CONSEIL FRANÇAIS DE L'ÉNERGIE
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Une évaluation des déterminants économiques, techniques et politiques de l'évolution du prix des panneaux photovoltaïques

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1. Introduction générale

L'objectif général de cette étude est d'identifier les déterminants des prix et des coûts des panneaux photovoltaïques et de quantifier leur effet en distinguant en particulier les facteurs économiques – par exemple, le prix du silicium, un intrant nécessaire à la production des panneaux photovoltaïques – et réglementaires – en particulier, le niveau des tarifs de rachat de l'électricité photovoltaïque.

Cet objectif général se décline en deux questions plus précises. La première consiste à identifier les facteurs permettant d'expliquer l'évolution du prix des panneaux photovoltaïques depuis 1990 grâce à l'estimation de courbes d'expérience (learning curves). Nous explorons l'effet de plusieurs facteurs : l'expérience (mesurée par la capacité de production installée), les effets d'échelle (la taille moyenne des usines de production de panneaux), le prix de deux intrants clé que sont le silicium et l'argent et la R&D. Nous utilisons ensuite ces résultats pour prédire le prix des modules à l'horizon 2020.

La seconde question porte sur l'effet des tarifs de rachat sur les prix des panneaux. Le développement de l'industrie photovoltaïque est la conséquence de politiques publiques volontaristes de soutien au déploiement de panneaux photovoltaïques dans quelques pays, notamment via des tarifs avantageux de rachat de l'électricité photovoltaïque (Allemagne, Espagne, Japon, Etats-Unis, France, etc.). Or la loi économique de l'offre et de la demande prédit que subventionner la demande conduit – à coût constant – à augmenter le prix des panneaux. Les tarifs de rachat créent donc potentiellement des rentes au profit des producteurs de panneaux et d'autres acteurs de la filière. Mais les régulateurs en charge des tarifs, conscients de ce risque, cherchent en réponse à minimiser au maximum cette rente en calant le niveau des tarifs au plus près du coût de l'électricité photovoltaïque. Ce schéma conduit à des liens de causalité complexes entre prix des panneaux et tarif de rachat :

- Le tarif de rachat influence le prix des panneaux via la loi de l'offre et de la demande
- Le régulateur cherchant à réduire au maximum le tarif de rachat induit une causalité inverse selon laquelle le prix des panneaux détermine le niveau du tarif.

Nous développons une approche économétrique pour identifier le sens de la causalité qui a pu être observé depuis 2007. Répondre à cette question fournit des éléments de réponse à la question de savoir si les régulateurs ont réussi depuis 2007 à limiter les rentes.

Le rapport est organisé en quatre parties. Dans une première partie, nous rappelons quelques éléments de contexte sur le développement de l'industrie photovoltaïque au cours de ces dernières années. Dans une seconde partie, nous présentons notre analyse de l'évolution des prix des modules depuis 1990 et les prédictions que nous sommes capables d'effectuer à l'horizon 2020. La troisième partie est consacrée aux interactions entre le prix des modules et les tarifs de rachat. Enfin, une dernière partie résume les résultats principaux de l'étude.

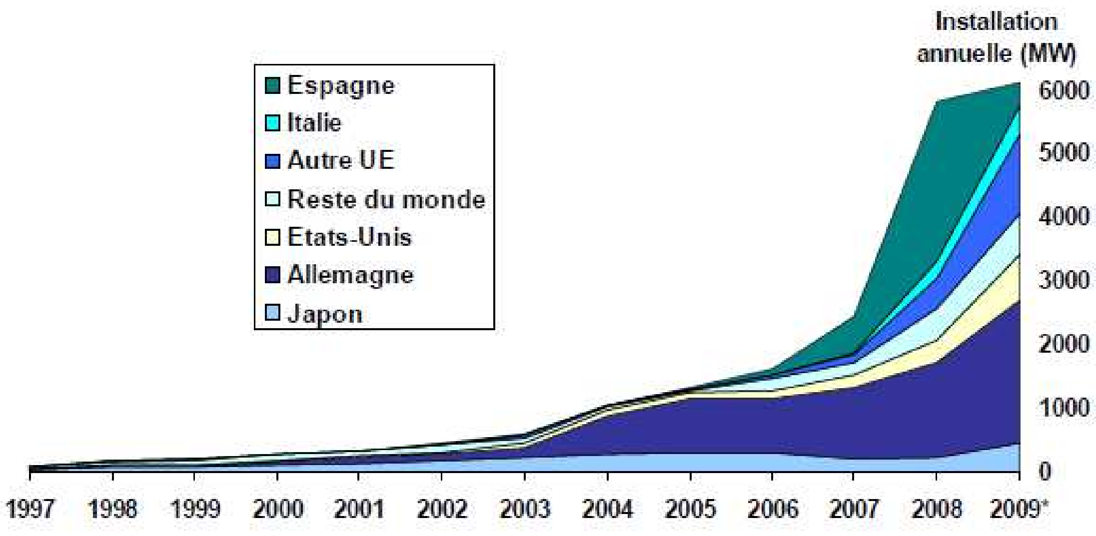
Deux annexes présentent deux articles en anglais issus de cette recherche :

- *Predicting the costs of photovoltaic solar modules in 2020 using experience curve models.*
- *How do solar photovoltaic feed-in tariffs interact with solar panel and silicon prices? An empirical study*.

1. Le développement de l'industrie photovoltaïque

Le marché des panneaux photovoltaïques a connu une croissance exponentielle au cours de la dernière décennie avec un doublement de la capacité installée tous les deux ans comme le montre le graphique 1. Il a même connu un taux de croissance annuelle de 45% sur la période 2003-2009. Cette accélération est principalement due à l'installation de systèmes photovoltaïques reliés au réseau dans les pays développés. Si en 1996, seulement 7.9% des systèmes étaient connectés au réseau, ce chiffre atteint 80% en 2007. Avant la fin des années 90, les panneaux solaires étaient installés pour alimenter des appareils non connectés au réseau tels les appareils de communication, ou les habitations isolées, pour lesquels l'électricité photovoltaïque était compétitive par rapport aux autres sources d'électricité décentralisée.

Graphique 1 : Installation annuelle de panneaux solaires – 1997 - 2009



Source IEA, 2009 and EPIA, 2009. * Prévision.

Cette augmentation spectaculaire de l’installation de panneaux solaires a été possible grâce à la subvention de la demande par des politiques incitatives, initialement mises en place dans un petit nombre de pays développés (Japon, Allemagne, Espagne, et Etats-Unis). En effet, l’électricité d’origine photovoltaïque ne peut pas concurrencer les autres sources sur le réseau électrique car son coût de production reste élevé. Elle n’est donc pas utilisée en l’absence d’incitation économique.

Outre différents types de réductions d’impôts, les principales politiques visant à stimuler l’utilisation d’énergies renouvelables sont les tarifs de rachat et les normes de portefeuilles renouvelables (Renewable Portfolio Standards, RPS en anglais).

Les tarifs de rachat obligent les distributeurs d’électricité à acheter une énergie d’origine renouvelable à un prix fixe défini par le régulateur. Ils ont été utilisés dans la majorité des pays développés. Ils sont en place depuis 1994 au Japon et depuis 2000 en Allemagne, ce qui explique le développement précoce et durable du marché dans ces deux pays (figure 1). L’Espagne a également mis en place un tarif de rachat en 2006. Mais celui-ci, trop généreux, a entrainé le développement d’un nombre excessif de projets, conduisant le gouvernement Espagnole à fixer en 2008 un plafond de 500MW par ans pour l’installation de systèmes photovoltaïques.

Les normes de portefeuilles renouvelables (RPS) obligent les électriciens à vendre un pourcentage minimum fixé par le régulateur de leur électricité à partir d’énergies renouvelables. Selon cette approche, c’est donc une quantité plutôt qu’un prix qui est fixée. Cet instrument a été largement utilisé aux Etats-Unis. D’autres mesures, telles que les appels d’offre de capacités ou des subventions à l’investissement ont également été développées, mais plus marginalement.

Ces politiques, au coût élevé pour le consommateur ou le contribuable, ont été tout d'abord mises en œuvre dans les pays développées de l'OCDE où l'industrie du photovoltaïque s'est donc initialement développée. Jusqu'en 2011, 35 % de la capacité solaire a été installée en Allemagne, suivie de l'Italie, du Japon, de l'Espagne et des Etats-Unis. La mise en place de politiques incitatives dans les pays émergents ne fait que démarrer. En particulier, la Chine ne représentait que 2.2% de la capacité de production d'électricité photovoltaïque en 2009 (EPIA 2010).

L'évolution du marché des panneaux photovoltaïques depuis 2005

Un effet indirect de la croissance du marché des panneaux photovoltaïques est la réduction rapide de leur coût de production. Cette tendance a seulement été interrompue pendant la période de pénurie de silicium qui a commencé à partir de 2005 en raison de l'augmentation de la demande du marché photovoltaïque. Comme le rappelle l'encadré, le silicium est la matière première essentielle pour produire les panneaux.

La construction d'une usine de fabrication de silicium prend plusieurs années et ceci a fait durer la pénurie de silicium jusqu'en 2009 avec un pic du prix à 396 $/kg en 2008, comparé à un prix de 56 $/kg en 2005. Cette tension sur l'amont de la filière a entrainé une augmentation du prix des modules durant cette période.

Depuis 2009, les conditions de marché se sont inversées et nous sommes à présent dans une période de surcapacité de l'offre de silicium. Ce changement a ramené le prix du silicium à son niveau d'avant la crise, provoquant à une diminution des coûts des modules encore plus rapide. Ce retournement structurel a cependant accentué l'écart entre les tarifs de rachats généreux et les coûts de production, entrainant des profits élevés pour les industriels et un emballement du marché qui n'était plus soutenable. Des mesures drastiques de révision des tarifs et de leurs conditions d'attribution ont alors été décidées – par exemple en France et en Espagne – créant une profonde incertitude pour l'ensemble de la filière et une surcapacité au niveau de la production des panneaux qui ont conduit à une forte baisse des prix. Ces nouvelles conditions de marché ont conduit à la faillite de nombreuses entreprises. Ceci a été accompagné de la perte de milliers d'emplois, en particulier dans les pays de l'OCDE.

Encadré: Etapes de la fabrication de panneaux photovoltaïques

La production de panneaux solaires implique cinq étapes, regroupées ici en quatre, les deuxième et troisième étapes étant rassemblées dans cette étude. En voici une brève description, de nombreux procédés secondaires ne nécessitant pas d'être précisés pour cette étude.

1. Purification du silicium : Le silicium est obtenu à partir du quartz trouvé dans le sable. Le degré de pureté très élevé requis pour l'industrie photovoltaïque (>99.999%, cependant 10 fois moindre que pour l'industrie des semi-conducteurs) est obtenu grâce à des processus chimiques lourds et difficiles à maitriser, qui consomment beaucoup d'énergie.

2. Production de lingots et gaufres de silicium cristallin : A partir du silicium purifié, des lingots de silicium monocristallins (un seul cristal) ou polycristallins (une multitude de cristaux plus petits) sont obtenus. Les lingots sont ensuite découpés en de fines tranches de silicium, ou gaufres. Des impuretés sont ajoutées pour les doper positivement ou négativement.

3. Fabrication d'une cellule : Deux gaufres de silicium dopées de manière opposée sont assemblées pour former une « jonction p-n », à l'origine de l'effet photovoltaïque. Les contacts métalliques sont ensuite ajoutés, et des traitements de surface sont effectués pour augmenter l'efficacité des cellules.

4. Assemblage des panneaux : Des cellules sont assemblées, la jonction électrique étant effectuée à la main ou automatiquement. Ces cellules sont ensuite encapsulées entre deux plaques de verre pour former le module, qui sera cuit dans une machine à laminer.

En parallèle, l'industrie photovoltaïque s'est mondialisée au cours de la dernière décennie. La production des modules a été progressivement déplacée vers la Chine, alors que la demande reste concentrée en Europe et dans les pays de l'OCDE. En conséquence, les exportations de panneaux photovoltaïques de la Chine vers l'Europe ont explosé, conduisant à un transfert des installations industrielles des pays de l'OCDE vers la Chine. La politique commerciale agressive de la Chine, et le ralentissement de la demande en Europe du fait de la crise économique, ont accentué le nombre de faillites d'entreprises du secteur en Europe. Cette situation fait aujourd'hui l'objet de différends auprès de l'Organisation Mondiale du Commerce (OMC) entre, d'un côté, les Etats-Unis et l'Europe et, de l'autre, la Chine. La Chine serait un passager clandestin qui bénéficierait des technologies développées dans les pays de l'OCDE développement permit grâce à des politiques de soutien massives et supportées dans ces pays par les contribuables et les consommateurs.

L'émergence de la Chine

Le développement de l'industrie photovoltaïque en Chine reste souvent mal compris en Occident et reste un sujet de controverses. La Chine est devenue en quelques années le premier producteur mondial de panneaux solaires. En 2011, elle était à l'origine de plus de la moitié de la production mondiale, dont une grande majorité a été exportée vers l'Europe.

Comme le montre l'article de De La Tour et al. (2011), 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 « clé 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 de l'OCDE dans les segments technologiques en amont de la filière. Leur récente progression dans la purification du silicium montre qu'ils sont en passe d'atteindre leur objectif. Il est donc aujourd'hui nécessaire pour les pays de l'OCDE de repenser la place qu'ils souhaitent occuper sur ce marché, notamment afin de garder une avance au niveau de la R&D.

3. Les déterminants de l'évolution du prix des modules à l'aide de courbe d'apprentissage. Implications pour le prix de l'électricité photovoltaïque à l'horizon 2020.

Dans cette partie, nous synthétisons une analyse développée dans l'article « Predicting the costs of photovoltaic solar modules in 2020 using experience curve models » présentée en annexe de ce rapport.

Rappelons pour commencer le principe d'une courbe d'expérience : elle décrit l'évolution du prix ou du coût d'une technologie – ici le prix d'un panneau photovoltaïque – en fonction de l'expérience le plus souvent mesurée par la production cumulée de panneaux. Cette courbe est quasiment toujours décroissante sous l'effet d'apprentissages incrémentaux dans la filière de production. Elle fournit un modèle simple permettant d'expliquer l'évolution au cours du temps du coût d'une technologie. Elle permet également des prédictions sur son évolution future. Alors que les courbes d'apprentissage se limitaient à l'expérience comme seule variable explicative, des courbes dites « multi-facteurs » ont depuis été développées pour y inclure des variables telles que l'échelle de production, le prix de certains intrants, la R&D, etc.

Dans l'industrie solaire photovoltaïque, les courbes d'expérience occupent une place centrale dans les discussions politiques sur l'avenir de l'énergie solaire. La technologie photovoltaïque n'est pas encore compétitive par rapport aux sources d'énergie conventionnelles. Il est toutefois prévu que des réductions de coûts apportées par ces effets d'apprentissage conduiront à des gains importants dans l'avenir à condition que la technologie soit dès à présent suffisamment déployée. Comme les bénéfices de ces effets d'apprentissage ne peuvent être facilement internalisés par une entreprise, leur existence constitue l'une des justifications des politiques publiques qui subventionnent le déploiement des installations photovoltaïques.

Dans ce contexte, une évaluation quantitative du niveau de la diminution des coûts auquel on peut s'attendre à l'avenir du fait du développement actuel du marché est importante pour justifier le coût immédiat de ces politiques. Cette évaluation peut s'appuyer sur l'estimation de courbes d'apprentissage. A court terme, les courbes d'expérience sont également utiles pour sélectionner le rythme auquel les subventions publiques devraient être réduites. Par exemple, une prévision trop pessimiste de l'évolution des coûts a conduit à un boom du marché incontrôlé en Espagne en 2008 et en France en 2010, déclenchant une révision brutale des instruments de soutien (au travers d'un plafond sur les installations en Espagne et d'un moratoire de trois mois avec une réduction drastique des tarifs de rachat en 2011 en France). Ce manque de stabilité politique a été dévastateur entraînant, dans l'activité de l'installation du système photovoltaïque, des dizaines de faillites et des milliers de pertes d'emplois. Une prédiction fiable des coûts est donc cruciale pour le développement durable de cette industrie.

Résultats

Notre étude est un exercice de prédiction du prix à l'horizon 2020 fondé sur l'estimation d'une courbe d'apprentissage « multi-facteurs ». Cette courbe est sélectionnée à partir d'une revue critique de la littérature et d'une comparaison du pouvoir prédictif des équations possibles à l'aide de données sur le prix moyen des modules, leur production cumulée, le stock de R&D (mesuré par des brevets) et le prix de deux intrants, le silicium et l'argent, sur la période 1990 – 2011.

La comparaison de différents modèles possibles nous amène à conclure que le modèle le plus fiable pour prédire le coût des modules doit prendre en compte, en plus de l'effet d'expérience, le prix du silicium comme facteur explicatif. Inversement, ajouter d'autres facteurs explicatifs aurait pour effet de dégrader la fiabilité du modèle.

Sur la base de ce modèle, nous prévoyons une baisse des coûts de 67% entre 2011 et 2020, l'expérience étant responsable de 75% de cette évolution, et le prix du silicium responsable des 25% restants.

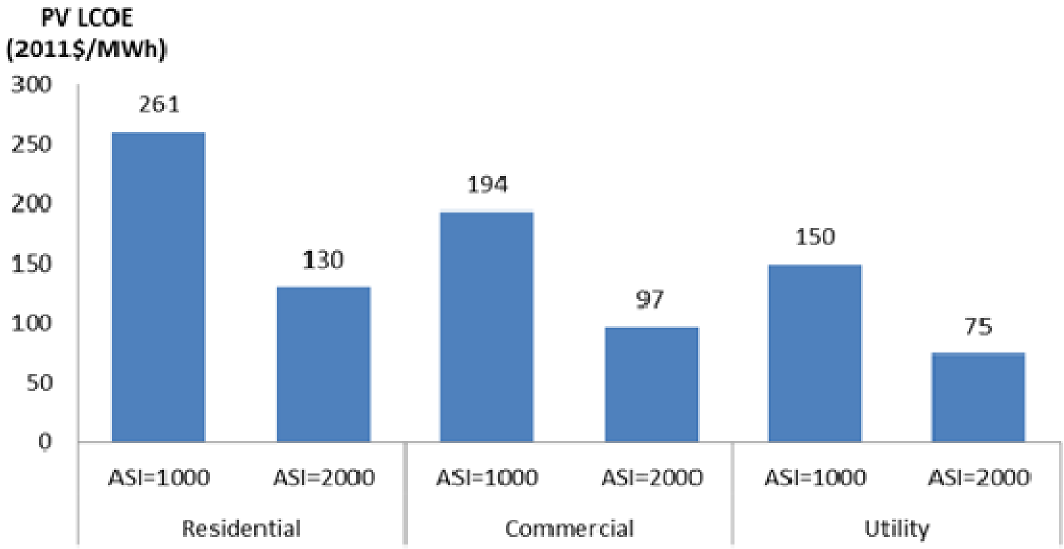
En se basant sur les prévisions existantes pour l'évolution des capacités solaires installées à l'horizon 2020, et sur l'évolution du prix du silicium, notre scénario de référence se traduit par une réduction du prix du module qui passerait de 1.52 $/Wp en 2011 à 0.5 $/Wp en 2020.

Ce résultat sur le coût des modules peut être utilisé pour estimer l'évolution du coût de l'électricité photovoltaïque et, éventuellement, sa compétitivité à long terme. A cette fin, nous mesurons le coût actualisé de l'électricité en faisant un certain nombre d'hypothèses sur le coût des autres composants, le type de système, le taux d'escompte, et les différents paramètres qui influent sur la quantité d'électricité produite, tels que l'ensoleillement ou la durée de vie du système.

Nous étudions différents systèmes : résidentiel, commercial ou industriel. Nous choisissons un taux d'escompte de 6,8 %, ce qui correspond au taux utilisé dans les études récentes de l'Agence Internationale pour l'Energie (AIE). Pour les trois types de système, deux scénarios sont construits en fonction du niveau d'ensoleillement (Annual Solar Irradiation, ASI) : (*1*) Un niveau d'ensoleillement faible, correspondant au Nord de l'Allemagne (ASI = 1000 kWh/an) et (*2*) un niveau d'ensoleillement élevé correspondant au Sud de l'Espagne (ASI = 2000 kWh/an).

Le graphique 2 résume notre prédiction du coût actualisé de l'électricité photovoltaïque à l'horizon 2020. Il illustre le fait que le coût du photovoltaïque dépend en grande partie de la localisation géographique, mais aussi du type de système installé. Par exemple, le coût pourra varier entre 75 $/MWh pour un système industriel installé dans une région à fort ensoleillement (comme le sud de l'Espagne) et 261 $/MWh pour un système résidentiel dans une région avec un faible ensoleillement (comme le nord de l'Allemagne).

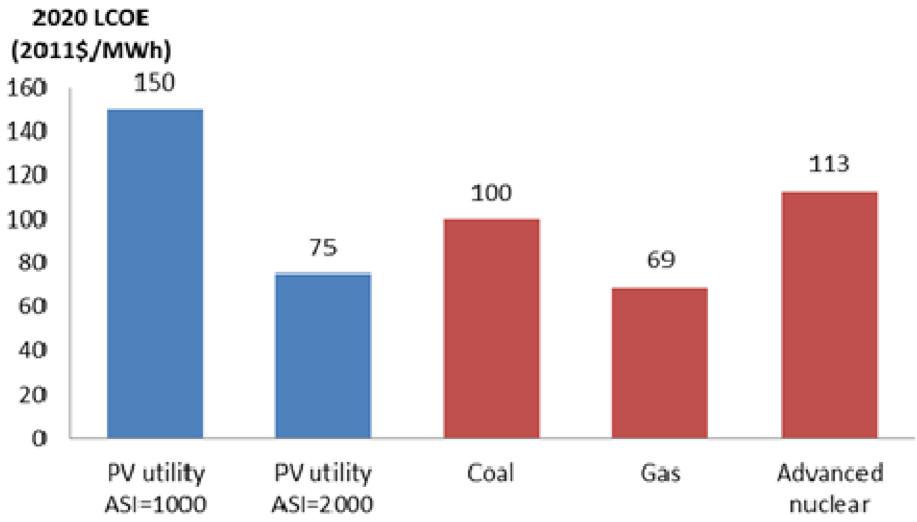
Graphique 2: Coût du photovoltaïque en 2020 avec un taux d’escompte de 6.8



%

Le graphique 3 compare nos prédictions sur le coût du photovoltaïque en 2020 avec des sources de production d’électricité classiques (cycle combiné gas, centrale charbon et nucléaire de génération 3+). Les résultats suggèrent que le coût moyen actualisé de l'électricité produite avec la technologie photovoltaïque pourrait être compétitif dans les endroits les plus ensoleillés par rapport aux technologies conventionnelles en 2020. Ceci correspond à des régions telles que la Californie, l'Italie, ou encore l'Espagne.

Graphique 3 : Comparaison du coût de différentes sources de production d’électricité en 2020



Il est cependant important de noter que ces résultats peuvent sous-estimer le coût réel de l'électricité photovoltaïque car cette mesure classique du coût ne prend pas en compte la nature intermittente de l’énergie solaire, ou l’incapacité pour la technologie photovoltaïque de s’ajuster à la demande. Ceci induit des coûts supplémentaires pour la capacité de stockage, l'extension du réseau, ou la capacité de back-up avec des centrales flexible plus coûteuses.

De même, le coût actualisé ne prend pas en compte le profil de production, c'est-à-dire la valeur de marché de l’électricité du fait des variations de l’offre et de la demande d’électricité durant la journée. Ce dernier aspect peut avoir un impact positif ou négatif sur la compétitivité du photovoltaïque en fonction de la synchronisation de la production et des profils de demande.

4. Comment les tarifs de rachat de l’électricité photovoltaïque interagissent avec le prix des modules et le prix du silicium?

Dans cette partie, nous synthétisons l’article “How do solar photovoltaic feed-in tariffs interact with solar panel and silicon prices? An empirical study » relégué en annexe.

Contexte

Les tarifs de rachat pour la production d’électricité solaire font partie des instruments les plus communs pour stimuler la mise en place de capacités de production solaires photovoltaïques, en particulier en Europe et au Japon, mais aussi dans un nombre croissant de pays émergents comme la Chine et l’Inde. Ces tarifs représentent des prix garantis pour une période donnée durant laquelle le gestionnaire du réseau électrique a l'obligation d'acheter de l'électricité à partir de sources d'énergie solaire.

Le photovoltaïque bénéficie de tarifs plus élevés par rapport à d’autres d’énergies renouvelables, ce qui reflète un coût plus important. Par exemple, le tarif de rachat pour le photovoltaïque résidentiel s’élevait en 2012 en Allemagne à 24 € - ct/kWh contre moins de 9 ct pour l’éolien terrestre.

Ces tarifs ne sont pas financés directement par le consommateur d’électricité. A court terme, une conséquence directe est alors de stimuler la demande de systèmes et de services photovoltaïques et donc le prix de ces marchés en amont. A l’inverse, à plus long terme, cet effet est compensé à travers les effets d’apprentissage qui réduisent les coûts. En fonction du niveau de concurrence, des effets de rente peuvent donc se créer pour les producteurs de système photovoltaïque et/ou pour les entreprises qui installent ces systèmes. Le rôle du régulateur est d'essayer de limiter ces rentes en révisant les tarifs en fonction de la réduction des coûts de production. Cependant, l'asymétrie d'information entre le régulateur et le producteur peut rendre cette tâche difficile.

L'étude vise à étudier les interactions dynamiques entre les tarifs de rachat et le prix des modules. Nous intégrons également dans l'analyse le prix du silicium comme variable de contrôle. Le silicium est un composant clé dans la chaine de production des panneaux photovoltaïques et son rôle a été mis en exergue pendant une période de pénurie avant 2009 où il a fortement contribué au coût élevé du photovoltaïque.

Nous cherchons plus précisément à répondre à la question suivante : Est-ce que les tarifs de rachat conduisent à une augmentation des prix ou, à l'inverse, est ce que les régulateurs sont capables de réviser les tarifs pour limiter les effets de rente ?

Cette question est particulièrement importante pour les décideurs pour deux raisons :

- Le prix des panneaux solaires représente une part importante (plus de 40 %) du coût de production de l'électricité photovoltaïque.
- Les tarifs de rachat induisent un transfert de rente entre le consommateur et le producteur. Ceci peut créer un risque de retournement de l'opinion publique vis-à-vis des politiques de soutien aux énergies renouvelables en cas de capture de rente importante, d'autant plus que la plupart des panneaux sont aujourd'hui produits en Chine. Cet aspect n'a pas une actualité immédiate pour les fabricants de module puisque nous sommes conjoncturellement dans une phase de surcapacité de production peu propice à la création de rente. Mais il peut resurgir à moyen terme.

Avant de développer les résultats de notre analyse, quelques points techniques sur la chaine de production des panneaux photovoltaïques sont nécessaires afin de souligner l’importance du silicium dans cette chaine de production, et l’articulation entre les tarifs de rachat et coût des modules. La chaine de production à partir du silicium nécessite plusieurs étapes. Le silicium est cristallisé, formant des lingots qui sont coupées en tranches. Les tranches sont ensuite transformées et assemblées par paire en cellules, qui sont soudées et encapsulées pour compiler le module. Le déploiement du système PV nécessite l’assemblage des modules avec des équipements complémentaires (comme les batteries et les onduleurs) dans les systèmes intégrés qui, une fois installés, vont produire de l'électricité. Cette production d’électricité restera évidemment tributaire du niveau d’ensoleillement et de la durée de vie de l’installation qui influenceront grandement la valeur économique de ces installations photovoltaïques. En 2006, les modules représentent 40% du coût global moyen actualisé des systèmes photovoltaïques.

La production de silicium est une étape clé pour la production du silicium et le principal input pour l'industrie photovoltaïque. Il représente 20% du coût d'un module et une part prépondérante de l’énergie grise consommée durant le cycle de vie de l’installation, depuis sa production jusqu’à son démantèlement. Les autres inputs sont le verre, l'aluminium, l'argent mais, soit ils représentent une faible part du coût de fabrication, soit leurs prix sont très stables. Notons également que le silicium est un produit standardisé : à partir du moment où il dépasse un niveau de pureté minimal de 99,99 %, il est difficile de faire une distinction sur la qualité de ce produit.

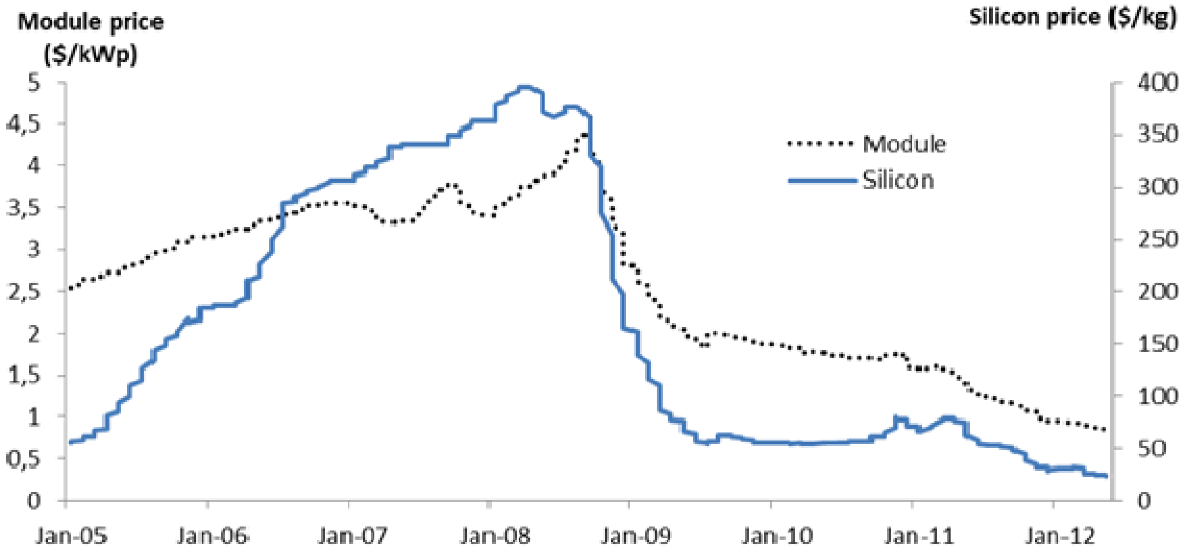
L'intensité de la concurrence est cependant fortement influencée par la capacité de production disponible. Celle-ci est en effet contrainte à court terme puisqu’il faut deux ans pour construire une usine de production. Ainsi au cours de la période pré-2009, le manque de capacité de production de silicium a donné un pouvoir de marché important aux producteurs de silicium, conduisant à des prix très élevés. Depuis, la construction de nombreuses usines a donné lieu à une situation de surcapacité qui conduit à des prix beaucoup plus faibles. Ces éléments descriptifs nous conduisent à intégrer le prix du silicium dans notre modélisation économétrique.

Dans une large mesure, les panneaux photovoltaïques cristallins sont également des produits échangés sur un marché, mais leur approvisionnement ne fait pas l’objet de contraintes de capacité aussi importantes. Leur prix résulte essentiellement des effets d’apprentissage qui réduisent les coûts régulièrement par l'accumulation de l’expérience des producteurs.

Statistiques descriptives sur les tarifs de rachat, prix des modules et prix du silicium

Il est tout d’abord important de noter la forte instabilité des prix du silicium et des modules au cours de ces dernières années. Cette évolution des prix et leur corrélation sont représentées dans le graphique 4. En particulier, le prix du silicium a été multiplié par sept entre 2005 et 2008, passant de 56 $/kg à 396 $/kg. Comme nous l’avons déjà évoqué, ceci correspond à une période de pénurie induite, en partie, par l’émergence de la filière photovoltaïque. Dans le même temps, le prix des modules a connu une hausse plus limitée de 43 % durant la même période, passant de 2,44 $/Wp à 3,56 $/Wp. L’augmentation plus limitée du prix des modules s’explique par le fait que le silicium ne représente que 20 % du coût des modules et par l’existence de contrats de long terme.

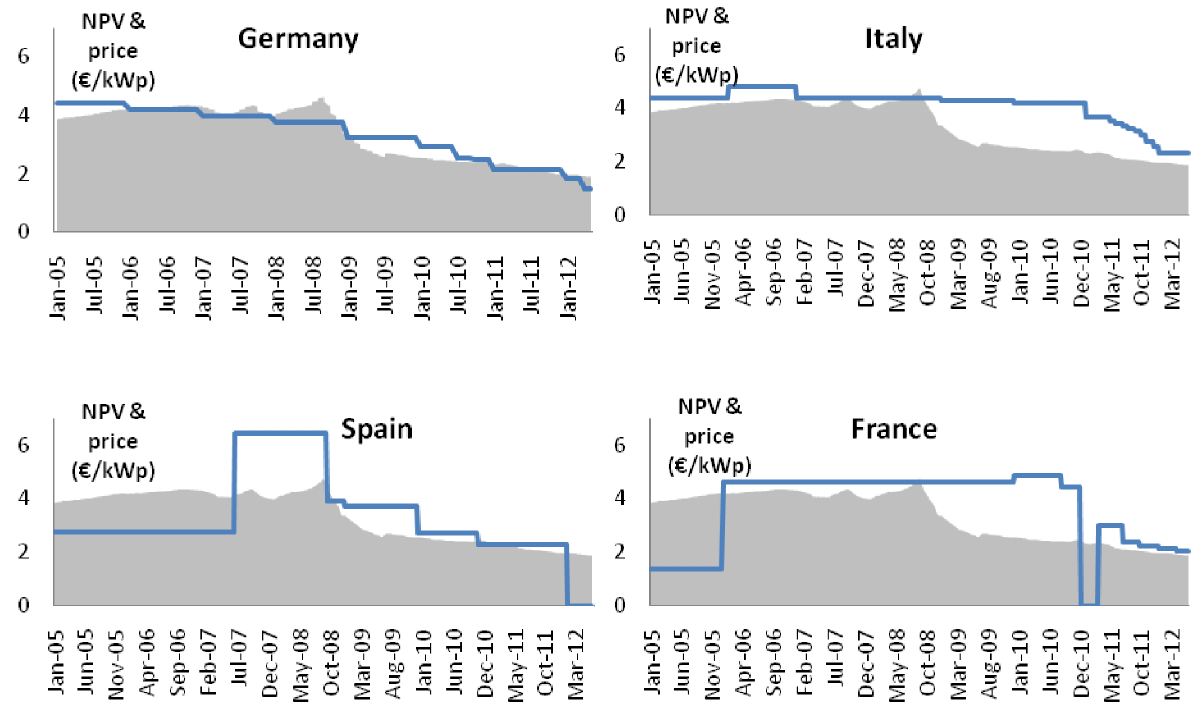
Graphique 4 : Evolution du prix du silicium et du prix des modules entre 2005 et 2012



Pour analyser l'effet des tarifs de rachat, nous avons retenu quatre pays – l'Allemagne, l'Espagne, l'Italie et la France - où les tarifs de rachat ont été le principal instrument de soutien à cette filière. Ces quatre pays représentent 60 % du marché mondial durant la période étudiée.

Nous calculons une moyenne pondérée des différents tarifs de rachat existants dans chaque pays. L'évolution des tarifs est réprésentée dans le graphique 5, ci-dessous, pour chaque pays. Ces tarifs sont comparés à l'évolution des prix des modules (en $/Wp). Pour ce faire, nous dérivons la valeur actuelle nette de l'électricité photovoltaique vendue aux tarifs de rachat (en $/kWh) afin d'en déduire la valeur des modules en $/Wp. Cette étape nécessite un certain nombre d'hypothèses qui sont détaillées dans l'article en annexe.

Graphique 5 : Comparaison des prix des modules (zone grise) et des tarifs de rachat actualisés (ligne bleu)



Le graphique 5 présente les évolutions comparées des prix des modules et des tarifs de rachat. Tout d'abord, nous pouvons noter que si l'Allemagne et l'Italie ont connu une réduction progressive de leurs tarifs de rachat, l'évolution des tarifs en France et en Espagne fut beaucoup plus instable. De plus, il apparaît que l'Allemagne et l'Italie n'ont pas seulement eu une politique plus stable, ils ont aussi eu des tarifs plus corrélées avec l'évolution des coûts des modules. Le coefficient de correlation entre ces deux varaiables est ainsi de 0,86 pour l'Allemagne et de 0,39 pour la France.

Analyse des causalités

Les données présentées dans la partie précédente montrent donc une corrélation entre le prix des panneaux et le niveau des tarifs. Il reste à déterminer le sens de la causalité. Notre analyse se base sur des données de prix hebdomadaires des modules et du silicium et sur les tarifs de rachat en Allemagne, Espagne, Italie et

France entre janvier 2005 et mai 2012 et sur des tests de causalité de Granger appliqués sur des modèles VAR. Des informations méthodologiques précises sont disponibles dans l'article en annexe.

Nous montrons que le lien de causalité entre prix du silicium et prix du module s'est inversé à la fin de la période de pénurie sur le marché du silicium en 2009. Le prix du silicium déterminait le prix des modules pendant la période de pénurie et l'inverse est observée depuis. Ce résultat est conforme à la théorie économique qui prédit que sur les marchés de commodités les producteurs ont uniquement un pouvoir de marché en période de sous-capacité. Ceci peut également provenir de l'augmentation des besoins de l'industrie photovoltaïque en silicium qui dépasse depuis 2007 les besoins de l'industie des semi-conducteurs.

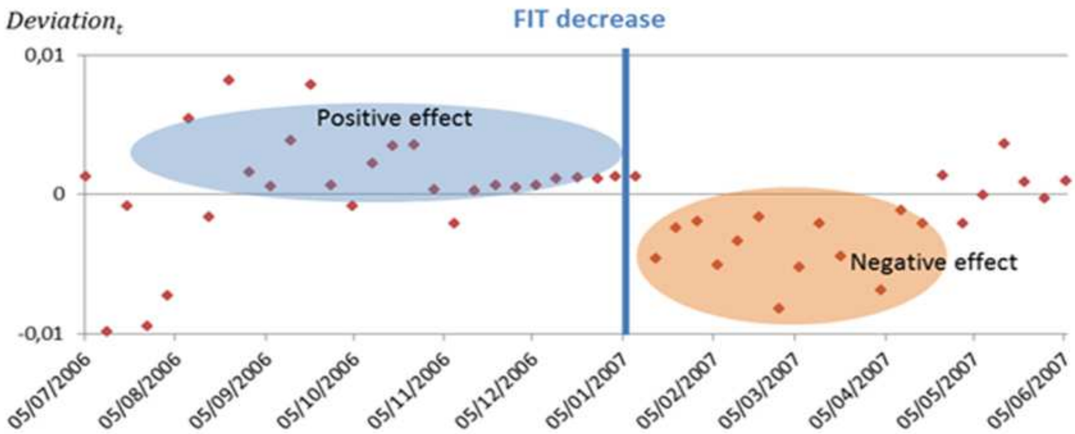
La causalité entre prix des modules et tarifs de rachat, qui constitue le cœur de notre analyse, est plus ambigüe. Jusqu'en 2009, nous ne trouvons pas de relation causale. A partir de 2009, nous identifions un lien de causalité indirect : les changements de tarifs sont déterminés directement par le prix du silicium, et donc indirectement pas le prix des modules puisque ce dernier détermine les évolutions du prix du silicium.

Au final, le sens global de causalité après 2009 est donc du prix des modules et du silicium vers les tarifs. Ce résultat est en accord avec l'idée que la forte concurrence sur le marché des modules et du silicium a limité la capacité des producteurs de modules à se constituer une rente avec les tarifs de rachat. Nos résultats suggèrent donc que les régulateurs en Allemagne, Espagne, France et Italie ont été capables de prévenir une inflation des prix des modules ce qui a limité les effets de rente dans l'industrie photovoltaïque.

Les effets d'anticipation

L'analyse causale qui précède identifie les liens entre les variables observés à la même date. Elle est donc incapable de mesurer d'éventuels effets d'anticipation de prix. Or le graphique ci-dessous suggère que, dans les semaines qui précèdent la révision des tarifs de rachat, l'anticipation de cette dernière conduit à une augmentation des prix des modules par rapport à un scenario de *business-as-usual*. Pour examiner ces effets d'anticipation de la révision des tarifs, nous développons une approche économétrique différente. Nous confirmons qu'à très court terme (quelques semaines), l'anticipation (ou l'annonce) de la révision des tarifs de rachat a un effet sur le prix des modules, ce qui suggère donc une causalité inverse à celle identifiée avec les modèles VAR. Cet effet reste marginal et disparait lorsque l'analyse porte sur les fondements du prix des modules à plus long terme.

Graphique 7 : Ecart du prix des modules en comparaison d'un scénario *business-as usual* scenario avant et après une réduction des tarifs de rachat en janvier 2007



En définitive, cette étude montre que la formation des prix dans l'industrie photovoltaïque reste complexe et difficile à prédire. Il apparait donc nécessaire de créer des tarifs de rachat suffisamment flexibles pour éviter une situation de rente ou, à l'inverse, une crise de la filière industrielle. Jusqu'à maintenant, trois principaux instruments ont été introduits pour créer plus de flexibilité : (*i*) autoriser des révisions de tarifs non prévues, (*ii*) augmenter la fréquence de ces révisions et (*iii*) rendre les changements conditionnels aux capacités déjà installées. Si les révisions non planifiées risquent avant tout de créer de l'incertitude dans l'industrie photovoltaïque, les changements plus fréquents peuvent permettre une adaptation plus rapide aux baisses des coûts et réduire également les incitations à faire des arbitrages de court terme avant les baisses de tarifs.

5. Conclusions et implications pour les politiques publiques

L'objectif de notre travail n'est pas d'évaluer l'efficacité des politiques de promotion de l'électricité photovoltaïque puisqu'il porte principalement sur les déterminants des prix des panneaux. Il permet toutefois de formuler quelques messages utiles au régulateur.

A quelle vitesse le coût des panneaux photovoltaïques va-t-il continuer à baisser ?

Nous avons construit un modèle destiné à prédire l'évolution du coût des modules dans le long terme en utilisant la capacité installée cumulée et le prix du silicium comme variables explicatives. Ce modèle peut aider les décideurs à mieux évaluer le potentiel de la technologie photovoltaïque dans le mix énergétique et de mieux connaître le rythme de réduction de son prix, une information clé pour paramétrer au plus juste le niveau des tarifs de rachat ou, plus généralement, celui des subventions à l'installation de panneaux photovoltaïques.

En utilisant ce modèle et différents scénarios sur l'évolution du prix du silicium et sur l'évolution des capacités installées, nous prévoyons une diminution de 67% du prix du module. Cela correspond à un taux d'apprentissage de 20,1%. En d'autres termes, le prix des modules photovoltaïques diminuerait de 20,1% à chaque doublement de la capacité photovoltaïque installée. Sous ces hypothèses, l'électricité photovoltaïque n'atteindra celui de l'électricité conventionnelle avant 2020 que dans les pays dans lesquels la radiation annuelle solaire est supérieure à 2000 kWh comme en Californie, en Espagne ou en Italie.

A quel niveau fixer les soutiens au déploiement des panneaux photovoltaïques ?

Notre analyse des interactions entre le niveau des tarifs de rachat et le prix des modules met l'accent sur le risque inflationniste des subventions qui, via l'augmentation de la demande, induit potentiellement une augmentation du prix des équipements et services nécessaires pour installer des panneaux. Ce risque doit conduire le régulateur à chercher en permanence à réduire l'écart entre prix et coût.

Notre analyse montre toutefois que le niveau du risque inflationniste dépend des conditions de marché. Très présent il y a quelques années quand les capacités de production en particulier de silicium étaient limitées, il n'est plus présent dans le contexte actuel de surcapacité de production (qui n'a pas de raisons structurelles à perdurer).

Fixer au bon niveau le niveau des subventions est donc un exercice très compliquée puisqu'il faut à la fois connaître les fondamentaux techniques déterminant l'évolution des coûts et des conditions de marché, plus conjoncturelles et volatiles, les secondes étant a priori plus difficiles à anticiper du fait de leur caractère conjoncturel et de leur volatilité. Une dernière difficulté tient au fait que l'ampleur de la différence entre les prix et les coûts dépend également du niveau des subventions en place dans les autres pays puisque le marché des panneaux est international.

Dans ces conditions, il apparaît inévitable d'autoriser une certaine souplesse pour corriger les erreurs dans la fixation des tarifs de rachat tout en prenant garde que les révisions n'ajoutent pas d'incertitudes supplémentaires. À cet égard, le système allemand semble être la meilleure solution à ce jour grâce à des ajustements plus fréquents en fonction des évolutions du marché et en utilisant des mécanismes qui dépendent de la capacité déjà installée. Nous montrons d'ailleurs que les tarifs de rachat allemands sont les plus corrélés avec l'évolution des prix des modules.

Une révision plus fréquente des tarifs induit des ajustements moins importants, réduisant l'ampleur des distorsions temporaires de prix mises en évidence dans la recherche lors des changements de tarifs. En outre, la transparence du mécanisme, qui dépend de la capacité installée, donne une certaine visibilité aux investisseurs.

Annexes

Predicting the costs of photovoltaic solar modules in 2020 using experience curve models[1]

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Abstract

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

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

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1 Introduction

Experience curves, also called learning curves, are widely used to predict cost paths in the mid- to long-term. In its simplest form, an experience curve relates production costs to the accumulation of experience (often measured by cumulative production). Experience curves are based on the theory of learning-by-doing which asserts that "technical change in general can be ascribed to experience, that it is the very activity of production which gives rise to problems for which favourable responses are selected over time" [1]. Strong empirical support has been demonstrated through its application across various industries[i].

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

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

In this paper, we seek to predict the cost of PV modules production out to 2020 using experience curves, and thereby the cost of PV generated electricity. As mentioned, experience curves in their basic form are derived by regressing the module price (a proxy for the cost) on experience measured by cumulative production. In the recent literature, additional explanatory variables have been included, such as input price, scale, or research and development [20, 23, 42]. However, little attention has been paid thus far on the influence of adding these explanatory variables on the predictive power of the model. This paper aims to fill this gap, by explicitly addressing methodological issues that influence the identifying and selecting of the most reliable experience curve model.

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

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

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

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

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

2 Literature review

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

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

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

$$\text{Learning rate} = 1 - 2^{-\mathrm{E}} \qquad (2)$$

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

$$\log(\mathrm{P}_t) = \log(\mathrm{P}_0) - \mathrm{E}\log(\mathrm{Y}_t) + \varepsilon_t \qquad (3)$$

with ε_t , an i.i.d. error term.

We find 15 studies that estimate one-variable equations with module price as the dependent variable (see Table 1). They differ in terms of time frame used for the estimation, geographical scale, and data source. The average learning rate is 20.2%, but they vary significantly from 10 to 26%. The range is however much lower if we exclude the study by Papineau [28] which gives very low rates in Germany and Switzerland (10-15%). This may be related to the experience variable used: Papineau uses cumulative capacity whereas all other studies use cumulative output. In

Data sources seem also to explain several gaps as illustrated by the studies by Parente et al. [29] and van Sark [38] who respectively find a learning rate of 22.6% and 29.6% over the same period 1991-2000. Most studies rely on two major data providers: Maycock, a historical expert of the PV industry, and Strategies Unlimited, a company specialised in semi-conductors selling market reports. Maycock's data suggests a steeper experience curve than Strategies Unlimited's one, due to very different values for PV module price prior to 1990: in table 1, 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%.

Nemet [26] finds the learning rates vary a lot with the estimation period. However, when silicon price is controlled, the learning rate is stable. 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 et al. [29] 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).

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 [25]	Global	1965-1973	20.0%	n.a.
Tsuchiya [35]	Japan	1979-1988	19.0%	n.a.
Williams and Terzian [40]	Global	1976-1992	18.4%	Strategies Unlimited
Cody and Tiedje [6]	US	1976-1988	22.0%	Maycock
Tsuchiya [36]	Japan	1979-1998	17.6%	n.a.
IEA [17]	Global	1976-1984	16.0%	EU-Atlas and Nitsch (1998)
		1987-1996	21.0%	
Harmon and Schrattenholzer [15]	Global	1968-1998	20.2%	Maycock
Parente et al. [29]	Global	1981-2000	22.8%	Maycock
		1981-1990	20.2%	
		1991-2000	22.6%	
Poponi [31]	Global	1976-2002	25.0%	Maycock
		1989-2002	19.5%	
Schaeffer et al. [32]	Global	1976-2001	20.0%	Strategies Unlimited
		1987-2001	23.0%	
	Germany	1992-2001	10.0%	Photex database
Papineau [28]	Germany*	1992-2000	15.0%	Extool Project, IEA
	Switzerland*	1992-2000	10.0%	
	US	1992-2001	23.0%	
Nemet [26]	Global	1978-2001	26.0%	Maycock
		1976-2001	17.0%	Strategies Unlimited
Van Sark [38]	Global	1976-2001	20.6%	Strategies Unlimited
		1981-1990	16.6%	
		1991-2000	29.6%	
Swanson [34]	Global	1979-2005	19.0%	Strategies Unlimited & other
Breyer et al. [5]	Global	1976-2003	22.8%	Strategies Unlimited & other
		1976-2010	19.3%	

In fact, several other factors other than experience [16] are omitted in the base model:

- Other forms of learning, including learning-by-searching (brought by R&D), learning-by-using (through feed-backs from users which helps optimising the product), and learning-by-interacting (transfer of knowledge between users, producers, research institutes and policy makers due to knowledge networks) [22].
- Knowledge spillovers, that is, the flow of knowledge that has benefits outside the organisation where it has been created, but with no automatic market compensation. Spillovers are more important between firms that are geographically or technologically close. For experience curves at the firm scale, they induce a cost reduction that is not generated by the firm's own experience, thus altering the experience parameter. However, for global experience curves based on world average cost, spillovers are included in the global experience effect. It explains the difference previously noted in Table 1 between country-level and world-level studies.
- Scale effect, which is the unit cost variation corresponding to an increase in production scale at the plant level.
- Product standardisation, reducing transaction costs in the industry.

To account for some of these factors, in more recent analysis, new explanatory variables such as input price, R&D, or scale effect have been included in three studies, leading to more complex experience curves (Table 2). Kobos et al. [23] find that R&D through learning-by-searching has a significant positive effect. Isoard and Soria [21] find constant return to scale. However, allowing for a flexible value of the parameter, they find decreasing return to scale before 1994. With more recent data, Yu et al. (2011) find increasing return to scale. These contradicting results are inconsistent with the constant parameters hypothesis. However, the variability of the scale parameter may be due to multicollinearity increasing the variance of the estimator. Yu et al. find a strong positive effect of silicon price on module price [42]. They also find a slight negative effect of silver price, explaining it by a substitution effect with other inputs.

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

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

Table 2: Review of multifactor experience curves for PV modules

Study	Time scale	**Learning-by-doing**	**Learning-by-searching (R&D)**	**Return to scale***	**Input price***	
					Silicon	Silver
Isoard and Soaria [21]	1976-1994	9.2%	-	1	-	-
Kobos et al. [23]	1975-2000	18.4%	14.3%	-	-	-
Yu et al. [42]	1976-2006	13.5%	-	1.066	0.285	-0.135

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

3 Selection of the specification with the highest predictive power

3.1 Methodology

Our methodological approach empirically evaluates the predictive power of 32 possible specifications with different sets of explanatory variables. One half of the specifications includes cumulative capacity as the experience variable. The others include cumulative capacity with a one year lag, to account for the time it takes for the learning process to take place. Apart from the experience variable, each specification is a particular combination of four variables identified in the literature: R&D, scale, silicon price, and silver price which lead.[iv] This leads to 16 combinations that are listed in Table 3.

Although it only accounts for 3% of total production cost, the silver price is included because Yu et al. [42] have shown it could have a significant impact.

Table 3: Sets of additional variables in specifications tested

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

The strategy then involves making predictions and comparing the predicted price with the actual value observed in the data, as we now explain by using an example. Using data from 1990 to 2010, the first step involves estimating the specification, indexed by *i*, on a ten-year period, for instance 1990 to 1999. The estimates are then used to predict the annual module prices from the subsequent year (2000 in this case) to 2011, the last year for which we have historical values. The predictions are based on historical data for the explanatory variables.

Let $\hat{P}_{i,t}$ denote the predicted price and $P_{i,t}$ the actual value where *i* is the specification's index and *t*, the time horizon (1 for the prediction in 2000, 2 for 2011 in the above example). The error is given by:

$$\left|\frac{\hat{P}_{i,t}-P_{i,t}}{P_{i,t}}\right| \tag{4}$$

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

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

$$MAPE_{i,t} = \frac{1}{n_t} * \sum_{i=1}^{n_t} \left| \frac{\hat{P}_{i,t} - P_{i,t}}{P_{i,t}} \right| \qquad (5)$$

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

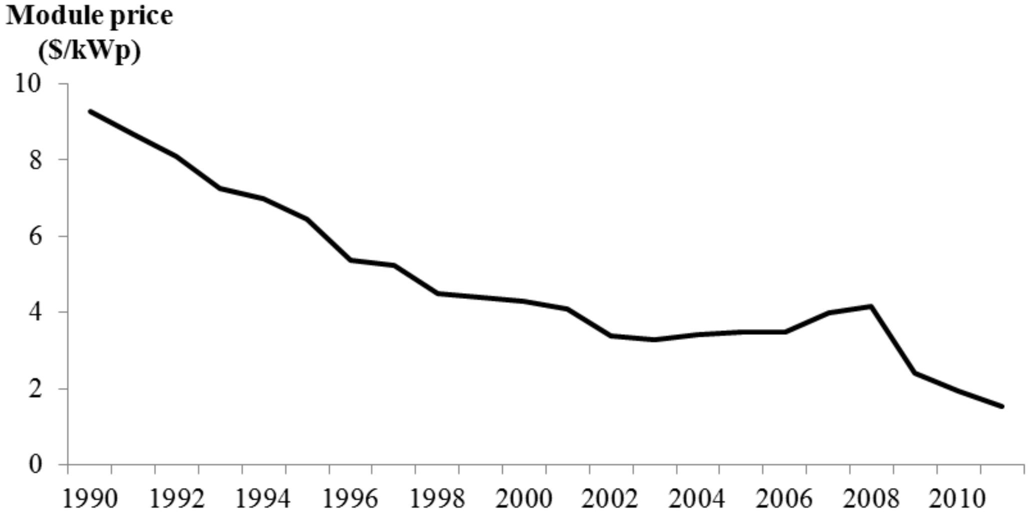
3.2 Data

The dataset consists of world average annual values of module price, cumulative capacity, plant size, silicon price, and R&D knowledge stock from 1990 to 2011, except R&D for which the data stops in 2007. Data sources are listed in annex A. The R&D knowledge stock has been measured using the cumulative number of patent families as proxy for innovation, according to the methodology developed by Dechezleprêtre et al. [8]. A patent family is the set of patents granted in different countries for the same innovation. Therefore one patent family represents one innovation. We use an annual depreciation rate of 10% to account for technology obsolescence. The patent data is obtained from the European Patent Office. (http://www.epo.org/)

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

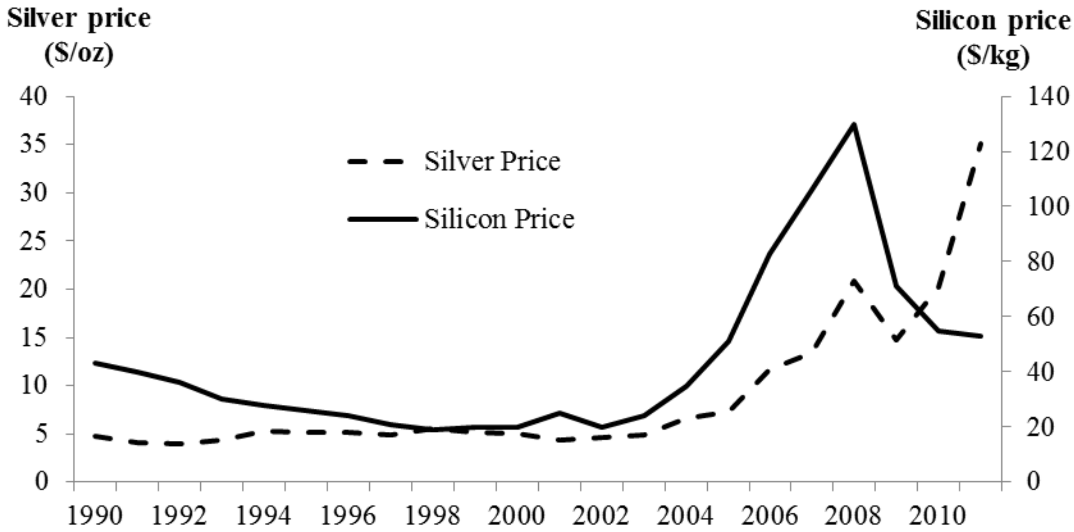
Table 4 presents descriptive statistics of the sample.

Figure 1: Evolution of module price from 1990 to 2011



Source: see Annex A

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



Source: see Annex A

Table 4: Descriptive statistics of the estimation sample

Variables	Mean	Std deviation	Min	Max
Cumulative capacity (MW)	5199	13596	0,32	69684
Module price ($/kWp)	12	14	1,52	69,093
Plant size (MW)	93	252	0,08	1185
Silicon price ($/kg)	67	45	19	176
Silver price ($/oz)	9	7	3,933	35,12
R&D stock (discounted number of patented inventions)	12014	9007	1027	30791

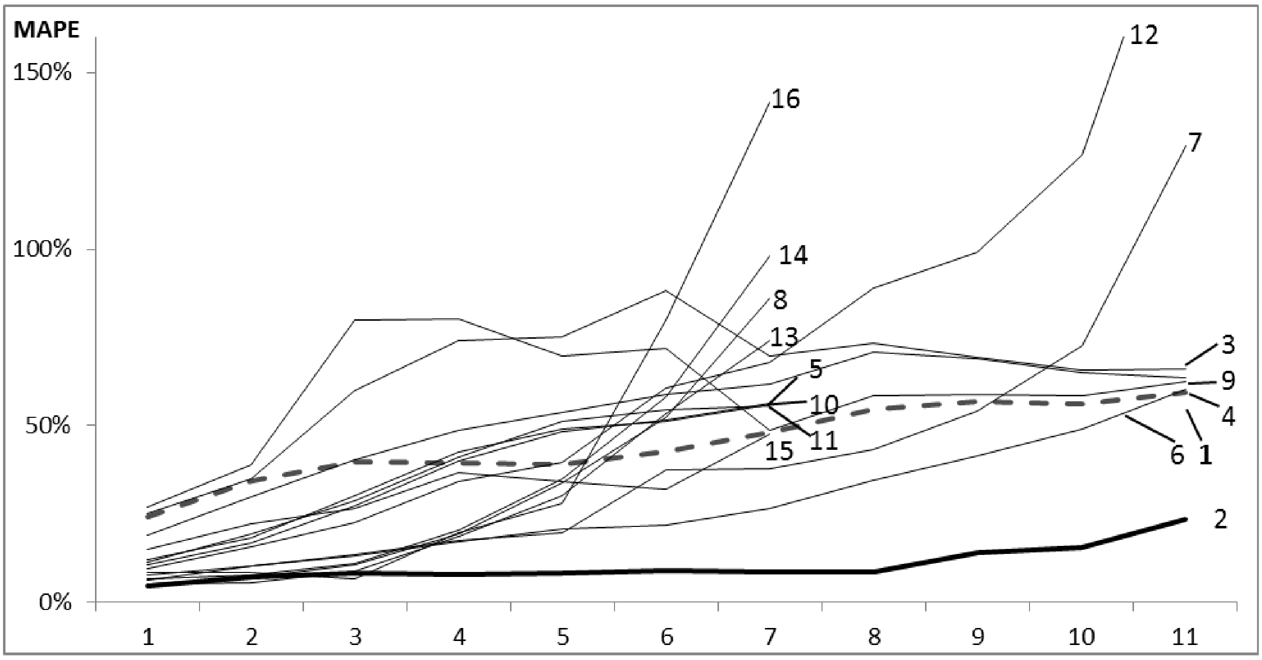
3.3 Results

Of the 32 estimations conducted, only results for the MAPE are reported in this subsection in the interest of space.[v] Figure 3 plots the MAPE over time for each of the 16 specifications, where cumulative capacity with one year lag is used as proxy for experience. These specifications perform better than those using cumulative capacity with no lag: the average MAPE is 41.6% with the lag and 44% without. Note that the specifications including R&D end after a time horizon of 7 years because we do not have data for R&D after 2007.

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

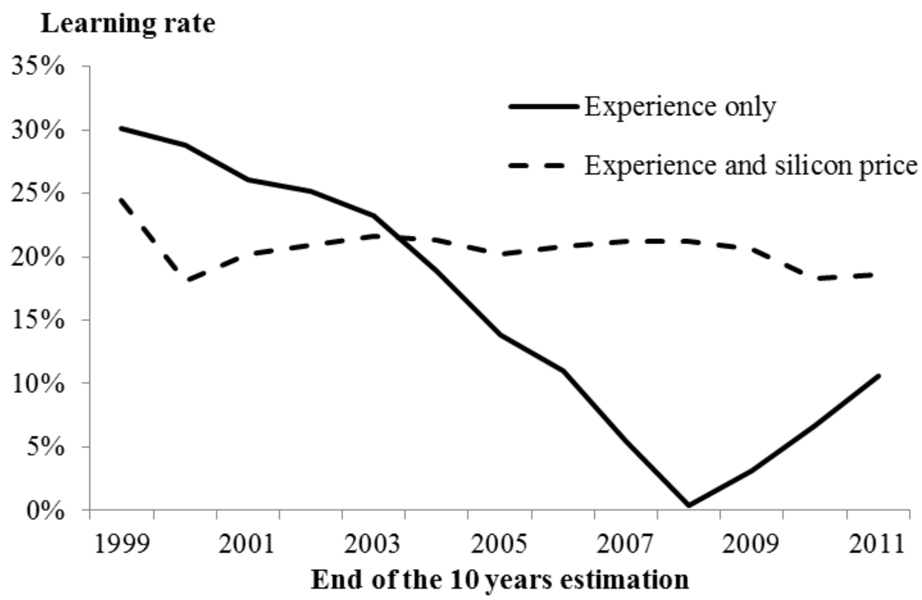
This result illustrates that adding explanatory variables does not necessarily improve predictive power. It can be interpreted in terms of the trade-off between omitted variable bias and multicollinearity. The inclusion of silicon price reduces the omitted variable bias. Figure 4 showing the learning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

Figure 3: MAPE for the 16 models in which experience cumulative capacity with one year lag as a function of time horizon



Notes: MAPE(t) is 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.

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



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

Table 5 shows the regression results for the selected specification that will be used to make module price predictions below. The estimation period is from 1990 to 2011. The experience parameter of -0.338 corresponds to a learning rate of 20.1%.

Table 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

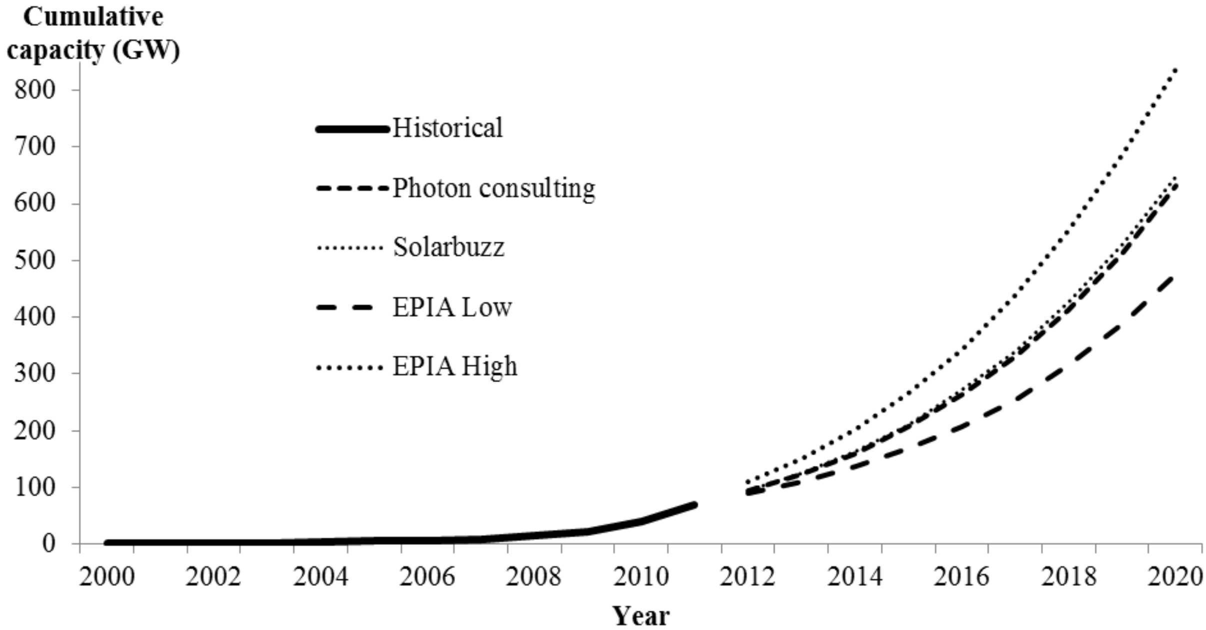
4 Prediction of module price beyond 2011

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

4.1 Cumulative capacity scenarios

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

Figure 5: Cumulative capacity forecast until 2020

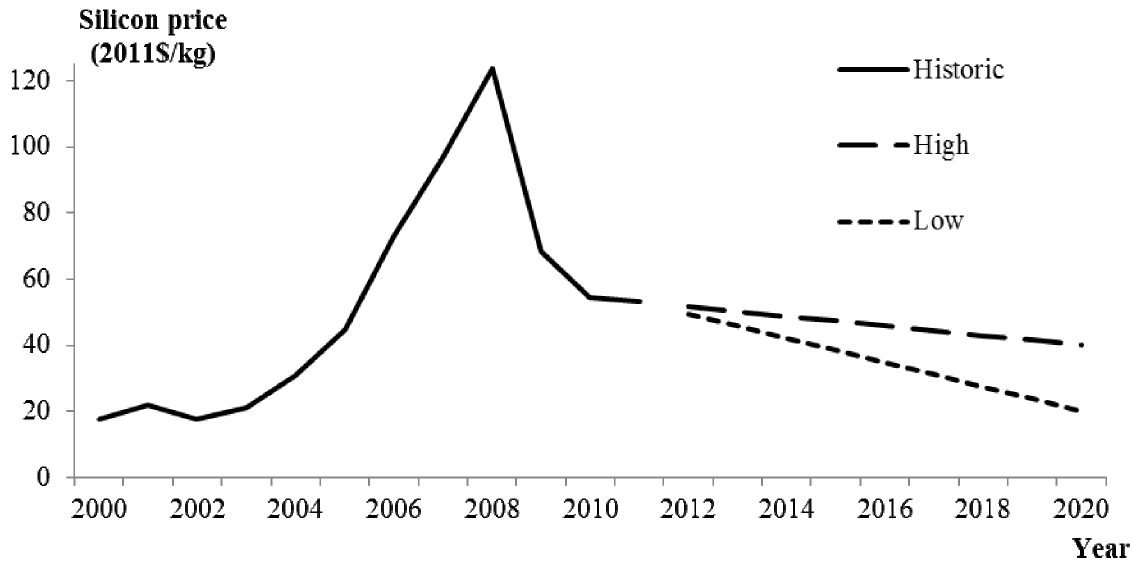


Source: Photon consulting [30], Solarbuzz [37], EPIA [12]

4.2 Silicon price scenarios

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

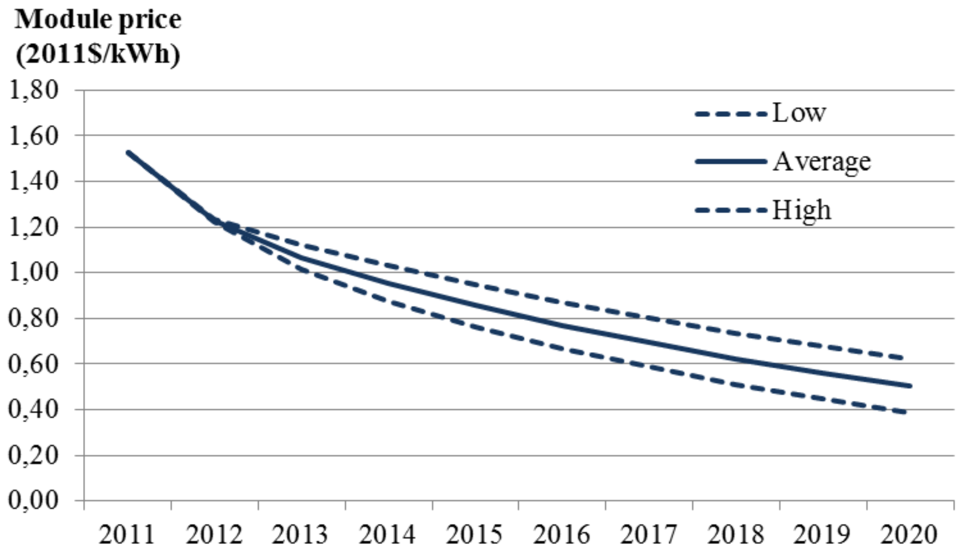
Figure 6: Silicon price forecast until 2020



4.3 Module price prediction until 2020

We now proceed to forecast the evolution of module price. The method consists in using the forecasted values of the explanatory variables which are described in sections 4.1 and 4.2 and the estimated model of Table 5 to predict the evolution of the module price from 2011 to 2020. The results are presented in Figure 7. The low scenario for module price corresponds to the high scenario for PV industry development, and the low scenario of the silicon price path. Conversely, the high scenario for module price corresponds to the low development of the industry and the high scenario for silicon price. On average, we find a 67% decrease of module price from 1.52 $/Wp in 2011 to 0.50$/Wp in 2020. The increase in cumulative capacity is responsible for 75% of this reduction, and the silicon price decrease for 25%.

Figure 7: Module price predictions until 2020



5 Impact on the cost of photovoltaic electricity

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

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

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

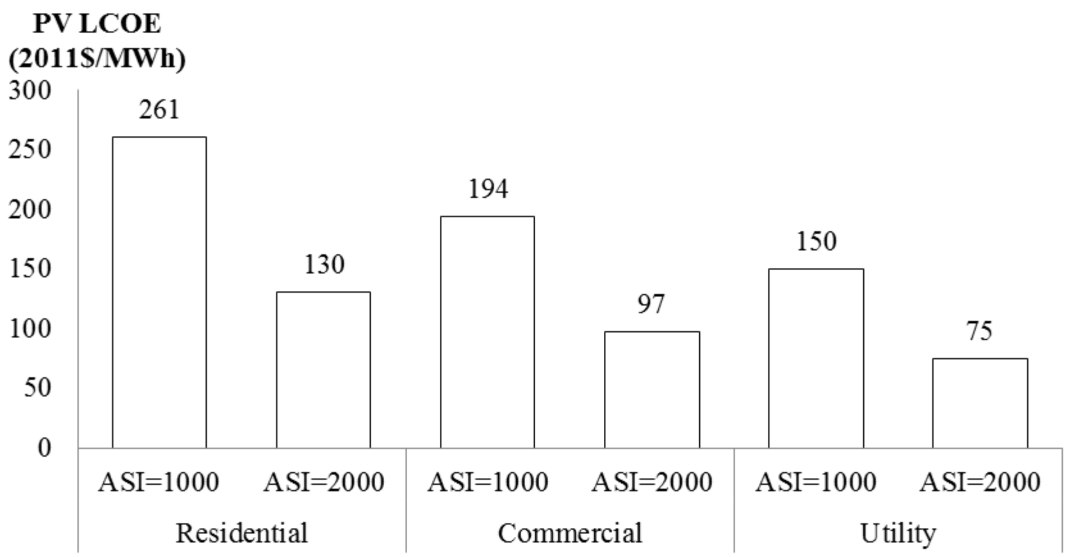
Sunlight availability, measured by the Annual Solar Irradiation (ASI), has important influence on LCOE. For example, the North of Germany or Alaska has an ASI of 1000 kWh/year, while the south of Spain, Italy, or California has an ASI of 2000 kWh/year. The discount rate is also an important determinant, since 95% of the cost of a PV system over its lifetime is capital expenditure (CAPEX).

As Branker et al. [4] noted in a survey of studies of PV LCOE, the assumptions regarding the discount rate are often not made explicit, although they typically lie between 5% and 10% in most studies. We use 6.8%, which is the rate used by the IEA [8] to compute LCOEs.

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

Figure 8 shows the predicted LCOE in 2020. The differences in the results illustrate the importance of the geographic location, and the type of PV system on the cost of PV electricity. These results are in line with those of Bosetti et al. [3] who predict a LCOE between 75 and 145 $/MWh for 2030 with an expert elicitation survey, with the most likely scenario being 108$/MWh, not differentiating the location or the type of system.

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



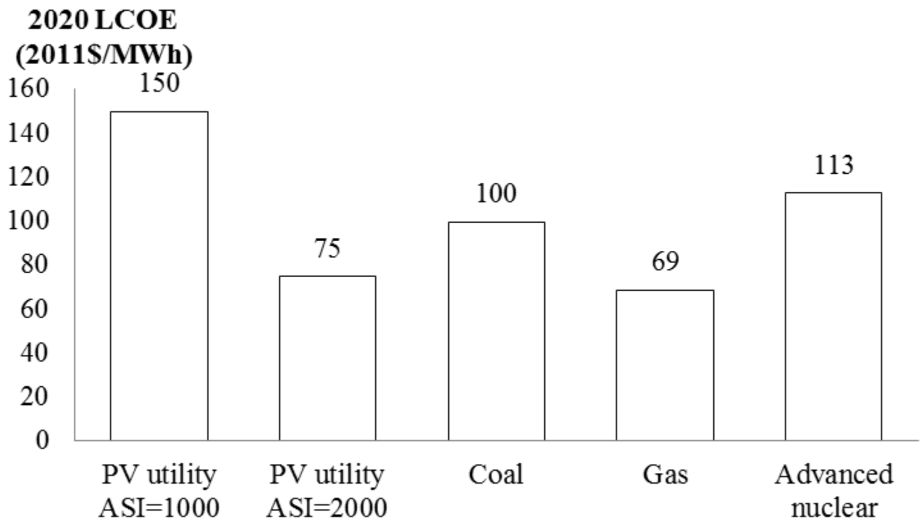
Note: ASI: Annual Solar Irradiation, 1000 kWh/year corresponds to the north of Germany or Alaska, and 2000 to the south of Spain, Italy, or California. Hypothesis used for the computation of the LCOE are explained in Annex B.

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

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

Moreover, the LCOE does not take into account the country specific load profile. Joskow [21] notes that, since the wholesale price of electricity varies throughout the day, different load profiles with different base- and marginal- technologies give different market values for the electricity produced. This can have either a negative or a positive impact depending on the synchronisation of the production and demand profiles.

Figure 9: Comparison of the LCOE of different electricity sources



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

6 Conclusion

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

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

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

7 Acknowledgments

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8 References

[1] Arrow KJ. The economic implications of learning by doing. The Review of Economic Studies 1962; 29(3): 155-173.

[2] Bernreuter J. Oversupply ahead. Sun Wind Energ 2011; 5: 2018-20.

[3] Bosetti V, Catenacci M, Fiorese G, Verdolini E. The Future Prospect of PV and CSP Solar Technologies: An Expert Elicitation Survey. FEEM Working Paper n° 1.2012; 2012.

[4] Branker K, Pathaka MJM, Pearce JM. A review of photovoltaic levelized cost of electricity. Renew Sust Energ Rev 2011; 15:4470-4482.

[5] Breyer C, Birkner C, Kersten F, Gerlach A, Stryi-Hipp G, Goldschmidt JC, Montoro DF, Riede M. Research and Development Investments in PV – A limiting Factor for a fast PV Diffusion? EU PVSEC Proceedings 2010; 5385-5408. DOI: 10.4229/25thEUPVSEC2010-6CV.5.22.

[6] Cody GD, Tiedje T. A learning curve approach to projecting cost and performance for photovoltaic technologies. AIP Conf. Proc. 1997; 404: 45-53. DOI: 10.1063/1.53464.

[7] De La Tour A, Glachant M, Ménière Y. Innovation and international technology transfer: The case of the Chinese photovoltaic industry. Energy Policy 2011; 39(2): 761-770

[8] Dechezleprêtre A, Glachant M, Haščič I, Johnstone N, Ménière Y. Invention and Transfer of Climate Change Mitigation Technologies: A Global Analysis. Rev Environ Econ Policy 2011; 5 (1):109–130.

[9] DOE. $1/W Systems: A Grand Challenge for Electricity from Solar. US Department Of Energy; 2010.

[10] Dutton J, Thomas A. Treating progress functions as a managerial opportunity. Acad Manage Rev 1984; 9(2):235–247.

[11] EPIA. Solar Photovoltaics competing in the energy sector ‐ On the road to competitiveness. European Photovoltaic Industry Association; 2011.

[12] EPIA. Global market outlook for photovoltaics until 2016. European Photovoltaic Association; 2012.

[13] Ferioli F, Schoots K, van der Zwaan BCC. Use and limitations of learning curves for energy technology policy: A component-learning hypothesis. Energy Policy 2009; 37(7):2525-2535.

[14] Flint A. Learning Spillovers in the PV Cell Industry. PhD thesis, University of New South Wales; 2009.

[15] Harmon C, Schrattenholzer L. Experiences curves of photovoltaic technology.Laxenburg: IIASA; 2000.

[16] Hall G, Howell S. The experience curve from the economist's perspective. Strategic Manage J 1985; 6:197-212.

[17] IEA. Experience curves for energy technology policy. Paris: OECD/IEA; 2000.

[18] IEA. Technology toadmap – Photovoltaic solar energy. Paris: International Energy Agency; 2010.

[19] IEA and NEA. Projected cost of generating electricity. 2010 Edition. Paris: International Energy Agency and OECD Nuclear Energy Agency; 2010.

[20] Isoard S, Soria A. Technical change dynamics: evidence from the emerging renewable energy technologies. Energ Econ 2001; 23:619-636.

[21] Joskow P. Comparing the costs of intermittent and dispatchable electricity generating technologies. Am Econ Rev 2011;101(3): 238-241.

[22] Kamp LM, Smits REHM, D, Andriesse CD. Notions on learning applied to wind turbine development in the Netherlands and Denmark. Energy Policy 2004; 32(14)):1625-1637.

[23] Kobos PH, Erickson JD, Drennen TE. Technological learning and renewable energy costs: implications for US renewable energy policy. Energy Policy 2006; 34:1645-1658.

[24] MacDonald and Schrattenholzer. Learning rates for energy technologies. Energy Policy 2001; 29(4): 255-261.

[25] Maycock PD, Wakefield GF. Business analysis of solar photovoltaic conversion. The Conference Record of the 11th IEEE Photovoltaic Specialists Conference 1975: 252-55.

[26] Nemet GF. Interim monitoring of cost dynamics for publicly supported energy technologies. Energy Policy 2009; 37(3): 825-835.

[27] OECD. Patent Statistics Manual. Paris: OECD; 2009.

[28] Papineau M. An economic perspective on experience curves and dynamic economics in renewable energy technologies. Energy Policy 2004; 34(4):422-432.

[29] Parente V. Comments on experience curves for PV modules. Prog Photovolt: Res Appl 2002, 10: 571–574. doi: 10.1002/pip.458.

[30] Photon Consulting. Solar Annual 2012: The next wave; 2012.

[31] Poponi D. Analysis of diffusion paths for photovoltaic technology based on

[32] Schaeffer GJ, Seebregts AJ, Beurskens LWM, Moor HHC, Alsema EA, Sark W, Durstewicz M, Perrin M, Boulanger P, Laukamp H, Zuccaro C. 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. ECN-C-04-035; 2004

[33] Strategies Unlimited. Photovoltaic five-year market forecast 2002-2007. Technical Report PM-52 Strategies Unlimited; 2003.

[34] Swanson RM. A vision for crystalline silicon photovoltaics. Prog Photovolt: Res Appl 2006; 14: 443–453.

[35] Tsuchiya H. Photovoltaic cost analysis based on the learning curve. Research Institute for Systems Technology Tokyoiya; 1992.

[36] Tsuchiya H. Learning curve cost analysis for model building of renewable energy in Japan. In: Wene CO, Voss A, Fried T, editors. Proceedings IEA Workshop on Experience Curve for Policy Making—the Case of Energy Technologies. Stuttgart, Germany; 1999, p.67–76.

[37] Solarbuzz, Marketbuzz Annual market report; 2012.

[38] Van Sark WGJHM. Introducing errors in progress ratios determined from experience curves. Technol Forecast Soc 2008; 75(3):405-415.

[39] Van Sark WGJHM, Alsema EA, Junginger HM, de Moor HHC, Schaeffer GJ. Accuracy of Progress Ratios Determined From Experience Curves: The Case of Crystalline Silicon Photovoltaic Module Technology Development. Prog. Photovolt: Res. Appl. 2008; 16:441–453.

[40] Williams RH Terzian G 1993 A benefit/cost analysis of accelerated development of photovoltaic technology PU/CEES Report No 281 Princeton University Princeton NJ.

[41] Yu CF. How to incorporate input price changes and scale effects into the learning curve? A PV case study. PhD Thesis, Utrecht University; 2008.

[42] Yu CF, van Sark WGJHM, Alsema EA. Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects. Renew Sust Energ Rev 2011; 15:324–337.

Annex A

Data sources

We use multiple data sources which are listed below.

(1) Cumulative output and Average prices:

- 1990-2001: Report PM-52, Five-Year Market Forecast 2002-2007, Strategies Unlimited, 2003 (through [41]).
- 2002-2005: Swanson, Progress in Photovoltaics, 2006 (through [41]).
- 2006: Photon International magazine (through [41]).
- 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 [41] 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 [41]
- 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. [8]. A patent family is the set of patents granted in different countries for the same innovation. Therefore one patent family represent one innovation. We use an annual depreciation rate of 10% to account for technology obsolescence, but no lag since we use patent and not R&D expenditure. The patent data set comes from the European Patent Office website (http://www.epo.org/)

Annex B

Assumptions for the LCOE simulation:

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

Performance ratio = 0.75

Lifetime: from 25 years in 2011 to 35 in 2020

Operation and maintenance costs: 6% of system cost

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

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

How do solar photovoltaic feed-in tariffs interact with solar panel and silicon prices? An empirical study[2]

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Abstract

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

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

[2] The authors gratefully acknowledge the financial support of the French Energy Council (Conseil Français de l'Energie)

Introduction

Preferential feed-in tariffs (FITs, hereafter) for solar-generated electricity are the most common policy tools to stimulate the installation of solar photovoltaic generation capacities, particularly in Europe and Japan, but also in a growing number of emerging economies such as China and India[3]. They consist of administratively-set guaranteed prices at which the grid operator has the obligation to buy electricity from solar energy sources. Solar PV is offered a higher price than that of other power sources, reflecting higher costs. Differences can be very substantial, even with other renewables like wind energy. For example, the FIT in Germany for rooftop mounted installations was about 24 €-ct/kWh in 2012, compared to less than 9 ct for onshore wind. This price premium is financed by the consumers' electricity bill.

A straightforward consequence of FITs is to stimulate the demand for photovoltaic systems and services. The economic law of supply and demand then predict that this will increase the price on these upstream markets, at least in the short run. Things get more complicated in the long run for installations generate learning-by-doing and cost reductions which can reduce prices. If competition is not fierce enough, FITs can then generate rents for the producers of PV systems and/or for the companies installing those systems. Obviously, the regulators in charge of setting the level of the tariffs seek to avoid such windfall profits by keeping FITs as close as possible to the cost of solar-generated electricity, but this is not an easy task for they are not perfectly informed about production and installation costs.

This paper seeks to participate in a better understanding of the impact of FITs on the PV price dynamics. We focus on the interactions between the FITS and two upstream markets: the market of photovoltaic panels and the market of polysilicon. Using time series of FITs, panel and polysilicon prices, we primarily seek to test whether FITs drive panel price increase, or the reverse, meaning that

[3] A notable exception is the US in which 29 states have opted instead for the use of Renewable Portfolio Standards (RPS). RPS are mandates requiring each utility to have a minimum percentage of power that is sold or produced be provided by renewable energy sources. That is, they prescribe a quantity, not a price as in the case of FIT

the regulators are able to adjust the level of FITs in order to minimize rents. The analysis takes into account the role of polysilicon for this is the main material input for the production of panels – the polysilicon shortage before 2009 shows that its price significantly influences the panel price, and experience.

From a methodological point of view, 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.

The understanding by policy makers of how they influence panel price is critical for several reasons. To begin with, the problem is of significant economic importance as panel prices represent about forty percent of the overall cost of PV electricity. Then the fact that FITs potentially induce a transfer from the consumers who finance the FITs to panel producers becomes extremely sensitive in certain industrialized countries as many PV panels are now produced in China. High rents can also induce market overheating which is costly and often followed by drastic cuts harming the whole industry as illustrated by the French or Spanish cases. Last, the potential increase of panel prices reduces the effectiveness of FITs as it increases the overall cost of PV systems.

A price is made of a 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. The drivers of profit margin - the difference between price and cost - are more market based elements, such as competition, demand and supply balance, strategic behaviours, etc. A substantial amount of literature focuses on the analysis and prediction of the cost of solar PV modules and systems relying on various methodologies: econometric estimation of learning curves (Yu et al., 2011; Poponi, 2003), expert elicitation surveys (Bosetti et al., 2012), or engineering studies (Nemet, 2006; Branker et al., 2011).

To the best of our knowledge, there does not exist any academic work on pricing issues, and more specifically on the interactions between FITs and panel prices although market effects are often mentioned in the grey literature. 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.

We give in the paper descriptive statistics which show that FITs changes and module price evolution are strongly correlated. However, econometric analysis shows that the direction of causality is from panel price to FITs since 2009, and not the reverse. This result suggests that regulators were able to adjust tariffs to module price, thereby limiting the rent of panel manufacturers. This is in line with the observation of fierce competition prevailing in the module manufacturing market which helps bridging the gap between cost and price. We also study the very short-term effects of a FIT change and show that module price increases before a FIT reduction, as a consequence of firms’ anticipations. But this effect is temporary.

The remaining of the paper is structured as follows: Section two introduces the analytical framework and the hypothesis that are tested later on. The 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.

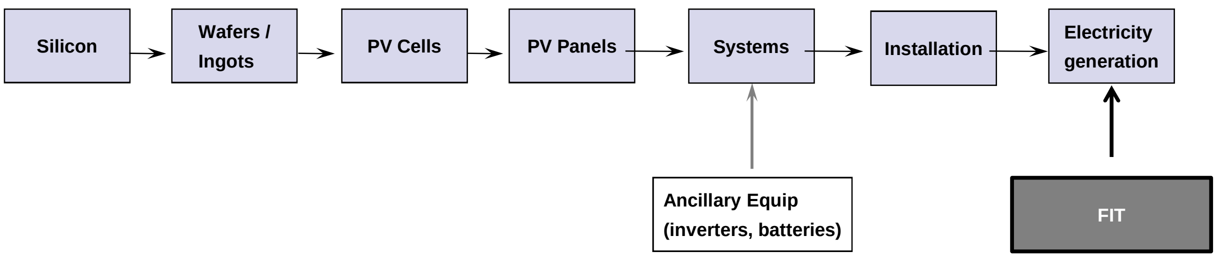
Background and tested assumptions

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

The production of polysilicon is a key step for 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. It is a commodity: Once silicon exceeds the minimum purity level of 999.999%, not much product differentiation can be achieved. Firms producing them compete on price. The intensity of competition is however strongly influenced by production capacity, which is constrained since it takes two years to build a production plant. To illustrate this point, silicon shortage gave much market power to silicon producers during this pre-2009 period, leading to dramatic price increase. Since then, overcapacity prevails so that the price is much lower. We come back on the evolution of the silicon market below.

To a large extent, crystalline PV panels are also commodities, but its supply is 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.

Figure 1: Crystalline photovoltaic production chain



Source: de la Tour et al. (2011)

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

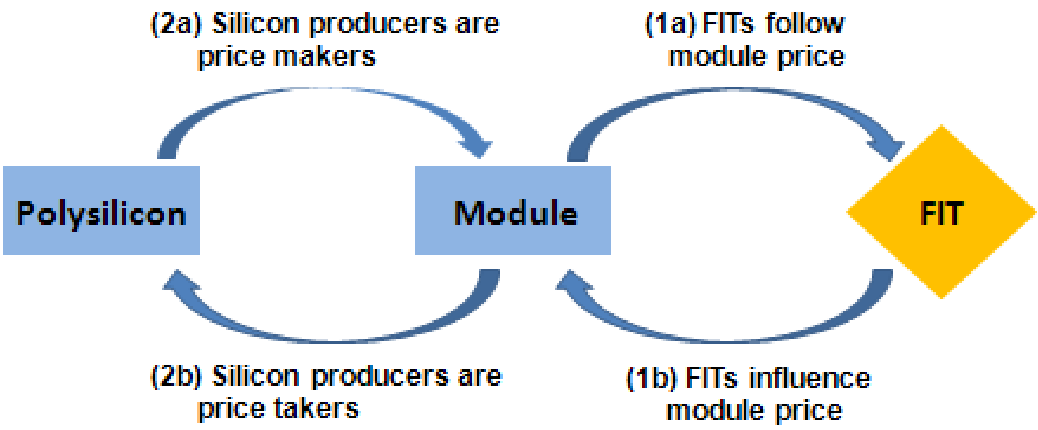
Hypothesis 1a: FITs follow module price, avoiding the creation of a rent in the downstream segments of the industry, PV systems installation and electricity production.

Hypothesis 1b: FITs influence module price, a higher FIT leading to increasing module prices and creating a rent in the cell and module production segments. It is just the opposite of Hypothesis 1a.

Hypothesis 2a: Silicon producers are price makers. They can integrate silicon price increase in module price. This implies that silicon price should be used as an exogenous variable in models predicting module price.

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

Figure 2**: Our four hypotheses**



Descriptive statistics

The hypothesis formulated in the preceding section are tested with a dataset of weekly silicon and module spot prices from PV Insight[4], and FITs values in Germany, Italy, France, and Spain (various sources, listed in annex 1). The time series start in January 2005 and end in May 2012.

As table 1 indicates, silicon and module price have been very unstable during the period considered, with a standard deviation of 75% of the mean for silicon price, and 38% for module price. This is illustrated by figure 3 representing silicon and module price 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.

[4] http://pvinsights.com/

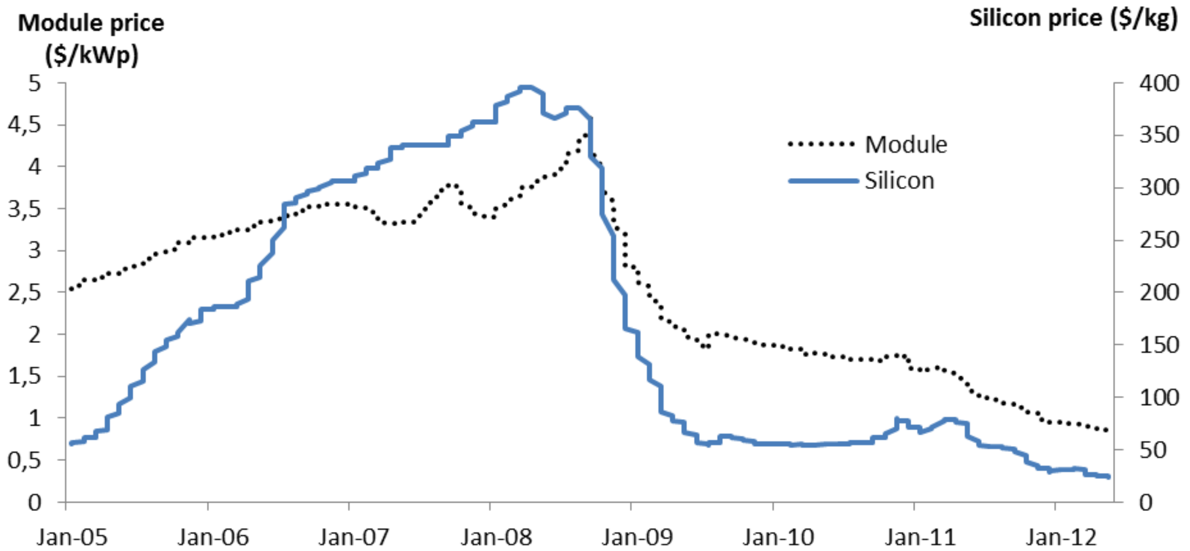
As shows the synchronised price increase of respectively silicon and module price between 2005 and 2008 (c.f. figure 3), silicon and module price are highly correlated (the correlation coefficient is 0.91). However, the price increase is much lower for modules (40%) compared to silicon (607%). Two facts explain this observation: First, silicon price represents only 20% of a module's total cost[5]. 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).

The high correlation between silicon and module price does not allow identifying the direction of the causality between the two variables, that is, which of the hypotheses 2a and 2b holds true.

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

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

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



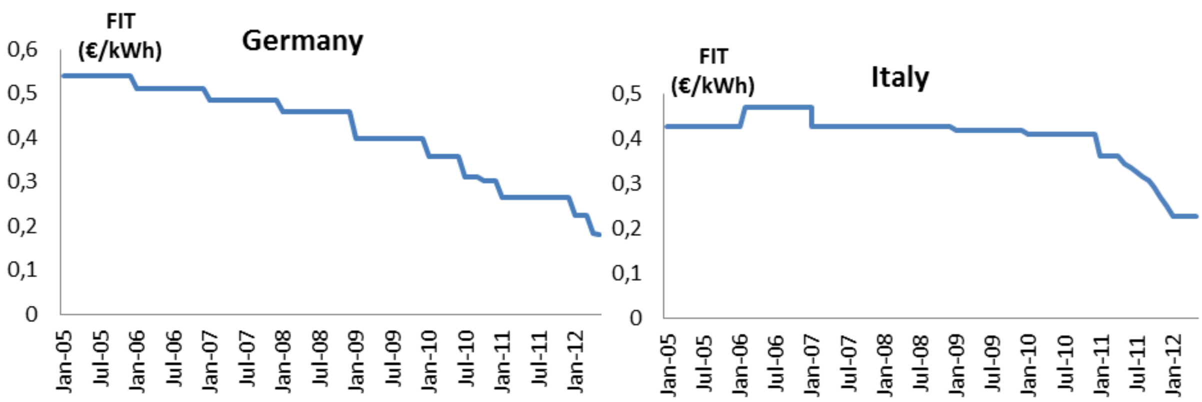
[5] Source: Photon consulting annual report 2012, p. 154.

Turning next to feed-in tariffs, we collected weekly values of FITs in Germany, Italy, Spain, and France from 2005 to may 2012. 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. The four countries included in the study covers more than 60% of the global market over the whole period.

Since for each country, there are different tariffs corresponding to various type 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.

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. 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.

Figure 4 Average FIT evolution in the main countries



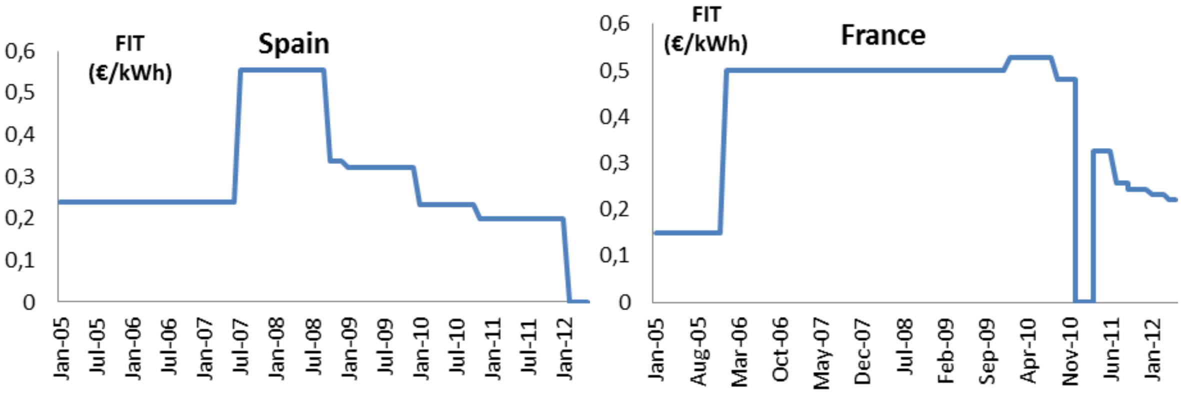


Table 2 Correlation table of module price and countries FITs

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

How does the evolution of panel price compare to that of the FITs implemented in the various countries? The comparison is not straightforward as the two variables are not expressed in the same unit: FITs correspond to the price of a quantity of electricity (in \$/kWh), while module price corresponds to the price of a production capacity (in \$/kWp[6]). To allow comparison, we convert the module price into the net present value of the electricity generated over its lifetime by a module of a standard capacity of 1kWp and sold at this FIT. The net present value of the electricity generated by the module in country *i* is given by the usual formula:

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

where $FIT_{i,t}$ is the feed-in tariff in country *i* at time *t*. *T* is the lifetime of the PV system, *r* is the discount rate. The product $PR * ASI_i$ is the electricity produced each year in country i by the PV system, with PR, the Performance Ratio of the installation (the ratio of the actual and theoretically

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

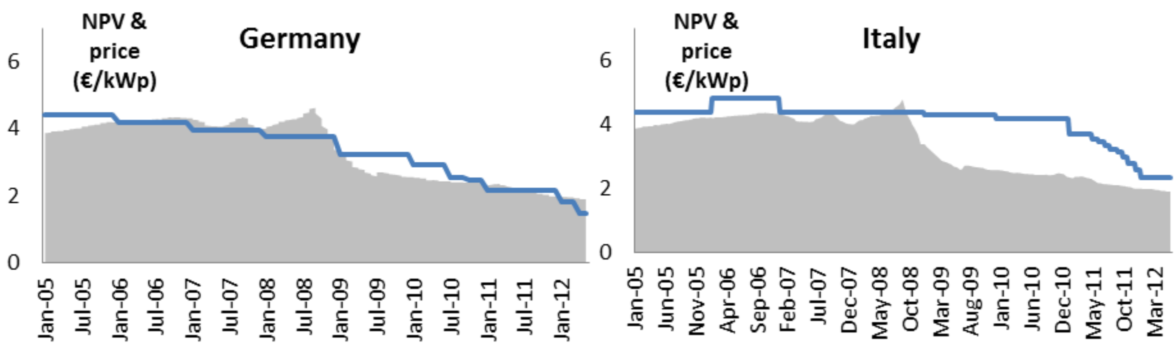
possible energy output) and, *ASI*, the Annual Solar Irradiation (the sum of the quantity of solar energy reaching the installation over a year) which is country-specific.

We take the following values for the different parameters: a discount rate of 10%, a lifetime of 25 years, a performance ratio of 0.75. The ASI is assumed to be 1200 kWh/kWp/year for Germany, 1500 for Italy, 1700 for Spain, and 1350 for France[7].

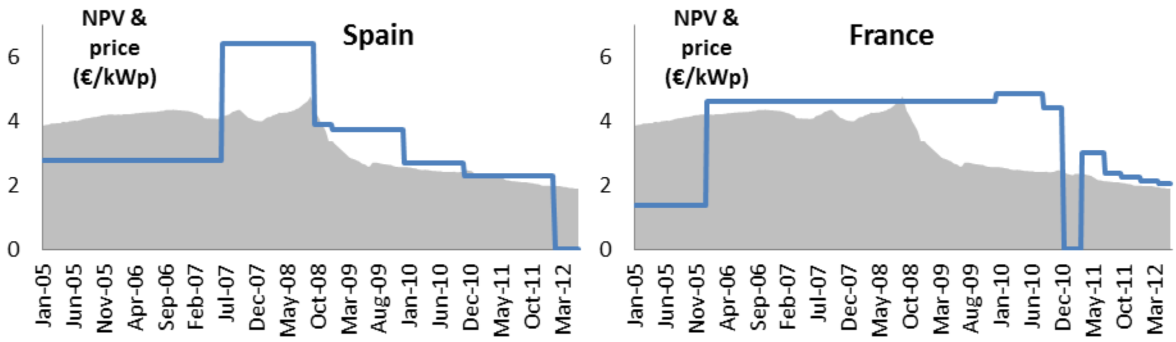
The net present value of electricity given by equation (1) needs to be compared to the price of the whole PV system, in which panel price represent about 40% in 2011 (Photon Consulting, 2012). To get the price of a PV system, we add to module price the price of other components: inverter, wire, mounting 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).

For each country, figure 5 compares the cost of a PV system (the shaded area) with the net present values of the electricity produced by a PV system sold at the national FIT. It shows that the German FIT follows PV system price the most closely, while important gaps in 2007/2008 in Spain and 2009/2010 in France explain the corresponding uncontrolled developments of the PV market, followed by sharp FIT cuts or moratorium. A significant gap 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 which are not taken into account here further increase the attractiveness of PV systems.

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)



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



Econometric methodology

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

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

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

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

where $module_t$ is module price at time *t*. cum_prod_t is the cumulative PV module production at the same date[8]. t_o is an arbitrarily chosen reference date. *E* is the experience parameter, measuring the intensity of the learning by doing process. Equation (2) is usually estimated econometrically. In this paper, we use an experience parameter of 0.338, corresponding to a learning rate[9] of 20.1%, which has been estimated in the study by de la Tour et al. (2013) who used the same data.

Using data on cumulative production[10], we are able to predict the value of $module_{t_0}$, which is the module price equivalent to $module_t$ if no learning would have happened since t_0. We denote $module_t^0$, the corresponding predicted value.

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

$$FIT_t = \sum_i FIT_{i,t} * elec_{i,t} \quad (3)$$

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

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

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

In this equation, $D.Y_t$ is the vector of the first order derivatives of the three price variables which are logged: $\ln(module_t^0)$, $\ln(silicon_t)$, and $\ln(FIT_t)$. γ_j is the vector of parameters to

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[8] 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).

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

[10] Photon consulting annual reports

be estimated and $\mathbf{E}_i$ is the vector of error terms, assumed to be independent and identically distributed.

The estimation is done by running a separate regression for each variable, regressing it on lags of itself and all other variables with ordinary least squares. 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 $\ln(silicon_t)$ (see annex 2). We therefore run the regressions of the VAR models on two periods: before and after 24/09/2009. The first period corresponds to the silicon shortage, while the second period starts after this event. The optimal lags are found by maximizing the AIC information criterion; 2 weeks during the silicon shortage, and 3 weeks after.

Results

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

Consider first causality between silicon and module price. There is a switch at the end of the silicon shortage period. During the silicon shortage period, silicon price causes module price (hypothesis 2b), while after the end of the shortage, it is the opposite (hypothesis 2a). These results are completely in line with economic theory which says that, in commodity markets, producers only have market power in case of production undercapacity. The 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).

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

Looking at figure 4 helps understand why module price causes FITs after 2009 but not before. Before 2009, FITs were very stable, modified only once a year in Germany, and even less frequently in other countries. Besides, their level was set well in advance, sometimes years ahead[11]. FITs were thus very rigid, explaining why they couldn't follow module price closely. On the contrary, after 2009, FITs became much more flexible, which 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 track module price more closely in the recent years should then be interpreted as a consequence of a modification of the FITs schemes.

Table 3 Granger causality test during the silicon shortage

Dependent variable	Excluded	chi2	df	Prob > chi2
$\ln(module_t^0)$	$\ln(silicon_t)$	22.48	2	0.000
	$\ln(FIT_t)$	0.120	2	0.942
	ALL	22.76	4	0.000
$\ln(silicon_t)$	$\ln(module_t^0)$	1.373	2	0.503
	$\ln(FIT_t)$	0.078	2	0.962
	ALL	1.468	4	0.832
$\ln(FIT_t)$	$\ln(module_t^0)$	0.724	2	0.696
	$\ln(silicon_t)$	4.288	2	0.117
	ALL	7.046	4	0.133

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

Table 4 Granger causality test after the silicon shortage

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

Anticipations of feed-in tariffs change

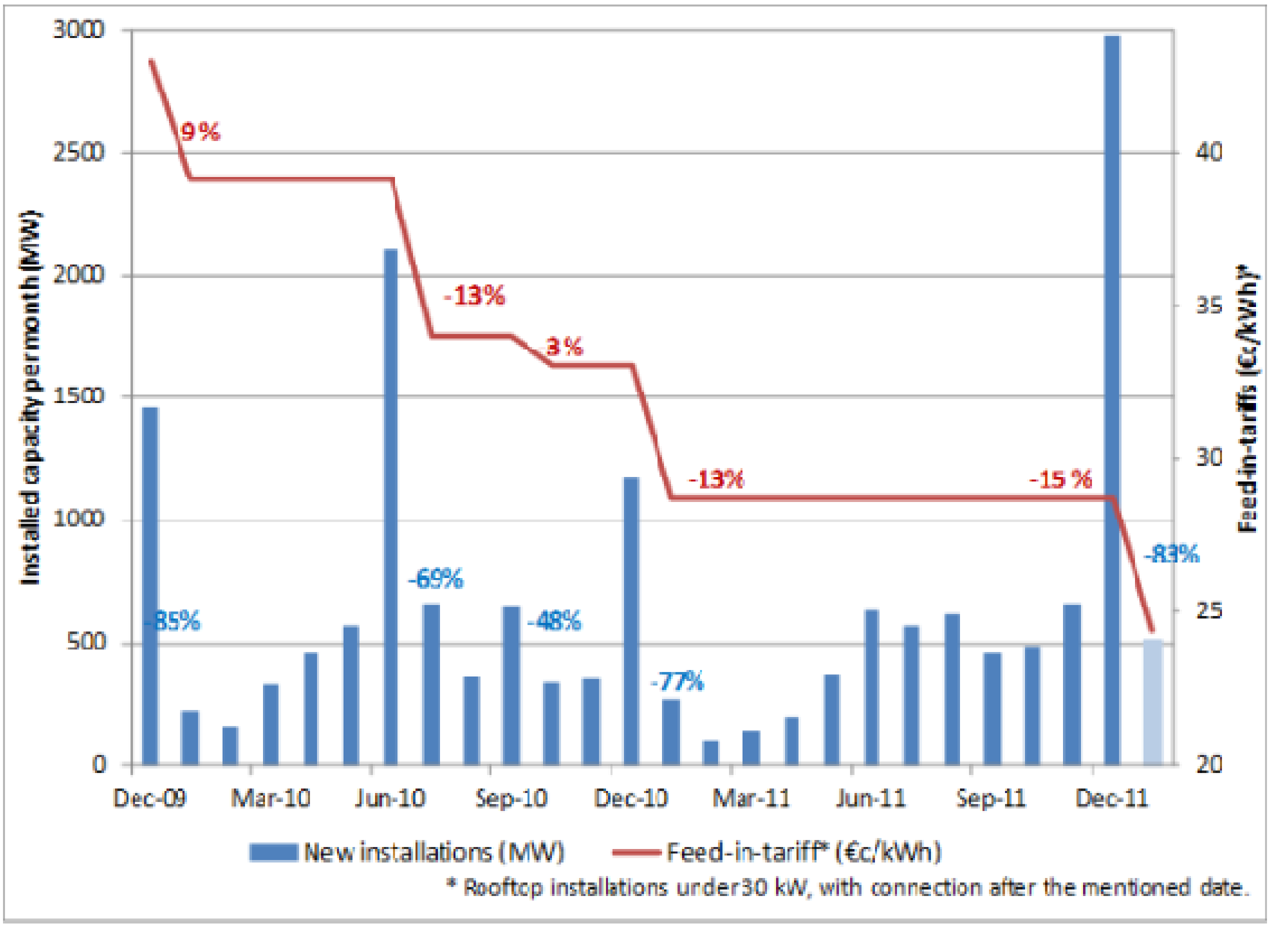
VAR models use past values as explanatory variables, while FITs are announced, and therefore anticipated, months or even years ahead. We go further in the analysis of FITs effect on module price in this section, by analysing the effect of *future* FIT changes on module price. Our approach consists in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

While figure 6 describes the impact of anticipations on quantities, what about the impact on module prices? To answer this question, we build a difference-in-difference indicator to measure short-term price variations: the variable $deviation_t$ is the deviation of the first order derivative[12] of module price compared to a business as usual (BAU) scenario at date *t*:

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

If $deviation_t$ is positive, it means that module price increased in week *t* more than what the BAU scenario predicted.

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



Source: Enerdata, from German Ministry for Environment, SolarWirtshaft

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

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

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

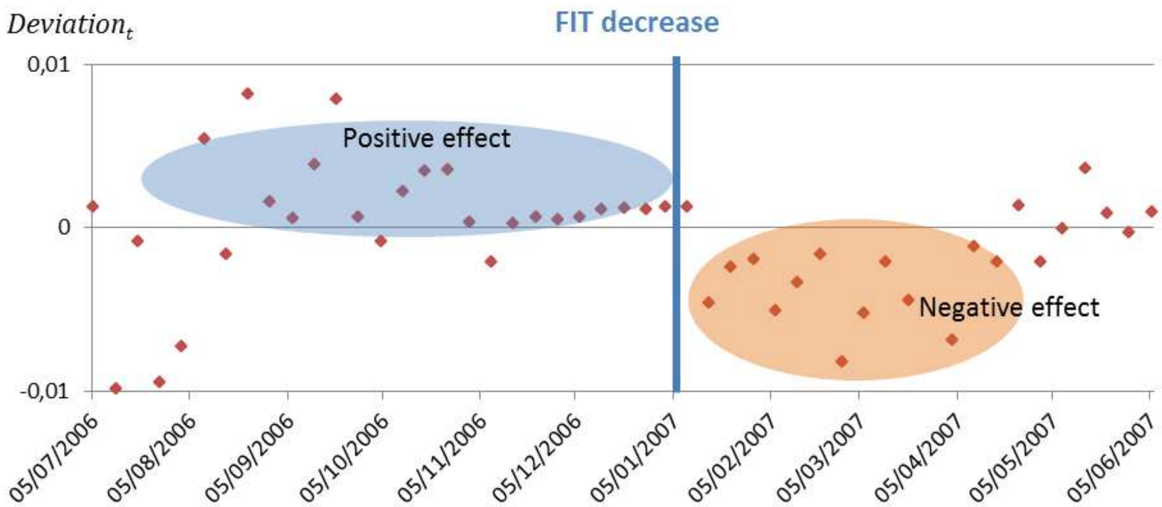
The length of the lag of silicon price used is two weeks as found in section 4.4. After the silicon shortage, the BAU price is assumed constant:

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

Regression results of (6) and (7) are relegated in appendix.

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

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



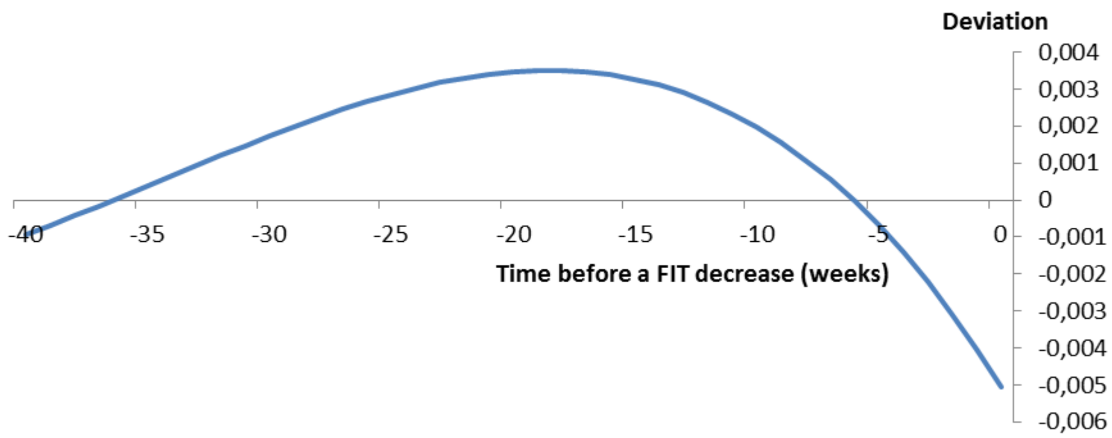
In order to go further in the understanding of the dynamic effect of a FIT decrease on module price, we now estimate a polynomial growth model. It explains the deviation of module price by a polynomial function of the time before the following FIT decrease. The regression equation is:

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

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

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

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



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

Conclusion

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

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

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

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

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

Annex

A1 Sources for FIT values

IEA

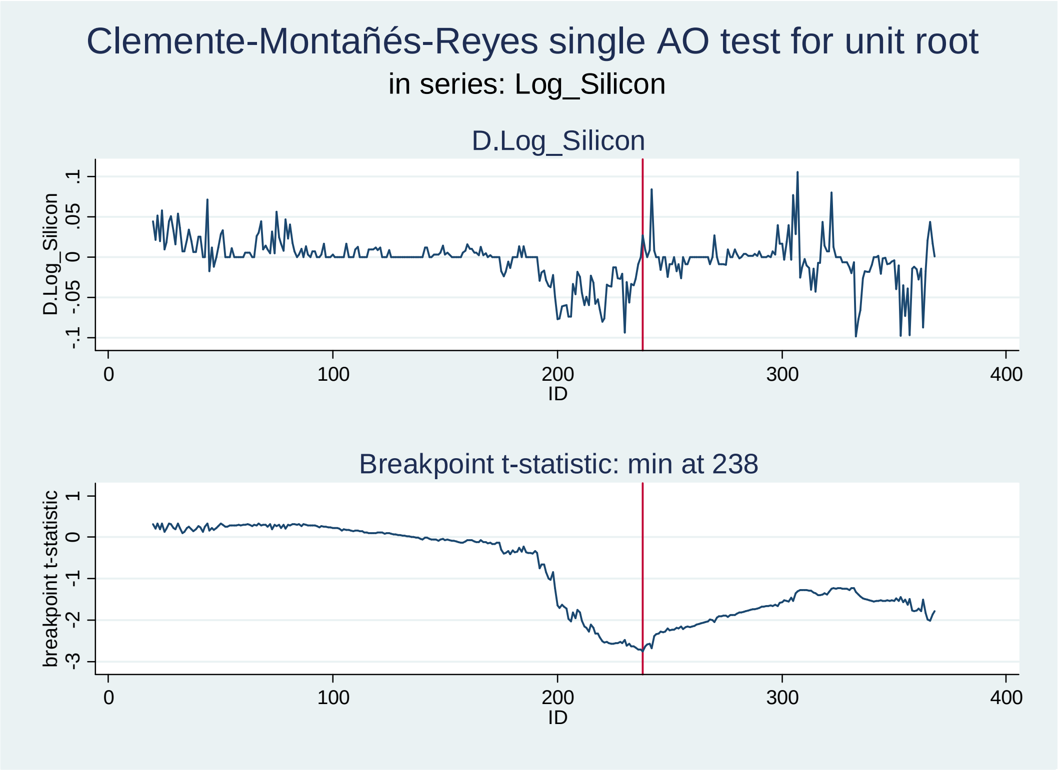
Solar Feed In Tariff website (http://www.solarfeedintariff.net)

PV Magazine

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

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

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



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

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

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

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

A4 Regression results of the polynomial growth model (8)

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

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

Bibliography

Abell, D.F. and Hammond, J.S. (1979), "Cost Dynamics: Scale and Experience Effects", in: *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.

Berndt ER. (1991) The Practice of Econometrics: Classical and Contemporary. Reading, MA, U.S.A.: Addison-Wesley; 1991.

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

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

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.

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.

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

De La Tour, A., Glachant, M., and Ménière, Y., 2013, What cost for photovoltaic modules untill 2012? Lessons from experience curves model, 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 (2011), Solar Photovoltaics competing in the energy sector – On the road to competitiveness, 8th European PV Industry Summit, during the 26th EU PVSEC, September 2011.

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

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

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.

Gruber, 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*

Hayward, J., and Graham, P., 2011. Developments in technology cost drivers dynamics of technological change and market forces, Garnaut Climate Change Review, March.

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

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

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

IEA (2010), Technology Roadmap – Photovoltaic Solar Energy

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 modeling: 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

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

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

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

Paul D. Maycock. 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

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)

Photex databese

Photon Consulting (2012): Solar Annual 2012:“The next wave”

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

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

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

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

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.

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.

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

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

Yu, C.F, van Sark, W.G.J.H.M., Alsema, E.A., 2011. Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects, *Renewable and Sustainable Energy Reviews* 15 (2011) 324–337

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

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[i] See for example Dutton and Thomas [10] who study the results of 108 experience curves in 22 industrial sectors

[ii] Note that public policies are justified because a share of these cost reductions are external in the sense that they do not benefit only the companies which install these capacities due to learning spillovers [14]. As a result the private return of installing PV panels is less than their social return.

[iii] To overcome this issue, Ferioli et al. [13] propose to consider overall costs as the sum of cost dynamics for individual subsystems.

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

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

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

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

[viii] The VIF for silver price is 5.95.

[ix] [30, p. 149] for prediction until 2015. Predictions from 2016 to 2020 have been made using the same trend in the CAGR.

[x] [37, p. 254] for prediction until 2016. Predictions from 2017 to 2020 have been made using the same trend in the CAGR.

[xi] See [12]. Predictions from 2017 to 2020 have been made following the same trend in the CAGR.

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

[xiii] Source: [2].

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

[xv] Source: [30, p. 84].

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