Research Paper

Innovation Performance and International Knowledge Spillovers: Evidence from the Renewable Energy Sector in OECD Countries

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ABSTRACT This paper aims at evaluating the sources of differences among countries' innovative performances in the renewable energy (RE) sector. Namely, we focus on the national innovative capacity, the knowledge developed abroad and the related knowledge spillovers. We claim that a country is more likely to develop RE innovation: (i) the larger the knowledge stocks of other countries in the same sector; (ii) especially when those other countries share established linkages with the focal country. Relying on a knowledge production function, we model country-level innovative performances in the RE sector for 18 OECD countries in the period 1990–2006. Our findings confirm that, once controlling for climate-energy policies, international knowledge spillovers contribute significantly to RE innovation, and their effect is comparable with domestic R&D and human capital. In addition, international spillovers are more likely if countries share stronger linkages.

KEY WORDS: Environmental innovation, renewable energies, knowledge production function, international knowledge spillovers

JEL Classification: O33, O38, Q42, Q55

1. Introduction

Ample consensus exists about the need of a better understanding of the drivers of innovation in the renewable energy (RE) sector (Arvizu et al. 2011; Nemet 2012).

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Indeed, an extensive diffusion of technologies that harness non-exhaustible, zero-carbon (or low-carbon) energy sources in a cost-effective manner is necessary to reduce carbon emissions without hindering energy uses, and to alleviate the supply security problems of many countries (Popp 2011; Peters et al. 2012). At the same time, however, invention and deployment efforts should continue because today most RE sources provide competitive energy services only in certain geographical contexts; in addition, RE technologies often need to be modified in order to be successfully integrated in each country's energy system (Arvizu et al. 2011). Finally, there is evidence that new high-quality mitigation technologies are developed by a small number of advanced economies, and RE technologies are no exception (OECD 2008; Dechezleprêtre et al. 2011).

Within this context, the role of international knowledge sources becomes crucial as most countries are likely to exploit new RE technologies that have been developed by other countries. The literature has already provided empirical and theoretical evidence that knowledge originating in one country transcends national boundaries and contributes to productivity growth and technological progress in other countries (e.g., Keller 2004; Mancusi 2008). However, empirical evidence on the role played by international knowledge spillovers in environmental and climate innovation is still scarce and mixed, and the contribution of international diffusion to innovation in energy sectors is still a relatively untapped area of research.

Among the factors explaining innovative capacity at the national level, the balance between international and domestic knowledge sourcing in influencing innovation in RE sector is an open and increasingly relevant question. In fact, follower countries cannot limit themselves to importing new technologies and/or benefit from technologies developed abroad as they should also engage in absorptive capacity and adaptive R&D (Lanjouw and Mody 1996; Popp 2006; Bosetti et al. 2008).

In addition, demand-pull and "interface" policies[1] are increasingly recognized to be relevant instruments to stimulate innovativeness and diffusion of technological change (Del Rio Gonzalez 2005; Fischer and Newell 2008; Taylor 2008; Popp 2011; Rennings and Rammer 2011; Horbach, Oltra, and Belin 2013). Although there are examples of innovations developed in response to foreign regulations, environmentally sound inventions are more likely to respond to domestic environmental policies (Lanjouw and Mody 1996), particularly as far as new energy technologies are concerned (Popp 2006).

This paper aims at evaluating the sourcing of differences among countries in the production of innovation in the RE sector. Namely, we focus on the role of the national innovative capacity (Furman, Porter, and Stern 2002), of the knowledge developed abroad, and the related potential knowledge spillovers, while controlling for the climate-energy policies. Specifically, we claim that (i) a country's innovative performance in the RE sector depends positively on the knowledge stocks of other countries in the same sector and (ii) this is especially so when the latter countries share established linkages with the former. In fact,

[1] Demand-pull policies raise the revenues of environment-friendly innovators (e.g., feed-in tariffs, RE obligations or tax credits reserved to RE investments), and have been found to spur incremental innovations; instead, technology-push policies reduce the costs that environment-friendly innovators have to bear (e.g., public energy R&D, or tax credits for energy R&D), and they have been shown to favor non-incremental innovations (Nemet 2009; Peters et al. 2012). Interface policies support technology deployment and learning by using, by reducing the transaction costs that arise between technology suppliers and users (Taylor 2008).

energy innovation systems are highly country-specific (Sagar and Holdren 2002; Sagar and van der Zwaan 2006; Taylor 2008), and the scope of market transactions in RE technologies is limited; thus, cross country knowledge spillovers in this sector are more likely when countries are highly interconnected through established linkages.

Relying on a knowledge production function à la Griliches-Jaffe (Griliches 1979; Jaffe 1986), we model country-level innovations in the RE sector as depending on domestic knowledge stocks, domestic human capital, spillovers stemming from international knowledge stocks, and climate-energy policies. Our empirical analysis refers to the innovation dynamics of 18 OECD countries in the period 1990–2006.

The paper is organized as follows. Section 2 provides a descriptive analysis of the geographic distribution of innovation in RE sectors. Section 3 reviews the literature on environmental innovations and international knowledge spillovers, and it formulates our research hypotheses. The sample, the variables and the econometric models are illustrated in Section 4, whereas the empirical findings are discussed in Section 5. Section 6 summarizes the main results and outlines some implications for environmental technology policy.

2. Geographical Distribution of Innovations in the RE Sectors: Evidence from OECD Countries

Empirical evidence on the characteristics and geographical distribution of innovations in the RE sector reveals a high concentration. Relying on patent data from the European Patent Office (EPO), Table 1 shows that Germany, the USA, Japan and Denmark account for the 65 per cent of the total RE patents. Likewise, data on public R&D budgets recorded by the IEA (International Energy Agency) and reported in Table 2 confirm that the top four countries, i.e. the USA, Japan, Germany and France, account for the 61 per cent of the R&D budget.[2] Overall, OECD countries account for almost 96 per cent of the EPO world patents in the RE sector during the 2000–2009 period. RE innovations exhibit a geographic concentration similar to other environmental technologies. Dechezleprêtre et al. (2011) found that Japan, the USA, Germany and China accounted for 67 per cent of the world's climate-mitigation patents in the 2000–2005 period. Moreover, despite the non-negligible role of large non-OECD economies such as China, Russia and Brazil, high-value inventions were more likely to originate in more developed economies (namely, Germany, Japan, the USA and France).

Nevertheless, the comparison with other technological fields sheds a different light on the geographic concentration of RE innovations. Table 1 shows that the patent shares cumulated by world leading countries in the RE sector are smaller than in other technological fields such as biotechnology, ICT and nanotechnology. Thus, innovation performances are more uniform across OECD countries in the RE sector than in other fields. In fact, the standard deviation of patent counts over a sample of 34 OECD countries, once normalized by the mean value, is smaller in RE than in other fields.

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[2] EPO classifies patents on the basis of highly relevant technology domains: biotechnology, ICT, nanotechnology and environment-related technology; the latter includes RE generation classes. IEA reports the budgets allocated by OECD governments to research, development and demonstration across energy technological fields, including RE sources.

Table 1. Distribution of patents over OECD countries, 2000–2009

	All fields	RE	Biotechnology	ICT	Nanotechnology
Cumulated shares					
World leader	27 per cent	24 per cent	42 per cent	30 per cent	35 per cent
Four top countries	71 per cent	65 per cent	71 per cent	72 per cent	75 per cent
Leading countries	USA	Germany	USA	USA	USA
	Germany	USA	Germany	Japan	Japan
	Japan	Japan	Japan	Germany	Germany
	France	Denmark	UK	France	France
Standard deviation divided by the mean value					
34 OECD countries	2.09	1.89	2.56	2.23	2.42

Note: The patent counts refer to the sum of patent applications made to the EPO, 2000–2009 period (application date), by 34 OECD countries (inventor's country of residence; Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, UK, USA).
Source: Our elaboration on OECD data (Patents according to technology fields).

The evidence on the geographic distribution of patents is consistent with the analysis of publicly funded R&D, a critical energy innovation input and policy measure (Garrone and Grilli 2010). Table 2 shows that only few governments are particularly active in financing the development (and demonstration) of new RE technologies. Four OECD countries account for

Table 2. Distribution of public R&D budgets, OECD countries, 2000–2009

	All fields	RE
Cumulated shares		
World leader	47 per cent	35 per cent
Four top countries	70 per cent	61 per cent
Leading countries	USA	USA
	Japan	Japan
	Germany	Germany
	France	South Korea
Standard deviation divided by the mean value		
Sample of OECD countries	2.67 (32 countries)	1.86 (27 countries)

Note: The budgets are government budget appropriations or outlays for R&D (GBOARD) in Million USD (2009 prices and PPP), for 32 OECD countries in all fields (Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, UK, USA), and 27 OECD countries in RE (the same as in all fields, except Estonia, Iceland, Israel, Mexico, Poland), 2000–2009 period.
Source: Our elaboration on OECD data (Main science and technology indicators), IEA data (RD&D statistics), IMF data (World Economic Outlook).

the 61 per cent of the public R&D budget in the 2000–2009 period. At the same time, both the cumulated shares and the ratios between standard deviation and mean value show that the geographic concentration is not that high in the RE sector. Efforts to support R&D activities are less heterogeneous across OECD countries in the RE sector than in other sectors.

This evidence is coherent with climate-economy models, which show that technological change is the result of both domestic R&D investments and learning-by-doing dynamics of the energy sector (e.g., van der Zwaan et al. 2002; Popp 2004; Popp, Newell, and Jaffe 2009). In other words, a well-developed energy innovation system is necessary to produce technological advancements (Sagar and van der Zwaan 2006). However, most countries are likely to use environmental technologies that were developed in foreign countries. In particular, late adopters need to undertake R&D activities to absorb and adapt foreign technologies, i.e. to make them compatible to local markets and regulations (Lanjouw and Mody 1996; Popp 2006), as well as to produce new technologies at home (Bosetti et al. 2008).

This intriguing evidence opens the question on the potential autonomy of countries, and conversely on the extent to which they may rely on international knowledge sourcing in this sector. In the following section, we focus on the role of international knowledge spillovers on the national innovative capacity in the RE sector.

3. The Role of International Knowledge Spillovers: Our Research Hypotheses

Diffusion of technological knowledge occurs to a great extent through cross-country knowledge or technology spillovers, which indeed have been shown to have a significant impact on the innovation activity of countries (Branstetter 1998; Frantzen 2000; Mancusi 2008; Keller 2009).

The literature on the role of international knowledge spillovers in environmental technologies acknowledges that relevant knowledge portions are sourced from other countries. However, studies focus mainly on the role of climate-energy policies on the development and diffusion of new energy technologies (e.g., Grubb, Hope, and Fouquet 2002; Taylor 2008; Nemet 2009; Garrone and Grilli 2010; Johnstone, Hascic, and Popp 2010; Popp 2011), and on the international diffusion of technologies that are embodied in technologies (Lanjouw and Mody 1996; Popp 2006). Other studies highlight that given the complex nature of the knowledge base underlying eco-innovations, the latter significantly require external sources of knowledge (Horbach, Oltra, and Belin 2013).

As international knowledge diffusion involves both market transactions and externalities (Keller 2004; Pizer and Popp 2008), increasing attention has been devoted to the latter, i.e. to channels for knowledge spillovers. Knowledge flows across countries, either embodied in traded goods or in various disembodied forms through cross-border flows of people, ideas, services, patents, products and face-to-face contacts (for a recent survey, see Belderbos and Mohnen 2013). A considerable body of theoretical and empirical work has focused on import-related international knowledge spillovers, i.e. the extent to which imports of manufactured goods could serve as channels for knowledge spillovers (e.g., Coe and Helpman 1995; Keller 2004; Lo'pez-Pueyo, Barcenilla-Visu's, and Sanau' 2008). At the same time, technology diffusion theories have long recognized the idea that international established linkages also underpin the geographic spread of new innovations (Rogers

1995). Cross-border contacts, communications and exchanges allow the involved actors to learn about innovations developed elsewhere (Simmons and Elkins 2004).[3] Technological knowledge can be gained through exports, i.e. learning by exporting (Salomon and Shaver 2005; Liu and Buck 2007). Likewise, foreign direct investment (FDI) has been already confirmed to be a potentially equally important channel for the mediation of such spillovers (Gorg and Greenaway 2004; Branstetter 2006). Accordingly, our first Hypothesis is the following:

H1: The innovative performance of a country in the RE sector positively depends on knowledge stocks of other countries in the same sector.

As in the general literature on international knowledge spillovers (e.g., Keller 2004; Belderbos and Mohnen 2013), previous empirical studies on environmental innovation also highlight that geographic distance is a major moderating variable. For example, Hosseini and Kaneko (2013) shows that a country's CO_2 intensity decreases if neighboring countries have a higher institutional quality. Verdolini and Galeotti (2011), using backward patent citations, find that greater international knowledge flows increase the innovation probability, but that geographical and technological distances between countries decrease the probability of knowledge flows.

Few studies add the role of linkages among countries as a strengthening factor for potential knowledge spillovers, the rationale being that spillovers are more likely when countries are connected somehow. Thus, for example, Liu and Buck (2007) consider the impact of multiple channels for international technology spillovers on the innovation performance of Chinese firms in high-tech industries; they find that export-related and import-related spillover channels are positively associated with the innovative capacity of domestic firms. Similarly, Perkins and Neumayer (2009) empirically tested the influence of three transnational linkages (namely, import and export, inward FDI and telephone calls) on domestic improvements in CO_2 and SO_2 efficiency. They found that import linkages with more environmentally efficient countries foster the transmission of CO_2 and SO_2 efficiency, while exports, inward FDI and telephone calls do not seem to play a significant role. More recently, the same authors find that FDI can impinge on the transmission of CO_2 efficiency toward countries that are less CO_2-efficient or that have a higher institutional quality (Perkins and Neumayer 2012). Hübler and Keller (2010) also found that inward FDI do not have a significant role in the variation of energy intensity of developing countries.[4] In this context, Bosetti et al. (2008), assuming that the effectiveness of spillovers depend on the country's absorptive capacity, show that high-income countries reduce their energy R&D investments due to international spillovers. Conversely, Braun, Schmidt-Ehmcke, and Zloczysti (2010), investigating the determinants of innovative activity in wind and solar technologies for OECD countries, find that international knowledge spillovers play a negligible role compared with

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[3] We are aware that patent citations can be used as a proxy for knowledge flows between different innovating firms, regions or countries (among others, Verdolini and Galeotti 2011, or Nemet 2012). Nonetheless, we have adopted a different modeling strategy because patent citations only capture a part of the knowledge flows.

[4] It is worth noting that the mixed evidence on the influence of FDI may be also due to the fact that foreign MNCs do not automatically leak technology to domestic firms either because MNCs may have an incentive to prevent leakages or because domestic firms must have an adequate absorptive capacity (Liu and Buck 2007).

domestic intra- and inter-sectoral spillovers. Similarly, Garrone and Grilli (2010) show that international public energy R&D has virtually no effect on domestic energy intensity, regardless of whether an un-weighted or import-weighted R&D pool is used as a proxy.

Thus, along the conceptualization adopted by Perkins and Neumayer (2009, 2012), we focus on the role of international linkages as a channel for spillovers between countries, and our second hypothesis states as follows:

> H2: The innovative performance of a country in the RE sector positively depends on knowledge stocks of other countries in the same sector, provided that the latter share established linkages with the former.

It might not be out of place here to remark that cross-country linkages are relatively independent from countries' innovative activities in one sector. Interactions between countries may be established for various reasons and are inherently cross-sectoral, even when they transmit knowledge spillovers related to a single sector. For this reason, international linkages can only marginally be touched by a country's efforts to source knowledge on RE technologies. The latter may well boost its trade flows in the RE sector, but the overall intensity and structure of its international linkages will change only slightly. This point can be illustrated through the following example, which is coherent with our measure of international linkages, i.e. trade flows (Section 4.3). The US imports of wind and solar equipment in 2010 amounted to 9,410 million US dollars (constant US dollars, base 2000; Sawhney and Kahn 2012). This accounts to less than 1 per cent of the total US imports of goods and services.

4. Empirical Analysis

4.1. The Model

According to previous empirical work (e.g., Furman, Porter, and Stern 2002; Liu and Buck 2007; Mancusi 2008), we model the innovation performance of a country through a knowledge production function (e.g., Czarnitzki, Kraft, et al. 2009). Specifically, we started from a traditional Cobb-Douglas knowledge production function:

$$Q_{iht} = D^{d}_{iht} F^{f}_{iht} C^{c}_{iht}, \tag{1}$$

Q_{iht} is the innovative performance of country i in industry h at period t; D_{iht} is the domestic R&D effort in industry h; F_{iht} is the stock of R&D accumulated in countries other than i; C_{iht} are control variables that account for industry and country specificities. The following transformation via natural logarithms would facilitate the interpretation of results:

$$\ln Q_{iht} = d \ln D_{iht} + f \ln F_{iht} + c \ln C_{iht}. \tag{2}$$

In order to measure innovative performance, we use the *number of patents RPAT* obtained in the RE sector by country i in t ($t = 1990, \ldots, 2006$). In addition, as in our case, several *controls* are binary variables (e.g., policy indicators), an ad-hoc elaboration would be necessary to transform dependent and control variables via logarithms; thus, we preferred to use a linear-log knowledge production function (i.e., we assume that innovative performances and control variables are pre-transformed by an exponential function). As far as explanatory variables, the domestic effort (*D*) has been proxied by the country's human capital (*HC*) and the domestic R&D stock in RE technologies (*DRD*), whereas foreign R&D (*F*) refers to international knowledge spillovers (*IKS*) associated to the international availability of knowledge that the country is likely to access. In order to have coefficients that are comparable in magnitude, both the explanatory variables and controls were normalized by their mean. The former, i.e., human capital, domestic R&D stocks and international knowledge spillover variables, were also lagged by one period, to reduce endogeneity problems.

Thus, we estimate the following model:

$$RPAT_{it} = \alpha + \beta_1 \ln HC_{it-1} + \beta_2 \ln DRD_{it-1} + \beta_3 \ln IKS_{it-1} + \sum_s \gamma_s C_{it}^s + \Phi_i + \varepsilon_{it}, \quad (3)$$

where C^S is the *s*th control variable, Φ are unobservable country-specific characteristics (e.g., countries that are under- or over-represented in the EPO, or have a larger or smaller stock of private R&D), and ε is the error term.

4.2. The Sample

Our sample includes 18 industrialized countries observed over the period 1990–2006: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, The Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UKm and the USA. In particular, we investigate innovation in RE technologies at the country level, by relying on patents obtained in the relevant technology from the EPO.[5] Data are sourced from the April 2010 version of Patstat (OECD, 2010). Patent classes are determined according to the classification used by Johnstone, Hascic, and Popp (2010), i.e. hydro technologies are excluded from the analysis, mainly because in most countries they are not supported by climate policies that are enforced to promote other REs.

Germany and the US lead the ranking of RE patenting activity in the observed period, while Japan and the UK are the most innovative followers. Nevertheless, in order to position properly countries in the race for energy-climate innovations, their innovation performances should be articulated in several sectors and through multiple indicators, as shown by Fankhauser et al. (2013).

4.3. Explanatory and Control Variables

As far as the domestic efforts (*D*), we considered the *human capital stock* (*HC*) and the *domestic knowledge stock* (*DRD*) of country *i*. Specifically, *HC* is measured by the average years of schooling for people over 25, as in Barro and Jong-Wha (2010). Data come from the Barro-Lee Educational Attainment Dataset (http://www.barrolee.com/). In order to proxy knowledge stocks, we collected the series of public energy R&D budgets of each sample

[5] We are aware that the EPO is likely to over-represent innovations of European inventors. Nevertheless, the bias toward European countries is a fixed effect that is largely wiped out by country-specific dummies that account for all unobservable country-specific characteristics (see Equation (3)).

country for RE technologies[6] from the IEA Energy Technology Research and Development Database (IEA, 2010a). Thus, the *domestic knowledge stock* (*DRD*) of country *i* is computed from the *public energy R&D budgets* (*RD*) through the perpetual inventory model[7]:

$$DRD_{i,t} = (1 - \delta)DRD_{it-1} + RD_{it}. \tag{4}$$

The initial value of the stock is defined as follows:

$$DRD_{it_0} = \frac{RD_{it_0}}{(\delta + g)}, \tag{5}$$

where δ, i.e. the depreciation rate, is set equal to 5 per cent, as in Coe and Helpman (1995), and the R&D growth rate, g, is set equal to 20 per cent, as in Braun, Schmidt-Ehmcke, and Zloczysti (2010).[8]

International knowledge spillovers, *IKS*, have been computed by aggregating the domestic knowledge stocks of other countries in three different ways. The first indicator of knowledge spillovers benefiting country *i* is POOLKS, the un-weighted pool of the R&D stocks of all other countries $j \neq i$ in the sample (as, for instance, in Garrone and Grilli 2010):

$$POOLKS_{it} = \sum_{j \neq i} DRD_{jt}. \tag{6}$$

However, as disembodied knowledge flows have been found to be possibly impeded by geographic distance, a second indicator for country *i*, *DISKS*, has been obtained by weighting the other countries' R&D stocks through inverse functions of geographic distance (Xu and Wang 1999):

$$DISKS_{it} = \sum_{j \neq i} DRD_{jt} \cdot wd_{ij} \tag{7}$$

with $wd_{ij} = (1/\ln gd_{ij})/\Sigma_{j \neq i} [1/\ln gd_{ij}]$. wd_{ij} is a function of the geographic distance between countries *i* and *j* (i.e., between the capital cities), gd_{ij}.

The third indicator, *CNTKS*, has been obtained by weighting other countries' R&D stocks through bilateral trade flows as a proxy of mutual connections. However, differently from studies adopting only bilateral import flows (e.g., Coe and Helpman 1995; Lichtenberg and van Pottelsberghe de la Potterie 1998), we also allow for learning by exporting (Clerides, Lach, and Tybout 1998; Salomon 2006; Liu and Buck 2007; Andersson and Lööf 2009) and the openness of the country (Grossman and Helpman 1991; Branstetter 2001; Cantwell and Piscitello 2014). Thus, trade flows are calculated as the sum of the total imports and exports between country *i* and partner country *j*, as reported in the UN Comtrade database (2010).

Specifically, we allow for the fact that country *i* benefits from country *j*'s R&D efforts if the bilateral trade flows are sufficiently large in comparison to both country *j*'s economy and

[6] According with our classification, hydro R&D budgets have been subtracted from the total R&D budget.

[7] In some countries, knowledge on new energy technologies is also produced by private firms through own R&D activities. This is modeled as an unobservable country-specific characteristic (see footnote 6).

[8] Sensitivity analyses are available upon request from the authors.

trade flows with other countries (Lichtenberg and van Pottelsberghe de la Potterie 1998; Xu and Wang 1999). Thus, we normalize the weight by the partner country's GDP, as follows:

$$CNTKS_{it} = \sum_{j \neq i} \left[DRD_{jt} \cdot wg_{ijt} \right], \tag{8}$$

with $wg_{ijt} = \ln[(\text{import}_{it}^{j} + \text{export}_{it}^{j})/GDP_{jt}]/\sum_{j \neq i} \ln[(\text{import}_{it}^{j} + \text{export}_{it}^{j})/GDP_{jt}]$.

The three indicators can be interpreted in a rather straightforward way. *POOLKS* represents a global pool of RE technologies, and it captures the essence of international spillovers only if there is no need to have repeated contact and interaction to facilitate the diffusion of knowledge (e.g., due to the global reach of computers and online documents). *DISKS* takes into account the geographic dimension, and it assumes that closer countries quite naturally have a larger amount of contacts and interactions to exchange technological knowledge, i.e. it captures localized knowledge spillovers. *CNTKS* has the purpose of representing the diffusion of those components of technological change that are more tacit and less codified and that, as such, need repeated contacts and interactions. Namely, trade flows are assumed to capture the frequency and intensity of cross-country interaction relationships.

4.3.1. Control Variables. Among the control variables, *GDP* has been included as a measure of the economy's size.

To capture the presence of climate-energy policies that support the development and diffusion of RE technologies, we inserted three binary variables: *OB*, for performance standards or obligations (e.g., portfolio standards, quota systems); *FIT*, for guaranteed prices or feed-in-tariffs; *REC*, for carbon emissions or RE certificate trade systems. These variables equal 1 if country *i* is enforcing the corresponding measure in year *t*, and 0 otherwise. The main reference source for these binary variables is IEA (2004). We have instead resorted to IEA Policies and Measures Database (2010b) for more recent years.

Finally, we also included the ratio between the import of capital goods from the world and the GDP of the focal country, i.e., CGI, as a control of the impact of spillovers that are embodied in capital goods imports, in order to reduce the risk of biased estimates for disembodied spillovers.

Table 3 shows the summary statistics of the variables. The final sample includes 285 observations because some data on patents, R&D budgets or policy indicators were missing.

Table 4 reports the correlation matrix between the variables transformed according to the model functional form (Section 4.1). The large and significant correlation between knowledge production inputs comes as no surprise, as all of them are significantly correlated to the economy size (*GDP*) and to the time trend.[9] High and significant correlation ratios between spillover variables should not be considered as a problem, because they are used in different models.

[9] It is worth anticipating that in order to check the robustness of empirical findings, control regressions will be run after excluding *GDP* or period-specific indicators (Section 5).

Table 3. Variables: descriptive statistics

Variable	Definition	No. obs.	Mean	SD	Min	Max
Dependent variable						
RPAT	Patent count	285	28.6	43.4	0	258
Explanatory variables						
HC	Human capital (no. years)	285	9.6	1.6	6	13
DRD	Domestic knowledge stock (million USD, 2008 and PPP)	285	751.6	1,352.8	12	6,094
POOLKS	Unweighted sum of international knowledge stocks (million USD, 2008 and PPP)	285	12,572.9	1,469.0	6,409.8	14,698.0
DISKS	Distance-weighted sum of international knowledge stocks (million USD, 2008 and PPP)	285	698.4	87.6	377.7	943.0
CNTKS	Trade-flow weighted sum of international knowledge stocks (million USD, 2008 and PPP)	285	856.4	146.4	362.4	1061.1
Control variables						
OB	Performance standards (binary)	285	0.3	0.5	0	1
REC	Tradable certificates (binary)	285	0.1	0.3	0	1
FIT	Feed-in tariffs (binary)	285	0.4	0.5	0	1
CGI	Capital goods imports divided by GDP	285	0.1	0.0	0.0	0.2
GDP	GDP (million USD, 2005 and PPP)	285	1,440,629	2,433,020	103,816	12,900,000

Finally, in order to mitigate the risk of omitted-variable bias, we should include a time trend (or year effects), although this may cause a loss of efficiency, because all dependent and independent variables but *GDP* are significantly and positively correlated with the time trend (Table 4). A two-way nonlinear models, i.e. the joint inclusion of time and country-fixed effects would determine inconsistent estimates, because of the so-called problem of incidental parameters (Hahn and Newey 2004; Charbonneau 2013, 34). Because the number of time periods is fixed, estimates of fixed effects cannot be consistent, and the bias contaminates estimates of the coefficients of interest. As a compromise strategy, we included two period-specific effects: *1996_2000* and *2001_2006* are binary variables that take value equal to 1, in the time window around Kyoto Protocol signature (i.e., 1996–2000 years) and in subsequent years; the period 1990–1995 is the baseline.

5. Empirical Results and Discussion

5.1. Econometric Strategy

An established body of literature emphasizes that panel innovation counts share two characteristics (Blundell, Griffith, and Van Reenen 1995, 1999; Blundell, Griffith, and Windmeijer 2002; Mancusi 2008; Czarnitzki, Kraft, et al. 2009). Unobserved heterogeneity is

Table 4. Correlation matrix

	RPAT	lnHC	lnDRD	lnPOOLKS	lnDISKS	lnCNTKS	OB	REC	FIT	CGI	GDP	Time trend
lnHC	0.324 (0.000)	1.000										
lnDRD	0.678 (0.000)	0.396 (0.000)	1.000									
lnPOOLKS	−0.592 (0.000)	−0.320 (0.000)	−0.668 (0.000)	1.000								
lnDISKS	−0.603 (0.000)	−0.196 (0.001)	−0.570 (0.000)	0.910 (0.000)	1.000							
lnCNTKS	−0.405 (0.000)	−0.436 (0.000)	−0.605 (0.000)	0.870 (0.000)	0.603 (0.000)	1.000						
OB	0.045 (0.452)	0.052 (0.379)	−0.016 (0.783)	0.191 (0.001)	0.127 (0.033)	0.228 (0.000)	1.000					
REC	0.091 (0.126)	0.135 (0.023)	0.151 (0.011)	−0.003 (0.959)	0.005 (0.936)	0.001 (0.983)	0.250 (0.000)	1.000				
FIT	−0.027 (0.650)	−0.379 (0.000)	−0.115 (0.052)	0.263 (0.000)	0.138 (0.020)	0.397 (0.000)	0.017 (0.771)	−0.062 (0.298)	1.000			
CGI	−0.331 (0.000)	0.020 (0.737)	−0.396 (0.000)	0.427 (0.000)	0.434 (0.000)	0.354 (0.000)	0.211 (0.000)	−0.074 (0.215)	0.128 (0.031)	1.000		
GDP	0.694 (0.000)	0.397 (0.000)	0.754 (0.000)	−0.869 (0.000)	−0.758 (0.000)	−0.806 (0.000)	−0.110 (0.064)	0.157 (0.008)	−0.252 (0.000)	−0.507 (0.000)	1.000	
Time trend	0.184 (0.002)	0.308 (0.000)	0.109 (0.067)	0.285 (0.000)	0.309 (0.000)	0.222 (0.000)	0.286 (0.000)	0.101 (0.090)	0.216 (0.000)	0.188 (0.001)	0.0707 (0.234)	1.000

Note: p-Values in parentheses.

a first feature of innovation activity across firms, industries or countries. When individual fixed effects are present yet not correlated to regressors, i.e. regressors are strictly exogenous, the conditional estimator for count data with fixed effects returns unbiased estimates (Hausman, Hall, and Griliches 1984; Wooldridge 1999a). However, dynamic feedback from the dependent variable to the future values of explanatory variables are also likely to be present, a feature that makes regressors predetermined, or weakly endogeneous.[10] As a consequence, the conditional estimator returns biased estimates (Blundell, Griffith, and Windmeijer 2002). In our setting, countries that are successful in RE innovation are likely to influence the knowledge stocks of other countries, and to strengthen their own innovation capacity. In order to address the endogeneity problem caused by dynamic feedback, we adopt the Pre-Sample Mean (PSM) estimation method. It replaces unobserved heterogeneity, i.e. fixed effects, by the historical innovation capacities with which countries enter the sample (Blundell, Griffith, and Van Reenen 1999; Blundell, Griffith, and Windmeijer 2002).[11] Thus, a large portion of unobserved heterogeneity is wiped-off residuals. While regressors are still influenced by the dependent variable through dynamic feedback, they are less likely to be correlated with residuals, and endogeneity is a lesser concern. In our setting, fixed effects are approximated by the country-specific means of RE patent counts over the 1980–1989 period innovation history, *PSM*.

In addition, *RPAT* is assumed to follow a negative binomial distribution, because *RPAT* variance results to be much larger than *RPAT* mean (Table 3); here, over-dispersion makes the Poisson distribution inappropriate. Finally, since unobserved fixed effects are replaced by *PSM*, a random negative binomial estimator can be used. Section 5.2 thus illustrates effect random effects estimates of negative binomial models that include *PSM* and, under different specifications of model (3), time period effects.

5.2. Main Results

Table 5 presents the estimates of a baseline model in which the knowledge spillover variable is not included (model (a)), and estimates of models where different international knowledge spillovers measures have been inserted (models (b)–(d)). In order to check the robustness of the results, we also run two control regressions.

As regards explanatory variables (i.e., knowledge production inputs), the domestic knowledge stock, *DRD*, has a positive effect on the country's patenting activities, at 1 per cent significance level in all the models (a)–(d)). Instead, human capital, *HC*, does not seem to have a significant influence, but this may be related to a global trend in schooling, i.e. to the correlation between *HC* and period-specific indicators (see also control regressions in Table 6).

International knowledge spillovers do encourage RE patenting activities throughout models ((b)–(d)) (Table 5). In model (b), international spillovers are proxied by the pool of

[10] Cross-country heterogeneity and its persistence are confirmed by Hausman test of no correlation between regressors and the error, and by the Wooldridge test of serial correlation. First-order autocorrelation is present, and fixed effects are favored against random effects in two models out of four (models (c) and (d)). Results are available upon request from the authors.

[11] Quasi-difference generalized methods of moments (GMM) for panel count data could be an alternative option, but they require large samples (Blundell et al., 2002). Thus, they are not appropriate in our setting.

Table 5. PSM negative binomial models (dependent variable: RPAT)

Full model	(a)	(b)	(c)	(d)
lnHC	0.249	0.236	0.170	0.309
	(0.259)	(0.248)	(0.252)	(0.247)
lnDRD	0.277***	0.326***	0.278***	0.384***
	(0.103)	(0.107)	(0.105)	(0.110)
lnPOOLKS		1.900***		
		(0.747)		
lnDISKS			1.663**	
			(0.785)	
lnCNTKS				1.655***
				(0.518)
OB	0.028**	0.042***	0.039***	0.041***
	(0.014)	(0.015)	(0.015)	(0.014)
REC	0.005	−0.001	−0.000	−0.002
	(0.006)	(0.007)	(0.007)	(0.006)
FIT	−0.058	−0.062*	−0.060	−0.066*
	(0.037)	(0.037)	(0.037)	(0.037)
CGI	0.238	0.078	0.098	0.092
	(0.164)	(0.175)	(0.176)	(0.170)
GDP	−0.136***	−0.207***	−0.199***	−0.187***
	(0.036)	(0.046)	(0.047)	(0.041)
1996–2000	0.117*	0.072	0.083	0.058
	(0.065)	(0.068)	(0.067)	(0.067)
2001–2006	0.368***	0.252***	0.280***	0.223**
	(0.080)	(0.092)	(0.090)	(0.090)
PSM (fixed effects)	0.042***	0.051***	0.052***	0.047***
	(0.008)	(0.009)	(0.009)	(0.009)
Constant	2.056***	2.297***	2.199***	2.463***
	(0.292)	(0.301)	(0.296)	(0.314)
No.	285	285	285	285
H_0: $\beta_{1996\_2000} = \beta_{2001\_2006} = 0$				
χ^2	29.16	10.72	13.54	9.53
p-Value	0.0000	0.0047	0.0011	0.0085

Note: PSM negative binomial models: PSM estimates of fixed-effects negative binomial models (Blundell, Griffith, and Van Reenen 1999); Standard errors in parentheses, *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; PSM (fixed effects): PSM of patent counts, as a measure of unobserved cross-country heterogeneity.

international knowledge stocks (*POOLKS*), and are shown to play a significant role at 1 per cent significance level. Model (c) includes international spillovers measured by *DISKS*, i.e. the international knowledge stocks weighted by the inverse functions of geographic distance; as in the previous case, international spillovers seem to significantly increase RE patents (at 5 per cent significance level). Finally, model (d) includes the spillover indicator *CNTKS* that consider the R&D stocks of "connected" countries. *CNTKS* has a significant and positive impact on patenting activities (at 1 per cent significance level).

Table 6. Control regressions: PSM negative binomial models, without time dummies or GDP

	(a)		(b)		(c)		(d)	
	No period specific variables	No GDP	No period specific variables	No GDP	No period specific variables	No GDP	No period specific variables	No GDP
lnHC	0.837***	0.321	0.479**	0.319	0.394	0.336	0.587**	0.368
	(0.269)	(0.277)	(0.241)	(0.277)	(0.252)	(0.278)	(0.236)	(0.275)
lnDRD	0.303***	0.255**	0.378***	0.252**	0.297***	0.256***	0.456***	0.319***
	(0.101)	(0.100)	(0.105)	(0.101)	(0.105)	(0.100)	(0.107)	(0.105)
lnPOOLKS			3.308***	−0.156				
			(0.683)	(0.625)				
lnDISKS					3.265***	−0.441		
					(0.756)	(0.609)		
lnCNTKS							2.472***	0.965*
							(0.482)	(0.551)
OB	0.042***	0.042***	0.059***	0.040**	0.058***	0.038**	0.052***	0.050***
	(0.015)	(0.014)	(0.013)	(0.016)	(0.014)	(0.016)	(0.012)	(0.015)
REC	0.013**	−0.005	−0.001	−0.004	0.000	−0.002	0.000	−0.011
	(0.006)	(0.005)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
FIT	−0.033	−0.023	−0.058*	−0.023	−0.053	−0.026	−0.065*	−0.025
	(0.037)	(0.036)	(0.035)	(0.037)	(0.036)	(0.037)	(0.035)	(0.036)
CGI	0.385***	0.345**	0.025	0.356**	0.041	0.374**	0.072	0.261
	(0.143)	(0.162)	(0.16)	(0.167)	(0.163)	(0.167)	(0.153)	(0.171)
GDP	−0.051*		−0.222***		−0.216***		−0.180***	
	(0.029)		(0.049)		(0.05)		(0.043)	
1996_2000		−0.010		−0.002		0.012		−0.055
		(0.057)		(0.065)		(0.064)		(0.065)
2001_2006		0.194**		0.208**		0.234***		0.098
		(0.068)		(0.090)		(0.087)		(0.087)
PSM (fixed effects)	0.037***	0.034***	0.056***	0.034***	0.059***	0.033***	0.048***	0.032***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.007)
Constant	1.862***	1.897***	2.399***	1.881***	2.257***	1.870***	2.613***	2.119***
	(0.276)	(0.285)	(0.284)	(0.293)	(0.281)	(0.290)	(0.303)	(0.301)
No. obs.	285	285	285	285	285	285	285	285

Note: PSM-negative binomial models: PSM estimates of fixed-effects negative binomial models (Blundell, Griffith, and Van Reenen 1999); Standard errors in parentheses, *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; PSM (fixed effects): PSM of patent counts, as a measure of unobserved cross-country heterogeneity.

As far as control variables, *OB* coefficients come out positive and significant throughout models (a)–(d) (5 per cent and 1 per cent significance level). Namely, obligations (e.g., portfolio standards) appear to play a role in the development of new RE technologies; instead, renewable certificates (variable *REC*) do not show a significant relationship with RE innovations, while two models (model (b) and (d)) report a negative and significant impact of the implementation of feed-in tariffs (10 per cent significance level, variable *FIT*). The latter result is puzzling, but it should be reminded that some relevant aspects of the policy adoption are not modeled. Policy variables have been included in the model mainly as controls, and are measured by binary variables that generally follow a step path. As a consequence, their role could be captured by period-specific indicators (see also Table 6). *CGI*, i.e. the capital goods import indicator, never reaches a standard significance level. Nonetheless, before concluding that embodied knowledge spillovers are not relevant in RE technologies, we checked this result through control regressions (Table 6). Namely, *GDP*, *PSM* and *2001_2006* do affect *RPAT* in models (a)–(d). Economy size, as measured by *GDP*, correlates negatively with patenting activities. This surprising result could be a symptom of heteroskedasticity or serial correlation issues.[12] Control regressions will cope with *GDP* and its inclusion in RE innovation models, and will give a hint that size effects may be captured by *PSM*. Robustness checks of Section 5.4 will also deal with this issue. The coefficient of country-specific pre-sample history in RE innovations, *PSM*, is positive, as expected (1 per cent significance level). The test of joint significance for period-specific indicators suggests that RE patent counts increase over time, and more importantly since 2001 (1 per cent significance level; bottom of Table 5).

We believe that some results reported in Table 5, as for instance the estimates of *HC*, *FIT*, *CGI* and *GDP* coefficients, are worth controlling further because there is a large and significant correlation between most regressors, on the one hand, and time trend and *GDP*, on the other hand. However, a variance-inflation factors (VIFs) test on the right-hand-side variables has allowed us to exclude that a multi-collinearity problem affects estimates. Overall, VIFs take a value far below 4 where, as a general rule of thumb, a value above 10 may indicate the possible presence of a serious problem of multi-collinearity (Kennedy 2003, 213). Nevertheless, in order to check further the robustness of the results, we excluded either period-specific indicators or *GDP* from control variables (results are reported in Table 6). The coefficient of *HC*, i.e. human capital, gains significance in three specifications that exclude period-specific dummies. This means that *HC* may be a relevant knowledge input, but period-specific variables capture its variation. As far as international spillovers are concerned, it is worth noting that only *CNTKS* maintains its significance at 1 per cent and 10 per cent levels in models (d). By contrast, *POOLKS* and *DISKS* lose in significance if *GDP* is excluded. As to control variables, only obligation policies, *OB*, are consistently found to exert a positive influence on the development of RE innovations, while under most specifications neither emissions trade, *REC*, nor feed-in tariffs, *FIT*, play a role. Finally, it cannot be excluded that imports of capital goods are a vehicle for embodied knowledge spillovers (i.e., *CGI* coefficients are positive at standard significance levels in a few cases).

Thus, innovative capacity in the RE sector become more intense if connections with research-intensive countries grow, if domestic R&D investments rise, if obligations to adopt RE technologies are maintained.[13]

Further checks of the robustness of our results are discussed in Section 5.4.

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[12] We thank an anonymous referee for raising this issue and suggesting us the course of analysis that we follow in Section 5.4.

[13] It is worth emphasizing that we are not suggesting that large quantities of imports and exports are per se necessary or sufficient for countries to produce RE innovations. Trade flows matter only if they are concentrated toward countries that have developed large stocks of knowledge about RE technologies, as is made clear by the definition of CNTKS (see Formula (8)).

5.3. Assessing the Role of International Stocks of Knowledge and International Knowledge Spillovers: Simulation Exercise

The effects of international knowledge spillovers are captured by *POOLKS*, *DISKS* and *CNTKS* coefficients. However, since the relevant variables have been divided by their mean value and transformed by natural logarithms, their estimated coefficients (reported in Tables 5 and 6) represent the variation in patent count that is caused by a 1 per cent increase, other things being equal. Nonetheless, in order to better assess the magnitude of the effects of international spillovers on innovation outputs and to compare the explaining strength of different spillover indicators, we focus on plausible variations. In fact, differences between countries and between years are better captured by the standard deviation statistics than by a uniform 1 per cent increase. In particular, the standard variations, i.e., the ratios between the sample standard deviations and means, of *POOLKS*, *DISKS* and *CNTKS* indicators are equal to 11.68 per cent, 12.54 per cent and 17.10 per cent, respectively. To this aim, each knowledge production function input has been given a realistic shock, other things being equal, and the response of *RPAT* has been simulated using the coefficients of Tables 5 and 6. Results of simulations are reported in Table 7.

When international knowledge spillovers are measured by pooled international R&D stocks (*POOLKS*), a typical increase in knowledge spillovers causes the patent count of countries to increase respectively by 0.222, in the full model, and by 0.386 in the model that does not include period-specific indicators, while it is not significant in the model with no GDP. Therefore, we cannot confirm our Hypothesis 1 in a robust way. Likewise, when considering international spillovers mediated by distance (DISKS), the relevant increase is 0.209 or 0.409 in the first two specifications, while it is still not significant in the model without GDP.

Instead, an increase in *CNTKS* yields an increase in the patent number count that is positive and significant throughout all model specifications. Thus, our Hypothesis 2 is confirmed. The *RPAT* variation is equal to 0.283, 0.423 or 0.165 (Table 7, models (d)). In other words, it seems that the R&D activities of connected countries have systematically a sizeable and significant impact on RE innovations, though it is smaller than the effect of domestic knowledge (*DRD*).

5.4. Additional Robustness Checks

A few complementary approaches have been adopted to deal with the possible presence of unit roots, heteroskedasticity and serial correlation of errors.

The stationarity of variables is a pre-requisite for the consistence of estimates. We acknowledge that unit roots have been detected in energy-related panel data analyses (Hübler and Keller 2010) and recent developments of econometrics warn against the presence of unit roots in cross-country panel data. Nevertheless, the test and treatment of unit roots in small micro-econometric panels are not without uncertainty because results are generally mixed (Baltagi 2013, 275 and 276). Thus, we view the unit root analysis as a relevant yet preliminary robustness check.[14]

[14] The associated tests and results are available upon request from the authors.

Table 7. Simulations: Variation in the number of RE patents (RPAT variation)

Independent variables, SD		(b) Full model	(b) No period specific variables	(b) No GDP	(c) Full model	(c) No period specific variables	(c) No GDP	(d) Full model	(d) No period specific variables	(d) No GDP
International knowledge spillovers										
POOLKS	11.68 per cent	0.222	0.386	ns						
DISKS	12.54 per cent				0.209	0.409	ns			
CNTKS	17.10 per cent							0.283	0.423	0.165
Domestic knowledge sourcing										
HC	17.03 per cent	ns	0.082	ns	ns	ns	ns	ns	0.100	ns
DRD	180.00 per cent	0.587	0.680	0.454	0.500	0.535	0.461	0.691	0.821	0.574

Note: Independent variables are given a variation equal to the ratio between the sample standard deviation and the mean value.
ns, not significant.

We sought unit roots in all variables relying on the methods developed by Im, Pesaran, and Shin (2003) and Levin, Lin, and James Chu (2002), i.e. the so-called IPS and LLC tests.[15] All the auto-regressive processes that have been tested allow for a global time trend due to the significant correlation of time trend with almost all variables (Table 4). Because we do not have precise conjectures about cross-country correlation for the model variables, we consider both models that demean the series and models that do not.

Unit root tests reveal that the risk of spurious correlations is not significant; indeed, because the dependent variable, *RPAT*, is found to be stationary, irrespectively of tests and specifications. Results on regressors, instead, are mixed. The unit root tests of first-differenced variables indicate that regressors may be either stationary or integrated of order 1. We adopted a cautionary approach, and estimated model (3) after replacing all regressors with their first-differenced counterparts. Some variables lose their significance (e.g., *DRD*) or take unexpected signs (e.g., *REC*). Nevertheless, the PSM estimates corroborate our central results, because the only explanatory variables that still have a positive and significant impact after differencing are *POOLKS* and *CNTKS* (10 per cent significance levels). Therefore, we conclude that our hypotheses are robust to possible stationarity problems of some explanatory variables.

PSM estimates of Tables 5 and 6 already address overdispersion and cross-country heterogeneity due to historical differences in innovation capacities, i.e. special forms of heteroskedasticity. Nonetheless, the risk of downward-biased standard errors is not eliminated, and a more general control is appropriate for corroborating empirical findings.

[15] The two methods are complementary. The LLC method can reject the presence of unit root tests in all panels, but it is less suitable for small-size samples. The IPS method is more suitable for small-size samples as ours (N and T fixed), but, at best, it can show that some panels are stationary.

In fact, a Wald test for groupwise heteroskedasticity has been run on ancillary linear regressions with fixed effects, and it shows that residuals are heteroskedastic.[16] The Poisson Quasi Maximum-Likelihood (PQML) estimator with fixed effects and robust standard errors can be seen as a consistent and flexible alternative to negative binomial estimates (Wooldridge 1999a, 1999b; Czarnitzki, Glänzel, et al. 2009). PQML estimates of model (3) that are reported in Table A1 of the Appendix are weaker than their PSM counterparts (Table 5). Whether this is caused by heteroskedasticity of PSM estimates or by inefficiency due to the small sample size is unclear. However, it is comforting that *CNTKS* and *OB* survive even this check. In particular, PQML estimates corroborate our empirical findings on the role of cross-country connections in driving knowledge spillovers on the RE technologies.

Finally, PQML estimates of *GDP* coefficients are negative and significant, not differently from PSM estimates. PQML estimates are robust to cross-country heteroskedasticity, but not to serial correlation; moreover, the underlying model assumes unobserved fixed effects and Poisson distribution, differently from our main regressions (Table 5). Thus, we summarize the main results of two further checks of robustness, which deal with possible heteroskedasticity and serial correlation of our core regressions.[17] We have chosen two compromise options, because to our knowledge standard methods for panel innovation counts do not estimate standard errors that are heteroskedasticity and autocorrelation consistent. First, we stick to the PSM negative binomial model with time period controls, and switch from random effects estimates to a pooled, or population-averaged, method that estimates heteroskedasticity robust standard errors. It is encouraging that estimates of *GDP* coefficients lose any significance, while knowledge spillovers maintain significant and positive impacts. Values of *POOLKS*, *DISKS* and *CNTKS* coefficients are similar to those reported by Tables 5 and 6. Second, we abandon the assumption of negative binomial distribution, and estimate pooled OLS regressions that extend the Newey and West approach, and provide kernel-based standard errors that are both heteroskedasticity and autocorrelation consistent (Baum, Schaffer, and Stillman 2007). The covariance matrix is computed after assuming the presence of arbitrary heteroskedasticity and serial correlation up to three lags. *GDP* coefficients are not significantly different from 0, but knowledge spillovers still have significant and positive impacts. Caution is necessary to interpret the latter results because they are not obtained from established methods for panel count data, but we believe that they confer, in combination with other ancillary analyses, a greater robustness to the empirical evidence illustrated by this paper.

6. Conclusions and Policy Implications

This paper addresses the role of international knowledge spillovers in RE innovations. Specifically, our empirical findings on 18 OECD countries observed in the period 1990–2006 confirm that foreign R&D has a potential as knowledge source for advanced economies that are developing new RE technologies and, more particularly, that

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[16] Results are available upon request from the authors.

[17] Results are available upon request from the authors.

international knowledge spillovers are a central element of climate-friendly technological change. Thus, our empirical analysis aims to contribute to the scholarly and policy debate on technological strategies that industrialized countries can adopt in order to cope with climatic change challenges. Indeed, our analysis allows us to identify factors that enable developed countries to build on foreign technologies and to join the environmental innovation arena. Specifically, we find that a country's innovative performance in the RE sector benefits from other countries' R&D in the same sector, but these benefits occur especially when the focal country maintains repeated contacts and interactions with those other countries. Instead, the empirical evidence on geographic distance as a barrier to the cross-country spread of knowledge on RE technologies is mixed, thus strengthening the idea that knowledge spillovers do benefit from established linkages between countries rather than being automatically fostered by geographical proximity.

Concerning implications for the design of environmental innovation policies, our results suggest that public energy R&D expenditure is a key input to innovation in the RE field, i.e. a relevant element in global efforts toward carbon stabilization. Public support to research should not be abandoned in favor of other measures, all the more because its effects help follower countries to join the environmental innovation race. Consistently with results of previous research (e.g., Bosetti et al. 2008; Dechezleprêtre, Glachant, and Ménière 2008; Popp 2011), policies aimed at strengthening international knowledge flows should be encouraged. Because linkages between countries are the outcome of various causes and are inherently cross-sectoral, they are only marginally touched by a country's efforts to source knowledge on RE technologies, i.e. they are exogenous with respect to RE innovative activities. Therefore, cross-country connections per se can hardly be the subject of policy recommendations for the RE sector. Nevertheless, international policies that favor technological cooperation between countries are warranted in order to reduce free-riding risks without haltering international spillovers. Interestingly, technological cooperation can be viewed as complementary to climate cooperation. An evolving strand of research investigates exactly the design of international technology-oriented agreements, with the purpose of remedying to the public good failure that characterizes climate stabilization (Kemfert 2004). Finally, technological knowledge in the RE sector is more likely to flow between countries that have already established intense mutual relations. International institutions that govern climate policies, such as for instance the European Commission or Intergovernmental Panel of Climate Change, should consider the presence of mutual linkages between international technological partners as an implementation criterion of the flexibility mechanisms for carbon reduction.

Our analysis has focused on connections related to bilateral trade flows as a proxy of cross-country linkages, but it has not explored the effectiveness of alternative instruments of cross-country interactions. This certainly ranks high in our research agenda as some scholars argue that also FDIs are related to international knowledge transmission. Another development of the present analysis could involve the extension to individual RE technologies, which are likely to exhibit different technological patterns and different proneness to benefit from foreign technological knowledge. However, as far as the latter, and given our purposes, the current domain-level perspective seems to be acceptable. Most climate-energy policies, a key variable of our model, are technology-neutral. Moreover, since international knowledge diffusion has been shown to foster the development of RE technologies overall, whatever their mutual differences, it can be claimed with greater confidence that the coordination of climate-energy policies at the international level is necessary. Although we believe that our analysis has yielded robust findings on spillovers in RE technologies and the importance of international linkages,[18] we recognize that a larger panel data sample would be necessary to attain more robust results on the presence of unit roots. More in detail, we believe that a cross-country panel with a greater time span, as well as more informative policy indicators, would be necessary in order to conclude about the impact of climate-energy policies on RE innovations.

Disclosure statement

No potential conflict of interest was reported by the authors.

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[18] It is worth acknowledging that, given the weighted variables adopted in our study, we are unable to disentangle the role of trade flows from the role of international R&D stocks. We thank an anonymous reviewer for stimulating us to clarify this point, which would certainly help to better address future research on that.

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Appendix A

Table A1. PQML models with robust standard errors (dependent variable: RPAT)

	(a)	(b)	(c)	(b)
lnHC	0.096	0.035	0.018	0.012
	(0.444)	(0.420)	(0.428)	(0.349)
lnDRD	0.388	0.345	0.348	0.320
	(0.242)	(0.246)	(0.242)	(0.240)
lnPOOLKS		1.804		
		(1.337)		
lnDISKS			1.476	
			(1.236)	
lnCNTKS				2.895**
				(1.248)
OB	0.026*	0.035*	0.033*	0.038*
	(0.016)	(0.018)	(0.018)	(0.019)
REC	0.002	−0.002	−0.001	−0.003
	(0.008)	(0.010)	(0.010)	(0.009)
FIT	−0.053	−0.050	−0.053	−0.039
	(0.048)	(0.046)	(0.048)	(0.041)
GDP	−0.135**	−0.228**	−0.202**	−0.296***
	(0.057)	(0.092)	(0.082)	(0.090)
CGI	0.267	0.162	0.179	0.076
	(0.200)	(0.214)	(0.207)	(0.201)
Fixed effects	Yes	Yes	Yes	Yes
1996_2000	0.171	0.142	0.143	0.127
	(0.158)	(0.159)	(0.163)	(0.154)
2001_2006	0.413**	0.329*	0.341*	0.254
	(0.200)	(0.194)	(0.201)	(0.193)
No. obs.	285	285	285	285

Note: PQML models with robust standard errors: Quasi-Maximum Likelihood estimates of fixed-effects Poisson models with robust standard errors (Wooldridge 1999b; Simcoe 2008). Standard errors in parentheses, *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.