UNIVERSITAT DE BARCELONA

On Renewable Energy Innovation and its Knowledge Flows' Sources and Nature

Diego B. Ocampo-Corrales

PhD in Economics

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A mis padres, Lourdes y Rubén.
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1. Introduction

This doctoral thesis tries to contribute in the literature and in policy debates regarding innovation in Renewable Energies (RE from now on). The three chapters that are the core of this study aim to contribute with the academic debate regarding the innovation in RE as an specific technological field that can serve as an example of a novel technology with economic and technological opportunities (Rennings 2000; Barbieri et al. 2020). They try to open the discussion about which knowledge, and which sources foster innovation in RE from a knowledge diffusion perspective. In general terms, they try to answer the question: *Where does the knowledge that feeds RE innovation comes from?*

The motivation of focusing in RE innovation lays in two foundations. One is the current climate change scenario, posing new challenges to society, and the second one is the endogenous growth theory, which states that economic growth can be sustained thanks to endogenous technological change. On the one hand, climate change poses a threat to economic growth. Climate change will cause sea levels to rise, variation in crops yields, affect water availability, human health, tourism and energy demand (Fankhauser and Tol 2005; Ronson and Van der Mensbrugghe 2012) and will disproportionally impact developing countries (Lecocq and Shalizi 2010; Dell et al. 2008). This could mean that failing to enter a sustainable growth path puts at risk future growth and development (Hayter 2008; OECD 2011). The focus on RE comes from the fact that the energy sector is the principal source of greenhouse gas emissions (IEA 2018) while there is evidence that the development and introduction of Renewable Energies can boost GDP at the global level (Ferrouki et al. 2016) and even in developing countries (Maji 2015).

On the other hand, innovation and technological change has been shown to be key for economic growth, as it would allow unbounded productivity growth (Romer 1986). As knowledge is the main input to produce more knowledge, the production of new ideas leads to sustain technological change and, consequently, of productivity (Romer 1990). In few words, technological change, along with human capital, lead to a sustained growth path. In this conceptual framework a fundamental argument is that knowledge is a public good and as such is subject to externalities. Innovators can take hand of the existing pool of ideas and produce more ideas without incurring in further costs, while enjoying from non-diminishing returns from this externality. This is possible due to knowledge being a nonrival good, that is, the use of an idea by one agent does not prevent from the use of the same idea by others, and also nonexcludable, meaning that one person or firm cannot totally exclude others from using one idea or piece of knowledge (Romer 1990). These characteristics of knowledge would allow growth to be sustained as agents could be able to exploit the total amount of knowledge in the society to innovate. This way, innovation turns to be the main driver of long run growth (Grossman and Helpam 1994; Hassan and Tucci 2010). In the climate change context, technological change can help lessen the impact of climate change and lower the costs towards a sustainable transition (Carraro and Siniscalco 1994; Popp et al. 2009 and Bretschger et al. 2017) and open a sustainable growth path.

Policy wise, hopefully this dissertation will present the opportunity for debate. Innovation in environmental technologies, including RE, suffer from the double externality problem (Rennings 2000). On the one side, RE innovation, as any other type of innovation, suffers from knowledge externalities. This is, firms have fewer incentives to invest in innovation due to the nature of knowledge as a public good. This makes hard for firms to internalize all the benefits of their investment, causing an overall investment in Research and Development (R&D) lower than the social optimum. On the other side, firms can also have few incentives to 'eco-innovate' because, again, they cannot fully appropriate of the environmental benefits of their investment. For example, when trying to accomplish a pollution reduction goal at the aggregate level, some firms may want to take advantage and wait for other firms to face the costs to accomplish the goal while they can save resources. Again, this could discourage some firms to invest in eco-friendly technology. This characteristic of eco-innovation makes the study of RE innovation an especially interesting field of research for innovation policy. Any policy design would have to cope with both kind of externalities in order to assure the necessary amount of RE innovation. In this sense, the results of this doctoral dissertation would hopefully serve as a small contribution to consider in policy design.

On top of the previous arguments, studying innovation in RE could allow making theoretical contributions to the fields of economic geography and innovation. On the one hand, implicit in the endogenous growth theory mentioned above, are the assumptions that knowledge can freely flow among agents and that it is a homogeneous good (Mattes 2012). However, it has been shown that knowledge does not travel far, as literature has found that knowledge flows are locally bounded (Jaffe et al. 1993; Audretsch and Feldman 2004; Murata et al. 2013), meaning that proximity matters for knowledge diffusion. Also, some literature states that knowledge can be thought as heterogeneous in nature, as some activities might have higher content of abstract, science-based knowledge; other more technical and applied knowledge content, and other more content concerned with culture, beliefs and social meanings (Moodysson et al. 2008; Asheim et al. 2011). In this regard, this dissertation will try to provide a new look at the knowledge nature of RE as a technological field.

At the same time, proximity (or distance) is not a homogeneous concept on its own. Boschma (2005) presents five types of proximity that would allow individuals to interact and exchange knowledge: cognitive proximity, that is the similarity of how individuals understand the same phenomenon; social proximity, which are the personal ties among peers hold by trust; organizational proximity, that is the institutional arrangements within corporations that allow the knowledge to flow framed by these arrangements; cultural/institutional proximity, which are the customs, values and beliefs of broad communities that allow common understanding and finally, geographical distance, that is the physical space between individuals. With this under consideration, this dissertation will try to explore how proximity (in its several shapes) influences the knowledge flows that feed RE innovation, taking into account that also knowledge can have different natures.

RE technologies offer a good ground to start exploring the interaction of knowledge and proximity, as eco-innovation is considered a new technological field at its early stage (Rennings 2000; Consoli et al. 2016; Barbieri et al. 2020) and at the same time, it has the characteristic of enjoying from a diverse set of knowledge sources (Dechezlepretre et al. 2011; Horbach et al. 2013; Ghisetti et al. 2015). Summing up, it could be said that this dissertation proceeds assuming that proximity is not a homogeneous concept, nor it is knowledge, and intends to explore the relevance of knowledge flows and their source. The conceptual contribution focus on the role of distance and its different shapes for the flow of knowledge in the generation of innovation.

In the pursue of this goal, the second chapter of this dissertation, after this introductory section, intends to shed light on how the specific knowledge content of RE innovation can have a role on the relevance of the scientific knowledge and the geographic pattern of the knowledge flows from which it feeds. This chapter takes as foundation the knowledge-base conceptual framework found in Moodysson et al. (2008) and Asheim et al. (2011) to investigate the nature of RE innovation. It is argued that, depending on the knowledge base, spatial diffusion patterns of knowledge flows can be different. It is stated that RE innovation tends to have stronger foundations on analytical knowledge (science-based and abstract content), then the ideas needed for its development are more codifiable and travel easier across space. Geographical proximity would be less important for the diffusion of relevant knowledge for RE. What matters the most 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. This would challenge the common finding of geographically localized knowledge flows and provide a new conceptualization of knowledge flows depending on the knowledge content. Also, the fact that RE knowledge has science base nature would be reflected on the fact that knowledge coming from a scientific background would be more relevant for RE than for other technologies.

The analysis uses geolocalized patent data to proxy technological innovation and patent citations to capture the knowledge flows (as Jaffe et al. 1993). Using data from European countries at the regional level, from the year 2000 to 2010, the regional production of RE innovation is measured by counting the number of patents of a region in this field as endogenous variable. As explanatory variables we use the citations made by all the patents in a region to capture the knowledge flows incoming to a region. A distinction between citations to scientific documents and other patents is made to capture the incoming knowledge from science and the knowledge coming from technical sectors. From a Knowledge Production Function set up, the results show that RE would enjoy from knowledge flows from science and academia in a higher extent than the bulk of innovation. Also, knowledge flows that feed RE innovation would be less localized than the ones that nurture other technologies. These results suggest that, contrary to previous literature, knowledge flows would be less geographically localized depending on the technology. The explanation could lay on the knowledge content of knowledge, suggesting that what matters is the cognitive proximity or interaction of individuals beyond borders.

While the second chapter focuses on the production of RE innovation at the regional level, the third (and fourth) focus on the inventors, in order to contribute in understanding how RE innovation can emerge. It focuses on the inventors, as they are the ones who recognize a new problem and that conventional methods are not sufficient to solve it (Arthur 2007). They are the ones who put together all the knowledge they have available to create something novel. Therefore, it is them who venture into something new when pursuing innovation in a new field. More precisely, the third chapter tries to explain the probability of an experienced inventor patenting in RE for the first time. The aim is to contribute with the understanding of how RE innovation arises.

This chapter intents to find out what are the most relevant sources from which an inventor obtains relevant knowledge to venture in RE innovation. It is argued that, in general, an inventor has three sources of knowledge that are related to a given type of proximity. These sources are the inventor's network, associated with social proximity; the firm, associated with organizational proximity; and the regional context, associated with geographical proximity. This setting allows to disentangle the role of the different types of proximity and social interaction to transfer knowledge that would drive RE innovation. Additionally, at each of these sources, it will be distinguished between the possible effect of overall knowledge (measured as the stock of patents in all fields but RE) and the effect coming from other inventors who already patented in RE before, in a 'peer effect' fashion, driven by either socialization or by the need of specific knowledge. It is argued that direct relationships induce more trust, facilitating individuals to share knowledge (Singh 2005), reason why the most relevant knowledge input would come from closer sources in terms of potentiality of direct interaction. Additionally, we study if knowledge flows coming from within the RE technological domain are more relevant, given that an inventor can be influenced by the fact that other inventors in its environment (geographical location, firm, or network) get involved in the development of renewable energies.

In this chapter, patent data is used to identify the inventors, their coauthors network, the firms where they work and the regions where they reside. It covers a broad period from 1981 to 2015 and focuses on inventors residing in Europe. The main finding suggests that the most important drivers for an inventor to patent in RE would be the influence from her/his professional network, specifically having a coauthor who already has innovated in RE. This would imply that close interaction and specific knowledge are necessary for an inventor to venture in patenting in RE. The main contributions of this chapter is to look at the role of the different proximity types and how they interact with each other. This chapter shows that social proximity seems to be more relevant than geographical proximity in the transmission of knowledge. This finding suggests that the relations of inventors with other inventors in their networks could transcend the local realm.

The fourth chapter goes deeper into trying to understand the role of proximity, its different shapes and the emergence of RE innovation, but focusing on the role of cognitive proximity and how this might interact with the other types of distance to explain the probability of an experienced inventor venturing in RE innovation. As cognitively proximate knowledge would be easier to communicate and transfer, innovation would be more easily generated when different pieces of knowledge within the same technological path are combined (Dosi 1982). On the other hand, when knowledge is cognitively distant, knowledge transfer would be harder, since concepts and information would not be easy to understand by the recipient part. Nonetheless, distant knowledge could contribute to produce radical and novel innovation. There should be an equilibrium between close knowledge and distant knowledge, not to fall in a creative lock-in or in unsuccessful communication. This chapter proposes that this equilibrium is reached thanks to the interplay of cognitive proximity and the other different forms of proximity.

To capture for cognitive distance, in this chapter we employ the concepts of technological relatedness and unrelatedness. This is based on the frequency of technological fields being assigned in the same patent document, assuming that if two technologies are recognized in the same patent often enough, it is because they might have a common cognitive background or they are related. Then, if this is not the case, it is said that these technologies do not have a common cognitive background or they are unrelated. With this tool, it is measured how proximate or distant is the knowledge of an inventor to the knowledge possibly available in her/his social network, firm or region (as these three could be think to be linked with different proximity types). Additionally, it is measured how proximate is the knowledge of an inventor to RE as a field on its own. With this framework, we evaluate how (cognitively) proximate or distant knowledge, when interacting with other forms of distance (social, organizational and geographical), can influence the probability of an inventor to venture in RE. This chapter shows that when an inventor's knowledge is cognitively close to RE, it is more likely for this inventor to venture in this field. Also, we obtain that the necessary cognitive distant knowledge that pushes an inventor to invent for the first time in the RE field comes from her/his patenting network.

All in all, this PhD thesis shows that for some technologies, especially novel ones as RE, the knowledge flows that influence more would come from within communities, in which close interaction is the rule. Additionally, cognitive proximity, rather than geographical one, would play a more important role in the knowledge transmission that generates new inventions in the RE domain. Chapter two finds that knowledge flows coming from the scientific sector and from further places are the ones that foster RE innovation, while in chapters three and four we find that knowledge coming from the network of inventors and specially containing knowledge in the RE technological field would be the key for emerging RE innovation. Although these results may look contradictory, they are not. Inventors' networks are not totally based on spatial criteria and can comprehend teams working in different regions or even countries. The need for specialized knowledge and resources can lead inventors to enter into networks based on skills and knowledge needs. Hopefully this dissertation will contribute with new insights about the relation of proximity and knowledge flows while putting on the table the topic of Renewable Energies in the context of climate change.

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

2.1. Introduction

This chapter 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 and explore whether the knowledge flows from the technological sector have the same spatial diffusion pattern for RE than for the rest of technological innovations.

The motivation behind this chapter 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. 2019), 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. 2020), 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 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).

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

[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).

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 chapter, we build on them and claim that these sources respond to the nature of eco innovation itself.

With this framework, 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. RE innovation needs new ideas to cover new needs, and part of these new ideas may come from sources with a higher content of scientific knowledge. Also, the importance of proximity could 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 chapter is organised as follows. In Section 2.2, we present the literature review and our theoretical framework and state the main hypotheses. Section 2.3 offers the formal model guiding our empirical approach and the data, and provides relevant issues about our main variables and their construction. Section 2.4 shows some stylised facts related to our hypotheses as well as our main econometric results, while Section 2.5 concludes.

2.2. 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).

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

[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 chapter.

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. 2020; 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 costlier. 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*.

2.3. Empirical framework

2.3.1. 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}.

$$Y_{it} = f(R\&D_{it}, HK_{it}, Z_{it}, A_{it}) \quad (2.1)$$

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

$$Y_{it} = e^{\alpha}. R\&D_{it}^{\beta}. HK_{it}^{\rho}. Z_{it}^{\theta}. A_{it}. e^{\mu_i} \quad (2.2)$$

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):

$$A_{it} = S_{it}^{\gamma_0} \prod_{j} KF_{jt}^{g(dist_{ij})} \quad (2.3)$$

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:

$$g(dist_{ij}) = \begin{cases} 0, & if\ dist_{ij} \notin k \\ \phi_k, & if\ dist_{ij} \in k \end{cases} \tag{2.4}$$

The index k captures a sequence of distance intervals within which the step function is constant. Replacing equation (2.3) in (2.2) yields the following expression:

$$Y_{it} = e^{\alpha}.R\&D_{it}^{\beta}.HK_{it}^{\rho}.Z_{it}^{\theta}.S_{it}^{\gamma_0}.\prod_j KF_{jt}^{g(dist_{ij})}.e^{\mu_i} \tag{2.5}$$

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

$$\begin{aligned} ln(Y_{it}) = \alpha + \beta ln(R\&D_{it}) + \rho HK_{it} + \theta ln(Z_{it}) + \gamma_0 \ln(S_{it}) \\ + \sum_j \phi_k ln(KF_{jt}) + \mu_i + \varepsilon_{it} \end{aligned} \tag{2.6}$$

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.

2.3.2. 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

[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 possesses. See section 4.3, page 64, and the corresponding footnote number 4 of the OECD Patent Statistic Manual (OECD 2009).

(*RE*) as identified by the Haščič 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 A2.1 and A2.2 of the appendix). 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 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).

[5] See Table A2.1 for the whole list of technology codes identified as renewable energies.

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 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:

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[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.

[8] This approximation does not go into more detail of the reasons why RE innovation might look further for knowledge, either because the specialization 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 chapter.

$$SPI_{it} = \frac{1}{2}\sum_{j}\left|\frac{P_{ijt}}{P_{it}} - \frac{P_{Cjt}}{P_{Ct}}\right| \quad (2.7)$$

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 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 A2.2 in Appendix 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 2.1 offers a descriptive analysis of the variables in the models.

[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.

Table2. 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

Source: Own calculations

2.4. 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.

2.4.1. Stylized facts

If patents in RE belong to the analytical knowledge base, as argued in section 2.2, 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 (2020). 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 2.2, 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 2.2, 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.

Table2. 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

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 2.3 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.

Table2. 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

2.4.2. 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 (2.6) 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 2.4, 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 2.4, 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 (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.

[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 A2.3 in the Appendix for the regression results.

[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).

Table2. 4: Knowledge production function for RE technologies. Fixed effects estimator

	(1)	(2)	(3)	(4)
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

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 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].

2.4.3. 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 2.5 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 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].

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[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. See Table A2.4 in Appendix.

[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 A2.5 in the Appendix, 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 chapter are maintained. We do not include this variable in the base estimation of the present chapter due to the lack of reliability of the data used to construct it.

[15] As the main goal of the chapter 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 chapter, 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

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 2.5 (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 2.5 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 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 2.5) 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.

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.

Table2. 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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 A2.6 of the 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).

2.5. Conclusions

The research conducted in this chapter 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.

2.6. Appendix

Table A2. 1: Renewable energies patent classification from Haščič and Migotto (2015)

4. CLIMATE CHANGE MITIGATION technologies related to ENERGY generation, transmission of distribution	**Y02E**
4.1. RENEWABLE ENERGY GENERATION	**Y02E10**
4.1.1. Wind energy	Y02E10/70
• Wind turbines with rotation axis in wind direction: blades or rotors, components or gearbox, control of turbines, generator, nacelles, onshore and offshore towers • Wind turbines with rotation axis perpendicular to the wind direction • Power conversion electric or electronic aspects; for grid-connected applications; concerning power management inside the plant, e.g. battery (dis)charging, operation, hybridisation	Y02E10/70
4.1.2. Solar thermal energy	Y02E10/40
• Tower concentrators; Dish collectors; Fresnel lenses; Heat exchange systems; Trough concentrators. • Conversion of thermal power into mechanical power, e.g. Rankine, Stirling solar thermal engines; Thermal updraft. • Mountings or tracking.	Y02E10/40
4.1.3. Solar photovoltaic (PV) energy	Y02E10/50
• PV systems with concentrators. • Material technologies: CuInSe2 material PV cells; Dye sensitized solar cells; Solar cells from Group II-VI materials; Solar cells from Group III-V materials; Microcrystalline silicon PV cells; Polycrystalline silicon PV cells; Monocrystalline silicon PV cells; Amorphous silicon PV cells; Organic PV cells. • Power conversion electric or electronic aspects: for grid-connected applications; concerning power management inside the plant, e.g. battery (dis)charging, operation, hybridisation; Maximum power point tracking [MPPT] systems.	Y02E10/50
4.1.4. Solar thermal-PV hybrids	Y02E10/60
4.1.5. Geothermal energy	Y02E10/10
• Earth coil heat exchangers; Compact tube assemblies, e.g. geothermal probes. • Systems injecting medium directly into ground, e.g. hot dry rock system, underground water. • Systems injecting medium into a closed well. • Systems exchanging heat with fluids in pipes, e.g. fresh water or waste water.	Y02E10/10
4.1.6. Marine energy	Y02E10/30
• Oscillating water column [OWC]. • Ocean thermal energy conversion [OTEC]. • Salinity gradient. • Wave energy or tidal swell, e.g. Pelamis-type.	Y02E10/30
4.1.7. Hydro energy	Y02E10/20
• Conventional, e.g. with dams, turbines and waterwheels. • Tidal, stream or damless hydropower, e.g. sea flood and ebb, river, stream.	Y02E10/20
4.2. ENERGY GENERATION FROM FUELS OF NON-FOSSIL ORIGIN	**Y02E50**
4.2.1. Biofuels	Y02E50/10
• CHP turbines for biofeed. • Gas turbines for biofeed. • Bio-diesel. • Bio-pyrolysis. • Torrefaction of biomass. • Cellulosic bio-ethanol. • Grain bio-ethanol. • Bio-alcohols produced by other means than fermentation.	Y02E50/00
4.2.2. Fuel from waste	Y02E50/30
• Synthesis of alcohols or diesel from waste including a pyrolysis and/or gasification step. • Methane production by fermentation of organic by-products, e.g. sludge; Methane from landfill gas.	Y02E50/30
4.3. COMBUSTION TECHNOLOGIES WITH MITIGATION POTENTIAL (e.g. using fossil fuels, biomass, waste, etc.)	**Y02E20**
4.3.1. Technologies for improved output efficiency (Combined heat and power, combined cycles, etc.)	Y02E20/10

• Heat utilisation in combustion or incineration of waste.	Y02E20/12
• Combined heat and power generation [CHP].	Y02E20/14
• Combined cycle power plant [CCPP], or combined cycle gas turbine [CCGT].	Y02E20/16
• Integrated gasification combined cycle [IGCC].	Y02E20/18
• Combined with carbon capture and storage [CCS].	Y02E20/185
4.3.2. Technologies for improved input efficiency (Efficient combustion or heat usage)	Y02E20/30
• Direct CO_2 mitigation: Use of synair, i.e. a mixture of recycled CO_2 and pure O_2; Use of reactants before or during combustion; Segregation from fumes, including use of reactants downstream from combustion or deep cooling; Controls of combustion specifically inferring on CO_2 emissions. • Indirect CO_2 mitigation, i.e. by acting on non CO_2 directly related matters of the process, e.g. more efficient use of fuels: Cold flame; Oxyfuel combustion; Unmixed combustion; Air pre-heating. • Heat recovery other than air pre-heating: at fumes level, at burner level.	
4.4. NUCLEAR ENERGY	**Y02E30**
4.4.1. Nuclear fusion reactors	
• Magnetic plasma confinement [MPC]: Tokamaks; Stellarators; Other reactors with MPC; First wall, divertor, blanket. • Inertial plasma confinement: Injection systems and targets. • Low temperature fusion, e.g. "cold fusion".	Y02E 30/10
4.4.2. Nuclear fission reactors	
• Boiling water reactors; Pressurized water reactors; Gas cooled reactors; Fast breeder reactors; Liquid metal reactors; Pebble bed reactors; Accelerator driven reactors. • Fuel. • Control of nuclear reactions. • Other aspects relating to nuclear fission.	Y02E 30/30
4.5. TECHNOLOGIES FOR AN EFFICIENT ELECTRICAL POWER GENERATION, TRANSMISSION OR DISTRIBUTION	**Y02E40**
4.5.1. Superconducting electric elements or equipment	Y02E40/60-69
• Superconducting generators: Superconducting synchronous generators; Superconducting homopolar generators. • Superconducting transmission lines or power lines or cables or installations thereof. • Superconducting transformers or inductors. • Superconducting energy storage for power networks, e.g. SME, superconducting magnetic storage. • Protective or switching arrangements for superconducting elements or equipment. • Current limitation using superconducting elements, including multifunctional current limiters.	Y02E40/60
4.5.2. Not elsewhere classified	
Flexible AC transmission systems [FACTS] Static VAR compensators [SVC], static VAR generators [SVG] or static VAR systems [SVS], including thyristor-controlled reactors [TCR], thyristor-switched reactors [TSR] or thyristor-switched capacitors [TSC] • Thyristor-controlled series capacitors [TCSC] • Static synchronous compensators [STATCOM] • Unified power flow controllers [UPF] or controlled series voltage compensators	Y02E40/10
Active power filtering [APF] • Non-specified or voltage-fed active power filters. • Current-fed active power filters; using a multilevel or multicell converter	Y02E40/20
Reactive power compensation. • Reactive power compensation; using synchronous generators; for voltage regulation	Y02E40/30
Arrangements for reducing harmonics	Y02E40/40
Arrangements for eliminating or reducing asymmetry in polyphase networks	Y02E40/50
Smart grids. • Systems characterised by the monitoring, control or operation of energy generation units, e.g. distributed generation [DER] or load-side generation; Systems characterised by the monitoring, control or operation of flexible AC transmission systems [FACTS] or power factor or reactive power compensating or correcting units; Computing methods or systems for efficient or low carbon management or operation of electric power systems	Y02E40/70
4.6. ENABLING TECHNOLOGIES (Technologies with potential or indirect contribution to emissions mitigation)	**Y02E60**
4.6.1. Energy storage	Y02E60/10

4.6.1.1. Batteries	Y02E60/12
• Lithium-ion batteries. • Alkaline secondary batteries, e.g. NiCd or NiMH. • Lead-acid batteries. • Hybrid cells	Y02E60/122
• Ultracapacitors, supercapacitors, double-layer capacitors.	Y02E60/13
• Sensible heat storage, Latent heat storage, Cold storage.	Y02E60/14
4.6.1.4. Pressurised fluid storage	Y02E60/15
• Mechanical energy storage, e.g. flywheels.	Y02E60/16
4.6.1.6. Pumped storage	Y02E60/17
4.6.2. Hydrogen technology	Y02E60/30
• Fuel cells: • characterised by type or design: Proton Exchange Membrane Fuel Cells [PEMFC], Direct Alcohol Fuel Cells [DAFC], Direct Methanol Fuel Cells [DMFC]; Solid Oxide Fuel Cells [SOFC]; Molten Carbonate Fuel Cells [MCFC]; Bio Fuel Cells; Regenerative or indirect fuel cells, e.g. redox flow type batteries. • integrally combined with other energy production systems: Cogeneration of mechanical energy, e.g. integral combination of fuel cells and electric motors; Production of chemical products inside the fuel cell; incomplete combustion.	
4.6.4. Smart grids in the energy sector	Y02E60/70
• Systems integrating technologies related to power network operation and communication or information technologies mediating in the improvement of the carbon footprint of electrical power generation, transmission or distribution, i.e. smart grids as enabling technology in the energy generation sector	Y02E60/70-7892
4.7. OTHER ENERGY CONVERSION OR MANAGEMENT SYSTEMS REDUCING GHG EMISSIONS	Y02E70
• Hydrogen from electrolysis with energy of non-fossil origin, e.g. PV, wind power, nuclear. • Systems combining fuel cells with production of fuel of non-fossil origin. • Systems combining energy storage with energy generation of non-fossil origin. • Energy efficient batteries, ultracapacitors, supercapacitors or double-layer capacitors charging or discharging systems or methods, e.g. auxiliary power consumption reduction, resonant chargers or dischargers, resistive losses minimization.	Y02E70/00

Table A2. 2: Variable definition

Variable	Definition
RE patents	Patents in renewable energies identified using the Y02 classification from WIPO (Haščič and Migotto, 2015). Three year moving average (t, t+1, t+2) of the patents per 100000 inhabitants
Rest of the patents	Patents not identified in the Renewable energies technological field. Three year moving average (t, t+1, t+2) of the patents per 100000 inhabitants
S	Non Patent Literature citations (NPL) per 100000 inhabitants. Three year moving average (t-1, t-2, t-3)
KF in distance ring k	Patent backward citations. Three year moving average (t-1, t-2, t-3). The distance rings were defined in two steps: 1) Measure the distance between all the NUTS2 regions; 2) Estimate the average distance between any two NUTS2 regions within the same country, within Europe and finally outside Europe.
KF[0-300)	Patent backward citations within the 75-300 km ring. Three year moving average (t-1, t-2, t-3).
KF[300-1200)	Patent backward citations within the 300-1200 km ring. Three year moving average (t-1, t-2, t-3).
KF[1200-)	Patent backward citations within the over 1200 km ring. Three year moving average (t-1, t-2, t-3).
R&D	R&D expenditure per 100000 inhabitants in t-1.
HK	Proxy for Human Capital: the proportion of population with tertiary education existing in the region in t-1.
SPI	Specialization Index. Constructed using the technological classification of Schmoch (2008) in t-1.
Ind_Share	Share of the employment of the industrial sector in the regional economy in t-1.
Population Density	Number of inhabitants per square kilometer in t-1.

Table A2. 3: RE knowledge production function. FE estimation including the share of service employment

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D	0.363***	0.321***	0.343***	0.309***	0.366***	0.321***	0.339***	0.304***
	-0.0418	-0.0418	-0.0421	-0.042	-0.04	-0.0401	-0.0403	-0.0403
HK	0.0522***	0.0419***	0.0489***	0.0401***	0.0532***	0.0429***	0.0483***	0.0401***
	-0.00601	-0.00616	-0.00609	-0.00619	-0.00581	-0.00596	-0.00589	-0.00599
Ind_Share					-2.443**	-2.393**	-2.512***	-2.450***
					-0.753	-0.743	-0.749	-0.74
Serv_Share	3.323***	2.690***	3.244***	2.646***	1.976**	1.399*	1.811**	1.322*
	-0.542	-0.543	-0.541	-0.541	-0.648	-0.645	-0.646	-0.643
SPI	-0.0748	-0.0585	-0.0487	-0.034	-0.125	-0.108	-0.1	-0.086
	-0.0684	-0.0676	-0.0684	-0.0675	-0.0656	-0.0648	-0.0655	-0.0648
Density	5.996**	4.359	6.218**	4.578*	7.675***	6.471**	7.855***	6.661**
	-2.249	-2.239	-2.241	-2.23	-2.187	-2.174	-2.176	-2.167
Density^2	-0.11	0.0398	-0.12	0.028	-0.305	-0.192	-0.31	-0.201
	-0.226	-0.225	-0.225	-0.224	-0.219	-0.217	-0.218	-0.217
S		0.116***		0.118***		0.116***		0.109***
		-0.0183		-0.0187		-0.0177		-0.0181

Table A2. 4: RE knowledge production function. FE estimation including the share of service employment (cont.)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KF[0-300)			-0.0400*	-0.0635***			-0.000579	-0.0226
			-0.0184	-0.0184			-0.0179	-0.018
KF[300-1200)			0.0733**	0.0566*			0.0784**	0.0631*
			-0.0284	-0.0282			-0.0268	-0.0267
KF[1200-)			0.0456*	0.0360*			0.0527**	0.0441**
			-0.0178	-0.0176			-0.0169	-0.0167
Constant	-32.17***	-27.42***	-32.69***	-28.05***	-34.16***	-30.61***	-34.36***	-30.99***
	-5.65	-5.637	-5.63	-5.611	-5.594	-5.565	-5.565	-5.545
Observations	1995	1986	1995	1986	1979	1970	1979	1970
Adjusted R-squared	0.236	0.254	0.243	0.261	0.273	0.29	0.281	0.296

Standard errors in parentheses. "* p<0.1, ** p<0.05, *** p<0.01"

Table A2. 5: RE KPF. 100 km distance rings. Fixed effects estimation

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
R&D	0.335***	0.344***	0.307***	0.326***	0.310***	0.278***
	-0.0396	-0.0389	-0.0391	-0.0413	-0.0406	-0.0406
HK	0.0463***	0.0496***	0.0410***	0.0361***	0.0386***	0.0292***
	-0.00576	-0.00555	-0.00572	-0.00647	-0.00617	-0.00638
Ind_Share	-3.310***	-3.591***	-3.252***	-2.268**	-2.631***	-2.238**
	-0.612	-0.607	-0.603	-0.7	-0.69	-0.686
SPI	-0.113	-0.104	-0.0891	-0.142*	-0.126	-0.115
	-0.0648	-0.0643	-0.0637	-0.0663	-0.0652	-0.0645
Density	6.311**	8.408***	7.276***	7.259**	8.304**	7.787**
	-2.175	-2.171	-2.163	-2.692	-2.65	-2.649
Density^2	-0.193	-0.434*	-0.321	-0.0953	-0.294	-0.208
	-0.218	-0.218	-0.217	-0.267	-0.264	-0.263
S	0.120***		0.0967***	0.130***		0.0992***
	-0.0176		-0.0178	-0.0195		-0.0196
KF[300-400)		0.0717*	0.0707*		0.127***	0.128***
		-0.0279	-0.0276		-0.0321	-0.0317
KF[400-500)		0.0541	0.048		0.0866*	0.0795*
		-0.0338	-0.0335		-0.0373	-0.0369
KF[600-700)		0.0822**	0.0798**		0.0958**	0.0947**
		-0.0299	-0.0296		-0.0329	-0.0326
KF[700-800)		-0.0620*	-0.0571		-0.0494	-0.0441
		-0.0316	-0.0313		-0.0337	-0.0333
KF[800-900)		0.103***	0.0972**		0.101**	0.0955**
		-0.0311	-0.0308		-0.0344	-0.034
KF[900-1000)		0.0933***	0.0873**		0.101***	0.0957**
		-0.028	-0.0277		-0.0302	-0.0299
KF[1100-1200)		0.0802**	0.0739**		0.106***	0.0979***
		-0.0252	-0.0249		-0.0287	-0.0284
KF[1400-)		0.0420**	0.0351*		0.0510**	0.0456*
		-0.0159	-0.0158		-0.0181	-0.0179
Constant	-28.81***	-30.53***	-28.08***	-36.96***	-33.77***	-33.78***
	-5.508	-5.477	-5.455	-7.04	-6.879	-6.898
Observations	1970	1979	1970	1602	1611	1602
Adjusted R-squared	0.289	0.307	0.319	0.221	0.256	0.27

Standard errors in parentheses. Not significant coefficients were excluded

* p<0.05; ** p<0.01; *** p<0.001

Table A2. 6: KPF estimation including the institutional environment proxy.

VARIABLES	(1)	(2)	(3)	(4)
R&D	0.520***	0.463***	0.501***	0.455***
	(0.121)	(0.113)	(0.119)	(0.112)
HK	0.0711***	0.0565***	0.0666***	0.0539***
	(0.00955)	(0.00972)	(0.00946)	(0.00970)
Ind_Share	-3.840***	-3.110***	-3.768***	-3.110***
	(1.031)	(1.041)	(1.006)	(1.021)
SPI	-0.349**	-0.285**	-0.340**	-0.269*
	(0.158)	(0.144)	(0.155)	(0.142)
Density	5.397	1.553	5.786	2.213
	(4.199)	(3.931)	(4.085)	(3.798)
Density^2	-0.237	0.0672	-0.283	0.00741
	(0.387)	(0.359)	(0.375)	(0.347)
Green votes	1.157*	0.809	0.956	0.701
	(0.634)	(0.615)	(0.594)	(0.587)
S		0.187***		0.176***
		(0.0320)		(0.0303)
KF[0-300)			0.00369	-0.0277
			(0.0413)	(0.0355)
KF[300-1200)			0.108*	0.0899
			(0.0594)	(0.0579)
KF[1200-)			0.0655**	0.0556**
			(0.0280)	(0.0276)
Constant	-24.13**	-12.99	-24.43**	-14.43
	(11.61)	(10.92)	(11.24)	(10.52)
Observations	1,551	1,542	1,551	1,542
R-squared	0.381	0.409	0.392	0.416
Number of region	222	217	222	217
S-H FEvRE Chi2	175.26	140.97	177.61	169.91
AIC	1051.1	970.7	1028.4	956.8
BIC	1088.5	1013.4	1081.9	1015.6

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2. 7: KPF of RE Triadic Patent families. Poisson fixed effects estimation

VARIABLES	(1)	(2)	(4)	(5)
R&D	0.572**	0.355*	0.410*	0.263
	(0.177)	(0.180)	(0.179)	(0.180)
HK	0.00882	-0.00500	0.00176	-0.00849
	(0.0136)	(0.0140)	(0.0139)	(0.0142)
Ind_Share	-1.107	0.743	0.553	1.767
	(1.655)	(1.705)	(1.725)	(1.755)
SPI	-2.395***	-2.079***	-1.923**	-1.755**
	(0.598)	(0.605)	(0.609)	(0.612)
Density	-2.528	-2.048	0.0351	0.138
	(5.431)	(5.427)	(5.373)	(5.401)
Density^2	1.198*	1.067*	0.997*	0.917
	(0.476)	(0.477)	(0.470)	(0.472)
S		0.322***		0.263***
		(0.0722)		(0.0746)
KF[0-300)			0.389***	0.325**
			(0.107)	(0.111)
KF[300-1200)			0.0248	-0.00920
			(0.0950)	(0.0958)
KF[1200-)			0.0742	0.0765
			(0.0592)	(0.0595)
Observations	1442	1438	1442	1438
chi2	226.5	243.0	248.1	257.7
p	4.35e-46	8.69e-49	2.56e-48	1.32e-49

Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Endogenous variable: Number of triadic patent families in RE.

Figure A2. 1: Regional (NUTS2) distribution of Renewable Energy Innovation. Full counting per 100 000 inhabitants. Accumulated 2000-2010

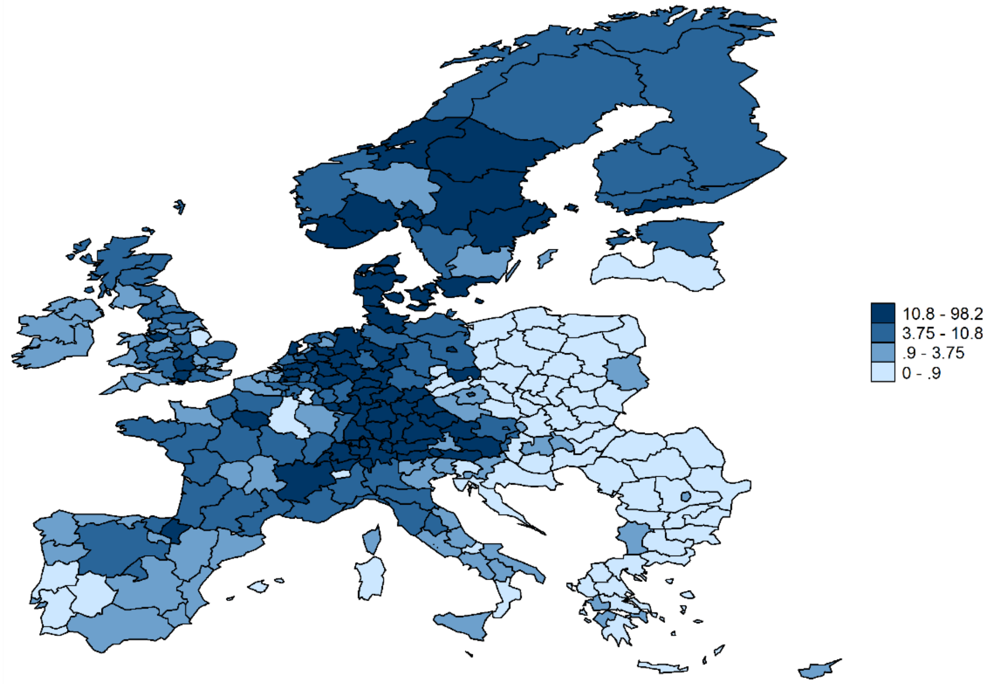
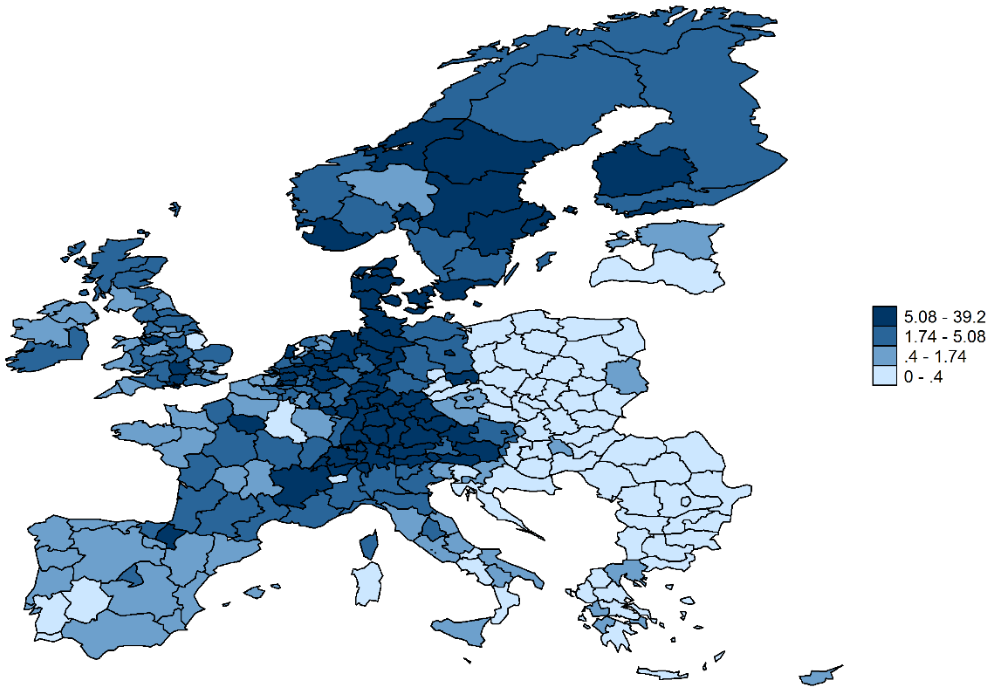


Figure A2. 2: Regional (NUTS2) distribution of Renewable Innovation. Fractional counting per 100 000 inhabitants. Accumulated 2000-2010.



3. Where do inventors get inspiration from? The role of different sources of knowledge for innovating in renewable energies

3.1. Introduction

Scholars in Economic Geography have focused on the question of how cities, regions or countries diversify into new industries or technologies and why they differ in their capabilities to do so. The field has been dominated by the path dependence (Dosi 1982) and related variety concepts, in which countries or regions diversify into technologies that are related to the ones they already possess (Hidalgo et al. 2007, Hidalgo and Hausman 2009; Boschma et al. 2013; Boschma et al., 2014; and Balland et al., 2017). The basic assumption is that knowledge is recombined to generate a new piece of knowledge. The underlying mechanism is social interaction, enabled by proximity, which facilitates the exchange of ideas, giving place to new knowledge. Nevertheless, little has been said about the role of the agents who tend to carry on this process: inventors. They are the ones who recognize a new problem and that conventional methods are not sufficient to solve it (Arthur 2007). They are the ones who put together all the knowledge they have available to create something novel. Therefore, it is them who venture into something new when pursuing innovation in a new field. This chapter tries to contribute understanding the role of different knowledge sources in explaining the probability of an inventor venturing in a field she/he had no previous expertise. Particularly, we will focus on how different knowledge sources influence an inventor to patent for the first time in Renewable Energies (RE from now on).

To our knowledge, scholars have not investigated how an inventor ventures into a new field or technology. As for inventors, some literature has focused on how inventors turn into entrepreneurs (Villanueva et al. 2012) or academic scientists going into patenting (Calderini et al. 2007). As for the adoption of new technologies, the issue has been approached from the firms' perspective, as a strategic decision processes that takes place in the firm (Langley and Truax 1994, and Hannan and McDowell 1984). or at the regional level (Collombelli et al. 2014, Boschma 2017, Boschma et al. 2017, Piirainen et al. 2017, Balland et al. 2019). However, no literature we could find goes deep in the relationship between knowledge sources and the probability of an inventor venturing into a technology novel for her/him (in our case, in which she/he has not patented before).

To answer this question, we focus on the technology of Renewable Energies. First, because studying how RE innovation emerges has value on its own: it is recognized the relation between technological innovation and the environmental sustainability of economic activity (Carraro and Siniscalco 1994, and Popp et al. 2010), innovation in green technologies could change the relative productivity of regions or countries (Arundel and Kemp 2009), and innovation in green technologies has been considered to have a positive effect on the productivity level of firms (Marin 2014; Colombelli et al. 2019) and regions (Aldieri et al. forthcoming). Second, because green technologies (and RE in particular) are recognised as radical when compared to other technologies as they 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). Third, a distinctive feature of green innovation is that it requires more heterogeneous sources of knowledge (Dechezlepretre et al. 2011; Horbach et al. 2013; Ghisetti et al. 2015), given that it is necessary the involvement of agents outside the firm, specially knowledge intensive partners, such as academics and scientist from universities, knowledge intensive business services, research institutions and other firms (Quatraro and Scandura 2019; Cainelli et al. 2015; De Marchi 2012; De Marchi and Grandinetti 2013, Tanner 2014). These characteristics pose RE innovation as a good candidate to explore the roles that different sources of knowledge could have over an inventor when she/he is about venturing into a new technological field. We consider the European patent data as, for the first time, Europe has surpassed the United States in innovation performance[1] and to, stay competitive, the European Commission proposed a budget of 100 billion euros in its research and innovation programme (Horizon Europe) to promote ground-breaking innovation (Hollanders et al. 2019). In this context, this chapter can contribute to the discussion and design of public policies.

Extant literature has already studied how green innovation emerges. At the regional level, for example, Colombelli and Quatraro (2019) find that for the emergence of green startups in Italian NUTS3 regions, the most important drivers are the general knowledge stock, the knowledge stock of green technologies, the degree of relatedness across technologies in the region, and the knowledge stock of technologies related to green technologies. That is, green start-ups are associated with a diversity of knowledge sources, although in related technological fields. Also, Corradini (2017) finds that for the emergence of green firms (those applying for a patent in environmental technologies) it is necessary a regional dynamic technological environment (measured as the total count of firms emerging in the region in different technologies). In the same line. When analyzing the emergence of the fuel cell industry, Tanner (2014) finds that the process of diversification at the regional level is driven by firm diversification or firm spin-offs. Additionally, the emergence of this kind of technology cannot only be attributed to a recombinatorial process of related varieties. According to this author, this industry also emerges where there are not related

[1] But still lags behind Japan and South Korea, while China is catching up (Hollanders et al. 2019).

technologies and, in these cases, the necessary knowledge is acquired from extra regional sources. Finally, Montresor and Quatraro (2017) finds that for regions to branch into green technologies, it is necessary the existence of both related green technologies and non-green related technologies, along with the presence of key enabling technologies.

All the studies in the paragraph above rely on the assumption that knowledge is available and create synergies that favor eco innovation. None of them go deep in looking at the channels through which knowledge flows, nor the agents who participate in the knowledge exchange. They leave aside the importance of the agents who actually produce the invention and where they acquire their knowledge. To our knowledge, the present chapter is the first study to examine the importance of the diverse knowledge sources of an inventor and how these affect her/his probability of inventing in a technology field in which she/he has not invented before, and particularly to invent in the technological field of RE. A similar previous study is the one by Orsatti et al. (2020), which analyses the drivers of the probability of a team of inventors patenting in green technologies, finding that the capability of the team to recombine the previous knowledge of its members is key for innovating in green technologies. Nonetheless, they do not focus on the way the inventors acquire the knowledge. In contrast, our study tries to understand where the inventors who innovate in renewable energies get their knowledge from.

The rest of the chapter is organized as follows. Section 3.2 presents the conceptual framework. Section 3.3 presents the data and the empirical model. Section 3.4 presents the results from the econometric estimation and Section 3.5 concludes.

3.2. Conceptual framework

Conceptually, inventors use two kinds of inputs to innovate: the internal ones and the external ones (Oldham and Cummings 1996; Hoisl 2007; Zwick 2017). The first ones are the own characteristics of the inventor, such as creativity, skills, education and training, psychological characteristics and so on. The second ones are the external factors that help an inventor develop a new idea. Indeed, inventors do not operate in isolation, but they use existing knowledge created by other individuals in different institutions/organizations not necessarily in the close proximity (Arora and Gambardella 1994; Breschi and Lissoni 2001; Fleming 2001; Weitzman 1998), meaning that inventors are susceptible to knowledge flows from their environment.

3.2.1. The geographical location of inventors

Behind the knowledge flow concept, the notion of social interaction is implicit, which is enabled by proximity and allows knowledge to flow (Boschma 2005). Geographical proximity provides an advantage to individuals and firms that are located close to each other by facilitating direct face-to-face interaction and a more direct access to knowledge. Colocated factors have a higher probability of meeting and collaborating, making learning easier (Beaudry and Breschi 2003; Boufaden et al. 2007). In this regard, the regional context is key for innovation, as it is shown in previous literature that knowledge externalities are spatially bounded (Bottazzi and Peri 2003) and that regions provide the innovation agents with the institutional infrastructure to produce new knowledge (Cooke 2002, Tödtling and Trippl 2005). The knowledge available in an inventor's region can be used as input for new ideas. Existing literature has documented the geographic localization of knowledge flows in regions and how important they are for innovation performance (Audretsch and Feldman 2004; Fritsch and Franke 2004; Peri 2005). Particularly, there is evidence of knowledge flows between inventors within regions and that these are spatially bounded (Jaffe et al. 1993 and Murata et al. 2013). Even more, Ibrahim et al. (2009) finds that the strongest defining characteristics of colocation of inventors is the access to collective knowledge (freely available in the vicinity).

3.2.2. The organization where the inventor works

At the same time, inventors are most of the times part of an organization and are therefore embedded in relations framed by the organization's institutionalized routines. This relates to the concept of organizational proximity, which is represented by organizational and institutional arrangements inside organizations (Boschma 2005). Organizational proximity facilitates invention since it reduces uncertainty, limits the risk of opportunism, and supports communication between actors (Cassi and Plunket 2014). A firm can be seen as a set of resources or capabilities targeted to get advantages from its competitors and gain profit (Wernerfelt 1984, and Rubin 1973). In order to do so, firms innovate to reduce costs, increase quality, capture or create new product markets and reduce reliance in unreliable production factors (Webster 2007). For Leonard-Barton (1992), firms' innovation capabilities can be classified in several groups. The first one refers to the firm's technological capabilities, usually measured by R&D size or R&D intensity (Bhattachayra and Bloch 2004). Evidence shows that there is a positive relationship between firms' R&D investment and patent productivity of the inventors (Kim et al. 2009). The second group complies human resource capabilities, which consist on the knowledge and skills embedded in the workers as a result of training (Song et al. 2003) or experience (Hoffman et al 1998). Finally, we find organizational capabilities, which include the administrative and managerial strategies (Webster 2007), the formalization of internal communication systems (Souitaris 2002) and the relation between work teams (Cooper 1990).

To be successful innovators, firms have to carefully analyze their personnel needs, put in practice adequate performance appraisal systems, implement reward systems to recognize and boost creativity and seek for a match between the employees' long-term career objectives and company's future goals (Gupta and Singhal 1993). To facilitate innovation, managers have to design schemes to facilitate the flow of information and create adequate conditions for knowledge transmission. Firms are a good environment for knowledge transmission, as inside them knowledge can flow faster because they possess the organization structure, procedures and routines to maintain and transfer the information and know-how from one agent to the other (Kogut and Zander 1992; Lai et al. 2016). In addition, the way a firm acquires knowledge is important for inventors' performance[2]. For instance, the amount of scientific knowledge in a firm can boost innovation production because it would enhance its absorptive capacity to take advantage of new knowledge produced outside the firm, say in universities or research institutes (Gambardella 1992).

3.2.3. The inventor's network

However, geographical or organizational proximity is not enough. Actors need to be embedded in networks to gain access to information and resources that influence innovation (Wittington et al. 2009). Inventors group as a way of sharing the risk of innovation (Crescenzi et al. 2016), as innovation in itself implies risks, especially in novel fields. At the same time, inventors innovate in teams to gain access to research infrastructure and funds (Freeman et al. 2014). Maybe, the most important reason why inventors group is the increasing sophistication of the scientific frontier. As the amount of knowledge increases and becomes more specialized, inventors have to group to gather the necessary pieces for creating something new, which reinforces the returns of specialization and promotes collaboration as means to handling what Jones (2009) calls the 'burden' of knowledge. Especially when more and more R&D projects require increasingly more diverse sets of complementary skills and competences to be successful (Agrawal et al. 2008).

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[2] Firms can access two sources of knowledge to innovate: the external ones and the internal ones. External knowledge comes from outside the firm through the interaction with customers, suppliers, and other institutions such as universities and research centers (Medase and Abdul-Basil 2019; Linder and Sperber 2019). Previous literature has underscored the importance of internal knowledge as it is the one that determines the absorptive capacity of firms to acquire external knowledge and how it enables innovation in more radical technologies (Vega-Jurado et al. 2008; Cohen and Levinthal 1990). Indeed, external knowledge needs a degree of understanding between the parts engaged in the exchange of knowledge, so that the more complicated the content of the exchange, the more difficult to be transmitted (Sorenson et al. 2006).

Social proximity within networks is increasingly acknowledged as a key mechanism to understand knowledge flows underlying interactive learning and innovation (Sorenson et al. 2006; Agrawal et al. 2008; Breschi and Lissoni 2009). Also, knowledge flows are localized to the extent that individuals and networks are also localized, essentially because individuals are not very mobile in space (Breschi and Lissoni 2009). Social networks provide formal and informal linkages through which information can flow between individuals, transcending the workplace and institutional settings without mediating market mechanisms (Lobo and Strumsky 2008). Social proximity enables trust, close collaboration and promotes accurate and efficient communication and information diffusion (Cowan and Jonard 2004, Schilling and Phelps 2007, Uzzi and Spiro 2005). For Sorensen et al. (2006), social or professional networks lower the cost of accessing knowledge of the members. Closer connection grants better access to knowledge and facilitates communication and interactive learning, and as a consequence, it may also increase innovative performance.

The knowledge accessible to an inventor through her/his network can affect her/his patent productivity. Melero and Palomeras (2015) finds that it is important to have a generalist inventor (inventors who have knowledge in many areas, but maybe not in depth) as part of the team, because they can serve as bridges between the highly specialized knowledge of other team members, enhancing the overall productivity. In a similar vein, Zacchia (2018) finds that working in a team with a ‘super inventor’ (an inventor with high productivity) increases the productivity of a ‘regular’ inventor and this effect is not persistent in time. These evidence support the idea that the knowledge available in an inventor team can foster her/his productivity.

Which knowledge sources are more influential on the probability of an inventor entering into the RE technological field?

As stated in the paragraphs above, previous theory and some evidence give arguments that there are different knowledge sources from which the inventor may nourish: the one coming from the region where the inventor is located, the knowledge in the organization she/he works in and the one available in her/his network of coauthors. However, little is known on to what extent they are influential for an inventor to enter and invent in a technological field different from the ones in which she/he has been working before. Even less, in the case of RE, given its characteristics as a technology that can be considered to be in an early stage of its life cycle (Consoli et al 2016). Specifically, we wonder not only to what extent these three knowledge sources are relevant, but also if such relevance is higher in the case the knowledge flows come from within the RE technological domain or from other fields.

Initially, direct relationships induce more trust, facilitating individuals to share knowledge (Singh 2005), whereas the transmission of knowledge should become more difficult as social distance increases. Indeed, previous literature has signaled that close links are potentially more useful for transferring knowledge that is complex and not easily codifiable (Ghoshal et al. 1994; Uzzi 1996; Hansen 1999). Indeed, Sorensen et al (2006) obtain that when knowledge is moderately complex, the closer the tie the better for knowledge transmission[3]. As eco innovation has been considered in previous papers to be more complex, in terms of its knowledge base, than other fields (Renning and Rammer 2009; Ghisetti et al. 2015; Marzucchi and Montresor 2017), the closest ties would be the most important sources of ideas for an innovator who ventures in RE for the first time. Consequently, it would be reasonable to expect that the firm and the network would be important knowledge sources for inventors to invent for the first time in RE.

Nevertheless, different sources of knowledge might provide different knowledge content and ideas to an inventor. In this sense, knowledge that is too familiar could end in a cognitive lock-in producing, at a certain stage, irrelevant innovation. This could be the case for knowledge coming from the same firm. In the same vein, Singh (2005) finds that accounting for the network of an inventor considerably drops the importance of geographic and organizational proximity on the probability of knowledge flow between inventors. Several additional papers obtain that social proximity can counteract spatial distance (Sorensen et al. 2006; Fleming et al. 2007; and Agrawal et al. 2008).

Additionally, according to previous literature, a distinctive feature of green innovation is that it requires more heterogeneous sources of knowledge (Dechezlepretre et al. 2011; Horbach et al. 2013; Ghisetti et al. 2015). Therefore, it would be necessary the involvement of agents outside the firm, specially knowledge intensive partners, such as academics and scientist from universities, knowledge intensive business services, research institutions and other firms (Quatraro and Scandura 2019; Cainelli et al. 2015; De Marchi 2012; De Marchi and Grandinetti 2013, Tanner 2014). These agents can be accessed thanks to the establishment of research networks.

It is because of all the reasons above that we believe that the knowledge coming from an inventor’s network would be the most influential for her/him to start inventing in RE, followed by the knowledge in the firm, and finally the one from the region. All this said, we set our first hypothesis:

H1: *The most relevant source of general knowledge for an inventor to patent for the first time in RE is the knowledge coming from her/his network.*

We turn now to the consideration of whether the different sources surveyed above present a higher relevance in the case the knowledge flows

[3] On the contrary, distant ties can bring more diverse knowledge and ideas.

coming from within the RE technological domain. Indeed, an inventor can be influenced by the fact that other inventors in its environment (geographical location, firm, or network) get involved in the development of renewable energies. This could be a herd behavior, which has been shown to play an important role in technological transitions (Borup et al. 2006; Van Lente et al. 2013). For example, Bikhchandi et al. (1992) develop a model in which agents adopt a new behavior (in his case a new technology) depending on the decision of previous agents. In this model, an inventor might disregard her/his own information and adopt a new technology if a large enough number of successors have adopted it. Another network mechanism that operates is the word-of-mouth, in which an agent adopts a new item (in this case a technology) considering the information provided by previous adopters who belong to her/his network (Solomon et al. 2000; Hohnisch et al. 2008; Campbell 2013).

In this same line, social influence can play an important role of the adoption of an innovation under a *domino* effect (Granovetter 1978). Inventors in the RE field might need specific knowledge in such field to build up new ideas, and it is sensible to think that she/he can access it by judging the knowledge base in her/his environment. Finally, there could be a niche externality when a new technology is emerging (Zeppini et al 2014, Lopolito 2013) so that the more inventors engaged in RE innovation around a given inventor, the more incentives for an inventor to venture in this field as she/he would be socially influenced and would enjoy the knowledge externalities of developing such niche. If an inventor sees that some of her/his closest peers innovate in this field, she/he may also think it is worth working in the field, as she/he would also be able to benefit from the experience and knowledge of her/his partners.

As far as we know, previous empirical evidence has been restricted to the regional level. Colombelli and Quatraro (2019) find that for the emergence of green startups in Italian NUTS3 regions, the most important drivers are associated with a diversity of knowledge sources, although in related and complementary technological fields. Indeed, the regional development of new green technologies tend to be based on existing new patterns, given that mastering their knowledge base is often quite complex and multidisciplinary, involving high uncertainty if started from scratch (Braungart et al. 2007). As a consequence, several researchers such as Simmie (2012) and Boschma et al (2017) consider that radical advances to regional sustainability tend to be the exception and only applicable for few regions with enough capacity to create a new green niche far from the existing technological path. In addition, Montresor and Quatraro (2017) find that for regions to branch into green technologies, it is necessary the existence of both related green technologies and non-green related technologies.

On the other hand, as stated above, given that green technologies are at an early stage of development and are complex technologies that need knowledge from a variety of sources (Barbieri and Consoli, 2019), they tend to recombine pieces of knowledge that may be less cognitively proximate (Barbieri et al. 2020, Orsatti et al. 2020; Quatraro and Scandura 2019). In this sense, Barbieri and Consoli (2019) obtained that both related and unrelated variety had a positive impact on green employment growth in US MSAs. Similary, Makitie et al.(2018) and Zeppini and van den Bergh (2011) offer examples of how green technologies may arise from recombinant innovations that comprise non-green knowledge from a core or 'dirty' sector of the economy. However, these recombinations would be possible if their effectiveness prevents from lock-in in non-green sectors.

All in all, although applied to different scopes, there are arguments and previous evidence that would point to the fact that agents would benefit from existing knowledge in both related green technologies and non-green related technologies. We can formulate the following scheme to visualize the external sources of knowledge for an inventor and the type of influence they exert.

Figure 3. 1: External sources of knowledge for inventors

	Direct influence	**Indirect influence**
Specialized RE knowledge	Knowledge from coauthors previously patenting in RE	Knowledge from inventors in RE in the firm and the region
General knowledge	Knowledge from coauthors in any technological field	Knowledge in any technological field available in the firm and the region

In the following sections we will provide evidence on the roles that different sources of knowledge may have over an inventor for her/him to venture into the technological field of RE. Basically, we are firstly interested in the benefit obtained from the existing knowledge in the region where the inventor is located, from the firm where she/he works and from her/his network of co-authors. Secondly, we want to discuss if the sources with knowledge in the RE technological domain are more beneficial that from non-RE fields.

3.3. Data and empirical framework

3.3.1. The Data

We use data coming from two different sources. The first database is the ICRIOS 2016[4] patent data with which we identify the inventors, besides obtaining patent specific information such as the technological classification of the patent, its priority year, the region -NUTS3- it belongs to, among the main ones. The second database is the HAN database 2018 edition, coming from the OECD, allowing us to identify the applicants of the patents through harmonized names, which we use as proxy for the firms where the inventor has made the invention. These two databases are merged together into a single one using the application id code of patents.

As the aim of this chapter is to analyze the roles that different sources of knowledge may have over an inventor for her/him to venture for the first time into the technological field of RE, First, we identify the RE patents as those in any of the fields identified as such according to Jonhstone et al (2010)[5]. The, the sample consists of all the inventors who have more than one patent in a single firm, considering them from their second patent onwards. Also, the inventors in this sample are considered only if their first patent was not a RE patent. Finally, once an inventor patents in RE it is removed from the sample for the following periods. Notice that inventors whose first, second, third, etc, patent is not in RE are still considered because they have the probability to patent in RE in the future. The reason for this sampling method is to reduce the possible self-selection of inventors being in firms with the explicit task to innovate into the RE field, or a firm hiring an inventor with the explicit purpose of innovating in RE for the first time. If an inventor has been for some time in a firm producing inventions (patents) in fields different than RE, it means that such inventor did not arrive to the firm with the explicit task to produce RE innovation, reducing the problem of self-selection into the firm. Also, given that the 'agenda' of an inventor tends to be set up by the company, the characteristics and knowledge in the firm should explain why one of its inventors has switched into a new field, given that she/he already innovated before in a different domain in the same firm. This is also the reason why not considering the first patent of the inventors. Finally, only the patents that never changed ownership were considered into the sample, as this facilitated the identification of the ownership of the patents[6]. At the end, we have in our sample 215,553

[4] See Coffano and Tarasconi (2014) for more detail.

[5] See Table A3.1 of the appendix to see the complete list of IPC codes used to identify RE innovation.

[6] We use the PATLEGAL data contained in the ICRIOS dataset, which contains the legal record of a patent. We use those patents which have never changed ownership because this

inventors of which 1,954 ‘venture’ in RE innovation, representing 0.91% of the total number of inventors. There are in total 24,053 firms and 290 NUTS2 regions from the countries in the EU plus Switzerland and Norway, from 1975 to 2015.

Table 3.1 presents the differences between inventors who patent in RE and those who never did it, in terms of the knowledge sources they have. The figures presented in the table correspond to the comparison between an inventor prior to patenting in RE for the first time (second column) and an inventor patenting in any other field (third column). The first will be denominated as a RE inventor and the later as a non-RE inventor. We want to compare if the different knowledge sources, measured through the number of patents or inventors in the inventor’s region, firm or network, present a different average for RE and non-RE inventors.

With respect to the region, there seems not to be a significant difference in the extent of the regional stock of knowledge between the group of RE inventors and non-RE inventors. As shown, the average number of patents in the region is almost the same (with no statistically difference) for both categories. With respect to the firm, there is a statistically significant difference in the stock of knowledge (measured as the average number of patents), with non-RE inventors working in firms with a larger average stock of knowledge than the firms in which RE inventors work. Looking at the inventors’ network, RE inventors seem to have a network that on average has a bigger stock of knowledge than the ones of non-RE inventors (measured with the cumulative number of patents of the coauthors of a given inventor). In the same line, RE inventors would have bigger networks than non-RE inventors (using as proxy the number of coauthors a given inventor has).

The second part of Table 3.1 shows the average number of RE inventors that an inventor could have “met or known” in her/his region, firm and network, proxied with the number of inventors who have patented in RE before a given inventor in the three different levels. The results show that on average, a RE inventor has in her/his region more inventors who already patented in RE (prior the inventor patenting in RE) than a non-RE inventor and although this difference is small, it is significant. Also, RE inventors seem to work in firms where there were more RE inventors than in the firms where non-RE inventors work. Finally, at the inventor’s network level, having coauthors who have patented in RE before is more common for RE inventors than non-RE inventors. These results suggest that there seems to exist peer effects influencing an inventor to patent in RE for the first time, or at least increasing the probability of doing so. Especially, the knowledge

way we minimize the possible error of assigning a patent to a given firm by mistake, even though the EPO only tracks the change of ownership during the first nine months after the priority is granted.

from the coauthors and the workmates already working in RE are the ones which are more different.

Table 3. 1: Knowledge sources characteristics

	RE inventors	Non-RE inventors	Differences
General knowledge effects			
Number of patents in the region	1144.91	1140.46	
Number of patents in the firm	134.08	155.22	***
Number of patents of coauthors	62.71	43.49	***
Number of coauthors	5.45	3.86	***
Inventor's community effects			
Number of RE inventors in the region	31.05	27.11	***
Number of RE inventors in the firm	24.75	9.26	***
Number of RE coauthors	0.078	0.010	***

*** Significance at 0.01

These results suggest that the larger difference between inventors who venture in RE for the first time and those who do not lies in the closest environment, particularly in their network of colleagues. Inventors who patent in RE have in average more coauthors and these seem to be more productive as they have more patents. Also, inventors who venture in RE tend to be in environments with more RE inventors, both at the firm and the network level.

3.3.2. The model and variables

As the aim of this chapter is to analyze the drivers of an inventor patenting for the first time in RE, we will be using a binary outcome model where the outcome variable, y_i, is equal to one when the inventor *i* patents for the first time in RE and zero otherwise. As control variables we include proxies for all the effects presented in the conceptual framework. All the variables are lagged one year from the outcome variable to avoid possible endogeneity due to circular causality. At the regional level, to control for the general knowledge effect we include the variable $RegK_{r-i}$, which is the number of patents in the region *r* where the inventor resides, after removing all patents of inventor *i*. To control for the general influence at the firm level, a variable representing the knowledge available in the firm, $FirmK_{f-i}$, stands for all the patents of firm *f* minus the ones in which inventor *i* is included. To control for the sources of general knowledge coming from the coauthors, we will introduce the knowledge portfolio of the coauthors of inventor *i*, $NetK_{c-i}$ (measured as the number of patents of the coauthors of inventor *i*, detonated c, excluding those copatented with inventor *i*). It is worth mentioning that for the construction of these variables we excluded the ones in the RE technological domain.

For the specialized knowledge coming from sources in the RE technologies, at the regional level, we include the variable $RegRE_{r\text{-}i}$ which is the number of RE inventors in the region before we observe inventor i patenting in RE for the first time. Then, at the firm level we include the variable $FirmRE_{f\text{-}i}$, being the number of inventors with RE patents in the firm prior to inventor i patenting in RE. Then, a dummy variable, $NetRE_{c\text{-}i}$, equals to one if an inventor i had coauthors who previously patented in RE or 0 otherwise. Finally, the variable $OwnK_i$ represents the own previous stock of patents of the inventor i, capturing its capability for generating innovation.

The estimation method is a binary response model including inventor fixed effects (δ_i), firm fixed effects (φ_f), region fixed effects (ρ_r) and year fixed effects (τ_t). The sub index t has been suppressed to make reading easier, but remember that the outcome variable refers to year t and the explanatory variables to year $t\text{-}1$, to smooth double causality:

$$y_i = \alpha + \beta_1 RegK_{r-i} + \beta_2 FirmK_{f-i} + \beta_3 NetK_{c-i} + \beta_4 RegRE_{r-i} + \beta_5 FirmRE_{f-i} + \beta_6 NetRE_{c-i} + \beta_7 OwnK_i + \delta_i + \varphi_f + \rho_r + \tau_t + \varepsilon_i$$

According to our conceptual framework, we would expect ß3 and ß6 to be positive and significant and bigger than the rest of coefficients, as they represent the possible influence of a close tie incorporating knowledge from outside the firm. Nevertheless, the literature provides arguments in favor and against the fact that one could be bigger than the other. Regarding the rest of the coefficients, ß1 and ß2 could be positive if the knowledge available in the region or firm foster an inventor to patent in RE, for example if the knowledge available is close in cognitive terms, making easier the translation of knowledge from on technology to the other, or it its complementary. Could also be the case that these two coefficients are negative if the knowledge in the region and firm is distant to RE in cognitive terms. Then, ß4 or ß5, could be positive if an inventor would follow the behavior of its peers as in a herd. On the other hand, they could be negative if an inventor perceives that there are too many individuals already working in RE and find no space for itself. Finally, ß7 could be positive if the knowledge an inventor has accumulated is technologically close to RE or negative it is not.

3.4. Results

Table 3.2 shows the estimation of the probability of an inventor to patent in RE for the first time, given that she/he did not patent before in this field. The method of estimation in columns one is a Linear probability model (LPM) by Ordinary Least Squares. The amount of general knowledge in the region, the firm and the network of coinventors have a negative and significant impact over the probability of patenting in RE. This would mean that the general knowledge available to an inventor may not provide with enough ideas to come up with a patent in RE, or at least to build up the knowledge required to patent in RE for the first time. On the other hand, the number of inventor who previously patented in RE in the region, the firm and among the coauthors, present positive and significant coefficients. At the regional level, this could respond to a herd behavior, in which firms and inventors follow a trend to respond the growing demand for cleaner energy; or to a niche effect, in which there is a critical mass of inventors engaged in RE innovation that foster other inventors to get into the field. Within the firm or among the inventors of a network, this effect could be explained due a domino effect caused by the spread of the word from mouth to mouth. Finally, the number of previous patents of the own inventor seems not to have effect over the probability of an inventor in engaging in the RE domain.

In the second column we estimate a LPM this time including region, firm, year and inventor fixed effects with the purpose of controlling for possible omitted variables that could not be directly measured in the model. Given the large number of fixed effects needed, we use the methodology of Guimaraes and Portugal (2010) which allows the use of a large number of fixed effects in different categories, but at the cost of excluding the observations that not vary within any category. The results point in the same direction as when no fixed effect was included. The main difference is that this time the variables capturing the regional knowledge loose significance. This could imply that there are other regional characteristics that may incline an inventor to venture in RE innovation, besides the available knowledge. Also different from before, the previous patenting experience of the inventor has a positive and significant effect.

Given that using a LPM can have some drawbacks[7], we use now a binary estimation method such as the logistic one. In column three, where no fixed effects are included, the results are consistent with those found with the LPM without fixed effects. The general knowledge of the region, firm, and coauthors have again negative effects on the probability of patenting in RE for the first time. At the same time, the influence coming from the knowledge of other inventors involved in RE innovation is positive and significant. Taking advantage that these are the average marginal effects, of these three, the biggest is the one of the inventor's network, followed by the one of the firm and lastly the one of the region. In column four the results with region and year fixed effects are presented. The results are consistent with the earlier

[7] As we know a LPM can predict probabilities outside the zero to one interval, suffer from heteroskedasticity (that is why we use robust Standard errors) and its error terms are not distributed normally (nevertheless this is only a problem with small samples).

ones, pointing to the fact that general knowledge coming from the region, firm or coauthors does not foster an inventor to go into RE innovation, given that it patented in other field before. As before, the biggest and positive effect belongs to the variable indicating that the inventor has coauthors who previously patented in RE. The effect of the number of RE inventors in the firm is positive and significant.

Table 3. 2: Probability of an inventor patenting for the first time in RE

	(1)	(2)	(3)	(4)	(5)
Variables	LPM	LPM	LOGIT	LOGIT	FIRTHLOGIT
RegK	-0.000607***	0.000455	-0.000414***	-0.000425	-0.000416***
	(0.000193)	(0.000855)	(0.000140)	(0.000298)	(0.000139)
FirmK	-0.00240***	-0.00421***	-0.00223***	-0.00203***	-0.00224***
	(0.000159)	(0.000601)	(0.000183)	(0.000196)	(0.000184)
NetK	-0.000925***	-0.00183***	-0.000633***	-0.000653***	-0.000614***
	(0.000138)	(0.000232)	(0.000164)	(0.000166)	(0.000163)
RegRE	0.000935***	0.000238	0.000514***	0.000318	0.000521***
	(0.000193)	(0.000388)	(7.78e-05)	(0.000262)	(7.63e-05)
FirmRE	0.00355***	0.00471***	0.00179***	0.00192***	0.00179***
	(0.000244)	(0.000620)	(8.26e-05)	(9.64e-05)	(8.27e-05)
NetRE	0.0201***	0.0341***	0.0163***	0.0159***	0.0162***
	(0.00216)	(0.00357)	(0.00185)	(0.00182)	(0.00185)
OwnK	1.51e-05	0.000982***	-0.000107	-4.70e-05	-0.000104
	(0.000130)	(0.000263)	(0.000143)	(0.000145)	(0.000144)
REGION FE	N	Y	N	Y	N
FIRM FE	N	Y	N	N	N
YEAR FE	N	Y	N	Y	N
INVENTOR FE	N	Y	N	N	N
Observations	441,400	314,441	441,400	420,849	441,400
R-squared	0.003	0.430			

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1.

Marginal effects in all estimations. All explanatory variables are lagged one period and Z-standardized.

To estimate this model presents the challenge that the number of inventors who patent for the first time in RE (number of 1s) is considerably small compared to the number of inventors who do not patent in RE. This causes that a conventional binary estimation method results in the underestimation of the probability of the positive outcome and in biased coefficients (King and Zeng 2001). For this reason, we employ a method that directly deals with the rare event problem (King and Zen 2001). We use the Firth's maximum likelihood penalization to obtain unbiased estimates (Leitgöb 2013 and Puhr et al. 2017)[8]. The results point in the same direction as before, as general knowledge from the region, firm or coauthors has a negative marginal effect over the probability of an inventor patenting for the first time in RE. On the other hand, the influence of the number of inventors who previously have patented in RE at the regional, firm and network levels is positive and significant. Even more, again the biggest of these effects belongs to the variable indicating that an inventor has at least one coauthor who patented in RE. Finally, the previous patenting experience of the inventor does not have a significant effect.

Our results go against our arguments which pointed that the knowledge of the region, firm and coauthors would foster an inventor to switch to RE innovation. Contrarily, they suggest that this existing knowledge deters an inventor to patent in RE. A plausible explanation for this result could be that RE innovation needs specific pieces of knowledge and in certain amount to allow an inventor to change from the technological field she/he patented before. Also, another explanation would be how related to RE technologies is the knowledge available to an inventor. If the knowledge accessible to an inventor is too far in cognitive terms to the RE technological field, this would make harder to transit to patent in RE.

However, the results fully support the idea that the biggest marginal effect over the probability of patenting in RE was the one represented by the direct influence of the coauthors, although this is only true in the case of the knowledge of the coauthors that have already patented in the RE technological field. The direct contact through the network of coauthors would allow the transmission of the specialized knowledge necessary to patent in RE, but also coauthors could contribute to make a new field appealing to someone by discussing, making suggestions or simply by talking about their projects and experiences. These results are very much in line with those found by Orsatti et al. (2020), who find evidence that the general previous experience of both the firm and the inventors team in general technologies have a negative impact on the probability of patenting in green technologies and on the contrary, the previous experience of the firm and the inventors team patenting in green technologies impacts positively the probability of the team patenting in green technologies. Finally, it is worth noticing that the previous patent experience of the inventor did not play an important role. This may be because an inventor who previously patented in

[8] Nonetheless, this method can provide overestimated predicted probabilities within the zero to one interval (Puhr et al. 2017).

a certain field would find costlier to patent in a different field. It would need less effort to pursue a new patent in a field where it has some expertise.

3.5. Conclusions

This chapter tried to understand where the inventors who innovate in renewable energies get their knowledge from. What is the role played by the different sources of knowledge an inventor may have access to patent for the first time in RE, given that it patented before in another(s) field(s).

We use patent data coming from the ICRIOS data set and from the HAN data set of the OECD. The analysis focuses in European patents from 1975 to 2015. We test if the knowledge of the inventor's region, her/his firm and coauthors was relevant to patent in RE for the first time. At the same time, we try to test if there is a significant influence of the knowledge coming from other inventors (in the inventor's region, firm or network) who already patented in RE over inventors who had not. To tackle the possible problem of individuals sorting into firms to patent in RE or firms setting a RE agenda to their inventors, we selected those inventors who already patented in any other field but RE in a given firm. We argue that if an inventor already patented in given field, it would be costlier for her/him to patent in a different technology.

Contrary to our expectations, we could not find evidence that the general knowledge coming from an inventor's network of coauthors and firm increases the probability of an inventor to patent in RE for the first time. This could be because RE innovation needs specialized knowledge, so that knowledge in general may not be enough and, on the contrary, it would be easier for an inventor to extract the knowledge required to continue patenting in the same technological field she/he patented before.

On the other hand, we found evidence that knowledge coming from other inventors who patented before in RE is relevant for an inventor to start patenting in RE for the first time. And this is, as expected, especially true in the case of the knowledge coming from the inventor's coauthors. A reason behind these results could be that invention in the RE field needs specialized knowledge and it is better transmitted by those who already have experience on it. Also, this could suggest that the more inventors 'adopt' a technology, the more probable is that a new inventor will do it, either because they spread the word, because some niche externalities are generated, or simple because of the desire of not lacking behind in what they consider a promising field.

A consistent result is that the knowledge coming from the network of coauthors of an inventor as well as from her/his firm's colleagues plays a significantly positive impact, if they have already worked in RE technologies. And more specifically, the impact of the network is higher than the one of the firm, probably due to the fact that green innovation requires more heterogeneous sources of knowledge which in many cases forces the involvement of agents outside the firm. As stated before, complex knowledge can be transferred easily when strong ties between agents are present. What these findings tell regarding any policy that aims to foster the emergence of RE (and perhaps any other technology) in a certain region or firm is that for knowledge transmission it is necessary the interaction with people who already is experienced in such technological field. Maybe the best way to facilitate the learning process that entails innovation in a new field is by engaging novel inventors with experienced ones. Even more, as Fitjar and Rodríguez-Pose (2016) say "nothing is in the air" implying that knowledge is not floating in the air and individuals can grab it freely, but that actual knowledge flows take place through purposely built relations for this end. Any policy attempting the emergence or the switch to a new technology has to account for it. Constructing links between academics, inventors or any other expert in a field must be a pillar when trying to foster the transition to a new technological field.

3.6. Appendix

Table A3. 1: IPC codes identified as Renewable Energies

RE FIELD	IPC CODE
WIND	F03D
SOLAR PHV	H01L031/04, H01L031/05, H01L031/06, H01L031/07, H02N006/00, H01L027/142, F03G006, F24J002, H02N003, E04D013/18
GEOTHERMAL	F24J003/08, F03G004/00, F03G004/02, F03G004/04, F03G004/06, F03G007/04
OCEAN	E02B009/08, F03B013/10, F03B013/12, F03B013/14, F03B013/16, F03B013/18, F03B013/20, F03B013/22, F03B013/24, F03B013/26, F03G007/05
BIOMASS	C10L005/40, C10L005/42, C10L005/44, C10L005/46, C10L005/48, F02B043/08, C10L001, C10L003, C10L005, B09B001, B09B003, F23G005, F23G007, F01K025/14, F23G005/46, F01K027, F25B027/02, F23G005, F23G007, F02B043/08, F02G005

4. **Where do spices come from? The role of knowledge Relatedness and Unrelatedness in the probability of an inventor venturing in Renewable Energies**.

4.1. Introduction

In Economic Geography, technological diversification has been mostly driven by recombinant innovation fed by the knowledge available in the vicinity. Both under the related variety theory (Frenken et al. 2007), or in the technological space approach (Hidalgo et al 2007), there are knowledge flows between economic sectors that are related to each other and regions, countries, or cities diversify into technologies that are related to the ones they already possess. At the corporative level, firms branch into technologies or sectors that are related to their core capabilities (Silverman 1999; Breschi et al. 2003), as this benefits growth (Sapienza et al. 2003) and innovative performance (Makri et al. 2010 and Chen et al. 2012). This strategy would reduce costs of knowledge acquisition (Cantwell and Piscitello 2000) and easier management inside firms (Katila and Ahuja 2002; Leten et al. 2007).

In any case, in economics of innovation, a distinction is made between incremental and radical inventions. Innovation is mainly a recombinant process of related pieces of knowledge (Weitzman 1998). This would lead to incremental innovation as most alike knowledge would be easier to combine inside what Dosi (1982) called ‘technological trajectories’. On the other hand, radical innovation is regarded as more novel and disruptive, bringing into existence new technological trajectories. They are considered to make combinations across existing technologies not combined before (Fleming 2001; Schoenmakers and Duysters 2010). Unrelated knowledge can provide the new ideas that allow for the emergence of radical innovation (Flemming 2001) and high value patents (Castaldi et al. 2015, Miguélez and Moreno 2018). At the same time, unrelated variety would serve as a mechanism of risk diversification to damp negative shocks to particular sectors (Frenken et al. 2007).

Little has been said about the role of inventors in technological diversification, and particularly how related and unrelated knowledge affects them in this process. This study tries to contribute in this regard by attempting to study the influence of related and unrelated knowledge on inventors. It stresses the role of the inventor as the agent who drives the innovative process and therefore the emergence of new technological fields and capacities. Inventors are the ones who recognize a new problem and that conventional methods are not sufficient to solve it (Arthur 2007). They are the ones who put together all the knowledge they have available to create something novel to satisfy a need. Therefore, it is them who venture into something new when pursuing innovation.

More precisely, here we explore how related or unrelated knowledge can lead an experienced inventor to patent for the first time in a technology field she/he has not patented before. This chapter proposes that the contribution of related and unrelated knowledge depends on the type of proximity of the knowledge source to the inventor and how her/his previous knowledge relates to the new field. Here it is stated that the probability of an experience inventor to venture in a new technological field depends on the level of relatedness of her/his prior knowledge with the new field and also on the level of relatedness (or unrelatedness) between her/his knowledge and the knowledge sources from which she/he can feed from.

The chapter focuses on Renewable energies (RE from now on). First, because studying how RE innovation emerges has value on its own, as it is recognized the relation between technological innovation and the environmental sustainability of economic activity (Carraro and Siniscalco 1994, and Popp et al 2009) and that innovation in green technologies could change the relative productivity of regions or countries (Arundel and Kemp 2009), as innovation in green technologies can have a positive effect in firms productivity (Marin 2014; Colombelli et al. 2019) and regions (Aldieri et al. 2019). Second, green technologies (and RE in particular) are recognised as radical when compared to other technologies as they 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). Also, a distinctive feature of green innovation is that it requires more heterogeneous sources of knowledge (Dechezlepretre et al. 2011; Horbach et al. 2013; Ghisetti et al. 2015), given that is necessary the involvement of agents outside the firm, specially knowledge intensive partners, such as academics and scientist from universities, knowledge intensive business services, research institutions and other firms, too (Quatraro and Scandura 2019; Cainelli et al. 2015; De Marchi 2012; De Marchi and Grandinetti 2013, Tanner 2014). Thus, RE can be a technological sector with specific interest in itself.

Even more, Marzucchi and Montresor (2017) argue that eco-innovation heavily relies on an ‘Analytical knowledge base’, through the interaction with scholars and academic institutions. That is, eco-innovation would rely importantly on scientific, universal laws and abstract knowledge (Asheim 2007). This would allow eco-innovation to enjoy from unrelated knowledge, as long as the knowledge gap with this unrelated knowledge could be saved thanks to science-based knowledge. In other words, Science-based, abstract knowledge would allow the interaction of seemingly unrelated knowledge (Asheim et al. 2017; Grillitsch et al. 2018). These characteristics pose the technological class of RE as a good candidate to explore the different roles that different sources of knowledge could have over an inventor when is about venturing into a new field.

Previous literature has already studied the relation of eco-innovation and knowledge relatedness. At the regional level, for example, Colombelli and Quatraro (2017) find that for the emergence of green startups (in RE) in Italian NUTS3 regions, an important driver is the knowledge stock of related technologies. Also, Corradini (2017), in the same line as the previous study, finds that regional related variety is positively related to green innovation[1]. Montresor and Quatraro (2019) find that for regions to branch into a kind of green technology, it is necessary the existence of both related green technologies and non-green related technologies, along with the presence of key enabling technologies. Tanner (2014) deviates a bit from the previous studies finding that for the emergence of the fuel cell industry at the regional level, the degree of relatedness of this field with the already existing technologies is an important factor, but also remarks that it is not a prerequisite as also finds evidence of the fuel cell industry emerging where there were no related technologies, making a claim for unrelated regional branching.

This chapter adds to the previous literature by looking at the individual level; it intends to construct on the above studies by looking at the very individuals who have to interact to acquire knowledge from their environment. As inventors do not work in isolation, they are exposed to different sources of ideas and new knowledge that are subject to different types of distances (Boschma 2005). Here we intend to construct on this idea by arguing that the role of related and unrelated knowledge is linked to the (kind of) proximity between the source and the recipient. Ultimately, as the interaction between individuals is what allows the knowledge to flow from one to the other, the closer they are (the closer their interaction), the easier would be the transmission of ideas between them.

We analyze the European case which, for the first time, has surpassed the United States in innovation performance[2] and to stay competitive, the European Commission proposed a budget of 100 billion euros in research and innovation programmes (Horizon Europe) to promote ground-breaking innovation (Hollanders et al. 2019). In this context this study can contribute to the discussion and design of public policies.

The rest of the chapter is organized as follows. In Section 4.2 the conceptual framework is developed. Section 4.3 presents the methodological approach and section 4.4 deals with the results. Finally, Section 4.5 concludes.

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[1] And particularly that the effect of related variety has an inverted U shape, meaning that at some point, the possibility to enjoy from a successful recombinatory process from related varieties is exhausted and regions reach a cognitive lock-in (Corradini 2017).

[2] But still lags behind Japan and South Korea, while China is catching up (Hollanders et al. 2019).

4.2. Conceptual framework

Literature has acknowledged different types of distance (or proximity) among individuals, but of all, cognitive distance would be the prerequisite for a meaningful exchange of knowledge that can give place to innovation (Nooteboom 2000, Boschma 2005). Meanwhile other types of distance (social, organizational, institutional and geographical) would be instrumental to bring agents together and to allow their interaction, and consequently, the exchange of ideas (Boschma 2005). For this author, geographical proximity along with cognitive proximity would be enough to make agents interact and engage in interactive learning, while the other types of proximity may act as substitutes of geographic proximity. Nonetheless this last one is neither sufficient, nor a prerequisite (Boschma 2005).

4.2.1. Cognitive proximity

For Nooteboom (2000), individuals have a cognitive function, which is the way they map what they observe into categories in their minds. Cognitive distance means having different cognitive functions. In other words, the cognitive distance between two individuals is the difference in how these two individuals *make sense of*' of a certain phenomenon. The more similar the way two individuals understand a phenomenon, the closer they are in cognitive terms. Too much cognitive proximity would not be good for the process of innovation, as agents that have too similar ideas would not add anything new to the exchange of knowledge to create a new idea, although the communication would be fluid. On the opposite side, agents that are too far in cognitive terms would not be able to convey information in an efficient way, as they would not understand each other, blocking the creative process. At the same time, in regional diversification literature it is argued that countries or regions diversify into technologies or sectors that share common knowledge and capabilities (Hidalgo et al. 2007; Boschma et al. 2014; Balland et al. 2019). This would be due to the ease to transfer skills thanks to cognitive proximity. This would imply that this happens at the individual level too.

As said before, inventors are the ones who recognize the new needs that emerge in societies and find new ways to solve them (Arthur 2007). An inventor who wishes to contribute in a certain field may have knowledge that is related and unrelated to this new field. The degree of relation between her/his stock of knowledge and the one in the new field would allow her/him to enter more easily into the new field due to the less cognitive distance between her/his own knowledge and the knowledge foundation of the new field. This would be due to that the learning rate is considerably higher among related tasks, than among unrelated or specialized tasks (Schilling et al.

2003). This is because the knowledge of one can be transferred to the other easier. Opposite, unrelated knowledge would harden the entrance of an inventor to a new field, as she/he would have harder time learning the insights of the new technology and at the same time communicating with her/his new peers. All this leads us to set the first part of our first hypothesis:

H1A: *The probability of an experienced inventor to patent in RE for the first time would be positively influenced by the degree of relatedness between the inventor's knowledge portfolio and the RE technological class.*

Also, as inventors do not operate in isolation, they use existing knowledge created by other individuals in different institutions/organizations (Arora and Gambardella 1994; Breschi and Lissoni 2001; Fleming 2001; Weitzman 1998) not necessarily in the close proximity (Whittle et al. 2020). To acquire this knowledge, they have to, in most cases, interact with other people. The knowledge an inventor possesses prior to any interaction would determine her/his absorptive capacity, that is, the capability of the inventor to understand and embrace new knowledge (Cohen and Levinthal 1990). We claim that the extent to which the new knowledge coming from different sources can be applied to a new field would depend on the level of relatedness between the inventor's prior knowledge portfolio and the knowledge in the new field (in our case, RE). In other words, the link between the external knowledge accessible to an inventor and how it is applied into a new field would be mediated by the level of relatedness between the knowledge of the inventor with the one in the new field. That is, the level of relatedness between the inventor's knowledge and RE would be the tool to channel the new knowledge found elsewhere into RE innovation. This leads to our next hypothesis:

H1B: *The level of relatedness between the inventor's knowledge portfolio and the RE technological class would mediate the effect of the knowledge flows to which an inventor has access on her/his probability to patent in RE for the first time.*

As said before, inventors interact with other individuals and can get ideas and knowledge from them. It would be necessary the interaction with agents not to close, not too far (in cognitive terms) from oneself to be able to engage in a productive interactive learning process that could end up in innovation (Nooteboom 2000). This suggests that there must be an optimal cognitive distance between the sender and the recipient of the knowledge that favors innovation (Nooteboom et al. 2007). We argue that the mentioned equilibrium would be reached by the mix of knowledge sources an inventor has. Different sources would contribute with closer or more distant knowledge in cognitive terms.

4.2.2. Cognitive proximity in relation to other types of proximity

We consider that an inventor can source knowledge for herself/himself in three different spheres, which would be linked to three different types of proximity. These are the inventor's network, linked to social proximity, the firm where she/he works, linked to the organizational proximity and her/his regional context, linked to the geographical proximity. The cognitive distance would interact with the social, organizational and geographical distances to reach the before mentioned equilibrium. The different types of distances would allow for a certain degree (or a way) of interaction between agents and, in this way, also influence the cognitive distance between them. For instance, the level of interaction between coauthors, that are purposely built relations (Crescenzi et al. 2016; Fitjar and Rodríquez-Pose 2017), would be much more intense than the interaction among agents in a local context just hearing the 'local buzz' of Bathelt et al. (2004).

Social proximity would diminish cognitive distance, as close ties would facilitate the transfer of cognitive far (or unrelated) knowledge, while organizational and geographic distance would favor mostly the flow of cognitive close (related) knowledge, as interaction between individuals would not that fluid or intense. As cognitive distance would be smaller among coauthors, they would be able to transmit more dissimilar knowledge among them. On the other hand, the related knowledge and ideas that foster venturing in a field in which one does not have previous expertise would come from the firm and regional sources. In this sense, an inventor, in order to venture in a new field, would take the knowledge from different sources and the main contribution of cognitively close or cognitively far knowledge would be linked with the type of distance that governs the interaction of the inventor and a given source. In other words, different sources of knowledge might contribute with different amounts of related (cognitively close) and unrelated (cognitively far) knowledge to the creative process of an inventor, particularly, to the probability of an inventor patenting in RE for the first time.

4.2.3. Relation between social proximity and cognitive proximity

Social proximity within networks is increasingly acknowledged as a key mechanism to understand knowledge flows underlying interactive learning and innovation (Sorenson et al. 2006; Agrawal et al. 2008; Breschi and Lissoni 2009). Inventors group as a way of sharing the risk of innovation (Crescenzi et al. 2016) and to gain access to research infrastructure and funds (Freeman et al. 2014). Also, as the amount of knowledge increases and becomes more specialized, inventors have to group to gather the necessary pieces for creating something new, which reinforces the returns of specialization and promotes collaboration as means to handling the growing demand for specialized knowledge Jones (2009). Maybe, most importantly, social networks provide formal and informal linkages through which information can flow between individuals, transcending the workplace and institutional settings without mediating market mechanisms (Lobo and Strumsky 2008)[3]. Social proximity enables trust, close collaboration and promotes accurate and efficient communication and information diffusion (Cowand and Jonard 2004, Schilling and Phelps 2007, Uzzi and Spiro 2005). For Sorenson et al. (2006), social or professional networks lower the cost of accessing knowledge of the members. Closer connection grants better access to knowledge and facilitates communication and interactive learning, and as a consequence, it may also increase innovative performance.

As tacit knowledge cannot be codified and transferred easily (Maskell and Malmberg 1999), close contact, as inventors in teams, would favor direct communication between agents and the process of interactive learning. Complementarily, close links are potentially more useful for transferring knowledge that is complex and not easily codifiable (Ghoshal et al. 1994; Uzzi 1996; Hansen 1999). Direct relationships induce more trust, improving individuals to share knowledge (Singh 2005). Then, it would be reasonable to expect that the most important knowledge source for inventors may be the network. Even more, when knowledge is moderately complex, closer ties are better for knowledge transmission (Sorensen et al. 2006)[4]. On the other hand, social proximity can have a detrimental effect on innovation, as agents can have opportunist behavior taking advantage of the trust of their peers, or by 'locking-in' in the knowledge of the network, losing sight of new opportunities and ideas (Uzzi 1997; Boschma 2005).

Empirical literature has found that the knowledge composition of inventors' teams can have influence on their innovation performance. For example, Melero and Palomeras (2015) find that it is important to have a generalist inventor (inventors who have knowledge in many areas, but maybe not in depth) as part of the team, because they can serve as bridge between the highly specialized knowledge of other team members, enhancing the overall productivity. In a similar vein, Bercovitz and Feldman (2011) find supportive evidence that the ability of a team to combine diverse knowledge (measured as the distance between the areas of expertise of its members) has a positive effect on the probability coming up with a successful innovation. Particularly for RE, Orsatti et al. (2020) found that the capacity of an

[3] Knowledge diffusion tends to be local rather than global, as for early stage technology innovation direct contact is necessary (Lobo and Strumsky 2008).

[4] On the contrary, distant ties can bring more diverse knowledge and ideas.

inventor’s team to recombine unrelated knowledge has a positive impact on the probability of the patenting in green technologies[5].

As complex and tacit knowledge is harder to transmit, social proximity in the form of a team of inventors would provide more cognitive proximity. Since eco innovation is more complex in terms of its knowledge base than other fields (Renning and Rammer 2009; Ghisetti et al. 2015) and would require more heterogeneous sources of knowledge (Dechezlepretre et al. 2011; Horbach et al. 2013; Ghisetti et al. 2015), then it could be expected that among co-authors, the social and cognitive proximity among them would facilitate the transfer of knowledge that would be unrelated (therefore harder to understand and transmit) to an inventor. With this argumentation, our second hypothesis would be:

H2: *The inventor’s network of unrelated knowledge would be more relevant than the network of related knowledge for the probability of an experienced inventor to patent in RE for the first time.*

4.2.4. Relation between organizational proximity and cognitive proximity

At the same time, inventors are most of the time part of a bigger organization and are therefore embedded in relations framed by the organization’s institutionalized routines. This is the organizational proximity, which is represented by institutional arrangements within organizations (Boschma 2005). Organizational proximity facilitates innovation since it reduces uncertainty, limits the risk of opportunism, and supports communication between actors (Cassi and Plunket 2014). A firm can be seen as a set of resources or capabilities targeted to get advantages from its competitors and gain profit (Wernerfelt 1984, and Rubin 1973). In order to do so, firms innovate to reduce costs, increase quality, capture or create new product markets and reduce reliance in unreliable production factors (Webster 2007).

To facilitate innovation, managers must design schemes to facilitate the flow of information and create adequate conditions for knowledge transmission (Cooper 1990 and Souitaris 2002). Firms are a good environment for knowledge transmission, as inside them knowledge can flow faster because they possess the organization structure, procedures and routines to maintain and transfer the information and know-how from one agent to the other (Kogut and Zander 1992; Lai et al. 2016). Also, the way a

[5] More interesting is that when the previous experience in green technologies is high, the effect of the recombinatory capacity has a negative effect on the probability of patenting in green technologies, while when the team has low green experience, then the recombinatory capacity exerts a positive impact on the probability of patenting in RE.

firm acquires knowledge is important for inventors' performance[6]. For instance, the amount of scientific knowledge of a firm can enhance its absorptive capacity which would boost its innovation production, take higher advantage of new knowledge produced outside the firm, say in universities or public institutes (Gambardella 1992). Firms use innovation to strength their core technological capabilities and improve their performance and consolidate their position among competitors (Teece 2007). In this sense, firms would diversify into related technologies as this would reduce risk (Valvano and Vannoni 2003), at the same time of acquiring new knowledge at a lower cost (Cantwell and Piscitello 2000). Most importantly, R&D efforts would be more useful in related fields and easier and cheaper to transfer among different business units. It could be said that firms would exploit cognitive proximity. The unrelated diversification of a firm would entail higher R&D costs, and would increase learning and communication costs, and R&D efforts could be disarticulated, making management more difficult (Katila and Ahuja 2002; Leten et al. 2007).

For example, Silverman (1999) finds that the probability of firm patenting in a new industry depends positively on the degree of relatedness between the new industry and the knowledge portfolio of the firm. Breschi et al. (2003) find that firms branch into technologies that are related to the firm´s portfolio; Sapienza et al (2003) find that the growth of firms' spin-offs are positively related to the core technologies of the parent firm. In a similar vein, Chen et al. (2012) find that related knowledge diversification boots innovation and growth. Finally, Makri et al (2010) finds that the innovative performance of post merged firms is positively correlated with the degree of knowledge relatedness of the two parts. The evidence in extant literature seems to point to the fact that firms would most likely diversify into related technologies. As it would be easier to internally circulate new knowledge that is close to the knowledge already existing, firms would contribute with the innovative process with related knowledge more than with unrelated knowledge. In this sense, interactive learning inside firms would be framed

[6] Firms can access two types of sources of knowledge to innovate: the external ones and the internal ones. External knowledge is the one coming from outside the firm, for example, from the interaction with customers, suppliers, and other institutions such as universities and research centers (Medase and Abdul-Basil 2019; Linder and Sperber 2019). The internal sources of knowledge are the characteristics of the firm that affect the innovation process and are part of the firm. Previous papers have underscored the importance of internal knowledge as it is the one that determines the absorptive capacity of firms to acquire external knowledge and how it enables innovation in more radical technologies (Vega-Jurado et al. 2008; Cohen and Levinthal 1990). The reason behind is that external knowledge needs a degree of understanding between the parts engaged in the exchange of knowledge, so that the more complicated the content of the exchange, the more difficult to be transmitted (Sorenson et al. 2006).

by the rules and mechanisms of the firm that would favor the flow of related knowledge. Following this reasoning, our third hypothesis would be:

H3: *The firm's related knowledge would have a positive and higher effect than the unrelated knowledge on the probability of an experienced inventor patenting in RE for the first time.*

4.2.5. Relation between geographical proximity and cognitive proximity

Also, geographical proximity matters, as it provides an advantage to individuals and firms that are located close to each other by facilitating direct face-to-face interaction and a more direct access to knowledge. The regional context is key for innovation, as it is shown in the literature that knowledge spillovers are spatially bounded (Bottazzi and Peri 2003) and that regions provide the innovation agents with the institutional infrastructure to produce knowledge (Cooke 2002, Todtling and Trippl 2005). The knowledge available in an inventor's region can be used as input for new ideas. Literature has documented the geographic localization of knowledge flows in regions and how important they are for innovation (Audretsch and Feldman 2004; Fritsch and Franke 2004; Peri 2005). Particularly, there is evidence of knowledge flows between inventors inside regions and that these are spatially bounded (Jaffe et al. 1993 and Murata et al. 2013). Even more, Ibrahim et al. (2009) finds that the strongest defining characteristics of colocation of inventors is the access to collective knowledge (freely available in the vicinity).

The spatial proximity between individuals would allow interaction, leading to exchange of ideas and knowledge mostly within related technological fields. Regional diversification literature has found that relatedness between technological fields can allow diversification into new related technological fields at the country level (Hidalgo et al. 2007) and at the regional level (Boschma et al. 2014, Balland et al. 2019). On the other hand, unrelated knowledge at the regional level can provide the new ideas that allow for the emergence of radical innovation (Flemming 2001) and high value patents (Castaldi et al. 2015, Miguélez and Moreno 2018). Technological relatedness implies not only proximity in cognitive terms, but also in terms of capabilities (Hidalgo et al. 2007) as in supply changes, where individuals from the innovative realm and from outside (suppliers, competitors, customers) have to interact. Interactive learning between individuals would have to be among agents with different backgrounds, so in order to transmit knowledge, it should be cognitively proximate to all. This would be the reason why countries diversify into related industries (Hidalgo et al. 2007). We argue that at the regional level, the knowledge that would be easier to transfer would be the related one, because there would be more heterogeneity of actors and knowledge. Therefore, knowledge flows would be of the related knowledge type rather than of unrelated knowledge type. Our fourth hypothesis emerges:

H4: *The region's related knowledge would have a positive and more important effect that unrelated knowledge over the probability of an experienced inventor patenting in RE for the first time.*

4.3. Methodology

This section will describe the data used, the main tools used to operationalize the concepts of proximity and will end describing the variables and model used to test the hypotheses.

4.3.1. The data

To test our hypotheses, we use data coming from two different sources. The first database is the ICRIOS 2016 patent data with which we identify the inventors (besides obtaining patent specific information such as the technological classification of the patent, its priority year, the region - NUTS3- it belongs, etc.) The second database used is the HAN database 2018 edition, coming from the OECD, allowing us to identify the applicants of the patents through harmonized names, which we use as proxy for the owner firms. These two databases are merged together into a single one using the application id code of patents.

The aim of this chapter is to predict the probability of an experienced inventor to go into RE for the first time. First, we identify the RE patents as those in any of the fields identified as such according to Jonhstone et al (2010)[7].Then, our sample consists of all the inventors who have more than one patent in the same firm, considering them from their second patent onwards. Also, the inventors in this sample are considered only if their first patent was not a RE patent. Finally, once an inventor patents in RE, she/he is removed from the sample for the following periods. Notice that inventors whose first, second, third, etc., patent is not in RE are still considered because they have the probability to patent in RE in the future. The reason for this sampling method is the possible self-selection of inventors into firms with the explicit task of innovating into renewable energies, or a firm hiring an inventor with the explicit purpose of innovating in RE. If an inventor has been for a while in a firm producing innovation (patents) in fields different from RE, it means that she/he did not arrived at the firm with the explicit task of inventing in RE. In other words, she/he did not self-select into the firm. Also, even if the 'agenda' of an inventor is set by the company, then the

[7] See Table A4.1 of the appendix to see the complete list of IPC codes used to identify RE innovation.

characteristics of the firm should help explaining why one of its inventors switched into a new field, given that it already innovated before. This is also the reason for discarding the first patent of the inventors. Finally, only the patents which never changed ownership are considered into the sample, as this facilitates the identification of the ownership of the patents[8]. At the end, our sample consists of 215,553 inventors of which 1,954 'venture' in RE innovation, representing only 0.91% of the total number of inventors. There are in total 24,053 firms and 290 NUTS2 regions from EU countries plus Switzerland and Norway, from 1975 to 2015.

4.3.1.1. Relatedness and Unrelatedness

First, we operationalize cognitive relatedness as technological relatedness, that is, when two industries share a common or complementary knowledge base and rely on common scientific and/or engineering principles (Breschi et al. 2003). We calculate the relatedness between technologies with the co-occurrence of two different IPC classification codes in the same patent document. We control for the fact that this co-occurrence can be random and caused by chance, by normalizing our measure using a probabilistic measure presented by Ferrer-i-Cancho and Solè (2001) and Van Eck & Waltman (2009) that controls for the fact that random co-occurrences exist. We take the four-digit, second level of disaggregation of IPC in order to get a total number of 612 technological classes (RE included)[9] for the period from 1981 to 2015. Specifically, the normalized co-occurrence between technologies *i* and *j* (ρ_{ij}) is calculated in the following way:

$$\rho_{ij} = \frac{nc_{ij}}{c_i c_j} \qquad (4.1)$$

where n is the total number of patents, c_{ij} is the number of patents in which technologies *i* and *j* are observed at the same time, c_i is the number of patents catalogued in technology *i* and c_j is the number of patents catalogued in technology *j*[10]. Two technologies are said to be related when $\rho_{ij} > 1$,

[8] We use the PATLEGAL data contained in the ICRIOS dataset, which contains the legal record of a patent. We use those patents which have never changed ownership because this way we minimize the possible error of assigning a patent to a given firm by mistake, even though the EPO only tracks the change of ownership during the first nine months after the priority is granted.

[9] The IPC codes corresponding to RE were grouped as a single one. Also, only the IPC codes that were present in all the years were considered.

[10] The probabilistic measure of co-occurrence can be expressed in terms of probabilities: $\rho_{ij} = \frac{P(i \cap j)}{P(i)P(j)} = \left(\frac{c_{ij}}{n}\right) \Big/ \left(\frac{c_i}{n}\right)\left(\frac{c_j}{n}\right)$

meaning that the two technologies i and j co-occur more frequently than would be expected by chance. Conversely, the two technologies are unrelated when they are not related i.e. when $\rho_{ij} = 0$, which means that technologies *i* and *j* are not observed in any patent[11]. We compute one co-occurrence matrix 612x612 where each entry is ρ_{ij} for five-year time windows from 1981-1985 to 2011-2015. These matrices are turned binary assigning 1 when $\rho_{ij} > 1$ and 0 when $\rho_{ij} = 0$, letting aside the values of ρ_{ij} higher than zero up to 1[12]. These matrices provide a list for every technology i of all the technologies that are related and another list of all technologies unrelated for each 5-year window.

4.3.2. The main variables

4.3.2.1. The inventor's knowledge

To construct the inventor's knowledge portfolio, first, for every inventor all her/his patents were collected along with their respective IPC technological classification. Then, for every year, a list of all the technologies is made. Finally, for every year t+1, the list of technologies was constructed adding the technologies in year t+1 and the ones up to year t in a cumulative process. This way, for every year a list of all different technologies in which an in inventor has patented so far in time is created. Note the assumption that knowledge is cumulative, and we are not using a discount factor for elder knowledge, as it is also assumed that the principles of a certain technology might change slowly. We call this final list of technologies by year the *inventor's knowledge portfolio*.

To capture the level of relatedness or unrelatedness of a given inventor's knowledge portfolio, this was contrasted with the list of technologies that are related to RE and with the list of unrelated technologies to RE[13]. Then, for every year we compute the ratio of the number of distinct technologies in the portfolio that are related to RE in the numerator over the total number of distinct technologies in the portfolio in the denominator. This provides an index between zero (no technologies are related to RE) and one (all technologies are related to RE). A similar procedure was performed using the list of unrelated technologies to RE. We called these two indexes, for

[11] $\rho_{ij} = \frac{P(i \cap j)}{P(i)P(j)} = \frac{P(i|j)p(j)}{P(i)P(j)}$, when $\rho_{ij} > 1$ implies $\frac{P(i|j)}{P(i)}$>1; $p(i|j) > p(i)$ meaning that observing j increases the probability of observing i than observing i on its own. When $\rho_{ij} = 0$ implies that $p(i|j) = 0$.

[12] As $0 < \rho_{ij} \leq 1$ would imply that $0 < p(i|j) < p(i)$, still a positive probability.

[13] Remember that no inventor has patented in RE so far and once she/he does, she/he is removed from the sample, so no inventor has RE in her/his knowledge portfolio.

inventor g in year t, *the inventor's related to RE portfolio* ($IRre_{gt}$) and *the inventor's unrelated to RE portfolio* ($IUre_{gt}$), respectively.

4.3.2.2. The coauthors' knowledge

To proxy the knowledge of the coauthors, first, for a given inventor (the focal inventor), all her/his coauthors are identified using the patents they share. Then, all the patents of this list of (co)inventors was constructed. After removing all the patents of the focal inventor from this list, the list of different technologies by year was built to apply a cumulative process as in the case of the inventors' knowledge portfolio. We called this list *the coauthors' knowledge portfolio*. Then, we count how many technologies from the inventor's portfolio are related (and unrelated) to the technologies in her/his coauthors' portfolio. Similarly as before, two indexes are constructed where in the numerator we find the number of distinct technologies of the inventor's portfolio that are related (or unrelated) to the coauthor's portfolio, and in the denominator the total number of distinct technologies of the inventor's portfolio (both related and unrelated technologies). We call these two indexes *the coauthors' related and unrelated portfolio*, respectively. This way, for inventor g, we name CRK_{gt} the rate of relatedness between inventor g's knowledge portfolio and her/his coauthors' in year t. In an analogous way, CUK_{gt} is the rate of unrelatedness between inventor g's knowledge and her/his coauthors'.

4.3.2.3. The firm's knowledge

In a similar way as with the coauthors, for a focal inventor all her/his patents in a given firm are identified, the same as all the patents of this firm from which we remove the ones of the focal inventor. Once more, the cumulative list of technologies of this firm was created and contrasted with the inventor's knowledge portfolio. Two indexes were constructed, where in the numerator goes the number of technologies of the inventor's knowledge portfolio that are related (unrelated) to the firm's knowledge portfolio, while in the denominator we find the total number of technologies in the inventors' portfolio. These two indexes are called *the firm's related knowledge for inventor g* in firm f and year t (FRK_{gft}) and *the firm's unrelated knowledge for inventor g* in firm f and year t (FUK_{gft}).

4.3.2.4. The regional knowledge

In the case of the regional knowledge portfolio, again all the patents of a focal inventor are removed from the patents listed in her/his region of residence. Then, a list of technologies by year is constructed in which only the technologies in which the region has revealed technological advantage are kept, as we assume that at this level the relevant knowledge flows would be from technologies in which the region is good compared to the rest of EU regions[14] as in Hidalgo et al. (2007), Boschma et al. (2014) and Balland et al. (2019). Again, the accumulation of different technologies by year is constructed and we call this list of technologies in which the region has revealed technological advantage *the regional knowledge portfolio*. We then proceed to count how many technologies of the inventor's knowledge portfolio are related (and unrelated) to the regional portfolio and we compute similar indexes as before. Therefore, the *index of knowledge relatedness of inventor g with her/his region* r in year t (RRK_{grt}) is the ratio between the number of technologies in the inventor's knowledge portfolio that are related to technologies in her/his region and the total number of technologies in her/his portfolio. In the same way, the *index knowledge unrelatedness of inventor g with her/his region* r in year t (RUK_{grt}) is the ratio of the number of technologies in the inventor's knowledge portfolio that are unrelated to technologies in her/his region and the total number of technologies in her/his portfolio.

4.3.3. The model

This section describes the method for testing the hypotheses. As the aim of this chapter is to analyze the drivers of the probability of an experienced inventor patenting for the first time in RE, the analysis will be using a binary outcome model, y_g, where the outcome variable is equal to one when the inventor *g* patents for the first time in RE and zero in any other case. The key explanatory variables are the ones presented before. Additionally, we control for the previous knowledge in RE of the coauthors of the given inventor (Cre_g), the previous knowledge in RE of the firm (Fre_{gf}) and the previous knowledge in RE in the region (Rre_{gr}). These variables are proxied with the number of patents in RE technologies in the coauthors team, in the firm and in the region, respectively. We estimate a binary response model including region fixed effects (φ_r) to control for characteristics at the macro level, like cultural issues at the regional level and year fixed effects (τ_t) to control for the current economic environment. The sub index *t* has been suppressed to make reading easier, but keep in mind that the outcome variable is year *t* and the explanatory variables are given in year *t-1* to avoid circular causality issues[15]:

[14] The revealed technological advantage, RTA, is defined in the following way:

If $\frac{patents_{ir}/\sum_i patents_{ir}}{\sum_r patents_{ir}/\sum_r \sum_i patents_{ir}} > 1$, then RTA = 1 and 0 otherwise.

where $patents_{ir}$ represents the total number of patents in technology *i* in region *r*. Having a RTA in technology *i* would imply that the region is more specialized in such technology than the EU average. The RTA is calculated for every one of the five years.

[15] See table A4.2 in the appendix for a definition of each variable.

$$y_{gfr} = \alpha + \beta_1 IRre_g + \beta_2 IUre_g + \beta_3 CRK_g + \beta_4 CUK_g + \beta_5 FRK_{gf} + \beta_6 FUK_{gf} + \beta_7 RRK_{gr} + \beta_8 RUK_{gr} + \beta_9 Cre_g + \beta_{10} Fre_{gf} + \beta_{11} Rre_{gr} + \varphi_r + \tau_t + \varepsilon_i \quad (4.2)$$

According to our conceptual framework, we would expect ß1 to be positive and significant and bigger than ß2, as this would mean that the inventor having a knowledge background close to RE would favor her/him entering this field. Meanwhile, if ß2 is positive and significant would mean that also unrelated knowledge to RE is necessary, maybe as a catalyzer of other's knowledge. On the other hand, if it is negative, it would imply that the cognitive distant to a technology field would be an obstacle to venture in it.

Regarding the knowledge coming from the coauthors, ß3 and ß4, according to our previous hypotheses, could be both positive and significant. Particularly, ß4 should be positive, as this would imply that those extra 'ingredients' to venture into a new field would come apart from an inventor's expertise. For ß3 we would expect to be positive, as the cognitive proximity between professional mates would allow knowledge to flow and contribute in the innovative process. Nevertheless, if ß3 is negative this would imply that among partners, too much cognitive proximity leads to an exchange of redundant knowledge.

Regarding the knowledge of the firm, ß5 is expected to be positive and significant, because, as said before, firms would encourage the flow of knowledge inside their core capabilities, making for them better to strength the capabilities of their inventors and exploiting them. On the other hand, ß6 would be expected to be negative as in line with the previous argument.

At the regional level, we claimed that the interaction between individuals would mostly allow related knowledge flows, as the proximity would be mostly driven by space, rather than in cognitive terms. Therefore, related knowledge flows would be more relevant, that is ß7 would be positive and significant. In the case of ß8, we would expect it not to be significant or negative, as only spatial proximity would be acting in the interaction of individuals and not cognitive proximity. Finally, ß9, ß10 and ß11 would be positive as they represent the direct effect that knowledge already specialized in RE have on the probability of an inventor to patent in RE for the first time. Although we would expect ß11 < ß10 < ß9, as the closest knowledge to the inventor would be more influential.

To investigate the mediating effect of the knowledge related to RE of an inventor over the knowledge she/he has access in her/his network, firm and region, we add to the previous equation the interaction terms between the knowledge related to RE of the inventor with the related and unrelated knowledge of the coauthors, the firm and the region. The degree of relatedness to RE of the knowledge of an inventor could enhance the effect of related knowledge from other sources and even make unrelated knowledge more useful as it could allow an inventor to make sense of distant pieces of knowledge into a way that could be applied to RE.

4.4. Results

Table 4.1 shows the results of the estimation of the model described before. The estimation method is a Logit regression (where all the coefficients represent the marginal effects), including region and year fixed effects. Regarding H1A the evidence supports it, as with the Logit, *IRre* would have a positive and significant coefficient. Then, in all the estimations of table 4.1, *IUre* has a negative coefficient (and significant), suggesting that the further the inventor's knowledge from RE in cognitive terms, the smaller the probability to venture in this field. And inventor whose previous knowledge is cognitively distant to RE might find difficult to understand key concepts of RE and apply her/his knowledge and skills. Also, learning the necessary knowledge and skills of RE technologies would be more challenging and costly, deterring her/his from pursuing innovation in this field. On the other hand, being cognitively close to RE, and inventor can apply some of her/his knowledge to understand concepts and knowledge specific to RE with less effort.

The level of relatedness of the coauthors' knowledge and the inventor's knowledge, *CRK*, has a negative and significant coefficient. This could be due to the fact that the related knowledge of the coauthors would be redundant and would not contribute with the necessary ideas to pursue innovation in a field where one does not have expertise or the knowledge of the coauthors would be not suitable or even divergent to RE. In fact, it could be blocking new ideas that could lead to venture in RE. On the contrary, as stated in H2, the coefficient of *CUK* is positive and significant, meaning that for an inventor to patent in a new field for her/him, departing from the knowledge of her/his peers would provide with the new ideas and knowledge she/he may need. Also, it could mean that the novel knowledge of the network of an inventor could provide with fresh and relevant knowledge to an inventor to venture in a new field.

The degree of relatedness between the firm's and the inventor's knowledge, *FRK*, has a negative significant coefficient, rejecting H3. It would be the case that the related knowledge of the firm is too apart from RE innovation and may discourage an inventor to venture in it. If the firm's knowledge on its own does is not close to RE, then would not incentivize an inventor to venture in this field. At the same time, the degree of unrelatedness, *FUK*, does not show conclusive evidence across the different estimations. We can say that these last two results refute H3. Knowledge of firms, being related or unrelated to that of the inventor, would not be what is necessary for an inventor to start inventing in RE.

Then, the degree of relatedness of the regional knowledge with that of the inventor (*RRK*) does not have a significant effect. In this case, we would reject H4. The knowledge that is in the region that is easy to grasp by the inventor because its proximity in cognitive terms would be redundant for her/him. On the other hand, the level of unrelatedness has a negative and significant coefficient, also rejecting H4. It could be that the amount of knowledge that is available at the regional scale is so big that the one that is at cognitive reach of an inventor is redundant, while the one that is cognitively distant is out of reach due to the lack of a bridge (as interactive learning with others) with the skills of an inventor. Finally, column 2 presents the estimations including the previous RE experience of the coauthors, the firms and regions. The variables *Cre* and *Fre* have positive and significant coefficients, suggesting that the previous experience in RE would provide with specific insights of this technology that might ease the path for a novel inventor in this field. This result is pretty much in line with that of Orsatti et al (2020), as the previous experience in eco-innovation of the members of a team of inventors or the one of the firm have a positive impact in the probability of a team of inventors patenting in eco-friendly technologies. On the other hand, *Rre* has a negative and significant coefficient maybe because once too many inventors enter a new field like RE, so a lot of the knowledge available in a region is related to this field, this can cause a crowding out effect for the ones that are planning to do so.

In the remaining columns of Table 4.1, interaction terms of *IRre* and the rest of the related and unrelated variables are introduced. First thing to notice is that the level of relatedness with the inventor's knowledge has a negative coefficient now, and also the level of unrelatedness as before. These two results would suggest that the knowledge an inventor has, no matter if it is related or unrelated to a technological field, is not enough to drive her/him into that field or to produce a new idea in it. This can be due to the higher degree of knowledge specialization needed. As innovating requires every time more specialized knowledge, being able to 'make sense of' the knowledge of a field would not be enough. The change of sign of the effect of *IRre* could be reflecting that the level of relatedness of the inventor's knowledge with RE incentivizes the inventor to venture in this field as long as it is combined with other's knowledge. This result would weaken H1A.

The level of relatedness of the knowledge of the coauthors with the knowledge of the inventors, again, has a negative effect on the probability of an inventor patenting in RE. On the contrary, the unrelatedness with the knowledge of the coauthors (*CUK*), again has a positive coefficient, strengthening the support to H2. The interaction of the degree of relatedness with RE and the relatedness of the coinventors has a positive and significant effect, suggesting that the knowledge of the coauthors would provide useful incremental ideas to RE as long as the knowledge of the inventor can direct that knowledge to RE, in line with H1B. The interaction of *IRre* and *CUK* presents a negative coefficient. This is inconclusive evidence for the role of *IRre* as a catalyzer of unrelated knowledge, in line of H1B. The coefficient of *FRK* alone is negative again, dropping H3 as before; while when interacted with *IRre*, it would turn positive. In line with the two previous estimations, *FUK* would not have an important effect on the probability of patenting in RE for the first time, even when interacted with *IRre*. This would mean that knowledge that is cognitively distant would be of no use to the inventor when considering entering to RE, even when her/his own knowledge is related to RE.

The level of relatedness or unrelatedness of the inventor's knowledge and the region's knowledge would not have a relevant impact on the probability of the inventor venturing in RE. The positive coefficient of the interaction of *RUK* and *IRre* is noticeable. It might be the case that having distant knowledge to the core capabilities of the regions is good for patenting in RE, especially if one's knowledge is related to RE. If the core capabilities of the region are distant to RE in cognitive terms, an inventor can turn this as a source of inspiration or of novel ideas. This, combined with her/his knowledge applicable to RE could be helpful to venture in RE. To end with Table 4.1, again, the results concerning the importance of the specialized experience of the coauthors and the firms in RE, show to have a positive effect. Probably, to patent in RE needs a specialized knowledge and inventors must take hand of it from their closest sources.

Table 4. 1: Probability of an inventor patenting in RE for the first time

VARIABLES	(1)	(2)	(3)	(4)
IRre	0.00263***	0.00258***	-0.0286***	-0.0283***
	(0.000263)	(0.000263)	(0.00269)	(0.00282)
IUre	-0.0139***	-0.0129***	-0.00983***	-0.00920***
	(0.000881)	(0.000858)	(0.000650)	(0.000639)
CRK	-0.00401***	-0.00379***	-0.00573***	-0.00536***
	(0.000237)	(0.000240)	(0.000311)	(0.000311)
CUK	0.00454***	0.00360***	0.00577***	0.00496***
	(0.000308)	(0.000313)	(0.000419)	(0.000422)
FRK	-0.0100***	-0.00947***	-0.0109***	-0.0104***
	(0.000348)	(0.000347)	(0.000443)	(0.000444)
FUK	0.000600*	3.96e-05	0.000919**	0.000578
	(0.000325)	(0.000333)	(0.000424)	(0.000435)
RRK	0.000382	0.000371	-0.00140	-0.00106
	(0.00171)	(0.00174)	(0.00158)	(0.00162)
RUK	-0.0146***	-0.0140***	-0.0145***	-0.0145***
	(0.00173)	(0.00176)	(0.00160)	(0.00164)
IRrexCRK			0.00835***	0.00771***
			(0.000661)	(0.000654)
IRrexCUK			-0.00277***	-0.00266***
			(0.000528)	(0.000538)
IRrexFRK			0.00796***	0.00757***
			(0.000792)	(0.000795)
IRrexFUK			-0.000969	-0.00102
			(0.000627)	(0.000636)
IRrexRRK			0.00399	0.00325
			(0.00436)	(0.00433)
IRrexRUK			0.0219***	0.0229***
			(0.00507)	(0.00512)
Cre		0.000211***		0.000178***
		(9.61e-06)		(8.53e-06)
Fre		3.54e-05***		2.66e-05***
		(2.47e-06)		(2.15e-06)
Rre		-6.22e-06***		-5.08e-06***
		(1.42e-06)		(1.36e-06)
Observations	420,740	420,740	420,740	420,740

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.5. Conclusions

The purpose of this chapter has been to analyze the interaction of cognitive proximity with other types of proximity and how these can influence the probability of an inventor to patent in a field in which she/he has not patented before. The chapter focused on the probability of patenting in RE, as this is a new field, which extant literature has recognized feeding from heterogeneous sources of knowledge. The main argument was that cognitive proximity would be the key, but other types of proximity would also allow for the diffusion of knowledge and hence influence the innovative process (Boschma 2005). For this purpose, we use European patent data of the European Patent Office, EPO, for the period 1981 to 2015, and focused on the inventors, as they are the ones who ultimately produce the innovation.

Our results suggest that for an inventor venturing into a new field, in our case RE, it is necessary for her/him to have knowledge that is cognitively close to the new field. More specifically, for an inventor entering RE innovation, she/he must have a background that allows her/him understanding the new field and apply her/him own skills. Also, we found evidence of the need of fresh ideas and knowledge to venture in a new field. Our results provide evidence that it is not only necessary to access knowledge that is distinct to the one we have to venture in new fields, but it is even more important that this knowledge comes from the source of external knowledge that allows more interaction: the coauthors. As they would have direct contact and hence interaction, they can build a common knowledge and, at the same time, would communicate and exchange their own distinguishing knowledge and skills. This would contribute with novel ideas that could lead to new fields.

This can be explained by the knowledge-based approach of Asheim et al. (2007), in which activities can be classified in broad epistemic categories rather than in technologies. For this approach, there are activities with a high analytical knowledge base, that is, activities whose core has a high content of science-based knowledge and abstract concepts[16]. This would allow the flow of seemly unrelated knowledge, but with high analytical content, which would make the communication between individuals with different backgrounds easier, as long as they stay in the realms of analytical knowledge based activities (Grillitsch et al. 2018). This could be relevant for RE innovation, as it is a new technological field with high science-based knowledge (Marzucchi and Montresor 2017).

[16] Other activities would have a synthetic knowledge base, in which knowledge is based in learning by doing knowledge and business relation, i.e. more practical knowledge. There is also the symbolic knowledge-based activities, in which knowledge is based in cultural values, meanings and symbols (Asheim et al. 2007).

Firm and regional knowledge would not play a role as important as the one from the coauthors. Firm knowledge would be mostly driven to reinforce its technological capabilities, so unless the firm is dedicated to eco-innovation, it would not have incentives to foster RE innovation. At the regional level, knowledge may be so disperse that when is cognitively close could be redundant to new ventures and when is cognitively distant would only be useful, and maybe so through a catalyzer or specific knowledge that would allow an inventor to see a new opportunity. Finally, although it is not part of our hypotheses, the importance of specialized RE knowledge among the coauthors and the firm was found an important driver for the probability of an inventor patenting in RE for the first time.

The 'not too close, not too far' knowledge would be reached by the interaction between cognitive and other kinds of distances. In fact, our results point to the idea that that equilibrium is reached by the knowledge composition of the team of inventors. In other words, the balance between close and distant knowledge necessary to avoid a 'cognitive lock-in' or inefficient communication would be reached inside the inventor's team. The results of this chapter support the idea that for innovation is necessary the interaction of individuals with diverse backgrounds, when the goal is to acquire new capabilities or enter a new technological field. When designing any innovation policy or drawing a managerial plan to boost innovation, this should be taken into account.

4.6. Appendix

Table A4. 1: Correlation between relatedness matrices

	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010	2011-2015
1981-1985	1.00						
1986-1990	0.57	1.00					
1991-1995	0.54	0.62	1.00				
1996-2000	0.53	0.60	0.64	1.00			
2001-2005	0.51	0.59	0.62	0.65	1.00		
2006-2010	0.50	0.58	0.60	0.63	0.66	1.00	
2011-2015	0.50	0.57	0.60	0.61	0.63	0.65	1.00

Table A4. 2: Variable definition

Name	**Description**
IRre	Inventor's knowledge related to RE
IUre	Inventor's knowledge related to RE
CRK	Level of relatedness between the inventor's and the coauthors' knowledge
CUK	Level of unrelatedness between the inventor's and the coauthors' knowledge
FRK	Level of relatedness between the inventor's and the firm's knowledge
FUK	Level of unrelatedness between the inventor's and the firm's knowledge
RRK	Level of relatedness between the inventor's and the regional knowledge
RUK	Level of unrelatedness between the inventor's and the regional knowledge
Cre	Level or relatedness between the coauthors' knowledge and the RE technological class
Fre	Level or relatedness between the firm's knowledge and the RE technological class
Rre	Level or relatedness between the regional knowledge and the RE technological class

Table A4. 3: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12
1. y	1.00											
2. IRre	0.01	1.00										
3. IUre	-0.04	-0.31	1.00									
4. CRK	-0.06	0.00	-0.11	1.00								
5. CUK	-0.01	0.08	-0.01	0.40	1.00							
6. FRK	-0.14	0.01	-0.02	0.28	0.13	1.00						
7. FUK	-0.06	0.07	0.03	0.19	0.25	0.49	1.00					
8. RRK	-0.23	0.02	0.02	0.04	0.03	0.09	0.05	1.00				
9. RUK	-0.23	0.02	0.03	0.04	0.03	0.09	0.05	0.99	1.00			
10. Cre	0.06	0.06	-0.04	0.07	0.18	0.02	0.04	-0.01	-0.01	1.00		
11. Fre	0.04	0.11	-0.07	0.09	0.16	0.08	0.19	-0.02	-0.02	0.18	1.00	
12. Rre	0.01	0.06	-0.11	0.11	0.16	0.07	0.08	0.02	0.02	0.06	0.08	1.00

5. Conclusions

5.1. Summary of findings

This PhD thesis tried to contribute in the Innovation and Economic Geography literature by studying the nature of knowledge flows that could foster innovation in Renewable Energies as a special technological field with economic and technological opportunities (Rennings 2000; Barbieri et al. 2018), in a climate change world scenario that threatens long run growth. More precisely, this dissertation tried to answer the general question *Where does the knowledge that feeds RE innovation comes from?* In the pursue of this goal, this dissertation included three chapters providing a different perspective of the role of knowledge flows in fostering RE innovation. Conceptually, it relies in two arguments, one is that knowledge flows from one individual to another, and second, the notion that knowledge and ideas are necessary to create new ideas. In other words, that innovation is conceptualized as a recombinatory process in which knowledge flows are a source of new ideas.

In the second chapter, the empirical analysis used geolocalized patent data to proxy technological innovation and patent citations to capture the knowledge flows (as Jaffe et al. 1993). The analysis was centered in European regions, from the year 2000 to 2010. A regional production of RE innovation was measured by counting the number of patents of a region in this field and used the citations made by all the patents in a region to capture the incoming knowledge flows. A distinction between citations to scientific documents and other patents was made to capture the incoming knowledge from science and the knowledge coming from technical sectors. Taking as foundation the knowledge-base conceptual framework found in Moodysson et al. (2008) and Asheim et al. (2011), it was stated that RE innovation tends to have stronger foundations on analytical knowledge (science-based and abstract content); then, the ideas needed for its development are more subject to codification and, consequently, travel easier across space. Hence, geographical proximity would be less important for the diffusion of relevant knowledge for RE. The results showed that RE would enjoy from knowledge flows from science and academia in a higher extent than the bulk of innovation. Also, knowledge flows that feed RE innovation would be less localized than the ones that nurture other technologies. These results suggest that, contrary to previous literature, knowledge flows would be less geographically localized depending on the technology. The explanation could lay on the knowledge nature of RE technologies.

Then, focusing on the inventor, as the agent generating new knowledge, the third and fourth chapters tried to explain the probability of an experienced inventor venturing in RE innovation. In the third chapter, the aim was to understand the role of possible knowledge flows from each of three sources: the inventor's network associated to social proximity, the inventor's firm associated to institutional proximity and the regional context associated to physical proximity. In each case, we differentiated whether the knowledge came from the RE technological domain or not. In this chapter, again, patent data is used to identify the inventors residing in Europe, their coauthors network, the firms where they would work and the regions where they reside, covering a broad period from 1981 to 2015. Using a binary response model, where the dependent variable was dichotomous equal to one when an inventor ventured for the first time RE, the main finding suggested that the most important driver for an inventor to patent in RE was the influence from her/his professional network, specifically having a coauthor who already have innovated in RE before (but not with the inventor herself/himself). This would imply that close interaction and specific knowledge are necessary for an inventor to venture in patenting in RE. This finding suggested that the relations of inventors in their networks transcend the local realm, if considered what it was found in chapter two.

The fourth chapter tried to understand the role of proximity in a different way. It tried to disentangle how the different shapes of proximity can influence the emergence of RE innovation. The corner stones for this chapter were i) the cognitive proximity concept, which is the similarity of how two agents understand the same phenomena (Nooteboom 2000); ii) that knowledge flows through interaction among individuals; and that iii) proximity (or distance) can have different shapes (Boschma 2005). It was argued that interaction between individuals can be framed inside networks, firms or regions, each linked to social distance, organizational and geographical respectively, each seen as a source of knowledge. Cognitive proximity would be the channel within these three sources to acquire knowledge, and use it to venture in RE innovation. We relied on the concepts of technological relatedness and unrelatedness (Hidalgo et al. 2007; Boschma et al. 2014, Balland et al. 2019) to capture cognitive proximity.

The main finding of this chapter would be the relevance of the cognitive proximity (or relatedness) of the knowledge of the inventor and RE technologies. It showed to be one of the keys for an inventor to venture in RE innovation, either because the inventor can directly apply it to RE or as channel to use the external knowledge into RE innovation. Additionally, an important message was that cognitive distant knowledge is also relevant for venturing in RE. As the unrelated knowledge of the coauthors showed to be relevant, it could be said that it is necessary some new, distant, knowledge to get new ideas, but this knowledge needs of social proximity to be transmitted.

5.2. Policy implications

The most important policy recommendation emanating from the findings of this dissertation is the fact that any policy design aiming to foster innovation in RE has to take into account the nature of this field of technology. First, one needs to take into account the higher content that scientific knowledge has in the case of RE. This implies that policy makers have to promote synergies and collaboration between academy and industry. Already previous literature has found the importance of the scientific community for innovation in RE (Marzucchi and Montresor 2017; Trajtenberg et al. 1997; Verhoeven et al. 2016; Quatraro and Scandura 2019; Fabrizi et al. 2018).

Also, policies aiming at fostering RE innovation should be designed taking into account the need of specific knowledge and, specifically, the consideration the collaboration between experienced inventors in RE and those without. Therefore, any policy that seeks to promote RE innovation should first try to identify the sectors from which it would be easier to transit to RE. In a similar vein, the findings from chapter four suggest that close interaction is necessary to convey distant, maybe complex, knowledge. As innovation in RE would be catalogued as more complex technology field (Renning and Rammer 2009; Ghisetti et al. 2015; Marzucchi and Montresor 2017), any policy has to seek to build teams that accomplish the collection of necessary specialized knowledge and capabilities and at the same time the novelty of ideas and points of view to provide freshly new ideas.

5.3. Limitations of the research

It is worth to say, however, that some limitations are present in this work. For starters, using patent data has some caveats. For instance, 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).

Also the nature of the data presents some limitations. In chapter two not counting with more detailed data about the citations to scientific sources poses challenge to the results, as would be interesting to find if these knowledge flows are also localized. Then in chapters three and four, identifying inventors and the firms they belong using patent data is challenging. Although the database used was already taking care of this caveat, identifying inventors and their firms in a precise way implied removing some inventors, as was not possible to identify all their patents in a confident way, nor the firms they worked in.

Another limitation is the external validity of the findings. Although along the dissertation, the internal consistency of the study was a priority, it could be argued that the external validity of the conclusions lacks strength. The results found for RE technologies could not hold for other technologies. Technologies that also are more recent could have more in common with RE than technologies that have been present for longer. Chapter two brought this topic into discussion. On the one hand, it was found evidence suggesting that the share of the industrial sector in the regional economies (in terms of employment) had a negative impact on the production of RE innovation. The reasons that were exposed there would be the still heavy reliance of industry in traditional energy sources, as RE are not good enough in producing intense heat yet, and the externalization of R&D services. Also in this same chapter, a comparison with other novel technologies was performed. The results also pointed to the singularity of RE innovation.

5.4. Future avenues for research

Finally, this dissertation hopefully can give place to further paths of research. First, from chapter two, 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 chapter, 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.

Chapter three and four lead to further research in the relation of the different types of proximity and innovation in RE. Cognitive proximity is what matters for knowledge exchange, and a thin equilibrium would be necessary to produce innovation. As Nooteboom (2000) states, proximity in cognitive terms is needed to enable understanding between individuals, but it is also necessary a certain extent of distance to allow novelty to emerge. These two chapters lead to a path of research in which the focus in how cognitive proximity relates to inventors networks. For example, how networks are constructed based on the knowledge proximity of its members in order to get this equilibrium of proximity and distance.

Also, in chapter four was explored the role of cognitive proximity between the inventor's knowledge with that of the possible sources of knowledge (network, firm or region). However, investigating the role of the level of cognitive proximity of the knowledge from these sources with respect to RE is a pendent task. Already in chapter three the influence of inventors with already experience in RE over inventor was studied. It was found that, for an inventor venturing in RE innovation, the most important factors are having as coauthors inventors who already patented in RE and also inventors in the firm that also did so. It is expected that these people contribute with knowledge specific to RE or at least related to RE. On the other hand, in chapter four was found that the level of unrelatedness of an inventor with that of her/his coauthors had a positive effect on the probability of an inventor venturing in RE.

Thus, it is necessary to investigate how these results from different chapters can be reconcile. One option is that the high importance of peers with previous experience in RE is the ingredient that offers that novel and necessary knowledge input for an inventor to venture in RE. This would imply that for an inventor, the effect of having among her/his coauthors, some that already patented in RE would be analogous to the effect of unrelated knowledge of the coauthors, so the unrelatedness would be between an inventor’s knowledge and the RE knowledge (RE experience from the coauthors). Another option is that the peer effect of the coauthors in chapter three is analogous to the effect of the level of relatedness between the coauthors’ knowledge in chapter four. As in chapter four the relatedness with the coauthors’ knowledge only has a positive effect on the probability of venturing in RE when combined with the level of relatedness of the inventor’s knowledge with RE, this would imply that the coauthor’s peer effect of chapter three would have to be complemented with already related knowledge to RE by the side of the inventor.

Additionally, turning back to the findings in chapter two, investigating if coauthors are academics would also enrich the debate. Measuring how important is the participation of academic inventors in RE innovation and their contribution would be an interesting insight. For this it would be necessary to count with information regarding the background of the inventor. With this, it would be possible to control for their relative participation inside teams or the academic fields they work on. Having information about the academic background of inventors, could allow to study if unrelatedness in technological terms can be bridged by having a similar knowledge base as claimed by Asheim et al. (2017) and Grillitsch et al. (2018).

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