Intra-EU knowledge flows in the renewable energy sector: a patent citation analysis[§]

by

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Abstract

We test whether demand-pull environmental measures, introduced with the 1997 Commission White Paper and following Directives, had an impact on the fragmentation of EU research and innovation effort in the strategic field of renewable energy. By focusing on knowledge spillovers, we study the pattern and evolution of knowledge flows within the EU and between the EU and two frontier innovators: the United States and Japan. This research question is motivated by increased concern that the fragmentation of EU renewable energy research and innovation systems may hamper the ability to address climate challenges at socially acceptable costs. Following a well-established tradition, we measure the intensity and the direction of knowledge flows by looking at patent citations. Our results suggest that after 1997 Member States' national innovation systems have evolved towards a more integrated innovation space at the EU level. Furthermore, environmental policies seem to have pushed the EU to become a frontier innovator, since the EU15's role as a source of knowledge for the US increased. However, innovative activity at EU level is still poorly integrated if compared to the American and Japanese systems.

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1 Introduction

The challenge of addressing climate change concerns and harmful greenhouse gas emissions promoted the implementation of various environmental policies in many countries around the world. Such policies shift economies towards more sustainable growth paths in two ways (Jaffe et al. 2003). First, by raising the relative costs of using polluting inputs, they push firms and consumers to adopt already available efficient technologies (static efficiency). Second, by raising the expected profits associated with cleaner technologies they promote investment in cleaner technologies innovation (dynamic efficiency). The presence and the magnitude of these two effects has been the focus of a wide theoretical and empirical literature to date (Laffont and Tirole, 1996; Jaffe and Palmer, 1997; Fisher et al., 2003; Kerr and Newell, 2003). Focusing on dynamic efficiency and the innovation incentives triggered by environmental policy, many mechanisms are at work. The literature has so far focused on two of them. First, environmental policy positively impacts innovation in the next periods (Popp, 2002). Second, higher innovation translates into a higher stock of clean knowledge in the following periods, which also positively impacts the innovative ability of a given country (Peri, 2005; Verdolini and Galeotti, 2011) Hence, inventors can “stand taller on the shoulder of the giants” (Caballero and Jaffe, 1993).

In this paper we explore yet another channel of the dynamic efficiency of environmental policy, namely the extent to which the implementation of environmental policies can contribute to the strengthening of knowledge networks (i.e., the rate at which knowledge diffuses). We test whether the EU demand-pull policies in the renewable energy sector, introduced by the 1997 White Paper and following Directives (see next section), have affected the knowledge flows in this technological area within the EU and between the EU and two frontier innovators: the United States and Japan. We focus in particular on knowledge flows across countries, measured by patent citations, interpreted as capturing the indirect links between research and innovative activities in different geographical areas.[1] This question is motivated by increased attention warranted to the fragmentation of EU renewable energy research and innovation systems. A poorly integrated innovation system can arguably hamper the ability to address the climate challenge at socially acceptable costs. The redesign of EU renewable energy policy will benefit from a clearer understanding of the links between research and innovative activities across Member States and of their evolution over time. Grasping whether environmental policy can contribute to a strengthening of knowledge networks, lowering the costs of climate mitigation and the burden for firms' competitiveness, is hence a relevant question for both researchers and policy makers. Notwithstanding the policy relevance of the problem, no study has yet addressed this topic.

Our study indeed represents the first attempt to understand the degree and the evolution of the fragmentation in EU technological space, focusing on innovation in renewable energy. This is a strategic field, subject to common regulation which has become increasingly stringent over time. This paper provides two main contributions. Firstly, it offers insights on the extent to which demand-pull measures did alone promote a greater integration of Member States innovation systems, contributing to the debate on the urgency of complementary technology-push policies. Secondly, it sheds light upon the role of EU as frontier innovator.

Section 2 provides a brief overview of EU renewable energy policy. We then discuss the relevant literature (Section 3) and offer some descriptive statistics (Section 4). Our empirical approach is described in Section 5. Section 6 presents the results and Section 7 the main conclusions.

[1] The fragmentation of an innovation system could also be studied by looking at other indicators, for instance co-inventions.

2 Environmental Policy in the EU

The cornerstone of renewable energy policy in the EU can be identified in the 1997 White Paper,[2] where the Commission laid down an action plan to increase renewable energy use by stimulating demand. Indicative 2010 targets on the contribution of renewable sources to the gross inland energy consumption at the EU (12%) and Member States level were adopted. The rationale of such measures was explained in terms of multiple goals: emissions mitigation, energy security and "stimulating world-class high tech industries".[3] Increased deployment of renewables was also expected to favor "greater social and economic cohesion within the Community". The White Paper thus assigned an important role to innovation in renewable technologies for addressing the Community climate challenge. Although some technology-push initiatives (such as FP7 programs on eco-innovation) were financed, the action plan consisted mainly of demand-pull measures presumed to have an indirect effect on innovation.

The insufficient integration of research and innovation activities in the renewable energy field across EU has instead attracted greater policy attention in recent years. To favor integration, specific technology-push initiatives were formulated in 2008 with the SET-PLAN (Strategic Energy Technology Plan), to complement the existing market pull policies.[4] It was expected that "the implementation of the SET-Plan will help overcome the fragmentation of the European research and innovation base" (COM(2007) 723 final, p. 8, 12). To implement the Plan, in 2010 the Commission launched new European Industrial Initiatives (EIIs) in priority energy technologies, including wind and solar power. EIIs are joint large scale research and development programs aiming at bringing together industry, academia and research institutions, in collaboration with the Commission and Member States. These technology-push policies are still in the making.

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[2] Energy for the Future: Renewable Sources of Energy COM(97) 599 final. A Green Paper (COM(96) 576) was released in 1996, but the document set only a broad framework with no detailed proposals. These measures were enacted in Directive 2001/77/EC establishing indicative targets. The Directive 2009/28/EC established tighter obligations setting mandatory targets. A global 20% share of renewable energy in the final EU energy consumption was set and mandatory national targets introduced.

[3] COM(2006) 848 final 3

[4] The SET-Plan is defined in COM(2013)253 as "the technology-push framework of the EU energy and climate policy".

3 Literature Review

The literature on the impact of environmental policy on innovation is vast.[5] The most commonly used proxies to measure innovation and knowledge flows are patent applications and patent citations, respectively. Both have shortcomings, but also significant advantages for the study of innovation dynamics (Griliches, 1990). For instance, Jaffe et al. (1993) show that patent citations can be interpreted as "bits" of previous knowledge that were important for developing the new knowledge contained in the citing patent. The in-depth analysis by Jaffe et al. (1998) recognizes that patents citations are a "valid but noisy measure of technology spillovers”.[6]

Two strands of the empirical literature are of particular interest for analyzing the fragmentation of European renewable energy innovation. The first line of research, started by Jaffe and Trajtenberg (1999), explores the patterns of patent citations across countries estimating the probability of citation with a double-exponential lag function. This econometric approach has been used by several authors to examine knowledge flows. Popp (2006) studies the process of knowledge diffusion from early innovators to follower countries. He focuses on air pollution control technologies since different timing in regulation across countries permits to identify early innovators and latecomers. The results suggest that the international transfer of these technologies occurred indirectly, that is through knowledge spillovers, rather than directly, through simple adoption of foreign technologies. Hu and Jaffe (2003) and Hu (2009), focusing on Asian countries, investigate patterns of North-South knowledge diffusion and test the hypothesis of increasing regionalization of knowledge flows in East Asia. The intensity of citations within a certain area is here interpreted as a measure of integration.

The second strand, which began with Maurseth and Verspagen (2002), concerns intra-EU spillovers at the regional level. The focus is on whether geographic distance or institutional features, namely national borders and language differences, represent barriers for the diffusion of knowledge across areas.

[5] See Popp et al. (2009) for a detailed review.
[6] On this point see also Jaffe et al. (2000).

Interestingly, these studies found that border effects are relevant, and in some cases dominate geographical distance effects (Fisher et al., 2009; Le Sage et al. 2000).

None of this studies is specifically concerned with renewable technologies and, with the exception of Popp (2006), does not consider clean technologies in general.

Based on this extensive literature, our strategy assumes that if the EU demand-pull environmental policy, initiated by the 1997 White Paper, had an effect on EU technological integration and innovative performance, we should see a change in the patterns of knowledge spillovers between the EU countries and other frontier innovators (the United States and Japan) and within the EU Member States. We measure knowledge flows by looking at EPO patent citations in clean energy technologies. The use of EPO patent citations as a proxy for knowledge flows has been validated by Duguet and MacGarvie (2005) and Criscuolo and Verspagen (2008). Citation-based measures have been widely used to estimate the amount of external knowledge available to a country (Peri, 2005; Mancusi, 2008; Verdolini and Galeotti, 2011) and to study localization effects (Bacchiocchi and Montobbio, 2010; Bottazzi and Peri, 2003).

Before addressing the implementation of our empirical strategy, we present some suggestive descriptive statistics on our sample.

4 Data and descriptive statistics

We collect data on patent applications at the European Patent Office (EPO)from the EP-CRIOS database, maintained by the CRIOS center at Bocconi University.[7]

[7] CRIOS created and is keeping updating a large database, known as EP-CRIOS. This contains information on patents applied for at the European Patent Office (EPO), from 1977 to 2012. Within this data base one may find: 1) patent data, such as the patent's publication number, its priority/application date, and main/secondary technological class, i.e. the IPC (International Patent Classification) code; 2) applicant (most often a firm or an institution) name and address, 3) inventor name and address, and, for each patent document, 4) all citations made to all prior EPO patents cited by the document itself.

Following the empirical literature on renewable energy technologies, we select patents classified in the sub-fields of wind, solar thermal, solar photovoltaic, geothermal, hydroelectric, ocean, biomass and waste, according to their IPC code.[8] We create the set of "potentially citing" patents extracting patents whose inventor resided in the US, Japan or one of the EU15 Member States, and with priority date between 1977 and 2010; data on EU15 Member States are pooled in order to consider EU15 as a single region. We count patents according to the priority date since it is the date closest to the invention. The use of the inventor's residence to allocate patents to countries is considered in the empirical literature the better way to identify where R&D was performed and the idea developed (Jaffe et al., 1993; Mancusi, 2008).

We then examine all citations made by the "potentially citing" patents to previous EPO patents (so-called *backward* citations) assigned to inventors belonging to the three areas under investigation; these citations are used to create the set of "potentially cited" patents.[9] Self citations (i.e. citations to previous patents held by the same applicant firm) are excluded from the data-set. There are about 12,500 "citing" patents, 25,600 "cited" patents and a total of 41,086 citations.

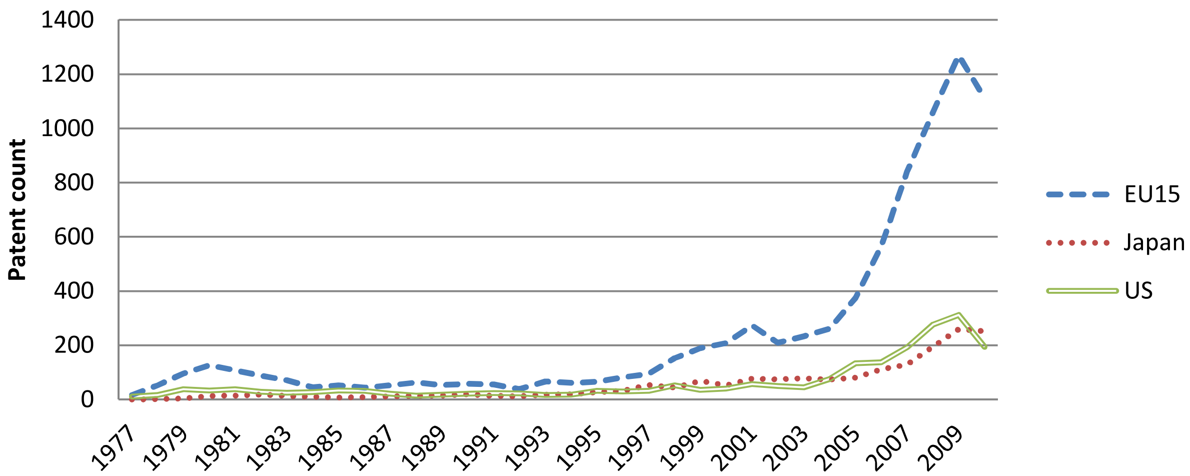
Table 1. Patents and Citations by Country Groups (1977-2010)

Country	*Potentially Citing Patents*	*% distribution (Potentially Citing)*	*Potentially Cited Patents*	*Forward Citations*	*Avg (Forward) Citation per Patent*
EU15	8512	0.68	14764	22970	1.56
JP	1827	0.15	3991	6378	1.60
US	2241	0.18	6852	11738	1.71
Total	12580	1	25607	41086	1.60

[8] A full list of the IPC classes used to identify these renewable energy technologies is available upon request.
[9] For a country, the set of "potentially cited" patents in a year t consists of the number of patents assigned in year t to that country both in renewable energy technologies (cited or not) and in other technological fields that have been cited at least once by a citing patent in our sample.

Figure 1 shows an impressive increase in the level of patenting activity over the last two decades, especially for EU15 countries. In particular, patenting activity started to grow in the late 1990s and increased at a faster rate in the EU15 as compared to other major innovating countries. The disproportionately high number of EU15 patents relative to US and Japanese patents registered in the later years of our sample is partly due to the home bias effect arising from the use of EPO patent data.[10] This problem partly affects the descriptive statistics shown below (as reflected in the percentage distribution of potentially citing patents displayed in Table 1). However, as we will explain more in detail later, our empirical estimation is robust to this concern.

Figure 1. Trend in patenting activity 1977-2010



The percentage distribution of citations across the three groups of countries can give some preliminary indication on the direction of knowledge flows. Within the EU15, we consider separately *national* citations (citing and cited patent belonging to the same country) and *international* citations (citing and cited patent belonging to distinct EU15 countries), since these two measures shed light on different phenomena underlying knowledge flows.

Tables 2 and 3 show some interesting patterns. Both tables summarize the shares of citations received by patents assigned to region *j* filed in a 3-year time period, from patents filed by region *i*'s inventors up to 7

[10] A similar pattern also emerges in Johnstone et al. (2010) where Germany, followed by US and Japan, exhibits the highest number of patents and a surge in patenting activity after 1997 (see Figure 2, p. 141). This is admittedly due to some extent to the presence of home bias when using EPO applications. The same effect is highlighted in OECD (2012) pp.23-24.

years after the end of the cited period,[11] where *i,j=EU15, US, JP*. Table 2 (Table 3) considers the distribution of backward citations from patents filed in period *t=1987,...,1997* (*t=2000,...,2010*) to patents with priority date *s=1987,...,1990* (*s=2000,...,2003*).

Table 2. Percentage distribution of citations by country (1987-1997)

		Cited country			
		EU15		JP	US
		National	$EU15_{-i}$ [(a)]		
Citing country	EU15	0.37	0.27	0.10	0.27
	JP	0.30		0.35	0.35
	US	0.26		0.13	0.61

Note: the percentages in the table refer to the share of citations from the citing country directed towards the cited countries (row sums are equal to 1). Citations taken into account to calculate the percentages are those from patent with priority date between 1987 and 1997 to patents with priority date between 1987 and 1990.

[(a)] $EU15_{-i}$ stands for the group of countries consisting of EU15 members except the citing country *i*.

Table 3. Percentage distribution of citations by country (2000-2010)

		Cited country			
		EU15		JP	US
		National	$EU15_{-i}$ [(a)]		
Citing country	EU15	0.35	0.41	0.09	0.15
	JP	0.31		0.55	0.14
	US	0.41		0.16	0.44

Note: the percentages in the table refer to the share of citations from the citing country directed towards the cited countries (row sums are equal to 1). Citations taken into account to calculate the percentages are those from patent with priority date between 2000 and 2010 to patents with priority date between 2000 and 2003.

[(a)] $EU15_{-i}$ stands for the group of countries consisting of EU15 members except the citing country *i*.

[11] The choice of lag is dictated by the fact that our dataset stops in 2010. Since the citation function generally peaks after 3/4 years, considering a minimum citation lag of 7 years would capture most citations.

$$p_{iTjt} = \frac{C_{iTjt}}{(N_{iT})(N_{jt})}$$

Three considerations emerge from these tables. First, over the two periods the percentage of citations between different EU15 countries increased considerably. Second, the percentage of US national citations decreased, while the percentage of citations from US to EU15 countries increased considerably. Third, Japan seems to rely more on its' own knowledge during the second period, but the share of citations to EU15 patents did not decrease.

This descriptive evidence points to the fact that citations flows (and hence, knowledge spillovers) change significantly over time. In particular it suggests a higher technological integration among EU15 countries and an increasing role of EU15 as a source of knowledge. However, though raw citation shares are informative, their use alone to draw inference about knowledge diffusion can be misleading. In fact, the share of citations that country *i* makes to country *j* is determined by two factors: the citation frequency (i.e. the probability of a patent from the citing country citing a patent from the cited country) and the overall level of patenting. In the next section we detail our empirical strategy which is meant to explore whether the changes shown in the tables above reveal indeed a change in citation patterns, potentially induced by the higher stringency of environmental policies within the EU15.

5 Modeling

To investigate possible changes in the intensity of knowledge flows across the countries of interest, we focus on the probability of citation and estimate a double exponential knowledge diffusion model, as proposed by Jaffe and Trajtenberg (1999). Following their approach, we measure the probability of citation with empirical citation frequencies:

$$p_{iTjt} = \frac{C_{iTjt}}{(N_{iT})(N_{jt})}$$

p_{iTjt} is the ratio of the number of citations (C_{iTjt}) made by country i's patents with priority date T to country j's patents with priority date t, to the product of the number of potentially citing (N_{iT}) and potentially cited (N_{jt}) patents. Citation frequencies are interpreted as an estimate of the probability that a randomly drawn patent in the citing group will cite a randomly drawn patent in the cited group.

Raw citation frequencies are afflicted by theoretical and actual biases. First, the observation of citation is always subject to truncation bias; moreover the number of citations made per patent has been rising significantly in the last decades (see Figure 1). Thus, citation frequencies need to be properly modeled taking into account these effects in order to use them to draw inference on knowledge flows.

According to Jaffe and Trajtenberg (1999), the knowledge diffusion process can be modeled as a combination of two exponential processes, one for the diffusion of knowledge and the other one for its obsolescence. The general formulation of the model is

$$p_{iTjt} = \alpha(i,T,j,t)\exp[-\beta_1(T-t)]\,(1-\exp[-\beta_2(T-t)]) \qquad (1)$$

where p_{iTjt} is the likelihood for patens in country j filed at time t, to be cited by patents in country i filed at time T. The parameters β_1 and β_2 represent the rate of obsolescence and diffusion, respectively, and both exponential processes depend on the citation lag $(T-t)$. We are particularly interested in the coefficient α, a shift parameter that depends on the attributes of both citing and cited patens: a higher α means higher probability of citations at all lags. In our model this proportionality factor is allowed to vary with the following attributes: citing year, cited year and all possible combinations of citing and cited country.

Since we are interested in changes in citing behavior after the implementation of the EU demand-pull policy, we extend the model adding dummy variables for selected country pairs in which the citing patent's priority date comes after 1997. The aim is to explore whether, given the changes in apparent citing behavior shown in Table 2 and Table 3, there are measurable differences in citation rates after 1997, controlling for other effects.

We estimate the following equation:

$$p_{iTjt} = \alpha_T \alpha_t \alpha_{ij} \left[1 + \phi_{ij} * D_{post97}\right] \exp[-\beta_1 (T-t)] \left(1 - \exp[-\beta_2 (T-t)]\right) + \varepsilon_{iTjt} \qquad (2)$$

where the dependent variable is the expected frequency of citations $p_{iTjt} = \frac{c_{iTjt}}{(N_{iT})(N_{jt})}$, $i, j = EU15, US, JP$ and $T, t = 1985 \ldots 2010$. The citing year fixed effects (α_T) and the cited year fixed effects (α_t) are grouped into 2-year and 5-year intervals, respectively. The fixed effect α_{ij} indicates the *relative* likelihood that the average patent from country *j* is cited by a patent from country i, and allows to identify differences in the intensity of citations between pairs of countries (interpreted as a measure of how two countries are "close"), controlling for time effects. Finally, the variable aimed to identify changes following 1997 is defined as $D_{post97} = \alpha_{ij} * post97$, where $post97$ is a dummy variable equal to one if $T > 1997$.[12]

Differently from linear models, here the null hypothesis of no effect corresponds to parameter values of unity rather than zero (except for β_1, β_2 and ϕ_{ij}). For each fixed effect, a group is omitted from estimation, i.e. its multiplicative parameter is constrained to unity. Thus the parameter values are interpreted as relative to the base group. The base group for country pairs fixed effects (α_{ij}) is $US - citing - US$;[13] if, for example, $\alpha_{EU15,US} = 0.8$ means that a patent belonging to EU15 group is 20% less likely to cite a US patent than is a US patent. The term $[1 + \phi_{ij} * D_{post97}]$ tests whether there are differences in the flows of knowledge concerning EU15 after 1997. ϕ_{ij} captures the additional likelihood of citation between a pair of countries, of which at least one of the two is EU15, for citing patents with priority date subsequent to 1997. Positive estimates can be interpreted as greater flow of knowledge after 1997.

We estimate equation 2 by non-linear least squares. Since the model is heteroskedastic (the dependent variable is an empirical frequency), we weight the observation by the reciprocal of the estimated variance $\sqrt{(N_{iT})(N_{jt})}$, as it is commonly done in the literature.

[12] For this variable we consider only the country pairs in which the citing country and/or the cited country is EU15, since we are interested in the effect of a policy affecting only EU Member States.
[13] The base group for citing year fixed effects (α_T) is 1985-1986 and for cited year fixed effects (α_t) is 1985-1989.

6 Results

Results from the estimation of equation 2 are presented in Table 4. We show only the estimates for the coefficients α_{ij} and ϕ_{ij}, our parameters of interest. Estimated values of β_1 and β_2 are displayed only for comparison with the existing literature.[14] We first estimate equation 2 considering as units of observation US, Japan and EU15 as a whole (column (1) and (2)), then we split intra-EU15 citations in *national* citations and *international* citations[15] (column (3) and (4)). In this way we try to identify two different effects: the reliance of European countries on national innovation system and the evolution of technological integration between EU15 members.

Column (1) presents the results of the basic specification of the model, in which intra-EU citations are taken as a whole and α_{ij} captures the overall likelihood of citations between country pairs across the entire period 1985-2010. In line with the findings of Jaffe and Trajtenberg (1999) and Bacchiocchi and Montobbio (2010), the bilateral coefficients α_{ij} display higher values when the citing and the cited patents belong to the same region, indicating a pattern of geographical localization. The highest value of α_{ij} corresponds to Japanese domestic citations ($\alpha_{JP,JPj} = 1.12$), confirming the status of Japan as the most closely integrated technological system. It must be stressed that the EU15 technological system turns out to be less integrated with respect to the US and Japanese ones, displaying an intra-regional coefficient considerably lower ($\alpha_{EU15,EU15} = 0.46$). However, when intra-EU citations are split in *national* and *international* (column (3)), the value of the coefficient concerning EU15 national citations ($\alpha_{EU15,EU15nat} = 0.81$) is closer to those associated to US and Japanese domestic citations; this suggests that national innovation systems are still the most relevant dimension for EU countries. Column (3) also shows a higher probability for EU15 patents to cite patents from other EU15 countries ($\alpha_{EU15,EU15int} = 0.33$), relative to the probability to cite patents from US ($\alpha_{EU15,US} = 0.24$) and Japan ($\alpha_{EU15,JP} = 0.18$). This can be interpreted as evidence of regionalization of knowledge flows in Europe.

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[14] Estimates of β_1 are in line with previous works. In our analysis the value of β_2 is larger than that found in previous studies using USPTO data, but it is consistent with the results of Pillu and Koleda (2011) which use EPO data.

[15] *National* citations refers to the case in which the citing patent and the cited patent belong to the same country, while *international* citations are those between two distinct EU15 countries.

Column (2) and column (4) refer to the specifications in which the term $[1 + \phi_{ij} * D_{post97}]$ is added to the base model to tests whether there are differences in the flows of knowledge concerning EU15 after 1997. A striking result displayed in column (2) is the increased importance of EU15 as a source of knowledge for the US; after 1997 the probability of citation from US patents to EU15 patents is 58% higher relative to the previous period. This is the only significant coefficient for the additional likelihood of citation after 1997 (ϕ_{ij}) resulting from the specification in column (2). The magnitude and the significance of $\phi_{US,EU15}$ are confirmed in column (4), where the intra-EU incremental probability of citations is split according to the national or international origin of the cited patent. While column (2) shows that there is no change in the overall probability of intra-EU citations after 1997, column (4) shows that its composition has changed considerably indicating that the presence of no effect at aggregate level is due to the combination of two contrasting effects: the fall in the probability of national citations ($\phi_{EU15,EU15nat} = -0.16$) and the increase in the probability of international citations across EU15 countries ($\phi_{EU15,EU15int} = 0.41$).

Table 4

Citation regression results

	(1)	(2)	(3)	(4)
Citing/cited country pairs ($\alpha_{i,j}$) [(a)]				
US citing US	1.000	1.000	1.000	1.000
	NA	NA	NA	NA
US citing EU15	0.400***	0.268***	0.398***	0.267***
	(-0.016)	(-0.027)	(-0.016)	(-0.027)
US citing JP	0.499***	0.500***	0.497***	0.497***
	(-0.026)	(-0.026)	(-0.026)	(-0.026)
EU15 citing EU15	0.460***	0.434***		
	(-0.015)	(-0.034)		
EU15 citing EU15 (National)			0.805***	0.939***
			-0.03	-0.082
EU15 citing EU15 (International)			0.328***	0.240***
			-0.012	-0.021
EU15 citing US	0.236***	0.248***	0.236***	0.247***
	(-0.011)	(-0.026)	(-0.011)	(-0.025)
EU15 citing JP	0.180***	0.197***	0.181***	0.196***
	(-0.008)	(-0.026)	(-0.008)	(-0.025)
JP citing EU15	0.176***	0.159***	0.176***	0.157***

	(-0.009)	(-0.019)	(-0.009)	(-0.019)
JP citing US	0.232***	0.233***	0.233***	0.233***
	(-0.013)	(-0.013)	(-0.013)	(-0.013)
JP citing JP	1.119***	1.125***	1.128***	1.130***
	(-0.060)	(-0.061)	(-0.061)	(-0.061)
Citing pattern differences for post-1997 patents (φ_{ij}) [(b)]				
US citing US		0.000		0.000
		NA		NA
US citing EU15		0.582***		0.582***
		(-0.169)		(-0.171)
EU15 citing EU15		0.073		
		(-0.089)		
EU15 citing EU15 (National)				-0.157**
				(-0.079)
EU15 citing EU15 (International)				0.413***
				(-0.133)
EU15 citing US		-0.052		-0.047
		(-0.107)		(-0.106)
EU15 citing JP		-0.091		-0.084
		(-0.124)		(-0.126)
JP citing EU15		0.135		0.142
		(-0.146)		(-0.149)
Decay (β_1) [(b)]	0.304***	0.305***	0.306***	0.307***
	(-0.011)	(-0.011)	(-0.010)	(-0.010)
Diffusion (β_2) [(b)]	0.002***	0.002***	0.002***	0.002***
	(-0.000)	(-0.000)	(-0.000)	(-0.000)
No. of obs.	3159	3159	3510	3510
R^2	1.000	1.000	1.000	1.000
Root MSE	0.000	0.000	0.000	0.000

Note. The table presents results for alternative specification of the citation regression. Column (1) and column (2) show the results of the regression in which intra-EU15 citations are taken as a whole, while column (3) and column (4) refer to the case in which intra-EU15 citations are split in *national* and *international* citations. Column (1) and column (3) do not consider variation over time of the coefficient α_{ij}; results on the additional likelihood of citation for patent posterior to 1997 are displayed in column (2) and (4).

[(a)] H_0 is parameter = 1; [(b)] H_0 is parameter = 0.

***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

7 Conclusions

Our results suggest two main developments. First, environmental policies seem to have pushed the EU to become a frontier innovator, since the EU15's role as a source of knowledge for the US increased. In addition we find that the integration of the EU innovation system in renewable energy technologies is progressing. After the demand-pull measures introduced in 1997 with the White Paper, EU innovators are more likely to source knowledge from other Member States and rely less on the home country knowledge stock. However this process is advancing at a moderate pace. We find that the overall probability of intra-EU citations (i.e. both national and across Member States) does not increase after 1997. Furthermore the innovative activity at the EU level is still poorly integrated if compared to the American and Japanese experience. This evidence indicates that demand-pull polices *per se* are insufficient for generating a well integrated EU innovative system in renewable energy technologies. This highlights the urgency of introducing complementary technology-push policies. The continuation of this research may contribute to offer insights on fine-tuning of these policies.

As to future research, we intend to analyze the role of MNEs in the diffusion of renewable energy technologies across Member States and thus in the integration of EU technological space in this area. Such study will require classifying data by country of assignee (instead of inventor) and by type of ownership. Although a large theoretical and empirical literature on the role of FDIs as a key knowledge diffusion mechanism has developed, these studies are not specifically concerned with renewable energies, a sector which is instead becoming increasingly critical for EU energy policy.

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