of innovation or technology diffusion process is then based on the number of families, that is to say the number of inventions.

However, a variable quantity of innovation can be embedded in those inventions. To take that into consideration, we use as a proxy of the "size" of the invention the number of patents granted in one country for this invention multiplied by the average patent breath in this country. The patent breadth of one country is the average "size" of the patents registered in the patent office of the country. In our example, the same invention has been protected by three patents in country A, while only 2 in country B. That is to say that with this single case, patent breadth in country A is 2/3 of that of country B. In our study, countries patent breadths have been computed using the US benchmark: for each countries "c", we kept only the patent families where patents have been at least granted in the US and in country c, and the patent breadth of country c is then defined as

$$PatentBreadth_c = \frac{NbPatent_{US}}{NbPatent_c} \qquad (1)$$

If the invention i has been patented in only one country (most of the case), the “size” of this invention (quantity of innovation embedded the invention) is then approximated by:

$$\mathrm{S}ize_{\mathrm{i}} = \mathrm{NbPatent}_{\mathrm{i,c}} * \mathrm{PatentBreadth}_{\mathrm{c}} \qquad (2)$$

Where $\mathrm{NbPatent}_{\mathrm{i,c}}$ is the number of patents granted for invention i in country c.

If the invention has been patented in several countries, the size of the invention is then approximated by the average of (2), that is:

$$\mathrm{S}ize_{\mathrm{i}} = \frac{1}{n}\sum_{c} \mathrm{NbPatent}_{\mathrm{i,c}} * \mathrm{PatentBreadth}_{\mathrm{c}} \quad (3)$$

Having this information, one can then approximate the innovation done by one country c in one year y in one segment s by summing the sizes of all the inventions done by this country, this year, in this segment ($i \in (c, y, s)$)

$$Innovation_{c,y,s} = \sum_{i \in (c,y,s)} \mathrm{S}ize_{\mathrm{i}} \qquad (4)$$

The technology transfer can be approximated the same way by keeping only the inventions that have been patented in a chosen country.

Limits of the indicator

Inventions do not have uniformly equal value, but this value can be approximated by the percentage of international families (meaning a patent that has been granted in at least two countries). Indeed, after the first patent application, the applicant has two years to patent the invention in other countries. The first application can only be an option for future commercial application while if the invention is patented in other countries, it proves that the applicant really shows some commercial interest in it. There is then a big gap in value between a patent that has been granted only in one country, and patents that have been granted in two or more countries.

A second, more difficult methodological issue is due to the fact that not all innovations are patented in practice. This is especially true for process innovations, which are often kept secret (Cohen et al., 2000). Since an important part of PV innovations concern manufacturing processes, this implies that our patent indicators probably do not account for all inventions

Annex 3 Database used

We built our dataset by downloading patent information from the espacenet website[10]. For this purpose, we choose research criteria designed for all PV segments in order to obtain the biggest part of the relevant patents (corresponding to the technology) while having as few irrelevant patents as possible. Not having all the patents does not matter as the sample is still representative, but having too many irrelevant patents is more problematic. This can be limited by using proper research criteria. Here are the research criteria used:

Keyword(s) in title or abstract:	International Patent Classification (IPC) code:
Silicon purification	
Silicon	C01B33 not C01B33/02
Ingot	
Silicon	C01B33/02 OR C30B
Wafer	
silicon wafer not semiconductor ?	H01L21
wafer	B24 OR B28
Cell	
(solar cell?) or photovoltaic not	H01L

[10] http://ep.espacenet.com is a free online service developed by the European Patent Office for searching information on patent and patent application.

module	
Module	
PV or solar or photovoltaic and module	H01L

We note that the fact that we obtain a different proportion of the patents really granted in each segment does not matter, as no absolute comparison will be done for the reasons explained in the previous section. We obtained 79,642 patents, published before 2010, covering the PV industry from silicon purification to module assembling.

Chapter two

What cost for photovoltaic modules in 2020?

Lessons from experience curve models

Abstract

Except in few locations, photovoltaic technology remains more expensive than conventional electricity sources. It is however expected that innovation and learning-by-doing will lead to drastic cuts in production cost in the near future. The goal of this essay is to predict the cost of PV modules up to 2020 using experience curve models, and to draw implications about the cost of PV electricity.

Experience curves relate production costs decrease to the accumulation of experience (in particular, cumulative production). Relying on annual data on photovoltaic module prices, cumulative production, R&D knowledge stock, and silicon and silver price over the period 1990 – 2011, we identify the experience curve model which minimizes the difference between predicted and actual module prices. The model is then used to make out-of-sample predictions up to 2020. We predict a 67% decrease of module price from 1.52 $/Wp in 2011 to 0.50 $/Wp

in 2020. The increase in cumulative capacity is responsible for 75% of this evolution, corresponding to a learning rate of 19.6%, and silicon price decrease is responsible for 25%.

Résumé français

L'électricité photovoltaïque est toujours plus chère que celle produite par des technologies classiques et plus matures comme celles liées aux énergies fossiles. Cependant, l'innovation et l'effet d'apprentissage vont conduire à une baisse importante du coût des panneaux solaires dans les prochaines décennies. L'objectif de ce chapitre est de prédire cette évolution jusqu'en 2020, en utilisant les modèles de courbe d'apprentissage, et d'en tirer des conclusions quant au prix de l'électricité photovoltaïque. Les courbes d'apprentissage modélisent le coût par l'expérience mesurée en production cumulée. A l'aide des données annuelles de prix des panneaux solaires, de production cumulée, de brevets et de prix du silicium et de l'argent de 1990 à 2011, nous identifions le model dont le pouvoir prédictif est le meilleur, c'est-à-dire qui minimise la différence entre les prédictions et le prix réel des modules sur cette période. Le modèle sélectionné est ensuite utilisé pour effectuer une prédiction du prix des panneaux solaires jusqu'en 2020. Nous attendons une réduction du prix de 67% entre 2011 et2020, de 1.52 $/kWp à 0.50 $/kWp, les trois quarts étant dus à l'effet d'apprentissage, le reste à la baisse du prix du silicium.

1 Introduction

Experience curves, also called learning curves, are widespread models used to predict cost in the middle and long term. In its simplest version, an experience curve relates production costs to the accumulation of experience (often measured by cumulative production). Experience curves are based on the theory of learning by doing which claims that "technical change in general can be ascribed to experience, that it is the very activity of production which gives rise to problems for which favourable responses are selected over time" (Arrow, 1962). Their success arises from their huge empirical support in various industries[11].

Experience curve is a familiar notion in the photovoltaic (PV) industry. PV technology is not yet competitive against conventional energy sources. However, it is expected that important cost reductions brought by learning by doing will lead to important gains in the future provided that the industry is developed enough now. Added to the fact that this learning cannot be internalised by the firms due to learning spillovers[12], this provides the rationale for public policies which subsidize the deployment of PV installation. In this policy context, a quantitative evaluation of the size of the cost decrease one can expect in the future by developing the market is important to justify the immediate cost of these policies. On the short term, experience curves are also useful to select the pace at which public subsidies should be reduced. For instance, a too pessimistic anticipation of cost evolution has led to an uncontrolled market boom in Spain in 2008 and in France in 2010, triggering sharp policy revisions (a cap on installations in Spain and a three-month moratorium together with a drastic cut of the feed-on tariff in 2011 in France). This stop-and-go policy was devastating, resulting in dozens of bankruptcies and thousands of job losses in the PV system installation activity. Reliable cost prediction is therefore crucial to the sustainable development of this industry.

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

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

In this chapter, we seek to predict the cost of PV modules up to 2020 using experience curves and to draw implications about the cost of PV electricity. As mentioned previously, the base version of the experience curve consists in regressing the module price (a proxy for the cost) on experience measured by cumulative production. More recently, additional explanatory variables have been added, such as input price, scale, or research and development (R&D) (Isoard and Soaria, 2001, Kobos et al., 2006, Yu et al., 2011). However, little attention has been paid in the literature to the influence on the predictive power of the model of adding these explanatory variables. This chapter aims at filling this gap, by identifying and selecting the most reliable model of experience curve applied to the PV industry.

Using data on world average annual value of module price, cumulative capacity, plant size, silicon and silver price, and the R&D knowledge stock[13] from 1990 to 2011, we select the specification with the best predictive power. That is, the set of explanatory variables which minimizes the difference between predicted and realized module prices. The model is then used to make out-of-sample predictions up to 2020.

Possible additional variables are identified through a survey of the literature on experience curves applied to the PV modules. We restrict the analysis to modules because they are standard products for which the price is available at the world level in dollar per Watt-peak for standard conditions. Other components of PV systems like inverter, battery, and wires are not specific to the PV industry. Moreover, the cost of local installation, and sunlight availability influencing the output, depend on local conditions. As a result, the estimation of a global experience curve[14] on PV systems, and a fortiori on PV electricity, is meaningless.

Most existing studies dealing with PV modules on a global scale like ours use experience as the only explanatory variable, with an average learning rate of 20.9%. Only three studies include other variables: R&D, scale, silicon price, or/and silver price. Our contribution is to carry out a systematic analysis by considering the inclusion of those variables and selecting the combination with the best predicting power.

[13] The data concerning R&D stops in 2007

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

Our analysis shows that only silicon price should be added to experience to predict module cost. Based on this model, we predict a 67% cost decrease from 2011 to 2020, experience being responsible for 75% of this evolution, and silicon price decrease the remaining 25%

The remainder of this paper is structured as follows: The next section recalls the history of experience curves. The third section presents the experience curve model and its classical limitations. A critical survey of experience curves applied to PV modules and their particular limitations is presented in section four. We perform an out of sample evaluation to choose the best specification of the model in section five. Section six presents scenarios for module cost until 2020 based on the best specification, and section seven the implications for PV electricity's competitiveness. Section eight concludes.

2 History of experience curves

Experience curves[15] are based on Arrow's theory (1962) basing endogenous technological change on "learning by doing", and analysing its economic implications. Learning by doing relies on the hypothesis that "technical change in general can be ascribed to experience, that it is the very activity of production which gives rise to problems for which favourable responses are selected over time" (Arrow, 1962). It arises from the empirical observation that experience increases performance (defined as an output/input ratio). This was earlier formalized in economics by Wright (1936) for the Aeronautical industry, who noticed that the number of labour-hours spent in the production of an airframe is a decreasing function of the number of similar airframes previously produced. The amount of labour-hours required for the Nth airframe was indeed proportional to $N^{-1/3}$. This relation was used as a production planning tool.

Based on 24 selected industrial products, the Boston Consulting Group (BCG, 1968) developed a modern approach of the experience curve, based on total unit cost rather than

[15] Both terms "learning curve" and "experience curve" are used interchangeably throughout the literature. We will only use the term "experience curve" thereafter.

only labour productivity. The model defines average unit cost as a function of cumulative output. As experience curve, we will refer to this modern approach from now on. Experience curves gained business planners interest, as they would help strategic planning of production. For example, an important first mover advantage was promised to firms riding down the experience curve to reduce costs, by expanding their market early through aggressive pricing. However, the outcome of such strategies happened to be disappointing (Lieberman, 1987), bringing up many critics, such as the impossibility to account for knowledge spillovers or market effects on price. This led to a certain loss of interest from strategic business planners.

Despite this relative loss of interest in business planning, the experience curve concept has not been neglected, as it drew attention for other purposes. Used on more global scales, it identifies the cost decrease potential from learning by doing for technologies that are not yet competitive, which justifies technology development policies when this learning is not fully captured by the firms. It is also one of the most common ways of endogenizing technological change in economic-energy-environment models such as MESSAGE (Messner, 1997) or MARKAL (Seebregts et al., 2000). As a result, many experience curves have been carried out in various industries (see for example Dutton and Thomas (1984) who study the results of 108 experience curves in 22 industrial sectors).

3 The experience curve model

3.1 The model

Experience curves are classical econometric models in which experience is always an explanatory variable, measured by cumulative production or another proxy such as cumulative installed capacity. If no additional explanatory variable is used, one gets the simplest specification, defined by:

$$\mathrm{C}_t = \mathrm{C}_0 \, \mathrm{Exp}_t{}^{-\mathrm{E}} \qquad (1)$$

With

C_t the cost of one unit of output at time t

C_0 the cost of the first unit

Exp_t experience at t, measured by cumulative output

To estimate the parameters econometrically, the following specification derived from (1) is used:

$$\log(C_t) = \log(C_{0)} - E \log(Exp_t) + \varepsilon_t \qquad (2)$$

With ε_t the error term, assumed to have a zero mean and constant variance, and to be independent and identically distributed

Based on the experience parameter E, the learning rate gives a practical evaluation of the percentage of change in cost corresponding to a doubling of experience:

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

A learning rate of 0.1 means that unit cost decreases by 10% for each doubling of experience.

Experience is always included in experience curves. It drives cost down through learning by doing as defined by Arrow (1962). However, other drivers of total cost[16], identified by Hall and Howell (1985) are often omitted:

- Other forms of learning, including learning by searching (brought by R&D), learning by using (through feed-backs from users which helps optimising the product), and learning by interacting (transfer of knowledge between users, producers, research institutes and policy makers due to knowledge networks, Kamp, 2002).
- Knowledge spillovers: the flow of knowledge outside the organisation where it has been created, without any market compensation. These spillovers are more important between firms that are geographically or technologically close. For experience curves at the firm scale, they induce a cost reduction that is not generated by the firm's own experience, thus altering the experience parameter. However, for global experience

[16] The experience curve defined by Wright (1936) and Arrow (1962) are applied to labour cost at a firm scale, which is reduced by learning by doing only. Being applied to total cost on a more global scale, other parameters drive cost dynamics for modern experience curves.

curves based on world average cost, spillovers are included in the global experience effect.

- Scale effect, which is the unit cost variation corresponding to an increase in production scale.
- Product standardisation, reducing transaction costs in the industry.

The econometric theory argues that if an explanatory variable is excluded from a model, the coefficients of the remaining variables will be biased unless the omitted variable is uncorrelated with every included variable (Berndt, 1991).

To limit the omitted variable bias, other explanatory variables have been recently added to the model, such as input price, R&D, or scale effect, leading to more complex experience curves with the following general specification:

$$C_t = A\,(P_t)^s\,(Exp_t)^{-E}(R\&D_t)^{\propto}\;\prod_j (p_{\,j,t})^{\,\beta_j} \qquad (3)$$

With:

P_t the average plant size at time t

Exp_t experience at time t

$R\&D_t$ the stock of knowledge brought by R&D at time t, the definition is explained in section 3.2.

$p_{\,j,t}$ the price of input j at time t

A,s[17], E, $\propto$, and β_j the parameters that can be estimated econometrically taking the logarithm of (3).

3.2 Econometric issues and other limitations

Experience curves are usually estimated with Ordinary Least Squares (OLS). This estimator is designed for classical linear regression models. However, this implies several assumptions with which experience curves do not always comply, mostly specification error (omitted variables as explained before and structural stability), serial correlation, simultaneity,

[17] 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.

and multicollinearity. Other concerns are not related to the econometric theory such as the use of price as a proxy for cost, knowledge spillovers, and the lack of product quality consideration. We describe those limitations with a particular attention to the consequences on the predictive power rather than the accuracy of the estimation of the parameters. We see to which extent those limitations apply to the PV industry in section 4.

3.2.1 Use of price as a proxy for cost

Cost data being difficult to obtain, average price is generally used as a proxy for average cost. It introduces a bias if price varies independently of cost. Such variations happen if the structure of the industry or the regulation changes.

While it is growing, an industry goes through different market structures with different impacts on price irrespective of cost. First market entrants can fix price below production cost in order to establish the market. Benefiting from market power, they can then maintain price while costs drop to benefit from a monopoly rent, increasing the gap between cost and price. Finally industry growth can lower entry barriers, increasing competition and reducing the gap between cost and price.

New disruptions such as technology breakthroughs can bring new phases of instability influencing price separately from cost. Market concentration could be controlled with the Herfindahl–Hirschman Index[18] (HHI). Lieberman (1984) for example finds a change in price behaviour at a HHI of roughly 0.2 (that is to say five firms of equal size) for chemical processing industries.

3.2.2 Knowledge spillovers

We distinguish intra-sectoral spillovers, for which the knowledge remains in the same sector, and cross-sectoral spillovers, for which it flows into another sector.

Cross sectoral spillovers bias all experience curves, since part of the experience effect is then due to the flow of knowledge from another industry. If it does not happen to the same extent after the estimation period, price reduction predictions are over-optimistic. Söderholm

[18] The HHI is defined as the sum of the squares of the market shares of the largest firms within the industry.

and Sundqvist (2007) recommend the introduction of a time trend in the experience curve equation to test the presence of external spillovers. If the experience parameter remains statistically significant, it really captures the impact of experience and not a general exogenous technical improvement.

The effect of intra-sectoral spillovers depends on the scale at which experience curves are carried out. At company level, they were acknowledged as an important limit of experience curves as a business planning tool, since early aggressive pricing didn't always prevent new entrants from penetrating the market, even those with strong learning rate. Using the BCG's data (BCG, 1968), Lieberman (1987) shows that a big part of the learning ultimately diffuses outside the firms. Gruber (1998) studies those spillovers in the semiconductor industry, separating the internal, national, and foreign components of the experience effect. He finds strong evidence that firms learn from external sources, but the origin of this external learning, domestic or foreign, does not seem to be relevant in this particular industry. However, at a global scale, experience curves aggregate cumulative output across all firms, therefore taking intra-sectoral spillovers into account as part of the global experience effect (Argote and Epple, 1990).

3.2.3 Multicollinearity

Multicollinearity arises when explanatory variables are highly correlated. If it does not bias the OLS estimators, and does not affect the R^2 statistic, it leads to high variances of the estimators. The regressions can then give absurd values of the parameters which affects predictions accuracy. This suggests that multicollinearity might be a major issue if some additional explanatory variables are highly correlated to experience.

3.2.4 Structural stability

To apply an OLS regression to experience curve equations, the parameters are assumed to be constant over time. If experience is the only explanatory variable, it does not allow any flexibility in the pace at which cost decreases with cumulative production, which can be inconsistent with economic theory. Grübler (1998) claims that cost reduction is fast during the initial development phase when R&D plays an important role, while it would slow down in the more mature phases. Additional explanatory variables can allow some flexibility, as for example R&D could account for the different phases described above[19].

Constant parameters also prevent from analysing technological breakthroughs. They can be modelled by breaking the experience curves in several linear parts having different parameters. To analyse the significance of breaking the adjustment into two periods, Isoard and Soria (2001) propose a structural change test procedure developed by Brown et al. (1975). A Chow structural break test can also be used.

3.2.5 Simultaneity

The causal relationship assumed in experience curves is that cost is brought down by the increase in experience through new production. Conversely, in their paper exploring the econometric issues of experience curves, Söderholm and Sundqvist (2007) note that a main reason why investments required to produce new output are made is that costs have been brought down. This suggests that new capacity installation and cost are determined simultaneously; hence that cumulative production is endogenous[20].

3.2.6 No perfect proxy of innovation

The R&D based knowledge stock at time t $R\&D_t$ in equation (3) is generally calculated according to:

$$R\&D_t = (1-r)\, R\&D_{t-1} + I_{t-x} \qquad (4)$$

With

r the depreciation rate

[19] Logistic curves or S curves can account for different learning rates corresponding to the different development phases (Pan and Köhler, 2007). However, they lack the empirical support experience curve have.

[20] Söderholm and Klassen (2007) use an econometric model with two equations: an experience curve including R&D to account for innovation, and a diffusion equation, in which cost, among other variables, explains new output production. However those equations are estimated independently because of the low correlation among the error terms of the two equations (correlation coefficient of -0.3). If the correlation would be important, they suggest using a three stage least square estimation instead of the OLS.

I_{t-x} innovation (R&D expenditure or patent application) at time t-x, with x a lag accounting for the time for innovation to become effective

The two most common proxies for innovation are R&D expenditure and patents application (OECD, 2009), which are far from perfect. Indeed, R&D expenditure does not measure the output of innovation, and patented innovation only represents a minor part of this output, which can also be protected by secrecy or lead time. Besides, public and private R&D should be differentiated as they have a different impact on the technological change process, and this differentiation would help better understand the impact of "technology push" policies.

3.2.7 Other

Product quality is not taken into account by experience curves, while it has important economic implications. Indeed, experience curves focus on unit cost. Change in quality is then beyond this measure.

In experience curves, there is theoretically no floor cost since the cost tends to 0 when cumulative production tends to infinite. However cumulative production is obviously limited, which constitutes a de facto limit. Some studies introduce a floor cost by adding a constant in the equation as Yang and Williams (2009).

The uncertainty is difficult to evaluate due to its high number of possible causes: the data source, the proxy used for experience, the econometric method, the methodology to correct for inflation or exchange rates, etc. The IEA (2000) suggests constant re-estimation of the parameters to lower this uncertainty while the technology is being developed. Van Sark (2008) notes that the standard error of the mean price used as dependent variable to compute the experience parameter, has to be considered as well. It can be included through the error propagation theory.

4 Critical literature survey of experience curves applied to photovoltaic modules

4.1 Survey of experience curves applied to photovoltaic modules

In this section, we survey experience curves applied to PV modules in academic publications and a report from the International Energy Agency (IEA). We obtain 20 studies, among which 17 explain module cost by experience only, listed in table 1, and only 3 include additional explanatory variables besides experience, listed in table 2.

All the experience curves listed in table 1 have the same specification, with module price as dependent variable, and experience as unique explanatory variable. They differ by the time frame used for the estimation, the geographical scale, and the data source. The average learning rate is 20.2%, meaning that module price is reduced by 20.2 % each time cumulative production doubles. The standard error of experience curves on a global scale is 3.2%, while it is 7.6% for experience curves at a country scale. We explain this difference in section 4.2.2 by knowledge spillovers.

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

Study	Geographical scale	Time frame	Learning rate	Data Source
Maycock & Wakefield (1975)	Global	1965-1973	20.0%	n.a.
Tsuchiya (1992)	Japan	1979-1988	19.0%	n.a.
Williams é Terzian (1993)	Global	1976-1992	18.4%	Strategies Unlimited
Cody and Tiedje (1997)	US	1976-1988	22.0%	Maycock
Tsuchiya (1999)	Japan	1979-1998	17.6%	n.a.
IEA (2000)	Global	1976-1984 1987-1996	16.0% 21.0%	EU-Atlas and Nitsch (1998)
Harmon (2000)	Global	1968-1998	20.2%	Maycock

Wiliams (2002)	Global	1976-2000	20.0%	Strategies Unlimited
Parente et al. (2002)	Global	1981-2000	22.8%	Maycock
		1981-1990	20.2%	
		1991-2000	22.6%	
Poponi (2003)	Global	1976-2002	25.0%	Maycock
		1989-2002	19.5%	
Schaeffer (2004)	Global	1976-2001	20.0%	Strategies Unlimited
		1987-2001	23.0%	
	Germany	1992-2001	10.0%	Photex database
Papineau (2004)	Germany	1992-2000	15.0%	Extool Project, IEA
	Switzerland	1992-2000	10.0%	
	US	1992-2001	32.0%	
	US	1992-2001	20.0%	US DOE
Nemet (2006)	Global	1978-2001	26.0%	Maycock
		1976-2001	17.0%	Strategies Unlimited
Van Sark (2006)	Global	1976-2001	20.6%	Strategies Unlimited
		1981-1990	16.6%	
		1991-2000	29.6%	
Swanson (2006)	Global	1979-2005	19.0%	Strategies Unlimited & other
Van Sark (2008)	Global	1976-2006	20.6%	Strategies Unlimited & other
Breyer et al. (2010)	Global	1976-2003	22.8%	Strategies Unlimited & other
		1976-2010	19.3%	

Besides experience, experience curves in table 2 identify four variables with a significant effect on modules cost:

- R&D, through learning by searching. Kobos et al. (2006) find that learning by searching has a significant positive effect.

- Scale, through return to scale. Isoard and Soria (2001) find constant return to scale. However, allowing for a flexible value of the parameter, he finds decreasing return to scale before 1994. With more recent data, Yu et al. (2011) find increasing return to scale. This suggests that returns to scale were decreasing in the early phase of the development of the PV industry, and then increasing, which is inconsistent with the constant parameters hypothesis. However, the variability of the scale parameter found in the studies can be due to multicollinearity increasing the variance of the estimator.
- Input price, which accounts for 30% of the cost of a module[21]. The most important are silicon (20% of module cost), flat glass (4%) EVA (3%) and silver (<3%). Yu et al. (2011) find a strong positive effect of silicon price on module price. They also find a slight negative effect of silver price, explaining it by the substitution effect: A rise in silver price urges firms to decrease their use of silver, leading to a reduction in the cost of PV production.

Table 2 Review of multifactor experience curves of PV modules

Study	Time scale	**Learning by doing**	**Learning by searching (R&D)**	**Return to scale**	**Input price**	
					Silicon	Silver
Isoard and Soaria (2001)	1876-1994	9.2%	-	1	-	-
Kobos et al. (2006)	1975-2000	18.4%	14.3%	-	-	-
Yu et al. (2011)	1976-2006	13.5%	-	1.066	0.285	-0.135

The average learning by doing rate found by experience curves with several explanatory variables in table 2 is 13.7%. It is calculated from the experience parameter too. However it is much lower than the learning rate from models with experience only, in table 1 (20.9% on a global scale). This is in line with the fact that when experience is the only explanatory variable, the parameter captures the influence of other drivers.

[21] Source: Photon consulting annual report 2012, p. 154, and US DOE (2010), p.22.

4.2 Main limitations of experience curves applied to photovoltaic modules.

Are those results weakened by the limitations listed in section 3? We check whether each limitation applies to experience curves applied to PV modules on a global scale.

Simultaneity does not seem to be an issue for experience curves applied to PV modules. With an intertemporal correlation analysis based on the Granger causality test (Granger, 1969), Isoard and Soria (2001) find that the null hypothesis can be accepted, which means that there is no proof that lower cost induces additional capacity in the following periods. Based on the same test, and a Hausman (1978) exogeneity test, Kahouli-Brahmi (2009) also shows that there is no evidence of endogeneity effect. Since on the middle and long term, FITs follow the price of PV electricity, the gap between PV electricity price and the FITs, driving demand, does not depend on PV module price. Therefore the price of PV modules is not likely to be an important driver of new capacity installation.

Structural stability does not seem to be an issue either. Nemet (2009) finds a high variability of the learning rates, which depend on the estimation period. However, when silicon price is controlled, the learning rate is stable (see figure 6 in section 5.3). The instability of the learning rate is therefore rather due to the omission of silicon price than to the variation of the actual learning rate. Based on a Chow structural break test, Parente (2002) found a significant break in 1991 for an experience curve based on experience only, interpreting it as a consequence of economies of scale and technology development driven by important PV development initiatives in various countries at that time (Japanese Sun Shine and the German 1000 Roofs). However Isoard and Soria (2001) find a temporal stability of the coefficients of his experience curve using CUSUM and CUSUM of square tests.

4.2.1 Omitted variables bias

Other than experience, four drivers of module cost are identified in the literature survey: R&D, scale, silicon and silver price. Therefore experience curves that do not take all these drivers into account might have an omitted variable bias in their remaining parameters, as shown by the difference between the average learning by doing rates in table 1 and 2. Omitted variable bias is therefore a major issue for experience curves, and can be reduced by the addition of explanatory variables.

If the omitted variable bias prevents from accurately measuring the effect of each variable, the consequence on the accuracy of the predictions is not straightforward. We show in annex 2 that the omitted variable bias affects the accuracy of the prediction only if the relation between the omitted variable and experience during the predicted period is different than during the estimated period.

4.2.2 Knowledge spillovers

Intra-sectoral spillovers take place in the PV industry. They have been identified by Flint (2009) calculating that firms benefited from 8.83% of the "total stock of learning", using a dynamic structural-empirical model on 2003/2008 data[22].

Those intra-sectoral spillovers explain the different learning rates found in every country in table 1. Countries producing more PV modules than the average have lower learning rates (Germany, average of 12.5%), because the increase in experience is higher, while the price follows the same trend as in other countries because of the global nature of the learning due to those spillovers. This global learning process advocates for the estimation of experience curves on a global scale.

Cross-sectoral spillovers could also be a limitation to experience curves applied to the PV industry. Köhler (2006) suggests that major spillovers happened from the semiconductor to the nascent PV industry, explaining part of past cost reductions, while this might not happen to the same extent in the future, since compared to the growing PV industry, the semiconductor industry is of diminishing importance. But Kahouli-Brahmi (2009) found that there is no significant time trend effect for rural photovoltaic energy, while the other coefficients remain significant[23], suggesting that these spillovers didn't play a significant role.

[22] Studying the Chinese PV industry, De La Tour et al. (2011) find that this knowledge transfer happens mainly through labour mobility and manufacturing equipment trade

[23] However the same test for decentralized PV show gives opposite results

4.2.3 Use of price as a proxy for cost

The use of price as a proxy for cost is likely to introduce a bias in the experience parameter since market conditions have been very unstable in the PV sector. Market effects affecting price independently of cost are analysed in chapter 3. Schaeffer et al (2004) notice that the first PV companies were subsidiaries of bigger firms, whose core business was not PV, but saw PV as a strategic investment where they could afford short term losses by setting a price below production cost. Then, benefiting from market power, they could maintain price while costs was dropping to take advantage of monopoly rent. The industry getting more mature, qualified workforce and turn-key manufacturing equipment became widely available as explained in chapter one, lowering entry barriers. Numerous new manufacturers, especially from China, entered the PV industry, increasing competition and decreasing margins. This resulted in important overcapacity in 2011 and 2012 pressuring price down[24].

PV demand being historically mostly driven by incentive policies, policy changes affect demand, eventually affecting price irrespective of cost. Söderholm and Sundqvist (2007) point out that it may be a bad practice for analysts to use an estimated econometric model found suitable for one time period when attempting to predict what will happen in another period under a different set of policy rules, for example with different feed-in tariffs for some major countries. Nevertheless, most previous experience curve studies are built on the presumption that the structure of the model employed is unaffected by any policy change over the time period considered. Chapter three confirms that the influence of feed-in tariffs on module price in not significant. However feed-in tariff changes cause short term distortions. For the PV industry, the frequency of policy changes is such that it is not possible to find a period of policy stability long enough to perform a regression.

Finally, we show in chapter 3 that the silicon shortage from 2005 to 2009 had a big impact on the structure of the PV industry. The capacity constraint gave silicon producers some market power allowing them to set high silicon price. As it is the main input for PV cells production, this raised cells and modules price over this period. This can be controlled by including silicon price in the model.

[24] http://www.pv-tech.org/news/solar_module_inventories_reach_a_massive_10gw_says_ims_research

4.2.4 Multicollinearity

Since the PV industry is growing quickly[25], each year's new production (defining the market size) accounts for an important part of cumulative production. Therefore scale and R&D that are linked to market size are likely to be correlated to cumulative production. This suggests that multicollinearity could be an important issue for experience curves applied to the PV industry including scale or R&D. With the Belsley et al. (1980) procedure, Isoard and Soria (2001) find no evidence of collinearity for PV with an experience curve with scale as additional variable. However Kobos et al. (2006) find multicollinearity for an experience curve including cumulative production and R&D knowledge stock with a VIF test, but only with some specific values of the time lag and the depreciation rate used to estimate the R&D knowledge stock. Kouvaritakis et al. (2000) suggest a solution to deal with the issue of multicollinearity by fixing the R&D parameter at different levels while estimating experience parameter econometrically. The final choice of the former parameter then depends on statistical criteria such as the value of the likelihood function and the robustness of remaining estimated parameters, and subjective ones.

4.2.5 Uncertainty concerning the data prior 1990

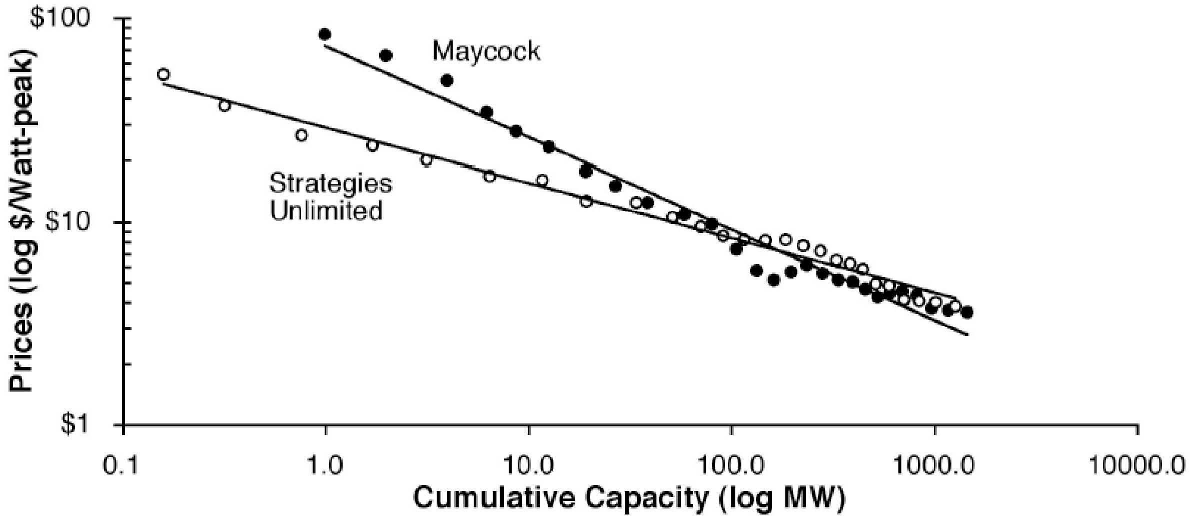
For old data (before 2005), all studies on a global scale except IEA (2000) are based on two major data providers: Maycock[26], a historical expert of the PV industry, and Strategies Unlimited[27], a company specialised in semi-conductors selling market reports. As figure 1 shows, Maycock's data suggests a steeper experience curve than Strategies Unlimited one, due to very different values for PV module price prior to 1990 (corresponding to 200 MW cumulative capacity). Experience curves listed in table 1 show that global studies following Maycock's data have an average learning rate of 22.3%, while those following Strategies Unlimited have an average learning rate of 20.6%. Since those datasets are the only one available for old data, this creates a high uncertainty concerning the data prior to 1990. To our knowledge, it is not possible to identify the best data source.

[25] The size of the market has been growing on a 57% compound annual growth rate from 2000 to 2011.

[26] Maycock and Wakefileld, 1975; Maycock, various PV news; Maycock, 2002, 2005; Maycock and Bradford, 2007

[27] See for example Strategies Unlimited, 2003

Figure 1 PV modules price evolution according to the two major data providers (Source: Nemet 2007)



4.2.6 Product quality consideration

For PV modules, the measure is often in dollar per Watt-peak[28] ($/Wp), which accounts neither for the lifetime nor for the reliability of power generation, while those two features are major determinants of PV electricity cost (in dollar per kWh). Those characteristics should then be taken into account when electricity cost is studied rather than module cost.

4.2.7 Influence of currency rates

International trade plays an important role in the PV industry. For example, while Europe accounted for 75% of the global market in 2011 (EPIA, 2012), 94% of the modules are assembled elsewhere, mainly in China. Fluctuations between the US Dollar, the Chinese Renminbi, and the Euro therefore affect PV module prices in dollars independently of technological progress.

[28] Watt-peak (Wp) is a measure of the nominal power of a photovoltaic solar energy device under Standard Test Conditions.

4.2.8 Synthesis

We focus on experience curves applied to PV modules on a global scale. The most important limitations are omitted variable bias, especially when experience is the only explanatory variable and multicollinearity when other variables are added. Moreover, the utilisation of price as proxy for cost is likely to introduce a bias in the unstable PV industry.

5 Determination of the best specification of the model

The purpose of experience curves is to predict future cost (or price). Therefore predictions are done out of the sample used to estimate the model. The accuracy of the predictions depends on two elements: (1) the predictive power of the model, and (2) the prediction of the explanatory variables used. In this section we focus only on the first one, by choosing the model specification with the best predictive power.

The addition of an explanatory variable has two opposite effects on the predictive power. On the one hand, it limits the omitted variable bias, which increases the predictive power of the model. But on the other hand, it can create multicollinearity if the additional variable is highly correlated to one or several other explanatory variables, which decreases the predictive power by increasing the variance of the estimator. Therefore, econometric considerations cannot help decide whether an explanatory variable should be added or not. In this section, we choose the best specification by evaluating empirically the predictive power of all the possible combinations of explanatory variables.

5.1 Methodology

We test 16 different specifications of the model listed in table 3. Indeed, if experience is always included, four variables identified in the literature can be added: R&D, scale, silicon price, and silver price. We didn't find a significant effect of other input prices on module cost[29]. Besides, we test two proxies to measure experience: cumulative capacity, and cumulative capacity with one year lag to account for the time for the learning process to take place.

Table 3 Sets of additional variables besides experience for the 16 specifications tested

<table>
<tr><td colspan="6">No additional variable</td></tr>
<tr><td colspan="6">1</td></tr>
<tr><td></td><td>Si (Silicon)</td><td>Ar (Silver)</td><td>Scale</td><td>R&D</td><td></td></tr>
<tr><td></td><td>2</td><td>3</td><td>4</td><td>5</td><td></td></tr>
<tr><td>Si and Ar</td><td>Si and Scale</td><td>Si and R&D</td><td>Ar and Scale</td><td>Ar and R&D</td><td>Scale and R&D</td></tr>
<tr><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td></tr>
<tr><td></td><td>Si, Ar,
and Scale</td><td>Si, Ar,
and R&D</td><td>Si, Scale,
and R&D</td><td>Ar, Scale,
and RD</td><td></td></tr>
<tr><td></td><td>12</td><td>13</td><td>14</td><td>15</td><td></td></tr>
<tr><td colspan="6">ALL (Si, Ar, Scale, and R&D)</td></tr>
<tr><td colspan="6">16</td></tr>
</table>

Since the model is built to predict future values, the predictive power of the specifications is evaluated on predictions out of the samples used to estimate them. For example, if a model is estimated from 1990 to 1999, the evaluation is done with predictions after 1999.

We estimate 192 models. Indeed, each of the 16 possible specifications is estimated on 12 ten years periods. The first one goes from 1990 to 1999, and the last one from 2001 to 2010. For each estimation, module price predictions are made for every year from the one following the estimation, to 2011, the last year for which we have historical values. The predictions are done using historical values of the explanatory variables. The error is measured by the

[29] Using the data explained in section 5.1, and flat glass price and synthetic rubber price from the US Bureau of statistics.

difference between the prediction $\hat{y}_i$ and the realised value of module price y_i. Since price decreases quickly, we need to consider the error relative to the price by taking the percentage error. Moreover, since error can be either negative or positive, we take the absolute value of those percentage errors.

For each specification/time horizon, we get several evaluations of the prediction's accuracy. Therefore, we compute for each specification/time horizon the Mean Absolute Percentage Error defined by:

$$MAPE(t) = \frac{1}{n_t} * \sum_{i=1}^{n_t} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \qquad (5)$$

With

t the time horizon

n_t the number of evaluations of the specification at this time horizon

This methodology provides us with the MAPE of the predictions for time horizons between 1 and 11 years for each of the 16 specifications.

5.2 Data

The dataset consists in world average annual values of module price, cumulative capacity, plant size, silicon price, and R&D knowledge stock from 1990 to 2011[30] represented in figures 2 to 5. It avoids the high uncertainty of the data prior 1990 noted in section 4. The sources of the data are listed in annex 3.

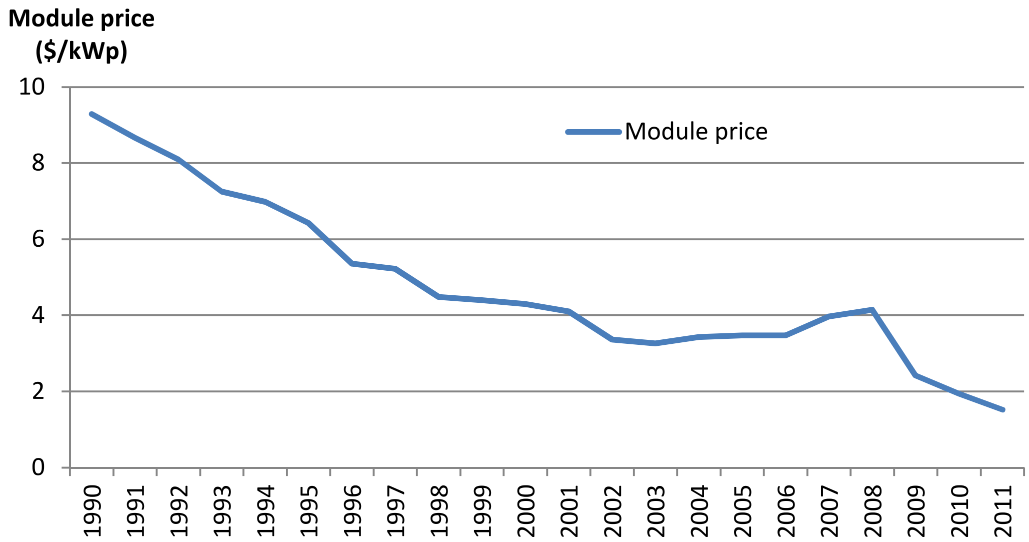
The high silicon price from 2004 to 2009 (figure 3) due to the silicon shortage with a peak in 2008 explains the slight increase in module price on the same period (figure 2). Silver price (figure 3) also started to rise in 2004, due to growing investor's interest in silver modifying the supply/demand balance.

The other variables, cumulative capacity and scale (figure 4), and R&D (figure 5), increase regularly over time with the size of the industry. As a consequence, they are highly correlated as confirmed by table 4 giving the correlation between the logarithms of the variables which

[30] Except R&D for which the data stops in 2007

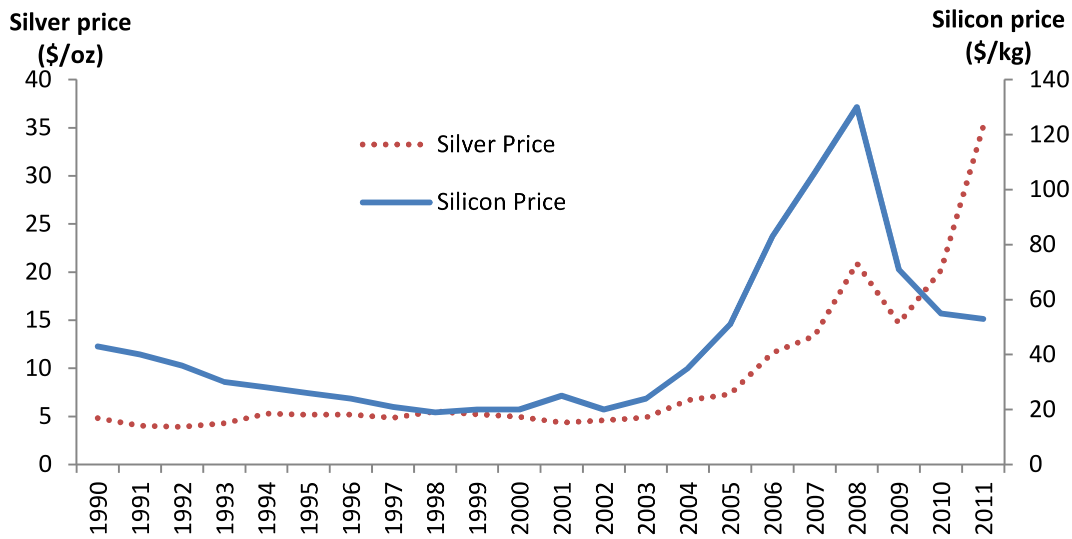
are used in the regressions: ρ(LogScale,LogExp)= 0.996, and ρ(LogR&D,LogExp)=0.984, with ρ the correlation coefficient.

Figure 2 Evolution of module price from 1990 to 2011



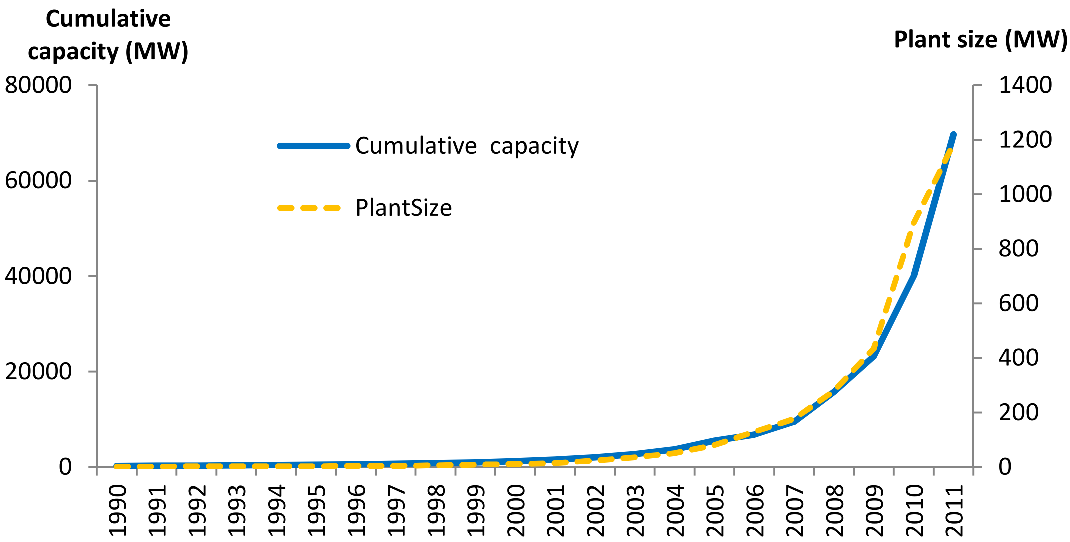
Source: see Annex 3

Figure 3 Evolution of silicon and silver price from 1990 to 2011



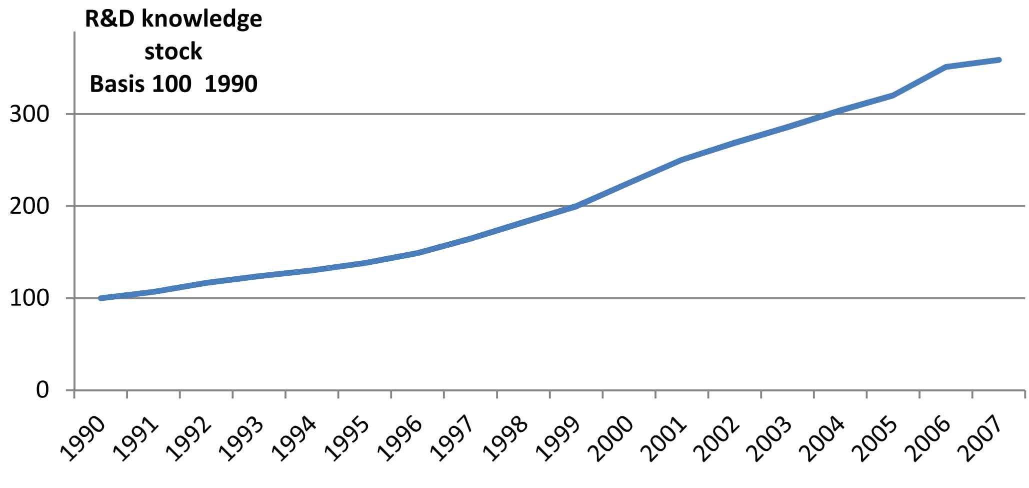
Source: see Annex 3

Figure 4 Evolution of cumulative capacity and plant size from 1990 to 2011



Source: see Annex 3

Figure 5 Evolution of R&D knowledge stock from 1990 to 2007



Source: see Annex 3

Table 4 Correlation between variables used in the specifications

	LogExp[a]	LogScale	LogSilicon	LogSilver	LogRD
LogExp[a]	1				
LogScale	0.996	1			
LogSilicon	0.455	0.499	1		
LogSilver	0.784	0.792	0.763	1	
LogRD	0.984	0.975	0.306	0.683	1

a: Here we use cumulative capacity as proxy for experience,

cumulative capacity with one year lag gives similar results

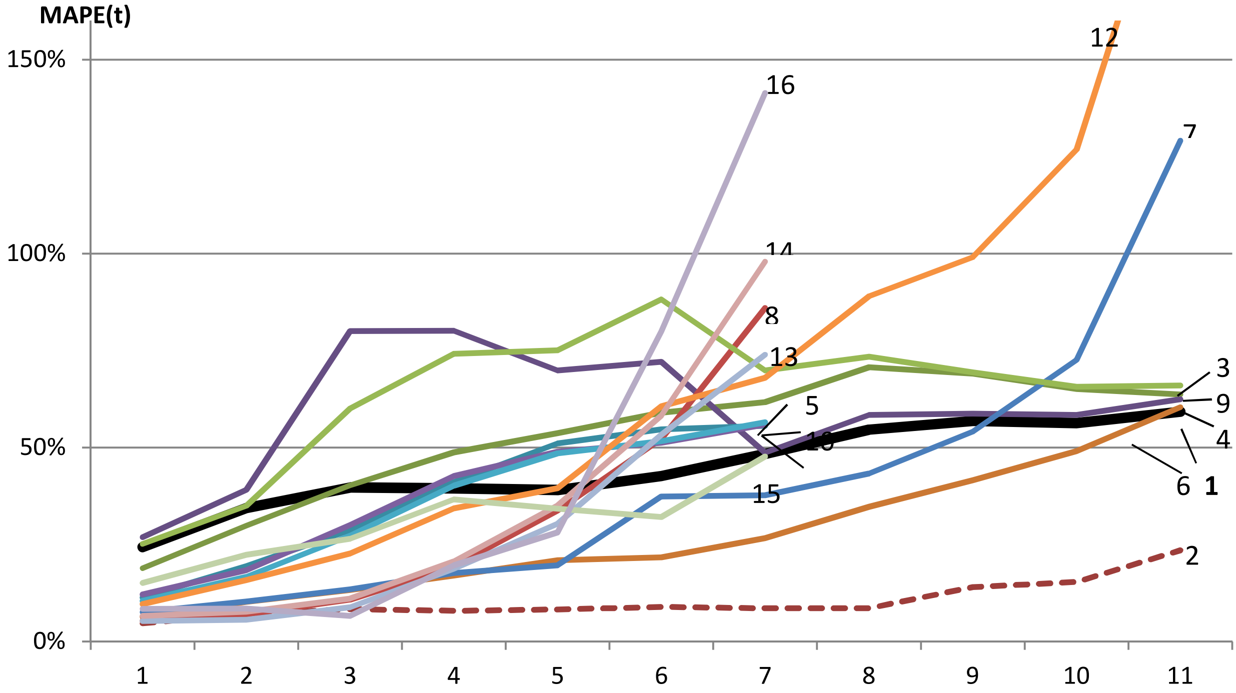
5.3 Results

The MAPE of the 16 specifications according to the time horizon is represented in figure 6. The proxy for experience used is cumulative capacity with one year lag. It performs better than cumulative capacity without lag (the results without lag are shown in annex 4) : the average MAPE is 41.6% with the lag and 44% without lag[31].

The numbers represent the specification numbers from table 3. The thick and dark curve represents the classic specification with experience only. It shows that the best set of explanatory variables is the number 2 with experience and silicon price (the doted curve). It performs better than the usual specification with experience alone, and the addition of any other explanatory variable decreases the predictive power of the model. We will therefore use this specification for the prediction post 2011.

[31] A two years lag gives worth predictions based on the same tests

Figure 6 Comparison of MAPE(t) for each model, MAPE(t) being the mean absolute percentage error according to the time horizon t



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

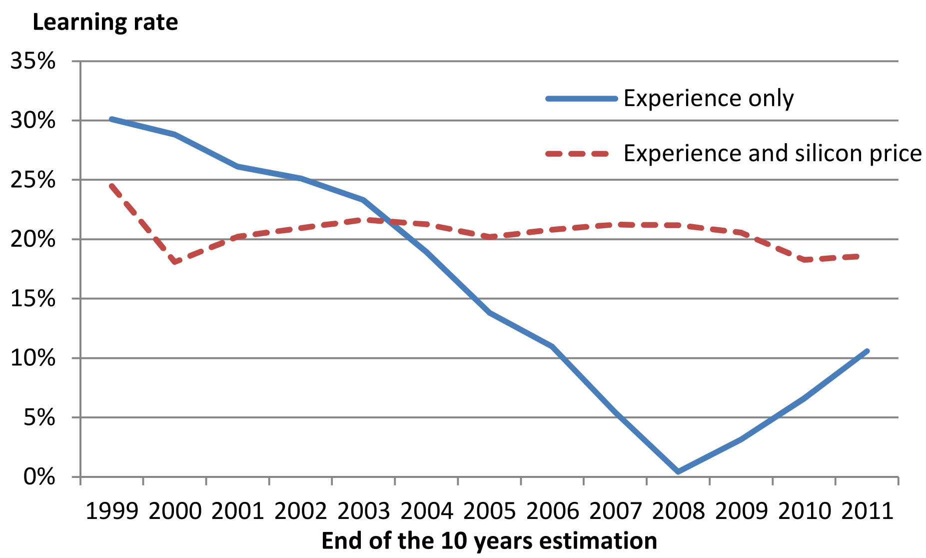
This result can be interpreted in light of the trade-off between omitted variable bias and multicollinearity. The inclusion of silicon price avoids the corresponding omitted variable bias. Figure 7 showing the learning rate of experience curves with or without including silicon price show that the bias corresponding to the omission of silicon price is important and temporally not stable because of the silicon shortage from 2004 to 2009. Moreover, since silicon price is poorly correlated to experience (ρ=0.46, c.f. table 3), its inclusion in the model does not create multicollinearity[32]. On the contrary, the introduction of scale or R&D decreases the accuracy of the model, because they are highly correlated to experience (ρ>0.98), so they create important multicollinearity[33]. But the bias resulting from their omission does not affect the predictions' accuracy much: because their relation with

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

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

experience is stable, the effect of this omitted variable bias in the predictions accounts for the real effect of the omitted variable (c.f. annex 2 for the justification). Silver price is less correlated to experience (ρ=0.78)[34], but it has only a small effect on module price, and the results show that it shouldn't be used in the model.

Figure 7 Learning rates according to the end of the 10 years estimations, for two specifications: experience only and experience and silicon price.



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

Note that the poor performance of the models in general, with a MAPE over 15% on a ten years horizon, is due to the short estimation periods (10 years). This leads to a high variance of the estimators. For the module price prediction post 2011 in next section, the selected model with experience and silicon is estimated over 22 years (from 1990 to 2011), which leads to much lower standard errors of the coefficients than for the 10 years estimations (more than five time for the intercept and experience, and 3.4 times for silicon price), suggesting that the predictions are more accurate than what figure 6 suggests.

[34] The VIF for silver price is 5.95.

Besides the predictive power of the model, the issue of explanatory variables prediction has to be considered as well. This will be treated in the next section by building scenarios of experience and silicon price evolution.

6 Prediction of module price post 2011

Following the results of section 5, we base the predictions post 2011 on an experience curve with experience and silicon price as explanatory variables. The proxy for experience is cumulative capacity with one year lag. We estimate the model on the whole period, from 1990 to 2011. The addition of a time trend is not significant, which suggests that no important extra sectoral spillovers happened during the estimation period. The result of the regression is shown in table 5. The experience parameter of -0.338 corresponds to a learning rate of 20.1%.

Table 5 Results of the regression of log(module price) on log(lagged cumulative capacity) and log(silicon price) on 1990/2011

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

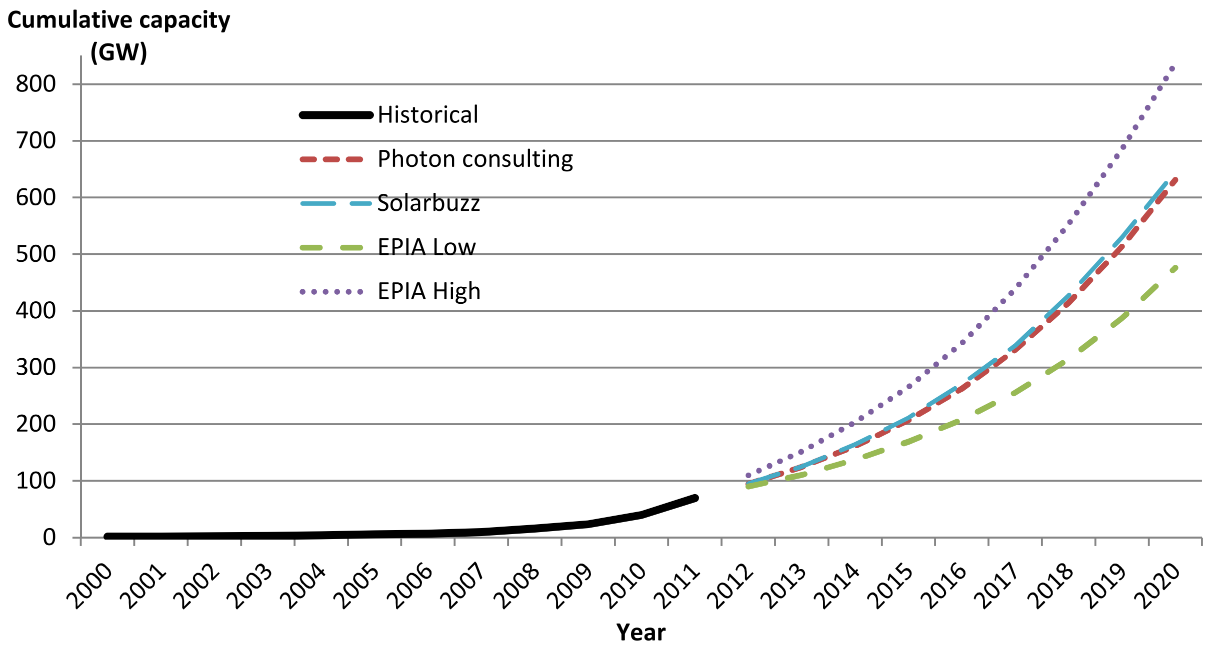
6.1 Prediction of the explanatory variables

We need to build scenarios about the evolution of the explanatory variables until 2020. All the prices are in dollar 2011. The construction of different scenarios helps to test the sensitivity of the model to the variables.

6.1.1 Cumulative capacity scenarios

Cumulative capacity scenarios made in 2012 by Photon Consulting[35] and Solarbuzz[36], the two leading market research companies in the PV sector, and the European Photovoltaic Industry Association (EPIA)[37], are shown in figure 8[38].They correspond to Compound Annual Growth Rates (CAGRs) of the market from 15% (EPIA low) to 23% (EPIA high) from 2011 to 2020. The CAGR was 55% from 2000 to 2011. The lower predicted CAGRs until 2020 are due to lower incentive policies expected in Europe, the main market.

Figure 8 Cumulative capacity forecast until 2020



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

---

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

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

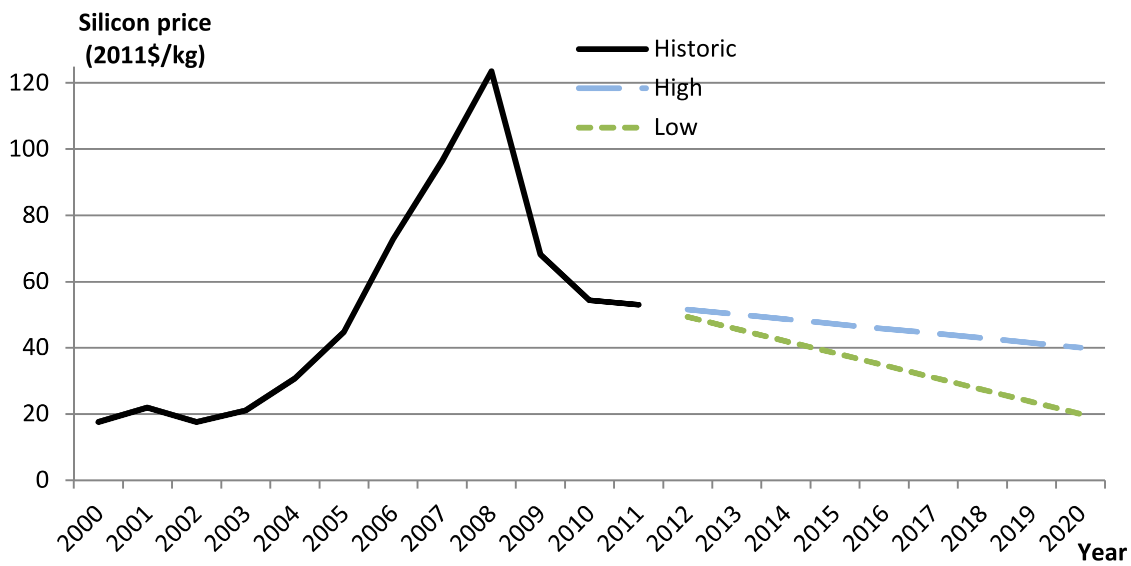
[37] EPIA (Global market outlook for photovoltaic until 2016), EPIA, May 2012. Predictions from 2017 to 2020 have been made following the same trend in the CAGR.

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

6.1.2 Silicon price scenarios

We build two scenarios of silicon price evolution until 2020, shown in figure 9. We consider a linear decrease from 53$/kg in 2011 to 20 $/kg in 2020 in the low case, which corresponds to the lowest price prevision found in market forecasts in 2012[39], or 40 $/kg in the high case, which corresponds to the highest price prevision[40]. We consider a regular decrease of silicon price, because after the shortage period from 2004 to 2009 explaining the sudden rise of silicon price until 2009 and the sudden decrease since then, there is now an oversupply of polysilicon, which is expected to be a long term situation given the announcement of new production capacity. The cost decrease is driven by scale increase, lower electricity cost, technology improvement, and long term contracts renegotiation reducing the gap with the lower spot price.

Figure 9 Silicon price forecast until 2020



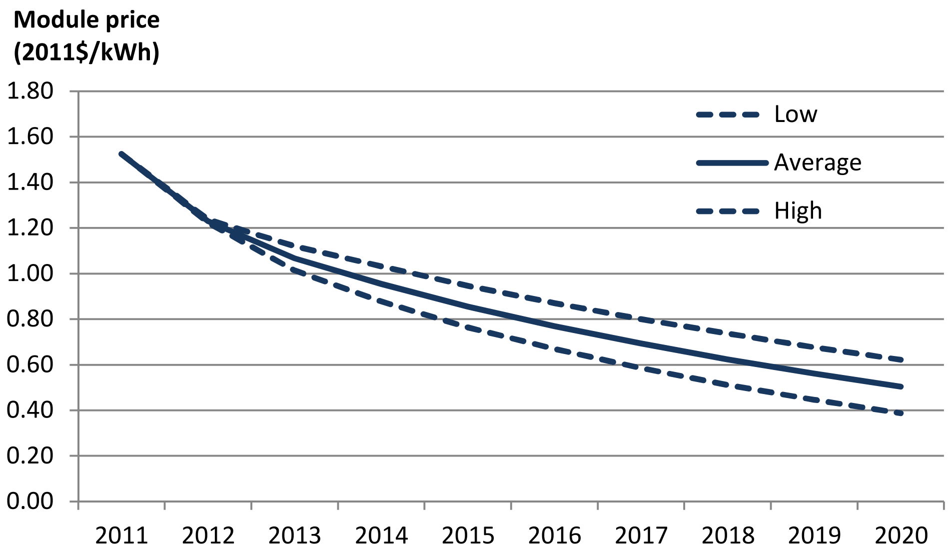
[39] Source: Sun & Wind Energy, 2011

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

6.2 Module price prediction until 2020

Using the specification chosen in section 5 and estimated from 1990 to 2011, and the two previous scenarios of the evolution of the explanatory variables, we are able to forecast the evolution of module price, presented in figure 10. The low scenario for module price corresponds to the highest scenario for PV industry development, and the lowest scenario of silicon price. The highest scenario for module price corresponds to the slowest development of the industry and the highest scenario for silicon price. On average, we find a 67% decrease of module price from 1.52 \$/Wp in 2011 to 0.50\$/Wp in 2020. The increase in cumulative capacity is responsible for 75% of this reduction, and the silicon price decrease for 25%.

Figure 10 Module price prediction until 2020



7 Impact on the cost of photovoltaic electricity

In this section, we predict the cost of PV electricity based on the prediction of module price from section 6. The standard measure of the cost of electricity is the Levelised Cost Of

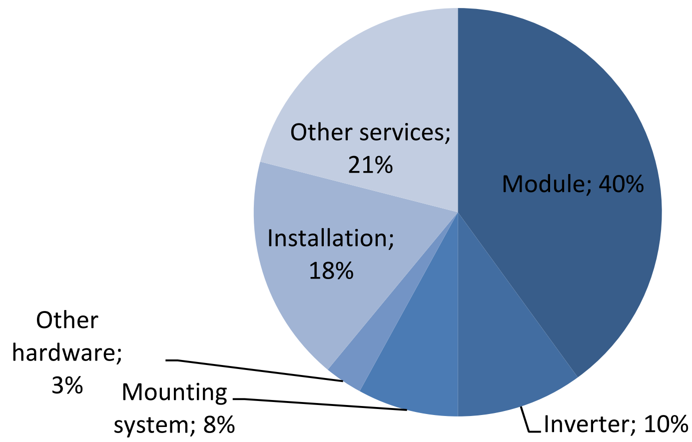
Electricity (LCOE), which is the average cost of generating electricity over the lifetime of the system, according to:

$$LCOE = \frac{Net\ Present\ Value\ (cost\ over\ the\ lifetime)}{Net\ Present\ Value\ (electricity\ produced\ over\ the\ lifetime)}$$

7.1 Calculation of the photovoltaic levelised cost of electricity

Module price accounts for 40% of the total price of an average system in 2011[41] as shown in figure 11.

Figure 11 Cost breakdown of a PV system in 2011 (source: Photon consulting 2012)



We are thus not able to directly infer the PV system or PV electricity cost from the results concerning modules. We need to make assumptions about the cost of other components, the type of system, parameters influencing the quantity of electricity produced such as sunlight availability and lifetime of the system, and the discount rate.

The system can be residential, commercial, or industrial (utility). Due to economies of scale, the LCOE is cheaper for bigger systems, and modules account for a more important part of total cost. The inverter has to be replaced once which accounts for most of the

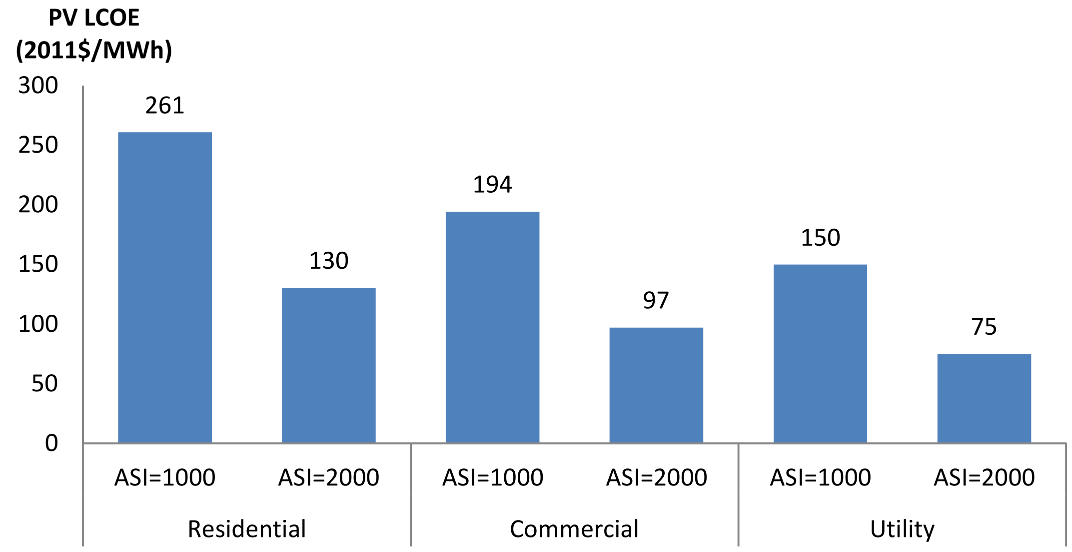
[41] Source: Photon Consulting (2012), p. 84

operation and maintenance cost. Moreover, the lifetime of the system has an influence on the LCOE. Other than the characteristics of the system, sunlight availability and discount rates are also important determinants. Sunlight availability is measured by the Annual Solar Irradiation (ASI). For example, the North of Germany or Alaska has an ASI of 1000 kWh/year, while the south of Spain, Italy, or California has an ASI of 2000 kWh/year. Since 95% of the cost of a PV system over its lifetime is CAPEX while the electricity is produced regularly over the whole lifetime, the discount rate is an important determinant of the LCOE. As Branker et al. (2011) noted in a survey of studies of PV LCOE, the assumptions relative to the discount rate are often not clear; it stands between 5% and 10% in most studies.

We computed the LCOE of three types of PV systems: residential, commercial, and utility. Two ASI are considered, 1000 kWh/year which corresponds the north of Germany, and 2000 kWh/year which corresponds to the sunniest areas such as California or south of Spain[42]. The lifetime of the systems increases from 25 years in 2011 to 35 years in 2020. Figure 12 shows the predicted LCOE in 2020 for a discount rate of 6.8%, as used by the IEA (2012) to compute LCOEs, and figure 13 shows the predicted LCOE for a 10% discount rate which correspond to the highest value used in LCOE studies. The other underlying assumptions are listed in annex 5. The differences in the results illustrate the importance of the geographic location, the type of PV system, and the discount rate on the cost of PV electricity. In comparison, Bosetti et al. (2012) predict a module price between 75 and 145 $/MWh for 2030 with an expert elicitation survey, with the most likely scenario being 108$/MWh, not differentiating the location or the type of system.

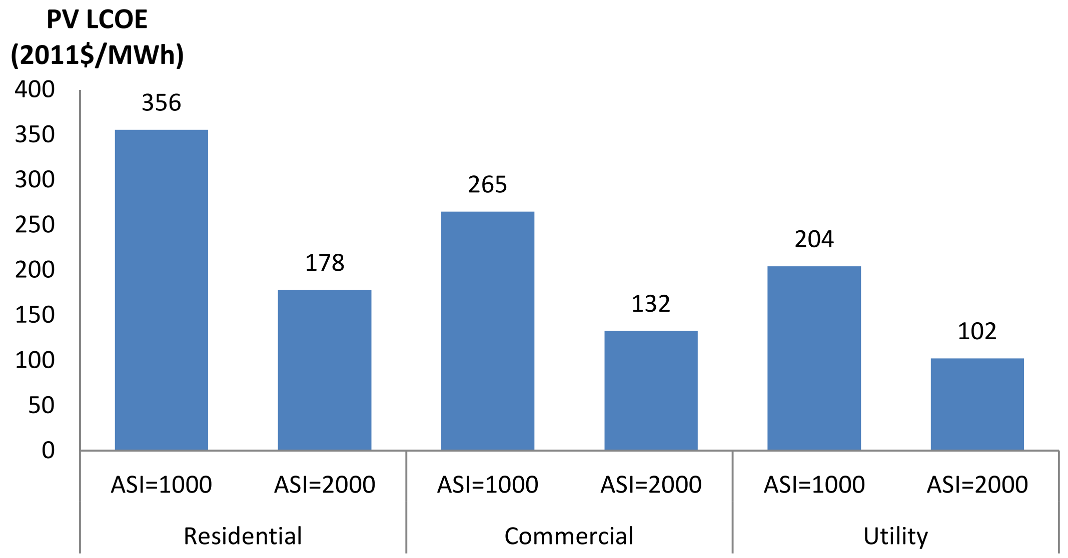
[42] Source : http://solargis.info/

Figure 12 PV LCOE prediction for 2020 with a 6.8% discount rate (source: Author)



ASI: Annual Solar Irradiation, 1000 kWh/year corresponds to the north of Germany or Alaska, and 2000 to the south of Spain, Italy, or California. Hypothesis used for the computation of the LCOE are explained in annex 5.

Figure 13 PV LCOE prediction for 2020 with a 10% discount rate (source: Author)

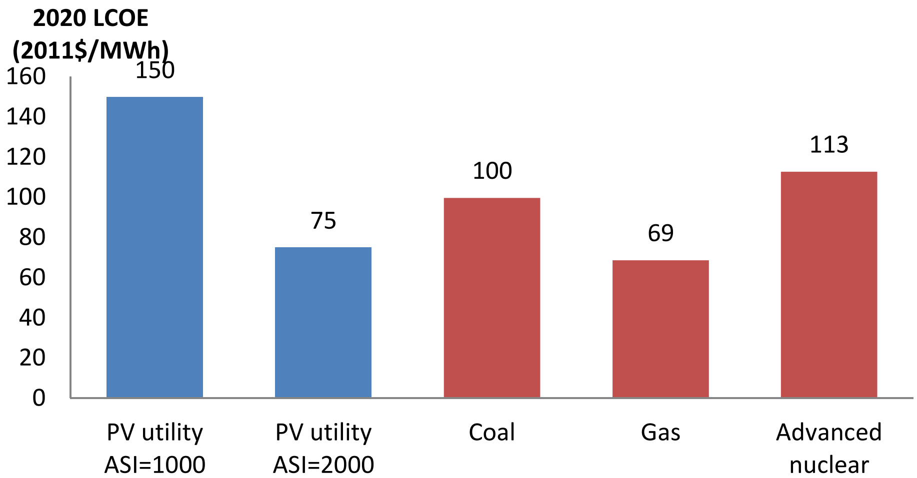


ASI: Annual Solar Irradiation, 1000 kWh/year corresponds to the north of Germany or Alaska, and 2000 to the south of Spain, Italy, or California. Hypothesis used for the computation of the LCOE are explained in annex 5.

7.2 Comparison with the levelised cost of electricity of other electricity generation technologies

We can compare the cost of generating electricity by comparing the LCOE of PV technology and conventional technologies. Figure 14 compares predictions of LCOEs in 2020 for conventional electricity sources and a PV utility system, with a 6.8% discount rate and for two locations: with solar annual irradiation of 1000kWh/year, and 2000kWh/year. The results suggest that the average cost of electricity generated with PV technology will only match the cost of conventional technologies in 2020 in the sunniest places.

Figure 14 Comparison of the LCOE with a 6.8% discount rate



ASI stands for Annual Solar Irradiation. 1000 kWh/year corresponds to the north of Germany or Alaska, and 2000 to the south of Spain, Italy, or California. Additional hypothesis used for the computation of the PV LCOE are explained in annex 5. Source: Author and EIA, 2012.

7.3 Comparison with retail price of electricity

The PV LCOE can also be compared to the retail price of electricity. Grid parity is reached when they are equal. Table 6 presents grid parity predictions for several countries for a residential PV system. It is already reached in Italy having high sunlight availability and high electricity price. It is expected to happen in 2013 in Spain, 2015 in Germany, 2018 in California, and 2020 in France.

Table 6 Grid parity predictions for residential PV systems in several countries

	Italy	Spain	Germany	California	France
Retail price of electricity[43] ($/MWh)	329	277	364	149	189
Annual Solar Irradiation[44] (kWh/year)	1800	1900	1100	2100	1400
Grid Parity	Reached	2013	2015	2018	2020

7.4 Synthesis

PV LCOE already reached the retail electricity price in some countries, but it will not match other technologies' LCOE until 2018 or 2020 in the sunniest areas, and a few years later elsewhere. This gap is due to the fact that retail price of electricity also takes into account the cost of transportation and distribution.

One should be aware about the caveats of those indicators. Grid parity compares the cost of PV electricity without transportation and distribution cost with retail price on the grid, so it makes sense only if all the electricity generated in used in situ. Moreover, both indicators are based on PV LCOE which does not take into account the production profile. Joskow (2011) notes that since the wholesale price of electricity varies throughout the day, different production profiles give different market values for the electricity produced. He suggests using more standard economic evaluation methods than the LCOE to evaluate intermittent technologies such as wind or PV. The market value of the electricity produced can be evaluated according to the production profile and the corresponding electricity price. This can lead to a higher value if production is synchronised with high price periods, and a lower value in the opposite case. Moreover, other costs are induced by the integration of intermittent

[43] Residential, Source: http://www.energy.eu/ and http://www.cpuc.ca.gov/

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

generation technologies into the grid. They cause short term operating challenges to balance supply and demand, which are costly. If the share of intermittent technologies becomes too important, additional cost can be caused by the need for storage capacity, grid extension, or back-up capacity with flexible and expensive power plants.

8 Conclusion

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

We find that the most accurate combination of explanatory variables includes experience (measured by cumulative capacity with one year lag) and silicon price. Based on this model and scenarios for the future evolution of the explanatory variables, cumulative capacity and silicon price, we are able to predict module price until 2020. We predict a 67% decrease of module price from 1.52 \$/Wp in 2011 to 0.50 \$/Wp in 2020. The increase in cumulative capacity is responsible for 75% of this evolution, corresponding to a learning rate of 19.6%, and silicon price decrease is responsible for 25% of module price reduction.

We determine the consequence on PV's Levelised Cost Of Electricity (LCOE). The LCOE highly depends on the type of PV system, its geographic location (sunlight availability), and the discount rate. A comparison against other technologies suggests that PV's LCOE will only reach conventional technologies' LCOE in 2018/2020 in the sunniest areas with an annual solar irradiation of 2000 kWh/year or more, such as California, Italy, or Spain. It should be kept in mind that the LCOE is not really appropriate to estimate the economic value of intermittent and non dispatchable technologies such as PV. The reason is that it does not take into account the different production profiles - which lead to different market values for the electricity generated - , and does not consider the additional cost of integrating intermittent sources into the grid.

Grid parity – when the LCOE of PV electricity falls below the retail price of electricity – is already reached in countries with high sun availability or high electricity price such as Italy. It will happen in 2013 in Spain, 2015 in Germany, and not before 2018 in California or France where retail price of electricity is low. However, this criterion should be interpreted with caution as it does not take into account the cost of transportation and distribution of PV electricity. Hence it only makes sense for residential system for which all the electricity is used in-situ.

Our models can still be improved. The main limitation is that we proxy the module cost with its price. Although intense competition suggests that it is a reliable proxy, there might be discrepancies between these two variables in reality. Dealing with this problem would require controlling for market effects such as market power, overproduction, or incentive policies which might create rents in the value chain. Chapter three explores some of these effects.

Annex

Annex 1 Theoretical basis of experience curves

Berndt (1991) derives experience curves from a cost minimization program (7) subject to a constraint defined by a Cobb-Douglass production function (8):

$$C_{total} = \sum (P_i \text{ Annex 3 } q_i) \qquad (7)$$

$$\text{s.c. } Q = A \, \Pi \, (q_i^{\delta i}) \qquad (8)$$

With

C_{total} the total cost

P_i the price of input i, q_i the quantity of input i

Q the maximum quantity produced with the set of input q_i, and δ_i the corresponding input elasticity of production

A representing the technical knowledge, which is assumed to be described by the learning effect:

$A = Exp^{-\sigma}$ Where Exp is experience (measured by cumulative production or cumulative capacity), and σ is a constant.

Solving this system, and with $r = \sum \delta i$, $a = r \, \Pi \, \delta i^{-\delta i/r}$, $s = (1-r)/r$, $\alpha = \sigma (s+1)$, and $\beta i = \delta i (s+1)$, Berndt (1991) finds the following cost function:

$$C_{unit} = a \, Q^{s} \, . \, Exp^{\alpha} \, . \, \Pi \, p_i^{\beta i} \qquad (9)$$

C_{unit} is the cost of one unit of output

Q stands for the production scale effects, and s the scale index, or plant size elasticity of unit cost

Exp stands for experience, and α experience elasticity of unit cost (=-E)

$\Pi \, p_i^{\beta i}$ represents the effects of inputs prices pi, βi being the corresponding input elasticity of unit cost

From equation (8), he obtains the classic experience curve equation (1) by adding two more assumptions (besides the description technical knowledge by the learning effects)

- The effects of input prices changes on total cost $\Pi\ p_i^{\beta i}$ can be accurately measured using a Growth National Product (GNP) deflator.
- Returns to scale s are constant (s=0).
-

By relaxing the last two hypotheses, this theory leads to the multi-factor experience curve (Isoard and Soria, 2001, Söderholm and Sundqvist, 2007, Yu, 2011). This attempt to find a theoretical basis relies on a strong hypothesis concerning the description of technical knowledge by the experience effect.

Pan and Köhler (2007) derive the experience curve from a two inputs Leontief cost function with time, but it is also based on a strong assumption concerning the role of learning by doing.

Annex 2 Consequence of the omitted variable bias on the accuracy of the predictions

If besides experience (Exp), a variable X has an effect on cost, and α is its corresponding parameter, the "correct" specification of the model is:

$$log(C_t) = log(C_0) - E\ LogExp_t + \alpha\ X_t + \varepsilon_t \quad (10)$$

The variable X_t can be described according to its relation with experience with (11), where β_1 and β_2 are specific to each period:

$$X_t = \beta_1 + \beta_2 LogExp_t + \mu_t \quad (11)$$

By substituting (11) into (10), we get (12) explaining $\log(C_t)$ by experience only. This is the model estimated if X is omitted and cost is regressed on experience only. Therefore the regression of the equation with experience as only explanatory variable estimates $-(E - \alpha *$

β_2) instead of $-E$. There is then an omitted variable bias[45] if the omitted variable X has an effect on cost ($\alpha \neq 0$), and X and LogExp are not uncorrelated ($\beta_2 \neq 0$). This can be easily generalized to multivariate regression for the case of omitted variable in multifactor experience curves (Greene, 2000, p.334).

$$\log(C_t) = \log(C_0) + \alpha\beta_1 - (E - \alpha\beta_2)LogExp_t + \varepsilon_t + \alpha\mu_t \quad (12)$$

To understand the consequence of this bias on the predictions accuracy, we consider a second period where cost is predicted. In this predicted period, the omitted variable X can be modelled by (13), with β'_1 and β'_2 specific to this period. We get the expression of the real value of cost (14).

$$X_t = \beta'_1 + \beta'_2 \text{LogExp}_t + \mu'_t \quad (13)$$

$$\log(C_t) = \log(C_0) + \alpha\beta'_1 - (E - \alpha\beta'_2)LogExp_t + \varepsilon_t + \alpha\mu'_t \quad (14)$$

By comparing prediction that would be done with the predictive model (12) without the error terms, and the real value (8), the prediction error is:

$$Error_t = \alpha(\beta_1 - \beta'_1) + \alpha(\beta_2 - \beta'_2)\text{LogExp}_t - \varepsilon_t - \alpha\mu'_t \quad (15)$$

Since ε_t and μ'_t have a 0 mean, the average error is then $\alpha(\beta_1 - \beta'_1) + \alpha(\beta_2 - \beta'_2)\text{LogExp}_t$. Therefore if the relation between the omitted variable and experience is similar during the estimating period and during the estimated period, $\beta_1 = \beta'_1$ and $\beta_2 = \beta'_2$, so there is no error in the predictions due to the omitted variable bias. But the more the relations between X and experience changes between the estimation and prediction period, the more the error due to the omitted variable bias is important.

Annex 3 Database sources

(1) Cumulative output and Average prices:

[45] The bias is $-\alpha * \beta_2$ with $\beta_2 = \rho(\text{LogExp}, X) * \frac{\sqrt{Var(X)}}{\sqrt{Var(LogExp)}}$ in the case of a bivariate regression.

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

(2) Plant size:

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

(3) Silver price:

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

(4) Silicon price:

- 1990-2002: Nemet (2007), (Through Yu, 2008)
- 2003: Photon International magazine, 4-2006, Page 30.
- 2004: Photon International magazine, 9-2006, Page 139.
- 2005-2006: Photon International magazine, 12-2007, Page 115.
- 2007-2011: Photon Consulting annual reports

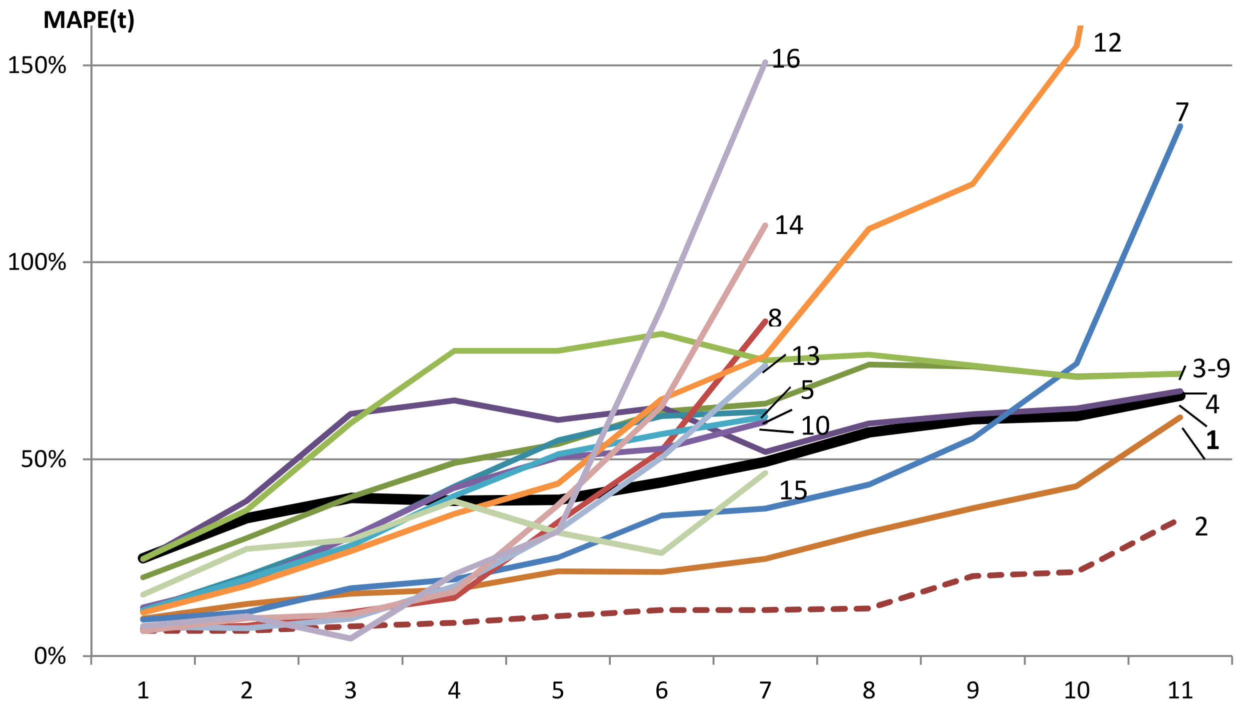
(5) R&D knowledge stock

- 1990-2007: Author. The R&D knowledge stock has been computed with the number of patent families as proxy for innovation according to the methodology developed by

Dechezleprêtre et al. (2011). A patent family is the set of patents granted in different countries for the same innovation. Therefore one patent family represent on innovation. We use an annual depreciation rate of 10% to account for technology obsolescence, but no lag since we use patent and not R&D expenditure. The patent data come from the European Patent Office website (http://www.epo.org/)

Annex 4 Result of the out of the sample evaluation with cumulative capacity as proxy for experience

Figure 15 Comparison of MAPE(t) for each model, MAPE(t) being the mean absolute percentage error according to the time horizon t. The proxy for experience is cumulative capacity without lag.



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

Annex 5 Hypothesis for the LCOE simulation:

Each year, Electricity produced = PR * ASI

With

- PR is the Performance Ratio of the installation: the ratio of the actual and theoretically possible energy output
- ASI is the Annual Solar Irradiation: the sum of the quantity of solar energy reaching the installation over a year

Discount rate=5% (figure 11) or 10% (figure 12)

Performance ratio=0.75

Lifetime: from 25 years in 2011 to 35 in 2020

O&M=6% of system cost

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

Module price evolution is defined by the results from the Author

Price evolution of other components is done by the extrapolation[46] of previsions made by photon consulting in 2012.

[46] The extrapolation has been done with a time trend only. We cannot use a learning curve since the learning is local for installation, and the other cost do not depend on the VP industry only.

Chapter three

Impact of photovoltaic feed-in tariffs and silicon price on module price

Abstract

Long term determinants of photovoltaic (PV) module cost have been extensively investigated, and cost prediction is traditionally done by using experience curves as in chapter two. Here, we focus instead on market drivers that influence price regardless of cost, by affecting the profit margin. In particular, we analyse the influence of silicon price, the main input, and feed-in tariffs (FITs), the main policy tool used to drive the development of the photovoltaic industry. Relying on weekly data from January 2005 to May 2012, and Granger causality tests applied to vector autoregressive models, we test several hypotheses that are important with regards to the design of FITs.

We find that FITs have followed module price more closely in the recent years, especially in Germany. This is important to avoid creating too high rents leading to market overheating. But FITs have no influence on module price in the long term, as its evolution is rather defined by production cost, and silicon price during the silicon shortage. However, FITs changes have

short term impacts on module price because firms anticipate those policy changes. As a consequence, module price rises in the months before important FIT cuts, and decreases just before and after. We use these findings to give practical recommendations on the design of an optimal FIT policy.

Résumé français

Les déterminants du coût des panneaux solaires ont plutôt un effet à long terme, et sont modélisés par des courbes d'apprentissage présentées dans le chapitre précédent. Ici, nous nous intéressons aux effets de marché, qui ont une influence sur le prix, indépendamment du coût. En particulier, nous regardons le prix du silicium, matière première majeure de l'industrie photovoltaïque et les tarifs de rachat de l'électricité, qui est la principale politique vouée à stimuler le développement de l'industrie photovoltaïque. Pour étudier leur influence, nous nous appuyons sur une base de données de prix spot hebdomadaires mondiaux du silicium et des panneaux solaires, et sur des tarifs de rachats, de 2005 à 2012. Nous étudions les liens de causalité grâce à des modèles dynamiques et des tests de causalité de Granger.

Nous arrivons à la conclusion que les tarifs de rachat suivent de plus près le prix des panneaux solaires depuis 2009, surtout en Allemagne. C'est un facteur important pour éviter la création d'une trop forte rente pour les installateurs de systèmes photovoltaïques, risquant d'engendrer une bulle comme en Espagne en 2008 ou en France en 2010. Nous trouvons que les tarifs de rachat n'ont pas d'influence sur le prix des modules, dont l'évolution à long terme est plutôt dirigée par le cout de production, et le cout du silicium pendant sa pénurie. Cependant, les changements de tarif de rachat ont une influence à court terme sur le prix des panneaux photovoltaïques, influence due à l'anticipation du marché. Le prix augmente pendant les mois précédent une diminution importante du tarif de rachat, alors qu'il diminue après. Nous utilisons ces conclusions pour donner des recommandations quant au mécanisme de tarif de rachat optimal.

1 Introduction

This chapter aims at identifying market effects, in particular the influence of feed-in tariffs and silicon price, on photovoltaic (PV) module price. Together with chapter two analysing technical drivers of module cost, it participates in a better understanding of PV price dynamics.

The price is made of the cost plus a margin. Cost drivers are technical elements, such as scale effect, R&D, learning by doing brought by the accumulation of experience, etc. They have long term effects as explained in chapter two. The drivers of profit margin - the difference between price and cost - are more market based elements, such as competition, demand/supply balance, strategic behaviours, etc.

The question at the core of this chapter is the following: How is module price affected by changes in feed-in tariffs and silicon price? This question is of particular importance for policymakers.

Feed-in tariffs (FITs) are administratively set prices at which the grid operator has the obligation to buy electricity from renewable energy sources. They are the most common policy tools to stimulate the development of the PV market. The understanding of their influence on module price is therefore critical for policymakers. In particular, while FITs aim at increasing the attractiveness of PV electricity, two constraints should be considered when designing them: First, they should follow module price to avoid creating a rent for companies installing PV systems. A high rent leads to market overheating which is costly and often followed by drastic cuts harming the whole industry. Second, FITs should not influence module price; in particular, they should not lead to module price increase and end up creating a rent for module producers, since an increase in module price reduces the incentive effect of the FITs. This issue is even more sensitive since most PV modules are produced in China: in this context, a FIT in Germany or France would create a rent which would benefit Chinese manufacturers.

Silicon is the main material input for the PV industry, accounting for 20% of a module cost, and most of the energy required to produce it. Other inputs are glass, aluminium, silver, but they either account for a small part of the manufacturing cost, or their price is very stable. A better understanding of the effect of silicon price on module price would be important to design FITs based on accurate module price evolution predictions. In addition, it would help reduce the uncertainty in the industry, thus removing a major obstacle to investment.

A substantial amount of literature focuses on the analysis and prediction of module cost. It has been explored in chapter two. However, if market effects are often mentioned in the grey literature, there is a lack of academic literature focusing on it. Hayward and Graham (2011) suggest that next 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 view is shared by the vast majority of market studies. However there is a lack of quantitative evidences. In this chapter, we aim at filling this gap.

To address those issues, we rely on a database 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 long term cost drivers measured by the experience effect. 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.

We find that FITs adaptation to module price evolution differs according to the period and the country, which provides some insight to policymakers in term of optimal FIT scheme. Besides, FITs do not seem to influence module price, which means that the rent of module manufacturers is not an issue when designing a FIT. We believe that this is due to the fierce competition prevailing in the cell and module manufacturing segments. However, in the short term, module price increases before a FIT reduction, and decreases after, as a consequence of firms' anticipations.

Regarding the influence of silicon price on module price, we find a fundamental change in 2009: If they are highly correlated over the whole period, silicon price causes module price only before 2009. We interpret this change as a consequence of silicon shortage giving market power to silicon producers during this pre-2009 period while overcapacity prevails post 2009.

As long as there is overcapacity in silicon production, silicon price is thus not likely to influence module price.

The remaining of this chapter is structured as follows: Section two introduces the analytical framework and the hypothesis that are tested later on. The data set is presented in section 3 together with a first correlation analysis. Section 4 aims at finding the direction of the causality to test the hypothesis made in the analytical framework. In section 5, we analyse the influence of past but also future FIT changes on module price with polynomial growth models. Finally, section 6 concludes.

2 Analytical framework and hypothesis

In this section, we introduce a framework used to formulate hypothesis about the influence of FITs and silicon price on module price.

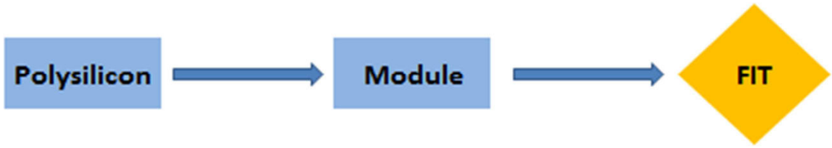
2.1 Introduction of the framework

To focus on the effects of silicon price and FITs on module price, we use the analytical framework presented in figure 1.

Purified silicon, also called polysilicon, is the main input for module production, accounting for 20% of a module cost (photon international 2012). Other inputs are glass, aluminium, silver, labour, but they either account for a small part of the manufacturing cost, or their price is very stable. Module production from silicon involves several steps. 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 electricity produced by modules is transformed into alternating current by an inverter, and sold at the FIT.

Figure 1 Analytical framework



Silicon and PV modules are commodities. Once silicon exceeds the minimum purity level of 999.999%, or modules meet the quality standards, not much product differentiation can be achieved. Firms producing them compete on price.

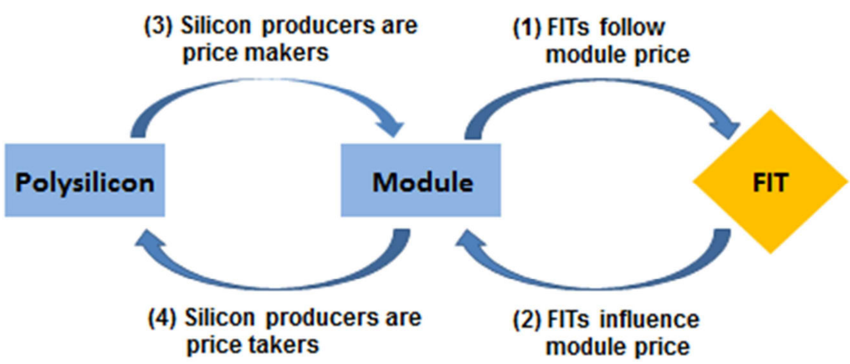
The supply of silicon depends on production capacity, which is constrained since it takes two years to build a production plant. The demand of silicon is more and more driven by module production, since the PV market is responsible for 87% of silicon consumption in 2011 compared to 53% in 2007 (SolarBuzz 2012).

Modules supply is not as much capacity constrained, and results from the experience effect reducing cost regularly through accumulation of experience, and possibly the price of silicon, hypothesis which will be tested later. The demand is defined by incentive policies, mainly FITs, which have been available in 50 countries over recent years (REN 21, 2011).

2.2 Hypothesis

Based on the previous framework, we formulate several hypotheses, represented in figure 2.

Figure 2 Hypothesis



2.2.1 Influence of feed-in tariffs

The first hypothesis (1) is that FITs follow module price, avoiding the creation of a rent in the most downstream segments of the industry, PV systems installation and electricity production. The idea behind FITs is to set a price for a fixed period of time to make the installation of PV systems attractive for investors, with an internal rate of return above a certain level. But if the attractiveness is too high, it provokes an uncontrolled market growth such as in Spain in 2008 and France in 2010.

This is an important issue since these market booms caused by poor adjustments of FITs to module price dynamics are costly and corrected a posteriori by drastic cuts harming the industry.

The second hypothesis (2) is that FITs influence module price, a higher FIT leading to increasing module prices and creating a rent in the cell and module production segments. FITs that would result in increasing module prices would therefore see their efficiency affected.

2.2.2 Influence of silicon

The first hypothesis about the influence of silicon is that silicon producers are price makers (3). Module producers would then integrate silicon price variation in module price since it represents 20% of the cost. This would imply that silicon price should be used as an exogenous variable in models predicting module price.

The second hypothesis is that silicon producers are price takers. Since module production is the main market for silicon (87% in 2011, SolarBuzz 20112), a module price variation changes the demand for silicon, impacting its price.

The prevailing situation depends on who has market power.

3 Data

The hypotheses formulated in section two are tested with a dataset of weekly silicon and module spot prices from PV Insight[47], 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.

3.1 Description

3.1.1 Silicon and module price

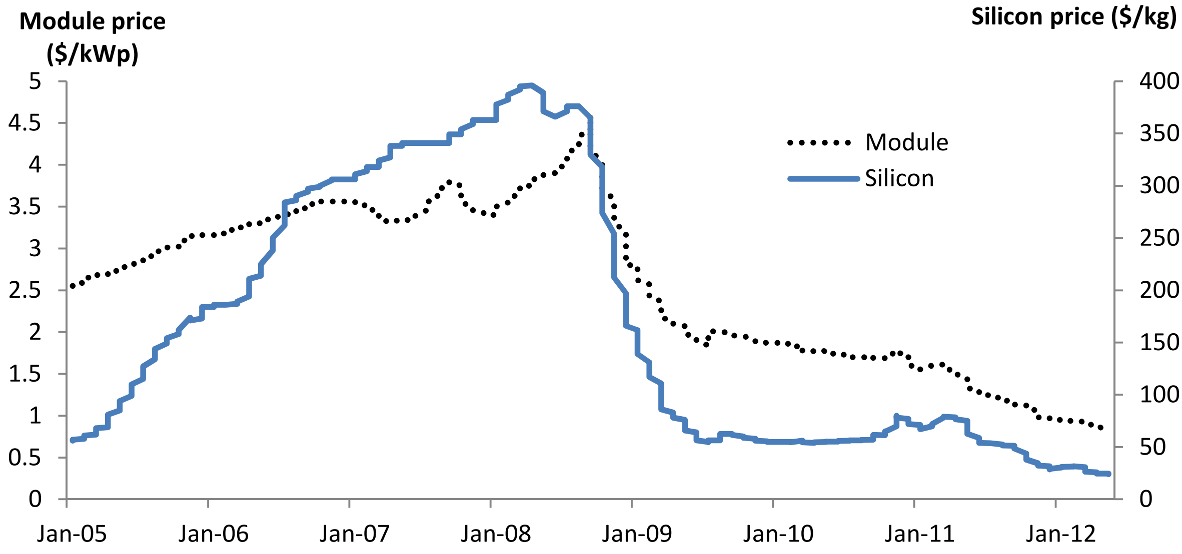
As table 1 indicates, silicon and module price has been very unstable during the period considered, with a standard deviation of 75% of the mean for silicon price, and 38% for module price. This is illustrated by figure 3 representing silicon and module price evolution from January 2005 to May 2012. Silicon price increased from 56 $/kg in 2005 to 396 $/kg in 2008. This corresponds to a silicon shortage from 2005 to 2009. Meanwhile, module price also increased from 2.55 $/Wp in 2005 to 3.56 $/Wp in 2008. From July 2009 on, prices are much more stable, with silicon price back to January 2005 level, indicating the end of the silicon shortage.

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

[47] http://pvinsights.com/

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



Source: PV insight

3.1.2 Feed-in tariffs

We gathered weekly values of FITs in Germany, Italy, Spain, and France from January 2005 to may 2012. As table 2 indicates, this covers more than 60% of the global market over the whole period. Other countries are not considered because they only implemented alternative PV technology development policies (RPS, investment subsidies, etc.) such as Japan or the US, or they do not account for a significant share of the global market.

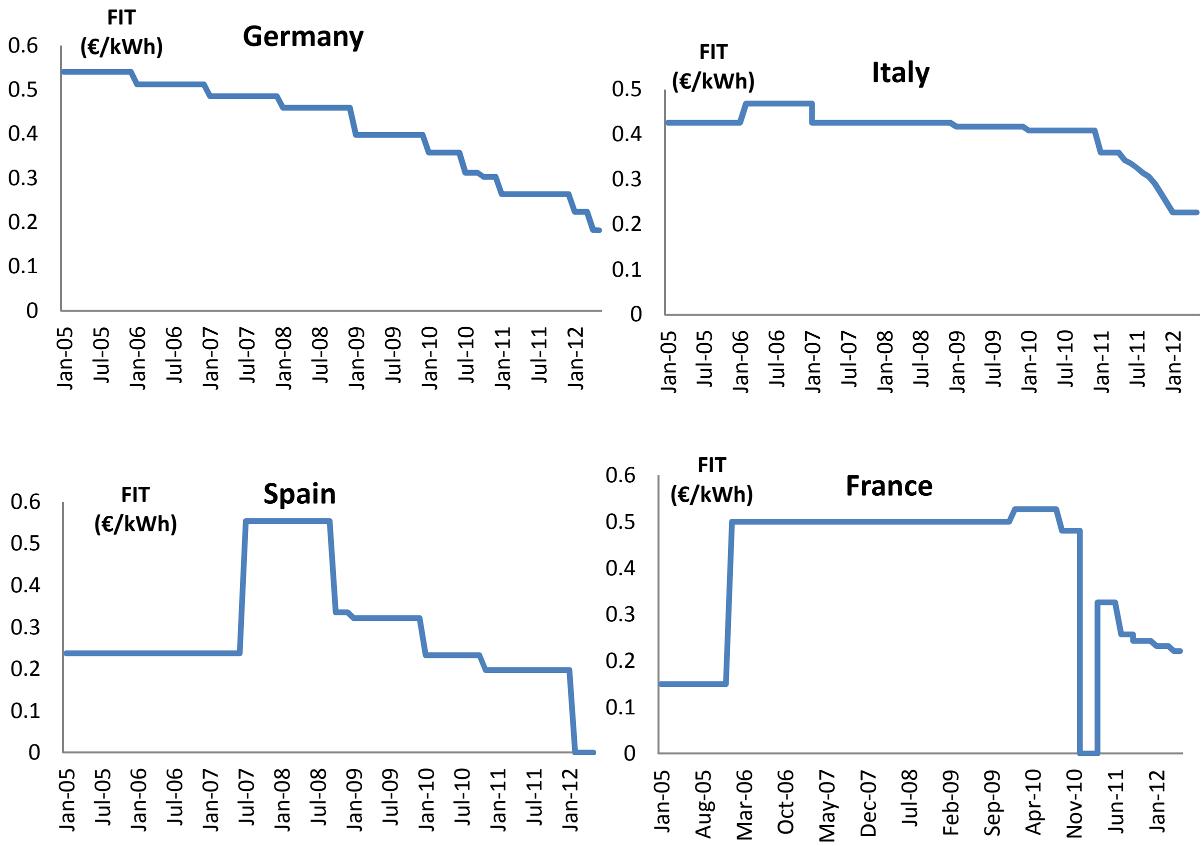
Table 2 Market sizes of the countries included in the surveyed FITs, and corresponding total share of the market covered (source: IEA 2011 and EPIA 2012)

Country	2005	2006	2007	2008	2009	2010	2011
Italy (MW)	6.8	12.5	70.2	338.1	723	2320.9	9284
Germany (MW)	906	951	1274	1955	3799	7411	7485
France (MW)	7	10.9	31.3	104.5	155.5	719	1671
Spain (MW)	25	99	557	2758	60	392	372
Total (MW)	1429	1575	2529	6330	7437	16817	29965
Share covered	**66%**	**68%**	**76%**	**81%**	**64%**	**64%**	**63%**

Since for each country, there are different tariffs corresponding to various types of PV sytems (ground based, commercial, residential, etc.), we calculate the average value weighted by the market share of each type. On the period considered, there have been 11 changes in Germany, 14 in Italy, 6 in Spain, and 9 in France, mainly reductions..

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 the Spanish and French ones show some chaotic variations.

Figure 4 Average FIT evolution in the main countries



3.2 Correlation analysis

We perform an analysis of the correlation, first between module price and silicon price, then between module price and countries' FITs.

3.2.1 Correlation between module price and silicon

Silicon and module price are highly correlated (the correlation coefficient is 0.91). This confirms what could be deducted from the synchronised price increase in silicon and module price between 2005 and 2008 (c.f. figure 3). However, the price increase is much 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[48]. Second, most of the silicon is sold through long term contracts (about 80%, Photon Consulting 2012), thus the average purchase price didn't rise in the same proportions as the spot price (143%, from 51$/kg to 124$/kg , photon consulting 2012).

This high correlation between silicon and module price suggests that at least one of the two hypotheses (3) and (4) is realistic. However it is not sufficient to choose which one, as this would require information about the direction of the causality. This is the purpose of section 4.

3.2.2 Correlation between module price and countries' feed-in tariffs

Table 3 shows the correlation of module price with the average FIT in the four countries we take into account. It points out that the German and Italian FITs are not only more stable than the Spanish and French ones, but also more correlated to module price. But once again, this gives no indication about the direction of the causality, which is investigated in next section.

Table 3 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

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

4 Causality analysis

Section three shows the high correlation between module price on the one hand, and silicon price and FITs on the other hand. In this section, we further analyse the interdependencies by disentangling the causal relationships. We test the hypothesis represented in figure 2 in the analytical framework (Figure 2, section 2). (1) Do FITs follow module price closely? (2) Do FITs influence module price by driving the demand? (3) Are silicon producer price makers or (4) price takers?

4.1 Methodology

We make no assumption about the direction of the causal relationships for now; therefore all the variables are endogenous. 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.

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. From now on, 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.

We control for the experience effect on module price, which represents long term drivers of cost as explained in chapter two. The experience effect, also called learning by doing, decreases price through the accumulation of experience measured by cumulative production, according to:

$$Price_t = Price_{t_0} * \left(\frac{Cumulative\ production_t}{Cumulative\ production_{t_0}}\right)^{-E}$$

Where

$Cumulative\ production_t$ is the cumulative PV module production at t[49]

E is the experience parameter, measuring the intensity of the learning by doing process. We use the results from chapter two finding an experience parameter of 0.338, corresponding to a learning rate[50] of 20.1%.

Learning by doing is a long term process which cannot be analysed based on weekly data, but rather annual ones as in chapter two. We therefore control for this effect on price by creating a variable $Module$ which is the equivalent module price if no learning would have happened since t_0 , according to:

$$Module_t = RealModulePrice_t * \left(\frac{Cumulative\ production_t}{Cumulative\ production_{t_0}}\right)^E \qquad (2)$$

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

$$FIT_t = \sum_i FIT_{i,t} * ElectricityMarketSize_{i,t} \qquad (3)$$

Where

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

$FIT_{i,t}$ is the FIT in country i at time t

4.2 Regression equation

We apply the VAR model to the first order derivative of the logarithm of module price, silicon price, and FIT with a lag l. It gives:

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

[49] Since the learning effect is a slow process which cannot be affected to the production of a particular week or even month, we created a proxy of the week cumulative production following the yearly production trend from photon consulting (2012).

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

With

$Y_t = \begin{pmatrix} Log\_Module_t \\ Log\_Silicon_t \\ Log\_FIT_t \end{pmatrix}$ the vector of the variables

$\gamma_j = \begin{pmatrix} \gamma_{j,1} \\ \gamma_{j,2} \\ \gamma_{j,3} \end{pmatrix}$ the corresponding parameters

$\mathrm{E}_i = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix}$ the vector of error terms, the $\varepsilon_{i,t}$ assumed to be independent and identically distributed

$D.Y_t = Y_t - Y_{t-1}$ the first order derivative of Y_t

Log_Module_t is the logarithm of $Module$ at t

$Log\_Silicon_t$ is the logarithm of silicon price at t

Log_FIT_t is the logarithm of FIT_t at t

The estimation is done by running a separate regression for each variable, regressing it on lags of itself and all other variables with ordinary least squares.

4.3 Econometric considerations

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 $Log\_Silicon$ (see annex 2). We therefore run the regressions of the VAR models on two periods: before and after 24/09/2009. The first period actually 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.

4.4 Results

The model (4) is estimated during and after the silicon shortage. The regressions are all significant. Table 4 and 5 show the results of Granger causality tests applied to the estimations of the model during (table 4) and after (table 5) the silicon shortage. 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. Excluded variables in the grey cases therefore cause the corresponding dependent variable of the equation estimated.

Regarding causality between silicon and module price, there is a switch at the end of the silicon shortage period. During the silicon shortage, silicon price causes module price, while after the end of the shortage, it is the opposite.

Results about causality between module price and FITs are more ambiguous. During the first period, between January 2005 and July 2009, the Granger test does not yield any conclusion regarding causal relationships, at least not at a 5% or even 10% significance level. During the second period, after July 2009, FIT still does not cause module price, but module price causes FIT. Indeed, the test indicates that silicon price causes FITs. And since module price causes silicon price, it means that module price also causes FITs.

Table 4 Granger causality test during the silicon shortage

Dependent variable	Excluded	chi2	df	Prob > chi2
Log_Module	Log_Silicon	22.48	2	0.000
	Log_FIT	0.120	2	0.942
	ALL	22.76	4	0.000
Log_Silicon	Log_Module	1.373	2	0.503
	Log_FIT	0.078	2	0.962
	ALL	1.468	4	0.832
Log_FIT	Log_Module	0.724	2	0.696
	Log_Silicon	4.288	2	0.117
	ALL	7.046	4	0.133

Table 5 Granger causality test after the silicon shortage

Dependent variable	Excluded	chi2	df	Prob > chi2
Log_Module	Log_Silicon	3.090	3	0.378
	Log_FIT	2.722	3	0.436
	ALL	7.006	6	0.320
Log_Silicon	Log_Module	17.47	3	0.001
	Log_FIT	0.567	3	0.904
	ALL	18.69	6	0.005
Log_FIT	Log_Module	1.518	3	0.678
	Log_Silicon	19.73	3	0.000
	ALL	21.50	6	0.001

4.5 Interpretation regarding module and silicon prices

The previous results suggest that there is a fundamental change in the market in 2009. The fact that before September 2009, silicon price was driving module price and not the opposite indicates that silicon producers were price makers. This can be interpreted as a consequence of the silicon shortage during this period, leading to a capacity constraint giving silicon producers market power.

After the silicon shortage, module price causes silicon price, while the opposite is not clear, which denotes a loss of market power from silicon producers, due to the end of the capacity constraint. This market power shift from silicon producers to module manufacturers can also be due to the PV industry becoming a more and more important market for silicon, the first one before semi-conductor since 2007 (SolarBuzz 2012).

4.6 Interpretation regarding module price and feed-in tariffs

4.6.1 Hypothesis one: do feed-in tariffs follow module price?

The hypothesis (1) assuming that FITs follow module price seems to be true after 2009, but not before. We now compare the evolution of FITs and module price in each country, before and after 2009.

In order to understand why there is a difference before and after 2009, we now compare the evolution of FITs and module price in each country. To do so, we need to convert them into the same unit. Indeed, FITs correspond to the price of a quantity of electricity (in $/kWh), while module price corresponds to the price of a production capacity (in $/kWp[51]). We therefore calculate the value of all the electricity produced by a module of a standard capacity of 1kWp over its lifetime, if this electricity is sold at a FIT. This gives the value of the FIT corresponding to a standard production capacity, as for the price of PV modules.

NPV_i, the net present value of the electricity produced by a standard 1kWp PV system when sold at the FIT in country i, is calculated according to:

$$NPV_i = FIT_{i,t} * \sum_{l=1}^{Lifetime} \frac{\mathrm{PR} * \mathrm{ASI}_i}{(1+r)^{t-1}} \qquad (1)$$

With

$FIT_{i,t}$ the FIT in country i at time t

$Lifetime$ the period for which FITs are granted, assumed to be the lifetime of a PV system

r the discount rate

PR the Performance Ratio of the installation: the ratio of the actual and theoretically possible energy output

ASI the Annual Solar Irradiation: the sum of the quantity of solar energy reaching the installation over a year. It depends on the country.

$\mathrm{PR} * \mathrm{ASI}_i$ is then the electricity produced each year in country i by a PV system

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

Besides FITs, the main difference between countries is sunlight availability. We consider annual solar irradiation of 1200 kWh/kWp/year for Germany, 1500 for Italy, 1700 for Spain, and 1350 for France[52]. The other assumptions are a discount rate of 10%, a lifetime of 25 years, and a capacity factor of 0.75.

The NPV has to be compared to the price of a PV system, not of a module only. Indeed, the incentive effect of a FIT depends on the difference between the NPV and the price of a PV system. Modules represent only 40% of the cost of a PV system in 2011 (photon consulting 2012). To get the price of a PV system from module price, we add the price of other components: inverter, wire, mounting system, etc. Weekly values of the price of other components of a system are computed following the trend of annual price given by Photon international (2012), as in chapter 2.

For each country, figure 5 compares the cost of a PV system (the shaded area) with NPV_i , 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, while important discrepancies in 2007/2008 in Spain and 2009/2010 in France explain the observed uncontrolled developments of the PV market. A significant discrepancy in 2010/2011 in Italy also explains the fast market growth during this period (multiplied by 13 in two years, from 720 MW in 2009 to 9300 MW in 2011, EPIA 2012). Note that additional incentive policies such as tax rebate are not taken into account here, although they further increase the attractiveness of PV systems.

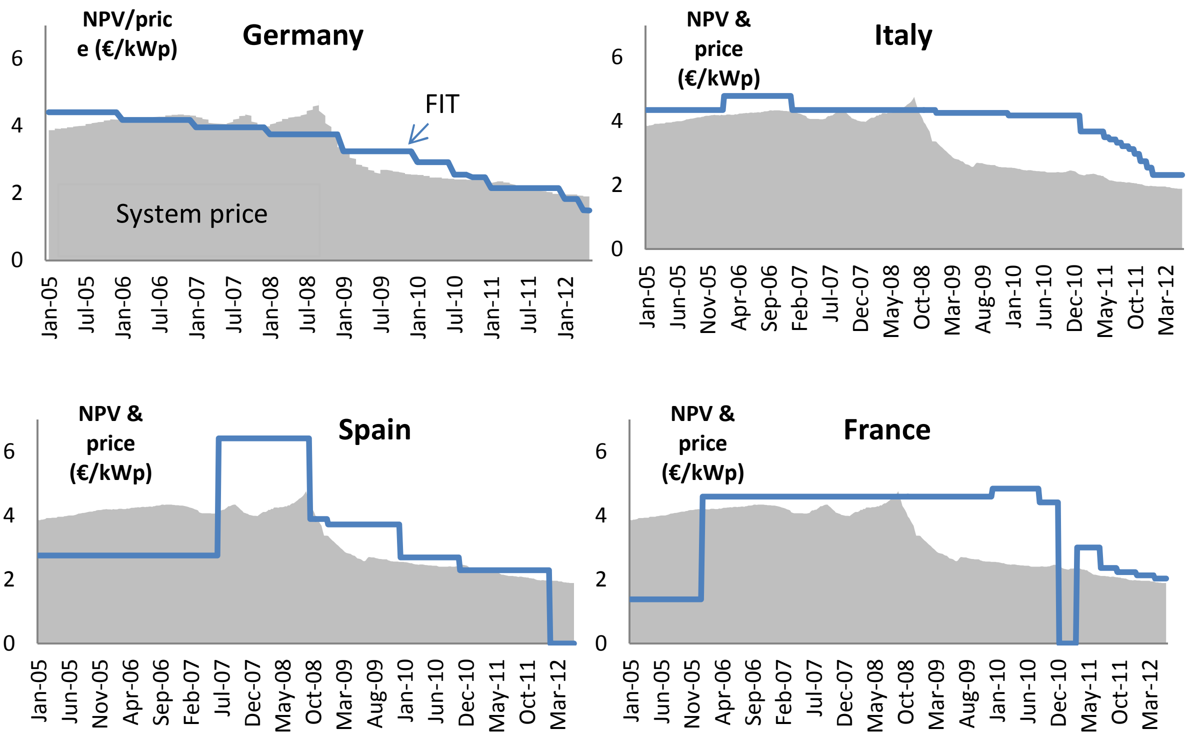
The observation of those graphs helps understand why module price causes FITs after 2009 but not before. Before 2009, FITs were very stable, modified only once a year in Germany, and even less frequently in other countries. Besides, their level was set well in advance, sometimes years ahead[53]. FITs were thus very rigid, explaining why they couldn't follow module price closely. On the contrary, after 2009, FITs became much more flexible, with intra-year adjustments, sometimes unscheduled, to follow module price more closely. Besides, volume responsive systems have been implemented such as the FIT corridor in Germany in 2009 and in France in 2011, further enhancing the flexibility. The fact that FITs

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

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

track module price more closely in recent years should then be interpreted as a consequence of a modification of the FITs schemes.

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)



4.6.2 Hypothesis two: do feed-in tariffs influence module price?

The hypothesis (2) assuming that FITs influence module price does not seem to be true. It means that module price does not depend on the level of the FITs. This can be interpreted as a consequence of the fierce competition prevailing in the cell and module market, keeping price close to production cost, preventing producers to get a rent from attractive FITs.

However, VAR models use past values as explanatory variables, while FITs are announced, and therefore expected, months or even years ahead. We go further in the analysis of FITs effect on module price in the next section, by analysing the effect of a past but also future FIT change on module price.

5 Short term effects of feed-in tariff modifications on module price

In this section, we analyse the variation of module price before and after a FIT decrease. We observe 24 FIT cuts during the period considered. We cannot analyse the effect of a FIT increase since it happened only twice during the period considered, which is not enough to get significant results. However, it is more important to analyse FIT decreases since they are the most common events, and will still be in the future as FITs are expected to decrease until PV electricity becomes competitive.

5.1 Hypothesis

We test the hypothesis of module price being influenced by future FITs changes through an anticipation effect. We indeed observe a positive effect during the few months before a FIT decrease, and a negative one after. This is illustrated by figure 6 and 7 showing the deviation of module price compared to a business as usual scenario (the methodology to calculate the deviation is explained in the next subsection). The FIT decrease considered in figure 6 occurred in Germany (-5%) and Italy (-9%) on January 1st 2007, and figure 7 focuses on a major FIT decrease in Spain in October 2008 (-37%). Those FIT changes can be observed in figure 4 (section 3).

Figure 6 Deviation of module price compared to a business as usual scenario before and after a FIT decrease in January 2007.

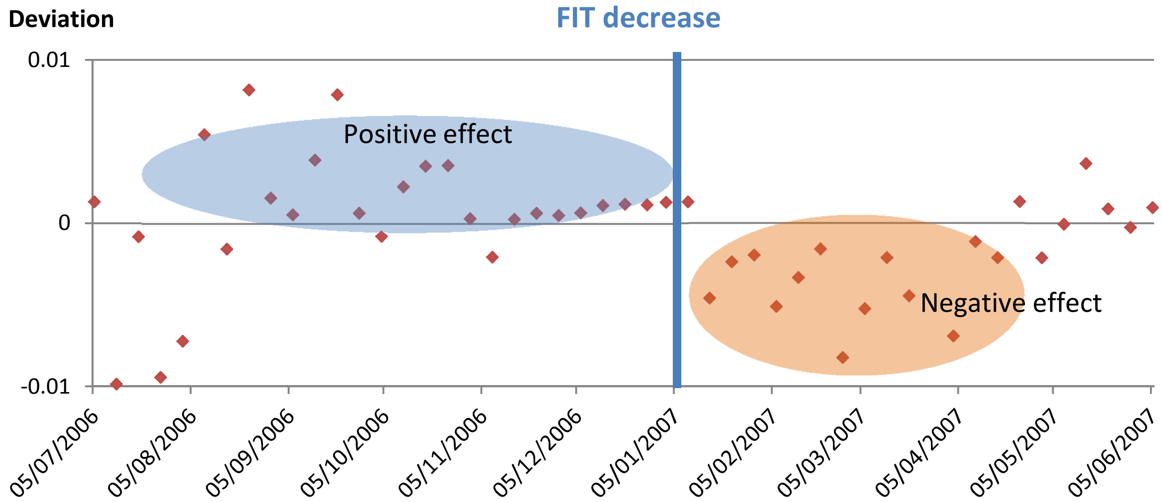
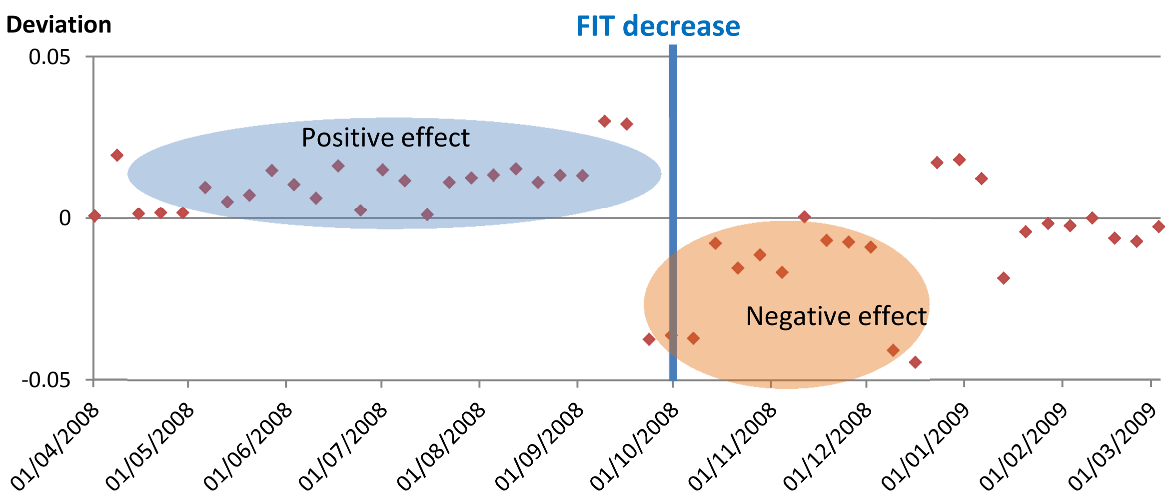


Figure 7 Deviation of module price compared to a business as usual scenario before and after a FIT decrease in October 2008.



5.2 Methodology

To capture the dynamic effect of a FIT decrease on module price, we use a polynomial growth model. It explains the deviation of module price by a polynomial function of the time before the following FIT decrease, or the time after the last FIT decrease.

To quantify the variation of module price compared to a scenario where no FIT change would have happened, we create the variable $Deviation$. It measures the deviation of the first order derivative of module price compared to a business as usual (BAU) scenario, according to (5). If $Deviation_t$ is positive, it means that module price increased more in week t than what the BAU scenario predicted.

$$Deviation_t = D.Module_t - D.Module_t^{BAU} \qquad (5)$$

Following the results from section 4.4., the BAU scenario is different during and after the silicon shortage. During the silicon shortage, it depends on lags of silicon price (6); while after the silicon shortage, it is constant (7):

$$D.Module_t^{BAU} = A + \sigma_1 D.SiPrice_{t-1} + \sigma_2 D.SiPrice_{t-2} \quad (6)$$

$$D.Module_t^{BAU} = B \quad (7)$$

The polynomial growth models consist in explaining $Deviation$ by a polynomial function of the time before the following FIT decrease, or the time after the previous one. This enables us to draw the dynamic profile of the deviation from a BAU scenario before and after a FIT decrease.

5.3 Equation

The regression equations of the polynomial growth models are:

$$Deviation_t = \sum_{x=1}^{3} b_x Before_t^{\,x} + \epsilon_t \qquad (8)$$

$$Deviation_t = \sum_{x=1,3} a_x\, After_t^{\,x} + \epsilon'_t \qquad (9)$$

Where

$Before_t$ is the number of weeks before the following FIT decrease

$After_t$ is the number of weeks after the previous FIT decrease

ϵ_t and ϵ'_t are the error terms, assumed to be independent and identically distributed.

5.4 Econometric considerations

Since $Module$ is not stationary, we use its first-order derivative, which is stationary, to calculate $Deviation$.

The length of the lag of silicon price included in (6), two weeks, is defined by the minimisation of the AIC information criteria as explained in the econometric considerations of the causality analysis (section 4.4).

The observation of figures 6 and 7 suggests that polynomial models should be at least quadratic, preferably or degree 3. However, when the three degrees of $After$ are used in (9), they are not significant. We therefore reject the variable of degree two. Besides, the coefficients are not significant when an equation with both explanatory variables $Before$ and $After$ is estimated. This explains why we perform two distinct regressions, one with a polynomial function of $Before$ as independent variables (8), and one with a polynomial function of $After$ (9).

5.5 Result

Using the results of the estimation of (8) and (9), given in annex 4, we simulate $Deviation_t$, the deviation of the first order derivative of module price compared to a BAU scenario, before (figure 8) and after (figure 9) a FIT decrease. Simulations cover a time scale of 40 weeks.

Before a FIT decrease, there is a positive deviation confirming the observation of real FIT decreases in figure 6 and 7. It means that before a FIT decrease, module price rises more than in a BAU scenario.

A negative effect starts 5 weeks before the FIT decrease (figure 8), and last until 8 weeks after, which corresponds to what is observed in figure 7. Module price thus decreases more than usual just before and after a FIT decrease.

Finally, ten weeks after a FIT decrease, there is a positive effect.

Figure 8 Simulation of the deviation of the first order derivative of module price from a business as usual scenario before a FIT decrease

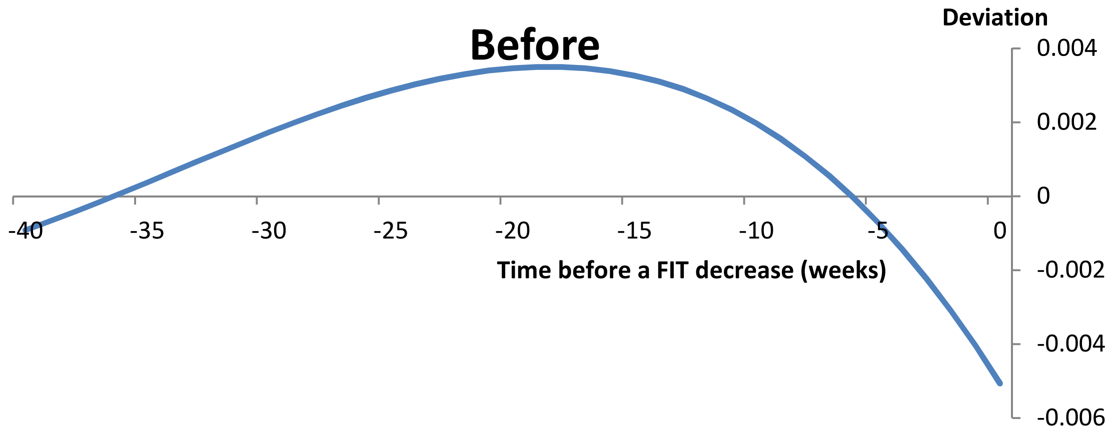
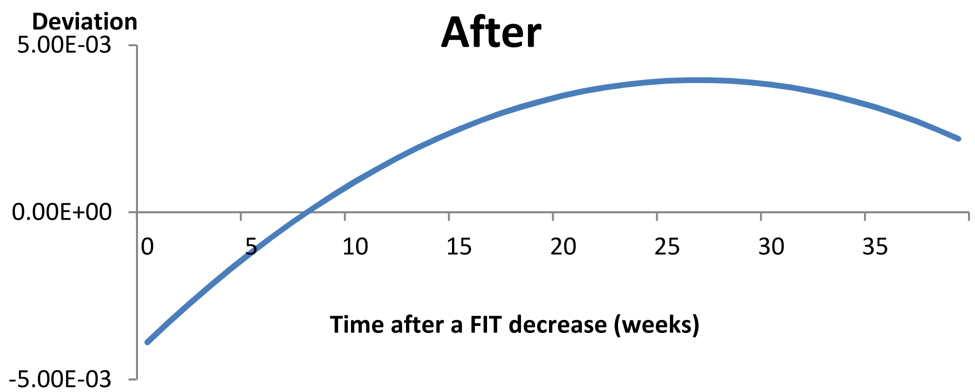


Figure 9 Simulation of the deviation of the first order derivative of module price from a business as usual scenario after a FIT decrease

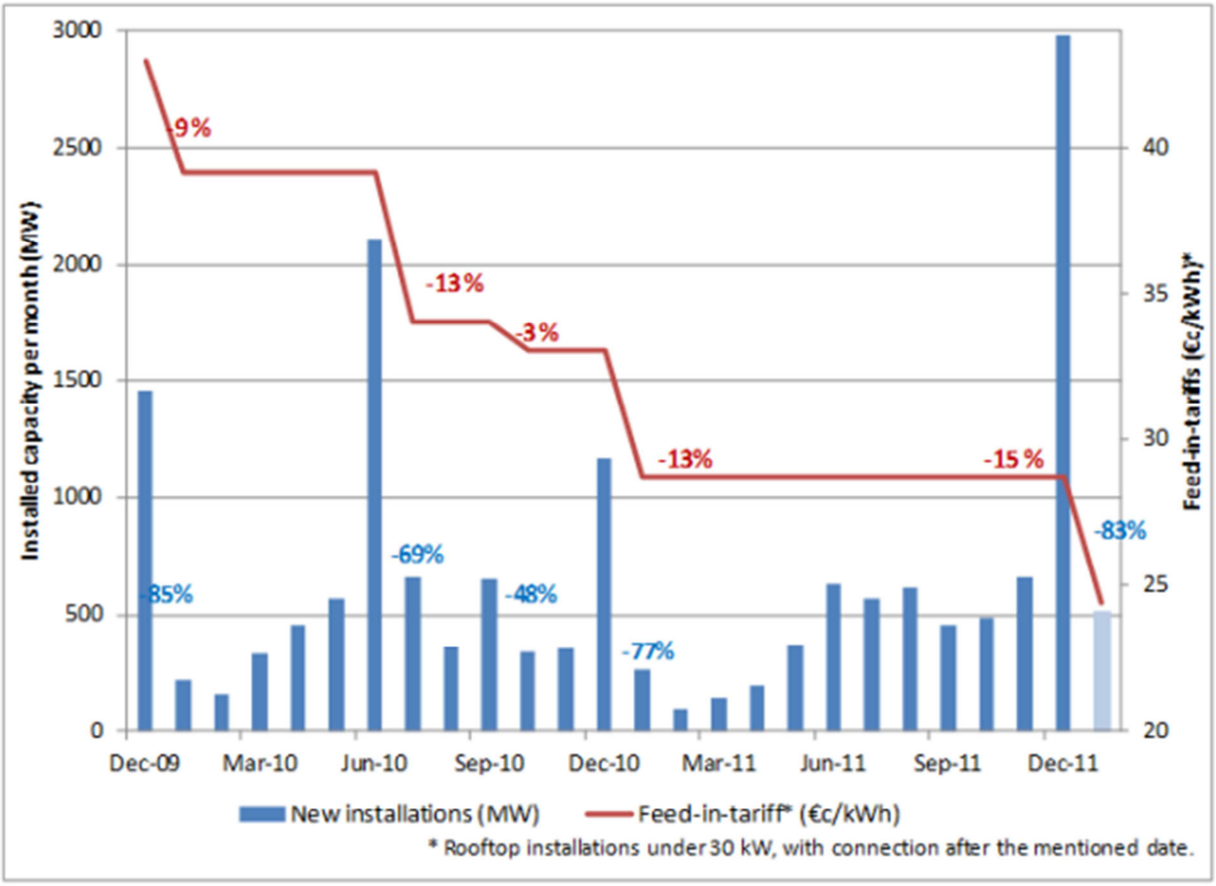


5.6 Interpretation of the results

The positive price deviation before a FIT decrease can be interpreted as a consequence of firms anticipating FIT changes, thus increasing modules demand before the FIT decreases to benefit from the higher FIT, which eventually increases price.

This assumption is supported by the observation of monthly PV installation and FIT evolution in Germany (figure 10). It clearly indicates that peaks of installation, measured by the number of connections to the grid, arise in the months before FIT decreases.

Figure 10 Impact of the feed-in tariff reductions on monthly capacity addition in Germany



Source: Enerdata, from German Ministry for Environment, SolarWirtshaft

The installation of PV systems requires some time, especially for big installations. To install them before the FIT decreases, firms thus 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 their price.

A few weeks before the FIT decreases, firms lose this incentive since they would not have time to complete the installation and connect it to the grid before the FIT changes. This lowers the demand, decreasing module price, which encourages firms to wait to benefit from this reduction, eventually decreasing price even further. This explains why module price decreases during the 5 weeks before the FIT modification, and after.

Finally, demand goes back to “as usual” a dozen weeks after the FIT decreases, pulling price back to “as usual” levels.

6 Conclusion

This chapter analyses market effects on module price. In particular, it focuses on the influence of feed-in tariffs (FITs) and silicon price, FITs being the main policy instruments used to stimulate the development of the PV market, and silicon the main input for the PV industry.

To analyse the influence of FITs and silicon price on module price, we rely on times series data 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. With polynomial growth models, we analyse the short term effects of FIT changes on module price. We reached several conclusions leading to practical recommendations for the design of a FIT policy.

First, FITs follow module price more closely in the recent period, especially in Germany. This is important since poor adjustment of FITs to module and PV system price can lead to market overheating such as in Spain in 2008 and France in 2010. This better adjustment in the second period comes from an increase in the frequency of the adjustments. Moreover, volume responsive mechanisms implemented in Germany since 2009 further increase this flexibility, while still allowing some anticipation from the industry.

Second, Granger causality tests are not conclusive with regards to the effect of FITs value on module price. This can be explained by the fierce competition prevailing on the module market, keeping module price close to production cost whatever the FITs level. However, polynomial growth models show that FIT changes have short term effects. In the months before a FIT decrease, module price increases. This is likely due to a higher demand triggered by market anticipation, increasing the installations before the FIT decreases. This should be avoided since price distortions give wrong signals to the industry. This also advocates for more frequent FIT changes, since they would thus be less important, reducing the magnitude of those distortions.

Finally, we find that silicon price has been influencing module price only during the silicon shortage, when silicon producers had market power. This explains the slight increase in module price during this period. This market power was due to a capacity constraint and a low contestability of the market[54]. After the end of the shortage period, they lost their market power. This can be explained by several factors: First the competition is increasing with new players entering the market, including many Chinese ones (cf chapter one). Then, the situation went from shortage to excess production, due to the arrival of new capacity planned a few years before - when important margins due to the shortage attracted investors.

This suggests that as long as there is over-capacity in silicon production, silicon price should not be taken into account to predict short term module variations. Rather, silicon price depends on the module market, which represents 87% of polysilicon consumption in 2011. However, the situation could change in the future if demand catches up with production capacity.

What are the implications regarding optimal FIT schemes?

The first lesson is that price formation in the PV industry is very complex, and difficult to predict. Therefore FIT mechanisms must be flexible, to avoid important discrepancies with PV electricity cost when price evolution has not been anticipated correctly. Such

[54] We explain in chapter one that silicon production requires advanced technical know-how which is an important entry barrier.

discrepancies create market overheating calling for violent adjustments harmful to the industry, as evidenced by the Spanish and French examples.

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 of previous PV installation through volume responsive mechanisms. a) Unscheduled FIT changes are certainly not a good solution since they increase the uncertainty in the PV industry. b) More frequent FIT changes allow a faster adaptation to module price. Moreover, a higher frequency implies smaller adjustments, reducing the magnitude of the price distortions around FIT changes. c) The volume responsive aspect enables fast responses to the market, while giving investors some visibility since it is a transparent process. More frequent FIT changes depending on previous market development then appears to be the optimal type of FIT scheme.

Annex

Annex 1 Sources for FIT values

http://www.solarfeedintariff.net

http://www.pv-magazine.com/news/details/beitrag/germany

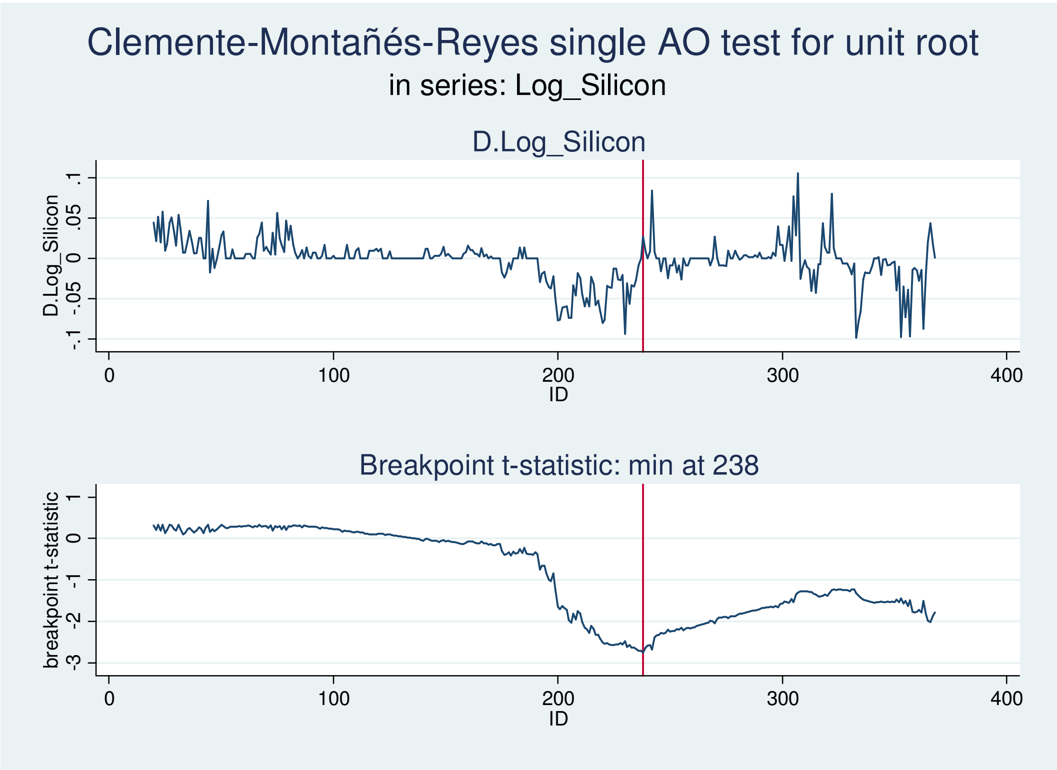
http://www.res-legal.de/en/search-for-countries/spain/single/land/spanien/instrument/price-regulation-regimen-especial/ueberblick/foerderung.html?bmu%5BlastPid%5D=95&bmu%5BlastShow%5D=5&bmu%5BlastUid%5D=239&bmu%5Brel%5D=1&cHash=4c1babe1c30c936ef618e7e942050f1b

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

http://www.iea.org/textbase/pm/?mode=re&action=result

http://www.columbia.edu/cu/cures/Stephen-Oroukes-presentation2.pdf

Annex 2 Clemonte-Montañés-Reyes test for unit root applied to log (silicon price)



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

Annex 3 Regressions of the BAU model

Table 6 Before

VARIABLES	(1) D. Log_Module
LD.Log_Silicon	0.2160***
	(0.041)
L2D.Log_Silicon	0.0935**
	(0.041)
Constant	0.0006
	(0.001)
Observations	234
R-squared	0.3746
Adj. R-squared	0.3692

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.2
Regression performed during the silicon shortage. L is the operator for Lag
F for Forward lag
and D for first order derivative

Table 7 After

VARIABLES	(1) D.Log_Module
Constant	-0.0022**
	(0.001)
Observations	150
R-squared	0.0000
Adj. R-squared	0.0000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.2
Regression performed after the silicon shortage. L is the operator for Lag
F for Forward lag
and D for first order derivative

Annex 4 Result of the regression (8) and (9)

Table 8 Result of the regression (8)

VARIABLES	Deviation
Before	0.001057984***
	(0.000)
$Before^2$	-0.000039290***
	(0.000)
$Before^3$	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

Table 9 Results of the regression (9)

VARIABLES	Deviation
After	0.0003988***
	(0.000)
$After^3$	-0.000000160***
	(0.000)
Constant	-0.0033644***
	(0.001)
Observations	335
R-squared	0.0613
Adj. R-squared	0.0557

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

Chapter four

Impact of firms' strategies on the optimal feed-in tariff policy

Abstract

Feed-in tariffs (FITs) are the main policy instruments used to stimulate the photovoltaic (PV) market. They set administratively a price at which the power grid operator must buy PV electricity. Taking into account the speed at which cost is reduced by learning by doing, there is an optimal path for the development of the PV industry. In this chapter, we analyse the consequences on firms' strategies on the FIT policy that should be implemented to reach the optimal installation timing. The analysis is based on a model of firms installing PV systems over two periods, the cost decreasing in period 2 thanks to the experience effect triggered by the quantity installed in period 1. A FIT can be implemented, and reduced in period two. We consider three situations: firms adopting a short term strategy (myopic firms), a long term one (rational firms), or a mix of both types of firms. Myopic firms relate to small firms, while rational firms relate to bigger players. For each situation, the installation timing without FIT is compared with the optimal situation, and we find the FIT policy that allows reaching the optimum.

We find that without FIT policy, the social welfare loss increases with the intensity of the learning by doing. But the optimum can be reached with a single FIT policy when firms

behave heterogeneously, whether is in a myopic or rational way. The initial FIT must be higher when firms are rational. However, when firms behave heterogeneously, the optimum can be reached only if two distinct FITs are implemented, each one addressing one type of firm.

Résumé français

Les tarifs de rachat de l'électricité sont les principales politiques publiques visant à stimuler le développement de l'industrie photovoltaïque. Un prix est fixé auquel les électriciens sont tenus d'acheter l'électricité d'origine photovoltaïque. En fonction de l'intensité de l'effet d'apprentissage qui réduit le coût en fonction de la production cumulée, il y a une vitesse optimale du développement de l'industrie photovoltaïque. Ce chapitre vise à analyser les conséquences du comportement stratégique des entreprises installant des panneaux photovoltaïques sur le tarif de rachat optimal. L'analyse est basée sur un modèle de deux périodes pendant lesquelles des entreprises installent des panneaux photovoltaïques. Le cout des panneaux diminue en période 2 grâce à l'effet d'apprentissage, en fonction de la quantité installée en période 1. Un tarif de rachat peut être instauré, et diminué en période 2. Nous considérons trois cas : les entreprises suivant une stratégie de court terme (myope), de long terme (rationnelle) ou un mélange des deux. Les entreprises myopes peuvent être assimilées aux petits acteurs de l'installation de systèmes photovoltaïques, alors que les rationnelles peuvent être assimilées aux acteurs plus importants. Dans chaque cas, nous comparons les quantités installées et le bien-être social sans tarif de rachat avec la situation optimale, puis nous déduisons le tarif de rachat qui permet d'atteindre la situation optimale.

Nous trouvons que sans tarif de rachat, la perte de bien-être social augmente avec l'intensité de l'effet d'apprentissage. Cependant, avec un tarif de rachat adapté, la situation optimale peut être atteinte si les entreprises adoptent la même stratégie. Ce tarif doit être plus élevé lorsque les entreprises sont rationnelles. Par contre, lorsque les deux types de stratégies existent, la situation optimale peut être atteinte uniquement en instaurant deux tarifs de rachat distincts, chacun visant un type d'entreprise.

1 Introduction

Feed-in tariff (FITs) are policy mechanisms guaranteeing a price for fixed periods of time for electricity produced by renewable energy sources. They were implemented in the US in 1978 and in Europe in 1990. The first FIT leading to a massive development of the photovoltaic (PV) market was implemented in 2000 in Germany, under the Erneuerbare Energien Gesetz. Following a steady decrease, it led the German PV market to regular and strong development, propelling it to the head of the world market for the last decade. However, FITs provoked uncontrolled market growth in other countries such as Spain and France, followed by dramatic cuts that harmed the industry. FITs can then be efficient to develop a young industry, but only if well designed.

The main purpose of FITs is to handle the externality that originates from learning by doing, which cannot be captured by firms due to knowledge spillovers[1]. Learning by doing identified by Arrow (1962) decreases unit cost with the accumulation of experience through cumulative production. But knowledge spillovers spread the cost reduction through the whole industry, preventing individual firms to internalise it in their strategic planning. Because of this positive externality, the production is under-optimal. Without incentive policies such as FITs, PV technology would be adopted at a too slow pace.

The issue we address in this paper is the impact of firm's strategies on optimal FIT policies. Is it always possible to reach the optimal installation timing with a FIT? Should the FIT vary depending on firms' behaviours? Over the last decade, the PV industry has undergone deep transformations. The many firms set up to take advantage of this new market have consolidated, creating bigger players. Traditional utility companies also entered the market. These bigger firms might have a long term strategy while small firms follow a short term strategy. Long term strategies take into account FITs changes, but also the module price reduction originating from learning by doing effect, which is a public good for firms installing PV systems. Indeed, learning by doing is achieved by firms located more upstream in the value chain, in the manufacturing segments, which

[1]The environmental externality that originates from conventional electricity sources' greenhouse gases emissions is often cited to justify FITs. However, this can also be sorted out by pricing those emissions.

are different players of the industry, among which knowledge spillovers take place on a large scale as explained in the first chapter.

To address the question of the impact of firms' strategies on the optimal FIT policy, we created a model with myopic firms (following a short term strategy) and rational firms (following a long term strategy) installing PV systems over two periods. The learning by doing effect decreases module price in period 2 depending on the total installation in the first period. We show that there is an optimal timing of PV systems installation which depends on the strength of the learning by doing effect. After analysing firms' behaviours when facing a FIT change, we draw some conclusions concerning the optimal FIT policy to reach the optimal installation timing.

We show that the optimal policy is different depending on whether firms are myopic or rational. The initial FIT must be higher when firms are rational. This result holds in a heterogeneous world made of a mix of both behaviours. However, if a single FIT can reach the optimal installation timing when firms all adopt the same strategy, it is impossible when firms behave heterogeneously. In this situation, only distinct FITs each targeting one type of firm can reach the optimum. This justifies different FITs according to the size of the projects, considering that big PV systems are installed by big firms having a long term rational strategy, while small systems are installed by smaller firms having a short term "myopic" strategy.

There is substantial literature comparing the efficiency of the numerous policies designed over the last decades to pull renewable energies' markets: FITs, Quotas such as Renewable Portfolio Standards (RPS), tendering schemes, investment subsidies, tax rebate, etc. This literature is not extensively explored here, but a few important results are reminded. Building on Weitzman's (1974) argument of the difference between price and quantity approaches in the presence of uncertainty, Menanteau et al. (2003) show that quantity based mechanisms such as RPS bring a better control of total cost. However, they point out that renewable energies markets have been growing faster when FITs were used, thanks to the attractiveness of fixed prices for investors, and lower transaction costs. In addition, Finon and Menanteau (2004) remind that if FITs have a poor static efficiency, they have a better dynamic efficiency than other instruments: if on a static side, the present cost is higher for the consumers, the upside is a rent on the producer/installator side, giving them resources to invest in R&D, reducing future cost. Moreover, they allow to differentiate immature from mature technologies. Midttun and Gautesen (2007) take a new look at this debate, arguing that FITs are more relevant for the early development phase, when the dynamic efficiency is important due to a strong learning effect, while in the later phase, RPS can allow more static efficiency by fostering cross-industry competition. The debate regarding which policy is the most efficient does not seem to reach a clear conclusion, since it depends on the regulators priorities. In this chapter, we focus on FITs since they are the main policy used today.

Regarding FITs dynamic efficiency, Rigter and Vidican (2010) establish a theoretically optimal initial FIT and digression rate for decentralised PV in China. The optimisation is based on the anticipation of PV systems price evolution and a required internal rate of return for investors. Benthem et al. (2008) develop an intertemporal model of the optimal policy in California, including environmental externality and various degrees of learning by doing with spillovers. They find that the California Solar Policy based on rebates cannot be justified by the environmental externality alone, but with a 20% learning rate, this policy is below the optimal level. Wand and Leuthold (2011) adapt this model to the German FIT policy. They find that with a 20% learning rate for solar panels, there is a net social welfare loss until 2030 for Germany, considering a 15% growth in the world market. However, in these models, the assumption is made that local installation does not influence the global installation. The learning effect is therefore determined exogenously. In this chapter, the learning is endogenous to highlight the dynamic effect. In addition, contrary to the previous cited papers modelling demand by a non-linear function of net present value of PV systems, we consider two different firms' behaviours to study the influence of firms' strategy on the optimal policy regime.

The paper is structured as follows: Section 2 presents the model and the social optimum, section 3 considers the case of myopic firms while section 4 envisages the case of rational firms. Then, section 5 considers a heterogeneous situation with a mix of both behaviours. Finally, section 6 concludes.

2 The model and the social optimum

This section presents the model of photovoltaic (PV) systems installation, and derives the first best solution for the installation timing.

To highlight the dynamic effect, we consider two periods (referred to 1 and 2), over which standard PV systems can be installed. Let Q_1 be the quantity installed over the first period, Q_2 over the two periods, and therefore $Q_2 - Q_1$ over the second period. Assuming limited module production capacity, a total quantity $Q_{\max}$ of PV systems can be installed over the two periods.

The cost of PV systems is composed of the cost of PV modules, which is exogenous in the first period, but endogenous in the second period to take the learning effect into account, and an additional cost (inverter, wires, mounting system, installation, land, etc.), which is responsible for PV systems heterogeneity.

Assuming a competitive PV module market, there is a unique module price, equal to the cost for each period. The module cost in period 1 C_1 is exogenous. Following the learning by doing theory, with complete knowledge spillovers, it decreases from period 1 to 2 depending on the total installed quantity in period 1, according to:

$$C_2 \ = C_1(\tfrac{Cum_2}{Cum_1})^{-\epsilon} = C_1(1 + \tfrac{Q_1}{Cum_1})^{-\epsilon}$$

Where Cum_j is the cumulative quantity of PV systems installed at the beginning of period j, and ϵ the experience parameter.

Since we consider the cost decrease from period 1 to period 2 rather than the marginal effect, the expression of the learning effect can be linearized giving:

$$C_2 \ = C_1(1 - \epsilon * \tfrac{Q_1}{Cum_1}) = C_1 - \beta Q_1 \qquad \text{with } \beta = \tfrac{\epsilon * C_1}{Cum_1} \text{ and } Q_1 < \tfrac{C_1}{\beta}$$

Additional cost is assumed to be heterogeneous, following a uniform distribution on $(0, +\infty)$ with a density $\frac{1}{\gamma}$. Since the positive discount rate implies that most profitable projects are installed first, the installation of one unit of PV system raises additional cost by γ. Therefore the total cost of the installation of a standard PV system when a quantity q has already been installed is:

$$C_1 + \gamma q \text{ in period 1}$$

$$C_1 - \beta Q_1 + \gamma q \text{ in period 2}$$

The electricity price E is assumed to be constant over the two periods. It corresponds to the net present value of all the electricity produced by a standard PV system over its lifetime. It can then be compared to the cost of a PV system.

Given a discount rate r, the first best installation program is defined by (Q_1, Q_2) maximizing the following expression of the social welfare:

$$W = \int_0^{Q_1} (E - C_1 - \gamma q) dq + \frac{1}{1+r} \int_{Q_1}^{Q_2} (E - C_1 + \beta Q_1 - \gamma q) dq \quad (1)$$

$$s.c. Q_{\max} \geq Q_2 \geq Q_1 \geq 0$$

The optimal total installed quantity can be bounded by $Q_{\max}$. Table 1 summarizes our findings in term of optimal installation, which are explained in proposition 1.

Table 1: Optimal installation in period 1 ($Q_1^{optimal}$) and 2 ($Q_2^{optimal}$)

<table>
<tr><th></th><th>$\beta < \beta_{bounding}$</th><th>$\beta_{bounding} < \beta < \beta_{\lim}$</th><th>$\beta_{\lim} < \beta$</th></tr>
<tr><td>$C1 > E$</td><td colspan="2">case 1
No installation</td><td>case 2 a $Q_{\max} < Q_{\lim}$
No installation
case 2 b $Q_{\max} > Q_{\lim}$
Bounded by Q_{max}
$Q_1^{optimal} = \frac{r(E-C_1)+\beta Q_{\max}}{2\beta+r\gamma}$
$Q_2^{optimal} = Q_{\max}$</td></tr>
<tr><td>$C1 < E$</td><td>case 3
Not bounded
$Q_1^{optimal} = (E - C_1) * \frac{\beta+r\gamma}{\nabla}$
$Q_2^{optimal} = (E - C_1) * \frac{2\beta+r\gamma+r\beta}{\nabla}$</td><td colspan="2">case 4
Bounded by Q_{max}
$Q_1^{optimal} = \frac{r(E-C_1)+\beta Q_{\max}}{2\beta+r\gamma}$
$Q_2^{optimal} = Q_{\max}$</td></tr>
</table>

$\beta_{\lim} = \gamma(1 + \sqrt{1+r})$

$Q_{lim} = \frac{(2\beta+r\gamma)(1+\sqrt{1+r})+r\beta}{\nabla}(E - C_1)$

$\nabla = 2\gamma\beta + r\gamma^2 - \beta^2$ which is positive for $\beta < \beta_{\lim}$ and negative for $\beta > \beta_{\lim}$

Proposition 1 *Depending on the value of initial module cost, and the strength of the learning effect, four optimal situations exist:*

Case 1: If initial module cost is higher than the cost of electricity ($C_1 > E$), and the learning rate is low, it is optimal to install nothing.

Case 2: If initial module cost is higher than the cost of electricity ($C_1 > E$), and the learning rate is high, it is optimal to install PV systems only if the maximum capacity is high enough to allow a strong learning effect to compensate for the high initial cost (case 2b). Otherwise, it is optimal to install nothing (case 2a).

Case 3 and 4: If initial module cost is lower than the cost of electricity ($C_1 < E$), it is optimal to install some PV systems. The optimal installed quantities increase with the learning effect (case 3) until it is bounded by Q_{max} (case 4).

Proof. *If $C_1 > E$ (case 3 and 4): If $\beta < \beta_{\lim} = \gamma(1+\sqrt{1+r})$, $\nabla = 2\gamma\beta + r\gamma^2 - \beta^2 > 0$, so $Q_2^{optimal}$ is strictly increasing, and $Q^{optimal} \to +\infty$ when $\beta \to \beta_{\lim}$. So there is a unique $\beta_{bounding} < \beta_{\lim}$ corresponding to $Q_2^{optimal}(\beta_{bounding}) = Q_{max}$ (limit between case 3 and 4). If $\beta \geq \beta_{bounding}$ (case 4), $Q_2^{optimal} = Q_{max}$.*

If $(C_1 > E)$ (case 1 and 2):

If $\beta < \beta_{\lim}$ (case1), $\nabla > 0$ so $Q_2^{optimal} < Q_1^{optimal} < 0$. Since the installed quantities cannot be negative, $Q_1^{optimal} = Q_2^{optimal} = 0$.

If $\beta > \beta_{\lim}$ (case2), the optimal installed capacity is bounded by Q_{max} (c.f. case $C_1 > E$). Since $(E - C_1) < 0$, $W_{Bounded}^{optimal} > 0$ only if $Q_{max} > Q_{\lim} = \frac{(E-C_1)}{\nabla} * \left[(2\beta + r\gamma)\left(1+\sqrt{1+r}\right) + r\beta\right] > 0$ (case2b). If $Q_{max} < Q_{\lim}$, it is optimal to install nothing (case 2a). ∎

These cases can be interpreted in terms of maturity and learning rate of the technology. Case 1 corresponds to a technology which does not show any potential since its low learning rate does not compensate for its high initial cost. Case 2 describes a very young technology having a high initial cost, but showing important cost reduction potential thanks to a high learning rate. Case 3 and 4 correspond to technologies for which best applications are profitable. In case 4, there is a bounding constraint on the installation rate. In case 3, the installation is not limited by any physical or logistic constraint.

From now on, we focus on case 3, which corresponds to the PV industry. Indeed PV systems are profitable in some niche markets such as for off-grid applications. Moreover the installation is not bounded, as it is acknowledged that module production and installation are much lower than actual production capacity, and the low penetration of PV technology in the electricity market allows further important development (0.6% of the gross electricity consumption in Europe in 2010, Jäger-Waldau et al., 2011). Other cases are treated in the annex 1.

In case 3, the optimal social welfare is defined by (2). This expression is used as a reference to assess the social welfare loss in business as usual or policy scenarios.

$$W^{optimal} = (E - C_1)^2 * \frac{2\beta + r\gamma}{2\nabla} \qquad (2)$$

3 The case of Myopic firms

In this section and the following ones, we assume that the electricity produced by the PV systems is sold at a fixed price over their whole lifetime. This feed-in tariff (FIT) is π in period 1, and $\pi - \delta\pi$ in period 2. The FIT policy is therefore defined by $(\pi; \delta\pi)$. As for the cost of electricity, π and $\delta\pi$ correspond to the net present value of all the electricity produced by a standard system over its lifetime. It can then be directly compared to the cost of a PV system.

The installed quantities Q_1 and Q_2 are now determined by firms' behaviour. Two behaviours are considered: myopic and rational. This can correspond to small firms having short term strategies, installing PV systems as long as they are profitable in a "myopic" manner, and bigger ones following a long term strategy, anticipating market and policy evolution in a rational way.

In this section, firms are myopic, anticipating neither the cost reduction triggered by the learning effect, nor the FIT change in the second period. They install PV systems as long the marginal project is profitable, following a short term strategy according to $\pi - C_1 - \gamma Q_1^M = 0$ in the first period, and $\pi - \delta\pi - C_1 + \beta Q_1^M - \gamma Q_2^M = 0$ in the second period, with $Q_2^M \geq Q_1^M \geq 0$. Solving these equations gives the following expressions of the installed quantities:

$$Q_1^M = \frac{\pi - C_1}{\gamma}$$

$$Q_2^M = \frac{(\pi - C_1)(\beta + \gamma) - \gamma\delta\pi}{\gamma^2}$$

Replacing Q_1^M and Q_2^M by those expressions in the definition of the social welfare (1) gives the expression of the social welfare when firms are myopic (3). See annex 1 for the other cases than 3. Two scenarios are considered: business as usual (BAU) and an optimal policy ($\hat{\pi}_M$,$\delta\hat{\pi}_M$).

$$W^M(\pi,\delta\pi) = \frac{(E-C_1)(\pi-C_1)}{\gamma} + \frac{(E-C_1)*[\beta(\pi-C_1)-\gamma\delta\pi]}{\gamma^2(1+r)}$$

$$-\frac{(\pi-C_1)^2}{2\gamma} + \frac{(\pi-C_1)^2*(\beta^2-2\gamma\beta)+2\gamma^2*(\pi-C_1)*\delta\pi-\gamma^2*\delta\pi^2}{2\gamma^3(1+r)} \qquad (3)$$

3.1 Business as usual scenario (Without policy)

To analyse the situation where no FIT policy is implemented, we consider a BAU scenario, where the electricity is sold at the market price E in both periods, which corresponds to $\pi = E$ and $\delta\pi = 0$ in our model. Using these values in the previous expression gives the following installed quantities and social welfare:

$$Q_1^{M,BAU} = \frac{E-C_1}{\gamma}; \;\; Q_2^{M,BAU} = \frac{(E-C_1)(\beta+\gamma)}{\gamma^2}; \; W^{M,BAU} = (E-C_1)^2\frac{\beta^2+\gamma^2(1+r)}{2\gamma^3(1+r)}$$

Proposition 2 *The business as usual situation is not optimal if and only if there is a learning effect.*

Proof. *If* $\beta = 0$, $W^{M,BAU} = W^{optimal}$

If $\beta > 0$, $W^{optimal} - W^{M,BAU} = (E-C_1)^2\frac{\beta^2(\beta-\gamma)^2}{2\gamma^3(1+r)\nabla} > 0$ *since* $\nabla > 0$ *in case 3.* ■

To illustrate proposition 2, it is interesting to consider a simulation, shown in figure 1 (quantities) and 2 (social welfare).

With a weak learning effect ($\beta < \gamma$), the cost decrease in period 2 does not compensate for the increase in additional cost. In this situation it would be optimal to wait for period 2 to install some of the systems that myopic firms install in period 1.

With a strong learning effect ($\beta > \gamma$), the corresponding cost decrease in period 2 is more important than the increase in additional cost. Therefore it is optimal to install more projects in period 1 than what myopic firms would do, to benefit from this strong learning effect in period 2. The gap between the optimal and BAU installed quantities and social welfares then increases with β.

Figure 1 Simulation of installed quantities in an optimal and BAU scenario according to the learning strength (β), in case 3. (Parameters: $\gamma = 0.001$, $\beta = various$, $E = 18$, $C_1 = 14$, $r = 0.15$)

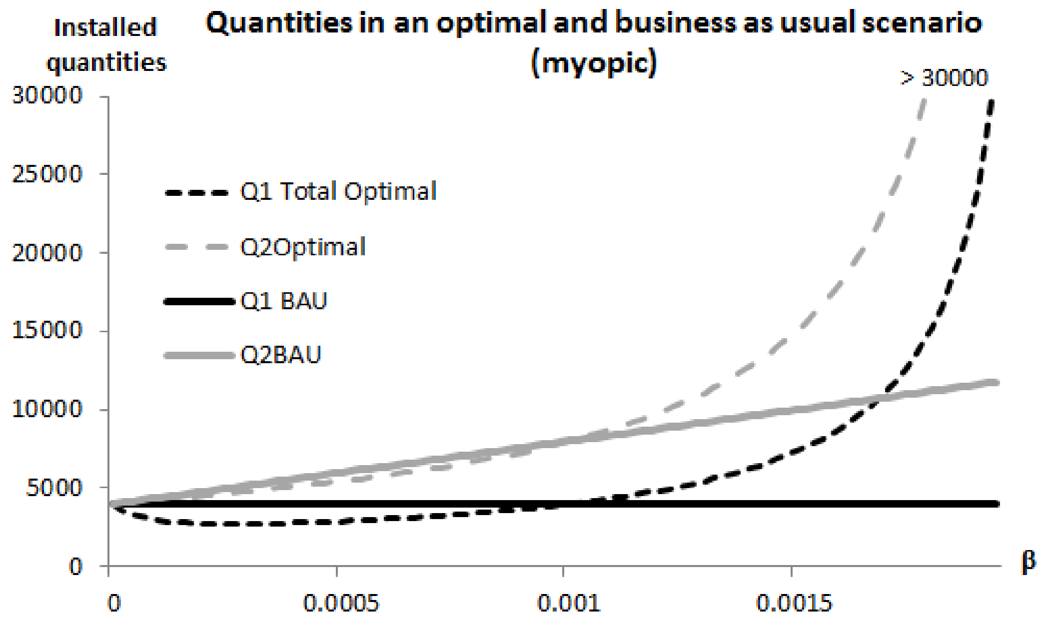
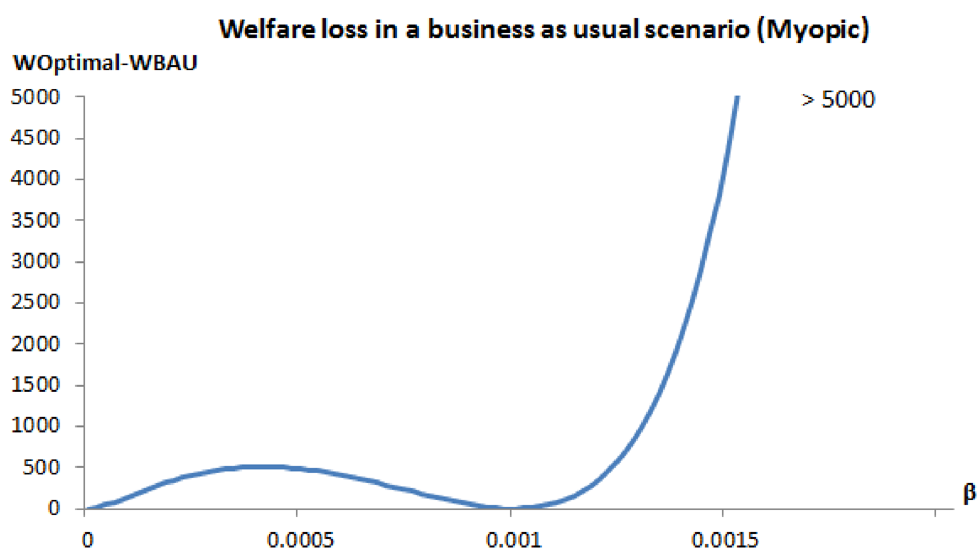


Figure 2 Simulation of the social welfare loss in a BAU scenario according to the learning strength (β), in case 3. (Parameters: $\gamma = 0.001$, $\beta = various$, $E = 18$, $C_1 = 14$, $r = 0.15$)



3.2 Optimal policy scenario

To see if it is possible to reach the optimal situation with a FIT policy, we now consider the optimal policy, which corresponds to $(\hat{\pi}_M; \delta\hat{\pi}_M)$ maximizing the social welfare defined by (3).

Proposition 3 *If all firms are myopic, it is possible to reach the optimal situation with an appropriate FIT policy* $(\hat{\pi}_M; \delta\hat{\pi}_M)$ *defined by* $\hat{\pi}_M = E + (E - C_1)\frac{\beta*(\beta-\gamma)}{\nabla}$ *and* $\delta\hat{\pi}_M = (E - C_1)\frac{\beta*(\beta-\gamma)}{\nabla}$.

Proof. *C.F. annex 2* ■

An appropriate FIT policy therefore allows reaching the optimal installation timing when all firms are myopic. See annex 1 for the optimal policy in the bounded case, which also leads to the optimal situation.

4 The case of Rational firms

In this section, firms are rational, anticipating the cost reduction triggered by the learning effect, and the FIT change in the second period. They follow a long term strategy.

We assume a high number of firms, thus each firm's production is negligible compared to the global production. Therefore the learning effect triggered by each firm is not separated from the global learning in rational firms' optimisation program. They install PV systems as long as they are profitable, but also provided that their net present value wouldn't be higher if installed in period 2. Their optimisation program is therefore $\pi - C_1 - \gamma Q_1^R = \frac{1}{1+r}(\pi - \delta\pi - C_1 + \beta Q_1^R - \gamma Q_1^R)$ in period 1, and $\pi - \delta\pi - C_1 + \beta Q_1^R - \gamma Q_2^R = 0$ in period 2, with $Q_2^R \geq Q_1^R \geq 0$.

Solving these equation gives:

$$Q_1^R = \frac{r(\pi - C_1) + \delta\pi}{\beta + r\gamma}$$

$$Q_2^R = \frac{(\pi - C_1)(\beta + r\beta + r\gamma) - \gamma r \delta\pi}{\gamma(\beta + \gamma r)}$$

Using those expressions in the definition of the social welfare (1) gives the social welfare in the general case when firms are rational (4). A BAU and an optimal policy ($\hat{\pi}$,$\delta\hat{\pi}$) scenario are considered.

$$W^R(\pi, \delta\pi) = \frac{(E - C_1)(\pi - C_1)}{\gamma} + \frac{(r\beta^2 - (\gamma r + \beta)^2)(\pi - C_1)^2 + 2\beta^2(\pi - C_1) * \delta\pi - (2\gamma\beta + \gamma^2 r)\delta\pi^2}{2\gamma(\gamma r + \beta)^2} \quad (4)$$

4.1 Business as usual scenario

As in the myopic case, the BAU scenario corresponds to $\pi = E$ and $\delta\pi = 0$, giving:

$$Q_1^{R,BAU} = \frac{r(E - C_1)}{\beta + r\gamma}, Q_2^{R,BAU} = \frac{(E - C_1)(\beta + r\beta + r\gamma)}{\gamma(\beta + \gamma r)},\ W^{R,BAU} = (E - C_1)^2 \frac{(\gamma r + \beta)^2 + r\beta^2}{2\gamma(\gamma r + \beta)^2}$$

Proposition 4 *The business as usual situation is non-optimal if and only if there is a learning effect.*

Proof. *If* $\beta = 0$, $W^{R,BAU}$ $=W^{optimal}$

If $\beta > 0$, $W^{optimal} - W^{R,BAU} = (E - C_1)^2 \frac{\beta^4(1+r)}{2\gamma(\gamma r + \beta)^2 \nabla} > 0$ *since* $\nabla > 0$ *in case 3.* ■

Simulations in figure 3 and 4 show that the gap between the optimal and the BAU installed quantities and social welfare increase with the strength of the learning effect (β). It illustrates the learning by doing externality.

Figure 3 Simulation of installed quantities in an optimal and BAU scenario according to the learning, in case 3. (Parameters: $\gamma = 0.001$, $\beta = various$, $E = 18$, $C_1 = 14$, $r = 0.15$)

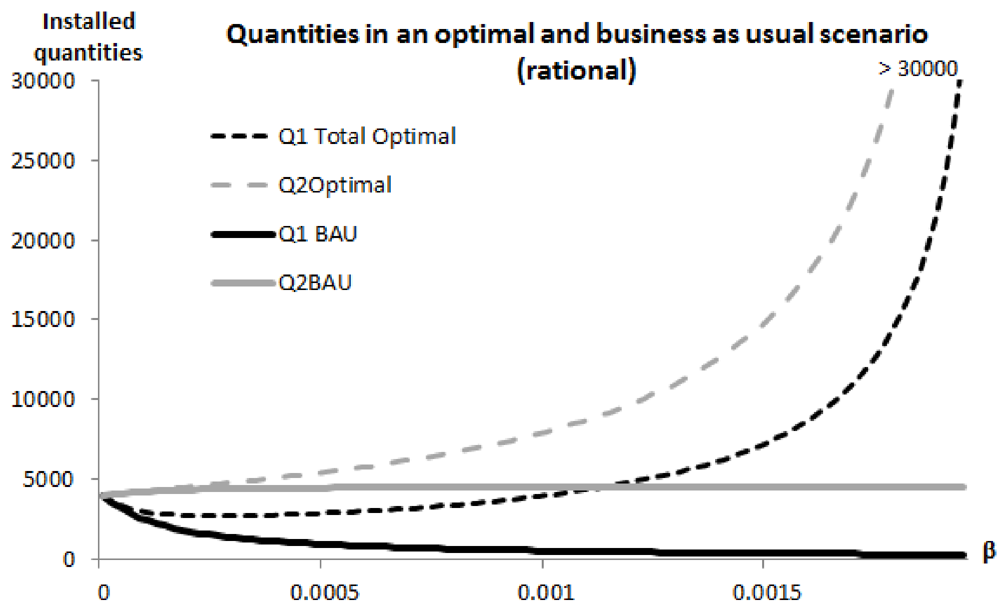
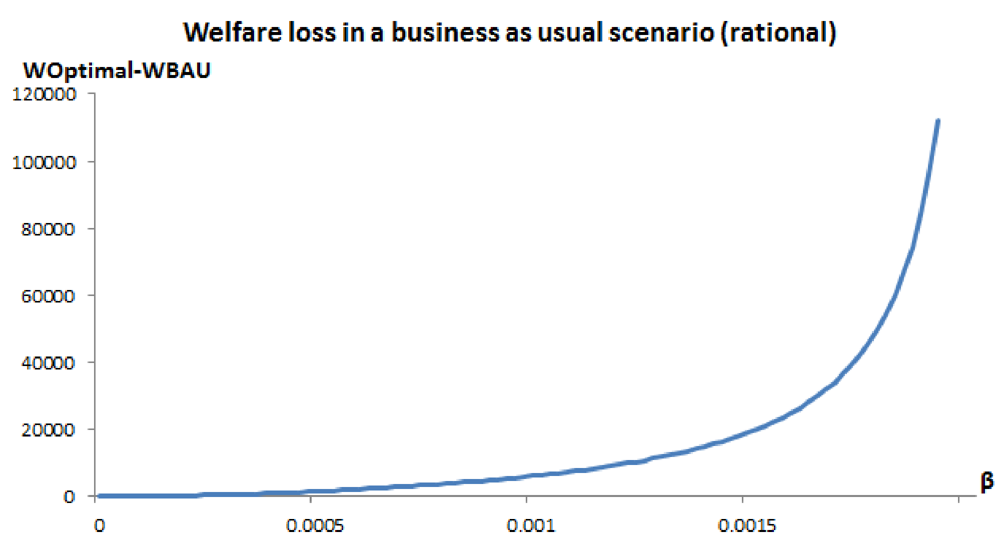


Figure 4 Simulation of the social welfare loss in a BAU scenario according to the learning, in case 3. (Parameters: $\gamma = 0.001$, $\beta = various$, $E = 18$, $C_1 = 14$, $r = 0.15$)



4.2 Optimal policy scenario

The optimal policy corresponds to $(\hat{\pi}_R, \delta\hat{\pi}_R)$ maximizing the social welfare defined by (4). It allows the model to reach the optimal installation timing (c.f. proposition 5).

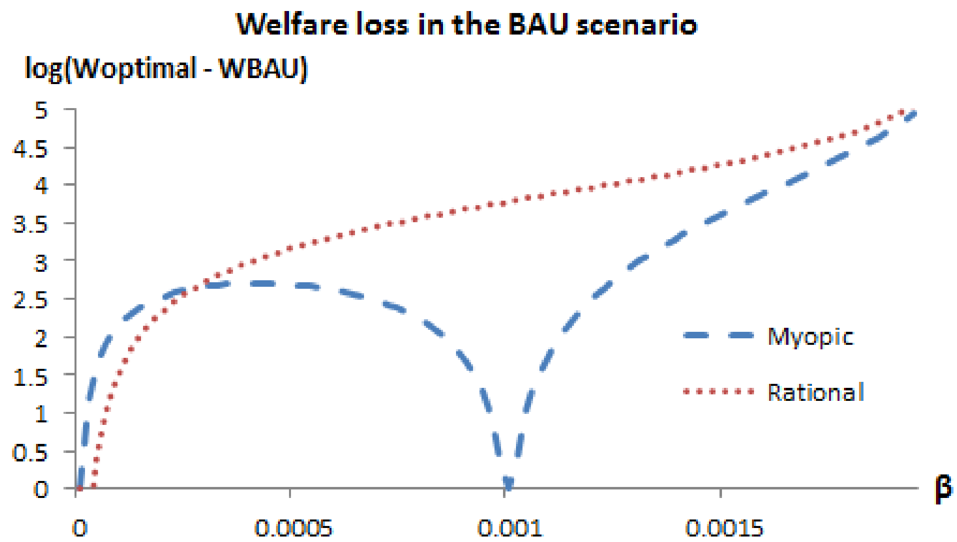
Proposition 5 *If all firms are rational, it is possible to reach the optimal quantities of PV systems installed in period 1 and 2 with an appropriate FIT policy $(\hat{\pi}_R, \delta\hat{\pi}_R)$, defined by $\hat{\pi}_R = E + (E - C_1)\frac{\beta^2}{\nabla}$ and $\delta\hat{\pi}_R = (E - C_1)\frac{\beta^2}{\nabla}$*

Proof. *C.F. annex 3.* ■

4.3 Comparison with the case of myopic firms

Whether firms adopt a myopic or rational behaviour, the business as usual scenario is not optimal if there is some learning by doing ($\beta > 0$). The social welfare loss is higher when firms are rational, except if the learning is really low ($0 < \beta < \gamma(\sqrt{r^2 - r} - r)$), in which case the over-installation by myopic firms leads to more social welfare loss than the under installation by rational ones. This is illustrated by the simulation in figure 5 showing the logarithm of the social welfare loss in the BAU scenario for both myopic and rational behaviours.

Figure 5 Simulation of the social welfare loss in a BAU scenario according to the learning strength, in case 3. (Parameters: $\gamma = 0.001$, $\beta = various$, $E = 18$, $C_1 = 14$, $r = 0.15$)



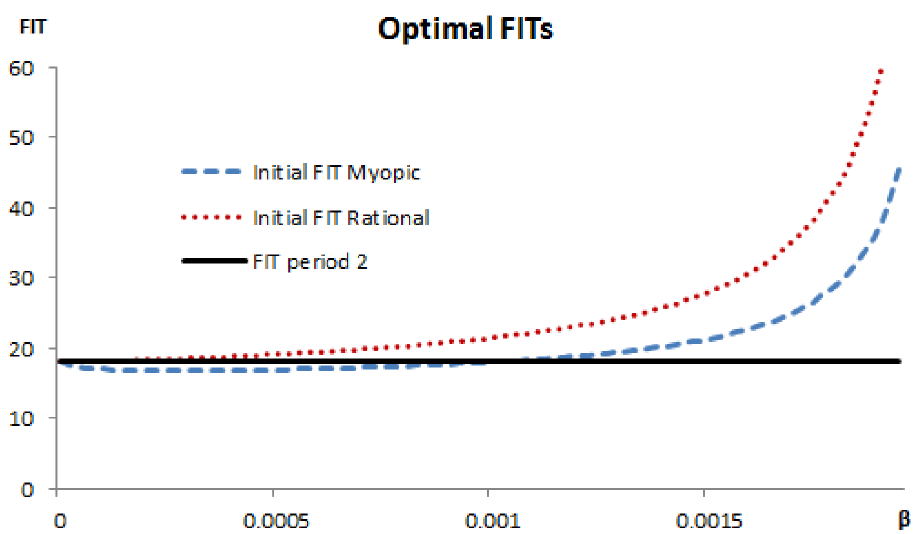
Whether firms are all myopic or all rational, the optimal situation can be reached with an appropriate FIT policy. However, these optimal initial FITs are different: It must be higher if firms are rational (c.f. proposition 6). The difference increases with the learning rate as shows figure 6 simulating the optimal initial FITs for myopic and rational firms. The economic rationals behind this result is that rational firms anticipate the future cost decrease, which increases their incentive to wait for period two. Therefore to reach the optimal installed quantity in period one, the incentive must be higher through a higher initial FIT. The FIT in period 2 is always the electricity price E, allowing to stop the installation when the marginal cost of installation reaches the cost of electricity[2].

Proposition 6 *The optimal initial FIT is higher when firms follow a long term strategy (rational).*

Proof. $\hat{\pi}_R - \hat{\pi}_M = \frac{\gamma}{\nabla} > 0$ *in case 3.* ■

[2] It would be higher if the consequences of the learning effect on the periods after would be considered

Figure 6 Simulation of optimal initial FITs for myopic or rational firms according to the learning strength (Parameters: $\gamma = 0.001$, $\beta = various$, $E = 18$, $C_1 = 14$, $r = 0.15$)



5 The case of homogeneous behaviours: mix of Myopic and Rational firms

In this section, we consider that a proportion a of the firms are rational, and $(1-a)$ are myopic. Additional cost then follows a uniform distribution on $(0+\infty)$ with a density $\frac{a}{\gamma}$ for rational firms, and $\frac{1-a}{\gamma}$ for myopic ones.

Myopic firms install PV systems until it is not profitable, therefore until $\pi - C_1 - \frac{\gamma}{1-a}Q_1^M = 0$ in the first period, and $\pi - \delta\pi - C_1 + \beta(Q_1^M + Q_1^R) - \frac{\gamma}{1-a}Q_2^M = 0$ in the second period. Rational firms install PV systems until $\pi - C_1 - \frac{\gamma}{a}Q_1^R = \frac{1}{1+r}(\pi - \delta\pi - C_1 + \beta(Q_1^M + Q_1^R) - \frac{\gamma}{a}Q_1^R)$ in period 1, and $\pi - \delta\pi - C_1 + \beta(Q_1^M + Q_1^R) - \frac{\gamma}{a}Q_2^R = 0$ in period 2.

Solving the previous equations gives the following result, with $Q_2^M \geq Q_1^M \geq 0$, and $Q_2^R \geq Q_1^R \geq 0$:

$$Q_1^M = \frac{(1-a)}{\gamma}(\pi - C_1) \text{ and } Q_1^R = \max(\frac{a}{\gamma} * \frac{(\pi - C_1)(r\gamma - \beta(1-a)) + \gamma\delta\pi}{a\beta + r\gamma}; 0)$$

$$Q_2^M = (1-a)Q_2 \text{ and } Q_2^R = aQ_2$$

$$\text{with } Q_2 = \frac{(\pi - C_1)(a\beta + r\gamma + r\beta) - r\gamma\delta\pi}{\gamma(a\beta + r\gamma)} \text{ if } Q_1^R > 0$$

$$Q_2 = \frac{(\pi - C_1)(\gamma + \beta(1-a)) - \gamma\delta\pi}{\gamma^2} \text{ if } Q_1^R = 0$$

With a proportion a of rational firms, the social welfare is now defined by:

$$W^H(a) = \int_0^{Q_1^M} (E - C_1 - \tfrac{\gamma}{1-a}q)dq + \int_0^{Q_1^R} (E - C_1 - \tfrac{\gamma}{a}q)dq$$

$$+\tfrac{1}{1+r}\int_{Q_1^M}^{Q_2^M} (E - C_1 + \beta(Q_1^M + Q_1^R) - \tfrac{\gamma}{1-a}q)dq + \tfrac{1}{1+r}\int_{Q_1^R}^{Q_2^R} (E - C_1 + \beta(Q_1^M + Q_1^R) - \tfrac{\gamma}{a}q)dq$$

Integrating and replacing Q_2^M,Q_1^M, Q_2^R,and Q_1^R by the previous expressions gives two expression of the social welfare $W(a,\pi,\delta\pi)$, depending on whether rational firms install PV systems in period one ($Q_1^R > 0$) or not ($Q_1^R = 0$) (c.f. annex 4). As for the homogeneous case, two scenarios are considered: BAU and an optimal policy $(\hat{\pi}, \delta\hat{\pi})$.

5.1 Business as usual scenario

The BAU scenario still corresponds to $\pi = E$ and $\delta\pi = 0$, giving the following expressions of the social welfare:

$$W^{BAU}(a) = (E - C_1)^2 \frac{2(a\beta + r\gamma + r\beta + r^2\gamma)(a\beta + r\gamma) - (a\beta + r\gamma)^2 - r(\beta + r\gamma)^2 + r\beta^2(1+r) - a(1-a)\beta^2}{2\gamma(1+r)(a\beta + r\gamma)^2} \text{ if } Q_1^R > 0$$

$$W^{BAU}(a) = (E - C_1)^2 \frac{\gamma^2 + (1-a)(2\gamma\beta + r\gamma^2) + (1-a)^2(\beta^2 - 2\gamma\beta)}{2\gamma^3(1+r)} \text{ if } Q_1^R = 0$$

Proposition 7 *Without learning effect ($\beta = 0$), the total installed quantity does not depend on a, and is optimal whatever the share of rational firms.*

If the learning effect is stronger than the additional cost decrease ($\beta > \gamma$), the BAU scenario leads to less installation than the optimal scenario. Otherwise ($\beta < \gamma$), the BAU situation can be an over installation if the share of rational firms and the learning are low enough.

Proof. *C.F. Annex 5.* ∎

To illustrate proposition 7, figures 7, 8, and 9 show simulations of installed quantities in a BAU scenario for shares of rational firms from 0 to 1, without learning effect (figure 7), with a strong learning effect (figure 8), or with a weak learning effect (figure 9). Without learning, the total installed quantity in period 1 is always optimal (therefore in period 2 as well). If the learning is strong ($\beta > \gamma$), rational firms anticipate the learning effect, so they do not install PV systems in period 1, unless their share is important. In any case, the total installed quantity in period 1 is lower than the optimal one. If the learning is low ($\beta < \gamma$), rational firms also install too few PV systems, but this does not compensate the over installation from myopic firms for high proportion of myopic firms (a low), leading to the installation of too many PV systems in period 1 in this case.

Figure 7 Simulation of installed quantities in the optimal and BAU scenario without learning effect, according to the share of rational firms. (Parameters: $\gamma = 0.001$, $\beta = 0$, $E = 18$, $C_1 = 14$, $r = 0.15$, $a = various$)

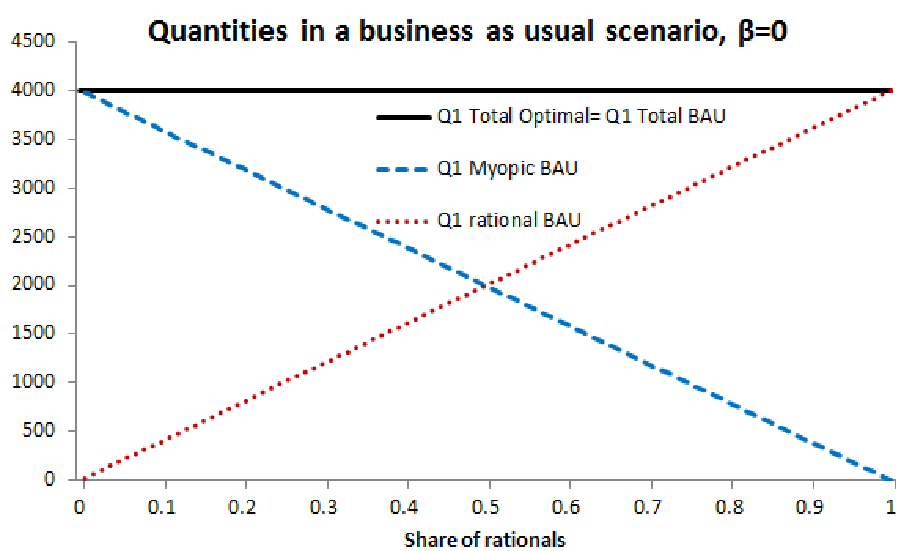


Figure 8 Simulation of installed quantities in the optimal and BAU scenario with a strong learning effect, according to the share of rational firms, if $\beta > \gamma > 0$. (Parameters: $\gamma = 0.001$, $\beta = 0.0012$, $E = 18$, $C_1 = 14$, $r = 0.15$, $a = various$)

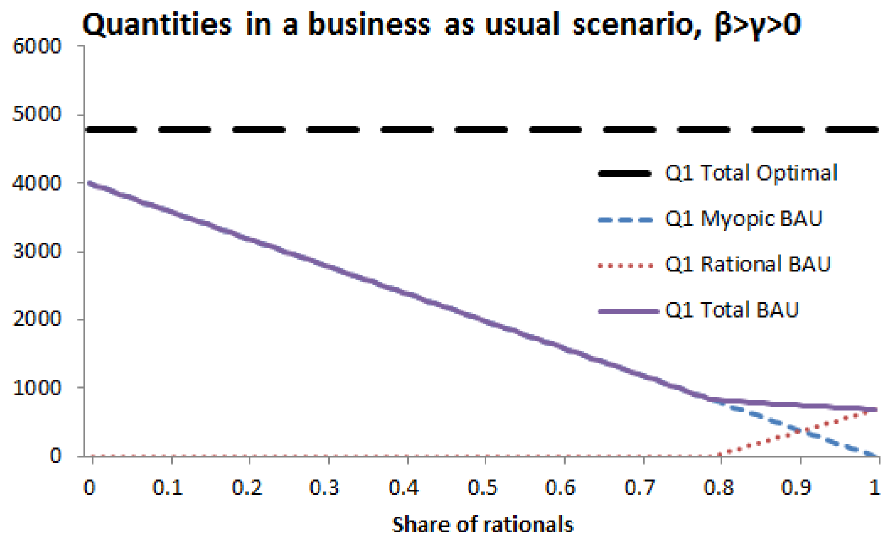
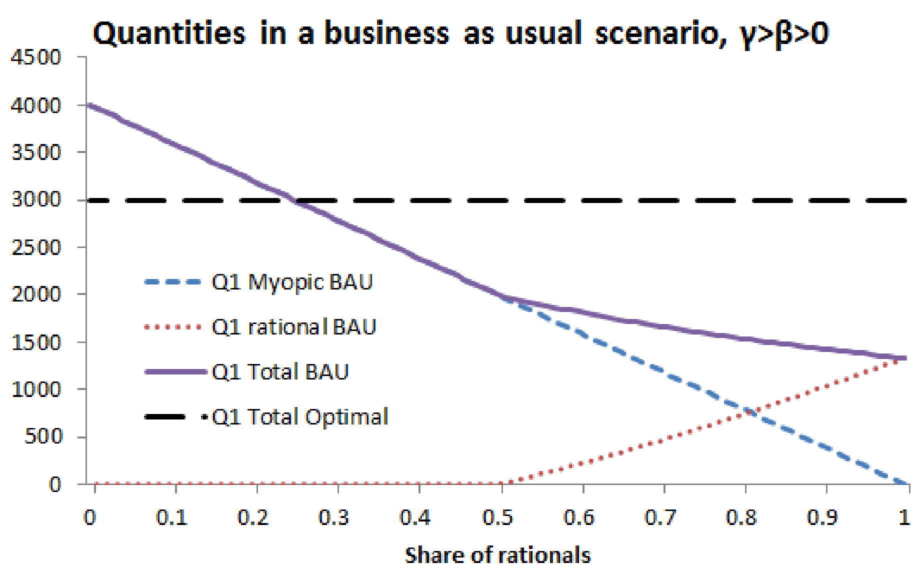


Figure 9 Simulation of installed quantities in the optimal and BAU scenario with a weak learning effect, according to the share of rational firms, if $\gamma > \beta > 0$. (Parameters: $\gamma = 0.001$, $\beta = 0.0004$, $E = 18$, $C_1 = 14$, $r = 0.15$, $a = various$)



5.2 Optimal policy scenario

As in the homogeneous cases ($a \in \{0,1\}$), the optimal policy is found by maximizing $W(a, \pi, \delta\pi)$ on $\delta\pi$ and π. The expression of $W^{OptimalPolicy}(a)$ is given in annex 7.

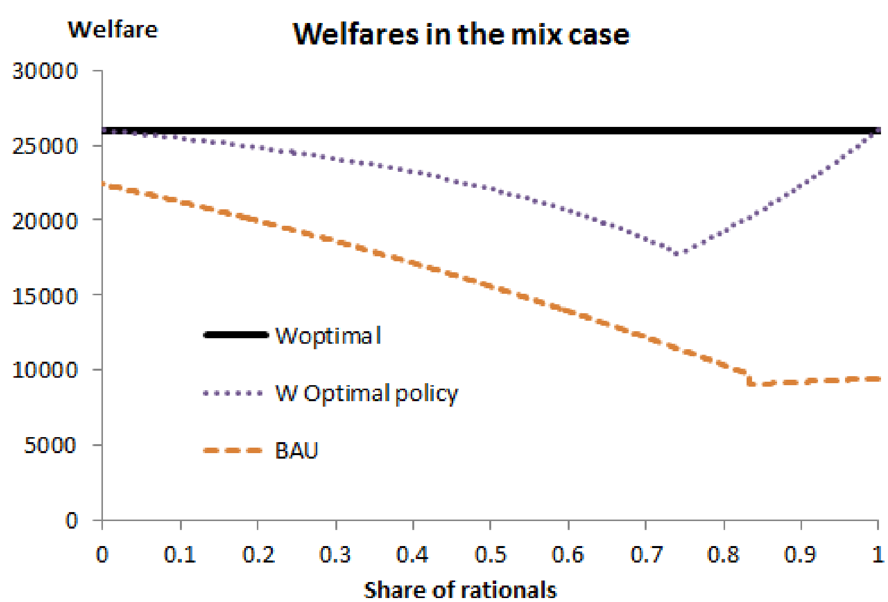
Proposition 8 *A unique FIT policy cannot reach the optimal situation when firms behave heterogeneously.*

Proof. See annex 7. ■

The result formulated in proposition 8 is illustrated in the simulation in figure 10. It shows that contrary to the homogeneous case, the optimal policy in the heterogeneous case ($a \notin \{0,1\}$) does not lead to the optimal situation.

Figure 10 Simulation of the social welfares in the mix case with an optimal policy.

(Parameters: $\gamma = 0.001$, $\beta = 0.0015$, $E = 18$, $C_1 = 14$, $r = 0.25$, $a = various$)



When firms' behaviour is homogeneous, the objective of the FIT policy is to get the optimal quantities of PV systems installed in period 1 and 2, to benefit from the learning effect without installing too many projects raising the additional cost. Let's call that the quantitative issue. This can be controlled by a unique FIT policy (proposition 3 and 5).

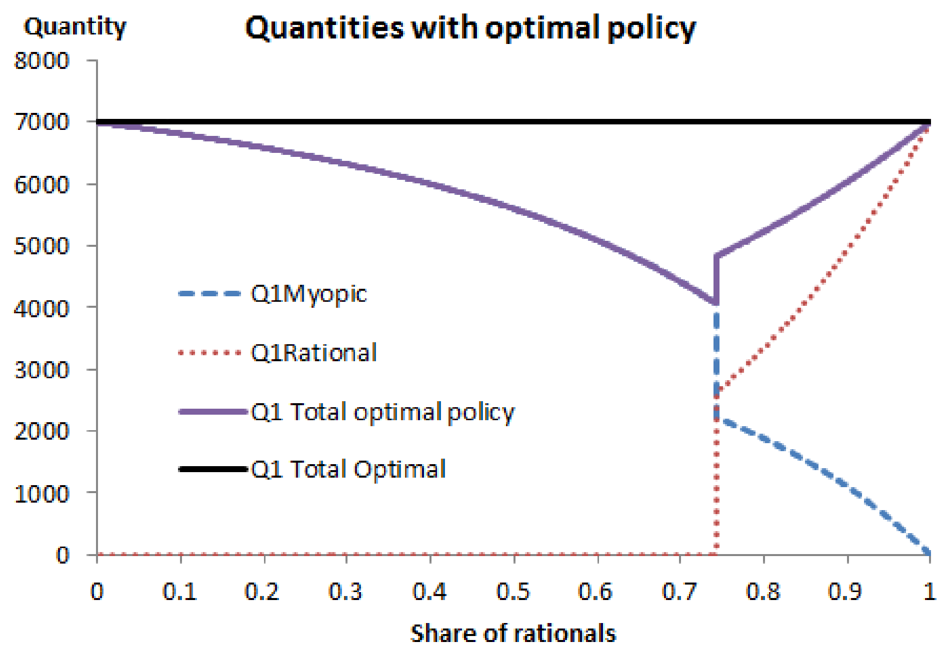
The inability of a unique FIT to reach the optimum in the heterogeneous case (proposition 8) is due to the emergence of another issue when both types of firms exist, that we call the heterogeneity issue: for any FIT policy, one type of firm installs PV systems in period 2 which are less costly than the last one installed by the other type of firm in period 1. This is not optimal since the positive discount rate implies that the most profitable projects should be installed first.

A trade-off has to be made between the two issues. Indeed, a higher FIT leads to more total installation in period one reducing the quantitative issue, but increases the heterogeneity issue since rational firms wait for period 2 to benefit from the learning effect caused by the installation by myopic firms. The optimal policy depends on the share of rational firms.

For low proportions of rational firms, the heterogeneity issue caused by their absence is not too important, so the optimal policy corresponds to no rational firms installing PV systems in period one (c.f. figure 11).

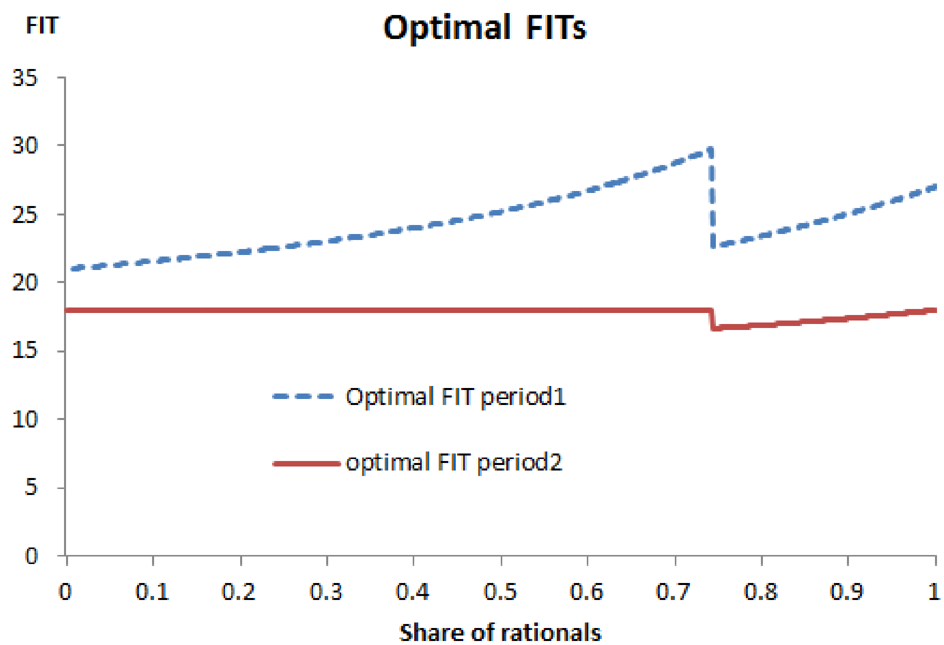
For high proportions of rational firms, the heterogeneity issue caused by their absence is important, so the optimal policy corresponds to the installation of PV systems by both types of firms in period one (c.f.. figure 11).

Figure 11 Simulation of installed quantity in period 1 according to the optimal FIT policy. (Parameters: $\gamma = 0.001$, $\beta = 0.0015$, $E = 18$, $C_1 = 14$, $r = 0.25$, $a = various$)



As figure 12 shows, the transition between these two optima corresponds to a decrease of the optimal initial FIT. But for both optima, the optimal initial FIT increases with the share of rational firms. If the FIT policy is designed considering that firms are myopic, a too small initial FIT would be implemented, since the fully myopic case ($a = 0$) corresponds to the smallest value of the optimal initial FIT. The installation in period 1 would be under-optimal. This shows that the result that the initial FIT must be higher when firms are rational (proposition 6) holds when firms behave heterogeneously. However in the heterogeneous, case the economic rationals behind this result is more complex, since rational firms also take into account the installation from myopic firms. This explains why if a high proportion of the firms are myopic, all rational firms prefer to wait for period two, to benefit from the learning effect triggered by myopic firms.

Figure 12 Simulation of the optimal FIT policy. (Parameters: $\gamma = 0.001$, $\beta = 0.0015$, $E = 18$, $C_1 = 14$, $r = 0.25$, $a = various$)



5.3 Optimal policy with differentiated feed-in tariffs

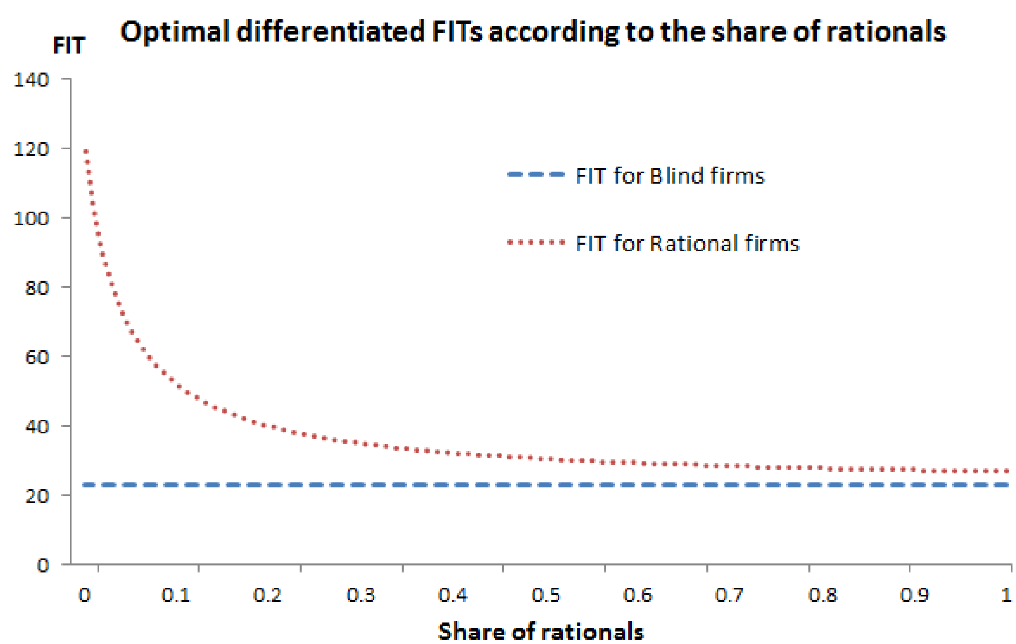
To deal with both issues at the same time, another policy instrument needs to be added. If myopic and rational firms can be differentiated ex ante, two different FITs can be applied to reach the optimum (c.f. proposition 9), each one targeting one type of firm. The differentiation can be based on the size of the PV systems, multi Megawatts ground based PV power plant being constructed by big companies anticipating FIT and module cost evolution, while smaller roof-top systems are installed by smaller firms when they are profitable, therefore in a "myopic" way.

Proposition 9 *For any proportion of rational/myopic firms, it is possible to reach the optimal situation with a differentiated FIT.*

Proof. See annex 8. ■

Using the expression of the optimal FITs (annex 8), we find that the FIT addressing rational firms has to be higher than the one addressing myopic firms, with the difference being more important for small shares of rational firms, as figure 13 shows, simulating the best combination of initial FITs. This gap increases with the strength of the learning effect.

Figure 13 Simulation of optimal differentiated FITs according to the share of rational firms. (Parameters: $\gamma = 0.001$, $\beta = 0.0012$, $E = 18$, $C_1 = 14$, $r = 0.25$, $a = various$)



6 Conclusion

This chapter explores the consequences of the strategic behaviour of firms installing photovoltaic (PV) systems on the design of an optimal feed-in tariff (FIT) policy.

Two consecutive periods are considered, during which firms install PV systems. The learning by doing effect decreasing module price in period 2 according to the global installation in period 1. A FIT at which firms sell the electricity produced by PV systems is implemented, and can be changed in period 2. Two types of behaviours are considered: myopic and rational. Myopic firms install PV systems as long as they are profitable, following a short term strategy. Rational firms install PV systems if they are profitable, but also if it is not more profitable to wait for the following period to benefit from the learning effect, following a long term strategy. Myopic firms can refer to small ones, while rational firms can relate to bigger companies resulting from the consolidation of the industry or the entry of utility companies such as EDF or Areva in France. Since rational firms are more and more present in the market, it is important to understand the consequences of these strategies concerning the FIT policy that should be implemented to reach the optimal installation timing.

We first show that with a positive learning rate, the business as usual (BAU) situation - without FIT policy - is not optimal whatever firms' behaviour. This corresponds to the situation of the PV industry[3].

A main finding of this chapter is that firms' strategies should be taken into account when designing a FIT policy. If firms follow a long term strategy, a higher FIT should be implemented initially, with a more important degression rate. The reason is that the anticipation of future module price reduction is an incentive to wait to benefit from this dynamic effect. Conducting those firms to install the optimal quantity of PV systems thus requires a higher incentive effect than for firms following a short term strategy, which is the induced by a higher initial FIT followed by more important degression. This result

[3] However, if we assume no spillovers and vertical integration with firms installing PV systems also producing them, the result would be different. Indeed, the cost reduction driven by their private production would peruade firms to install more PV systems.

holds when firms behave heterogeneously (some pursuing short term strategies, other long term strategies): the augmentation of the share of rational firms requires a higher initial FIT.

The second main result is that if it is possible to reach the optimum with a unique FIT when firms are homogenous (all myopic or all rational), it is not possible when firms behave heterogeneously (mix of myopic and rational firms), which is the most realistic situation. In this case, only a combination of two FITs allows reaching the optimal situation, one addressing myopic firms, and one addressing rational firms. However this requires being able to differentiate myopic from rational firms. This is possible if myopic firms are small ones installing PV systems on rooftops while rational firms are big companies installing multi Megawatts PV power plant. Another policy instrument could be used to prevent rational firms from waiting for future cost reductions, such as a cap on future installation.

7 Annex

7.1 Annex 1: Bounded case

Social welfare in the optimal installation timing

$$W^{optimal}_{Bounded} = \frac{1}{2*(1+r)*(2\beta+r\gamma)}\left[-\nabla * Q_{\max}^2 + 2*(2\beta + r\gamma + r\beta)(E - C_1) * Q_{\max} + r^2 * (E - C_1)^2\right]$$

Expression of installed quantities and social welfare In the bounded case the installed quantities and social welfares are:

With myopic firms:

$$Q_1^M = \frac{E-C_1}{\gamma} \qquad Q_2 = Q_{\max}$$

$$W(\pi, \delta\pi, Q_{\max}) = \frac{[r(E-C_1)+\beta Q_{\max}]*(\pi - C_1)}{(1+r)\gamma} - \frac{(2\beta+r\gamma)*(E-C_1)^2}{2(1+r)\gamma^2} + \frac{2*(E-C_1)Q\max - \gamma Q_{\max}^2}{2(1+r)}$$

With rational firms

$$Q_1 = \frac{r(E-C_1)}{\beta+r\gamma} \qquad Q_2 = Q_{\max}$$

$$W^{BR}(\pi, \delta\pi, Q_{\max}) = \frac{[r(E-C_1)+\beta Q_{\max}]*[r(\pi-C_1)+\delta\pi]}{(1+r)(\beta+r\gamma)} - \frac{(2\beta+r\gamma)*[r(E-C_1)+\delta\pi]^2}{2(1+r)(\beta+r\gamma)^2} + \frac{2*(E-C_1)Q\max - \gamma Q_{\max}^2}{2(1+r)}$$

Business as usual

Myopic:

$$W(\pi,\delta\pi,Q_{\max}) = \frac{[r(E-C_1)+\beta Q_{\max}]*(\pi-C_1)}{(1+r)\gamma} - \frac{(2\beta+r\gamma)*(E-C_1)^2}{2(1+r)\gamma^2} + \frac{2*(E-C_1)Q\max - \gamma Q_{\max}^2}{2(1+r)}$$

Rational:

$$W(\pi,\delta\pi,Q_{\max}) = (E-C_1)^2\frac{r^3\gamma}{2(1+r)(\beta+r\gamma)^2} + (E-C_1)Q_{\max}\frac{\beta+r\gamma+r\beta}{(1+r)(\beta+r\gamma)} - Q_{\max}^2\frac{\gamma}{2(1+r)}$$

Proposition 10 *The business as usual situation is not optimal only in case 2b or 4 (and 3 as shown before), whether firms are myopic or rational.In case 1 or 2a (no installation in the optimal situation). For any proportion of rational/myopic firms, it is possible to reach the optimal situation with a differentiated FIT.*

Proof. *In case 2b, there is no installation over the two periods, while it would be optimal to install PV systems (c.f. proposition 1). Therefore the business as usual case is not optimal in case 2b.*

In case 4:

for myopic firms $W^{optimal} - W^B(E,0) = (2(E-C_1) - \gamma Q_{\max})^2\frac{\beta^2}{2\gamma^2(1+r)(2\beta+r\gamma)} > 0$

for rational firms, $W^{optimal} - W^R(E,0) = (r(E-C_1) - (\beta+r\gamma)Q_{\max})^2\frac{\beta^2}{2(1+r)(2\beta+r\gamma)(\beta+r\gamma)^2} > 0$ ■

Optimal policy

Proposition 11 *It is always possible to reach the optimal case with an appropriate FIT policy* $(\pi;\delta\pi)$ *in the bounded case as well. These FIT policies maximising the welfare for each case are describe bellow.*

Proof. *See annex 2 for myopic firms, and 3 for rational firms.* ■

$$\text{Rational: } r(\pi - C_1) + \delta\pi = \frac{\beta+r\gamma}{2\beta+r\gamma}\left[r(E-C_1)+\beta Q_{\max}\right]$$

$$\text{myopic: } \pi - C1 = \frac{\gamma}{2\beta+r\gamma}\left[r(E-C_1)+\beta Q_{\max}\right]$$

7.2 Annex 2: Proof of proposition 3

7.2.1 Not bounded case

With a FIT $(\pi, \delta\pi)$, the social welfare when firms behave in a myopic way is:

$$W^B(\pi, \delta\pi) =$$
$$\frac{(E-C_1)(\pi-C_1)}{\gamma} + \frac{(E-C1)*[\beta(\pi-C_1)-\gamma\delta\pi]}{\gamma^2(1+r)} - \frac{(\pi-C1)^2}{2\gamma} + \frac{(\pi-C_1)^2*(\beta^2-2\gamma\beta)+2\gamma^2*(\pi-C1)*\delta\pi-\gamma^2*\delta\pi^2}{2\gamma^3(1+r)}$$

Step 1: Best FIT change according to the FIT in period 1:

$$\frac{\delta(W^B)}{\delta(\delta\pi)} = \frac{2\gamma(\pi-E-\delta\pi)}{2\gamma^2(1+r)} = 0 \Leftrightarrow \delta\pi = \pi - E$$

The corresponding $\delta\pi$ is a maximum since $\frac{\delta^2(W^B)}{\delta^2(\delta\pi)} = -\frac{1}{\gamma(1+r)} < 0$

Step 2: Best FIT in period 1

With the previous expression of $\delta\pi$ in $W^B(\pi, \delta\pi)$, we get

$$W^R(\pi) = (\pi - C_1)^2 \frac{-(2\gamma\beta+r\gamma^2-\beta^2)}{2\gamma^3(1+r)} + (\pi - C_1)(E - C_1)\frac{\beta+r\gamma}{\gamma^2(1+r)} + (E - C_1)^2 \frac{1}{2\gamma(1+r)}$$
$$\frac{\delta(W^B)}{\delta(\pi-C_1)} = \frac{-(2\gamma\beta+r\gamma^2-\beta^2)}{\gamma^3(1+r)}(\pi - C_1) + (E - C_1)\frac{\beta+r\gamma}{\gamma^2(1+r)} = 0 \Leftrightarrow (\pi - C_1) = \frac{\gamma(\beta+r\gamma)}{2\gamma\beta+r\gamma^2-\beta^2}$$

This is also a maximum since $\frac{\delta^2(W^B)}{\delta^2(\pi-C_1)} = -\frac{2\gamma\beta+r\gamma^2-\beta^2}{\gamma^3(1+r)} < 0$ since $2\gamma\beta + r\gamma^2 - \beta^2 = \nabla > 0$ in case 3.

The optimal FIT policy $(\pi^o; \delta\pi^o)$ is then defined by $\pi^o = E + (E - C_1)\frac{\beta^2}{\nabla}$ and $\delta\pi^o = (E - C_1)\frac{\beta^2}{\nabla}$. The corresponding social welfare is:

$$W(\pi^o; \delta\pi^o) = (E - C_1)^2 \frac{2\beta+r\gamma}{2\nabla} = W^{Optimal}$$

7.2.2 Bounded case

With a FIT $(\pi, \delta\pi)$, the social welfare when firms behave in a myopic way is:

$$W(\pi, \delta\pi, Q_{\max}) = \frac{[r(E-C_1)+\beta Q_{\max}]*(\pi-C_1)}{(1+r)\gamma} - \frac{(2\beta+r\gamma)*(E-C_1)^2}{2(1+r)\gamma^2} + \frac{2*(E-C_1)Q\max - \gamma Q_{\max}^2}{2(1+r)}$$

It does not depend on $\delta\pi$, so any $\delta\pi$ which allow to reach $Q_{\max}$, that is to say $\pi^o - \delta\pi^o \geq E$, is optimal.

$$\frac{\delta(W)}{\delta(\pi-C_1)} = \frac{\gamma(r(E-C_1)+\beta Q_{\max}) - (2\beta+r\gamma)(\pi-C_1)}{\gamma^2(1+r)} = 0 \Leftrightarrow (\pi - C_1) = \frac{\gamma(r(E-C_1)+\beta Q_{\max})}{2\beta+r\gamma}$$

This is a maximum since $\frac{\delta^2(W^B)}{\delta^2(\pi-C_1)} = -\frac{2\beta+r\gamma}{\gamma^2(1+r)} < 0$

The optimal FIT policy $(\pi^o; \delta\pi^o)$ is then defined by $\pi^o = C_1 + \frac{\gamma(r(E-C_1)+\beta Q_{\max})}{2\beta+r\gamma}$ and $\pi^o - \delta\pi^o \geq E$. The corresponding social welfare is:

$$W(\pi^o; \delta\pi^o) =$$

$$\frac{1}{2*(1+r)*(2\beta+r\gamma)}\left[-\nabla * Q_{\max}^2 + 2*(2\beta + r\gamma + r\beta)(E - C_1) * Q_{\max} + r^2 * (E - C_1)^2\right]$$

$$= W^{Optimal}$$

7.3 Annex 3: Proof of proposition 5

7.3.1 Not bounded case

With a FIT $(\pi, \delta\pi)$, the social welfare when firms behave in a rational way is:

$$W^R(\pi, \delta\pi) = \frac{(E-C_1)(\pi-C_1)}{\gamma} + \frac{(r\beta^2-(\gamma r+\beta)^2)(\pi-C_1)^2+2\beta^2(\pi-C_1)*\delta\pi-(2\gamma\beta+\gamma^2 r)\delta\pi^2}{2\gamma(\gamma r+\beta)^2}$$

Step 1: Best FIT change according to the FIT in period 1:

$$\frac{\delta(W^B)}{\delta(\delta\pi)} = \frac{\beta^2(\pi-C_1)-(2\gamma\beta+r\gamma^2)\delta\pi}{\gamma(r\gamma+\beta)^2} = 0 \Leftrightarrow \delta\pi = (\pi - C_1)\frac{\beta^2}{2\gamma\beta+r\gamma^2}$$

The corresponding $\delta\pi$ is a maximum since $\frac{\delta^2(W^B)}{\delta^2(\delta\pi)} = \frac{-(2\gamma\beta+r\gamma^2)}{\gamma(r\gamma+\beta)^2} < 0$

Step 2: Best FIT in period 1

With the previous expression of $\delta\pi$ in $W^B(\pi,\delta\pi)$, we get

$$W^B(\pi) = \frac{(E-C_1)(\pi-C_1)}{\gamma} + \frac{(\pi-C_1)^2}{2}\frac{\beta^2-2\gamma\beta-r\gamma^2}{\gamma(2\gamma\beta+r\gamma^2)}$$

$$\frac{\delta(W^B)}{\delta(\pi-C_1)} = \frac{(E-C_1)}{\gamma} - (\pi - C_1)\frac{2\gamma\beta+r\gamma^2-\beta^2}{\gamma(2\gamma\beta+r\gamma^2)} = 0 \Leftrightarrow (\pi - C_1) = \frac{2\gamma\beta+r\gamma^2}{2\gamma\beta+r\gamma^2-\beta^2}$$

This is also a maximum since $\frac{\delta^2(W^B)}{\delta^2(\pi-C_1)} = -\frac{2\gamma\beta+r\gamma^2-\beta^2}{\gamma(2\gamma\beta+r\gamma^2)} < 0$ since $2\gamma\beta + r\gamma^2 - \beta^2 = \nabla < 0$ in case 3.

The optimal FIT policy $(\pi^o;\delta\pi^o)$ is then defined by $\pi^o = E + (E - C_1)\frac{\beta^2}{\nabla}$ and $\delta\pi^o = (E - C_1)\frac{\beta^2}{\nabla}$. The corresponding social welfare is:

$$W(\pi^o;\delta\pi^o) = (E - C_1)^2\frac{2\beta+r\gamma}{2\nabla} = W^{Optimal}$$

7.3.2 Bounded case

With a FIT $(\pi,\delta\pi)$, the social welfare when firms behave in a rational way is:

$$W(\pi,\delta\pi,Q_{\max}) = \frac{[r(E-C_1)+\beta Q_{\max}]*(\delta\pi+r(\pi-C_1))}{(1+r)(\beta+r\gamma)} - \frac{(2\beta+r\gamma)*[\delta\pi+r(\pi-C_1)]^2}{2(1+r)(\beta+r\gamma)^2} + \frac{2(E-C_1)-\gamma Q_{\max}}{2(1+r)}Q_{\max}$$

It does not depend on $\delta\pi$, so any $\delta\pi$ which allow to reach $Q_{\max}$, that is to say $\pi^o - \delta\pi^o \geq E$, is optimal.

$$\frac{\delta(W)}{\delta(\delta\pi)} = \frac{-[\delta\pi + r(\pi - C_1)](2\beta + r\gamma) + (\beta + r\gamma)[r(E - C_1) + \beta Q_{\max}]}{(1+r)(\beta + r\gamma)^2} = 0 \Leftrightarrow \delta\pi + r(\pi - C_1) = \frac{\beta + r\gamma}{2\beta + r\gamma} [r(E - C_1) + \beta Q_{\max}]$$

This is a maximum since $\frac{\delta^2(W^B)}{\delta^2(\delta\pi)} = -\frac{2\beta + r\gamma}{(1+r)(\beta + r\gamma)^2} < 0$

The optimal FIT policy $(\pi^o; \delta\pi^o)$ is then defined by $\delta\pi^o + r(\pi - C_1) = \frac{\beta + r\gamma}{2\beta + r\gamma} [r(E - C_1) + \beta Q_{\max}]$. The corresponding social welfare is:

$$W(\pi^o; \delta\pi^o) = \frac{1}{2*(1+r)*(2\beta + r\gamma)} \left[-\nabla * Q_{\max}^2 + 2*(2\beta + r\gamma + r\beta)(E - C_1) * Q_{\max} + r^2 * (E - C_1)^2\right] = W^{Optimal}$$

7.4 Annex 4: Social welfare with a mix of myopic and rational firms

With a FIT policy $(\pi, \delta\pi)$

If $Q_1^R > 0$

$$W(a, \pi, \delta\pi) = \frac{(E - C_1)\left[(\pi - C_1)(a\beta + r\gamma + r\beta + r^2\gamma) - (1-a) r\gamma\delta\pi\right]}{\gamma(1+r)(a\beta + r\gamma)} + \frac{-(\pi - C_1)^2\left[(a\beta + r\gamma)^2 + r(\beta + r\gamma)^2 - r\beta^2(1+r) + a(1-a)\beta^2\right]}{2\gamma(1+r)(a\beta + r\gamma)^2} + \frac{2(\pi - C_1)\delta\pi\left[r\gamma(1-a)(a\beta + r\gamma) + (a+r)a\beta^2\right] - \delta\pi^2(a+r)(2a\gamma\beta + r\gamma^2)}{2\gamma(1+r)(a\beta + r\gamma)^2}$$

If $Q_1^R = 0$

$$W(a, \pi, \delta\pi) = \frac{(\pi - C_1)^2[(1-a)^2(\beta^2 - 2\gamma\beta) - (1-a)r\gamma^2 - \gamma^2] + 2(E - C_1)(\pi - C_1)\gamma[\gamma + (1-a)(\beta + r\gamma) + 2\gamma^2(\pi - E)\delta\pi - \gamma^2\delta\pi^2}{2\gamma^3(1+r)}$$

7.5 Annex 5: Proof of proposition 7

If $\beta = 0$:

$$W^{BAU}(a) = \frac{(E-C_1)^2}{2\gamma} = W^{Optimal}$$

If $\beta > 0$:

The installed quantities in the BAU case are:

$$Q_1^M = (E - C_1)\frac{1-a}{\gamma}$$

$$Q_1^R = \max\left(\frac{a}{\gamma} * \frac{(E-C_1)(r\gamma-\beta(1-a))}{a\beta+r\gamma}; 0\right)$$

$$Q_2^M = (1-a)Q_2 \text{ and } Q_2^R = aQ_2$$

$$\text{with } Q_2 = \frac{(E-C_1)(a\beta+r\gamma+r\beta)}{\gamma(a\beta+r\gamma)} \text{ if } Q_1^R > 0$$

$$Q_2 = \frac{(E-C_1)(\gamma+\beta(1-a))}{\gamma^2} \text{ if } Q_1^R = 0$$

Therefore in period 1:

from myopic firms:

$$\frac{1-a}{\gamma}(E - C_1)$$

from rational firms:

$$0 \text{ if } a < 1 - \frac{r\gamma}{\beta}, \text{ and } \frac{a}{\gamma} * \frac{(E-C_1)(r\gamma-\beta(1-a))}{a\beta+r\gamma} \text{ if } a > 1 - \frac{r\gamma}{\beta}$$

This gives two cases:

Case A: If $a < 1 - \frac{r\gamma}{\beta}$

$Q_1^{optimal} - Q_{BAU}^1 = (E - C_1)(a + \beta\frac{\beta-\gamma}{\nabla})$, so $Q_{BAU}^1 > Q_1^{optimal}$

Case B: If $a > 1 - \frac{r\gamma}{\beta}$

$Q_1^{optimal} - Q_{BAU}^1 = (E - C_1)\frac{\beta}{\nabla(a\beta+r\gamma)}\left[r(\beta-\gamma) + a(\beta + r\gamma)\right]$

If $\beta > \gamma$, $Q_{BAU}^1 < Q_1^{optimal}$ in both cases

If $\beta < \gamma$,

In case A, $Q_{BAU}^1 < Q_1^{optimal}$ if $a > \beta\frac{\gamma-\beta}{\nabla}$

In case B, $Q_{BAU}^1 < Q_1^{optimal}$ if $a > r\frac{\gamma-\beta}{\beta+r\gamma}$

7.6 Annex 6: Optimal policy in the mix case, and corresponding social welfare

Taking the expressions of the social welfare from annex 5, and maximizing on $\delta\pi$ then π:

If $Q_1^R > 0$, the optimal policy is

$$(\pi - C_1) = (E - C_1)(a\beta + r\gamma)\frac{(1-a)r\gamma\left[r\gamma(1-a)(a\beta+r\gamma)+(a+r)a\beta^2\right]-(a+r)(2a\gamma\beta+r\gamma^2)(a\beta+r\gamma+r\beta+r^2\gamma)}{\left[r\gamma(1-a)(a\beta+r\gamma)+(a+r)a\beta^2\right]^2-(a+r)(2a\gamma\beta+r\gamma^2)\left[(a\beta+r\gamma)^2+r(\beta+r\gamma)^2-r\beta^2(1+r)+a(1-a)\beta^2\right]}$$

$$\delta\pi = \frac{\left[r\gamma(1-a)(a\beta+r\gamma)+(a+r)a\beta^2\right](\pi-C_1)-r\gamma(1-a)(a\beta+r\gamma)(E-C_1)}{(a+r)\gamma(2a\beta+r\gamma)}$$

Which gives the following social welfare

$$W^o(a) = (E - C_1)^2\frac{(1-a)^2r^2\gamma^2\left[\left[r\gamma(1-a)(a\beta+r\gamma)+(a+r)a\beta^2\right]^2-(a+r)(2a\gamma\beta+r\gamma^2)\left[(a\beta+r\gamma)^2+r(\beta+r\gamma)^2-r\beta^2(1+r)+a(1-a)\beta^2\right]\right]}{2\gamma^2(a+r)(1+r)(2a\beta+r\gamma)\left[\left[r\gamma(1-a)(a\beta+r\gamma)+(a+r)a\beta^2\right]^2-(a+r)(2a\gamma\beta+r\gamma^2)}$$

$$-\frac{\left[(1-a)r\gamma\left[r\gamma(1-a)(a\beta+r\gamma)+(a+r)a\beta^2\right]-(a+r)(2a\gamma\beta+r\gamma^2)(a\beta+r\gamma+r\beta+r^2\gamma)\right]^2}{2\gamma^2(a+r)(1+r)(2a\beta+r\gamma)\left[\left[r\gamma(1-a)(a\beta+r\gamma)+(a+r)a\beta^2\right]^2-(a+r)(2a\gamma\beta+r\gamma^2)\left[(a\beta+r\gamma)^2+r(\beta+r\gamma)^2-r\beta^2(1+r)+a(1-a)\beta^2\right]\right]}$$

If $Q_1^R = 0$, the optimal policy is

$$(\pi - C_1) = (E - C_1)\frac{\gamma(\beta + r\gamma)}{(1-a)(2\gamma\beta - \beta^2) + r\gamma^2} \text{ and } \delta\pi = \pi - E$$

Which gives the following social welfare

$$W^o(a) = (E - C_1)^2 \frac{2\beta(1+r)(1+a) + r\gamma(1+r+ar)}{2(1+r)[(1-a)(2\gamma\beta - \beta^2) + r\gamma^2]}$$

7.7 Annex 7 Proof of proposition 8

To reach the optimum, the additional cost has to be the same for the last PV system installed in period 1 (first condition). It implies that

$$\frac{\gamma}{a}Q_1^R = \frac{\gamma}{1-a}Q_1^M \quad \text{(i)}$$

Replacing Q_1^R and Q_1^M by their expressions gives

$$\delta\pi = (\pi - C_1)\frac{\beta}{\gamma}$$

Another condition is that $\pi - \delta\pi = E$

Therefore $(\pi - C_1) = (E - C_1)\frac{\gamma}{\gamma - \beta}$ (ii)

So $Q_1^R = (E - C_1)\frac{1-a}{\gamma - \beta}$

Using (i),

$$Q^1_{Total} = Q_1^R + Q_1^M = \frac{Q_1^R}{a} = (E - C_1)\frac{1-a}{a(\gamma - \beta)} \neq Q^1_{TotalOptimal}$$

So the optimum cannot be reached

7.8 Annex 8 Proof of proposition 9

With $\delta\pi$ such that $\pi - \delta\pi = E$, the optimal simultaneous FITs in period 1 are:

For myopic firms:

$$(\pi_B - C_1) = (E - C_1)\frac{\gamma(\beta + r\gamma)}{\nabla}$$

For rational firms:

$$(\pi_R - C_1) = (E - C_1)\gamma\frac{\gamma\beta(2 + r2ar) - \beta^2(1-a) + r\gamma^2(1+r)}{\nabla[\gamma(1+r) - \beta(1-a)]}$$

This gives

$$Q_1^{total} = Q_1^M(\pi_B, \delta\pi_B) + Q_1^R(\pi_R, \delta\pi_R) = (E - C_1)\frac{\beta + r\gamma}{\nabla} = Q_1^{Optimal}$$

Since the expression of the social welfare only depends on the installed quantities, if they are optimal, then the social welfare is optimal to.

Conclusion

This Ph.D. dissertation contributes to further understanding the mechanisms driving the main transformations of the photovoltaic (PV) industry. We have analysed how China acquired the technology and know-how required to enter the PV industry and outperform pioneer firms from developed countries. It also provides some elements to feed the debate around technology transfers in the context of international negotiations on climate change mitigation. A prediction of module cost until 2020 has been carried out based on experience curves models, to assess long term PV competitiveness. Finally, several aspects of feed-in tariffs' efficiency (FITs) have been investigated relying on a theoretical model. We have analysed how they affect module price, how they are able to best adapt to module price volatility, and why policymakers should take firms' strategies into consideration. These issues are of crucial importance since FITs will drive the market until the PV industry reaches maturity and the energy it produces reaches competitiveness.

We will not go through the results in this conclusion as they are available in the general introduction and in the conclusion of each chapter. We will rather focus on policy implications and opportunities for further research.

Policy implications

International technology transfers in the context of climate change negotiations

Drivers of the success of the technology transfers to China

Looking at technology transfers in the sense of the technical knowledge required for the manufacturing activity, developing countries traditionally call for more flexible intellectual property rights (IPR) policies. In light of the results from **chapter one**, we highlight different technology transfer mechanisms.

International trade: The Chinese industry has been driven by European-based demand. In addition, trade also played a role through import of turnkey production lines from Europe, Japan, and the US which enabled the first Chinese firms to start production without much prior knowledge. There is also a transfer of know-how as local staff training comes along with equipment sales. Finally, the Chinese industry is relying on polysilicon feedstock massively imported from industrialised countries.

Competition: Fierce competition in the manufacturing equipment market prevented a single company from controlling the necessary technology.

Absorptive capacity: the technology transfer has also been made possible thanks to the important Chinese Diaspora and available local skilled workforce. The local labour mobility also drove this success, the diffusion of technical knowledge between Chinese firms being accelerated by the high employee turnover of their middle management.

No role of IPR: We show that IPR didn't play a significant role in the transfer of PV technology to China: There was almost no licensing, and IPRs were not an impediment. To understand to what extent this result can be transferred to other technologies, it is important to consider which characteristics of the PV industry this conclusion is based upon. Although the PV industry is young, its core underlying patents are old and were already in the public domain. New patents protect only incremental innovations, which can be bypassed thanks to a wide availability of manufacturing equipment on an open and competitive market.

In this respect, low trade barrier, labour mobility and a competitive market seem to be more powerful drivers of international technology transfers than IPR relaxation. However, these results are specific to the PV industry; therefore they may not be applicable to other industries.

What are the consequences of such a technology transfer in terms of greenhouse gases emission reductions?

If transfer of technology refers to the transfer of technological solutions to reduce greenhouse gases (GHG) emissions, the positive impact on climate change mitigation is not questionable. However, if it refers to the transfer of technical knowledge required to produce those solutions, the consequences in term of GHG emission reductions are not so clear. On the positive side, it reduces cost, fostering the adoption of the technology. However our case study shows that the PV production in China did not trigger its local adoption. Rather, the vast majority of the production is exported, which raises some concerns due to the GHG emitted in the process. A positive evolution can be seen on this topic since China is starting to install PV systems domestically, but this issue should be taken into account in the technology transfers debate. More importantly, Chinese electricity mainly originates from coal burning. PV production, which is highly energy intensive, especially in the upstream silicon purification activity, would therefore be responsible for much more GHG emissions if produced in China. Another drawback could be a dynamic inefficiency: if Chinese competition leads to lower costs in the short term, it’s domination would reduce the global innovation since Chinese firms innovate less, and thus jeopardise future cost reduction. This is an important issue for the technology intensive PV industry.

How fast will photovoltaic module cost further decrease?

In **chapter two**, we build a model intended to predict module cost evolution in the long term using cumulative installed PV capacity and silicon price as explanatory variables. This model can help policymakers better assess the potential of PV technology in the energy mix and grasp the dynamic aspect of price reduction in the design of incentive policies. The predictive model is:

$$Module\ Price = 12.06 * (\text{Cumulative Capacity})^{-0.338} * (Silicon\ Price)^{0.385}$$

Using this model, and scenarios of silicon price and cumulative capacity evolution, we predict a 67% decrease of module price from 1.52 $/Wp in 2011 to 0.50 $/Wp in 2020. The increase in cumulative capacity is responsible for 75% of this evolution, corresponding to a learning rate of 19.6%. In other words, it means that each time the cumulative installed PV capacity will double, the price of PV modules will be reduced by 19.6%.

To precisely assess the evolution of the competitiveness of PV electricity, the price of other components of PV systems must be predicted too, but this is beyond the scope of this thesis. However, we can affirm that the PV industry will not be competitive against conventional technologies soon in most countries. The role of research and development in PV price dynamics is also beyond the scope of this study since it couldn't be included in the predictive model because of technical reasons.

How to design an efficient feed-in tariff?

In this thesis, we focus on feed-in tariffs (FITs). Other incentive policies are beyond its scope. **Chapter four** shows that there is an optimal timing for PV installation that depends on the speed of module cost decrease due to the learning by doing effect. An optimal feed-in tariff is one that allows the achievement of this optimal timing by creating the right incentive effect. It means that the difference between FIT and PV electricity cost must be carefully controlled. If it is too low, the market stagnates but if it is too big, it leads to market overheating calling for violent adjustments, eventually harming the industry. In light of the result of this thesis, we suggest the following recommendations for the design of a FIT:

Firms strategies should be considered

The impact of a FIT depends on the gap between its value and PV electricity cost. **Chapter four** suggests that it also depends on the strategy of the firms installing the PV systems. If they have a long term strategy, the optimal installation timing is reached with a higher initial FIT which decreases more quickly than if they follow a short term strategy. Indeed, if companies follow a long term strategy, they anticipate future price reduction linked to learning by doing, so they need a stronger incentive to install PV systems at a given time. Besides, if firms behave heterogeneously, only distinct FITs, each targeting one type of firm, will help reach the optimal installation timing.

Market effects on module price should be considered to anticipate module price

FITs need to be planned in advance to give the market some visibility. This requires module price anticipation since the incentive effect depends on the gap between the FIT and PV electricity cost. Chapter two predicts long term cost evolution. However, FITs are set in a shorter time scale in which market effects on price dominate. **Chapter three** shows that the silicon market influences module price only when silicon producers have market power. This was the case during the silicon shortage from 2005 to 2009, but the situation is now an overproduction of silicon, preventing producers from enjoying market power. The silicon market is therefore not influencing module price as long as there is no silicon shortage. This chapter also shows that FIT changes induce module price distortion, a consequence of firms' anticipation. The module price increases in the months before a planned FIT decrease as companies rush to install PV systems. Conversely, the demand and thus the price decreases when it is too late, a few weeks before the FIT decrease. The impact of FIT changes in major countries should thus be also taken into consideration when forecasting prices.

Allow some flexibility to correct for errors in feed-in tariff tuning

Module price is difficult to predict. Therefore FITs should be flexible enough to adapt to unpredicted variations in module price, in order to keep the gap between PV price and FIT under control. But it should not create uncertainty. In this respect, the German system seems to be the best solution so far, thanks to more frequent FIT changes and adjustments based on previous market developments using volume responsive mechanisms. This is what is suggested in **Chapter three** showing that the German FIT was the best at tracking PV price evolution. A higher frequency also implies smaller adjustments, reducing the magnitude of the price distortions around FIT changes noted in the same chapter. In addition, the transparency of the volume responsive mechanism gives investors some visibility. However unscheduled FIT changes are certainly not a good solution since they increase the uncertainty in the PV industry. Therefore, they should only be used in case of emergency.

Opportunities for further research

Further analysis of market effects on module price

In this thesis, the influence of silicon price and FITs has been analysed. However, other market effects susceptible of affecting price regardless of cost could be investigated, such as intensity of competition, utilisation rate of manufacturing lines, foreign exchange rates, etc… The main benefit would be to reduce short term uncertainty which would in turn help policymakers design policies and investors rely on stable business plans. Besides, the results could be used to control for price variations independent of cost in models of long term module cost prediction.

Better understand the incentive effect of feed-in tariffs

The numerous countries implementing FITs in the recent years are a growing source of information, which would allow carrying out further empirical analysis of FITs influence on module price. In particular, this would enable deeper quantitative analysis of the effect of the particularities of each country's FIT.

When empirical research does not provide answers, theoretical models could help better understand the underlying mechanisms of FITs influence on the PV market. The model proposed in the fourth chapter is basic, and several hypotheses could be changed:

- Several countries can be included in the model, with allowing for international spillovers. This could shed light on strategic behaviours like free-riding.
- A social cost of the FIT could be integrated, which is lacking in the model.
- Other policies could be implemented, which would be an opportunity to better understand their interactions.

Definition of a framework for global cooperation in the photovoltaic industry

Today, The PV industry is facing a critical situation: it can continue on the path of increasing protectionism, or countries can instead cooperate if they manage to find a common ground. Since protectionism is likely to slow down the development of the industry and the positive effect of the diffusion of technology, it seems important and urgent to assess what the opportunities are for a global cooperation, in which framework, and what would be the limitations.

An opportunity worth exploring is the integration of incentive mechanisms on a global scale. This globalisation would bring the stability the PV market is begging for, since national policies are unpredictable and too dependent on local economic and political situations. Bringing this predictability would be a major benefit to all stakeholders.

Bibliography

Abell, D.F. and Hammond, J.S., 1979. Cost Dynamics: Scale and Experience Effects. *Strategic Planning: Problems and Analytical Approaches*, Prentice Hall, Englewood Cliffs, N.J. Book.

Alberth, S., 2008. Forecasting technology costs via the experience curve — Myth or magic? *Technological Forecasting & Social Change,* 75 (2008) 952–983.

Argote, L. and Epple, D.,1990. Learning curves in manufacturing. *Science*, VOl. 247.

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

Arthur D. Little, 2001, Potential cost reduction in PV systems.

Barreto, L. and Kypreos, S., 2004. Endogenizing R&D and market experience in the "bottom-up" energy-systems ERIS model. *Technovation,* Volume 24, Issue 8, August 2004, Pages 615-629.

Bartlett, J.E.; Margolis, R.M.; Jennings, C.E. (2009). The Effects of the Financial Crisis on Photovoltaics: An Analysis of Changes in Market Forecasts from 2008 to 2009. National Renewable Energy Laboratory. *Technical Report* NREL/TP-6A2-46713.

Barton, J., 2007. Intellectual Property and Access to Clean Energy Technologies in Developing Countries. An Analysis of Solar Photovoltaic, Biofuel and Wind Technologies. ICTSD Programme on Trade and Environment, Issue Paper No. 2

Belsley, D.A., Kuh, E., Welsch, R.E., 1980. Regression Diagnostics: Identifying Influential Data and Sources of Collinearity. John Wiley & Sons.

Benthem, A.V., Gillingham, K., Sweeney, J., 2008. Learning-by-Doing and the Optimal Solar Policy in California, *The Energy Journal, International Association for Energy Economics*, vol. 0(Number 3), pages 131-152.

Berndt, E.R., 1991. The Practice of Econometrics: Classical and Contemporary. *Reading*, MA, U.S.A.: Addison-Wesley; 1991.

Bosetti, V., Catenacci, M., Fiorese, G., and Versolini, E, 2012. The future prospect of PV and CSP solar technologies: An expert elicitation survey, (February 14, 2012), *FEEM Working Paper* No. 1.2012.

Boston Consulting Group, 1972. Perspectives on experience, *Technical report*.

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

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

Brown, R., Durbin, J., Evans, J., 1975. Techniques for testing the constancy of regression relationships over time. *J. R. Stat. Soc.* Series B 37, 149_172.

Butler, L., Neuhoff, K., 2008. Comparison of feed-in tariff, quota and auction mechanisms to support wind power development. *Renewable Energy*, 33 (2008), pp. 1854—1867.

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

Cohen, W.M., Nelson, R.R., Walsh, J.P., 2000. Protecting their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not). *NBER Working Paper* no. 7552

Couture, T., Gagnon,Y., 2010. An analysis of feed-in tariff remuneration models: Implications for renewable energy investment, *Energy Policy*, Volume 38, Issue 2, February 2010, Pages 955-965, ISSN 0301-4215

Criqui, P., Klaassen, G., Schrattenholzer, L., 2000. The Efficiency of Energy R&D Expenditures. Economic Modelling of Environmental Policy and Endogenous Technological Change Workshop. Institute for Environmental Studies, Amsterdam November 16–17.

Darling, S. B. , You ,F., Veselka, T., Velosa, A., 2011. Assumptions and the levelized cost of energy for photovoltaics. *Energy environment science*, 2011,**4**, 3133-3139

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

Dechezleprêtre, A., Glachant, M., and Ménière, Y., 2010. What Drives the International Transfer of Climate Change Mitigation Technologies? Empirical Evidence from Patent Data. CERNA Working Paper.

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

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

EIA, 2011. Annual Energy Outlook 2011, US Enegy Information Administration. DOE/EIA-0383(2012

EPIA (European Photovoltaic Industry Association), 2009. Global market outlook for photovoltaics until 2013. European Photovoltaic Association, May 2009.

EPIA, 2010. Global market outlook for photovoltaics until 2014. European Photovoltaic Association, May 2010.

EPIA, 2011. Global market outlook for photovoltaics until 2015. European Photovoltaic Association, May 2011.

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

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

European Commission, DG Joint Research Center, PV status report 2005, 2008 and 2009

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

Finon, D., and Menanteau, P., 2004. The Static and Dynamic Efficiency of Instruments of Promotion of Renewables. *Energy Studies Review*, Volume 12, Issue 1 Article 3

Energy Studies Review: Vol. 12: Iss. 1, Article 3.Flint, A. 2009. Learning Spillovers in the PV Cell Industry, thesis work.

Granger, C.W.J., 1969. Investigating causal relations by econometric models and cross-spectral models. *Econometrica* 37, 424_438.

Greene, W. H., 2000. Econometric Analysis, Fourth Edition.

Grübler, A., Gritsevskyi, A., 1997. A Model of Endogenous Technological Change Through Uncertain Returns on Learning (R&D and Investments). Paper presented at the International Workshop on induced Technical Change and the Environment. 26-27, June. International Institute for Applied Systems Analysis. Laxemburg, Austria.

Grüber, H. 1998. Learning by doing and spillovers: further evidence for the semiconductor industry, *Review of Industrial Organization* 13: 697–711, 1998.

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

Hausman, J.A., 1978. Specification tests in econometrics, *Econometrica 46, 1251-1271*

IEA (International Energy Agency), 2009. Trends in photovoltaic applications, Survey report of selected IEA countries between 1992 and 2008.

IEA 2010. Technology Roadmap – Photovoltaic Solar Energy.

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

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

Jäger-Waldau, A., Szabó, M., Monforti-Ferrario, F., Bloem, H., Huld, T., Lacal Arantegui, R., 2011. Renewable Energy Snapshots 2011.

Jamasb, T, 2007, Technical change theory and learning curve: Patterns of progress in electricity generation technologies, *The energy journal*, Vol. 28.

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

Junginger, M., Faaij, A., Turkenburg, W.C., 2005. Global experience curves for wind farms, *Energy Policy*, 133-150.

Junginger, M., Lako, P., Lensink, S., van Sark, W., Weiss, M., 2008. Technological learning in the energy sector. CLIMATE CHANGE SCIENTIFIC ASSESSMENT AND POLICY ANALYSIS.

Kahouli-Brahmi, S., 2008. Technological learning in energy-environment-economy modelling: A survey, *Energy Policy* 138-162

Kahouli-Brahmi, S., 2009. Testing for the presence of some features of increasing returns to adoption factors in energy system dynamics: An analysis via the learning curve approach, *Ecological Economics* 6 8 (2 0 0 9) 1 1 9 5 – 1 2 1

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

Keller, W., 2004. International Technology Diffusion, *Journal of Economic Literature* 42:3, 752-782

Keller, W., 2008. Diffusion of Technology, *New Palgrave Dictionary of Economics*, 2nd edition, edited by L. Blume and S. Durlauf, Macmillan, 2008

Kirkegaard, J.F., Hanemann, T., and Weischer, L., 2009. It Should Be a Breeze: Harnessing the Potential of Open Trade and Investment Flows in the Wind Energy Industry. Working Paper

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

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

Kouvaritakis, N., Soria, A., Isoard, S., 2000, Modelling energy technology dynamics: methodology for adaptive expectations models with learning by doing and learning by searching, *International Journal of Global Energy Issues*, Volume 14, Numbers 1-4 / 2000

Lieberman, M.B., 1984. The learning curve and pricing in the chemical processing industries. *Rand Journal of Economics*. Vol 15, No 2, 1984.

Lieberman, M.B., 1987. The learning curve, diffusion, and competitive strategy, *Strategic management journal*, vol. 8, No.5, pp. 441-452.

Lipp, J., 2007. Lessons for effective renewable electricity policy from Denmark, Germany and the United Kingdom. Energy Policy, 35 (11) (2007), pp. 5481—5495.

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

Marigo, N., 2007. The Chinese Silicon Photovoltaic Industry and Market: A Critical Review of Trends and Outlook, *Progress in Photovoltaic: Research and application*, 2007; 15:143–162 10.1002/pip.716.

Maskus, K.E., 2004. Encouraging technology transfer, *UNCTAD-ICTSD Project on IPRs and Sustainable Development.*

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

Maycock. P.D., 2002. The world photovoltaic market. Report, *PV Energy Systems*, January 2002.

Maycock, P.D., 2005. PV technology, performance, cost 1995–2010. Report, *PV Energy Systems*

Maycock, P.D., Bradford, T., 2007. PV technology, performance, and cost. Report, *PV Energy Systems*, 2007 update.

McKinsey, 2008. The economics of solar power.

Menanteau, P., Finon, D., Lamy, M.-L., 2003. Prices versus quantities: choosing policies for promoting the development of renewable energy. *Energy Policy*, 31 (8) (2003), pp. 799--812

Midttun, A., Gautesen, K., 2007. Feed in or certificates, competition or complementarity? Combining a static efficiency and a dynamic innovation perspective on the greening of the energy industry, *Energy Policy*, Volume 35, Issue 3, March 2007, Pages 1419-1422.

Mo-lin, H. and Dan-wei, Z., 2012. Lessons from photovoltaic policies in China for future development, *Energy Policy*, Volume 51, December 2012, Pages 38-45, ISSN 0301-4215, 10.1016/j.enpol.2011.12.063.

Messner, S., 1997. Endogenized technological learning in an energy systems model. *Journal of Evolutionary Economics* 7, 291-313.

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

OECD, 2009. Patent Statistics Manual

Pan, H., Köhler, J., 2007. Technological change in energy systems: Learning curves, logistic curves and input–output coefficients, *Ecological Economics* 63 (2007) 749–758

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

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

Photon Consulting, 2012. Solar Annual 2012:"The next wave"

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

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

REDP (China Renewable Energy Development Project), 2008. Report on the development of the photovoltaic industry in China (2008)

REN21 (Renewable Energy Policy Network for the 21st Century), 2008. Renewables 2007 Global Status Report

Rigter,J., Vidican,G., 2010. Cost and optimal feed-in tariff for small scale photovoltaic systems in China, *Energy Policy*, Volume 38, Issue 11, November 2010, Pages 6989-7000

Ruoss, D., 2007. Global Photovoltaics Business and PV in Malaysia, *Envision report*

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

Seebregts, A., Kram, T., Schaeffer, G.J., Bos, A., 2000. Endogenous learning and technology clustering: analysis with MARKAL model of the western European energy system. *International Journal of Global Energy Issues* 14 (1-4), 289-319.

Söderholm, P. and Klassen, G., 2007. “Wind Power in Europe: A Simultaneous Innovation-Diffusion Model.” *Environmental and Resource Economics* 36(2): 163-190.

Söderholm, P. and Sundqvist T., 2007. Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies, *Renewable Energy* 32 (2007) 2559–2578

SolarBuzz 2012, *Annual report*.

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

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

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

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

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

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

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

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

Wand, R.,Leuthold,F., 2011. Feed-in tariffs for photovoltaics: Learning by doing in Germany?, *Applied Energy*, Volume 88, Issue 12, December 2011, Pages 4387-4399,(http://www.sciencedirect.com/science/article/pii/S0306261911003060)

Watanabe, C., Wakabayashi, K., Miyazawa, T., 2000. Industrial dynamism and the creation of a ‘‘virtuous cycle’’ between R&D market growth and price reduction. The case of photovoltaic power generation (PV) development in Japan. *Technovation* 20, 299–312.

Weitzman, M.L., 1974. Prices vs quantities. *The Review of Economic Studies* 41 (4), 477--491.

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

Winegarner, R. M., 2009. Report 1 Silicon Industry 2008, A comprehensive report on the use of silicon wafers, silicon ingot, and polysilicon in the semiconductor industry on a fab by fab basis, Sage Concepts

Wright, T.P., 1936. Factors affecting the costs of airplanes, *Journal of the aeronautical sciences*, 3 (1936): 122-128

Yang, Y., Williams, E., 2009. Theoretical efficiency and asymptotic cost of grid-connected photovoltaic systems, issst, pp.1, 2009 IEEE International Symposium on Sustainable Systems and Technology, 2009

Yanga, H., He Wanga, Huacong Yub, Jianping Xib, Rongqiang Cui, Guangde Chen, 2003. Status of photovoltaic industry in China, *Energy Policy* 31 (2003) 703–707

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

Yu, C.F, van Sark, W.G.J.H.M., Alsema, E.A., 2011. Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects, *Renewable and Sustainable Energy Reviews* 15 (2011) 324–337

Analyse économique de l’industrie photovoltaïque : mondialisation, dynamique des coûts, et politiques publiques

RESUME : Au cours de la dernière décennie, le marché photovoltaïque a été multiplié par 10, le prix des panneaux solaires réduit de 60%, et la Chine est devenue le premier producteur mondial. L’objectif de cette thèse est d’identifier les mécanismes à l’origine de ces fortes mutations. Grâce à des entretiens auprès d’acteurs de l’industrie photovoltaïque chinoise, et l’analyse de données de brevets, nous expliquons comment la Chine a réussi à acquérir la technologie et le savoir-faire nécessaires à ce succès. Le transfert de technologie a eu lieu grâce au déploiement du marché d’équipement de production et au recrutement de cadres formés dans les pays industrialisés. En revanche, la propriété intellectuelle n’a joué aucun rôle. L’analyse de l’évolution du coût des modules grâce au modèle de courbe d’apprentissage nous permet de prédire une réduction du coût de deux tiers d’ici à 2020. Elle donne des indications quant à la future compétitivité de l’électricité photovoltaïque. Enfin, une attention particulière est portée aux tarifs de rachat de l’électricité, qui ont largement contribué au développement du marché photovoltaïque. Nous analysons leur influence sur le marché et leur capacité à s’adapter à la volatilité du prix des modules, en analysant des séries temporelles. Nous construisons aussi un modèle théorique pour analyser l’influence du comportement stratégique des entreprises sur l’efficacité d’un tarif de rachat. Cela permet de suggérer des recommandations quant à la conception de ces instruments incitatifs.

Mots clés : Solaire, photovoltaïque, courbe d’apprentissage, tarif de rachat, Chine, transfert de technologie

Economic analysis of the photovoltaic industry: globalisation, price dynamics, and incentive policies

ABSTRACT : In the last decade, the photovoltaic market was multiplied by 10, module price was reduced by 60%, and China increased its share in cell and module production from almost nothing to more than half. The purpose of this thesis is to shed light on the mechanisms driving these transformations. We analyse how China managed to acquire the photovoltaic technology, relying on interviews with actors of the Chinese photovoltaic industry, and data gathered on patents related to the photovoltaic technology. We show that intellectual property rights did not play a significant role, Chinese firms getting access to the technology by buying manufacturing equipment from industrialised countries, and from labour mobility. The cost decrease is analysed with experience curves models, allowing us to forecast a further cost decrease of two thirds by 2020, provided that the market follows the high predicted expansion. It gives some insight regarding when photovoltaic technology will become competitive. An important attention is dedicated to feed-in tariffs which largely participated in driving the demand so far. Their influence on the photovoltaic market, and their ability to adapt to module price volatility to avoid too attractive profits, is analysed using weekly data. A theoretical model analysing the influence of firms’ strategies on the incentive effect of feed-in tariffs allows us to give further recommendations concerning an optimal feed-in tariff scheme.

Keywords : Solar, photovoltaic, learning curve, feed-in tariff, China, technology transfer

MINES ParisTech

ParisTech
INSTITUT DES SCIENCES ET TECHNOLOGIES
PARIS INSTITUTE OF TECHNOLOGY