DISCUSSION PAPER SERIES

No. 7865

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Available online at: **www.cepr.org/pubs/dps/DP7865.asp**

ISSN 0265-8003

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Discussion Paper No. 7865
June 2010

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CEPR Discussion Paper No. 7865

June 2010

ABSTRACT

Innovative Activity in Wind and Solar Technology: Empirical Evidence on Knowledge Spillovers Using Patent Data*

This paper studies technological change in renewable energies, providing empirical evidence on the determinants of innovative activity with a special emphasis on the role of knowledge spillovers. We investigate two major renewable energy technologies wind and solar across a panel of 21 OECD countries over the period 1978 to 2004. Spillovers may occur at the national level, either within the same technology field or economic sector (intra-sectoral spillovers) or in related technologies or sectors (inter-sectoral spillovers), or at the international level. We find that innovation is strongly driven by knowledge spillovers, especially those occurring at the national level. Wind and solar technologies exhibit distinct innovation characteristics: both are stimulated by intra-sectoral spillovers, but respond differently to inter-sectoral spillovers, which are only influential in the case of wind technology. We also find evidence that public R&D stimulates innovation, particularly in solar technologies.

JEL Classification: O31, Q42 and Q55
Keywords: climate change, innovation, knowledge spillover, patents, renewable energy and technological change

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* This paper is produced as part of the project Growth and Sustainability Policies for Europe (GRASP), a Collaborative Project funded by the European Commission's Seventh Research Framework Programme, Contract number 244725. We thank for their helpful comments and support Irwin Collier, Bronwyn Hall, Christian von Hirschhausen, Claudia Kemfert, Alexander Kritikos, Arik Levinson, and Karsten Neuhoff. We also express our gratitude to Doreen Triebe and Alexander Plum for their excellent research assistance.

Submitted

1 Introduction

Technological progress is generally viewed as a key answer to sustainable and less carbon-intensive energy use. In this context, Acemoglu et al. (2009) recently talked about the need of turning the "green innovation machine" on. Increased awareness of the likely impacts and costs of climate change have spurred interest in power generation from renewable sources so as to reduce greenhouse gas emissions. Various forms of this technology exist, but they are not usually competitive with the use of fossil fuels. Their larger-scale use is dependent reducing their cost by means of technological innovation and improvements. We know very little, however, about the determinants of innovation in these technologies. This paper seeks to fill this research gap by empirically investigating the determinants of innovative activity with a special emphasis on the role of knowledge spillover in two major renewable energy technologies—wind and solar—across a panel of 21 OECD countries over the period 1978 to 2004.[1]

Our point of departure is the observation that knowledge spillovers have had a considerable impact on technological advances for energy saving technologies. Our study focuses, first, on renewable energy technologies and, second, on analyzing different sources of knowledge spillovers: on the one hand, at the national and international level and, on the other hand, within and between sectors.

Generally speaking, knowledge spillovers occur when one inventor's original idea "spills over" to competitors, other sectors of the economy, or other countries, thereby enriching the available stock of knowledge and stimulating the development of further ideas without the recipient having to pay for it. This phenomenon may occur at the national level, either within the same technology field or economic sector (intra-sectoral spillovers) or in related

[1] Countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Great Britain, Greece, Hungary, Italy, Japan, Netherlands, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, United States.

technologies or sectors (inter-sectoral spillovers). In fact, such inter-industry spillovers have occurred in the solar photovoltaic technology sector, which is strongly entwined with the semiconductor industry, particularly in Japan, using its silicone by-products for solar cell manufacturing and taking advantage of its process know-how. However, the distinction between inter- and intra-sectoral spillovers has so far been neglected in other studies on innovation in renewable energy or environmental technologies.

Knowledge that spills across international borders is also expected to be a critical channel for advancing new technologies. The emerging Spanish wind industry, for instance, acquired valuable expertise via technology licensing from the Danish wind industry in the mid 1990s and has further assimilated this know-how for its own wind technology innovations.

We therefore investigate the relative importance of inter-sectoral spillovers and intra-industry spillovers in the innovation process of wind and solar technology. It is, moreover, crucial to distinguish between national and international sources of knowledge. Additionally, we account for the fact that solar and wind technologies each involve their own distinct innovation process. Even though both are evolving and dynamically growing technologies, they are characterized by significant differences in the underlying technical principles and are therefore characterized by different innovation dynamics. We therefore allow for different processes by estimating separate regressions for each technology.

Methodologically, we use a knowledge/ideas production function framework to model the relationship between innovative output, as measured by the number of patent applications in wind or solar technology, and knowledge-generating inputs such as R&D expenditures, human capital, policy instruments, and spillover sources. The input variables for national, international, intra- and inter-sectoral spillovers are also constructed from counts of patent applications. Furthermore, public support contributes to the innovation process of renewables as this technology still operates at a cost disadvantage. Renewables rely, first, on support to spur their development, as evidenced by public R&D funding, and, second, on incentives for technology adoption and subsequent power production.[2]

The empirical literature on innovation in energy or environmental technologies does not systematically examine the role of various sources of spillovers, but there is one strand of this work that uses patent data to analyze innovation in these fields. By legal definition, obtaining a patent requires novelty and inventiveness and they are thus a strong and frequently employed source of data for measuring innovation (Griliches 1990). To our knowledge, the only studies explicitly on innovation in renewable energy technology are Johnstone et al. (2010).[3] The authors analyze the impact of various policy instruments, including obligations, tariffs, and tradable certificates, on the number of patent applications in wind, geothermal, solar, ocean, biomass, and waste technologies. Policy instruments are found to induce innovation in renewables, but the particular choice of an instrument matters. There are important differences between the technologies: obligations and tradable certificates work well for wind power innovations, which the authors explain by noting that wind is the most cost-competitive technology and hence development efforts focus on this less expensive field to meet regulatory obligations. Innovation in more costly technologies such as solar power, on the other hand, is more responsive to feed-in tariffs.

Articles with a broader technological scope include Popp (2002) on energy-saving innovations and Verdolini and Galeotti (2010) on energy-efficient technologies. Popp (2002) examines how energy prices and the existing knowledge influence energy-saving innovations.[4] Results confirm a strong stimulating effect of energy prices and, moreover,

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[2] The latter incentive schemes fall into one of two categories. In a price-based scheme, a tariff is guaranteed per unit of renewable power supplied (feed-in tariff). A quantity-based scheme requires a particular quantity or share of energy to be produced from renewable sources (obligation). Recently, certificate trading systems have also been set up, under which renewable power generators can sell power on the market and sell certificates on the green certificates market (Menanteau et al. 2003; IEA, 2004).

[3] Some researchers also study diffusion of renewable energy technologies by using patent data, e.g., Popp et al. (2009) and Glachant et al. (2010).

[4] Innovation is measured by the number of patents in diverse energy-saving technologies, for instance, fuel cells, or renewables, compared to the overall number of patents in the United States. The knowledge stock serves as a

establish the knowledge stock as a crucial driver for patenting in energy-saving technologies. Verdolini and Galeotti (2010) study which supply and demand factors induce innovation in energy-efficient technologies. Using U.S. patent data from between 1975 and 2000, energy prices and externally available knowledge are confirmed to be strong drivers of innovative activity in these technologies. Results also reveal that the closer countries are in terms of technology or geography, the more knowledge flows between them.[5]

Our work deepens the understanding of innovation in renewable energy technologies by, first, emphasizing the importance of knowledge spillovers for technological change and, second, studying the impact of various spillover sources. We find substantial evidence that innovation is driven by knowledge spillovers, especially at the national level. Hence, knowledge spillovers are predominantly a domestic phenomenon; international spillovers are found to have a negligible influence. Wind and solar technologies exhibit distinct innovation characteristics: both are stimulated by intra-sectoral spillovers, but respond differently to inter-sectoral spillovers, which are only influential in the case of wind technology. We also find evidence that public R&D stimulates innovation, particularly in solar technologies.

The paper proceeds as follows. Section 2 introduces the database and discusses the use of patent data to measure innovative activity. Section 3 outlines our model of innovative activity using a knowledge production function framework and describes the estimation approach. Section 4 presents the results of the analysis; Section 5 concludes.

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proxy for the supply of ideas. It is measured by the aggregate of *all* U.S. patents or, alternatively, by a quality-controlled aggregate of the latter where patent citations are used to obtain the quality weightings.

[5] A number of studies investigate the link between environmental regulation, often measured by pollution abatement expenditures, and innovation (e.g., Brunnermeier and Cohen 2003; Carrión-Flores and Innes 2010). In contrast to our work and that of Johnstone et al. (2010), these scholars focus on the United States and rely on national firm- or sector-level data.

2 Data and Descriptive Statistics

The econometric analysis is based on a balanced panel of 21 OECD countries over the period 1978 to 2004 (see Tables 1 and 2).[6] We focus on solar and wind technologies, two prominent and intensively studied technologies within the field of renewable energy generation. Each can be considered an emerging technology compared to more mature technologies such as hydropower. In the OECD, wind accounted for 5.81% of gross electricity generation from renewable sources in 2005 (IEA 2008b). Wind energy generation is close to being cost competitive—at least in very favorable sites (see, e.g., Neuhoff 2005). Solar energy is still very expensive and its relative contribution is small (0.13% in 2005) (IEA 2008b), but its potential is enormous (Neuhoff 2005).

2.1 Usage of Patent Data

A crucial aspect in tracking innovative activity is its measurement, an issue that is discussed extensively in the literature on innovation. Given this paper's research focus, —studying the role of knowledge spillovers in "green innovation"—patents are a powerful indicator, since, by definition, they involve truly new ideas and have a common legal framework within each patenting authority. They thus assure comparability across countries and over time. In addition, patent applications contain detailed information on inventors, technological classification, timing of the invention, and protection coverage that can be exploited to track innovation in wind and solar technologies.

Nevertheless, there are a number of drawbacks when using patents as a proxy for innovative output (Griliches 1990). First, the distribution of the value of patents is highly skewed to the right since only a few inventions are of remarkable economic value (Harhoff et al. 2003). Second, the propensity to patent varies across countries and industries due to different legal

[6] To compile a representative sample for innovative activity in renewable energies, we imposed the restriction that any form of public R&D last for at least in one year and that domestic inventors applied for at least five patents in wind and solar technology.

and political environments (Kortum and Lerner 1999). Third, since an invention must be fully disclosed to obtain patent protection, some firms may prefer the strategic option of secrecy, instead of a patent, so as to prevent imitation (Arundel 2001).

We use all patent applications filed with the European Patent Office (EPO) having a priority date[7] between 1978 and 2004. EPO applications, in contrast to those made at a national authority, can be taken as a signal that the patentee believes the invention to be of high enough value to justify the expense of an international application. By exploiting patent applications, we assume that the knowledge they contain diffuses as soon as the patent application is published, which usually happens 18 month after the filing date (Ramani et al. 2008).

We use these patent data to determine our output variable—innovation in wind and solar technology—by using a classification scheme developed by Johnstone et al. (2010). In addition, patent data are used to construct our key exogenous variables: the sources of spillovers are obtained by building four different types of knowledge stocks for solar and wind technology—existing knowledge in the specific technology (wind or solar) and existing knowledge in related technologies, distinguished according to whether the inventor is domestic or foreign (see Appendix A for details).

2.2 Other Explanatory Variables

Other exogenous variables in our ideas-generation framework are R&D expenditures, policy instruments, and human capital. Annual data on publicly funded R&D in solar and wind energy are from the IEA Energy Technology Research and Development Database (IEA

[7] The term "priority date" refers to the date when the underlying invention was protected by a patent for the first time, regardless of whether this first application was made at a national or an international authority. The first filing for an invention usually occurs at the national level and therefore the majority of patent applications at the EPO are second filings (de Rassenfosse and von Pottelsberghe 2007). The priority date, then, is in a considerable number of cases preliminary to the EPO application date. Accordingly, we date patent applications using the priority date instead of the application date because it is closest to the date of invention and the decision to apply for a patent (OECD 2009). From an economic point of view, this is the only information of importance Dernis et al. 2001.

2008a). Data on private R&D energy expenditures are not easy to obtain, a common problem faced by energy or climate researchers (Newell 2008). However, in the context of energy technology projects, governments are often heavily involved via publicly funded research or demonstration programs (Harborne and Hendry 2009).

Information on the number of R&D personnel involved in renewable technologies is not directly available for use in measuring the human capital input in knowledge production. We can at least approximate the research potential present in a country by an intensity measure relating the general number of researchers to the total labor force. Even though researchers are no doubt working in various fields, their knowledge or innovations may have the potential to spur technological development in renewable energies, especially in case of basic research. Data on researchers per 1,000 employees in a country are from the Main Science Technology Indicators published by the OECD (2008). Since information on researchers is available only from 1981 onward, we are restricted to the time frame of 1981 to 2004 when including this variable in our estimations.

Johnstone et al. (2010) find that policy instruments play a substantial role in encouraging innovation in renewable energy technologies. Such promotion schemes fall into one of two categories: price-based systems (feed-in tariffs)) or quantity-based systems (obligations and certificates) (Finon and Menanteau 2004). Similar to Johnstone et al. 2010, we follow the categorization of IEA (2004) and introduce time dummies that indicate the time period during which any of the three policies were in effect in a country. The policy dummies provide a somewhat narrow picture of the support schemes; it would be preferable to have more elaborate data to evaluate the relative effectiveness of these policy schemes, such as international rankings of the renewable support schemes. However, such information is not available and cannot be easily compiled.[8]

2.3 A First Look at the Data

Tables 1 and 2 display the summary statistics for the variables of interest in wind and solar technologies. The average amount of (real) public R&D expenditure is roughly $6.3 million for wind and $24 million for solar technologies, with substantial country-level variation. The 1970s oil shocks markedly intensified research into power generation from alternative sources. Government R&D spending—particularly in the United States—was high afterwards, at levels unprecedented until now. Wind R&D support peaked around the beginning of the 1980s at about $300 million and—apart from a small upward trend around 1995—stayed at a much lower level of about $100 million (Figure 1). Solar technologies underwent a similar dynamic, though at a higher overall level (Figure 2). Support was highest, at $1,200 million, at the beginning of the 1980s and has been significantly lower ever since (around $400 million). The oil crises of the 1970s substantially increased political awareness of issues of energy security, and substantial funds were allocated for research on alternative, nonfossil fuel technologies by governments worldwide. However, in the face of lower energy prices from the 1980s on, political interest in alternative energy technologies projects declined.

In the case of solar energy, patenting dynamics mirror, in part, R&D support: an early peak at the beginning of the 1980s, followed by a trough lasting until 1989. Then, from 1990 onward, we observe a steady increase in innovative activity in solar technology until 2004. Patenting activities of the main applicants of interest are shown in Figure 4. Since the early 1990s,

[8] Support schemes are comprised of several elements that are critical to their functioning and credibility. For instance, feed-in-tariffs vary not only by technology and tariff level, but also by the period over which the tariff is granted, design (fixed tariff versus premium on the electricity price), size, and location of applicability. This information is, first, neither well documented nor easy to obtain and, second, requires a consistent approach to compile the data and evaluate the characteristics of the national support schemes in a comparable standard for each technology. Currently, we are not aware of any such quantitative attempt in the literature.

Japan and Germany have played the leading roles in solar technology, although the United States appears to be catching up. The United States was a strong market for solar energy applications up to the beginning of the 1980s, but the substantial decline in public support under the Reagan administration appears to have severely dampened U.S. technology developments in this field. Only when Japan and Germany began their large-scale support schemes, did solar innovation increase again. Japan concentrated its renewable energy technology efforts on solar technology to take advantage of knowledge already developed in the integrated circuit and consumer electronics industry.

In contrast, patent applications in wind technology were filed at a steady, fairly low level until 1995 (Figure 3). After that year, we observe a boom in wind technology patenting that continues to the present day. The age of modern wind technology started in the aftermath of the 1970s oil crises. California experienced a major boom in wind power installations; however, the turbine technology and other components were largely imported from Denmark. While the U.S. interest in wind technology faded during the 1980s, European countries such as Germany, the Netherlands, and Denmark spurred technology development with major research and, especially, demonstration projects from the 1980s on. In Japan, wind technology development has usually had low priority due to little domestic expertise in this field and in an effort to avoid reliance on imports of this technology.

Germany dominates innovative activity in wind technology. The United States and Spain have only recently improved their performance in this domain. Spain is a late starter in this field, not even starting technology until the 1990s, at which time it actively pursued a strategy of encouraging foreign manufacturers to establish plants in Spain and form joint ventures with local partners.

Summary statistics for patent applications in wind and solar technology show that patenting activity is rather infrequent, leading to a large number of zero observations combined with low mean values of slightly more than 2 in the case of wind technology (Table 1) and about 5.5 for solar technology (Table 2). This pattern is mainly driven by the fact that the classification identifying relevant inventions in wind and solar is quite narrow and technologically specific (see Johnstone et al. 2010).

3 An Empirical Model of Innovative Activity in Renewable Energy Technologies

3.1 A Knowledge Production Function Framework

Following the framework developed by Griliches 1979, we estimate a knowledge production function to discover the determinants of innovative activity in wind and solar technology. Innovation is assumed to be the product of knowledge-generating inputs, comparable to the process of physical goods production. The vector of determinants usually encompasses the quantity of human capital or R&D expenditures and the total stock of knowledge available to researchers. Hence, the productivity of new knowledge is assumed to be strongly dependent on existent stock of ideas (Porter and Stern 2000), the "standing on shoulders" effect (e.g., Bosetti et al. 2008).

Formally, knowledge production in technology *j* and country *n* can be summarized as follows:

$$I_{nj} = f\left(H_{nj}, K\right),$$

where I_{nj} is innovation in technology *j* (wind or solar), *H* stands for human capital, and *K* is the overall knowledge stock available to researchers.

To enrich our understanding of the knowledge-production process, we further distinguish between domestic and international knowledge spillovers. The latter could be an especially important channel of knowledge transfer for smaller countries whose existing knowledge base is narrow or highly specialized.

To fully understand the externalities of national and international technological knowledge, empirical work on R&D spillovers often distinguishes between intra- and inter-sectoral spillovers by referring to sector-country observations (e.g., López-Pueyo et al. 2008). We transfer this approach to the field of renewable energies and study not only the impact of domestic and international spillovers in wind and solar technology (intra-sectoral level), but also knowledge externalities in related fields (inter-sectoral level). Our specification can be expressed as follows:

$$I_{nj} = f\left(H_{nj}, K_{nj}, K_{n-j}, K_{-nj}, K_{-n-j}\right),$$

where K_{nj} stands for the knowledge stock available in the same technology in the same country, K_{n-j} is knowledge in the same country but in related technologies, K_{-nj} is the stock in other countries in the same technology, and K_{-n-j} is knowledge from related technologies in other countries. In short, K_{nj} and K_{n-j} represent domestic spillover, whereas K_{-nj} and K_{-n-j} proxy international knowledge spillover.

3.2 Econometric Approach

As explained in Section 2, we measure innovative activity in wind and solar technology by the number of patent applications. The resulting dependent variable is a nonnegative-integer-valued variable with many zeros and small values, especially at the beginning of our estimation period. Thus, in the specification of our econometric model we follow the seminal work of Hausman et al. (1984) and assume a Poisson process with parameter λ_{ij} for the number of patents applied for in country *i* in technology *j*:

$$E\left(I_{nj}\right) = \lambda_{nj} = \exp\left(X_{nj}'\beta\right)$$

$$P\left(I_{nj} = i_{nj}\right) = \frac{\exp\left(-\lambda_{nj}\right)\lambda_{nj}^{N}}{i_{nj}!}.$$

Again, I_{nj} is the number of patents in country *n* related to technology *j* and the vector X_{nj} encompasses R&D expenditures, human capital, our constructed knowledge stocks, and additional explanatory variables such as policy measures, year dummies, and a time trend. Time effects are often neglected in the empirical literature on "green innovation" but are important for capturing general changes in the propensity to patent and strategic patenting behavior across countries. R&D expenditures, human capital, and knowledge stocks are measured in logarithms;[9] hence the estimated coefficients can be interpreted as elasticities.

The most critical part of the Poisson model is the implicit assumption of conditional mean and variance both being equal to λ_{nj}. If this assumption is violated by the dataset, the model will produce misleading predictions of zeros and large counts (Davidson and MacKinnon 2004, a phenomenon known as overdispersion. The mean-variance equality rarely holds in empirical applications on patenting behavior (e.g., Hu and Jefferson 2009). One option is the application of a negative binomial estimator, which allows for flexibility in the parameterization of the mean-variance relationship. The negative binomial density is obtained by combining the Poisson distribution with a gamma distribution for the unobserved heterogeneity in the parameter λ_{nj}.

Our dataset raises a more pressing concern; we need to handle a considerable number of zero patent counts, roughly 50%.[10] This kind of problem occurs more often in the case of firm-level micro data where one is always confronted with certain firms that do not appear to innovate at all. In the case of wind and solar technology, we need to tackle this issue at the country level because there is only a very small number of innovations in these fields and we

[9] Hall and Ziedonis (2001) suggest using logarithms when estimating a knowledge production function.
[10] The portion of zero counts in wind technology is slightly above 50%; that of solar slightly below.

therefore do not observe relevant patenting activity for all countries and years. This paucity of observations could be due, on the one hand, to some countries never innovating at all in a certain technology and, on the other hand, to other countries that may have tried to innovate but failed. This leads to a different data generating process and a standard Poisson model cannot be used to describe it. We hence apply a zero inflated Poisson (ZIP) model as proposed by Lambert 1992. Assuming that the probability of not innovating is given by *p* and, accordingly, the likelihood of innovating is *1-p*, the ZIP model can be summarized as follows:

$$P(I_{nj} = i_{nj}) = \begin{cases} p_{nj} + (1 - p_{nj})\exp(-\lambda_{nj}) & i_{nj} = 0 \\ (1 - p_{nj})\exp(-\lambda_{nj})\dfrac{\lambda_{nj}^{N}}{i_{nj}}, & i_{nj} = 1,2,3,... \end{cases}.$$

The probability of exhibiting zero patents is modeled using the logistic distribution:

$$p_{nj} = F(Z_{nj}'\gamma) = \frac{1}{1 - \exp(-Z_{nj}'\gamma)},$$

where we model the choice of not innovating as a function of public R&D support in the technology. The compound distribution is then maximized by means of maximum likelihood estimation.

Conditional on R&D support, the rate of innovation is given by:

$$I_{nj} = \exp(\alpha + \beta_1 \ln(R\&D_{nj}) + \beta_2 \ln(K_{nj}) + \beta_3 \ln(K_{n-j}) + \beta_4 \ln(K_{-nj}) + \beta_5 \bar{X}_{nj}),$$

where $\bar{X}_{nj}$ contains additional control variables such as human capital and policy and time measures. Note that we omit the knowledge stock stemming from related technologies in other countries. As could have been predicted, the various knowledge stocks are correlated to a certain extent and the high correlation of above 0.75 between the two international stocks make this omission necessary.[11] Furthermore, this type of knowledge stock is by far the most diffuse since it flows from numerous locations and several technologies.

Additionally and consistent with recent literature on innovative activity, a lag structure on inputs is imposed to account for the fact that R&D efforts do not immediately lead to innovative output (Hall et al. 1986). Therefore, we lag all inputs—except the policy dummies—by two periods. In line with Johnston et al. (2010), we do not lag the policy dummies because the legislative process takes time and rational innovators are likely to start research activity during the political decision-making process, instead of waiting until the policy becomes legally effective (Nemet 2009).

In Section 4.3, we also account for individual heterogeneity and apply a negative binomial panel data estimator.[12]

4 Empirical Findings

A key aspect of our work is to explore the role of knowledge spillovers in the knowledge-production process in two renewable energy technologies, wind and solar. We look at three sources of knowledge spillovers—first, domestic spillovers originating from the domestic knowledge stock within the same technology; second, domestic spillovers from closely related fields in the economy; and third, international spillovers from either wind or solar technology. Our empirical results are presented in three parts. We begin by discussing the findings for innovation in wind energy technologies, followed by those for solar energy. In the last part we discuss the robustness of our results.

[11] The correlation between the other stocks is considerably smaller and ranges between 0.06 and 0.6.

[12] For details on the negative binomial panel estimator see e.g., Cameron and Trivedi (2005). A ZIP panel data estimator is not yet available.

4.1 Determinants of Innovative Activity—The Case of Wind

We start with a base specification that includes public R&D expenditures, human capital, policy support instruments, and the stock of extant domestic knowledge in wind technology (Table 3, Model 1).[13] The domestic spillover variable (**Wind_stock**) has a significant and positive coefficient in the model—preliminary evidence in favor of the relevance of knowledge spillovers in the innovation process of renewable energy technologies. An increase in the national knowledge stock of 1% induces a growth in wind patent counts of 0.83% on average. A second important driver of the wind innovation process is public R&D. Such a link might not be as clear-cut in the case of renewable energies as we proxy R&D by public funding. Governments tend to fund basic or risky research projects that are less likely to result in innovative outputs such as patents. Nonetheless, we find that government R&D appears to be directed to research activities that result in patenting output or that at least increase the productivity and innovation output.[14]

The human capital variable is not significant. Hence, there is no evidence that the overall national innovative capacity is critical to innovative developments in wind technology.[15] We also control for time effects by including a trend. As expected, its estimate shows that the number of patent applications follows a strong growth path over time.

The model also includes policy measures: these include demand-side schemes aimed at inducing the installation of the technology for power production, but that may also have a stimulating effect on technology development via learning-by-doing effects (Nemet 2009). In contrast to Johnstone et al. (2010), we find no evidence of a significant link between any of the support measures and innovative activity. Note, however, that these policy dummies

[13] All estimations apply robust standard errors, which have been adjusted by clustering at the country level.

[14] For a more detailed discussion on the relationship between private and public R&D expenditures, see David et al. (2000).

[15] Although the variable is not significant in this first estimation, we retain it in the specification to, first, be consistent in the usage of the knowledge production function framework, which would be susceptible to an omitted variable bias if differences in the national human capital/researcher endowment are not controlled for.

measure only a certain aspect of the renewable support scheme, i.e., the period of time during which obligations, feed-in tariffs, or certificates were in effect. They do not take other important elements into consideration and therefore may provide only a narrow picture of the support mechanisms in place.

Model 2 now extends the analysis to study in addition the impact of knowledge originating from technologically closely related fields. We find support for the hypothesis that national inter-sectoral sources are an important factor affecting knowledge generation in wind technology by providing an additional opportunity for know-how transfers. The inclusion of this variable (**Wind_rel_stock**) results in small reductions in the magnitude of the R&D and domestic wind spillover coefficient estimates, but overall results remain robust. The inter-sectoral stock is, as would be expected, less influential than the direct wind spillover source, with the size of the coefficients differing by a factor 4. Anecdotal evidence suggests that knowledge in wind technology field itself has a higher effect on innovation output than state-of-the-art technology of related industries.

Model 2 is consistent with our notion of knowledge creation in renewable energy technologies—spillovers are critical drivers of innovation. Wind developers are exploiting and learning from technological know-how originating in the domestic wind "area"/sector itself and from knowledge gleaned from closely related sectors in the economy, such as machinery. Some key players in the wind industry have historical roots in established industries such as agricultural equipment or the steel industry. However, the role these long-established sectors of an economy play in innovation in wind technology has rarely been made explicit in empirical analyses.

As discussed in Section 3, a serious weakness of the Poisson model is that it fails to account for excess zeros in the dependent variable. We accordingly reestimate the previous model

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Second, we next extend our specification for the various sources of spillover, which might affect the role of with ZIP (Model 3). There are some minor changes in the size of estimates but, again, we find a strong link between each of the two domestic spillover sources and innovative activity. Our analysis clearly suggests that the exclusion of these knowledge spillovers omits an important element of the innovation process of wind technology.

The previous Poisson regressions found R&D to be accelerating innovative wind technology developments, but that link becomes nonsignificant in the main ZIP regression. Turning to the regression equation for the excess zeroes, however, public R&D is a significant determinant in the model predicting whether a country is an active innovator in wind technology (bottom half of Table 3).[16] It is evident that public R&D funding is pivotal in explaining whether a country generates *any* innovation output. Using the Vuong test to compare the ZIP and Poisson models, we find a significant positive value of the test statistic, providing clear evidence in favor of the ZIP approach.

To this point, all models have included a trend as our time measure. Alternatively, year dummies can be used to control for the upward dynamics in wind patent applications (Model 4). The results are in line with the previous regressions—both types of domestic knowledge spillovers work are significant drivers of wind innovation even though the innovative response to the stock of domestic wind knowledge is to some degree smaller than in Model 3, whereas the impact of inter-sectoral spillovers appears to be somewhat stronger. We will further elaborate on time effects in Section 4.3, where we also cover subperiods of our sample. Overall, the inclusion of year dummies comes at the price of losing degrees of freedom, leading us to prefer a trend specification.

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human capital due to different conditional expectations.

[16] We experimented with several alternative specifications of the inflate equation (not reported). Potential candidates were all variables already being covered in the Poisson stage of the regressions. They turned out to be insignificant and did not affect our results. Additionally, we added a "demand-push" perspective and controlled for existing wind energy capacity in a country. Again, our specification and conclusion remained robust.

The wind technology business exhibits a strong export orientation and internationalization. Thus, we would expect a positive coefficient of the international wind knowledge stock (**Int_wind_stock**) in Model 5 (Table 3). Contrary to our hypothesis, knowledge spillovers across international boundaries do not seem to be an important driver of technological progress in wind. The elasticities of the domestic spillover variables remain significant and the coefficient of wind-related knowledge spillovers drops slightly.

These findings lead us to conclude that although the market for the technology itself is international, research and technology development appear to predominantly occur in a domestic setting. A possible explanation for this is that the pool of knowledge available domestically is still large enough that acquiring knowledge from abroad is generally redundant. Though innovators have contact and are in exchange with international business and research communities, appropriation from foreign knowledge is likely to be more costly that that occurring through domestic knowledge.

Turning to policy relevance, our results suggest that if an innovation system is predominantly characterized by domestic spillovers, and has the opportunity and means to exploit its existing strong knowledge base, then a country that is a technology leader is likely to maintain that position. This may also imply that "late movers" will have difficulty stimulating innovation in wind technology as they lack their own knowledge base.

4.2 Determinants of Innovative Activity—Solar Technology

Solar energy is still in a relatively early phase of development. This sector faces the specific technological challenge of improving the efficiency of solar energy conversion while significantly reducing the manufacturing costs.

We start from the same base knowledge production specification using a Poisson estimation approach (Model 1, Table 4), with the only difference being that the knowledge spillover stock now stems from the domestic solar industry (**Solar_stock**). The findings reveal a picture similar to that obtained for wind: domestic spillovers within the same technology, i.e., solar, and R&D are the main drivers of solar innovation output. As a comparison of the elasticity estimates reveals, domestic intra-industry spillovers are again superior to R&D in stimulating innovation. We also find that the effect of domestic intra-industry spillovers—relative to R&D—is less strong in the case of solar than for wind (the ratio of elasticities of spillover to R&D is about 2.1 in solar technologies and 3.4 in wind technologies). Other variables, such as human capital intensity and policy instruments, are not significant factors in explaining innovation.

Next, we include national knowledge that could flow to the solar industry from technologically closely related fields (**Solar_rel_stock**, Model 2). Interestingly, this factor contributes little to innovative activity in solar technologies, whereas it had a strong effect in the wind case. Possible explanations for this include, first, that solar technology is still in its infancy (compared to wind) and it is most especially the exchange of knowledge and expertise within the same technological field that is accelerating technology development. Second, solar technology is more complex than wind technology (for details see Section 3 and Appendix A). There are more and heterogeneous potential opportunities for innovational complementarities. This implies that it could be more difficult to measure how innovation responds to related knowledge because the related knowledge is so diverse.

Do these findings hold in a ZIP specification? The Vuong test indicates that the ZIP model is better suited to the data. The inflate regression is specified similarly to the wind case regression. Public R&D expenditures are again found to be a critical determinant in modeling the zero patenting outcomes.[17] The ZIP model shows that innovation production is only

[17] Again, we tested several specifications for the inflate equation (not reported). Additional variables were not significant and did not change our results.

accelerated by absorption and utilization of knowledge available in the domestic solar industry; inter-sectoral effects are negligible.

As a robustness check, we reestimate the model including year dummies instead of a trend (Table 4, Model 4). The time dummies are mostly significant and positive; their size, as expected, is increasing over time (see also Figure 2). Coefficient estimates remain otherwise robust.

A third factor hypothesized to spur innovation is international spillovers. We accordingly extend the analysis to investigate the role international knowledge spillovers plays in innovation performance (Model 5). Again, international spillovers do not affect innovation performance. The coefficient of **Int_solar_stock** is very small and insignificant. Our analysis suggests that knowledge embodied in domestic spillovers from the solar sector is superior in creating new knowledge compared to solar knowledge from abroad or from related fields in the economy.

We now examine another model to explore the robustness of the insignificant role of international spillovers in the knowledge-creation process in solar energy. As national related technology knowledge was previously found to be insignificant (Model 3 or 4), we estimate a model including domestic and international solar stocks to elaborate on the role of the specific solar knowledge base. The results show considerable support for our earlier observation: solar innovative activity is predominantly spurred by domestic spillovers within its industry and, to a lesser extent, by R&D, but is not stimulated by international knowledge transfers (Model 5). It is not possible to state whether this is due to international spillovers being less conducive to innovation or whether the lack of influence is due to an incapacity, for whatever reason, of countries to exploit international knowledge. For an evolving technology like solar, the learning opportunities within the home country and the same technology field still seem to be sufficiently large to foster technological advances. However, it could be that in the future, as the technology matures, international knowledge spillovers will be more influential.

4.3 Robustness

In this section we test the robustness of our results by applying panel estimation methods and considering different time periods. To this point, we adopted a pooled ZIP regression approach, but as this method is not able to account for country-level heterogeneity, we use a negative binomial (Negbin) panel data estimator (e.g., Johnestone et al. 2010; Brunnermeier and Cohen 2003).

Beginning with wind technology, Model 1 in Table 5 shows random effects and Model 2 the fixed effects results. The Hausman test clearly rejects the assumption that error terms are uncorrelated with the individual effects. Most coefficients in the fixed effects model remain similar in magnitude, but the one for domestic wind spillovers is about one-third smaller than that previously obtained. Knowledge from related sectors no longer has a significant impact on innovation; however, one should be wary of concluding that inter-sectoral spillovers do not matter in case of wind. As Hall et al. 2005 argue, R&D and, consequently, knowledge accumulation usually changes slowly over time, implying that national spillover sources (stocks) could be highly correlated with the individual effect.

We also reestimated the solar innovation model using a panel Negbin setting. Using a fixed effects approach, we find a somewhat stronger effect of R&D on innovation output (Table 5, Model 6). Compared to the results using a ZIP approach, we no longer detect a significant role of domestic intra-sectoral spillovers, possibly because the country dummies capture all permanent heterogeneity in each country and, accordingly, the coefficient is determined by the remaining less pronounced within-country variation over time. In line with our earlier results (Table 4, Model 3), spillovers from closely related sectors still have no influence on innovation in solar technologies (Table 5, Model 7). Interestingly, a different picture emerges when we include international spillovers (Model 8). Here, international knowledge spillovers within the solar industry are found to induce innovation, whereas the domestic solar spillovers remain insignificant. Why this should be so is not immediately clear, but it should be kept in mind that the effect described previously is only marginally significant.

Both solar and wind technologies have been around for several decades, but it is only in the last decade that they have become the subject of renewed interest and rapid commercialization. We therefore investigate whether significant changes in the set of determinants and their relative strength for knowledge production can be observed. We reestimate our ZIP model for two subsamples of the data, one for the period of 1982 to 1994 and the other encompassing 1995 through 2004.

Wind technology development in the earlier subsample is significantly driven by domestic knowledge spillovers within the wind industry and by obligations (Model 3). For the more recent period, we see that related-sector technology has become a stimulating factor (Model 4).[18]

Finally, a comparison between different time horizons for solar technologies reveals a very similar picture (Models 9 and 10). Domestic knowledge spillovers within the solar technology field have a major influence on innovation output. The magnitude of the effect is revealed to be even stronger in the subsample covering the last decade. One interesting difference is that R&D is significant in the early period only. Apparently, solar technology innovation went through a phase during which R&D and human capital were critical to innovative activity, but later on, when the knowledge base in the solar industry expanded, innovation in this domain is chiefly the result of within-field knowledge spillovers.

[18] We also conducted estimations including year dummies (results not reported), the results of which are not in conflict with our previous findings.

5 Conclusion

Innovation is no panacea for mitigating climate change, but it is a crucial factor in reducing greenhouse gas emissions and limiting the costs associated with that task. This paper is one of the first to empirically study the channels through which innovative activity in solar and wind technologies is spurred. Our work contributes to the literature on innovation in renewable energy technologies by, first, emphasizing the importance of knowledge spillovers for technological change and, second, studying the impact of various spillover sources. A distinction is drawn between intra- and inter-sectoral spillover sources, as well as between domestic and international spillovers.

Our analysis yields several important findings. Knowledge spillovers are an important input in the knowledge-generation process of wind and solar technologies. Innovators in both wind and solar technologies absorb and utilize existing own-field knowledge in making technological advances. However, spillovers are predominantly a domestic phenomenon—i.e., they chiefly occur within a country; international spillovers play a negligible role. Another important finding from our estimation results is that wind and solar technologies have distinct innovation characteristics and thus should be considered separately in innovation analyses. Wind and solar technologies are both stimulated by intra-sectoral spillovers, but they respond differently to inter-sectoral spillovers, which are influential only in the case of wind technology.

Our results suggest that if an innovation system is predominantly characterized by domestic spillovers, and it has the opportunity and means to exploit its existing strong knowledge base, then a country that is a technology leader is likely to maintain that position. This implies that "late movers" will have difficulty in creating their own research in renewable energy technologies as they lack a corresponding knowledge base; international spillovers do not seem to be to sufficient for activating innovation. The use of renwable energy technologies in developing countries is expected to provide significant benefits at the global level in terms of climate change, and also at the local level for environmental sustainability and development. There is an important debate on how to best support a North-South technology transfer. An important lesson from our study on OECD countries is that international knowledge flows have to date played a negligible role and that successful technology development is currently contingent on a solid domestic knowledge base in the same technology or, to a lesser extent, in related sectors. This raises some concern over the ability of developing countries to develop, not to mention improve, their own renewable energy technology sector. It should be emphasized here, that we only analyzed the conditions for innovation in renewable energy technology, not for patterns of production. There other factors such as factor cost, particularly for labor, or commodity costs play a more prominent role. International policy commitment will be needed to bring renewable energy technologies to these countries. In some cases, increasing or building the capacity of these countries to absorb knowledge transfers and spillovers may be effective but, as our results reveal, the self-sustained development of renewable energy technologies will not come easily in developing countries. That international knowledge spillovers are so insignificant is additionally unfortunate as it could lead to a costly duplication of research effort if each country independently engages in developing renewable energy technologies.

Coordination of R&D efforts, priorities, and the exchange of failure and success stories could avoid such duplication and, moreover, accelerate overall technological progress. In this paper, we find that public R&D support stimulates innovation in renewable energy technologies, a result that is particularly robust for solar technologies.

The importance of knowledge flows between sectors has to date been mostly ignored in policy debates. If developers of clean technologies are able to learn from other sectors in the economy, it could well reduce the costs of innovation. However, it is not a priori clear whether policy intervention would in actuality enhance inter-sectoral knowledge transfer and, if it could, how it should be designed to work most effectively.

There is still much to learn about the mechanisms of and incentives for absorbing and using external knowledge. In general spillover mechanisms are weakly understood and there is a great deal of room for further research on them. One extension of our work would be to construct measures of "proximity" in technology space case studies or geographical distance. Additionally, studies based on micro data (e.g., from firms in renewable energy technologies) could greatly expand our understanding of the underlying knowledge-generation process. A further extension of our study would be to include national patent data or make a detailed investigation of how knowledge flows across countries and technologies as evidenced by patent citations.

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Appendix A

Calculation of the Spillover Variables

To derive knowledge stocks, we use information on patent applications from the European Patent Office's (EPO) Worldwide Patent Statistical Database. This database contains all national and international patent applications. Note that patents often have more than one inventor from different home countries. In the empirical literature, the analysis is often restricted to the first inventor, which might be misleading, especially in case of transnational research collaborations. We allow for multiple inventors when calculating our patent counts. Given the possibility of affiliation with more than one country, our patent counts might be larger than the total number of patent applications at the EPO, e.g., a co-invention by a French and a German inventor counts twice, once in the count for Germany and a second time in the count for France.[1]

Patents in wind and solar technology are collected according to a classification scheme published by Johnstone et al. 2010 that links technology classes, more specifically the International Patent Classification (IPC) classes, to renewable energy technologies. Methodologically, these relevant classes were determined by using a set of keywords related to technological developments in this area.

Domestic knowledge stocks in wind and solar technology are derived by applying the perpetual inventory method to the yearly patent applications in these fields in a certain country. Accordingly, the knowledge stock available at time t is determined by:

$$K_t = (1+\delta)K_{t-1} + p_t.$$

[1] This approach helps approximate the underlying value of innovative output since one might argue that international co-inventions are of higher economic value due to the origination of larger costs. We also experimented with first inventor patent counts in the estimations and it had very little influence on our results.

Hence, the stock is equal to the stock at time t-1 K_{t-1}, minus depreciation δ,[2] plus patent applications in period t p_t. The initial stock is approximated using an initial growth rate of 20%. Foreign knowledge stocks in wind and solar are calculated as the sum of the domestic stocks minus those of the country of interest.

Another influential factor in determining innovative activity is knowledge spillover from technologically closely related industries. To extract patent applications in related industries, we combine the classification on renewable energy technologies by Johnstone et al. 2010 with a sectoral concordance provided by Schmoch et al. 2003 that links industrial fields to IPC classes.[3] Based on this concordance, we identify those fields that encompass the IPC classes defining innovation in wind and solar technology and denote them as being related to wind or solar energy. According to Johnstone et al. 2010, patents with IPC class "F03D" belong to the field of wind energy. The class "F03D" belongs to the industrial field "energy machinery." We hence derive the patent stock in wind-related industries by summing over all applications belong to the field "energy machinery" except for those belonging directly to wind energy ("F03D"). In case of solar energy, the procedure is slightly more complicated because solar energy patents are found in five different fields: "mineral products," "metal products," "energy machinery," "electrical motors," and "electronic components." We perform the calculation in the same manner as for the case of wind. Detailed classifications for deriving related stocks are provided in the tables below. Foreign stocks are determined according to the method described previously.

[2] We impose a depreciation rate of 15%, which is common in the literature (e.g., Guellec and van Pottelsberghe 2004).

[3] Expert assessments and micro-data evidence on the patent activity of firms in the manufacturing industry are used to link technology classes to industry sectors.

Table A.1

Related wind technology

Field	IPC Classes	Except for wind technology IPC Class
Energy machinery	B23F, F01B, F01C, F01D, F03B, F03C, F03D, F03G, F04B, F04C, F04D, F15B, F16C, F16D, F16F, F16H, F16K, F16M, F23R	F03D

Table A.2

Related solar technology

Field	**IPC Classes**	**Except for solar technology IPC Class**
Mineral products	B24D, B28B, B23C, B32B, C03B, C03C, C04B, E04B, E04C, E04D, E04F, G21B	E04D 13/18
Metal products	A01L, A44B, A47H, A47K, B21K, B21L, B22F, B25B, B25C, B25F, B25G, B25H, B26B, B27G, B44C, B65F, B82B, C23D, C25D, E01D, E01F, E02C, E03B, E03C, E03D, E05B, E05C, E05D, E05F, E05G, E06B, F01K, F15D, F16B, F16P, F16S, F16T, F16B, F22B, F24J, G21H	F24J 2
Energy machinery	B23F, F01B, F01C, F01D, F03B, F03C, F03D, F03G, F04B, F04C, F04D, F15B, F16C, F16D, F16F, F16H, F16K, F16M, F23R	F03G 6
Electrical motors	H02K, H02N, H02P	H02N 6
Electronic components	B81B, B81C, G11C, H01C, H01F, H01G, H01J, H01L	H01L 27/142 & 31/04-078

Figure 1
Innovative activity in wind technologies, EPO patent applications

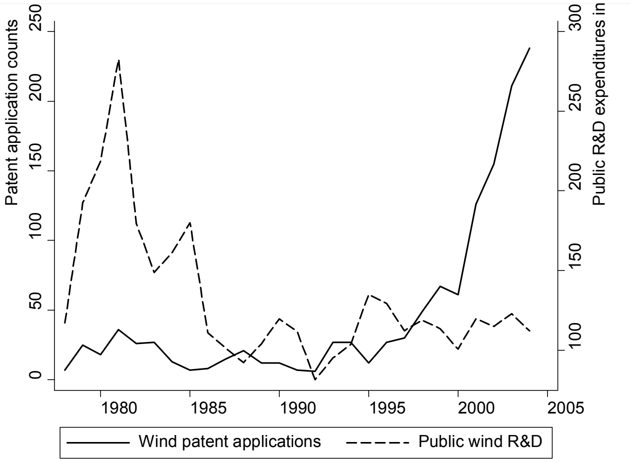

Figure 2
Innovative activity in solar technologies, EPO patent applications

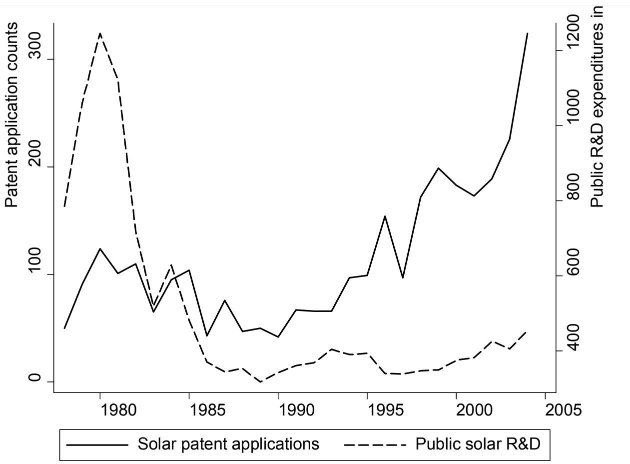

Figure 3
Wind patent applications by major innovators, EPO patent applications

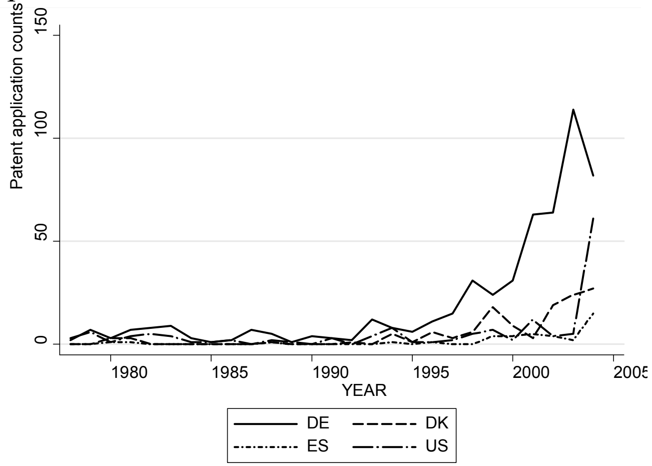

Figure 4
Solar patent applications by major innovators, EPO patent applications

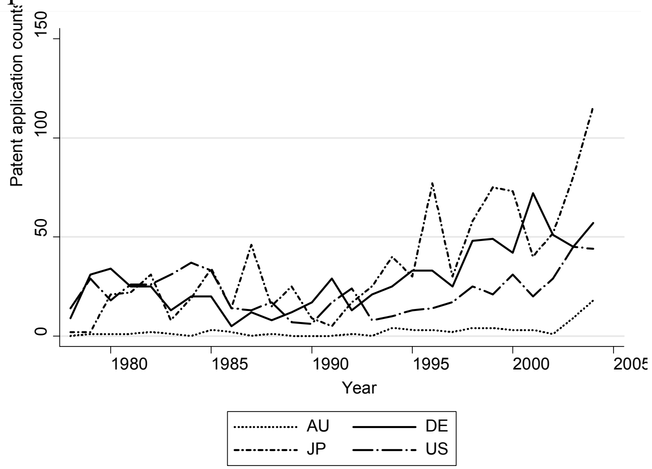

Table 1

Summary statistics: wind technology (1978–2004)

Variable	Description	Mean	S.D.	Min	Max
Patent_Wind	Patent applications in wind technology	2.240	8.220	0	114
R&D	R&D expenditures in mio. U.S. dollars, 2008 prices and PPP	6.313	14.254	0	156.836
Human_capital	Researchers per 1,000 employees	5.530	2.670	1.013	17.713
Wind_stock	Stock of patent applications in wind technology, domestic inventors	9.060	22.988	0	318.374
Wind_rel_stock	Stock of patent applications in wind-related technology, domestic inventors	1074.329	2505.399	0	20698.110
Int_Wind_stock	Stock of patent applications in wind technology, foreign inventors	181.019	148.353	20	731.927
Int_Wind_rel_stock	Stock of patent applications in wind-related technology, foreign inventors	21479.750	14743.550	1123.750	54948.520
Feed-in Tariffs	Policy instrument, dummy	0.349	0.477	0	1
Obligations	Policy instrument, dummy	0.233	0.423	0	1
Certificates	Policy instrument, dummy	0.072	0.259	0	1

Notes: ***Human-capital*** is only available from 1981 onward.

Table 2

Summary statistics: solar technology (1978–2004)

Variable	Description	Mean	S.D.	Min	Max
Patent_Solar	Patent applications in solar technology	5.485	12.584	0	116
R&D	R&D expenditures in mio. U.S. dollars, 2008 prices and PPP	24.019	70.261	0	859.348
Human_capital	Researchers per 1,000 employees	5.530	2.670	1.013	17.713
Solar_stock	Stock of patent applications in solar technology, domestic inventors	26.615	53.637	0	404.447
Solar_rel_stock	Stock of patent applications in solar-related technology, domestic inventors	5337.713	11838.390	0	64453.970
Int_Solar_stock	Stock of patent applications in solar technology, foreign inventors	531.579	231.913	106.75	1196.473
Int_Solar_rel_stock	Stock of patent applications in solar-related technology, foreign inventors	106720.700	71807	5186.75	254810.500
Feed-in Tariffs	Policy instrument, dummy	0.289	0.454	0	1
Obligations	Policy instrument, dummy	0.219	0.414	0	1
Certificates	Policy instrument, dummy	0.072	0.259	0	1

Notes: ***Human-capital*** is only available from 1981 onward.

Table 3

Determinants of innovative activity in wind technologies

	Model 1: Poisson	Model 2: Poisson	Model 3: ZIP	Model 4: ZIP	Model 5: ZIP
R&D	0.244**	0.199**	0.074	0.056	0.074
	(0.095)	(0.100)	(0.114)	(0.110)	(0.106)
Human_capital	0.204	0.065	0.056	0.037	0.116
	(0.229)	(0.213)	(0.249)	(0.218)	(0.254)
Wind_stock	0.833***	0.728***	0.721***	0.713***	0.723***
	(0.072)	(0.076)	(0.078)	(0.073)	(0.070)
Wind_rel_stock		0.152**	0.150**	0.170**	0.130**
		(0.068)	(0.062)	(0.069)	(0.059)
Int_Wind_stock					-0.199
					(0.205)
Feed-in Tariffs	-0.026	0.068	0.041	0.090	-0.002
	(0.178)	(0.177)	(0.207)	(0.183)	(0.198)
Obligations	0.221	0.077	0.120	0.009	0.130
	(0.167)	(0.161)	(0.148)	(0.149)	(0.142)
Certificates	0.266	0.396**	0.236	0.283	0.273
	(0.179)	(0.200)	(0.232)	(0.214)	(0.251)
Trend	0.103***	0.104***	0.087***	-	0.101***
	(0.022)	(0.023)	(0.023)		(0.016)
Year dummies	-	-	-	Yes	-
Intercept	-3.746***	-4.253***	-3.377***	-2.659***	-2.614**
	(0.272)	(0.341)	(0.380)	(0.578)	(1.068)
Inflate regression					
R&D			-0.644***	-0.693***	-0.660***
			(0.193)	(0.201)	(0.187)
Trend			-0.112***	-0.098**	-0.104***
			(0.035)	(0.041)	(0.032)
Intercept			1.707**	1.242	1.554**
			(0.790)	(0.919)	(0.725)
Observations	254	253	253	253	253
Countries	19	19	19	19	19
Log-likelihood	-520.787	-506.684	-480.313	-450.218	-478.697
Vuong test			2.35***		

Notes: 1. Dependent variable: number of EPO patent applications in wind technologies, 1981–2004. Countries not included are Australia and Hungary.
2. Robust standard errors are calculated by clustering at the country level. Standard errors are given in parentheses below the coefficient estimates.
3. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4

Determinants of innovative activity in solar technologies

	Model 1: Poisson	Model 2: Poisson	Model 3: ZIP	Model 4: ZIP	Model 5: ZIP	Model 6: ZIP
R&D	0.322***	0.312***	0.271***	0.209***	0.270***	0.269***
	(0.061)	(0.065)	(0.076)	(0.077)	(0.074)	(0.079)
Human_capital	0.252	0.194	0.363	0.383	0.367	0.331
	(0.292)	(0.273)	(0.294)	(0.292)	(0.296)	(0.311)
Solar_stock	0.682***	0.633***	0.688***	0.605***	0.688***	0.661***
	(0.078)	(0.115)	(0.126)	(0.103)	(0.126)	(0.092)
Solar_rel_stock		0.072	-0.052	0.126	-0.044	
		(0.109)	(0.138)	(0.109)	(0.133)	
Int_Solar_stock					0.064	0.091
					(0.450)	(0.451)
Feed-in Tariffs	-0.111	-0.111	-0.069	0.006	-0.071	-0.075
	(0.159)	(0.158)	(0.165)	(0.175)	(0.176)	(0.183)
Obligations	-0.237	-0.231	-0.242	-0.144	-0.258	-0.261
	(0.151)	(0.148)	(0.153)	(0.172)	(0.261)	(0.261)
Certificates	-0.020	0.001	0.023	0.133	0.023	0.031
	(0.067)	(0.075)	(0.085)	(0.164)	(0.084)	(0.080)
Trend	0.060***	0.055***	0.060***	-	0.057***	0.054***
	(0.008)	(0.010)	(0.013)		(0.012)	(0.012)
Year dummies	-	-	-	Yes	-	-
Intercept	-2.791***	-3.036***	-2.319***	-45.359*	-2.741	-3.071
	(0.392)	(0.704)	(0.873)	(24.469)	(2.938)	(2.759)
Inflate regression						
R&D			-0.902***	-1.592*	-0.902***	-0.886***
			(0.257)	(0.929)	(0.260)	(0.266)
Trend			-0.056	-0.010	-0.056	-0.056
			(0.051)	(0.146)	(0.051)	(0.050)
Intercept			0.900	-0.455	0.882	0.813
			(1.351)	(3.347)	(1.351)	(1.286)
Observations	260	260	260	260	260	260
Countries	21	21	21	21	21	21
Log-likelihood	-686.650	-685.759	-675.461	-575.617	-675.374	-675.579
Vuong test			1.33*			

Notes: 1. Dependent variable: number of EPO patent applications in solar technologies, 1981–2004.
2. Robust standard errors are calculated by clustering at the country level. Standard errors are given in parentheses below the coefficient estimates.
3. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 5

Robustness checks—alternative model specifications and estimation methods

	Wind Model 1: Negbin RE Full sample	Wind Model2: Negbin FE Full sample	Wind Model 3: ZIP Subsample: 1982–1994	Wind Model 4: ZIP Subsample: 1995–2004	Solar Model 5: Negbin RE Full sample	Solar Model 6: Negbin FE Full sample	Solar Model 7: Negbin FE Full sample	Solar Model 8: Negbin FE Full sample	Solar Model 9: ZIP Subsample: 1982–1994	Solar Model 10: ZIP Subsample: 1995–2004
R&D	0.222***	0.196**	0.331	0.064	0.441***	0.460***	0.448***	0.485***	0.361**	0.155
	(0.077)	(0.097)	(0.289)	(0.118)	(0.082)	(0.106)	(0.107)	(0.106)	(0.140)	(0.095)
Human_capital	0.038	-0.241	-0.012	0.043	0.271	0.285	0.013	0.536	1.106**	0.149
	(0.270)	(0.459)	(0.723)	(0.268)	(0.263)	(0.439)	(0.515)	(0.460)	(0.495)	(0.253)
Wind|Solar _stock	0.532***	0.347***	0.629**	0.678***	0.433***	0.163	0.102	0.139	0.612***	0.723***
	(0.117)	(0.127)	(0.271)	(0.092)	(0.099)	(0.123)	(0.137)	(0.125)	(0.171)	(0.090)
Wind|Solar _rel_stock	0.136*	0.077	0.134	0.179**	-	-	0.153	-	-	-
	(0.080)	(0.137)	(0.300)	(0.078)			(0.157)			
Int_solar _stock	-	-	-	-	-	-	-	0.501*	-	-
								(0.302)		
Feed-in Tariffs	-0.136	-0.234	-0.634	0.241	0.142	0.022	0.022	0.054	-0.210	-0.079
	(0.188)	(0.208)	(0.387)	(0.221)	(0.162)	(0.199)	(0.198)	(0.200)	(0.322)	(0.138)
Obligations	0.022	-0.030	1.607*	0.047	-0.035	-0.029	-0.018	-0.135	0.716*	-0.281
	(0.176)	(0.193)	(0.830)	(0.165)	(0.147)	(0.166)	(0.166)	(0.179)	(0.425)	(0.230)
Certificates	0.314	0.375	dropped	0.338	-0.006	0.024	0.051	0.036	droppped	0.056
	(0.223)	(0.244)		(0.244)	(0.164)	(0.184)	(0.187)	(0.183)	-	(0.120)
Trend	0.109***	0.132***	0.122	0.102**	0.054***	0.068***	0.059***	0.050**	-0.023	0.052
	(0.019)	(0.024)	(0.117)	(0.048)	(0.014)	(0.018)	(0.020)	(0.021)	(0.028)	(0.039)
Intercept	-4.450***	-3.451***	-3.624***	-3.925***	-3.367***	-2.709***	-3.185***	-5.862***	-3.376***	-1.879**
	(0.490)	(0.719)	(1.009)	(1.077)	(0.426)	(0.605)	(0.759)	(1.991)	(0.458)	(0.802)

Inflate regression										
R&D			-0.195	-0.750***					-166.553***	-1.288***
			(0.324)	(0.252)					(9.196)	(0.355)
Trend			0.047	-0.239*					-6.321***	0.026
			(0.088)	(0.140)					(0.396)	(0.219)
Intercept			-0.794	4.599					89.748***	-0.724
			(1.601)	(3.226)					(5.308)	(5.165)
Observations	253	237	121	132	260	249	249	249	122	138
Log-likelihood	-406.552	-336.541	-134.525	-337.221	-526.225	-445.970	-445.503	-444.627	-251.058	-383.987
Hausman test		chi2(8): 22.92***					chi2(8): 3058.37***			

Notes: 1. Dependent variable: number of EPO patent applications in wind or solar technologies, respectively.
2. Standard errors are given in parentheses below the coefficient estimates.
3. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.
4. Note that variable **Certificates** dropped due to lack of variation in the early subsample 1982-1994.