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Does foreign environmental policy influence domestic innovation?

Evidence from the wind industry

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Abstract

This paper analyses the relative influence of domestic and foreign demand-pull policies in wind power across OECD countries on the rate of innovation in this technology. We use annual wind power generation to capture the stringency of the portfolio of demand-pull policies in place (e.g., guaranteed tariffs, investment and production tax credits), and patent data as an indicator of innovation activity. We find that wind technology improvements respond positively to policies both home and abroad, but the marginal effect of domestic policies is 12 times greater. The influence of foreign polices is reduced by barriers to technology diffusion, in particular lax intellectual property rights. Reducing such barriers therefore constitutes a powerful policy leverage for boosting environmental innovation globally.

JEL CLASSIFICATION: O31, Q42, Q55

KEYWORDS: innovation, international technology diffusion, renewable energy policy, wind power

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1 Introduction

One of the central objectives of environmental policies is to foster innovation in environment-friendly technologies and pave way towards 'green' growth. Political leaders across countries frequently argue that ambitious environmental and climate domestic policies can help local firms achieve technological leadership, thereby boosting the competitiveness of the national economy and creating jobs.[1] However, domestic policies may also boost innovation activities abroad, and thus strengthen foreign competitors. Indeed, the fact that 44% of the applications for patents worldwide in 2008 were filed by non-residents (WIPO 2010) clearly indicates that innovators look beyond national borders.

If innovators are influenced not only by domestic, but also foreign market conditions, then environmental policies may fail to give rise to competitive advantage for domestic companies. This concern has led to particularly heated political debates in the renewable energy sector, as this source of energy has been heavily subsidized through guaranteed feed-in tariffs in many developed countries, while major global suppliers of wind or solar photovoltaic equipment are located in China or India. Yet the existence of cross-country policy spillovers implies a stronger overall impact of domestic policies on global innovation, and thus on green growth.

A first objective is to study the relative impact of domestic and foreign policies promoting wind power on innovation. We primarily focus on policies that stimulate the deployment of wind power capacities, such as feed-in tariffs or renewable portfolio standards. These are usually referred to as demand-pull policies as they foster the demand for innovation. A major practical difficulty to study the cross-border impact of demand-pull policies, however, is finding data measuring the level of demand-pull regulation that are reliable and comparable across countries. We overcome this difficulty by using annual wind electricity generation in each country to proxy for the level of demand-pull policies for wind generation. We also examine the influence of public R&D support in wind technologies.

When developing a technology, innovators look forward to the diffusion stage, at which time they will reap the benefits of their invention. Considering the diffusion stage is thus necessary to understand the impact of foreign determinants on innovation. A second objective of the paper is to investigate the drivers of the international diffusion of wind power technology.

Reasoning backward, we first identify the factors driving international technology diffusion based on a panel dataset describing the cross-border transfer of inventions, as measured by patent filings, from 28 OECD (inventor) countries to 79 recipient countries between 1991 and 2008. We show that local demand for wind power exerts a positive influence on technology inflows. However, barriers to trade and lax intellectual property rights regimes significantly hinder the transfer of patented inventions. This suggests that foreign demand might be less effective in inducing innovation relative to domestic demand.

We test the latter assumption by estimating the relative impact of domestic and foreign demand for wind power on innovation with a panel covering the same 28 inventor (OECD) countries[2] over the period 1991-2008. In certain specifications, we use our results on technology diffusion to weigh the variables capturing the level of foreign policies, the idea being that foreign demand originating from countries with lower barriers to diffusion are more likely to influence inventors. We find that innovation efforts increase in response to both stronger domestic and foreign demand. However, the marginal effect of domestic demand on the rate of innovation is much stronger than that of the foreign demand.

Our focus on wind power is motivated by three reasons. First, wind power accounted for the largest additions of renewable energy capacity in recent years, ahead of hydro power and far ahead of solar, geothermal, biomass and marine energy (IEA, 2012). Second, the wind turbines market is a globalized market, with the top 10 companies in 2009 based in six different coutries, including two emerging economies[3], making it an interesting case to study cross-country spillovers of innovation. Third, the competition from these emerging economies has given rise to heated policy debates, in particular over the pertinence of introducing measures to protect domestic industries.

The topic of this paper makes a contribution to the well-developed empirical literature on green innovation. Most studies ignore cross-country policy spillovers as they relate domestic innovation to domestic policies (Jaffe and Palmer 1997; Brunnermeier and Cohen 2003; Newell et al. 1999; Popp 2002; Crabb and Johnson 2010; Johnstone et al. 2010). Our finding that environmental policies also promote foreign innovation means that these studies underestimate their overall impact.

A few empirical studies have begun exploring the effect of foreign environmental or climate regulation on technological innovation. Their conclusions are, however, mostly based on correlation analysis, which may not provide sufficient evidence of causality. Lanjouw and Mody (1996) observe that strict vehicle emission regulations in the US seemingly spurred innovation in Japan and Germany. Popp (2006), by contrast, finds that innovation in air pollution control devices for coal-fired power plants is positively correlated with stringency of environmental regulation in the home country, but is not influenced by the stringency of foreign environmental regulation. Popp et al. (2011) examine the case of chlorine-free technology in the pulp and paper industry and find a positive correlation between both domestic and foreign regulation and innovation. But whether these results can be interpreted as causation remains an open question.

In a paper developed independently and at the same time as ours, Peters et al. (2012) analyse the impact of foreign demand-pull policies on innovation in the photovoltaic energy sector. They also find that a positive and significant effect of foreign demand on domestic innovation, which suggests that this pattern is robust, at least across renewable energy technologies. However, the magnitude of the impact of foreign demand is smaller than in this paper. Although differences in sample and in explanatory variables make it difficult to compare the results of the two papers[4], this may suggest that barriers to technology diffusion are higher in the solar PV than in the wind industry, which is a relatively more mature technology.

This paper is also related to the literature on the international diffusion of clean technologies. In particular, Dechezleprêtre et al. (2012) examines the drivers behind the flows of climate-related patents across countries. This paper's approach and results are similar, but whereas Dechezleprêtre et al. (2012) primarily assesses the influence of generic policy variables (IPR, barriers to trade and FDI), this paper looks specifically at environmental policy variables. Dekker et al. (2012) uses patent data to look at the impact of the Convention on Long-Range Transboundary Air Pollution on innovation and international technology diffusion. They show that signatory countries experience an increase in the inflow of foreign patents as well as in domestic innovation. Yet it does not address the influence on innovation *by foreign inventors*, which is the central question of this paper.

The paper proceeds as follows. Section 2 briefly presents the recent trends in the deployment of wind power technology at the global level and discusses the policies that support this deployment. Section 3 presents the data. We explain how we extracted patent data from the World Patent Statistical Database (PATSTAT) and discuss the use of patents to measure innovation and technology diffusion. We also explain how we proxy the level of wind policies and present descriptive statistics on innovation and demand, both at home and abroad. In section 4, we present and discuss our hypotheses. Section 5 presents our econometric strategy and results on the international diffusion of technologies. Section 6 is dedicated to the econometric analysis of innovation. The final section summarises the main findings.

2 Background information on wind power

The wind power industry is developing very quickly: between 2000 and 2009, installation of wind capacity has grown at an annual average rate of 30% at the global level. This corresponds to a doubling of capacities every three years. Globally, wind turbines produced 340 terawatt-hours (TWh) of electricity in 2009, representing less than 2% of total electricity generation. In a few countries, however, high levels of wind power penetration have been achieved. These include Denmark (20% of total electricity production), Portugal and Spain (14%), Ireland (11%), and Germany (8%).

The cost of generation associated with wind technology remains high relative to the conventional fuels used for power generation, although this might change in the near future as costs have been constantly diminishing during the past 20 years. Costs vary according to a number of factors, including the size of the turbine and wind availability. According to the IEA Wind Technology Roadmap, the life-cycle cost of electricity generation from wind ranges from a low of 70 USD/MWh under the best circumstances to a high of 130 USD/MWh (IEA, 2009). This is in contrast to coal plants, where costs range from 20 USD/MWh to 50 USD/MWh. Gas-fired electricity costs range between 40

USD/MWh and 55 USD/MWh and nuclear electricity costs range between 20 USD/MWh and 30 USD/MWh (IEA, 2005).

Since wind power generation is not yet competitive with conventional technologies, the massive deployment of wind turbines across the world has been driven mainly by public policy support.[5] These include feed-in tariffs, a guaranteed price at which electricity suppliers must purchase renewable electricity from producers and a popular measure implemented in European countries. Germany introduced an attractive feed-in tariff for wind power in 1990 and wind power capacity increased by 60% annually between 1990 and 2001.[6] In the US, 30 States, including Texas, Florida and California, have adopted Renewable Portfolio Standards, which place an obligation on electricity supply companies to produce a specified fraction of their electricity from renewable energy sources. Other states have implemented investment tax credits, production tax credits, feed-in tariffs, and tradable certificates. As a result, the US represented 26% of the wind capacities installed worldwide in 2009.

Several policies usually coexist in a given jurisdiction. For instance, in his study on the development of wind power in California, Nemet (2009) shows that up to four policies were in place at the same time in the 1980s, including federal investment tax credit, oil windfall profits tax credit, the California alternative energy tax credit, and standard offer contracts. This has important methodological implications for the empirical study of innovation: estimating the specific impact of one component of the policy mix on innovation is hardly feasible.[7] In this paper, we overcome this difficulty by focusing directly on the joint result of these policies; that is, annual wind power generation.

3 Data

Addressing the paper's questions requires variables to measure innovation activity, international technology transfer and the stringency of wind-power support policies. We rely on patent data for innovation and diffusion and on wind power generation data for the policy stringency. In this section, we justify these choices, describe data sources and give a first description of world innovative activity and technology transfer.

3.1 Innovation and technology transfer

We use the EPO World Patent Statistical Database (PATSTAT, 2012) to extract information on patents granted in wind power technology worldwide between 1991 to 2008 (as well as citations made to these patents). To mitigate the well-known problem that many patent applications are of very low value, our outcome measure focuses on patents that, after scrutiny, have been granted by the patent office. We need a truncation period to account for the time it takes for an patent application to be granted, so 2008 is our end year[8]. Our dataset includes 16,649 patents granted in 84 patent offices.[9] In PATSTAT, patent documents are categorised using the international patent classification (IPC) system. To select the patent related to wind power technologies, we follow Johnstone et al. (2010) and extract all patents included in the "F03D" group, which covers "wind motors". A recent study by the UK intellectual property office showed that this category includes 96% of all wind-power related patents and therefore accurately covers wind technology[10] (Buchanan and Keefe, 2010). Since we are primarily interested in the influence of public policies (including public R&D expenditures) on private innovation activity, we exclude patents filed by public research institutions. We use the ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table (EEE-PPAT, 2012) in order to identify public research institutions among patent applicants.

Importantly, the same invention may be patented in several countries. This could lead to double-counting of some inventions. However, once patent protection has been requested in one country, subsequent patents covering the same invention in other countries must designate the original patent as their "priority patent". The set of patents covering the same invention in several countries is referred to as a patent family. Our measure of innovation is thus based on counts of patent families. This allows us to avoid issues with double counting.

Every patent includes information about the inventor, including their country of residence. We use this information to determine where each innovation was developed.[11] If a Canadian researcher working in a US-based lab files a patent, this invention is attributed to the US.[12]

Patent data have been extensively used as a measure of innovation in the recent empirical literature (Popp 2002, 2006; Johnstone et al. 2010; Aghion et al., 2012). The advantages and the limitations of this indicator have been discussed at length in the literature (see Griliches 1990, and OECD 2009 for an overview). One of the main limitations is that the value of individual patents is highly heterogeneous. As explained above, to mitigate this problem our outcome measure focuses on granted patents, as opposed to the more expansive category of all patent applications.[13] Citation data, which has been widely used in the literature to control for the quality of patents, is also used to address this issue. With this method, patents are weighted by the number of times each of them is cited in subsequent patent applications (see Trajtenberg 1990; Lanjouw et al. 1998; Harhoff et al. 1999; Hall et al. 2005). We implement this method to construct quality-weighted knowledge stocks available to inventors (see below)[14].

It should also be emphasised that patents fail to capture informal modes of innovation through “learning-by-doing”, which may be particularly important in the wind sector (Hendry and Harborne 2011). This is not without consequence for our analysis as demand-pull policies arguably have a higher impact on learning-by-doing than public support for R&D.

Patent data is also used to measure technology flows across countries. Patents indicate not only the countries where inventions are developed, but also where the patent owner intends to use the patented technology. Because patents are granted by national patent offices, inventors must file a patent in each country in which they seek protection. An advantage of using an international patent database is thus that for every patented innovation in the world, we know where it was invented and the set of countries where it was filed. These features make it possible for us to analyse the diffusion of inventions because holding a patent in a country gives the holder the exclusive right in that country to exploit the technology commercially. The count of patents filed in country *j* by inventors located in country *i* (and subsequently granted by the patent office in country *j*) is thus a proxy for the size of transfers between the two countries. This way of measuring international technology flows has been used for example by Eaton and Kortum (1996, 1999) and more recently by Dekker et al. (2012) and Dechezleprêtre et al. (2012). Although we restrict our focus on granted patents, patents are counted by the year of their application, as the date of grant is mostly determined by administrative idiosyncrasies of the various patent offices.

Using patents as an indicator of technology diffusion is not without drawback. For instance, a patent grants the exclusive right to use the technology only in a given country; however, this does not mean that the patent owner will actually use the technology in that country. This limitation could significantly bias our results. For example, if applying for patent protection did not cost anything, then inventors might patent widely and indiscriminately. However, in practice this is not the case.

Dechezleprêtre et al. (2011) show that the average invention is patented in only two countries[15]. Patenting is costly, in both the preparation of the application and the administration associated with the approval procedure (see Helfgott 1993). In addition, possessing a patent in a country is not always in the inventor's interest if that country's enforcement is weak. Additionally, publication of the patent in a local language can increase vulnerability to imitation (see Eaton and Kortum 1996, 1999). Therefore, inventors are unlikely to apply for patent protection in a country unless they are relatively certain of the potential market for the technology covered. Finally, because patenting protects an invention only in the country where the patent is filed, inventors are less likely to engage in strategic behavior to protect their inventions and prevent the use of their technology in the production of goods imported by foreign competitors into their domestic markets.

3.2 Demand-pull policies

A major practical difficulty in cross-country empirical studies on environmental innovation is finding data that are reliable and comparable across countries to act as a proxy for the level of demand-pull regulation. Many country-specific studies measure the level of regulation with pollution abatement and control expenditures (PACE), which are collected through surveys in various countries. The problem is that survey methodologies and the precise scope of PACE vary from one country to another.

An attractive proxy for the strictness of policies promoting the demand for wind innovation is the annual added wind power capacity in each country. This variable is used by Peters et al. (2012) in their analysis of innovation in the photovoltaic industry and is available from the International Energy Agency (IEA) Renewables information database for OECD countries.[16] The main limitation of this variable is that data is not readily available for developing countries. For non-OECD countries, the IEA only provides data on energy production from wind power but not on installed capacity. However, capacity and generation are strongly correlated (the correlation coefficient is 0.98 for OECD countries). We thus use annual added wind power production as a proxy for the level demand-pull policies.[17]

This approach is similar to using PACE. Environmental regulation leads to investments in pollution abatement devices, which are measured by PACE. Similarly, national energy policies induce new investments in wind energy, which are reflected by added power capacity (and thus increased wind power generation). The difference is that PACE is expressed in monetary units, whereas wind power generation is expressed in megawatt-hour (MWh). The production of wind electricity in any given country is mostly attributable to government regulation, as its generation cost has been significantly higher than that of conventional electricity during the time-period covered by our analysis (see Neuhoff 2005, and IEA 2003). Moreover, most policy instruments used to promote wind energy directly target electricity generation: for instance, a feed-in tariff consists in a subsidy per kWh generated; renewable portfolio standards require electricity producers to supply a certain minimum share of their electricity from designated renewable resources.

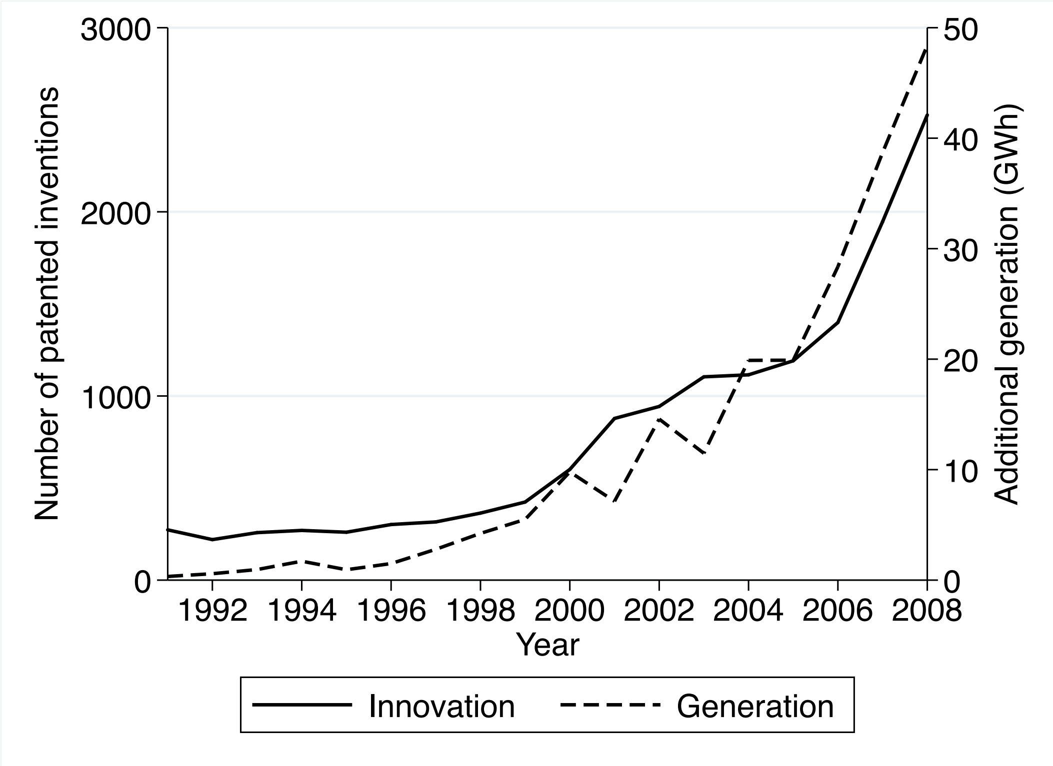
It remains, however, that wind power generation not only reflects policy strictness, but captures also a number of different factors, notably climatic conditions and country size. This does not pose any problem if, when interpreting the results, we keep in mind that power generation is not a direct indicator of the policy strictness, but captures the size of the demand induced by policies. To a large extent, the same remark applies to previous studies that rely on PACE to act as a proxy for regulation. Note that to the extent that such non-policy factors influencing the demand size are country-specific and do not vary over time, they are controlled for by country fixed effects included in our analysis.

3.3 A first description of global innovation and technology diffusion

In this subsection, we highlight some features of the data and provide some preliminary evidence on the influence of foreign markets on innovators. Figure 1 compares the trends in innovation activity with additional wind generation between 1991 and 2008. Annual global patenting activity for wind power technology increased ten folds between 1991 and 2008. Acceleration in innovation activity occurred at the end of the 1990s and again in 2005. Meanwhile, additional generation increased dramatically from 332 GWh in 1991, to 48,403 GWh in 2008. At the global level, the correlation between added wind generation and innovation is striking. Determining whether this evolution indicates simple correlations or causations is an objective of our empirical analysis.

Public R&D expenditure for wind in OECD countries (available from the IEA energy information database) increased but to a lesser extent. They increased by 93% between 1991 and 2008; i.e., from 115 million USD to 223 million USD.

Figure 1. Annual number of patented inventions and annual additional generation



The data strongly suggest that foreign markets matter for inventors: 49% of the patents in the data set are filed by inventors whose country of residence is different from the country in which protection is sought.[18] "International" inventions (i.e. inventions patented in several countries) are on average patented in 4.7 countries (including the country of origin). Interestingly, the proportion of international inventions tripled during the 1990s.

Table 1 shows the share of patents filed abroad for the 10 main OECD inventor countries. The rate of export is defined as the share of the country's inventions that are patented in at least one foreign country. The rate varies widely across countries: nearly 70% for US inventions, around 50% for European countries, and only 10% for Japan and South Korea.

Table 1. Share of patents also filed abroad for the 10 main OECD inventor countries in wind technology

Country	Export rate
Canada	44.8%
France	31.8%
Germany	49.0%
Japan	11.0%
Netherlands	61.4%
S Korea	11.7%
Spain	57.7%
Sweden	66.7%
UK	45.5%
USA	68.7%

4 Analytical framework and hypotheses

In this section, we formulate and justify on theorectical grounds the assumptions that will be tested in the rest of the paper. Technology development can be viewed as a process where an innovation is made in the first stage and disseminated in the second stage. As innovators are forward looking – they anticipate what will happen at the second stage–, we need to reason backward by analyzing first diffusion to properly understand innovation decisions as usually done when analyzing sequential games.

At the diffusion stage, increasing the generation of wind electricity in a country raises the local demand for wind-powered electric generating sets. As technology is an input to the production of wind equipment, it is expected that more inventions are made available in countries with stricter demand-pull policies. This leads to a first assumption:

- **Assumption D1:** The increase of wind power generation in a country raises technology inflows.

While almost all patented inventions are filed in the inventor's country, Section 4.2 shows that foreign patenting only occurs in a limited number of countries. This suggests the existence of barriers to international transfer, which reduce the potential size of foreign demand for technologies. This has been long recognised by the general literature on the economics of technology diffusion (see Keller 2004, for a comprehensive survey).

This literature identifies three main channels of diffusion. The first channel is international trade in goods. The idea is that certain goods embody new technologies which a country can access through imports. This applies particularly to capital goods, such as machinery and equipment. The second channel of international technology diffusion is foreign direct investment (FDI): multinational enterprises transfer firm-specific technology to their foreign affiliates or to joint-ventures. The third channel of technology diffusion—and the most direct—is licensing. That is, a firm may license its technology to a company abroad that uses it to upgrade its own production. This suggests that the strictness of intellectual property (IP) law and the height of barriers to trade and to FDI are important drivers of international technology transfer:

- **Assumption D2:** Stricter IP rights in the recipient country increase technology inflows.
- **Assumption D3:** Lower barriers to trade in the recipient country increase technology inflows.
- **Assumption D4:** Lower barriers to FDI in the recipient country increase technology inflows.

Moving backward to innovation, deriving assumptions is straightforward once we recognize that innovation is centrally driven by expectations about diffusion. Assumption D1 on demand and Assumptions D2-4 on the potential existence of barriers to international technology transfer imply the following three hypotheses:

- **Assumption I1**: The addition of wind power generation in the inventor's country induces more innovation by local inventors.
- **Assumption I2:** The addition of wind power generation abroad induces more innovation by local inventors.
- **Assumption I3:** The marginal impact on domestic innovation of foreign wind power generation is lower than the marginal impact of domestic wind power generation.

5 The analysis of cross-border technology diffusion

We now develop an empirical strategy to investigate these assumptions. We start with the analysis of international technology diffusion (Assumptions D1-4).

5.1. Empirical specification

The goal of this section is to assess the importance of barriers to international technology diffusion in the wind industry. Our dependent variable is $n_{i,j,t}$, the number of patents granted in country *i* that are filed in country *j* in year *t,* which we use as a proxy of the flow of inventions between the two countries. We base our choice of explanatory variables on Assumptions D1-4. More specifically, we estimate the following count model:

$$\begin{aligned} n_{i,j,t} = \exp(& a_1 \ln demand_{j,t} + a_2 \ln trade_{i,j,t} + a_3 fdi_{j,t} + a_4 ipr_{j,t} \\ & + a_5 \ln K_{j,t-1} + a_6 \ln gdp_{j,t} + a_7 \ln N_{i,t-1} + \eta_{i,j} + \beta T_t + \nu_{i,j,t}) \end{aligned} \quad (1)$$

In this equation, $demand_{j,t}$ is the demand for wind power in the recipient country *j* in year *t* as previously described. $\ln trade_{j,t}$ is the trade flow of wind power devices from country *i* to country *j*. This data was extracted from the COMTRADE database (COMTRADE, 2012).[19] $fdi_{j,t}$ is an index which measures the stringency of international capital market control based on data from the International Monetary Fund (IMF, 2012). The IMF reports on up to 13 different types of international capital controls. The zero-to-10 rating is the share of capital controls levied as a share of the total number of capital controls listed multiplied by 10. $ipr_{j,t}$ is the index developed by Park and Lippoldt (2008) that measures the stringency of the intellectual property regime in country *j* at time *t*.

In addition, we add several control variables. $K_{i,t}$ is the discounted stock of citation-weighted wind patents previously filed by inventors from country *j*. More specifically, we have:

$$K_{i,t} = \sum_{k=1}^{\infty} (1-\delta)^k P_{i,t-k}$$

with $P_{j,t-k}$, the number of citation-weighted patents granted in year $t - k$ in the recipient country *j*. In the literature, this is a usual proxy for the stock of knowledge available at year *t* (see for instance Popp 2002, 2006 and Peri 2005). This allows controlling for past supply and demand factors and local absorptive capacities. We set the value of the discount factor δ at 15%, a value commonly used in the literature, and conduct tests to show that the results are not sensitive to using other values of δ. To weight patents by citations, we simply use $P_{i,t} = \sum_k (1 + C_{ikt})$ where C_{ikt} is the number of forward citations (excluding self-citations) received by patent *k* invented in country *i* in year *t* within five years after its publication.[20] When a patent has multiple family members, we count citations to every member of the family.

$\ln N_{i,t-1}$ is the (log) number of granted patents in the inventor country *i*. This measures the number of inventions available for export.

We decompose the error term into a country-pair fixed effect ($\eta_{i,j}$), a vector of time dummies T_t and an error term that is uncorrelated with the right-hand side variables ($\nu_{i,j,t}$). Country-pair fixed effects control for any time-invariant differences in country and country-pair characteristics.

5.2 Sample description

Our panel runs from 1991 to 2008 and includes 28 inventor countries which export inventions to 74 recipient countries. This represents 2,072 country pairs. Note that since we use a fixed-effects estimator the final estimation samples include fewer country-pairs because the number of patent transfers between some country pairs is always equal to zero. The descriptive statistics for the variables used in the analysis are presented in Table 2.

Table 2. Descriptive statistics

Variable	Mean	Std deviation	Min	Max
$n_{i,j,t}$	0.18	1.65	0.00	83.67
$\ln demand_{j,t}$	1.50	2.31	0.00	9.96
$\ln trade_{i,j,t}$	0.38	1.52	0.00	13.74
$ipr_{j,t}$	7.17	1.81	1.66	9.76
$fdi_{j,t}$	4.98	3.03	0.00	10.00
$\ln K_{j,t-1}$	1.64	1.90	0.00	7.51
$\ln N_{i,t-1}$	7.28	16.89	0.00	128.00

5.3 Results

Results are presented in Table 3. Column 1 estimates a Poisson model while column 2 uses a negative binomial estimation. The results appear to confirm our assumptions. To begin with, diffusion is positively influenced by additional wind generation in the recipient country: a 10% increase in local demand in country *j* induces a 0.7% increase in the number of patents transferred from country *i*. This result shows that foreign demand has an impact on the diffusion of technologies. In section 6, we investigate whether this translates into an impact on the *development* of new technologies.

We also show that technology transfer is positively influenced by stricter IP rights and by larger trade flows from the inventor country to the recipient country. Increasing the zero-to-ten rating of IPR strictness in the recipient country by one unit induces between 11% and 29% more patent imports. The associated elasticity is 0.75 (i.e., a 10% increase in IPR strictness induces a 7.5% increase in the number of patents transferred). A 10% increase of trade flows entails less than 0.3% additional imported patents. Barriers to foreign direct investment in the recipient country lower the incentive to transfer new technologies, but the magnitude of the effect is smaller than that of patent rights: increasing the zero-to-ten rating of capital market controls in the recipient country by one unit reduces patent flows by 5% to 6% and the associated elasticity is 0.07. Absorptive capacity reflected by the variable $\ln K_{j,t-1}$ also raises the inward flows of technology. This effect is large: a 10% increase in (quality-weighted) local knowledge stock raises patent flows by 1.7% to 2.1%.

Having established that there are barriers that hinder the international transfer of wind inventions, we assess in the next section the extent to which these barriers dampen the effect of foreign demand on innovation relative to domestic demand.

Table 3 — Estimation results of the diffusion equation

Model	(1) Poisson	(2) Negative binomial

$\ln demand_{j,t}$	0.0724***	0.0715***
	(0.0175)	(0.0124)
$\ln trade_{i,j,t}$	0.0232*	0.0161**
	(0.0134)	(0.0075)
$ipr_{j,t}$	0.2905***	0.1157***
	(0.0987)	(0.0396)
$fdi_{j,t}$	-0.0527**	-0.0660***
	(0.0274)	(0.0139)
$\ln K_{j,t-1}$	0.2150*	0.1778***
	(0.1306)	(0.0340)
$\ln N_{i,t-1}$	0.0135***	0.0102***
	(0.0015)	(0.0011)
Country-pair FE	yes	yes
Year dummies	yes	yes
Observations	8434	8434
Country pairs	469	469

Note: *=significant at the 10% level, **=significant at the 5% level, ***=significant at the 1% level. The dependent variable is the number of patents transferred from country *i* to country *j* in year *t*. Column 1 is estimated by Poisson conditional ML with fixed effects with standard errors clustered by country pair in parentheses. Column 2 is estimated by a fixed effects negative binomial conditional ML model.

6 The analysis of innovation

6.1 Econometric framework

We measure country *i*'s innovation output in year *t* by $N_{i,t}$, the number of inventions for which private inventors from country *i* have sought patent protection.[21] As $N_{i,t}$ is a count variable, we adopt the following reduced form specification:

$$\begin{aligned} N_{i,t} = \exp(&\alpha_1 \ln demand_{i,t} + \alpha_2 \ln demand_{-i,t} + \beta \ \ln rd_{i,t-1} \\ &+\gamma_1 \ln K_{i,t-1} + \gamma_2 \ln K_{-i,t-1} + \eta_i + \rho T_t + \varepsilon_{i,t}) \end{aligned} \quad (2)$$

In this equation, the two key variables derived from Assumptions I1-3 are $demand_{i,t}$ which is the domestic demand in country *i* in year *t* and $demand_{-i,t}$ which describes foreign demand in countries other than *i*. We return to the description of the variable $demand_{-i,t}$ in the next subsection. $rd_{i,t-1}$ is the value of public R&D expenditures in year *t*-1 in country *i*. $K_{i,t-1}$ is the discounted stock of citation-weighted wind patents previously granted to inventors from country *i*. $K_{-i,t-1}$ is the stock of patents granted to inventors from all other countries. We include this variable to control for the impact of cross-country knowledge spillovers. η_i are country fixed effects which control for any time-invariant differences in countries' characteristics (such as wind availability and public attitude towards wind technology) that may influence their innovation performance and for cross-country differences in the propensity to use patents as a means of protecting new inventions. T_t is a full set of time dummiers and $\varepsilon_{i,t}$ a random noise that is uncorrelated with the right hand side variables.

Note that all explanatory variables are expressed in natural logarithms in the estimation, so that coefficients can be easily interpreted as elasticities.

We now discuss in greater detail how we construct the policy variables and identify methodological pitfalls.

Domestic and foreign demand for wind power ($demand_{i,t}$ *and* $demand_{-i,t}$*)*

These variables deserve three remarks. First, there might be a problem of endogeneity. Inventions in the field of wind energy are developed in order to cut wind energy production costs, hence stimulate the production of wind electricity. In our case, this problem is limited as the variables describes current generation whereas innovation may only have an impact on future generation.

The second remark pertains to the rationality of innovators. If they are rational, they base their decisions on *expectations* about future demand. A practical problem is that we do not observe expected demand. The data only describe *actual* wind power generation. To overcome this difficulty, one can assume that innovators form adaptive expectations based on past observations, as is done in Popp (2002). The problem is that the adaptive expectations model is only able to produce an estimate of generation in year t + 1, whereas innovators obviously look beyond that date. In addition to this, this model yields a formula where expected demand in year t + 1 is given by a weighted sum of past demand. As annual generation is increasing quickly over the period 1991 - 2008, it is doubtful that past power generation constitutes a better predictor of expected generation than current generation. This reasoning has led us to keep using the contemporaneous generation variables $demand_{i,t}$ and $demand_{-i,t}$.

The last remark specifically concerns the foreign variable $demand_{-i,t}$. A simple way to measure the demand for wind power abroad is to sum the demand in the n – 1 foreign countries:

$$\sum_{j \neq i} w_{ijt} demand_{j,t}$$

We consider two variants of this demand indicator. The first, in which w_{ijt}=1, gives the same weight to each country pair so that the coefficient α_2 reflects the impact on innovation of the demand in the average foreign country. In the second variant, the weights reflect the importance of the various foreign markets for the inventor country. We construct weights based on the results of the diffusion model. More specifically we define:

$$w_{i,j,t} = \frac{\hat{n}_{i,j,t}}{\hat{n}}$$

where $\hat{n}$ is the value of the patent transfer between a country pair predicted by the diffusion model for an average observation (that is, holding all explanatory variables at their means). $\hat{n}_{i,j,t}$ is similar except that we take the observation-specific value for the three variables describing potential barriers: $trade_{i,j,t}$, $fdi_{j,t}$, and $ipr_{j,t}$. The weights approximate the height of barriers to technology transfer related to the IP regime, restrictions on trade and on foreign direct investments. Thus, a country with high barriers will be given a low weight, while a country with low barriers (whose market is thus more easily accessible by foreign inventors) will be given a high weight.

A side benefit of introducing different weights is to mitigate a possible identification problem. By construction, the unweighted version of the variable $demand_{-i,t}$ does not vary much in a cross-section of countries: It is the sum of all countries' demand worldwide, which is common to all countries, minus demand in country *i*, which is country-specific but usually much smaller than world demand. This potentially creates multicollinearity with year dummies used to control for unobserved time-varying factors. Compared to the unweighted sum, the weighted variable has the advantage that it varies much more across the cross-section dimension.

The drawback is that the coefficient obtained for the weighted version of $demand_{-i,t}$ is much harder to interpret. It does not directly reflect the impact of the foreign market, but rather, the impact of the fraction of the foreign market that we assume by construction to have an influence on inventors. The results section below will discuss the sign and significance of the coefficients on the weighted variable. However, when it comes to determining the magnitude of the effects, it is the size of the coefficient on the unweighted variable that will be of primary interest.

R&D public support ($rd_{i,t-1}$)

In line with previous studies, we use public R&D expenditures at year t - 1 to explain innovation in year t (see Popp 2002; Johnstone et al. 2010; Verdolini and Galeotti 2009). Data on public R&D expenditures is available from the IEA energy information database. $rd_{i,t-1}$ could pose a simultaneity problem as domestic R&D expenditures are inputs of the innovation process, which leads to new patents at home, in particular in organisations that receive public R&D money. This endogeneity concern has led us to exclude patents filed by public organisations from the dependent variable. But this might not be sufficient as public R&D expenditures, as reported by the IEA, also consist of tax credits on private R&D expenditures. We address this issue by using an instrumental variables approach in alternative specifications (see Appendix). We use annual R&D public expenditures in solar and hydro power in the same country and year as instruments. R&D expenditures in these domains present the necessary properties. First, they do not directly influence the number of wind patents as they differ from wind energy from a technological point of view. Second, they are positively correlated with $rd_{i,t}$ as there is arguably a degree of jointness in the policy decisions to support R&D in specific renewable technology fields. Since our estimation uses a Poisson model we adopt the control-function approach suggested by Wooldridge (2002). In the first stage we regress $\ln rd_{i,t}$ on the instrumental variables and the exogenous variables in Eq. (2) using a log-linear estimation, and in the second stage we include the residual of the first stage estimation as an additional regressor in Eq. (2). Schlenker and Walker (2011) provide a recent application.

We do not include public R&D support in foreign countries in the equation. The reason is that foreign public R&D cannot have a direct effect on innovation as subsidies are obviously not granted to foreign-based inventors. It might indirectly influence innovation through internation knowledge spillovers. But this effect is controlled for by the foreign knowledge stock $K_{-i,t-1}$.

6.2 Sample description

The panel is balanced and extends over 18 years, from 1991 to 2008. It covers 28

OECD countries. Descriptive statistics for the variables used in the analysis are shown in Table 4.

Table 4—Descriptive statistics

Variable	Definition	Mean	Std dev.	Min	Max
$N_{i,t}$	Number of patents developed in country *i* in year *t* and granted	7.81	17.40	0.00	128.00
$\ln demand_{i,t}$	Domestic demand	2.87	2.64	0.00	9.96
$rd_{i,t-1}$	Public R&D expenditures in country *i* in year *t*-1 (million USD)	8.52	1.48	5.24	10.79
$K_{i,t-1}$	Discounted stock of previously granted patents (citation-weighted)	9.93	1.74	5.93	13.58
$\ln demand_{-i,t}$	Unweighted foreign demand	0.13	1.85	-2.30	4.15
	Weighted foreign demand	3.02	2.02	0.00	7.51
$K_{-i,t-1}$	Discounted stock of previously granted patents (citation-weighted) in foreign countries	8.20	0.43	7.33	8.84

6.3 Results

Estimation results are shown in Table 5. As can be seen from Table 4, the dependent variable is overdispersed, hence a negative binomial model is used in our main estimations. We estimate by unconditional maximum likelihood.[22] Because unconditional maximum likelihood estimation may be subject to the incidental parameter problem (Greene 2004 a, b), we re-estimate all our equations as a robustness test using a simpler Poisson model with the conditional maximum likelihood approach introduced by Hausman et al. (1984) (see Appendix).

Table 5 displays the results of the two models. The models vary in the way foreign variables are included (weighted or unweighted). In column (1), the foreign demand is left unweighted. All three domestic variables enter with a positive and significant coefficient, which is consistent with our hypotheses: (i) stricter domestic demand (a proxy for demand-pull policies) fosters innovation in wind power technology; (ii) higher public R&D expenditures increase private innovation; and (iii) a larger stock of knowledge available to inventors stimulates faster innovation in wind power technologies. In addition, we find that foreign demand has a positive impact on innovation. The effect is strongly significant (p-value=0.018). This suggests that foreign demand also matters for innovators.

In column (2), foreign demand enters in its weighted specification. We again find evidence that foreign demand positively influences innovation. The effect is still strongly significant.

A key conclusion emerges from Table 5: the demand for wind power both at home *and* abroad fosters innovation in wind power technology. Importantly, as shown in Table A1 (Appendix), this result is robust across various specifications. The point estimates obtained for domestic and foreign demand variables (both weighted and unweighted) are remarkably stable and always statistically significant.

Table 5 — Estimation results

Model	**(1) Unweighted foreign demand**	**(2) Weighted foreign demand**
$\ln demand_{i,t}$	0.0575** (0.0248)	0.0491*** (0.0163)
$\ln demand_{-i,t}$ (unweighted)	0.6495** (0.2756)	
$\ln demand_{-i,t}$ (weighted)		0.5491*** (0.1678)
$\ln rd_{i,t-1}$	0.1619** (0.0801)	0.1441** (0.0799)
$\ln K_{i,t-1}$	0.3843*** (0.1084)	0.3264*** (0.1154)
$\ln K_{-i,t-1}$	-1.6170	-1.2893

	(1.2400)	(0.8774)
Country FE	yes	yes
Year dummies	yes	yes
Observations	502	502
Countries	28	28

Note: *=significant at the 10% level, **=significant at the 5% level, ***=significant at the 1% level. The dependent variable is the number of inventions in all columns. All columns are estimated by negative binomial unconditional ML with country dummies. Standard errors clustered by country in parentheses.

We now turn our attention to the magnitudes of the effects. Since all our right-hand side variables are expressed in natural logs, the coefficients can be easily interpreted as elasticities. We find that a 10% increase in domestic demand induces a 0.5% increase in innovation while a 10% increase in foreign demand increases innovation by 5.5 to 6.5%. This does not come as a surprise as the size of the overall foreign market is on average 30 times larger than the domestic market.

It is interesting to note that, in their study of the solar PV sector, Peters et al. (2012) find that the coefficient on foreign demand is – except in one model – not statistically higher than the coefficient obtained for domestic demand, whereas it is ten times larger (and always statistically significantly so) in this paper. This suggests that barriers to technology diffusion might be higher in the solar PV industry, or that companies place a higher priority on meeting domestic demand in this relatively less mature technology[23].

If we now calculate the marginal effect of domestic and foreign demand at the sample mean, we find that an additional typical 20 MW wind farm[24] installed at home induces 0.210 additional domestic private inventions, whereas the same wind farm installed abroad only increases that number by around 0.016.[25] Hence whilst a spillover effect exists, we estimate that the marginal effect of demand for wind power on innovation is 12 times larger within national borders, than across borders. Our results clearly show that – whathever the exact magnitude of this difference – the marginal effect of domestic demand is much stronger than that of foreign demand. This suggests that the barriers to technology diffusion identified in the previous section discourage inventors from considering foreign markets as a potential outlet for their technology.[26] The difference in marginal effects suggests that barriers to diffusion are high.

Importantly, however, each wind farm installed abroad induces around 0.016 invention, but this effect occurs in 27 countries (all the 28 countries of the dataset except the one where the wind farm is installed). Hence, one should multiply these figures by 27 to obtain the overall impact of foreign installations in OECD countries.[27] This leads to 0.452 invention induced abroad, which is twice as higher as the number of inventions generated at home (0.210). Again, the exact numbers do not matter much here, but they suggest that demand-pull policies have a higher aggregate impact on foreign innovation than on domestic innovation.

Turning next to the impact of public R&D, Table 5 shows that a 10% increase in domestic public expenditures increases local innovation by around 1.5%. The marginal effect of 1 million USD lies in between 0.28 invention in column 2 and 0.36 in column 1. However, although the results are consistent across specifications (see table A1 in Appendix), the size of the coefficient varies much more than those obtained for the demand variables, in particular when we implement an instrumentation strategy to deal with the potential endogeneity of public R&D. Therefore we caution against inferring too much of the marginal effect of public R&D expenditures.

With respect to the local stock of knowledge, the coefficient is positive and significant as expected. The models estimate elasticities between 0.32 to 0.38. From a policy point of view, this means that demand-pull policies and public R&D also increase innovation in the long-term through the increase in the stock of knowledge, which feeds into future innovation.[28] In contrast, the stock of foreign knowledge $\ln K_{-i,t-1}$ is not statistically significant, confirming that knowledge spillovers have a strong local component (Jaffe, Trajtenberg, and Henderson 1993; Peri 2005).[29]

7 Summary of the results and policy implications

In this paper, we use patent data from OECD countries to analyse the relative influence of domestic and foreign policy incentives for innovation activity in wind power generation technologies between 1991 and 2008.

We envision innovation as a two-stage process, whereby inventors generate new technologies in the first stage and transfer the technologies to the countries where they plan to exploit them in the second stage. As innovators are forward looking, we analyse these two steps recursively.

We first analyse the international diffusion of wind power patents. We find that local demand for wind power exerts a positive influence on technology inflows, providing evidence that foreign markets matter for inventors. However, barriers to trade, lax IP rights and strong controls over capital market significantly hinder the transfer of patented inventions. This indicates that foreign markets are likely to have less influence on innovation than domestic markets.

We then estimate the relative impact of domestic and foreign demand for wind power on innovation with a panel covering 28 OECD countries over the period 1991-2008. We find that efforts to produce new innovations increase in response to higher domestic and foreign demand. This means that policies that drive demand for wind energy, such as feed-in tariffs, induce innovation both at home and abroad. However, the marginal effect of domestic demand on the rate of innovation is 12 times larger than the marginal effect of foreign demand. We attribute this difference to the barriers to technology diffusion.

But the aggregate effect of foreign markets on innovation is larger: we find that a 10% increase in domestic demand induces a 0.5% increase in innovation while a 10% increase in foreign demand increases innovation by 5.5 to 6.5%. This does not come as a surprise as the size of the overall foreign market is on average 30 times larger than the domestic market.

Our paper has policy implications. In a hypothetical world where technologies could be transferred from one country to another without frictions, innovators would be equally influenced by domestic and foreign demand. Therefore, a consequence of our findings is that barriers to technology diffusion also discourage innovation, implying that lowering these barriers to diffusion constitutes a powerful policy leverage for boosting environmental innovation.

Our paper also bears a finding with respect to the literature on directed technological change. The finding that domestic (policy-induced) demand for wind energy has a larger aggregate effect on foreign innovation than on domestic innovation suggests that previous empirical studies, which only look at the effect of environmental policies on domestic innovation, may have significantly underestimated the overall impact of demand-pull policies on innovation. From a global green growth perspective, the significant cross-country spillovers of innovation uncovered in this study may reinforce the case for stronger environmental policies.

Notes

[1] See, for example, President Obama's speech at the Massachussets Institute of Technology, October 23rd, 2010: "The world is now engaged in a peaceful competition to determine the technologies that will power the 21st century. (…). The nation that wins this competition will be the nation that leads the global economy. And I want America to be that nation." Similar statements were made by political leaders in many countries.

[2] The restriction to OECD countries stems from the unavailability of data on public R&D expenditures for non-OECD countries. For consistency we estimate the diffusion equation on the same sample.

[3] These are Sinovel, Goldwind, Dongfang, United Power (China) and Suzlon (India). The other companies in the top 10 in 2011 were Vestas (Denmark), GE (USA), Enercon and Siemens (Germany) and Gamesa (Spain).

[4] Peters et al. (2012) look at 15 OECD countries across 1978-2005, while we consider 28 OECD countries between 1991 and 2008. Furthermore, they distinguish between continental and intercontinental demand, while we aggregate both into foreign demand.

[5] An overview of the measures adopted by every country, including the timing of their adoption, is available from the IEA/IRENA Global Renewable Energy Policies and Measures database, available at http://www.iea.org/policiesandmeasures/renewableenergy/ (last accessed 1 July 2013).

[6] Most recently in July 2012, Japan introduced a feed-in tariffs scheme, obliging incumbent power companies to buy the output from solar, wind, geothermal, small hydro and some biogas and biomass-fueled plants at premium prices.

[7] Johnstone et al. (2010) is a notable exception. However, except for feed-in tariffs, they only measure the strictness of the different policy instruments by a binary variable, with one indicating that the particular instrument is in place.

[8] We use the October 2012 version of the PATSTAT database, and it takes on average 3 years for a patent to be granted. Note that our results are robust to changing the end year to 2007 or 2009.

[9] Note that Least Developed Countries are not present in our dataset, for two related reasons: their patenting activity is extremely limited, and available statistics are not reliable.

[10] In addition, we randomly sampled 100 patents from the F03D category and checked their relevancy based on title and abstract. We found only three irrelevant patents, which lead us to believe the patent classification is accurate for wind power technologies.

[11] For 1.4% of the patent applications included in our dataset, the inventor's country of residence is not available. When this information is missing, we simply assume that the inventor's country corresponds to the first patent office in which protection was taken (i.e. the priority office).

[12] Patents with multiple inventors are counted fractionally. For example, if two inventor countries are involved in an invention, then each country is counted as one half.

[13] Our results are robust to using all filed patent applications, however.

[14] Family size (the number of countries in which a patent is filed) is another way of assessing the value of a patent. But we think it is better to use patent citations in this particular paper, given the questions addressed. The problem is that family size is not only a value indicator; it also captures the degree of internationalization of the invention, which is, roughly speaking, the central topic of the paper. This suggests using family size as a dependent variable, not as a weight when constructing an independent variable. To a certain extent, this is what we do in section 5 where the dependent variable is the bilateral flow of patent between countries.

[15] In fact, about 75% of inventions are patented in only one country.

[16] Available at http://data.iea.org/.

[17] An alternative option is to estimate installed capacity in non-OECD countries by running a regression of energy capacities on energy production using the data from OECD countries and then use this model to make out-of-the-sample predictions for capacities in non-OECD countries based on their production. We implemented this method, which gives qualitatively similar results. It however has two weaknesses: first, the relationship between capacity and production might differ between OECD and non-OECD countries; second, using predicted values would lead us to underestimate standard errors in the subsequent regression analysis.

[18] Excluding patents filed at the European Patent Office, the figure is 42%.

[19] We downloaded data on wind-power generating sets (product code HS 850231).

[20] More precisely we count all citations made by patents *applied for* up to five years after the publication of each patent. Note that PATSTAT includes citation information from 98 patent offices.

[21] As mentioned above, inventions patented in several countries are only counted once in order to avoid double-counting. We restrict patent data to private inventions only to avoid potential endogeneity problems.

[22] In other words, we include a full set of country dummies in the estimation. Another way to deal with fixed effects would be to use the conditional maximum likelihood estimator introduced by Hausman et al. (1984) and available in STATA as the xtnbreg command. However this model is known to imperfectly control for fixed effects (Allison and Waterman 2002; Greene 2007; Guimaraes 2008). Another issue is that xtnbreg does not report any robust or clustered standard errors and the small size of our sample has not allowed us to compute bootstrapped standard errors.

[23] Recall however that differences in sample size and in the way explanatory variables are constructed make it difficult to accurately compare the results between the two papers (see note 4 above).

[24] See http://www.thewindpower.net/ (last accessed 24 May 2013). This corresponds to an annual production of 37.4GWh.

[25] Recall that the value of patents is heterogeneous. Therefore, these figures describe the effect of policies on the *average* invention.

[26] Cognitive limitations of innovators could provide an alternative explanation: they simply ignore the installations of new wind farms in certain foreign countries, which lead them to infer that the demand is actually zero. Note this interpretation rests on a bounded rationality assumption: A rational decision maker under uncertainty will consider the *expected* size of the market derived from a prior subjective probability distribution.

[27] Note that multiplying the effect by 27 only yields the aggregate effect in OECD countries. We cannot calculate the effect of innovation in non-OECD countries as they are not included in the estimation sample.

[28] The size of this effect centrally depends on the value of the discount rate δ. With δ=0.15, the additional long term impact of both demand-pull policies and public R&D through increased knowledge stock is about one half of the short-term impact.

[29] Peri (2005) shows that only 12% of the knowledge created in a country spills over to foreign countries.

References

Aghion P, Dechezleprêtre A, Hemous D, Martin R, Van Reenen J (2012). Carbon taxes, path dependency and directed technical change: Evidence from the auto industry. NBER Working Paper 18596, National Bureau of Economic Research, Inc.

Allison PD, Waterman RP (2002) Fixed-effects negative binomial regression models. Sociol Methodol 32:247-265

Brunnermeier SB, Cohen MA (2003) Determinants of environmental innovation in US manufacturing industries. J Environ Econ Management 45: 278-293

Buchanan B, Keefe P (2010) Environmentally Sound Technology (EST): An Analysis of the Classification of EST Energy Sectors in the IPC; and of UK EST Innovation through the IPC. Paper presented at the Patent statistics for decision makers conference, 17-18 November 2010, Vienna, Austria.

COMTRADE (2012) United Nations Commodity Trade Statistics Database, available at http://comtrade.un.org/db/ (last accessed 1 July 2013)

Crabb J, Johnson D (2010) Fueling Innovation: The Impact of Oil Prices and CAFE Standards on Energy-Efficient Automotive Technology. Energy J 31(1):199-216

Dechezleprêtre A, Glachant M, Ménière Y (2013) What Drives the International Transfer of Climate Change Mitigation Technologies? Empirical Evidence from Patent Data. Environ Resour Econ 54(2):161–178

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

Dekker T, Vollebergh HRJ, De Vries FP, Withagen C (2009) Inciting protocols. J Env Econ Management 64(1):45-67

Eaton J, Kortum S (1996) Trade in ideas: Patenting and productivity in the OECD. J Int Econ 40 (3–4):251–278

Eaton J, Kortum, S (1999) International Technology Diffusion: Theory and Measurement. Int Econ Rev 40 (3):537–70

ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table (EEE-PPAT) database (2012). http://www.ecoom.be/nl/eee-ppat (last accessed 1 July 2013)

Greene W (2004a) Fixed Effects and Bias Due to the Incidental Parameters Problem in the Tobit Model. Economet Rev 23(2):125-147

Greene W (2004b) The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. Econometrics J 7(1):98-119

Griliches Z (1990) Patent Statistics as Economic Indicators: A Survey. J Econ Lit 28 (4):1661–1707

Greene W (2007) Fixed and random effects models for count data. Working paper Department of Economics, Stern School of Business, New York University, New York

Helfgott S (1993) Patent filing costs around the world. J Pat & Trademark Off Society 75: 567–580

Hendry C, Harborne P (2011) Changing the view of wind power development: more than bricolage. Res Policy 40(5): 778-789

IEA (2003) Renewables for power generation. International Energy Agency, Paris

IEA (2005) Projected costs of electricity generation. International Energy Agency, Paris

IEA (2009) Wind technology roadmap. International Energy Agency, Paris

IMF (2012) Annual Report on Exchange Arrangements and Exchange Restrictions, International Monetary Fund

Jaffe A B Palmer K (1997) Environmental regulation and innovation: a panel data study. Rev Econ Stat 79(4):610-619

Johnstone N, Haščič I, Popp P (2008) Renewable Energy Policies And Technological Innovation: Evidence Based On Patent Counts. Environ Resour Econ 45(1):133-155

Keller W (2004) International technology diffusion. J Econ Lit 42 (3):752–782

Lanjouw JO, Mody A (1996) Innovation and the International Diffusion of Environmentally Responsive Technology. Res Policy 25: 549–571

Lanjouw J, Pakes A, Putnam J (1998) How to Count Patents and Value Intellectual Property: Uses of Patent Renewal and Application Data. J Ind Econ 46 (4):405–432

Nemet G (2009) Demand-pull technology-push and government-led incentives for non-incremental technical change. Res Policy 38(5): 700-709

Neuhoff K (2005) Large-Scale Deployment of Renewables for Electricity Generation. Oxford Rev Econ Policy 21(1) 88-110

Newell RG Jaffe AB Stavins RN 1999) The Induced Innovation Hypothesis and Energy-Saving Technological Change. Q J Econ 114: 941-75

OECD (2009) OECD Patent Statistics Manual. Paris

Park WG, Lippoldt DC (2008) Technology Transfer and the Economic Implications of the Strengthening of Intellectual Property Rights in Developing Countries. OECD Trade Policy Working Papers 62, OECD Trade Directorate, Paris

PATSTAT (2012) Worldwide patent statistical database, European Patent Office. October 2012.

Peri G (2005) Determinants of knowledge flows and their effect on innovation. Rev Econ Stat 87 (2):308–322

Peters M, Schneider M, Griesshaber T, Hoffmann VH (2012) The impact of technology-push and demand-pull policies on technical change – Does the locus of policies matter? Res Policy 41(8):1296-1308

Popp D (2002) Induced innovation and energy prices. Am Econ Rev 92(1):160-180

Popp D (2006) International innovation and diffusion of air pollution control technologies: the effects of NOX and SO2 regulation in the U.S. Japan and Germany. J Environ Econ Management 51: 46-71

Popp D, Hafner T, Johnstone N (2011) Policy vs. Consumer Pressure: Innovation and Diffusion of Alternative Bleaching Technologies in the Pulp Industry. Res Policy 40(9):1253-1268

WIPO (2010) World Intellectual Property Indicators 2010

Wooldridge (2002) Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, MA

Appendix: Robustness checks

A number of robustness tests were conducted and the main ones are reported below.

Poisson estimator

As an alternative to the negative binomial specification, we reestimate equations presented in Table 5 using conditional maximum likelihood Poisson with fixed effects (Hausman et al. 1984). Results are closely similar (see Table A1, columns 1 and 2). Most importantly, the foreign installations variable remains positive and highly statistically significant in both specifications.

Accounting for the potential endogeneity of public R&D expenditures

The variable $\ln rd_{i,t-1}$ may pose a simultaneity problem as domestic R&D expenditures are inputs of the innovation process. Although we exclude public patents from the dependent variable, public R&D expenditures as reported by the IEA include tax credits on private R&D expenditures, which may give rise to endogeneity bias. We address this issue by using an instrumental variables approach. R&D public expenditures in solar and hydro power in the same country and year are used as instruments. R&D expenditures in these domains present the necessary properties. First, they do not directly influence the number of wind patents as they differ from wind energy from a technological point of view.[1] Second, they are positively correlated with $rd_{i,t}$ as there is arguably a degree of jointness in the policy decisions to support R&D in specific renewable technology fields. Since our estimation uses a Poisson model we adopt the control-function approach suggested by Wooldridge (2002). In the first stage we regress $\ln rd_{i,t}$ on the

[1] This is the reason why we did not use R&D expenditures in marine energy as an instrument. The technologies used for marine and wind energy production have some similarities. We considered adding public R&D expenditures in biomass and geothermal energy as additional instruments but none of them turned up significant. However, the results are completely robust to including them.

instrumental variables and the exogenous variables in Eq. (2) using a log-linear estimation, and in the second stage we include the residual of the first stage estimation as an additional regressor in Eq. (2) (see Schlenker and Walker 2011, for a recent application).

The first stage estimation together with the usual statistics are presented in Table A2. Column 1 shows the results from the unweighted specification and column 2 shows the results from the weighted specification. The coefficient of the excluded instruments is statistically significant and positive. The cluster-robust F-statistics of joint significance of the two instruments are 5.18 and 5.28 (p-value of 0.01 in both cases) respectively. This suggests the instruments do a resonably good job. Results from the second stage equation are shown in columns 3 and 4 of Table A1. The results remain similar to our baseline estimates but the point estimates for $\ln rd_{i,t}$ increase in both specifications. However, the coefficient on the residuals from the first stage equation are not significantly different from 0, suggesting that the hypothesis that $\ln rd_{i,t-1}$ is exogenous cannot be rejected. Overall, results from these tests suggest that our baseline estimates should be viewed as a lower bound estimate of the impact of public R&D expenditures. Importantly, results concerning domestic and foreign demand are robust to instrumenting public R&D.

Other tests

As is commonly the case with patent data, the distribution of patents across countries is highly heterogeneous, with a few countries accounting for a large share of innovations. For this reason, it is necessary to check that our results are not driven by outliers. Columns 5 and 6 of Table A1 reports the results obtained when we drop Japan, by far the top inventor in our sample with 35% of the total patented inventions. Our findings are robust, although the point estimate obtained on domestic installations decreases.

Finally, applying alternative discount rate values which are used to calculate the knowledge stocks – specifically, 10 and 20 per cent – made no difference to the results (robustness test results not shown).

Table A1 — Robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln cap_{i,t}$	0.0800***	0.0624***	0.0523**	0.0484***	0.0427*	0.0471***
	(0.0231)	(0.0137)	(0.0228)	(0.0173)	(0.0251)	(0.0180)
$\ln cap_{-i,t}$	0.6467***		0.4759**		0.5388*	
	(0.1869)		(0.2220)		(0.2903)	
$\ln cap^{w}_{-i,t}$		0.5116***		0.5514***		0.5819**
		(0.1149)		(0.1749)		(0.2345)
$\ln rd_{i,t-1}$	0.1473**	0.1387*	0.2641*	0.2445**	0.1653**	0.1546*
	(0.0719)	(0.0765)	(0.1548)	(0.1182)	(0.0831)	(0.0793)
$\ln K_{i,t-1}$	0.5176***	0.4434***	0.3388***	0.2733**	0.3742***	0.3131***
	(0.1157)	(0.1082)	(0.1131)	(0.1203)	(0.1070)	(0.1145)
$\ln K_{-i,t-1}$	-1.1597	-0.7941	-2.3714	-2.0960*	-1.5820	-1.8353**
	(1.0306)	(0.9700)	(1.6144)	(1.0726)	(1.4979)	(0.8237)
$resid_{-i,t-1}$			-0.1091	-0.1060		
			(0.1467)	(0.1022)		
Country FE	yes	yes	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes	yes	yes
Observations	502	502	472	472	484	484
Countries	28	28	28	28	28	28

Note: *=significant at the 10% level, **=significant at the 5% level, ***=significant at the 1% level. The dependent variable is the number of inventions in all columns. Columns 1 and 2 are estimated by Poisson conditional ML with fixed effects. Columns 3 to 6 are estimated by negative binomial unconditional ML with country dummies. Standard errors clustered by country in parentheses.

Table A2 — First stage equations

	(1)	(2)
$\ln rdsolar_{i,t}$	0.3446** (0.1280)	0.3503** (0.1291)
$\ln rdhydro_{i,t}$	0.2037* (0.1078)	0.2092* (0.1096)
$\ln cap_{i,t}$	-0.0054 (0.0349)	0.0079 (0.0347)
$\ln cap_{-i,t}$	-0.5993 (0.5261)	
$\ln cap^{w}_{-i,t}$		0.4926 (0.4385)
$\ln rd_{i,t-1}$	0.2595 (0.2902)	0.2130 (0.2769)
$\ln K_{i,t-1}$	5.3232* (2.7923)	6.1218*** (2.0914)
$\ln K_{-i,t-1}$	0.3446** (0.1280)	0.3503** (0.1291)
Country FE	yes	yes
Year dummies	yes	yes
Observations	498	498
Countries	28	28
R^2	0.823	0.825

Note: *=significant at the 10% level, **=significant at the 5% level, ***=significant at the 1% level. The dependent variable is the log of public R&D expenditures in wind power. All columns are estimated by OLS with standard errors in parentheses (clustered by country). The external instruments are public R&D expenditures in solar and hydro power.