Knowledge flows and technologies in renewable energies at the regional level in Europe

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Keywords: Innovation, Renewable Energies, Knowledge bases, Patents, Citations.

JEL classifications: O3, Q4.

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Abstract

This study gives new insight into the impact of knowledge flows for renewable energy (RE) technologies. With patent data for the European regions in the 2000–2010 period, we observe that RE technologies have more analytical knowledge content than the rest of technologies. They also seem to benefit highly from scientific knowledge flows and from technological knowledge flows coming from distant places. This pattern is peculiar to the RE field and different from other cutting-edge technologies and even different from those technologies related to energy generation coming from traditional energy sectors.

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1. Introduction

This study explores the importance of knowledge flows for the generation of innovation[1] in the field of renewable energies (RE) and identifies which sources of knowledge flows may be more important for innovation in this specific field. To this end, first we analyze the importance of knowledge flows coming from sources characterized by its high content of scientific knowledge. Second, we study the role of physical distance under the assumption that proximity would not be as important in the case of RE innovation given its high content in analytical knowledge, being easier to codify it, and allowing benefitting from knowledge sources located in distant places.

The motivation behind this study is twofold. On the one hand, the current Climate Change scenario shows the energy sector as the principal source of greenhouse gas emissions (IEA 2018), calling for the awareness that RE technologies are of great importance for future sustainable growth and development. Some studies have shown that innovation in green technologies can exert a positive effect on the productivity levels of firms (Marin 2014; Colombelli et al. 2019) and regions (Aldieri et al. forthcoming), which could shift its relation with other regions or countries (Arundel and Kemp 2009). If we fail to enter a sustainable growth path we could be putting at risk future growth and development (Hayter 2008; OECD 2011).

On the other hand, in this scenario, it is important to understand how regions diversify into RE. Green technologies (and RE in particular) challenge the existing energy system, providing new economic and technological opportunities with new ideas (Rennings 2000; Barbieri et al. 2018), and tend to be at an early stage of their life-cycle (Consoli et al. 2016). Even more, RE innovation provides new means to satisfy a new

[1] In this study, we use the term innovation to refer to technological innovation, although we acknowledge that the term innovation is broader.

need[2], which according to Arthur (2007), is the main characteristic of a radical innovation: to satisfy a need with new means because existing methods are not satisfactory. Literature about the production or emergence of green innovation and the sources that enhance it, is still scarce and has not considered the specific sources on which new knowledge and new solutions are based on.

Most studies at the firm level have looked at the innovation strategies to acquire the necessary knowledge for firms to produce green innovation (De Marchi 2012; De Marchi and Grandinetti 2013; Horbach et al. 2013; Cainelli et al. 2015; Ghiseti et al. 2015; Marzucchi and Montresor 2017). Other research has focused on the regional level, stressing the importance of regional knowledge and technological capabilities (Tanner 2014; Colombelli and Quatraro 2017; Quatraro and Scandura 2019), while less research has considered the national level, focusing on the relevance of national regulation (Garrone et al. 2014; Fabrizi et al. 2018). These studies provide valuable insight about the knowledge sources that are used to eco-innovate. In this paper, we build on them and claim that these sources respond to the nature of eco innovation itself.

We try to contribute to the previous literature by bringing in the Knowledge-base theory of Asheim et al. (2011) and argue that the knowledge base of RE technology shapes the effect of its main knowledge sources. With this framework, we can explain that RE innovation need new ideas to cover new needs, and part of these new ideas may come from sources with a higher content of scientific knowledge. At the same time, we explore the significance of proximity, as both spatial and cognitive proximity are crucial

[2] The need for sustainable energy only emerged when the sustainable development concept came to the world´s political agenda (Du Pisani 2006; Grober 2007).

for the emergence of new technologies in regions (Neffke et al. 2011), and we plan to explore whether this is also the case for RE technologies.

We claim that RE innovation is an analytical knowledge-base type of innovation, which is characterised by its high content of scientific knowledge. Consequently, we hypothesise that it would benefit intensively from knowledge flows coming from more scientific sources. Also, the importance of proximity would be different to common findings. Given that RE presents a high analytical content, which in turn is easier to codify, less localised knowledge flows would be relevant, allowing benefitting from knowledge produced in distant places. To our knowledge, this is the first time the knowledge-base approach has been applied to a specific technological field to study the knowledge flow patterns using patent data.

Indeed, a distinctive feature of green innovation concerns the nature of knowledge spillovers as it requires more heterogeneous sources of knowledge (Dechezleprêtre et al. 2011; Horbach et al. 2013; Ghisetti et al. 2015). Dechezleprêtre et al. (2017) showed that green technologies are characterised by substantially larger knowledge spillovers in contrast to other comparable knowledge-intensive domains. In a similar vein, studying the creation of green start-ups, Colombelli and Quatraro (2017) provided evidence about the positive relationship between related technological variety and the creation of green new firms. Building on the above, we propose to focus on the forms of knowledge flows that enable innovation to deal with environmental sustainability. We expect that the specificities of this empirical domain of innovation will bring to the fore more interesting peculiarities of the general processes at hand. We do this by extending the traditional Knowledge Production Function—KPF—with some specificities of knowledge flows, and estimate it for the case of RE technologies across 254 European (NUTS2) regions in the period 2000–2010.

The rest of the paper is organised as follows. In Section 2, we present the literature review and our theoretical framework and state the main hypotheses. Section 3 offers the formal model guiding our empirical approach and the data, and provides relevant issues about our main variables and their construction. Section 4 shows some stylised facts related to our hypotheses as well as our main econometric results, while Section 5 concludes.

2. Knowledge spillovers and innovation in renewable energies

Knowledge production is a recombinatory process, in which pre-existing knowledge is used as input for the production of new knowledge (Weitzman 1998). It has been shown that knowledge flows are spatially bounded (Jaffe et al. 1993 and Murata et al. 2013), meaning that distance (or proximity) matters for the acquisition of knowledge. The capacity to absorb knowledge from other places becomes relevant along with the pool of available ideas in a location. This means that not only spatial distance matters, but also cognitive, organisational, institutional and social proximities are also relevant (Boschma 2005). Nevertheless, this way to understand proximity reflects the lack of a fundamental aspect: It treats knowledge as a homogenous concept, when actually it should be regarded as a heterogeneous entity (Mattes 2012).

To help fill in this gap, Moodysson et al. (2008) and Asheim et al. (2011) argued that to understand the regional process of learning and knowledge creation and its relationship with the concept of distance, it is necessary to comprehend the particularities of the knowledge nature. Economic activities can have three distinct knowledge natures or bases. The first one is the analytical knowledge-base type, which encompasses the activities where knowledge is based on scientific laws and models, has high abstract content and is highly subject to codification. It is constructed on research and, consequently, is mostly developed in universities and research institutes. The second type are the synthetic knowledge-base activities, where knowledge is created by the application or new combination of existing knowledge; it is based on learning by doing and is shaped by the relation between customers and suppliers. Finally, the symbolic knowledge-base entails those activities where innovation consists of the creation of meaning, images and symbols with aesthetic and cultural attributes. The concept of distance goes along with the knowledge base, making some knowledges more place dependent than others.

We argue that eco-innovation, and RE in particular, are by nature an analytical knowledge-base technology. As signalled by Marzucchi and Montresor (2017), ‘Eco-innovators mainly rely on knowledge sourced by interacting with epistemic communities of actors (e.g., scholars and inventors) and/or institutions (e.g., universities and labs), organised around specific disciplines. This is mainly, though not exclusively, an analytical kind of knowledge’ (p. 209). Indeed, the development of new solutions based on reliable low-carbon energy implies a new paradigm competing against an established system which nurtures from analytical knowledge sourced from the ‘world of science’ and can be decisive in providing agents with an understanding of the complexity of their prospected innovations while at the same time contributing to create radical ideas (Trajtenberg et al. 1997; Verhoeven et al. 2016).

Previous studies have pointed out the importance of scientific sources of knowledge for RE innovation. For example, Quatraro and Scandura (2019) found that the involvement of academic inventors fosters innovation in green technologies. De Marchi (2012) and De Marchi and Grandinetti (2013) showed that firms engaged in environmental innovation relied more on external knowledge by externalising research and development (R&D) and engaging in cooperation with universities, research centres, knowledge-intensive business services (KIBS) and other firms[3]. Tanner (2014) found support for the importance of actors, such as universities and research institutes, for this kind of innovation. Fabrizi et al. (2018) pointed to the fact that networks play a more key role for environmental innovations than for standard innovations, with environmental networks being more qualified, with a larger presence of members outside the business world, such as universities and research centres. These actors can reinforce firms in innovating in environmental fields by transferring complex knowledge, as is needed in the case of eco-innovations. With this in mind, we state the first hypothesis:

H1: *Knowledge coming from science might have a positive and relatively more important role for innovation in RE than it does for other technologies, or innovation in general, as this would be a reflex of it belonging to the analytical knowledge-base type of activities*.

We now put to the forefront the widely accepted assumption from the years in the geography of innovation literature that agents usually source their innovations from their immediate vicinity. Recent empirical works have extensively documented the influence of extra-local knowledge sources on firms' innovative performance and knowledge acquisition (Rosenkopf and Almedia 2003;Gertler and Levitte 2005). In addition, Boschma (2005) highlighted the increasing importance of agents' needs to access extra-local knowledge pools to overcome potential situations of regional 'lock-in'. In the same line, 'distant contexts can be a source of novel ideas and expert insights useful for innovation processes…' (Maskell et al. 2006, p. 998).

[3] We acknowledge that the literature used as background looks mostly at the firm level and refers to the firms' innovation strategies, which entail aspects like adoption, adaptation, commercialization, etc., and not just the knowledge development stage of innovation used in this paper. We thank a referee for highlighting this point.

We argue that, depending on the knowledge base, spatial diffusion patterns of knowledge flows can be different. If RE innovation tends to have stronger foundations on analytical knowledge, then the ideas needed for its development are more codifiable and easier to travel across space. Geographical proximity would be less important for the diffusion of relevant knowledge for RE. What matters more would be technological and cognitive proximity, in part enabled by the higher degree of codification and abstract content of relevant knowledge. Consequently, innovation could benefit from geographically distant knowledge. For example, it could be the case that the specific pieces of necessary knowledge for a technology are not available in the vicinity (Asheim and Isaksen 1997); hence, it would be necessary to look for them further away.

According to previous literature, environmental innovation benefits more from heterogenous knowledge sources than other technologies (Dechezleprêtre et al. 2011; Horbach et al. 2013; Ghisetti et al. 2015), needs a broader variety of knowledge (Barbieri et al. 2018; Fabrizi et al. 2018) and, even more, RE innovations spill over more than other technologies, reaching more technology fields and further distances (Dechezleprêtre et al. 2011). It could be the case that if the necessary knowledge from which RE feeds is not available in the region, then RE innovation would feed from further places. For example, Garrone et al. (2014) found positive international R&D externalities at the national level for RE innovation, whereas Tanner (2014) found that fuel cell technology emerged where there were not related technologies and extra-regional sources.

Nevertheless, there is also evidence that states the opposite. Keller and Yeaple (2013) stated that the more knowledge intensive a process, the less likely its knowledge will diffuse in space. Braun et al. (2010) maintained that knowledge spillovers for RE technologies are important at the country level but not between countries because the domestic pool of knowledge is still large enough, and acquiring knowledge from abroad is more costly. Bjørner and Mackenhauer (2013) found evidence that research in energy spills over less than other kinds of research, so that spillovers in energy are strongly geographically bounded.

The question continuing from the two contradictory arguments in the previous paragraphs is whether the knowledge flows from the technical sector have the same spatial diffusion pattern for RE than for the rest of technological innovation in general, which tends to come from short distances. In this sense, we state our second competing hypotheses:

H2A: *Less localised knowledge flows would be relevant for RE innovation because its high content in analytical knowledge would allow benefitting from knowledge produced and codified in places that are distant*.

H2B: *Localised knowledge flows would be important for RE innovation because the more knowledge intensive a process is, the less likely its knowledge will diffuse in space*.

3. Empirical framework

3.1 The Knowledge Production Function augmented with knowledge flows

To test our hypotheses, we specified a Knowledge Production Function (KPF) to evaluate the relevance of knowledge flows from scientific sources and their geographical range contributing to innovate in RE. In the KPF, we considered that new ideas (Y_{it} as the innovative output of region i in time period t) are generated using two main inputs: *R&D* investments ($R\&D_{it}$) and existing ideas (A_{it}). Also, human capital

(HK_{it}) is a driver of innovation, and to capture the local characteristics that would influence innovation, a variety of local variables were included in vector Z_{it}.

$$Y_{it} = f(R\&D_{it}, HK_{it}, Z_{it}, A_{it}) \tag{1}$$

Assuming *f(.)* takes the form of a Cobb-Douglass function, we get the following multiplicative functional form:

$$Y_{it} = e^{\alpha}. R\&D_{it}^{\beta}. HK_{it}^{\rho}. Z_{it}^{\theta}. A_{it}. e^{\mu_i} \tag{2}$$

where e^{α} is a constant term capturing the impact of all common factors affecting innovation and $e^{\mu i}$ is a region-specific term that captures time invariant unobservable regional characteristics that affect innovation (regional time-invariant fixed-effects). *R&D* resources are particular for each region, while ideas can spill over the borders of the regions. To account for this, the term A_{it}, the ideas available in region i in time period t, were formalised as a function of knowledge flows. We assumed that knowledge flows based on scientific knowledge (S_{it}) are a driver of innovation and can be distinguished from those from technical sources, irrespective of their geographical distance. Additionally, to provide evidence on our second hypothesis, we introduced both local and extra-local technological knowledge flows, according to the distance between the region receiving the flow (i) and the region from which the flow departs (j):

$$A_{it} = S_{it}^{\gamma_0} \prod_j KF_{jt}^{g(dist_{ij})} \tag{3}$$

g(.) is a step function taking the value of ϕ_k, which will measure the elasticity of A_{it} to knowledge flows, if the distance between regions i and j, $dist_{ij}$, belongs to one of the distance intervals k = {[dist$_0$, dist$_1$), [dist$_1$, dist$_2$), … [K, ∞) } and zero otherwise:

$$g(dist_{ij}) = \begin{cases} 0, & if\ dist_{ij} \notin k \\ \phi_k, & if\ dist_{ij} \in k \end{cases} \tag{4}$$

The index k captures a sequence of distance intervals within which the step function is constant. Replacing equation (3) in (2) yields the following expression:

$$Y_{it} = e^{\alpha}.R\&D_{it}^{\beta}.HK_{it}^{\rho}.Z_{it}^{\theta}.S_{it}^{\gamma_0}.\prod_j KF_{jt}^{g(dist_{ij})}.e^{\mu_i} \tag{5}$$

Taking natural logarithms and adding an error term, ε_{it}, we obtain:

$$ln(Y_{it}) = \alpha + \beta ln(R\&D_{it}) + \rho HK_{it} + \theta ln(Z_{it}) + \gamma_0 \ln(S_{it}) \tag{6}$$

$$+ \sum_j \phi_k ln(KF_{jt}) + \mu_i + \varepsilon_{it}$$

when $dist_{ij} \epsilon k$. With the estimation of this equation, the parameter γ_0 will show the value of the elasticity of the innovative output to scientific knowledge so as to be able to test our second hypothesis. Additionally, the value of the elasticities of technological knowledge flows coming from different distances, ϕ_k, will provide evidence in relation to our third hypothesis.

3.2 Data and variables

Our dependent variable (Y_{it}) was proxied with the number of patents per 100,000 inhabitants in a region (identified by the inventor's region[4]) in renewable energy technologies in generation, transmission or distribution (*RE*) as identified by the Haščič

[4] As we are using patents as ideas or pieces of knowledge and not for aggregation purposes to count and compare among regions, we used full counting of patents to assign them to regions instead of the fractional counting. The use of fractional count raises the issue of the extent to which a fraction of a patent with multiple inventors might be less valuable for a given unit of analysis (country, region, etc.) than a patent with a single inventor. When a patent is assigned to more than one region, the knowledge is shared during the production process as well as the final outcome among all the participants. In this sense, the knowledge belongs to the all regions involved in creation of a new patent and it would be difficult to attribute how much of that new idea is embraced by each region. As single ideas, a new patent cannot be attributed by shares. Nevertheless, this does not mean that one region, when engaged in the production of a patent, does not develop new knowledge of its own or apply the specialized knowledge it possess. See section 4.3, page 64, and the corresponding footnote number 4 of the OECD Patent Statistic Manual (OECD 2009).

and Migotto (2015)[5]. Using patent data has some caveats. For example, not all inventions are patented, nor do they all have the same economic impact (Griliches 1990). Moreover, patented inventions inherently differ in their market value (Giuri et al. 2007); firms patent to a large extent for strategic motives, such as building up a patent portfolio in order to improve their position in negotiations or their technological reputation (Verspagen and Schoenmakers 2004). Despite these arguments, the related literature widely uses this variable to proxy innovation outcomes. Indeed, patent data have proved useful for proxying inventiveness as they present minimal standards of novelty, originality and potential profits—and they constitute good proxies for economically profitable ideas (Bottazzi and Peri 2003). One of the advantages is that patents contain the references to prior knowledge as citations, indicating the knowledge they were built upon (Collins and Wyatt 1988). We took advantage of this property of patent information and used citations to test our hypotheses. From our data, the regions that innovated more in RE were mostly located in Germany and northern Europe, while the regions that innovated less were mostly located towards the East (Figures A1 and A2 of the appendix online). The importance of analytical knowledge for RE was captured through the effect that scientific knowledge might have on it. If it is the case that RE has higher analytical content, then it should be more susceptible to scientific knowledge. To proxy for scientific knowledge (S), used non-patent literature (*NPL*) citations, which are the citations made to scientific documents. These citations refer to peer-reviewed scientific papers, databases, conference proceedings and other relevant literature and not to other patent documents. NPL citations can be used to measure the contribution of scientific knowledge to industrial technologies (Narin et al. 1997; Meyer

[5] See Table A1 for the whole list of technology codes identified as renewable energies

2000; Tijssen 2001; Verbeek et al. 2003) and help to depict the proximity of technological and scientific developments (Callaert et al. 2006).

It is important to say that when using NPL citations to capture knowledge flows from science, we did not intend to depict a network structure or imply specific localisation effects. We employed NPL citations to point to a body of knowledge that the inventors (or the examiner) considered relevant for the invention (Brusoni et al. 2005) because they tended to refer to the scientific general background rather than a specific contribution (Meyer 2000). It should also be noted that, while patent citations refer to prior art, they do so also to show the novelty of the invention and its scope for protection, not necessarily because the knowledge embedded in such citations was relevant for the invention itself. On the contrary, NPL citations are more likely to refer to more relevant knowledge for the invention (Collins and Wyatt 1988).

To test the second hypothesis, the focus was on knowledge flows measured by the backward citations in all fields in patent applications. Even though the use of patent citations does not come without limitations (Alcácer and Gittelman 2006)[6], they have been widely used in innovation economics as a proxy for knowledge flows. Patent citations were distinguished in three distance categories (in kilometers): first, citations coming from a range between 0 and 300 km (*300Km*); second, citations from the range 300 to 1200 (*1200Km*); and third, citations from a distance bigger than 1200 km (*over1200Km*)[7]. The number of patent citations between each pair of regions, say region's *i* citations of region's *j* patents, were normalised by the total number of patents

[6] An important issue regarding the use of citations to proxy for knowledge flows is the difference between the citations introduced by the applicant and those by the examiner. It has been suggested that EPO applicants have the incentive to cite the entire prior art to avoid future patent opposition (Akers 2000).

[7] The distance ranges were constructed taking the average distance in kilometers from the centroid of any NUTS2 region to all the other regions from which the citations come. These distances were classified in three categories: Same country, Within Europe and Outside Europe. The average of all the distances in the category *Same country* was 300 kilometers; for the Within Europe category it was 1200 kilometers, and more than 1200 kilometers for the Outside Europe category.

produced in region *j*. This approach is similar to the one used by Bottazzi and Peri (2003) and Moreno et al. (2005) to measure the reach of knowledge spillovers. In our case, distinguishing the source of the cited patent allowed us to observe how far the knowledge externalities can reach. Previous literature has found strong evidence supporting the hypothesis that knowledge spillovers are localised; but taking into account that innovation in RE is more based on analytical knowledge, it could be the case that flows coming from extra-regional sources can be more relevant than in the case of other technologies.[8]

As controls, the R&D investment of each region was considered (per 100,000 inhabitants). As a proxy of human capital (*HK*), we used the proportion of population with tertiary education. To control for the effect of the technological composition of the region, we used a specialisation index (*SPI*), which was built using the IPC technological classification of patents grouped in 30 broad technological sectors contained in the patent applications, with the following formula:

$$SPI_{it} = \frac{1}{2}\sum\nolimits_{j}\left|\frac{P_{ijt}}{P_{it}} - \frac{P_{Cjt}}{P_{Ct}}\right| \tag{7}$$

where P is the number of patents in region i for sector j, and C represents the whole sample of regions.

To account for the fact that the industrial composition of the regional economies could affect the innovation production, the share of the employment in the industrial sector (*Ind_Share*) was also included in the model. Finally, population density and its squared

[8] This approximation does not go into more detail of the reasons why RE innovation might look further for knowledge, either because the specialisation within the region does not incentivise RE technologies or because it needs from a combination of diverse technologies which are not present in the region. This would imply a deeper analysis on the impact of relatedness for the generation of RE patents that goes beyond the scope of this paper.

term (*Density* and *Density^2*) were considered to account for the urbanisation and agglomeration economies as in Gossling and Rutten (2007) and Miguélez and Moreno (2013) (see Table A2 in Appendix online for a detailed definition of the variables).

For the construction of the variables based on patents, we used the OECD REGPAT September 2015 Database, while for the citation variables, we employed the OECD Citation Database September 2015 edition. Only the patents in the European Patent Office, EPO, from a European country were considered. To construct the explanatory variables, we used data from the Eurostat Office available on its website. Particularly, the data for R&D investment came from the CRENOS institute. Our data covered the period 2000–2010 for 254 NUTS2 regions in Europe[9].

To avoid lumpiness along years in the case of the endogenous variable, a three-year moving average was used (using the values of t, t+1 and t+2). Because the citation (to patents and non-patent literature) variables might show the same lumpiness, we also took a three-year moving average, but from the three previous years (the values in t-1, t-2 and t-3). The use of lagged explanatory variables contributes to dealing with a possible endogeneity problem and the possible fact that when new knowledge comes into a region, it takes some time to be assimilated. Both the endogenous variable and the citation variables were introduced in the estimation in logarithms. The rest of the control variables were introduced in t-1 and, in the case of the R&D investment and population density, they are also in logarithms. Table 1 offers a descriptive analysis of the variables in the models.

[TABLE 1 AROUND HERE]

[9] The countries covered are Austria, Belgium, Bulgaria, Switzerland, Cyprus, Czech Republic, Germany, Estonia, Greece, Spain, Finland, France, Hungary, Ireland, Italy, Luxemburg, Latvia, Malta, The Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovakia and the United Kingdom.

4. Results

This section is divided in into two parts. First, we present some stylized facts about the pattern shown by patents and citations looking for evidence in relation to our hypotheses. Second, we show a regression analysis with the econometric estimation of our KPF model.

4.1 Stylized facts

If patents in RE belong to the analytical knowledge base, as argued in section 2, they should comply with some of the characteristics signalled by Asheim et al. (2011); that is, the use of more basic knowledge and the use of knowledge coming from further locations than the rest of technological fields. With these figures we do not intent to make an in-depth comparison of RE innovation and Non-RE innovation as it is done in Barbieri et al (2018). We just try to point out some characteristics of RE patents which we argue tend to be related with an analytical knowledge base technology.

These two characteristics can be analysed with the information contained in patent documents. Identifying patent applications that cite non-patent literature, we can have an idea of how important scientific references are for patents in RE and for the rest of technological fields (we refer to the latter as 'rest of patents'). As shown in Table 2, in our sample, 31.1% of RE patents cited at least one scientific reference, while in the case of the rest of patents this figure is 26.2%. This implies that innovation in RE is more prone to cite scientific literature than innovation in the rest of technological fields. Also, we would expect that NPL citations represent a higher share of the total number of citations in the case of RE patents. Indeed, an average of 18.2% of the total number of citations in RE patents are to NPL, while for applications in the rest of technologies, the average is 15.3%.

We also claim that the cooperation for the development of eco-innovation, in general, and in RE, in particular, can come from longer distances. Taking as a simple proxy of this fact the percentage of patents assigned to at least two different regions (NUTS3), 43.6% of RE patents were assigned to more than one region, while the share decreased to 39.1% for the rest of patents. Even more, the average distance between the inventors that collaborate in generating a new idea in RE—co-patenting—is 127 kilometers whereas in the rest of fields it is of 113 kilometers.

Finally, as argued in section 2, RE innovation relates to technologies that are at an early stage of their life-cycle (Consoli et al., 2016), trying to provide new ideas to cover new needs, which may imply that its knowledge base is thus quite complex. Using the methodology of Squicciarini et al. (2013) we construct a radicalness index whose underlying idea is to count for the number of technological classes (IPC) the cited patents belongs to, that are different from the classes in which the citing patent has been classified. RE patents score on average 0.36 and patents in the rest of technologies score 0.34, providing evidence that would support that the degree of radicalness of RE innovation is higher than for the rest of innovation.

[TABLE 2 AROUND HERE]

As stated in the second section, as a consequence of RE innovation being more based on analytical knowledge than other kinds of innovation, we expect that knowledge flows that feed innovation in this field come from more distant places than the ones rest of technological fields. However, it could also be the case that localised knowledge flows are more important for RE innovation because the more knowledge intensive a process is (as in the case of RE), the less likely its knowledge will diffuse in space. In order to give some descriptive in favour of one argument or the other, we proxy knowledge flows with the (backward) citations patents they have and consider the distance between each pair of citing and cited patents. The distance is taken in kilometers from the home region of a patent and the region to which the cited patent belongs to (taking into consideration their centroids). Table 3 shows that, on average, the citations made by RE patents come from 10 kilometers farther away than the citations made by the rest of technological fields. Although this difference is small, it is statistically significant.

When inspecting the distribution of citations in the different ranges of distances from where they came, we first observe that RE has 2.2% more citations made to patents in regions more than 1200 km away (the biggest difference). Second, the share of citations made to patents from regions within the closest range is 1.6% lower for patents in RE. In both cases, the differences are small but statistically significant. All in all, these figures show a behaviour that seems to indicate that for RE, probably due to its higher content in analytical knowledge, the ideas coming from longer distances are more important than local ones.

[TABLE 3 AROUND HERE]

4.2. Econometric estimation

The previous statistics provide evidence that point in the same direction as that of H1 and H2A. To more exhaustively test both, we estimate equation (6) through a fixed effects (FE) unbalanced panel model for the KPF with data for 254 NUTS2 regions in Europe along 11 time periods (2000–2010). Using longitudinal data, controlling for FE allows us to account for a number of time-invariant unobservable characteristics of the regions that might bias the results if not included (if it is the case that these are correlated with regressors). The panel structure lets us control for these unobserved effects while some degree of correlation between the exogenous regressors and the unobserved effects could exist. Nevertheless, we assume strict exogeneity of the explanatory variables conditional on the unobserved effects; that is, the explanatory variables in each time period are not correlated with the idiosyncratic error in each time period. Particularly, we pursue to ensure this assumption by using the lag values of our explanatory variables. In all the models, fixed effects are preferred over the random effects estimation procedure according to the Hansen's J statistic, which is equivalent to the traditional Hausman fixed-vs-random effects test when using robust to heteroskedastic errors, as in our case. The results of the estimations are presented in Table 4, having as the endogenous variable the natural logarithm of the number of patents in RE per 100,000 inhabitants. We start with a basic KPF and then add the scientific knowledge variable, S, and the knowledge flows variables (columns 1 to 4).

Regarding the control variables, in all the columns of Table 4, the elasticity of patents with respect to R&D expenditures presents significant and positive values. The elasticity of patents in RE with respect to R&D investment ranges from 32% to 39%. The role of human capital (*HK*) is consistently positive and significant in all specifications as expected. The share of industrial employment (*Ind_Share*), meant to capture the economic structure of European regions, has a negative and significant impact on the innovation in RE[10]. The reason behind this coefficient may be the fact that the manufacturing sector still relies heavily on traditional sources of energy. De Marchi

[10] We also included the share of the service sector instead and in combination of the share of industrial employment and, as expected, it has a positive and significant coefficient. The rest of the results remain in line with the ones presented here. See Table A3 in the Appendix online for the regression results.

(2012) argued that the development of new and green products calls for competences that are far from the traditional industrial knowledge base. According to the International Energy agency, 73% of the energy used in the industrial sector of the world in 2010 still came from fossil fuels, and this declined to 70% in 2017. In fact, RE are not capable to produce intense heat efficiently while fossil fuels are a better option for this purpose (IRENA, 2015)[11]. The coefficient of the technological specialisation index (*SPI*) is negative and statistically significant for RE innovation. This can be interpreted under the Jacobs theory, in which diversity rather than specialisation would boost innovation and productivity growth to the expense of specialisation economies—MAR externalities. Finally, the evidence suggests that RE innovation is influenced by agglomeration externalities as pointed out by the positive coefficient for the density of population.

In order to test our first hypothesis, we introduce the scientific knowledge variable (*S*), proxied by the number of non-patent literature citations. This variable has a positive and significant coefficient, confirming that scientific knowledge influences RE innovation. An increase of 10% in *S* implies an increase of innovation in RE of around 1.2%. Next, in column 3 we introduced in the basic KPF model, the technical knowledge citation variables. We observe that for RE technologies, distant knowledge is more relevant than knowledge coming from the closest distance ring. In fact, the elasticity of RE patents to a 10% change in the knowledge flows coming from the middle-distance ring is about 0.8% and the elasticity to knowledge coming from the furthest distance band is about 0.53%, the latter being highly significant. Finally, when S is also included, its

[11] Industries like iron and steel, chemicals and textile require high temperatures that cannot be reached with RE technologies (IRENA, 2015). Even more, there are programs which intend to expand the RE technology into the service sector. The Energy Performance Contracts, EPCs, are a mechanism to finance the improvement of energy efficiency and savings in energy in the tertiary sector (health, accommodation, tourism, services, etc.). For example, in the case of energy savings in buildings, countries like Germany, Austria or Sweden have mature markets to externalize to an Energy Service Company—ESCO, projects to manage and save energy to comply with the regulations (Frangou et al. 2018).

coefficient is significant, and the knowledge flows coming from the furthest distance remain with a significant coefficient[12]. This last finding would support hypothesis 2A, under which RE innovation would benefit from less localised knowledge flows.[13,14]

[TABLE 4 AROUND HERE]

4.3. Robustness analysis

We check whether the knowledge flows coming from the scientific domain as well as the technological knowledge flows coming from very distant places are only or mainly relevant in the case of the RE field if compared to their relevance in other technological areas. Initially, we check whether the generation of innovation in the rest of technologies which are not within the RE field (rest of patents, P) follows a similar recipe to that of RE. Table 5 shows that the elasticity of patents to non-patent literature is around 5% and significant, lower than it was for RE (around 12%). In addition, we observe that the only significant technological knowledge flows are the ones that come from the middle-distance range (300-1200Km), whereas the elasticity that was significant in the case of RE is the one referred to knowledge flows from more than 1200Km. Another difference lies in the lower elasticities found for R&D expenditures

[12] As a robustness check, we re-ran the regressions with 100 km rings and we also tried removing the largest countries (France, Spain and Sweden). In both cases, the results were in the same line as the ones presented here. We thank one referee for suggesting such robustness exercises. See Table A4 in Appendix online.

[13] As a robustness check of our main results, instead of using three-year moving averages for the main variables computed with patent data, we re-ran our main regressions considering one-year lagged regressors. Our main conclusions were maintained. Results are available upon request.

[14] We are aware of the fact that regulation plays an important role for RE innovation. In Table A5 in the Appendix online, we provide the estimation of equation 6 adding a variable meant to capture the regional political attitude towards environmental issues, approaching the willingness to regulate in this area. The key results of the paper are maintained. We do not include this variable in the base estimation of the present paper due to the lack of reliability of the data used to construct it.

and human capital. This suggests that the technologies in the RE domain might have some characteristics that distinguish them as a technological field on their own[15].

[TABLE 5 AROUND HERE]

It could be the case that the specific pattern observed for RE compared to the rest of patents is common to other cutting-edge technologies that are novel, as in the case of RE. In Table 5 (columns 2 to 4), we re-estimate the KPF specification in the case of three new technologies: Information Technology (IT), Biotechnology (BIO) and Nanotechnology (NANO), identified following the IPC code identification as in Dechezlepretre et al. (2017). We observe that the elasticities of patenting activity to scientific knowledge flows in the IT and NANO sectors are much lower than in the case of RE, and more similar to the ones obtained for the rest of patents, whereas in the case of the BIO technology, it does not turn out to be significant. On the other hand, for these technologies, the role of knowledge flows coming from other patents (the technical sector) is not significant, irrespective of the distance range considered. Consequently, the pattern observed for the influence of knowledge flows in the patenting activity in these cutting-edge technologies diverges from the one found for RE technologies.

In addition, we wanted to check whether the pattern of the influence of knowledge flows on the patenting activity in the RE field is not due to specificities of the energy generation sector to which it also belongs. With this idea in mind, column 5 in Table 5 offers the estimation of the KPF in the dirty energy generation technologies, which we have identified by again following the IPC code identification proposed by

[15] As the main goal of the paper is showing the analytical nature of RE innovation, its comparison with other technologies or with innovation in general is not the main point of the paper, although we use such comparison to strengthen our point. We just intend to make a claim about the relative importance of each explanatory variable (especially knowledge flows) for the respective knowledge production. As we state in the text, this is just a comparison of different weights each input has in the 'recipe' for producing RE innovation or other technologies. As the coefficients represent the elasticities of the outcome variable, and given that the variables are expressed in the same units, the comparison would still be feasible just for argumentative purposes. We thank the referee for pointing out this issue.

Dechezleprêtre et al. (2017). We observe that the elasticity of patenting activity in the dirty energy technologies with respect to non-patent literature is about the same size as the one obtained for the rest of patents (provided in Table 5) and is lower than for RE technologies. The same happens when distinguishing among the different distance ranges from which patent citations come, since the results for the dirty energy sector have a very similar pattern to the ones obtained for the rest of technologies: Patent citations coming from the middle band are the relevant ones and not the ones from the longest distance, as it was for RE innovation.

All in all, our results suggest that when analysing the influence of scientific knowledge flows as well as technological knowledge flows in the case of the RE technologies, we observe a pattern which is peculiar to this technological field and different from the rest of technologies, different from other cutting edge technologies and even different from those related to energy generation coming from traditional energy sectors.

Finally, we analyse if the results hold when only patents that present high quality are considered. Following Barbieri et al (2020), we focus on triadic patent families, which are those patents filed at the three most important patent offices for the same invention, by the same applicant or inventor: the EPO, the USPTO and the Japan Patent Office. Triadic patents represent higher value inventions as the patentees are willing to pay the cost to protect it in different areas, that is, family size is considered a good proxy for high value inventions (OECD 2009). We use as dependent variable the count of triadic patent families of RE innovation generated in a region. As there are few triadic patents in RE per region, we use a Poisson fixed effect estimation method to deal with this count variable. The results (presented in Table A6 of the online Appendix) show that scientific knowledge is an important driver of the production of high value RE innovation, as the coefficient of S is positive and significant, very much in line with the previous results. Then, and in contrast to our previous findings, the knowledge flows coming from close distance are the only ones that seem to matter for this kind of. Although this last result is different from the results provided before, we have to keep in mind that there are reasons and previous evidence stating that localised knowledge flows would be important for RE innovation because the more knowledge intensive a process is, the less likely its knowledge will diffuse in space (as stated in our hypothesis H2B).

5. Conclusions

The research conducted in this paper tried to contribute to the knowledge flows literature by introducing the knowledge-base theory to explain the role of knowledge flows in the generation of innovation in renewable energies. First, we argued that renewable energy technologies belong to the analytical knowledge base and, therefore, knowledge flows coming from science would be of high relevance. Second, we posited that the spatial behaviour of technological knowledge flows would not be so localised for renewable energy innovation, but that it could feed from knowledge produced far away. Indeed, the evidence for European regions in the period 2000–2010 showed that innovation in renewables have these two characteristics. In addition, this behaviour does not seem to be due either to the fact that RE technologies belong to the group of 'new technologies' or to the fact they belong to the energy generation sector.

Eco-innovation, in general, and RE, in particular, suffer from the double externality problem, meaning that from on the one hand, they suffer from the negative externality of technological innovation, and on the other, from the externalities of eco-innovation. For both reasons, agents could be reluctant to engage in this field of innovation. There is also the fact that RE is a novel field, making it more subject to uncertainty. As a consequence, there is a place for policy intervention to accomplish the climate goals. The nature of RE innovation is more of the analytical knowledge type, meaning that it would benefit more from the synergies between universities and research institutions, benefiting both sides as uncertainty would be shared (Gander 2017). Already Carraro and Siniscalco (1994) and Popp et al. (2009) stated the need for addressing climate change through both emission taxes and R&D subsidies: taxing the polluters to fund the innovation. In this sense, any policy would have to seek to encourage and strengthen the collaboration of research institutions and universities with companies in the RE field, prioritising the development of new RE technologies.

Nevertheless, our results should not be interpreted as a recipe to foster RE innovation at the regional level in the 'picking the winner' fashion. Asheim et al. (2011) already warned about the issues of such a policy and recommended an approach where the regional advantages and characteristics have to be considered when designing any policy. This means that not all regions may have the appropriate conditions to develop RE technologies. Simply by targeting more R&D resources to basic research or towards the RE industry would not necessarily trigger the necessary synergies to innovate in this field. For example, literature has found evidence on the importance of the local characteristics, such as business environment, policies and even the existence of related industries for the success of university spin-offs. In this sense, it is crucial to design policies that allow the close interaction of RE innovators with the academic sector and with the business sector (Marzucchi and Montresor 2017).

Some issues remain in the research agenda. First, it would be interesting to study the nature of the knowledge in the renewable energy technology from the perspective of the complexity it embeds. This would allow giving a step forward in understanding how innovation in renewable energy takes place from a theoretical point of view. Second, in this study, we did not have more detailed information on the source of the non-patent literature citations. The availability of information about the location and institutional nature of the source of these citations would provide us with a deeper understanding about the relation between this type of knowledge flows and innovation in renewable energies.

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TABLES

Table 1. Variable summary statistics

Variable	Obs.	Mean	Std.	Min.	Max.
RE	3037	0.7	1.3	0.0	18.7
R&D	2739	40.0	46.5	0.0	358.4
HK	2934	22.4	8.6	3.7	54.5
Ind_Share	2876	0.2	0.1	0.0	0.4
SPI	3102	0.5	0.2	0.0	1.0
Density	2926	305.9	620.2	3.3	6902.0
S	3037	29.3	59.4	0.0	1113.0
KF[0-300)	2893	0.3	0.4	0.0	4.4
KF[300-1200)	2959	0.4	0.7	0.0	8.2
KF[1200-)	3080	0.8	1.7	0.0	24.1

Table 2: Analytical knowledge characteristics of patents in EU regions, 2000-2010.

	NPL		Inventors network		Radicalness
	% of patents citing NPL	% of NPL citations	% of patents with more than 1 location	Average distance between inventors (Km.)	Average index of radicalness
RE patents	31.1	18.2	43.6	127	0.359
Rest of patents	26.2	15.3	39.1	113	0.335
t-statistic	10.46[a]***	-9.80***	11.64[a]***	-9.94***	-11.1***

*** p<0.01, ** p<0.05, * p<0.1. [a] Z-statistics for the difference in sample proportions. Source: Own calculations

Table 3: Patent citations distance and distance distribution of patent citations for EU regions, 2000-2010

	Citation distance (Km)	KF[0-300)	KF[300-1200)	KF[1200-)
RE patents	366.8	35.7%	23.5%	40.8%
Rest of patents	356.2	37.3%	24.1%	38.6%
t-statistic	-5.43***	8.73[a]***	3.51[a]***	-11.54[a]***

*** p<0.01, ** p<0.05, * p<0.1. [a] Z-statistics for the difference in sample proportions. Source: Own calculations

Table 4. Knowledge production function for RE technologies

	(1)	(2)	(3)	(4)
	Fixed Effects Estimator			
R&D	0.390***	0.335***	0.359***	0.317***
	(0.0617)	(0.0579)	(0.0607)	(0.0574)
HK	0.0586***	0.0463***	0.0531***	0.0432***
	(0.00822)	(0.00833)	(0.00852)	(0.00857)
Ind_Share	-3.763***	-3.310***	-3.718***	-3.316***
	(0.858)	(0.867)	(0.844)	(0.851)
SPI	-0.132**	-0.113**	-0.107**	-0.0901*
	(0.0511)	(0.0479)	(0.0505)	(0.0478)
Density	7.507**	6.311*	7.707**	6.515*
	(3.487)	(3.497)	(3.397)	(3.357)
Density^2	-0.312	-0.193	-0.317	-0.202
	(0.345)	(0.345)	(0.335)	(0.331)
S		0.120***		0.113***
		(0.0238)		(0.0234)
KF[0-300)			0.000855	-0.0223
			(0.0259)	(0.0247)
KF[300-1200)			0.0818*	0.0650
			(0.0466)	(0.0458)
KF[1200-)			0.0536**	0.0444*
			(0.0236)	(0.0231)
Constant	-31.76***	-28.81***	-32.17***	-29.30***
	(9.117)	(9.127)	(8.860)	(8.747)
Obs.	1,979	1,970	1,979	1,970
R-squared	0.367	0.383	0.376	0.389
N. of regions	260	255	260	255
Hansen's J Chi2.	186.2	165.8	199.7	191.0
AIC	1250.2	1190.0	1228.6	1177.1
BIC	1283.8	1229.1	1279.0	1232.9

Dependent variable: Ln(patents per 100000 inhabitants). Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Knowledge production function for Non-RE technologies

	All non-RE technologies, P	IT	BIOTECH	NANOTECH	Dirty Energy Generation technologies
R&D	0.135**	0.0733**	0.0992**	0.0270*	0.117**
	(0.0569)	(0.0357)	(0.0405)	(0.0138)	(0.0464)
HK	0.0266***	0.0149**	0.0101	0.00570**	0.0150**
	(0.00576)	(0.00639)	(0.00708)	(0.00234)	(0.00672)
Ind_Share	0.821*	2.092***	2.008***	-0.775***	-1.872**
	(0.456)	(0.556)	(0.609)	(0.288)	(0.792)
SPI	-0.0371	-0.0991**	-0.0423	0.0103	-0.0739**
	(0.0654)	(0.0413)	(0.0543)	(0.0110)	(0.0344)
Density	0.0496	3.238	8.742***	1.410	2.307
	(2.639)	(2.929)	(2.575)	(1.588)	(2.628)
Density^2	-0.245	-0.465	-0.942***	-0.108	-0.170
	(0.240)	(0.317)	(0.256)	(0.165)	(0.277)
S	0.0524*	0.0408*	-0.0186	0.0154**	0.0546***
	(0.0311)	(0.0224)	(0.0253)	(0.00650)	(0.0189)
KF[0-300)	-0.00761	-0.0312	-0.0425**	-0.000146	0.00200
	(0.0195)	(0.0204)	(0.0191)	(0.00530)	(0.0171)
KF[300-1200)	0.0483**	0.0366	-0.0265	-0.00958	0.0946***
	(0.0221)	(0.0285)	(0.0303)	(0.0137)	(0.0273)
KF[1200-)	0.0223	-0.0156	0.0276	0.0118	-0.00996
	(0.0168)	(0.0189)	(0.0222)	(0.00757)	(0.0190)
Constant	7.022	-5.771	-20.66***	-6.448*	-8.375
	(7.279)	(6.771)	(6.653)	(3.724)	(6.749)
Obs.	1,970	1,970	1,970	1,970	1,970
R-squared	0.167	0.052	0.051	0.056	0.155
N. of regions	255	255	255	255	255
Hansen's J Chi2.	0.897	167.28	286.88	44.49	60.59
AIC	3178.5	-55.22	82.04	-2395.52	-36.73
BIC	3240.0	0.64	137.90	-2339.66	19.13

Dependent variable: Ln(patents per 100000 inhabitants). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1