Public Policies and Solar PV Innovation: An Empirical Study Based on Patent Data[*]

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Abstract

The objective of this paper is to examine the innovation impacts of different renewable energy support policies and their interaction in the empirical context of solar photovoltaic (PV) technology. This is achieved using data on patent applications for 13 countries over the time period 1978-2008. Three policies are included in the analysis: public R&D support to solar PV, fixed feed-in tariffs (FIT), and renewable energy certificate (REC) schemes. The results are overall robust to alternative model specifications, and indicate that: (a) both FIT schemes and REC schemes induce more solar PV patenting activity even though the impact of the former policy appears to be more profound; (b) (lagged) public R&D support has an important impact on solar PV innovation; and (c) policy interaction exists in that the impact of public R&D support on innovation is greater at the margin if it is accompanied by the use of FIT schemes for solar PV. A corresponding interaction effect does not emerge in the case of public R&D and the use of REC schemes, possibly due to the relatively strong technology selection pressure under the latter policy.

Keywords: innovation; patents; solar PV; renewable energy policy; policy interaction.

JEL classifications: O34; O38; Q55; Q58.

1. Introduction

1.1 Background and Contribution

Given the need to limit the increase in global average temperatures to avoid unacceptable impacts on the climate system, the development of low-carbon energy technology such as solar energy and wind power has been a policy priority in many countries. In liberalized energy markets the circumstances can often be unfavorable for renewable energy sources; at present these are typically relatively more expensive than the incumbent technologies and especially if the price of carbon dioxide emissions is low. Moreover, there may also be path dependency in the direction of technological change that locks the economy into the use of fossil fuel-based energy technology (Acemoglu et al., 2012). For the above reasons there is a need to understand more closely the process of technological innovation in the renewable energy sector, and the ways in which different public policies can be used to promote this process.

The empirical research linking energy and environmental policy and innovation constitutes a growing literature stream, and overall the results from such studies indicate a positive effect of public policy on innovation (e.g., Brunnermeier and Cohen, 2003; Lanjouw and Mody, 1996; Noailly and Batrakova, 2010; Popp, 2002). Previous research specifically addressing policy-induced innovation in the renewable energy sector is scarcer, and some of it is based mainly on qualitative and/or theoretical analysis (e.g., Menanteau et al., 2003; Foxon et al., 2005; Sagar and Zwaan, 2006; Fischer and Newell, 2008). A number of recent empirical studies using quantitative data investigate technological change in the energy sector, and the role of energy prices and policy. For instance, Lanzi and Sue Wing (2011) find a positive relationship between energy prices and innovation in the renewable energy sector. This result is confirmed in Verdolini and Galeotti (2011) who address the innovation impacts of energy prices on different types of energy technologies while also accounting for the influence of international knowledge spillovers. Other important quantitative studies addressing renewable energy innovation include Karmarkar-Deshmukh and Pray (2009), Rübbelke and Weiss (2011), Walz et al. (2008), Noailly and Smeets (2012), and Nesta et al. (2014). Many of the published studies, though, employ aggregate data for the renewable energy technology sector, and therefore tend to downplay the heterogeneous nature of this sector. For instance, some technologies are technically and commercially relatively mature (e.g., wind power, hydro-power etc.) while others, such as solar photovoltaic (PV), are less developed but may nevertheless show great future potentials. This suggests in turn the existence of differential policy impacts across various types of technologies.

This paper addresses the relationship between public policy support to renewable energy and innovation in the specific empirical context of solar PV, and it considers the specific policies targeting solar PV development in 13 different countries since the late 1970s. These policies include public R&D support to solar PV as well as two different types of production support schemes: feed-in tariffs (FIT) and renewable energy certificates (REC). A FIT scheme is a price-based support in which the producers of renewable electricity sell at a pre-set (guaranteed) price per kWh generated over a given time period (e.g., Couture and Gagnon, 2010). The price levels are typically differentiated with respect to the technology supported. A REC scheme involves an obligation for retailers to purchase a predetermined amount (in MWh) of renewable electricity. Each MWh of renewable electricity produced in power plants eligible for certificates yields one certificate that can be sold. In this way a market for the certificates is established, where the price of these equals the premium revenue (per MWh) that renewable electricity producers must receive to fulfill the obligation. The REC schemes seldom include separate targets for different types of renewable energy technologies; instead they promote direct competition between the different energy sources (e.g., IEA, 2004, 2012a, 2012b). By focusing on the above policies we acknowledge that innovation may be induced both through basic knowledge generation resulting from public R&D, and learning-by-doing (e.g., tacit knowledge acquired during manufacturing). The latter is induced by the FIT and REC schemes, which support renewable energy technology diffusion. Moreover, the innovation impacts of these diffusion-promoting policies may vary due to differences in design (e.g., targeting single versus multiple technologies).

The only published cross-country analysis specifically investigating in detail the differential relationships between renewable energy policies and innovation (measured through patent application counts) is the frequently cited work by Johnstone et al. (2010). The results of this study support the notion that FIT and REC schemes could have different impacts on innovation, and the authors report that only the FIT schemes induce innovation in solar energy technology, while the REC schemes instead appear to favor innovation in more mature technologies (e.g., wind power). The present paper draws on this important work, but it also develops the analysis of Johnstone et al. (2010) in a number of important respects.

First, Johnstone et al. (2010) focus on solar energy as an aggregate, thus addressing also solar thermal innovation (e.g., innovations in residential solar thermal systems applied for heating and cooling). At first glance our sole focus on solar PV may appear like a marginal research contribution, but it permits us to establish a more valid link to the two renewable electricity support schemes (both focusing on electricity generation), as well as to the targeted public R&D efforts. In fact, our empirical results shed some new light on the differential impacts of FIT and REC schemes, respectively (see section 4). Second, in contrast to Johnstone et al. (2010), we provide a more detailed assessment of the role of public

R&D support by addressing different ways of measuring such policy schemes. Our analysis considers both the role of direct R&D expenditures (with lagged impacts), as well as a specification in which the public R&D expenditures instead add to a knowledge stock with a time lag.

Third and finally, no previous econometric study (including Johnstone et al., 2010) devote specific attention to the potential interactions between public R&D efforts on the one hand and policy support leading to the diffusion of renewable energy technologies on the other. While the existing theoretical and qualitative literature acknowledges the importance of both R&D and learning-by-doing for innovation outcomes (see also section 2.1), the often frequent iterations between learning and R&D are typically ignored in quantitative work. Specifically, learning-by-doing may induce more R&D and raise the rate-of-return on basic research.[1] In the present paper we therefore explicitly test whether the (marginal) impacts of public R&D on solar PV innovation differ depending on the presence of FIT and REC schemes, respectively.

1.2 Purpose and Overall Approach

Following the above, the specific purpose of this paper is to investigate the differential impacts of various types of renewable energy support policies on technical innovation in solar PV technology. In doing this we address the roles of public R&D expenditures, FIT schemes and REC schemes, as well as the interaction between public R&D on the one hand and the two renewable energy production support schemes on the other. Technical innovation is measured by the use of counts of patent applications filed under the so-called Patent Cooperation Treaty (PCT), which can be disaggregated to specific technological areas, including solar PV.

The empirical analysis builds on a detailed panel data set of 13 countries over the time period 1978-2008. We specify reduced form negative binomial (NB) regression models in which the dependent variable, patent application counts, are explained by the stringency of the different renewable energy policies, their interaction as well as a selection of control variables (see further section 2.2). Based on the estimation results we calculate elasticities of patenting activity with respect to (marginal) changes in the independent variables, thus permitting us to comment on important differential effects of the respective policies and policy interactions.

Specifically, in the empirical section of the paper we: (a) reexamine the often made claim that FIT schemes are more innovation-promoting than REC schemes in the renewable energy sector (e.g., del Río and Bleda, 2012; Johnstone et al., 2010); (b) investigate whether R&D support induces more solar PV innovation than support to technology diffusion through FIT and REC schemes; and (c) test the null hypothesis that a marginal increase in public R&D expenditures to solar PV will have the same impact on patenting activity regardless of whether either FIT or REC schemes are in use or not. Sensitivity analyses are conducted to check the robustness of the results.

1.3 The Case of Solar PV

Solar energy is a very promising renewable energy source (de Vries et al., 2007); the solar energy reaching Earth during a single hour roughly corresponds to the amount of energy used by all human activities during one year (IEA, 2010). Our sole focus on solar PV permits the use of clean patent categories (see further section 3.1), thus avoiding innovations in non-electric solar systems applied for residential heating and cooling and therefore facilitating the matching with relevant policy instruments.[2]

During more than a decade solar PV has been the fastest growing renewable energy technology in terms of installed capacity (Kirkegaard et al., 2010). The global PV market has grown by an average rate of 40 percent each year and in 2008, the global cumulative installed PV capacity reached 14 GW (IEA, 2010). According to EPIA (2011), the bulk of this capacity is distributed among the following countries: Germany (with a 36 % market share), Spain (23 %), Japan (15 %), USA (8 %), Italy (3 %), Korea (2 %), France (1 %), and China (1 %).[3] Solar PV systems can either be grid-connected or stand-alone (off-grid) systems and in 2009, about 85 percent of the global PV capacity was grid-connected (REN21, 2010). This capacity can be installed on private estates and business buildings, but it can also be installed on the ground for large scale applications.

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[1] This is also evident in the literature specifying so-called two-factor learning curves for different renewable energy technologies (e.g., Klaassen et al., 2005; Ek and Söderholm, 2010), and in which public R&D (learning-by-searching) and learning-by-doing are treated as variables independent of each other.

[2] Solar thermal technology also includes electric systems, i.e., concentrating solar power (CSP) (Bradford, 2006; Timilsina et al., 2011). However, although CSP is also primarily used for electricity generation, the global installed capacity is only a fraction of that of solar PV (Braun et al., 2011).

[3] Our data sample (see section 3) includes countries with both high and low shares of the globally installed PV capacity.

Kirkegaard et al. (2010) argue that the increases in global solar PV capacity can largely be attributed to the implementation of domestic policy support schemes. FIT schemes, REC schemes and public R&D support have all been used to stimulate solar PV market growth (Timilsina et al., 2011; Campoccia et al., 2009; Dusonchet and Telaretti, 2010; IEA, 2004). The FIT schemes, it is frequently asserted, have played a particularly important role since they guarantee a specific remuneration for certain time periods and the support levels (per kWh) often have been based on technology-specific generation costs (Mendonça, 2007; Fouquet and Johansson, 2008; Langniss et al., 2009; Klein et al., 2010). In contrast, in all of the sample countries using REC schemes, the remuneration varies over the years due to demand and supply changes in the certificate market. Usually in a REC scheme, all renewable energy technologies compete and receive the same level of support (per kWh) (Campoccia et al., 2009; IEA, 2004, 2012a, 2012b). In brief, the solar PV case is motivated both because it is a very promising renewable energy technology and because of variations in the use and the stringency of policy support across countries over time.

1.4 Outline of Paper

In the next section we briefly present some key theoretical underpinnings of the empirical analysis, discuss the pros and cons of patent data as innovation proxies, and outline the model specifications as well as the related econometric issues. Section 3 presents the relevant data sources and definitions, while section 4 displays the empirical results and discusses the key implications of these. In section 5 we outline some final concluding remarks, and provide some suggestions for future research.

2. Methodological Approach and Model Estimation Issues

2.1 Endogenous Technological Change and Patenting Activity

During the last decades, the economics literature on environmental policy and innovation has devoted increased attention to the role of endogenous technological change and innovation (e.g., Gillingham et al., 2008). This implies explicitly addressing the feedback mechanisms by which market signals and policy may change the direction of technological change towards cleaner (e.g., carbon-free) technology.[4] The literature suggests that public policy may induce innovation in a number of ways, and large scale models investigating the interrelationship between the energy system, the climate and the economy typically rely on one of two main channels of policy-induced innovation. The first channel is through learning-by-doing in the sense that performance improves as capacity and production expands (e.g., Grubb et al., 2002). In the second case endogenous technological change is instead introduced by assuming that technical progress is the result of past investments in R&D and the ensuing accumulation of a knowledge stock (e.g., Sue Wing, 2006; Löschel, 2002).

Public policies in the renewable energy sector comprise both diffusion-promoting production support (e.g., feed-in tariff (FIT) and renewable energy certificate (REC) schemes) as well as R&D efforts. However, these two policy approaches may also interact in important ways. The innovation process is typically complex, non-linear and highly iterative (e.g., Foray, 2009). For instance, the introduction of new technology will affect future innovations (the re-development of a technology) through learning and vice versa. R&D programs that are entirely designed in isolation from practical applications could therefore be less effective (Arrow et al., 2009). Hendry et al. (2010) provide empirical examples of R&D-learning iterations in the solar photovoltaic (PV) and wind power sectors, e.g., the diffusion of new technology leads to learning that in itself may raise the rate-of-return of additional R&D. Thus, while innovation may be induced directly through the use of single policy instruments, we must also acknowledge the interaction between different types of policies (e.g., production support schemes focusing on demand-driven innovation versus R&D policies addressing technological opportunities).

In this paper we investigate the role of different public policies – and their interaction – in solar PV innovation activities. The analysis adopts the same approach as many other studies (e.g., Lundmark and Bäckström, 2012; Rübbelke and Weiss, 2011; Johnstone et al., 2010), and employ patent counts as a measure of solar PV innovation. Compared to other commonly used innovation proxies, such as R&D expenditures, scientific personnel etc., patent counts are probably a more suitable indicator. One important reason for this is that patents are an output measure of innovation activity as opposed to, for instance, R&D expenditures that serve as inputs to such activities (Johnstone et al., 2010). In addition, patents have a close link to inventions, and each patent contains information about the applicant, the inventor and the invention which enable detailed statistical analysis (OECD, 2009). Still, using patent data as indicators of innovation has certain drawbacks, in particular since not all inventions are patented and that the value distribution of patents is highly

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[4] This notion dates back to Hicks (1932), who claimed that a change in the relative prices of two production factors will encourage innovations with the aim to economize on the use of the factor which have become relatively more expensive. See Popp (2002) and Newell et al. (1999) for empirical applications on the energy sector.

skewed (OECD, 2009; Schankerman, 1998). One should note, though, that significant fees are attached to the examination of a patent application (and to renewals if the patent is granted). So at least in the expectations of the applicant or the patent holder, the prospects for commercialization are favorable. In section 3.1 we discuss the relevant patent classes for solar PV as well as the corresponding data sources.

2.2 Model Specifications

The reliance on patent application data necessitates the use of so-called count data modeling. Count data models, using Poisson or negative binomial distributions, have been suggested for estimating the number of occurrences of an event, or event counts (e.g., Maddala, 1983; Cameron and Trivedi, 1998). An event count is defined as the realization of a non-negative integer-valued random variable. In our case, an event count corresponds to the number of solar PV patent applications for a given country and time period. We first specify the two following reduced form models, which do not address any policy interactions:

$$PCT_{i,t} = \beta_0 + \beta_1\left(FIT_{i,t}\right) + \beta_2\left(REC_{i,t}\right) + \beta_3\left(TOT_{i,t}\right) + \beta_4(TRIPS_t) + \quad\quad [1]$$
$$\beta_5\left(RDEXP_{i,t-x}\right) + \sum_{i=1}^{n-1}\beta_{5+i}D_i + \varepsilon_{i,t}$$

$$PCT_{i,t} = \beta_0 + \beta_1\left(FIT_{i,t}\right) + \beta_2\left(REC_{i,t}\right) + \beta_3\left(TOT_{i,t}\right) + \beta_4(TRIPS_t) + \quad\quad [2]$$
$$\beta_5\left(RDSTOCK_{i,t}\right) + \sum_{i=1}^{n-1}\beta_{5+i}D_i + \mu_{i,t}$$

where i indexes the cross-section unit (i.e., country) and t indexes time. *PCT* is the dependent variable and measures the total number (counts) of solar PV patent applications (see further section 3.1). These are assumed to depend on the stringency of the renewable energy support schemes (*FIT* and *REC*), as well as the role of public R&D support to solar PV.

In the empirical analysis we choose to test two ways of measuring the role of public R&D. The first specification (equation [1]) follows previous work (e.g., Johnstone et al., 2010), and assumes that solar PV patenting activity is influenced directly by annual public R&D expenditures although with a certain time lag (x). This variable is denoted *RDEXP*. In the second model specification (equation [2]) we assume instead that what matters for solar PV innovation is the build-up of a stock of knowledge over time. Hence, in this approach annual R&D expenditures add to this knowledge stock (*RDSTOCK*) with a time lag, and it is also assumed that knowledge depreciates over time at a certain rate. In section 3.2 the details of these variable specifications are presented.

The models outlined in equations [1]-[2] also include two control variables. In general, factors such as market conditions, scientific capacity and openness to trade will also affect the tendency to innovate (Jaumotte and Pain, 2005), and to address this overall propensity to patent we include the variable *TOT,* which represents all patent applications filed across the whole spectrum of technological areas. Moreover, the characteristics of intellectual property rights regimes may have a significant influence on the propensity to seek property rights protection rather than relying on some other means to protect intellectual property (e.g., industrial secrecy). For this reason the binary variable *TRIPS* is included to control for the so-called TRIPS agreement signed in 1994 regulating the trade related aspects of intellectual property rights. This agreement was signed by the WTO member countries, including all of the countries included in our sample, potentially making it easier and more meaningful for innovators to apply for patents (also in other countries). Finally, country-specific dummy variables (*D*) have been included in both model specifications to control for fixed effects attributed to unobserved factors such as regulatory framework etc. All residual variation in the two models is captured by the additive error terms ($\varepsilon_{i,t}$ and $\mu_{i,t}$).

In order to address the potential interaction between public R&D and the two different solar PV support schemes, we also consider two additional model specifications. Specifically, we multiply *RDEXP* with two discrete dummy variables indicating whether or not a FIT or a REC scheme, respectively, are in place for each country and time period. This gives us the following two model specifications, again differing with respect to the way in which public R&D support has been operationalized:

$$PCT_{i,t} = \beta_0 + \beta_1\left(FIT_{i,t}\right) + \beta_2\left(REC_{i,t}\right) + \beta_3\left(TOT_{i,t}\right) + \beta_4(TRIPS_t) + \quad\quad [3]$$
$$\beta_5\left(RDEXP_{i,t-x}\right) + \beta_6\left(EXPFIT_{i,t}\right) + \beta_7\left(EXPREC_{i,t}\right) + \sum_{i=1}^{n-1}\beta_{7+i}D_i + \pi_{i,t}$$

$$PCT_{i,t} = \beta_0 + \beta_1\left(FIT_{i,t}\right) + \beta_2\left(REC_{i,t}\right) + \beta_3\left(TOT_{i,t}\right) + \beta_4\left(TRIPS_t\right) + \qquad [4]$$

$$\beta_5\left(RDSTOCK_{i,t}\right) + \beta_6\left(EXPFIT_{i,t}\right) + \beta_7\left(EXPREC_{i,t}\right) + \sum_{i=1}^{n-1} \beta_{7+i}D_i + \phi_{i,t}$$

where the added interaction variables are denoted *EXPFIT* and *EXPREC*, respectively. These specifications can be used to test the null hypothesis that the impact of a marginal increase in public R&D support to solar PV has the same impact on patenting activity regardless of whether FIT and/or REC schemes are in place. Finally, $\pi_{i,t}$ and $\phi_{i,t}$ are additive error terms.

In brief, the empirical analysis is thus based on four model specifications, hereafter denoted S1-S4: (a) no policy interaction effects and public R&D support measured through lagged R&D expenditures (S1); (b) no interaction effects and public R&D support measured through an R&D-based knowledge stock (S2); (c) interaction effects and lagged R&D expenditures (S3); and (d) interaction effects and the R&D-based knowledge stock (S4).

2.3 Econometric Issues

Given a count nature of the dependent variable, negative binomial (NB) or Poisson estimators are generally used. According to Hilbe (2011), the Poisson model is however derived from a distribution that is equidispersed. Violation of this distributional assumption has similar qualitative consequences to violation of the assumption of homoscedasticity in the linear regression model (Cameron and Trivedi, 1998). Hence, when dealing with overdispersed count data (i.e., the variance exceeds the mean), the standard errors may be underestimated by the Poisson model and this makes it an unreliable estimator. Against this background and since patent data typically are overdispersed, a NB model is employed (see further section 4.1). This approach is also in line with related empirical studies (e.g., Johnstone et al., 2010; Lundmark and Bäckström, 2012).

A number of different NB models have been developed and those most commonly used to accommodate overdispersion are the so-called NB1 and NB2 models (Cameron and Trivedi, 1998). Since country-specific dummy variables are included in our model specifications, we employ a fixed effects NB model. Allison and Waterman (2002) analyze the performance of different fixed effects NB models, and conclude that the conditional fixed effects NB1 model proposed by Hausman et al. (1984) is not a true fixed effects estimator. Guimarães (2008) reasserts the results of Allison and Waterman (2002) by demonstrating that this model does not control for country-specific fixed effects unless a very specific set of suppositions are met. Moreover, by conducting a simulation experiment, Allison and Waterman (2002) find that the unconditional NB model (i.e., a conventional NB2 model with dummy variables to address the fixed effects) performs well even though this model is accompanied by downward bias in the standard error estimates. Given these findings, for our purposes it is suitable to rely on the unconditional NB model. In order to adjust for any potential bias in the standard error estimates, bootstrapped standard errors are computed as suggested by both Hilbe (2011) and Cameron and Trivedi (1998).

All model specifications are estimated using Stata 12 and a modified Newton-Raphson algorithm (i.e., the default setting when employing maximum likelihood estimation). In order to avoid perfect collinearity, the country-specific dummy variable for Germany was omitted from the estimations. Hence, Germany is the reference country in all regressions.

3. Data Sources and Definitions

The empirical analysis in this paper builds on an unbalanced panel data set covering 13 countries over the time period 1978-2008. These include Austria, Belgium, Denmark, France, Germany, Italy, Japan, South Korea, the Netherlands, Spain, Sweden, Switzerland and the United Kingdom (UK). This sample represents both the most progressive countries in the solar photovoltaic (PV) field (e.g., Germany, Japan etc.), as well as countries with less developed solar PV sectors (e.g., Belgium, Austria, Sweden etc.). Due to delays in the publishing of patent information, the patent applications decrease in recent years (2009-2012) thus motivating us to limit the panel data set to an earlier year.

3.1 The Dependent Variable: Solar PV Patent Counts

In order to measure solar PV innovations (the dependent variable), we have extracted data from the OECD Statistics Database (2013) related to patent applications filed under the so-called Patent Cooperation Treaty (PCT).[5] In line with

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[5] Although PCT applications provide less data for estimation than patent applications filed under the respective domestic patent offices, the PCT data have a number of advantages including less home bias and less variation of patent quality.

the recommendations of OECD (2009), the total number of PCT applications has been sorted by inventor country of residence and priority date, and the data are rounded to the nearest integer. In contrast to, for instance, Johnstone et al. (2010), we employ a purer patent category and focus solely on solar PV. In practice, this means that we consider patent categories concerning: (a) PV systems with concentrators; (b) PV material technologies; and (c) power conversion (all of which are contained and provided in a certain ready-for-use PV category in the OECD Statistics Database).[6]

Figure 1 displays the PCT data for the sample countries in terms of the number of solar PV patent applications, and their share of the total number of PCT applications (filed over all technological areas). The figure indicates that solar PV patenting activity has increased rapidly since the beginning of the 1990s. The same trend can be observed for the share of solar PV patents in relation to all patent applications. However, there are also significant differences between the sample countries. For instance, since the mid-1990s patent applications in Japan and Germany have increased at a relatively high rate, making these countries the most prominent in solar PV patenting activity. The remaining sample countries did not experience a similar take-off, and most of them saw their solar PV patent applications increase only in the beginning of the 2000s. Among these, the UK, South Korea, France and Italy stand out with the highest number of applications while the figures for Sweden, Denmark and Austria display virtually no positive trend at all.
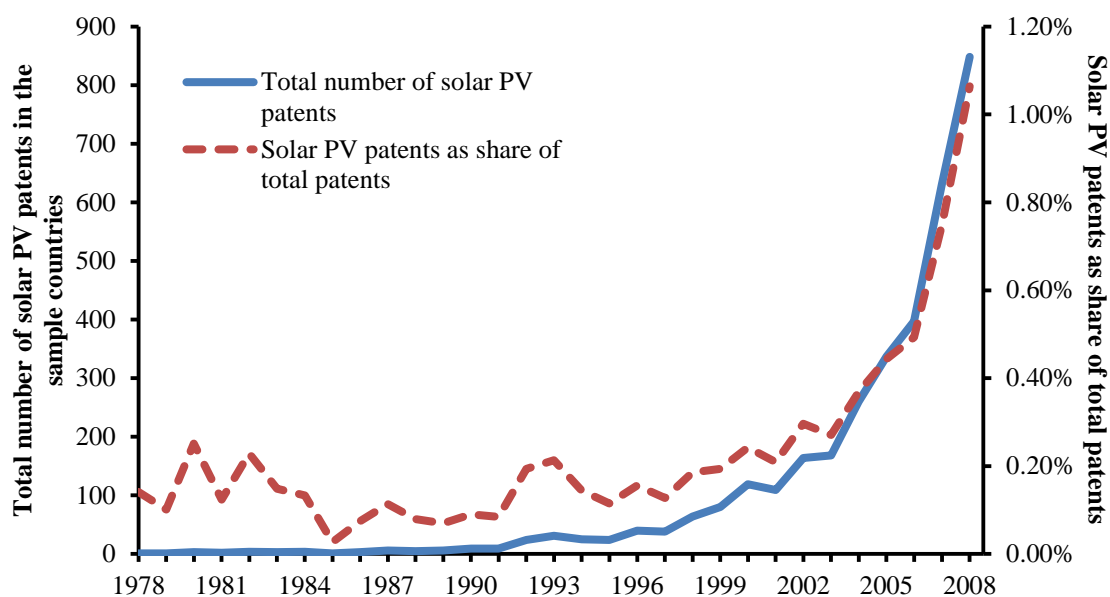

Figure 1: Solar PV Patent Applications (PCT) in the Sample Countries, 1978-2008

Source: OECD (2013).

3.2 The Independent Variables

The independent variables in our model specifications can be divided into three main categories: (a) policy variables; (b) policy interaction variables; and (c) control variables. The policy variables include different measures of the level of support to solar PV either through feed-in tariff (FIT) or renewable energy certificate (REC) schemes or public R&D expenditures. In the FIT case we have collected data on the total remuneration granted to per unit of electricity generated with solar PV. Specifically, the FIT variable measures the annual tariff levels in US cents per kWh (in 2005 prices), and the data used to construct this variable were obtained from IEA (2004, 2012a, 2012b), Cerveny and Resch (1998), Gipe (2013) and various country-specific sources.[7] For most countries that have implemented this policy, the schemes specify a fixed total tariff over a certain time period while in a few cases, the schemes involve a premium above the (variable) market retail price for electricity. In the latter cases we include both the market price and the premium. In the case of REC schemes, we follow Johnstone et al. (2010) and measure policy stringency as the percentage of total electricity use

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[6] Specifically, the following patent classes are contained in this category (expressed in European Classification (ECLA) code): Y02E 10/52 (PV systems with concentrators), Y02E 10/541-546, 10/548 (PV material technologies) and Y02E 10/56 (power conversion, electric or electronic aspects).

[7] The FIT data were taken as nominal currency for the year of the publication or legislation, and were then converted to US cents by using market exchange rates. The figures were deflated (to 2005 prices) using a consumer price index since the producer price indexes provided in several official databases suffered from missing observations.

that must be generated by renewable energy sources (including solar PV). These data were obtained from IEA (2004, 2012a, 2012b) and various country-specific sources.[8]

Figure 2 illustrates the introduction of FIT and REC schemes, respectively, in the sample countries. Some of the countries introduced a FIT scheme already during the 1990s, while the REC schemes were introduced after the turn of the century. All in all, FIT schemes are more prevalent in the solar PV field than are REC schemes. Over the years the average FIT support in real US cents per kWh has increased from approximately US 2 cents in 1991 to about 31 cents in 2008.
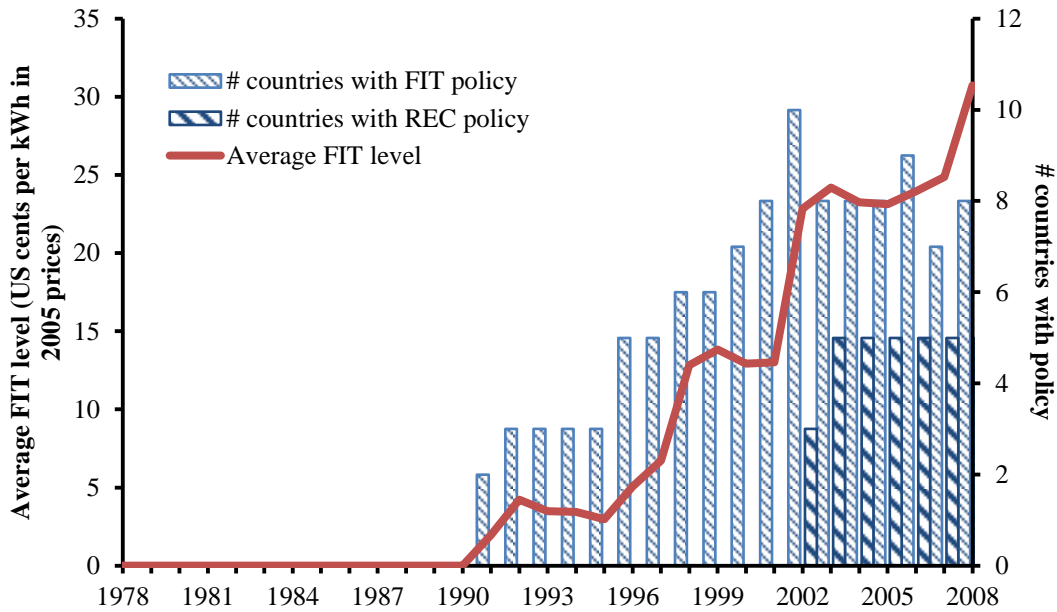

Figure 2: The Level of FIT Support and the Introduction of FIT and REC Schemes, 1978-2008

Sources: IEA (2004, 2012a, 2012b), Cerveny and Resch (1998),
Gipe (2013) and various country-specific sources.

Public support to solar PV R&D is another important policy variable, and, as was noted above, we have introduced two different ways of measuring the role of this policy. Both measures were constructed by employing annual public R&D expenditure data (million US dollars in 2012 prices) from the International Energy Agency (IEA) (2013).[9] In model specifications S1 and S3, we include a variable measuring public R&D expenditures to solar PV with a two year time lag (e.g., Braun et al., 2010; Klaassen et al., 2005). Thus, the specification implies that public R&D efforts cannot instantaneously result in more patent applications.

Figure 3 shows the development of public support to solar PV R&D for all 13 sample countries over the time period 1978-2008 (without a time lag). Following the oil crises in the 1970s several of the sample countries increased their energy R&D budgets, often with a strong emphasis on renewable energy sources (Rübbelke and Weiss, 2011). In the mid-1980s, though, public R&D support to solar PV decreased, but started to slightly increase again from the late 1980s and onwards. Over the entire time period, public R&D support was highest in Germany and Japan but relatively generous support was also provided in Italy, the Netherlands and Switzerland. Interestingly, when considering the entire time period, public R&D support in the respective sample countries has been relatively stable. Still, the data for France, Germany, Italy, Korea, and the UK display an increasing trend during the 2000s.

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[8] The comparison of policy stringency across countries is far from straightforward since the specific policy designs may differ. This concerns, for instance, what PV systems that are eligible for support and for how long the support will be available (IEA, 2004). In most sample countries small, home-based PV systems are eligible for higher tariffs than relatively large, industrial scale PV systems.

[9] The IEA database covers public expenditures on demonstration activities in addition to R&D. However, the contents of the database are heavily biased towards the latter thus making it suitable to consider the data as mainly related to R&D (e.g., Wiesenthal et al., 2009).
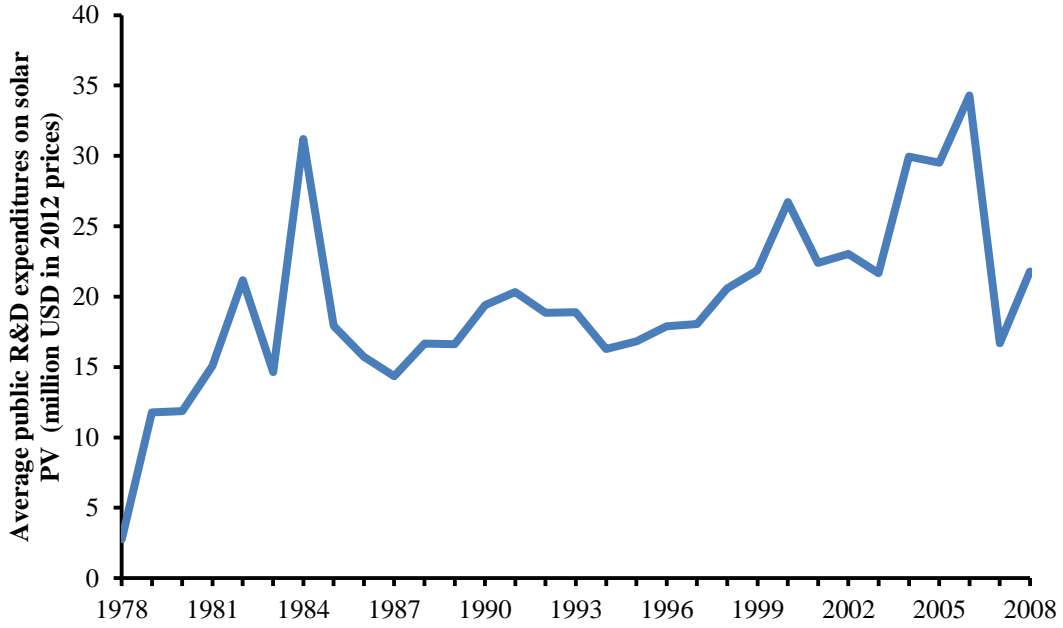
Figure 3: Public R&D Expenditures on Solar PV in the Sample Countries, 1978-2008

Source: IEA (2013).

Model specifications S2 and S4 take into account the notion that previous R&D expenditures add to an R&D-based knowledge stock (e.g., Klaassen et al., 2005; Ek and Söderholm, 2010). We have:

$$RDSTOCK_{i,t} = (1 - \delta)RDSTOCK_{i,t-1} + RDEXP_{i,t-x} \qquad [5]$$

where i indexes the sample countries, t indexes time. In this equation *RDSTOCK* is the R&D-based knowledge stock for solar PV in country i and time period t, *RDEXP* are the annual public R&D expenditures, x is the number of years it takes before R&D expenditures add to the knowledge stock, and δ is the annual depreciation rate of the knowledge stock ($\delta \in [0,1]$). In other words, this formulation takes into account that: (a) public R&D support to solar PV does not have an instantaneous effect on the generation of new knowledge, but will only lead to tangible results after some years have lapsed; and (b) knowledge depreciates in that the effects of previous public R&D expenses gradually become outdated (Griliches, 1995).

To construct the knowledge stock variable, we assume a time lag of two years ($x = 2$), and a depreciation rate of 10 percent ($\delta = 0.10$). This suggests a fairly high rate of depreciation of knowledge (e.g., Griliches, 1995; Nordhaus, 2002), but this is reflected in the relatively rapid development of renewable energy technology since the oil crises in the 1970s (McVeigh et al., 2000). Given the uncertainties inherent in these parameter assumptions, though, we conduct a sensitivity analysis investigating the consequences of using alternative depreciation rates and time lags, respectively.

The IEA provides public R&D data for solar PV starting in the year 1974. In this year the respective domestic R&D expenses were close to zero. These low figures represent our initial conditions when constructing the R&D-based knowledge stock. For instance, the knowledge stock reported in 1990 for a specific country is a function of the annual public R&D expenditures on solar PV during the time period 1974-1988, and with the above depreciation rate attached to the stock. Our two policy interaction variables investigating the relationship between public R&D and the FIT and REC schemes, respectively, draw from the same IEA (2013) data.

Finally, all four model specifications (S1-S4) include two control variables. First, we introduce a dummy variable taking the value of one (1) with the enforcement of the so-called TRIPS agreement in 1995. In this way we control for the agreement's potential effect on the propensity to patent (see section 2.2).[10] Second, we also include a variable measuring

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[10] The number of patent applications rose significantly on a global level between the mid-1990s and the mid-2000s, in part as a result of the signature of the TRIPS agreement in 1994 (OECD, 2009). Thus, the inclusion of the TRIPS dummy

total patent applications filed under the PCT regardless of technological area, using data sorted by inventor country and priority date reported in OECD (2013). As was noted above, this provides a proxy for the overall propensity to patent, which may differ across countries as well as over the years.

Table 1 summarizes the variables employed in the empirical investigation, and provides some descriptive statistics for each of these. In a few cases (e.g., for the R&D expenditure data), a few observations were missing and this was dealt with by replacing the missing observations with a mean value for the relevant country.

Table 1: Variable Definitions and Descriptive Statistics*

Variables	Description and units	Mean	S.D.	Min	Max
Dependent variable					
PCT	Total number of solar PV patent applications (counts)	9.303	31.231	0	345
Independent variables					
FIT	Feed-in price granted to solar PV electricity producers (US cents per kWh in 2005 prices)	8.557	17.838	0	78.416
REC	Target for electricity produced from renewable energy sources (% out of total electricity use)	0.325	1.737	0	16.3
RDEXP	Public R&D expenditures to solar PV with a two-year lag (million USD in 2012 prices)	18.802	32.682	0	225.739
RDSTOCK	Public R&D-based knowledge stock for solar PV (see section 3.2 for detailed definition)	121.307	207.918	0	1237.652
EXPFIT	*RDEXP* multiplied with a dummy variable taking the value one (1) if a FIT scheme is in place, 0 otherwise	5.248	14.102	0	90.17
EXPREC	*RDEXP* multiplied with a dummy variable taking the value one (1) if a REC scheme is in place, 0 otherwise	3.238	22.243	0	225.739
TRIPS	Dummy variable taking the value of one (1) for the years succeeding 1994, 0 otherwise	0.454	0.499	0	1
TOT	Total PCT patent filings (count in thousands)	2.355	4.344	0	27.236

* The S2 model specification is estimated using a total of 352 observations, while the remaining models build on the use of 350 observations (due to a couple of missing observations for the *RDEXP* variable).

4. Empirical Results and Discussion

4.1 Estimation Results from the Negative Binomial Model Specifications

Table 2 presents the regression results of the four model specifications using the negative binomial model (NB2) with bootstrapped standard errors and country-specific fixed effects.[11] In terms of overall model performance it can be noted that the Newton-Raphson algorithm converged to a maximum after relatively few iterations for all model specifications. In addition, a concave (marginally declining) convergence path could be observed. This suggests that all four log-likelihood functions are well-behaved (Gould et al., 2006). Moreover, all model specifications are statistically significant according to the *p*-values associated with the Wald x^2-statistics, thus rejecting the null hypothesis that all of the estimated coefficients are equal to zero. Finally, as a formal test of whether the solar patent data are overdispersed, a likelihood-ratio test and a Wald test were conducted (see Cameron and Trivedi, 1998), and both tests confirm that the data are overdispersed (i.e., the null hypothesis that the overdispersion parameter is equal to zero is rejected). Hence, this confirms that the NB estimation procedure is more appropriate than the Poisson model.

Overall, the empirical results in Table 2 indicate that public policy has been a major driver of solar photovoltaic (PV) patents among the sample countries. Specifically, increases in the feed-in tariff (FIT) and renewable energy certificate (REC) support levels, respectively, and in public solar PV R&D expenditures have implied more fertile ground for innovation in solar PV. The results also show that some policy interaction is present in that a given increase in solar PV

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variable allows us to control for this. Moreover, according to OECD (2009), the use of the PCT patenting route expanded during the 1990s, which also motivates the inclusion of this variable.

[11] The accuracy of the bootstrap estimate (i.e., the bootstrap distribution) in part depends on the number of bootstrap replications. For this reason we ran all four models (S1-S4) using both 200 and 5000 replications as a robustness check. The results indicated only small differences with respect to the bootstrapped standard errors, and in Table 2 the results are based on the use of 5000 replications.

public R&D expenditures will (ceteris paribus) have a stronger impact on patenting activity if a FIT scheme is in place compared to the case where such a scheme is not in use. The overall propensity to innovate (measured by total patents) as well as the TRIPS agreement are also important determinants of solar PV patenting behavior. Finally, some of the coefficients associated with the country dummy variables were found to be statistically significant (see Table A1 in the Appendix), suggesting that country-specific heterogeneity (assumed to be fixed over time) also explains the variation in solar PV patent applications.

Table 2: Estimation Results for the Negative Binomial Model with Fixed Effects

	S1		S2		S3		S4	
Control variables								
TOT	0.069***	(0.001)	0.050*	(0.086)	0.109***	(0.000)	0.089***	(0.004)
TRIPS	1.895***	(0.000)	1.769***	(0.000)	1.809***	(0.000)	1.774***	(0.000)
Public policies								
FIT	0.024***	(0.000)	0.023***	(0.000)	0.016***	(0.000)	0.016***	(0.000)
REC	0.135***	(0.000)	0.146***	(0.000)	0.138***	(0.000)	0.143***	(0.000)
RDEXP	0.015***	(0.002)	-----		0.012***	(0.001)	-----	
RDSTOCK	-----		0.003***	(0.008)	-----		0.002*	(0.067)
Policy interaction								
EXPFIT	-----		-----		0.017**	(0.038)	0.019**	(0.030)
EXPREC	-----		-----		-0.005	(0.325)	-0.001	(0.745)
Log-likelihood (NB)	-630.994		-633.122		-624.203		-626.228	
Log-likelihood (Poisson)	-892.609		-896.592		-823.097		-829.739	
α (overdispersion parameter)	0.449 s.e. 0.102		0.473 s.e. 0.010		0.395 s.e. 0.109		0.418 s.e. 0.109	
x^2	1088.92		1188.43		1097.01		1074.98	
$p > x^2$	0.000		0.000		0.000		0.000	
N	350		352		350		350	

Note: *p*-values in parentheses (based on bootstrapped standard errors); * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Stata automatically provides the log-likelihood of fitting a Poisson model. This statistic is necessary when conducting a likelihood-ratio overdispersion test.

However, while the coefficients reported in Table 2 provide useful information about the signs of the relevant impacts, they do not lend themselves to any meaningful interpretation of the economic significance (i.e., size) of these impacts. Specifically, the estimated coefficients can formally be understood as the difference between the natural logarithms of expected counts (e.g., Hilbe, 2011).[12] In order to avoid this interpretation in log-counts and to assess the differential innovation effects of the independent variables, we compute elasticities by taking $\hat{\beta}_j \bar{x}_j$ which is a measure of the elasticity of $E[y|\boldsymbol{x}]$ with respect to x_j (i.e., the jth regressor) (Cameron and Trivedi, 1998). The resulting elasticities are presented in Table 3, and they can be interpreted as the percentage change in solar PV patenting activity following a one percentage change in the relevant independent variable. All but two of these elasticities are statistically significant (at the 10-percent significance level or lower). In the S3 and S4 model specifications, the elasticities for the interaction variable that address the relationship between public solar PV R&D expenditures and REC schemes are statistically insignificant.

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[12] Mathematically this can be expressed as $\beta = \log(\mu_{x_{0+1}}) - \log(\mu_{x_0})$, where β corresponds to the estimated coefficient and μ is the expected count. The subscripts denote the observation at which an independent variable (x) is evaluated.

Table 3: Estimated Elasticities of Solar PV Patent Counts with Respect to Public Policy Support

	S1		S2		S3		S4	
Control variables								
TOT	0.15	***	0.11	*	0.23	***	0.19	***
TRIPS	0.85	***	0.80	***	0.81	***	0.80	***
Public Policies								
FIT	0.19	***	0.18	***	0.13	***	0.13	***
REC	0.05	***	0.06	***	0.05	***	0.05	***
RDEXP	0.28	***	-----		0.22	***	-----	
RDSTOCK	-----		0.36	***	-----		0.24	*
Policy interaction								
EXPFIT	-----		-----		0.09	**	0.10	**
EXPREC	-----		-----		-0.02		0.00	

Note: *p*-values based on bootstrapped standard errors; * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

The estimated elasticities in Table 3 confirm the positive relationship between different public policies, the overall propensity to patent and the TRIPS agreement on the one hand, and solar PV patent applications on the other. However, the economic significance of the different independent variables differs in important respects. For instance, it is worth noting that while an increase in the overall propensity to patent (*TOT*) appears to have a positive effect on patent applications in solar PV, this impact is not particularly strong. A one percent increase in *TOT* only induces a 0.11-0.23 percent increase in solar PV patents (depending on the model specification). One plausible reason for this relatively small effect may be that solar PV is still an immature industry, which is strongly dependent on public support.

Table 3 shows that all in all public policy, both in terms of production support schemes and in terms of public R&D expenditures, has profound impacts on solar PV patenting activity. Initially we focus on the results from the S1 and S2 model specifications (with no policy interaction effects). First, the elasticities suggest that the levels of support provided through both the FIT and REC schemes have a positive impact on patent applications.[13] The estimated elasticities are however relatively low (ranging from 0.05 to 0.19). Notable is that the estimated FIT elasticities are about three times higher than the REC elasticities, suggesting that the FIT schemes appear to have been more innovation-promoting than the REC schemes. Second, the role of public R&D support for solar PV innovation is also found to be important. The S1 and S2 model specifications differ in the way the R&D impacts are operationalized, but both indicate positive (lagged) impacts of public R&D support on solar PV patent counts.[14] Overall, the role of public R&D is found to be more economically significant for solar PV innovation than that of different production support schemes (not the least the REC scheme).

In model specifications S3 and S4, we test the notion that there could exist important interaction effects between the two different policy categories (public R&D expenditures and production support schemes). The results suggest that we can reject the hypothesis of no interaction effects between public R&D and FIT schemes. Specifically, a marginal increase in any of the two public R&D variables implies (ceteris paribus) a greater spur to patenting activity if a FIT scheme for solar PV is present, compared to a situation where no such scheme is in place. The results from the S3 model specification suggest that a ten percent increase in (lagged) public R&D expenditures will induce a 2.2 percent increase in solar PV patenting activity in the absence of a FIT scheme, but 3.1 % (2.2 + 0.9) if such a scheme is in use. No

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[13] Johnstone et al. (2010) also include the price of electricity as an explanatory variable, and they report a statistically significant and positive correlation between this price and the patent counts for solar energy. In our model specifications, though, the FIT variable includes the total remuneration to solar PV production (i.e., the retail market price of electricity plus any premium), thus making the inclusion of the electricity variable redundant. Indeed in most cases the FIT scheme involves a minimum guaranteed fixed price. As a robustness check we included the electricity price in all our models (using the same IEA source as Johnstone et al., 2010), but the associated coefficients were highly statistically insignificant, and the inclusion of this variable also had negligible effects on the remaining parameter estimates.

[14] The construction of the R&D-based knowledge stock is based on a two year time lag and a depreciation rate of 10 percent. Since these are uncertain parameters it is useful to test how sensitive these results are to the inclusion of varying assumptions. Such a sensitivity analysis is provided in Table A2 in the Appendix, and it shows that the results are overall robust with respect to different time lags (three-year) and discount rates (5 and 15 percent, respectively). The coefficients associated with the knowledge stock are positive and statistically significant in all alternative models except one, and the changes with respect to the remaining coefficients are overall minor.

corresponding interaction effect between public R&D and REC schemes can be found as the associated elasticities are not statistically significant (see Table 3). This result reinforces the conclusion that the FIT schemes tend to be more innovation-promoting than the REC schemes.

4.2 Discussion

In this sub-section we discuss some of the empirical results, and compare them to the findings of other studies. Overall the results are in line with other work, e.g., the result that renewable energy patents are influenced by the general propensity to patent (e.g., Johnstone et al., 2010; Lundmark and Bäckström, 2012), but we also report some new results and insights.

Our results indicate a positive correlation between the FIT levels and solar patenting activity, and this is consistent with the findings of Johnstone et al. (2010). Nevertheless, while we report a statistically significant but markedly lower impact of REC schemes, Johnstone et al. (2010) cannot reject the null hypothesis that this impact is non-existent. They argue that REC schemes are not likely to stimulate innovations in renewable energy technologies that are relatively immature. One plausible explanation for this difference in results is that in the present work we focus explicitly on solar PV technology, while Johnstone et al. (2010) adopt a broader definition of solar energy technology that embraces also solar thermal innovations (i.e., innovations in residential systems applied for heating and cooling). Since the REC schemes specifically target technologies used for electricity generation purposes (including solar PV) other types of solar energy technology will not be directly affected by this policy.[15]

The heterogeneous impacts of the different support schemes deserve a more in-depth discussion. Both the FIT and the REC schemes can *a priori* be assumed to have positive innovation impacts, but in practice the two schemes rely on different conceptions of what nurtures technology learning and innovation. In simple terms this boils down to the question of whether innovation is best nurtured by deliberatively making innovation vulnerable to competition from other technologies (e.g., Hommels et al., 2007), or whether it instead requires the targeted support of protected technological 'niches' (e.g., Smith and Raven, 2012).[16] The REC schemes encourage direct competition among different energy technologies because of the pressures of the bidding process and the embracement of a large number of renewable energy sources, thus building on the notion that 'selection pressure' is important for inducing innovation. The FIT schemes instead provide a fixed production support for selected technologies such as solar PV, and thus a 'nursing market' in which the technology can develop without much direct competition from other energy sources.

Our empirical results suggest that the protecting strategy has been more successful in inducing solar PV patents than the strategy emphasizing the importance of 'selection pressure'. The stronger FIT impact may be due to the fact that even though these schemes do not promote strong competition across technologies, technical progress increases the producers' surplus and in this way encourages them to innovate. Within a REC scheme, however, the surplus that is attributed to producers may be significantly more limited since the marginal price could decrease as a result of technical advances (e.g., Menanteau et al., 2003). Moreover, in REC schemes producers will choose to devote most attention to the currently most cost-effective renewable energy technology options accepted under the policy (e.g., Jaffe et al., 2002; Johnstone et al., 2010; Popp, 2003). Given that solar PV has been relatively expensive compared to other technology options over the time period studied (IEA, 2004), it has not been a strong competitor to, for instance, wind power. This implies that REC schemes have only stimulated limited production of solar PV electricity, and therefore also relatively limited learning-by-doing and innovation activities.

Turning to the role of public R&D in the solar PV field, our results are in line with those reported by, for instance, Braun et al. (2010) and Johnstone et al. (2010), although these studies do not consider nor test different ways of measuring the role of R&D support (i.e., direct expenses versus a build-up of knowledge over time). The results in Table 3 suggest that public R&D has been more influential in inducing solar PV patenting activity than policies supporting the diffusion of solar PV (i.e., FIT and REC schemes). These results are also consistent with some previous two-factor learning curve studies showing higher R&D-induced cost reductions for renewable energy technology such as wind power and solar PV, and often a less prominent role for learning-by-doing following the diffusion of the technology (e.g., Nemet, 2006; Söderholm and Klaassen, 2007; Pizer and Popp, 2008).

Still, the role of R&D in the solar PV innovation process needs further scrutiny and not the least the relationship between public and private R&D. It can be difficult to model these impacts in a consistent manner, this since public R&D support

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[15] Braun et al. (2011) also point to the problem of mixing different types of solar technologies when investigating innovation patterns and policy impacts.

[16] In the economics literature it is often stressed that a proper balance between competition and monopoly (e.g., oligopoly markets) provides the most fertile ground for innovation (e.g., Baumol, 2002).

may be used to promote private firms to conduct applied research and run pilot and demonstration projects. Moreover, in practice the roles played by private and public R&D, respectively, likely differ as different technologies develop. In most cases private R&D efforts become more pronounced as a technology matures, while public R&D policy normally should encourage more risk-taking and exploratory R&D activities that are characterized by greater uncertainty in the distribution of project payoffs (e.g., Ek and Söderholm, 2010).

Nevertheless, public R&D programs should not necessarily cease entirely as the technology matures. Innovation requires both R&D and learning-by-doing and for this reason R&D programs should typically not be designed in isolation from practical application (e.g., Arrow et al., 2009). In addition, the gradual diffusion of a certain technology can reveal areas where additional R&D would be most productive. Our results support the notion that public R&D support to solar PV is more effective in the presence of FIT schemes, and this provides quantitative support for the argument made by del Río and Bleda (2012) that complementing FITs with public R&D support will promote innovation. Moreover, our results manifest themselves in one of the practical lessons of the failed so-called 'Million Solar Roofs' (1997-2005) program in the USA. This program was criticized for lacking the necessary alignment with R&D efforts, and for not permitting R&D to influence the program plans and methods (Strahs and Tombari, 2006). A follow-up demonstration program, the so-called Solar America Initiative, has therefore been designed to evade this mistake by mixing technology and market development, with the latter being accompanied with substantial R&D and venture capital (Hendry et al., 2010).

In the light of our result on policy interaction, it is worth noting that following the oil crises in the 1970s most developed countries introduced substantial public R&D support for various renewable energy technologies (including solar PV). Still, during the 1980s this support was typically not accompanied by explicit production support schemes. Our empirical results suggest that this implied (ceteris paribus) less solar PV innovation during this decade.

As was noted above, the positive interaction between public R&D and diffusion-promoting policies was not found with respect to the presence of REC schemes. A plausible explanation for this result is that in the REC case more mature technologies tend to become prioritized, and this policy provides only little opportunity for continuous technology learning in solar PV in turn augmenting the impact of R&D. The limited innovation impacts of REC schemes have been argued by Bergek and Jacobsson (2010) in their assessment of the Swedish REC policy.

5. Concluding Remarks and Avenues for Future Research

This paper investigates the effect on solar photovoltaic (PV) innovation of renewable energy policies and their interaction. Our results appear robust to alternative model specifications, and indicate that: (a) both feed-in tariff (FIT) schemes and renewable energy certificate (REC) schemes induce more solar PV patenting activity even though the impact of the former policy is found to be more profound; (b) public R&D support has an important impact on solar PV innovation; and (c) policy interaction exists in that the impact of public R&D support on innovation is greater at the margin if it is accompanied by the use of FIT schemes for solar PV.

The results confirm the notion that innovation in the renewable energy field is endogenously determined, and induced by more or less targeted policy instruments. The important role of FIT schemes implies in turn that technical innovation (at least in the case of less mature energy technologies) could, in part, be nurtured through some amount of policy protection. The interaction between public R&D and diffusion-promoting policies does not emerge in the case of public R&D and REC schemes. This is likely due to the relatively strong technology selection pressure under the latter, mainly favoring currently cost-effective renewable energy technologies.

Still, it should be clear that a number of issues deserve increased attention in future research. First, the presence of international knowledge spillovers may play an important role in fostering domestic innovation, and this requires different sets of model specifications (e.g., Verdolini and Galeotti, 2011). Second, while this paper identifies an important impact of public R&D efforts on solar PV innovation, this effect may be less pronounced in the case of more mature technologies such as wind power as well as over time as less-developed technologies mature. Greater understanding of such differential impacts across various technologies is important information for policy making.

Third, the interaction between private and public R&D during the innovation process also deserves more in-depth empirical research. This also addresses the more general notion that the role of public policy changes (and should change) as the technology develops from basic R&D, through the pilot and demonstration phase, to adoption in the market. Our empirical results confirm the importance of acknowledging the interaction and the iterations between R&D and diffusion policy (e.g., FIT schemes), but this also calls for more detailed studies employing more disaggregated data on the design of innovation policy (e.g., the allocation of public funds between basic R&D and pilot plants). Furthermore, Liang and Fiorino (2013) argue that for renewable energy innovation, the level of R&D support loses explanatory power to policy stability in the long run, thus suggesting that the ways in which policies are implemented (e.g., perceived stability over time) may matter just as much as the level of support provided. Fourth, and finally, it

should of course be emphasized that the type of empirical research presented in this paper must also be complemented with more normative research on the economic efficiency of different innovation policies as well as policy mixes in the renewable energy sector (e.g., Aalbers et al., 2013).

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Appendix

Table A1: Estimated Coefficients for the Country-specific Dummy Variables

Country dummies	S1		S2		S3		S4	
$D_{AUSTRIA}$	-1.267***	(0.000)	-0.928**	(0.020)	-0.198	(0.689)	-0.153	(0.781)
$D_{BELGIUM}$	-1.274*	(0.054)	-1.019*	(0.090)	-0.440	(0.476)	-0.419	(0.465)
$D_{DENMARK}$	-1.547**	(0.013)	-1.210*	(0.083)	-0.750	(0.233)	-0.705	(0.292)
D_{FRANCE}	0.087	(0.731)	0.538	(0.119)	0.710**	(0.037)	0.869**	(0.038)
D_{ITALY}	-1.257***	(0.002)	-1.209***	(0.002)	-0.486	(0.295)	-0.565	(0.265)
D_{JAPAN}	-0.066	(0.871)	0.081	(0.846)	0.808*	(0.054)	1.027**	(0.035)
D_{KOREA}	0.181	(0.697)	0.798	(0.150)	1.033**	(0.038)	1.296**	(0.020)
$D_{NETHERLANDS}$	0.000	(1.000)	0.280	(0.438)	0.739*	(0.080)	0.810*	(0.089)
D_{SPAIN}	-0.934**	(0.034)	-0.656	(0.149)	0.060	(0.909)	0.076	(0.893)
D_{SWEDEN}	-1.440***	(0.003)	-1.134**	(0.043)	-0.737	(0.180)	-0.691	(0.247)
$D_{SWITZERLAND}$	0.364	(0.291)	0.594	(0.108)	1.027***	(0.008)	1.041**	(0.020)
D_{UK}	0.359	(0.254)	0.737*	(0.075)	1.000**	(0.014)	1.109**	(0.020)

Note: *p*-values in parentheses (based on bootstrapped standard errors); * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A2: Sensitivity Analysis with Respect to Alternative Time Lags and Depreciation Rates

	S2			S4		
Lag	2 year		3 year	2 year		3 year
Discount rates	5%	15%	10%	5%	15%	10%
Control variables						
TOT	0.038	0.057 **	0.058 **	0.080 **	0.096 ***	0.092 ***
	(0.244)	(0.029)	(0.038)	(0.023)	(0.001)	(0.003)
TRIPS	1.762 ***	1.788 ***	1.765 ***	1.791 ***	1.764 ***	1.779 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Policy variables						
FIT	0.022 ***	0.024 ***	0.023 ***	0.015 ***	0.016 ***	0.015 ***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
REC	0.149 ***	0.143 ***	0.150 ***	0.144 ***	0.142 ***	0.142 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RDSTOCK	0.002 ***	0.004 ***	0.003 **	0.001 *	0.002 **	0.001
	(0.007)	(0.005)	(0.015)	(0.079)	(0.043)	(0.111)
Policy interaction						
EXPFIT	-----	-----	-----	0.020 **	0.018 **	0.020 **
				(0.023)	(0.037)	(0.024)
EXPREC	-----	-----	-----	-0.000	-0.002	-0.000
				(0.938)	(0.598)	(0.952)
Log-likelihood (NB)	-634.217	-632.433	-638.716	-626.632	-625.749	-622.430
Log-likelihood (Poisson)	-887.249	-897.738	-898.132	-814.614	-831.744	-832.418
α (overdispersion parameter)	0.480 s.e. 0.105	0.468 s.e. 0.099	0.479 s.e. 0.107	0.420 s.e. 0.114	0.414 s.e. 0.110	0.419 s.e. 0.111
x^2	1407.99	1180.88	1409.73	1039.24	983.38	1016.73
$p > x^2$	0.00	0.00	0.00	0.00	0.00	0.00
N	352	352	350	350	350	346

Note: *p*-values in parentheses (based on bootstrapped standard errors, 5000 replications), where * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.