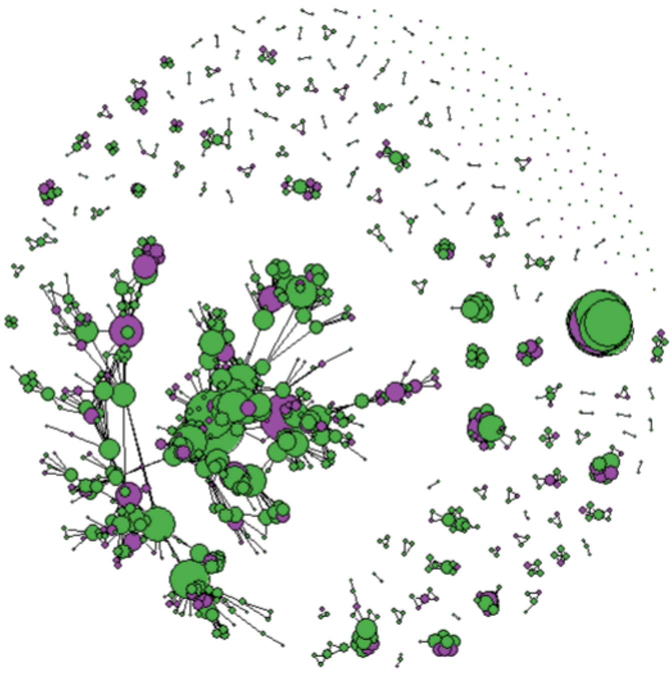
Master's Thesis – master Innovation Sciences

Regional knowledge networks towards innovation in the field of renewable energy



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Abstract

Climate change is one of the greatest threats that humanity is facing today. Minimizing its effects can only be achieved through a future of renewable energies (REs). Therefore, innovation in this sector plays a key role in achieving environmental objectives to curb this threatening scenario before it is too late. Previous studies have shown the great impact the characteristics of knowledge networks have on the innovative performance of regions in general and in certain technologies in particular. These networks are defined as a variety of actors, which are interconnected by collaborative relationships that enable or constrain the diffusion, transfer and acquisition of knowledge and information, and thus influence innovative output. Interestingly, this approach has hardly been investigated in the energy sector despite the emphasis on collaboration being key towards successful energy innovations. Therefore, the main objective of this thesis is to answer the question of how the characteristics of a region´s RE sector knowledge network influence regional innovation in this sector.

To this end, several hypotheses are proposed relating different characteristics of regional knowledge networks to the RE innovative performance of 270 European NUTS 2 regions between 2003 and 2017. These include characteristics referring to both intra-regional and inter-regional collaborations and are classified in three main types: structural (overall connectedness and cohesive subgroups), proximity (geographic and technological proximity) and actor-specific (intermediaries and gatekeepers). For the construction of the variables, RE patents were used. Hypothesis testing has been done using regression analysis on three main models. One considering all patents in removable energy (baseline model), and two energy-specific for solar energy (solar model) and wind energy (wind model).

The results reveal that an overall a loosely coupled regional network structure impulse innovation in RE, although, it is important that there are cohesive subgroups of inventors within it. It is also key that the region receives external knowledge from beyond its closest neighbours and that this is to some extent similar to the region's RE technology base. Finally, it is desirable to have actors in charge of disseminating internal and external knowledge throughout the groups of actors of the regional network.

This thesis offers a new point of view through the analysis of knowledge networks to the study of regional innovation in RE, which we consider useful both for future studies in this field and for policy makers seeking to improve the regional performance of their regions in RE.

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Abbreviations

CDD	Cooling Degree Days
CPC	Cooperative Patent Classification
EU	European Union
GDP	Gross Domestic Product
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
NB	Negative Binomial
NECP	National Energy Climate Plan
NUTS	Nomenclature of Territorial Units for Statistics
OECD	Organisation for Economic Co-operation and Development
PV	Photovoltaics
RE	Renewable energy
R&D	Research and Development
SNA	Social Network Analysis
UN	United Nations
UK	United Kingdom
VIF	Variance Inflator Factor

1. Introduction

Addressing climate change is a major global concern that has been gaining increasing attention over the years. More effort is needed to change the current situation, or the or the consequences will be very harmful for to ecosystems, economic sectors, human health, and well-being (Boehm et al., 2021; IEA, 2019). Two of the most influential bodies in providing international policy advice regarding the energy transition, the International Renewable Energy Agency (IRENA) and the International Energy Agency (IEA), have claimed the importance of promoting technological innovation in the energy sector to accelerate the energy transition and meet the global net-zero emissions target by 2050 (IEA, 2019; IRENA, 2021). This relevance of energy innovation is also supported by several scientific studies (Böhringer et al., 2020; Bointner et al., 2016; Markard, 2018). Fundamentally, they claim that innovation is critical to deliver solutions in the energy system towards increasing its efficiency and sustainability.

However, innovating in the energy sector is not an easy task, quite the contrary. Energy technologies tend to be large, complex and designed to endure for many years (Laimon et al., 2020; Ridha et al., 2020). Thus, the IEA on its report on "Technology Innovation to Accelerate Energy Transitions", highlights that counting with a strong regional innovation ecosystem is key to guarantee sustainable energy results over time (IEA, 2019). This ecosystem is complex, requiring the interaction of a wide range of actors (private firms, public and private research organizations, government, citizens, etc.) not only to generate innovativeness but to integrate it in the energy system. Furthermore, attention at the regional level to accelerate the energy transition is growing (Larruscain et al., 2017; Li et al., 2020a, 2021). The main reason is that international frameworks set global policies and targets, however, states have autonomy to set their own low-carbon targets and specific measures. A reason being that the regional energy context is key to determining their objectives (Hoppe & Miedema, 2020; IEA, 2019).

At the European level, we can observe significant inequalities in countries' progress in innovation towards transition by looking at how their share of renewable energy (RE) in their final energy consumption has evolved over the years. For instance, when comparing Denmark with Slovenia between 2004 and 2019, we can find a considerable difference. In Sweden the share of RE energy from the total consumed grew by 21.7%, while in Slovenia only 6.6% (Eurostat, 2022b).

Moreover, scientific literature in sustainable transition studies increasingly claims that research should take a more systemic and collaborative approach on the energy transition (Larruscain et al., 2017; Markard, 2018). In particular, the lack of collaborative perspectives prevents us from having a more complete vision of how the different actors and technologies that conform the innovation system in the energy sector interact to develop new innovations towards the energy transition (Larruscain et al., 2017).

In this regard, a large body of research in innovation studies has claimed the importance of knowledge networks in facilitating innovation (Breschi & Lenzi, 2016; Graf, 2017; Innocenti et al., 2020; Krätke, 2010). Here, knowledge networks are understood as a variety of individuals and organizations, which are interconnected by collaborative relationships that enable or constrain the dissemination, transference and acquisition of knowledge and information, and thereby the creation of new innovations (Schutte & du Preez, 2008). Knowledge development and diffusion related to sustainable energy technologies has been claimed to be fundamental for innovation and technological development for climate change mitigation (Li et al., 2021). This study follows this research tradition by investigating how the role of knowledge network structures can influence for regional innovation in the sustainable energy sector.

A promising method to study collaboration between (energy sector) actors and its influence on innovation to accelerate the energy transition is Social Network Analysis (SNA). Numerous studies have already analysed knowledge networks and their impact on innovation employing SNA (Boschma & Frenken, 2009; Guan & Liu, 2016a; Hemphälä & Magnusson, 2012). However, most of these studies focus on specific companies or territories, depriving us of a more systematic vision of innovative systems, across companies and regions. Moreover, a new body of research has found evidence of the impact of knowledge networks on regional innovation performance (Innocenti et al., 2020; Kauffeld-Monz & Fritsch, 2013; Marrocu et al., 2013; Pan et al., 2020). They claim that the innovative capacity of the region varies depending on different structural network properties of a region, for example its cohesion, proximity to the regions with which it collaborates, and types of organizations that comprise it.

However, despite the calls for a more systematic understanding of collaboration in sustainable innovation systems (Markard, 2018), and the claims for a regional approach to combat climate change (Hoppe & Miedema, 2020), very few articles have looked into regional knowledge networks specifically for the renewable energy sector (Larruscain et al., 2017; Li et al., 2021; Nordensvard et al., 2018). Furthermore, most studies on both regional knowledge networks towards innovation in general and in the sustainable energy field, are focused on specific characteristics of the network. Those are for instance in relation to its structure (Innocenti et al., 2020), the position of certain actors (Gallo & Plunket, 2020; Kauffeld-Monz & Fritsch, 2013) or the different types of proximity of inter-regional collaborations (Marrocu et al., 2013; Pan et al., 2020).

This thesis aims to fill those gaps by analysing a broad set of network characteristics (structural, proximity and actor-specific) of regional energy sector knowledge networks and how they influence innovation in RE towards accelerating the energy transition.

Therefore, the following research question guides this research:

> ***How do the structural, proximity, and actor-specific characteristics of a region´s renewable energy sector knowledge network influence regional innovation in renewable energy?***

Firstly, the focus is on the overall network connectedness and degree of cohesion among subgroups of the regional network as those properties prove to have a strong influence on regional innovation (Innocenti et al., 2020). Secondly, we look at two types of inter-regional proximities and its effect on the regional innovation in RE. Collaboration with external regions has been claimed to be important in the development of sustainable energy innovations (IEA, 2019; Li et al., 2021). According to several authors, how proximate are these collaborations impacts the innovative the innovative performance of a region (Kalapouti & Varsakelis, 2015; Marrocu et al., 2013; Pan et al., 2020). In this research we focus on geographical and technological proximity as both have been claimed to be the highly relevant on regional innovation (Marrocu et al., 2013; Pan et al., 2020). Specifically, those who act as a bridge in the transfer of knowledge between groups of actors in the network and who are key to the dissemination of new knowledge in the region, which are gatekeepers and brokers. Both types of actors are widely recognized in the literature to play a key role in innovation at the regional level (Graf, 2011; Graf & Krüger, 2011; Kauffeld-Monz & Fritsch, 2013; Piazza et al., 2019).

In this way, in order to support the central question, three sub-questions relating to the three sets of network characteristics (structural, geographic and actor-specific) are formulated:

1. **Structural characteristics**: *How does the structure of the renewable energy knowledge network of a region, in terms of overall connectedness and cohesion of its subgroups, affects its innovative performance in the RE sector?*

2. **Proximity characteristics**: *How does the inter-regional proximity of a region's actors' collaborations with other regions, in terms of geographical and technological proximity, affect its innovative performance in the RE sector?*

3. **Actor-specific characteristics**: *How does the presence of gatekeepers and brokers in the renewable energy knowledge networks of a region affects its innovative performance in the RE sector?*

To address each of these sub-questions, we study inventor networks in the renewable energy sector in European Union (EU) regions plus the United Kingdom (UK), Norway and Switzerland in the period 2003 to 2017. A series of hypotheses based on regional network theory and its influence on regional innovation, as well as regional innovation in RE, are proposed. Regression analysis is used to test these hypotheses, while SNA tools are employed to construct the variables of the study.

This thesis presents several contributions to the literature. First, by investigating the characteristics of knowledge networks in RE, it responds to the demand for a new collaborative approach to research innovation in the sector. Second, it adds to existing studies on knowledge networks and regional innovation by combining in a single study multiple characteristics that have proven to be relevant. In this way, it is possible to know whether they are all equally significant, or whether some are more important than others. Finally, the thesis adds interesting empirical evidence on the relevance of RE innovation for progress in the energy transition, by investigating both the temporal and spatial evolution of renewable energy patents in European regions. Furthermore, from the results of the analysis, several recommendations can be derived to regional policy makers seeking to improve the innovative performance in RE in their regions.

After this first introductory section, the next section delves into the theoretical and conceptual background of the study. The third section presents the methodology followed. Then, the fourth section describes the results obtained. This leads to a fifth section where these results are summarized, and the derived conclusions presented. Finally, we conclude with the discussion section where the contributions of the thesis, limitations, and suggestions for future research are outlined.

2. Theoretical and conceptual background

In this section we start proving an overview of the RE sector in Europe. Then, we present a theoretical background on the influence of knowledge networks on regional innovation. And lastly, we develop several hypotheses based on previous studies on innovation in RE and knowledge networks, with the objective of solving the thesis research sub-questions.

2.1. Renewable energy in Europe

Renewable energy plays a key role in achieving the EU's climate targets, including becoming the first climate-neutral continent by 2050 (Eurostat, 2022a). It contributes to the reduction of greenhouse gas emissions and pollutants and, consequently, to the mitigation of climate change and the enhancement of air quality (European Commission, 2020; FSR, 2020). Innovation in RE is crucial to reach this path towards environmental sustainability. As with all innovation, new technologies and processes in RE improve current technologies and increase the range of options available and the possible strategies for achieving these sustainable goals (IEA, 2019).

Innovation in renewable energy has contributed to making the EU the frontrunner of global renewable energy deployment for more than two decades (European Commission, 2018). Moreover, its growth has been steady, going from 9.6% share of its gross energy consumption from renewable sources in 2004 to 22.1% in 2020 (Eurostat, 2022a). To reach this share, each EU Member State contribute with its particular targets defined by its own national energy and climate plan (NECP)[1]. Accordingly, this share varies considerably depending on the country. Sweden and Finland lead the European ranking with a share of 60% and 44% respectively in 2020. At the other extreme are Malta (11%) and Luxembourg (12%) (Eurostat, 2022a).

Renewables are currently the leading source of electricity generation in the EU (European Commission, 2020). Technological advances, accompanied by measures to facilitate their expansion, have led to a considerable cost reduction of renewables over the years, making them very competitive on the market (European Commission, 2018). For instance, the cost of solar energy production has fallen by 75% from 2009 to 2018, and wind energy is the same or even cheaper than gas, coal and nuclear (European Commission, 2020).

The main renewable energy sources in Europe are solar and wind, hydro energy and bioenergy. In general, by 2020 the largest source of removable energy in Europe is bioenergy, with almost 60% of renewable energy generated (European Commission, 2021). Regarding the generation of electric energy, the two main ones are wind (36%) and hydro (33%). At a further distance, solar (14%) and bioenergy (8%) follow. The remaining 8% is accounted for by other renewable energies (Eurostat, 2022a).

Specifically in the period of analysis of this study (2003-2017), solar and wind energy are the two energies that have experienced the highest growth (European Commission & IRENA, 2018; Schremmer et al., 2018). The following figure (Figure 1) shows a comparison of the growth of cumulative installed capacity of solar PV and wind energy from 2000 to 2020 globally. As can be seen in the graph, both technologies have had similar development phases. Wind energy started a little earlier and its growth has been sustained since 2007. On the other hand, solar PV energy began to grow from 2007 onwards, but at a relatively faster rate.

[1] NECPs are are the roadmaps where EU member states define their environmental objectives and how they will achieve them. In particular, they address energy efficiency planning, renewables, greenhouse gas emissions reductions, interconnections and research and innovation. NECPs were introduced by the Regulation on the governance of the energy union and climate action (EU)2018/1999 and adopted in 2019 (European Commission, n.d.-b).

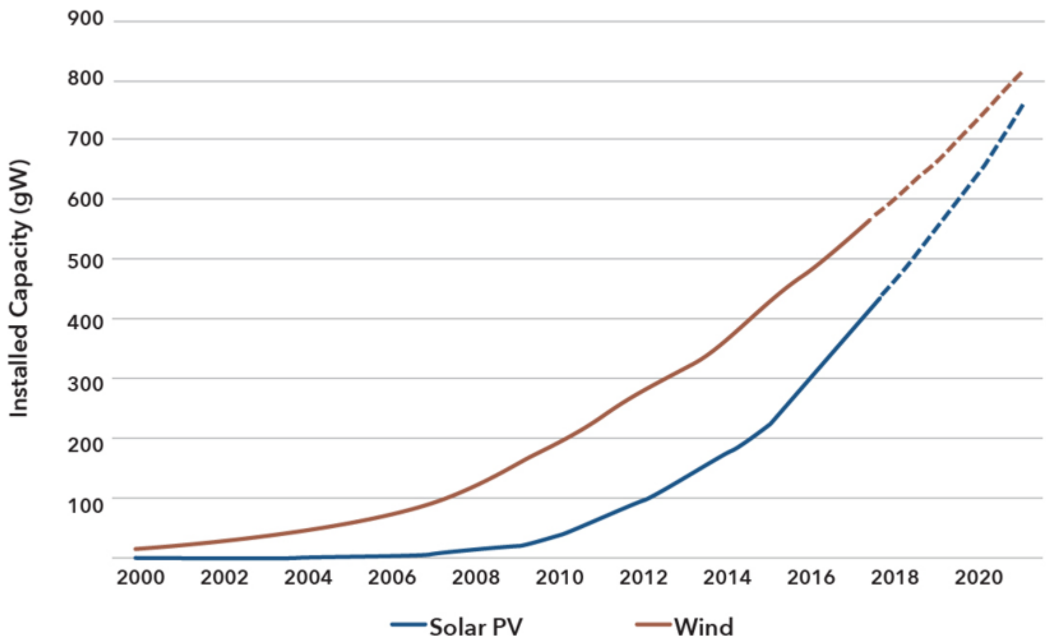

Figure 1. Global cumulative installed solar PV and wind capacity from 2000 to 2020. Source: (GWEC, 2021).

Focusing on solar energy, this can be found as solar photovoltaic or solar thermal. Photovoltaic technologies are oriented to the generation of electricity while solar ones are suitable for the production of domestic hot water. On a smaller scale there are also Thermal-PV hybrids technologies, which, being a combination of both, are able to convert solar radiation into usable thermal and electrical energy (Huide et al., 2017). Solar PV energy is the fastest growing energy source in Europe in recent years. Indeed, it has gone from generating only 1% of electricity with a total of 7.4 TWh in 2008 to 14% and 144.2 TWh in 2020 (Eurostat, 2022a). The origins of solar PV energy in Europe lie in Germany, which was one of the few countries in Europe to embrace it before 2008. Germany was followed by Italy and Spain, countries with great potential for this energy due to their large number of daylight hours. To date, these three countries are still the largest producers of solar power in Europe[2] . However, solar thermal energy entered the market globally somewhat earlier than solar PV, and in general solar energy has experienced rapid growth in Europe since 2000 (Schremmer et al., 2018; Solar-energia, 2020). The price of solar energy has fallen more than 70% in the last decade, making it very competitive in many parts of the EU (European Commission, 2021). Innovation throughout the supply chain, within the manufacturing plants, as well as improvements in efficiencies contributed to this reduction in price. Geographically, the potential of this renewable energy technology varies across Europe, with the southern regions with the most hours of sunshine, such as Italy, Spain, Portugal and Greece, the ones that can take the most advantage of solar energy. However, its deployment in Europe is very spread out, where regions with less potential for this type of energy such as Germany, Belgium or Switzerland also present a large installed capacity of solar energy (Schremmer et al., 2018).

Wind energy technologies are based on the creation of electricity using the kinetic energy generated by moving air. The history of the wind energy industry in Europe goes back almost 40 years. In 1982 the first wind farm build in the Greek island of Kythnos. Nine years later, the first offshore wind farm opened in 1991 in Denmark (European Commission, 2020). Denmark's commitment to this technology has always been very high, being both a pioneer and European

[2] In 2021, Germany generated 58TW from solar power, followed by Italy and Spain with 22 TW and 16TW respectively.

frontrunner in wind energy. In 2021, 44% of its electricity came from wind energy, the highest share in Europe (Komusanac et al., 2022). The rest of Europe joined Denmark in the deployment of wind power from around 2000 (EWEA, 2012). Denmark is followed by Ireland (31%) in share of the electricity demand covered by wind in 2021, with the EU average being 14% (Komusanac et al., 2022). Technological developments have been key. This is reflected in the progressive increase in turbine capacity from 22kW in the first models in 1982 to 10MW in today's offshore wind turbines. The greatest potential for electricity generation by wind power is found in areas of northern Europe, such as the United Kingdom, Denmark and northern France, characterized by a very windy climate, which enhances the efficiency of this technology. Unlike solar energy, most of the wind power generation takes place in these regions with high wind energy potential(Schremmer et al., 2018).

As mentioned, hydro energy is the second most generated renewable energy in Europe to generate electricity. Its basic principle is using the power of moving water to produce electricity. In 1849, the British-American engineer James Francis developed the first modern water turbine, which is still the most widely used in the world (International Hydropower association, 2022). The first half of the 20th century saw the greatest growth of this energy source in Europe., with the creation of large-scale projects and a succession of innovations that improved its design and performance (trvst, 2022). It is therefore the most mature type of renewable energy at the present time. In the current century, hydropower production has stabilised at around 650 TWh per year, which varies mainly due to the annual hydrogeological situation (Hydropower Europe, n.d.). One limitation that constrains the potential of this technology is that it is highly dependent on the geological characteristics of the region. It is therefore not surprising that the countries that generate the most hydro energy in Europe are Norway, France and Sweden, while in flatter countries such as Lithuania or the Netherlands there is no hydro energy at all (Hydropower & Dams World Atlas, 2019*)*.

Lastly, as mentioned above, bioenergy is the main renewable energy source in Europe. It consists on the use of organic material, such as trees, organic waste, and agricultural crops to create energy. This energy, depending on how it is obtained, can be used for electricity generation, transport fuel or heating. 75% of all bioenergy in the EU is used in the heating sector (European Commission, 2021). Humans have a long history of burning biomaterials for heating and cooking from the time fire was discovered. However, the use of bioenergy for environmental purposes did not occur until the end of the 20th century, marked by the growing environmental concerns (Guo et al., 2015). In the EU the largest bioenergy consumers in absolute terms are Germany, France, and Italy, while per inhabitant are the Baltic and Scandinavian countries and Austria. European legislation considers bioenergy a renewable energy source and is considered key to the energy transition. (European Commission, 2019). However, there are studies that question how beneficial this energy source is, considering it to be a major source of carbon emissions (Stephenson et al., 2014; Sterman et al., 2018).

For the future of renewable energies in Europe, solar PV and wind energy are expected to experience the greatest growth, as has already been the case for the last decade (European Commission & IRENA, 2018). In 2019, solar and wind energy in the EU overtook coal for the first time, and in 2021 surpassed that generated by gas (Moore, 2022). Although they are already competitive, it is expected that their investment and energy prices will continue to fall by increasing their performance and reliability. In particular, innovations are expected to facilitate their integration into the grid, dealing with the challenge of their volatile nature (IEA, 2019). Consequently, wind and solar PV together are expected to account for 21% of renewable energy consumption by 2030. While hydropower will drop to 12% and bioenergy to 55%[3] (European Commission & IRENA, 2018).

This thesis is intended to delve into renewable energy innovation in Europe. Although it is known which regions are leading in renewable energy production in Europe and what type of renewable energy is generated in each of them, we seek to find empirical evidence of their relationship with the development of regional RE innovation. For this purpose, a descriptive analysis of the temporal evolution of renewable energy innovation in Europe, especially from 2003 to 2017, is included.

2.2. Theoretical background on the influence of knowledge networks in regional innovation

It is an acknowledged fact in the literature that the combination and recombination of previously unconnected ideas leads to the production of new knowledge, which in turn results in technological innovations (Arthur, 2007; Miguelez & Moreno, 2018). In the case of renewable energy innovation this is not different (IEA, 2019; Li et al., 2020a). This recombination of ideas to generate novelty can occur in two ways, either through one's own past learning processes or via interaction with other actors (Graf, 2011). Regarding the latter, the IEA states that the effectiveness of renewable energy innovations depends to a large extent on knowledge-sharing networks between industry, academia, research centres, policy makers and international associations (IEA, 2020). A growing body of research shows that the characteristics of social relationships and the networks they constitute influence the effectiveness and efficiency with which individuals and collectives innovate (de Noni et al., 2017; Innocenti et al., 2020; Miguelez & Moreno, 2018; Phelps et al., 2012). The main reason is that the nature of the network influences the ability of its individuals to access, absorb, apply and transfer this knowledge (Phelps et al., 2012). These studies are commonly referred to as "knowledge network" research.

Knowledge networks are defined as sets of nodes whose social interconnections enable or constrain their ability to capture, transmit and create knowledge (Phelps et al., 2012). A node can be any type of actor involved in the task of creating new knowledge. Thus, nodes can be individuals, such as inventors, or collectives such as firms, universities, and research centres(Graf, 2011). At the regional level, several authors have found evidence that the innovativeness of a region is influenced by the characteristics of its knowledge network (de Noni et al., 2017; Graf, 2017; Innocenti et al., 2020; Marrocu et al., 2013). These characteristics can be defined by both intra-regional collaborations and inter-regional collaborations.

Intra-regional collaboration analysis explores the collaborations that occur within the regional network and how those influence the recombination and exchange of knowledge within and between actors in a regional network (Belussi et al., 2010; Kauffeld-Monz & Fritsch, 2013; Sun, 2016). Typical characteristics of this approach are those related to the structure of the regional network, such as its size, which corresponds to the number of actors that make it up, or its overall connectedness, related to the extent to which the network is interconnected (Hemphälä & Magnusson, 2012; Juhász & Lengyel, 2018; Zhang & Luo, 2020). In addition to the structure, some studies focus their analysis on the actors that conform the regional network (Kauffeld-Monz & Fritsch, 2013; Piazza et al., 2019). Special attention is given to the network brokers, actors in the network that transfer knowledge between other actors that are not linked directly,

[3] In 2010, of the total renewable energy consumed, bioenergy accounted for 67%, hydro energy for 21% and wind energy for 9% (European Commission, 2018).

and therefore play a key role in the dissemination of knowledge in the region. (Kauffeld-Monz & Fritsch, 2013).

Additionally, an **inter-regional regional approach** focuses on the collaborations of a region with other regions. Several authors consider that this type of relationship is key to fostering a region's innovative capacity (de Noni et al., 2017; Graf, 2011; Marrocu et al., 2013; Miguelez & Moreno, 2018). The main reason for this is that external knowledge inputs help to prevent a region from entering into a spatial lock-in generated by an excessive propensity to collaborate intra-regionally (R. A. Boschma, 2005). Seeking for extra-regional collaborations seems to be especially important in the case of renewable energy technologies. In fact, the EU has organizations, such as EIT innoEnergy, that promote cross-border partnerships in the energy sector with the objective of accelerating sustainable energy innovations (IEA, 2020).

In the analysis of knowledge networks, a common approach to understanding interregional relationships is to examine the proximity of relationships (Lalrindiki et al., 2016; Marrocu et al., 2013; Pan et al., 2020). Proximity does not only refer to the distance between collaborating actors (geographical proximity). Other types of proximity have also been shown to influence regional innovation, such as technological proximity, institutional proximity, social proximity and organizational proximity (R. Boschma & Frenken, 2009). Technological proximity refers to the similarity of the knowledge base of the collaborating regions. Institutional proximity concerns similarity at the institutional level, i.e. whether they share the same culture, traditions and political framework. Social proximity refers to the degree to which the collaboration between regions is based on friendly relationships. And organizational proximity means whether relationships take place between the same type of organizations (R. A. Boschma, 2005; Marrocu et al., 2013). Furthermore, as with intra-regional analysis, some authors focus on the key actors in the transmission of knowledge in the region, but in this case from outside the region (Gallo & Plunket, 2020; Graf, 2011; Punt et al., 2021). These actors are known as gatekeepers, who by maintaining connections with actors outside the region have access to knowledge externally produced, which transfer across the regional network via local connections (Gallo & Plunket, 2020).

In this thesis we combine in a single analysis all these characteristics that have been shown to have an impact on regional innovation. Thus, as mentioned in the introduction, the network characteristics are grouped into three groups. The first, focused on intra-regional regional connections, bringing together structural characteristics of each regional network. The second focuses on the proximity characteristics of the relationships between regions. And finally, we focus on actor-specific network characteristics by looking at intra-regional brokers and gatekeepers.

In the following section, the characteristics chosen for each group are elaborated and the hypotheses are developed.

2.3. Hypothesis development

2.3.1 Structural characteristics

As it was mentioned above, it is generally recognized that the structure of knowledge networks affects the innovative capacity of its members. In this study we specifically look at the overall connectedness of the knowledge network and the cohesion of its subgroups.

The *overall network connectedness* refers to the proportion of connections in the network that have been reached in relation to all those that would be theoretically possible (Y. Zhang et al., 2013). Regarding its influence on regional innovation, there are opposing views. Innocenti et al. (2020) discovered a negative effect of having a higher rate of connectivity between network members than between members of a region. They claim that a high connectivity favours the circulation of redundant knowledge and the eventual lock-in of the region in certain technologies. Loosely coupled networks would solve this problem (R. A. Boschma, 2005).

On the other hand, Graf et al (2017) and Fritsch et al. (2009) found a positive relation, arguing that a highly connected network facilitates the transfer of knowledge and information. A highly fragmented network prevents regional innovators from exchanging information with each other, making it more difficult to recombine ideas to generate new innovations. However, the latter makes an important remark, claiming that the degree of connectedness and its influence on innovation depends on the maturity of the field. In this way, the more mature technology sectors are not interested in the regional network being overly connected. The reason is that as the sector becomes more mature the circulation of redundant knowledge in the region also grows, as over time there is a tendency towards technological specialization (Crespo et al., 2014).

According to some authors the renewable energy sector has recently entered this mature phase (Barbieri et al., 2020; Sbadella et al., 2018). However, others claim that we can still observe novel developments, implying that this mature phase has not yet been fully reached (Hille et al., 2020). Our analysis covers the period from 2003 to 2017. At the beginning of this period, as mentioned above, the use of renewable energies, especially solar and wind, was taking off in Europe. Over the years it seems clear that the sector has been maturing, which can be observed by its progressive growth in the global energy mix. Therefore, given the relative closeness in time of the expansion of renewable energy sources, even if it loses its positive influence over time, we expect that a higher network density at the regional level favours innovation in renewable energies.

H1. *The higher the overall connectedness of a region RE sector knowledge network, the higher its regional innovation performance in REs.*

Cohesive sub-groups in the network or *ego-networks* refers to the subset of actors in a knowledge network between which there are relatively strong, direct, intense, frequent, or positive links (Innocenti et al., 2020). Articles reviewed found a positive relationship between the presence of cohesive subgroups within a region and regional innovation (Fritsch & Kauffeld-Monz, 2009; Graf, 2017; Innocenti et al., 2020). The reason is that ego-networks usually exhibit a high level of trust among their members, which promotes collaboration. Trust facilitates risk sharing, resource pooling and information dissemination (Crespo et al., 2014). In addition, the complexity of renewable technologies makes collaboration a necessity, requiring expertise in different domains (Laimon et al., 2020). Hence, we can also expect that the presence of subgroups enhances regional innovation on renewable energy.

H2. *The higher the presence of cohesive subgroups in a region renewable energy sector knowledge network, the higher its regional innovation performance in REs.*

2.3.2. Proximity characteristics

It is widely accepted in literature that proximity of actors influences the ability to innovate in a collaboration or network (Balland et al., 2015; R. A. Boschma, 2005; Juhász & Lengyel, 2018). The most investigated type of proximity is geographical proximity (Lazzeretti & Capone, 2016a). However, other forms of proximity have also proven to influence the innovativeness of network actors (i.e., technological proximity, social proximity, institutional proximity, and organizational proximity). In this thesis only geographical and technological proximity are considered in the analysis. There are several reasons for this. First, it is very tricky to operationalize variables at the regional level corresponding to social and organizational proximity (Marrocu et al., 2013). Social proximity is based on friendship, which in itself is difficult to measure. The fact that our analysis includes many inventors at the European level makes it even more complicated. The geographic scope also affects the organizational proximity since it would require identifying the type of organizations to which each inventor belongs, in order to then relate the collaborations. Second, of the few papers that analyse various types of inter-regional proximity in innovation and knowledge transfer, the strongest association was found in geographical and technological proximity (Marrocu et al., 2013; Pan et al., 2020).

To begin with, *geographical proximity,* several authors have argued that it is both catalytic and detrimental to innovation in clusters and intra-regional networks (Balland et al., 2015; R. Boschma & Frenken, 2009; Lazzeretti & Capone, 2016b). A certain level of proximity reduces the costs of information and knowledge transmission, as the communication channels between agents should be more efficient, facilitating the development of new inventions (R. Boschma & Frenken, 2009; Lazzeretti & Capone, 2016b). However, excessive geographic proximity can also be detrimental to innovation (R. Boschma & Frenken, 2009; Broekel & Boschma, 2012). Known as "proximity paradox", it is claimed that too much proximity between actors in any of the proximity dimensions might harm their innovative performance, leading to lock-in problems (Broekel & Boschma, 2012).

As mentioned, the literature at the regional level in terms of inter-regional proximity is more limited. Several studies found a positive relationship between the geographical proximity of collaborations between regions and their innovative performance (Kalapouti & Varsakelis, 2015; Marrocu et al., 2013; Pan et al., 2020). Kalapouti & Varsakelis (2015) suggest that sharing social and economic context reduces semantic difficulties, facilitating the transfer of tacit knowledge, which is key to be able to develop innovations. At the country level, (Verdolini & Galeotti, 2011)is one of the few studies to investigate the effect of geographical proximity in the renewable energy sector. In line with studies concerning regional innovation in general, they found that collaboration between higher geographical distance countries was associated with lower probability of knowledge flow. Based on the results at the regional level, we assume that the negative effects of excessive proximity could be mitigated by the fact that there is already a certain distance when it comes to inter-regional collaborations. Hence, the following hypothesis is proposed.

H3. *The more geographically proximate the collaborations of a region with others in the field of sustainable energy are, the higher its regional innovation performance in REs.*

As for *technological proximity*, at the actor/firm level, several authors also refer to the proximity paradox. On the one hand, it is argued that some overlap in knowledge bases is necessary to have meaningful interaction between actors (Balland et al., 2015; R. A. Boschma, 2005). Basically, sharing knowledge and communication codes facilitates effective and efficient communication and makes it easier to disseminate or create new knowledge (Balland & Rigby, 2017). On the other hand, they argue that when the knowledge bases between actors are too similar, the scope for mutual learning is reduced. There is a tendency to share redundant knowledge, which makes it more difficult to recombine it to generate new inventions (Balland et al., 2015). At the regional level, two regions are technologically proximate if their knowledge bases are similar. This means that they carry out activities in similar fields (Marrocu et al., 2013).

Papers analysing inter-regional technological proximity discovered that knowledge spillovers were easier to happen between technological proximate regions, enhancing their innovativeness (Marrocu et al., 2013; Pan et al., 2020; Verdolini & Galeotti, 2011). In particular, Marrocu et al., (2013), found in technological proximity the highest influence on regional innovation among the other proximities they studied (geographical, institutional, social and organizational). In this line we also expect that regions that collaborate with others that are technologically proximate in terms of sustainable energy are more innovative in this sector. Although we do not doubt that an excess of technological proximity can hinder innovation, we believe that when comparing regions, it is more complicated to reach that limit. It will be easier for two organizations to be technologically similar than two that are composed of a wide variety of actors from different technological backgrounds. Consequently, we state the following hypothesis.

H4. *The more technologically proximate the collaborations of a region with others in the field of sustainable energy are, the higher its regional innovation performance in REs.*

2.3.3. Actor-specific characteristics

Finally, we focus on the typology of the actors participating in regional sustainable innovation networks. In particular, actors which are the most influential when it comes to disseminating knowledge in the network and thus, enhancing its innovativeness.

First, we focus on brokers, defining them as those actors who link other actors that are not linked directly within the regional knowledge network. The presence of brokers in a network is claimed to be key to guarantee the innovative performance of the region (Kauffeld-Monz & Fritsch, 2013; Piazza et al., 2019; Winch & Courtney, 2007). The main reason being that they play a key role in the dissemination of knowledge on the network (R. Boschma & Frenken, 2009) pointed out that one of the solutions to the phenomenon of regional lock-in would be the creation of links between network actors who are not proximate, not only geographically but also in other dimensions. Acting as bridges between actors, brokers help this to happen as they as they enable indirect exchanges of knowledge that otherwise would not happen. Moreover, in some cases brokers act as mediators between third parties and can help to avoid misunderstandings, making the transfer of information more efficient (Fritsch & Kauffeld-Monz, 2009). In addition, brokers can themselves collaborate in enhancing regional innovation. Thanks to their position as intermediaries, they can take advantage of the variety of knowledge flows that reach them and recombine them to generate new inventions (Piazza et al., 2019). Given the benefits of the presence of brokers in regional innovation studies, we expect the same to happen in the renewable energy sector. As such, we formulate the following hypothesis.

H5. *The higher the presence of brokers in a region renewable energy sector knowledge network, the higher its regional innovation performance in REs.*

Second, we put our attention on the gatekeepers of the network. Similar to brokers, these actors also act as intermediaries between otherwise unconnected actors, with the difference that, in this case, those are internal and external actors (Graf, 2011). Although brokers help to disseminate and recombine knowledge within the network, for some authors this is insufficient to guarantee that the region does not fall into lock-in (Gallo & Plunket, 2020; Graf, 2011). As mentioned above, the entry of external knowledge into the regional network is key to guarantee the renewal of its knowledge base by providing potentially diversified and non-redundant ideas (Gallo & Plunket, 2020). Particularly, the importance of external knowledge to boost regional innovation in the RE has already been reiterated in this work on several occasions. Thus, the presence of gatekeeper in the region is a way for the region to be connected to "global pipelines". Moreover, gatekeepers have the ability to translate externally produced knowledge into a form that can be assimilated by local actors, enhancing the efficiency of information transmission (Gallo & Plunket, 2020). In addition, like intra-regional brokers, access to multiple sources of knowledge makes gatekeepers potential inventors in the region. Consequently, we also expect that the presence of gatekeepers in the energy knowledge network at the regional level has a positive effect on its capacity to innovate in renewable energy.

H6. *The higher the presence of* gatekeepers *in a region renewable energy sector knowledge network, the higher its regional innovation performance in REs.*

3. Methodology

This research focus on European regions (NUTS 2[4]) and analyses how different properties of knowledge networks in the renewable energy sector at the regional level help to enhance their innovativeness in this sector. To address this topic, several hypotheses described in the previous section have been proposed, which are tested through quantitative methods combining SNA analysis techniques on knowledge networks and regression analysis. Regional knowledge networks are constructed based on co-inventions (Breschi & Lenzi, 2015; de Noni et al., 2017) and in the field of renewable energy.

For the creation and management of all variables, modelling and calculation of the results and figures, the software program for statistical analysis RStudio has been used.

In this section, we begin by explaining how network and regional innovation data is obtained and their characteristics. Next, the operationalisation of the variables to address the hypotheses of the study are discussed. Finally, it is described the econometric analysis that to be followed. It is composed of a descriptive part focusing on innovation in RE and a quantitative part consisting of a regression analysis to confirm or reject each of the hypotheses.

3.1. Data

The basic idea underpinning this research is that regional innovation capacity in RE is driven by knowledge spillovers facilitated by knowledge network structures within the region. Different sources for constructing regional innovation networks can be found in the literature, each with its advantages and disadvantages.

Due to the characteristics of this research, we have chosen patents to construct the variables of our analysis. Several reasons explain this decision. Firstly, patents are one of the most widely used measures of innovation because, as by definition, they involve inventiveness (Nelson, 2009). Second, several studies claim that patents are a good indicator to address knowledge spillovers (Boschma & Frenken, 2009; Nordensvard et al., 2018; Yan & Guan, 2018; Zhang & Luo, 2020). They provide details about the actors involved in an inventive process, making it possible to relate them to each other in a technological, temporal, and geographical framework. These collaborations act as knowledge canals that together form the regional knowledge network. In addition, it has been decisive that patents are highly accessible (Guan & Liu, 2016a, 2016b). Lastly, there are already several studies that have used patent data to build knowledge networks in the energy sector (Nordensvard et al., 2018; Yan & Guan, 2018). For instance, Yan & Guan

[4] Defined by Eurostat, Nomenclature of Territorial Units of Statistics or NUTS is a geocoding standard to refer to country subdivisions for statistical purposes. NUTS 3 level is the smallest regional subdivision of a country within this classification (Eurostat, n.d.-a).

(2018) patents granted in the alternative energy field to construct knowledge networks with the aim of exploring how the position of an inventor affects its inventiveness.

Nevertheless, it is important to mention that working with patents to construct regional knowledge networks carries some drawbacks. A major one for this research is related to the determination of where the innovative activity has occurred. Ideally, the address of the exact location where the R&D was performed should be used (Graf & Krüger, 2011). However, patent data do not provide this information. The use of the applicant's address entails the problem that many times, organizations, especially large ones, have subsidiaries located in other places, wherethe innovation process takes place (Graf, 2017). However, they typically apply for patents centrally, at their headquarters. To deal with this issue, most papers that use patents to construct regional networks use the inventor's residence instead, assuming that people work close to where they live (Graf, 2011, 2017; Graf & Krüger, 2011; Innocenti et al., 2020). Then, the same logic is used for this thesis.

For the collection of patents data, we use the OECD REGPAT database (July 2021 edition) (OECD, 2021). The main reason to use this database is that it includes information regarding the location of inventors in Europe (Laurens et al, 2019), which is crucial in this study.

As already stated, the geographical scope of this thesis is European regions at the NUTS 2 level. In particular, regions from all 27 EU countries are included, with the exception of the Republic of Cyprus because its patents are not listed in the version of the REGPAT database in use. In addition, regions from the United Kingdom (UK), Norway, and Switzerland are also included, making a total of 29 countries and 270 regions considered.

In defining patents in the renewable energy sector and classifying them by subtypes, we refer to class Y02E of the Cooperative Patent Classification (CPC) (Veefkind et al., 2012). Specifically, we look into the Y02E-10 subclass, which covers patents relating to the generation of energy from renewable energy sources and includes geothermal energy (Y02E-10/10); hydro energy (Y02E-10/20); energy from the sea (Y02E-10/30); solar thermal energy (Y02E-10/40); photovoltaic (Y02E-10/50); thermal-PV hybrids (Y02E-10/60) and wind energy (Y02E-10/70)(USPTO, 2022).

Regarding the time window of the analysis, the period from 2003 to 2017 is chosen. The main reason is to have a sufficiently extended period of analysis to be able to analyse regional renewable energy innovation knowledge networks from a dynamic perspective, but also, to have enough data to be able to construct the regional networks. Therefore, several different attempts have been undertaken to find this balance between data and years until this period of analysis is chosen. The 2003 to 2017 period accumulates 82.73% of the patents in renewable energies of all those available in the REGPAT database of the selected European regions. Noteworthy, we use the "priority year" to classify each patent by year. It corresponds to the year of the first date on which the patent was applied for, and therefore, it is the closest to the actual time of the invention (Breschi & Lenzi, 2015; de Noni et al., 2017).

Additionally, this period has been divided into three non-overlapping sub-periods of 5 years (Period 1: 2003-2007; Period 2: 2008-2012; Period 3: 2013-2017). By doing this, we account for the regional variation of innovative activity across time and to prevent the impact of the patent statistics' volatility on the estimation of our dependent variable (Kalapouti & Varsakelis, 2015; Li et al., 2021; Yan & Guan, 2018). The following figure (Figure 2) shows the number of patents per year and period. We can see how the second period is the one that accumulates the most patents in RE, followed by the third.

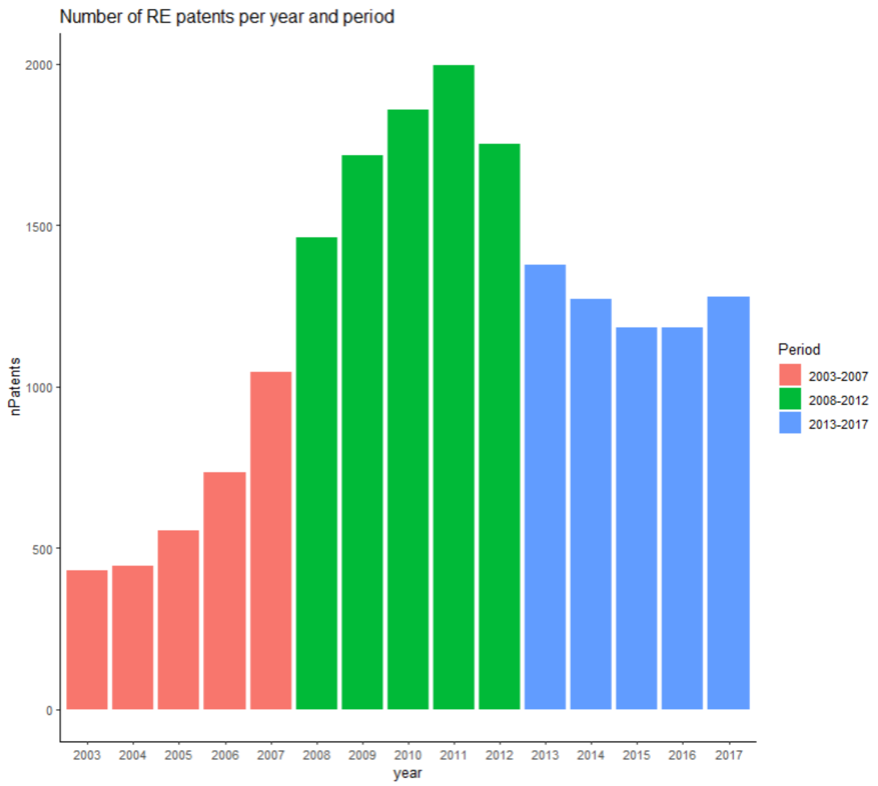

Figure 2. Distribution of patents in RE (Y02E-10 class) by period and year in EU plus UK, Norway, Switzerland classified by priority year.

Summarizing, our data consist of patents in RE (Y02E-10 class) for the period 2003 to 2017, divided into three 5-year sub-periods (2003-2007, 2008-2012, 2013-2018) and collected from all the countries of the EU (except for the Republic of Cyprus) plus UK, Switzerland, and Norway. This results in 270 NUTS 2 European regions with at least one patent registered in RE in the time window of analysis.

Nevertheless, in the regression analysis this number of regions is reduced. The reason for this is that regions with no or very few patents in RE have not been included. Specifically, for the construction of the variables, regions without patents and those belonging to the third tercile in number of patents in RE in the time window of analysis have not been considered. The reason is to have enough data to construct the variables that define the characteristics of the regional network and that these are not biased by having none or very few collaborations. Furthermore, for this quantitative analysis, three databases have been developed to create three different types of models with which to evaluate each of the hypotheses. The first, known as the "baseline model", includes patents from the seven renewable energies distinguished in the Y02E-10 class of the CPC. After removing those regions belonging to the third tercile, we are left with 180 regions in this model. Furthermore, two additional models are created in which only one type of renewable energy patents are considered for the creation of the variables. In particular, a model is dedicated to solar energy, called "solar model", which contains only patents of the subclasses Y02E-10/4 (Photovoltaic), Y02E-10/5 (Solar-thermal), Y02E-10/6 (Thermal-PV hybrids). The second field-specific model corresponds to wind energy, and is therefore called "wind model", and contains patents of its corresponding subclass, Y02E-10/7. Likewise, by eliminating the regions belonging to the third quartile, the solar model is left with 166 regions and the wind model with 162. The main purpose behind creating three different models is to explore to what extent there are differences between regional network characteristics considering all renewable energies (general model) and focusing on a single type of RE (wind and solar models). As seen in section 2.1, solar and wind energy have grown the most during the last two decades, coinciding with our period of analysis. Consequently, these are the two technologies that accumulated the highest number of patents between 2003 and 2017, which is key to have enough data to create meaningful regional knowledge networks at this level of analysis. The fact that both technologies are at a similar stage of development may allow us to explore whether the technological differences affect the characteristics of their networks, since there are not strong differences in the maturity of the technologies that could influence them.

3.2. Operationalization of variables

The adoption of patent data as relational data source allows regional knowledge networks to be constructed and examined using SNA methods (Breschi & Lenzi, 2016). In this framework, inventors are the nodes of the network, and the edges are based on co-inventions, i.e. they link inventors who have collaborated on the same patent (Breschi & Lenzi, 2016). In other words, two inventors are linked if they are jointly named as inventors in one or more patent documents. As already mentioned, in order to associate each inventor with a region and thus delimit each regional network, the location of the inventor's residence is used. In particular, the REGPAT database provides the exact address, city, regional code (NUTS 3) and country of residence of the inventor [5]. Furthermore, it is important to mention that we are not using fractional counting when attaching a patent to a region when it has been created by several inventors residing in different regions. Following Yang et al. (2020), we argue that knowledge is knowledge is arguably a non-divisible asset, and hence we assign the same patent application to each NUTS 2 involved region.

Having established how the regional network is constructed in our analysis, we now proceed to define the operationalization of each of the variables that are used in our regression analysis. The main objective of this regression analysis is to test whether or not each of the previously stated hypotheses are fulfilled. By doing this, we are able to ascertain the main objective of the thesis, which is none other than to investigate the extent to which the characteristics of the regional network in RE affect its innovative performance in the sector.

3.2.1. Dependent variable

Many of the reviewed studies use patent counts as proxy of regional innovation performance (Graf, 2011, 2017; Miguelez & Moreno, 2018; Tavassoli & Carbonara, 2014). There are also studies that use patents to account innovation in the energy sector (Noailly & Shestalova, 2013; Yan & Guan, 2018), and in particular, at the regional level (Abramovsky & Simpson, 2011).. It is true that patents do not precisely reflect the innovation performance of a region, since not all inventions are patented, nor do they all have the same impact. However, patent data is considered for proxying innovativeness as it presents the minimum standards of novelty, potential economic benefit and originality, and, consequently, they are a good indicator of economically profitable ideas and knowledge production (European Commission, 2021; Miguelez & Moreno, 2018). Therefore, the dependent variable is the number of renewable energy patents (Y02E-10 subclasses by EPO) by region and sub-period.

[5] The NUTS classification always consists of five characters. To move from NUTS level 3 to NUTS level 2, it is only needed to delete the last character, which, depending on the region, can be a number or a letter.

3.2.2. Independent variables: Network characteristics

This section describes how the independent variables of the study are calculated according to the group of network characteristics to which they belong (structural, proximity and actor-specific characteristics).

Structural characteristics

We assess the structure of the regional knowledge network in terms of its overall connectedness and the cohesion of its subgroups. The *overall connectedness* of a network can be measured by its *density* (Innocenti et al., 2020). This is the number of ties within a regional network relative to the number of potential ties in the same network (Graf, 2017; Kauffeld-Monz & Fritsch, 2013). As mentioned above, ties are formed when the inventors have collaborated on the same RE patent. A "potential tie" is a connection that might exist between two nodes, independently of whether or not it actually exists. In this case, two inventors can potentially collaborate as long as they belong to the same regional network. The following formula summarizes how the density of each regional knowledge network has been calculated.

$$PT_i = \frac{n_i * (n_i - 1)}{2} \quad (1)$$

$$D_i = \frac{NT_i}{PT_i} \quad (2)$$

Subindex i refers to any region of the analysis; PT_i refers to the number of potential ties in region i; n_i is the total number of inventors in region i; NT_i is the total number of ties in region i; and finally, D_i is the density of the knowledge network of region i.

Moreover, the *transitivity* of the regional networks is used as proxy of the cohesion of its subgroups (Guler & Nerkar, 2012). A number of empirical studies measure the immediate network of an actor, such as the presence of connections between the actor's direct ties (Fleming et al., 2007; Hansen et al., 2001; Obstfeld, 2016). As we explained, cohesive subgroups are expected to enhance the regional networks innovativeness in RE because they are often characterized by a high level of trust, which facilitates knowledge sharing among their actors. To capture something similar but at the overall network level, Guler & Nerkar use the transitivity of the network, which measures the tendency of nodes to cluster. In our case, a region with high transitivity means that the regional network has groups of nodes that are densely interconnected. The transitivity is measured as the ratio of the count of "triangles" and connected "triples" in a knowledge network(Nykamp, n.d.). A triangle is a set of three nodes where each node is connected to the other two. A triple occurs when three nodes are connected by two (open triple) or three (closed triplet) ties. In our case, for a region i this is formulated as follows.

$$T_i = \frac{3 * nTriangles_i}{nTriples_i} \quad (3)$$

$nTriangles_i$ refers to number of triangles in a regional network; $nTriples_i$ is the number of connected triples in the regional network; and T_i is the transitivity coefficient of the regional network. The factor of three multiplying the number of triangles is because each triangle contributes to three different connected triples in the network.

Proximity characteristics

We now turn to explain how the inter-regional proximity variables are constructed. Starting with *geographical proximity*, for each region it is measured by the average inverse distance (in Km) of its collaborations with other European NUTS 2 regions (Marrocu et al., 2013). The REGPAT database provides information on the NUTS 2 region in which each inventor resides. Therefore, the distance between collaborations between inventors is taken between the centroids of each pair of regions in which each inventor lives (Breschi & Lenzi, 2015; Marrocu et al., 2013). With this way of measuring distances, some accuracy is lost with respect to taking the distance between the exact addresses of the inventors. However, this decision was taken primarily because information on the inventors' addresses is not always available or reliable for all inventors.

Regarding technological proximity, it is estimated as the average technological similarity in RE between a region and the other regions with which it has collaborated (Marrocu et al., 2013). First, the similarity between each pair of regions is calculated based on their patenting activity in each RE energy type. Named *technological proximity index* by Marrocu et al. (2013), for the general model, which includes the seven REs considered (geothermal energy, hydro energy, energy from the sea, solar thermal energy, PV energy, thermal-PV hybrids, and wind energy), it is calculated as follows.

$$t_{ij} = 1 - \left(\frac{1}{2} \sum_{k=1}^{k=7} \left| I_{ik} - I_{jk} \right| \right) \quad (4)$$

where I_{ik} corresponds to the sectoral share of RE energy *k* in region *I*; I_{jk} is exactly the same but in region j; k goes from one to seven and refers to each type of renewable energy; t_{ij} is the technological proximity index and is set between zero (perfect dissimilarity) and one (perfect similarity). For the field-specific models, solar and wind, this is the only formula for the operationalization of variables that slightly changes. As in these cases only patents related to solar energy for the solar model and wind energy for the wind model are considered, the subcategories of each RE have been considered. As a result, the only thing that changes in the formula is the maximum value of k, which depends on how many subcategories each RE has[6]. As a result, maximum k of the technological proximity index in the solar model is 15 and in the wind model it is 5. By calculating this index for each pair of regions we obtain a symmetric matrix with the technological similarity in RE between all regions.

Additionally, another symmetric matrix is calculated with the number of interactions between each pair of regions according to the number of times their inventors have collaborated. Both matrices are multiplied. Then, for each region, the average of the previous result of all the regions with which it has collaborated is obtained and divided by the total number of collaborations it has had with other regions. This final result is the proximity index, which in our

[6] Considering that in the solar model we have combined solar thermal energy (Y02E 10/40), Photovoltaic [PV] energy (Y02E 10/50), Thermal-PV hybrids (Y02E 10/60) the subcategories are: PV systems with concentrators, 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 systems. In the case of wind energy (Y02E 10/70) the five subcategories are: wind turbines with rotation axis in wind direction, offshore wind turbines, onshore wind turbines, wind turbines with rotation axis perpendicular to the wind direction, power conversion electric or electronic aspects (USPTO, 2022).

case corresponds to the inclination of a region to collaborate with other regions that are more technologically similar to it in terms of RE. As a formula and for each region i:

$$TP_i = \frac{\sum_j^z (S_{ij} * a_{ij})}{C} \quad (5)$$

Where S_{ij} is the similarity index between regions i and j; z is the number of regions with which the region i and therefore varies with each region; a_{ij} is the number of interactions between regions i and j based on the number of times that inventors from both regions have collaborated; and C is the total number of collaborations between the two regions. TP_i ranges between 0 and 1, being 1 in the case that region i has collaborated only with regions technologically identical in RE to itself, and 0 in the opposite case.

Actor – specific characteristics

By acting as a bridge between different groups of inventors, the presence of *gatekeepers* and *brokers* in the regional network is expected to enhance their innovative performance in RE. An inventor from one region is considered a gatekeeper if they have collaborated with inventors from other regions as well as from his/her own region (Gould & Fernandez, 1989; Graf & Krüger, 2011). Based on this definition, the brokerage() function from the SNA package in R (RDocumentation, n.d.-a) provides a score related to the frequency of gatekeepers in a given network[7]. In order to standardise the value and make it comparable across regions, it has been divided by the total number of inventors in each regional network.

Shifting attention to the brokers of a regional knowledge network, those are identified as inventors who link any groups of inventors within the network (Kauffeld-Monz & Fritsch, 2013). On this basis we count the frequency of inventors in the regional network whose position in the network interconnects two or more groups of inventors. In the same way as with the gatekeeper's variable, we standardise the value by dividing it by the total number of inventors in each network. Consequently, our final variable is the share of brokers in each regional knowledge network.

3.2.3. Independent variables: Control variables

Several control variables that proved to have an influence on regional innovation are included in the model. Firstly, we include *cooling degree days (CDD)* index as proxy of *energy demand* (Calignano & Trippl, 2020). Here, the assumption is that demand for energy enhances regional innovation in the sector due to market pull (Vincent Emodi et al., 2015). The CDD index is a weather-based technical score designed to describe the energy needs of buildings in terms of cooling (Eurostat, 2022).

Secondly, *human capital* boosts regional innovation because very specific competences are needed to produce new ideas and capture external knowledge (de Noni et al., 2017). Hence, a region's propensity to innovate is dependent on the average level of human capital in its local

[7] In more detail, for each regional knowledge network the arguments passed to the *brokerage()* function are: a symmetrical matrix with the number of times each pair of inventors in the regional network have collaborated in the creation of a patent, known as affiliation matrix; and a membership vector indicating which inventors are from the region and which are from outside the region (only those external inventors who have collaborated with other internal inventors are considered). The function calculates the "brokerage score" for each network node, considering the number of brokering positions held by this inventor. The brokerage() function provides a score for the whole network by summing all of its individual node scores.

economy. We use tertiary education attainment to measure regional human capital (de Noni et al., 2017; Marrocu et al., 2013). Specifically, this variable is defined as the share of the population aged 25-64 who have successfully completed tertiary studies (Breschi & Lenzi, 2015; de Noni et al., 2017).

Fourthly, we add the *population* as a control to account for size effects (Miguelez & Moreno, 2018). A large region is bound to have more inventors among its population and therefore more patents. Lastly, we control for the *Research and Development (R&D) intensity* in each region, which is proxied as the ratio of R&D capital stock over real gross domestic product (GDP) (de Noni et al., 2017; Yang et al., 2020).

All data for control variables are provided by Eurostat (Eurostat, n.d.-b). Eurostat provides data for each control variable by year and region. In this way our only manipulation of this data is to filter them for the European regions considered and calculate its average by sub-period of analysis.

In the next page, the following table (Table 1) summarizes how each variable is calculated.

Table 1.Summary of each variable including its type, a brief description, and the source from which the data was obtained for its calculation.

Type	Variable	Description	Source
Dependent variable	Regional innovation in RE	Number of RE patents by NUTS 2 region and period (Graf, 2011; Tavassoli & Carbonara, 2014)	OECD REGPAT database, Own calculation
Independent variables	H1. Network connectedness	Measured by the density of the network (Innocenti et al., 2020). Hence, the ratio of all actual links of inventors to the total number of all possible links within the network.	OECD REGPAT database Own calculation
	H2. Cohesive subgroups	Estimated by the transitivity of the network (Guler & Nerkar, 2012). Fraction of pairs of inventors with common links to another inventor.	OECD REGPAT database, Own calculation
	H3. Geographical proximity	The inverse of the average distance of collaborations of the region's inventors with those of other regions (Marrocu et al., 2013).	OECD REGPAT database, Own calculation
	H4. Technological proximity	Average technological similarity of each region with other regions based on the number of collaborations between inventors (Marrocu et al., 2013)..	OECD REGPAT database, Own calculation
	H5. Brokers	Share of brokers in the regional network. Brokers are identified as those inventors who interconnect two or more groups of inventors (Kauffeld-Monz & Fritsch, 2013)..	OECD REGPAT database, Own calculation
	H6. Gatekeepers	Gatekeeper score defined by Gould & Fernandez (1989) by the total number of inventors. Gatekeeper are identified as those inventors who hold connections with actors within and outside the regional network	OECD REGPAT database. Own calculation
Control variables	Energy demand	Measured by the CDD index. A weather-based technical score based on the energy needs of buildings in terms of cooling.	Eurostat
	Human capital	Estimated by tertiary education which is measured as the share of the population aged 25-64 who have successfully completed tertiary studies.	Eurostat
	Population	Number of inhabitants of a given area on 1 January of the year in question	Eurostat
	Population density	Ratio between the annual average population and the land area of the region	Eurostat
	R&D intensity	Share of R&D expenditure by the total GDP of a region	Eurostat

3.3. Data analysis and econometric regression

First of all, a descriptive analysis is carried out. The main objective is to get an overview of the construction and development of innovation in the RE sector in Europe. To this end, we study how the different REs (geothermal energy, hydro energy, energy from the sea, solar energy, and wind energy) have evolved over the years and which regions were leading these developments. The descriptive analysis also allows us to see empirically whether there is a relationship between innovation in renewable energy and renewable energy production, something that has been advocated in the theoretical part but which we are now able to test with our data.

This descriptive-explorative analysis is followed by the descriptive statistics and distributions of the dependent and independent variables of the study. In a second step, the regression analysis is conducted to evaluate the relationship between regional patent production in RE and the independent variables selected to characterise the regional knowledge networks. The ultimate goal is to test the hypothesis outlined in Section 2.3.

Given the spatial structure and panel nature of the dataset, a country and period fixed effects model is chosen. It is expected that innovation production in RE in the European regions is not random but influenced by the territorial particularities of the countries where the regions are located. In addition, this aims to control for the regulatory and policy differences among European countries (Paatero & Lund, 2007). For instance, Germany was the first European country to implement a feed-in-tariff for different RE technologies in the year 2000 (Dewald & Truffer, 2012). In addition, as mentioned above (section 2.1), each country has its own NECPs, which defines its sustainable objectives and national measures to achieve them, including specific actions in the area of renewable energy.

In addition, the dependent variable is lagged by one period with respect to the independent and control variables. The reason for doing so is to minimize reverse causality and endogeneity issues in our estimated coefficients caused by using RE patents to calculate both dependent and independent variables (Breschi & Lenzi, 2015; Miguelez & Moreno, 2018). In addition, the time lag allows regional innovation to change in response to the input factors we have considered (de Noni et al., 2017).

The following is a general formulation of the regression model employed.

$$Y_{i,t+1,l} = \alpha_i + \lambda_i + \beta_1 Density_{i,t,l} + \beta_2 Transitivity_{i,t,l} + \beta_3 GeoProx_{i,t,l} + \beta_4 TecProx_{i,t,l} + \beta_5 GKbyInv_{i,t,l} + \beta_6 Brokers_{i,t,l} + \beta_6 Gatekeepers_{i,t,l} + \phi Controls_{i,t,l} \tag{6}$$

$Y_{i,t+1}$ represents the dependent variable, which is the number of patents in RE per region i and $t+1$ means that it is lagged one period. This implies that the dependent variable is calculated for periods 2 (2008-2012) and 3 (2013-2017) of the time windows. l refers to the country dummy. Each independent variable is shown together with its corresponding coefficient, β. $\phi Controls_t$ represent the control variables of the study together with their coefficients, ϕ. Both independent and control variables are not lagged, hence they are obtained for the periods 1 (2003-2007) and 2 (2008-2012). Finally, α represents the country dummy variables and λ represents the time dummy variables, relating to the fixed time and country effects respectively.

In modelling the relationship between our regional innovation outcome and network variables, we have to consider two specific features of our data: First, the dependent variable (i.e. number of RE patents in a region) is a count variable which can only take non-negative values. Consequently, the most suitable models for this type of data are either Poisson models or negative binomial (NB) models (Guan & Liu, 2016; Miguelez & Moreno, 2018). Poisson models require the variance of the dependent variable to be equal to its mean. Negative binomial models are similar to Poisson models but deal with overdispersion in the dependent variable (Barnett, 1997).

In this study to determine which model to use, overdispersion is tested by fitting a Poisson regression model with period and country fixed effects using the *dispersiontest()* function in R

(RDocumentation, n.d.-b)[8]. Briefly, if the test result is above zero, it means that there is overdispersion in the model. In our case, the result of the overdispersion test in the baseline model is 14.93, in the solar model it is 12.03 and in the wind model it is 25.47. In all three cases well above zero, thus we conclude that the negative binomial model is the best fit to our data.

In addition to the analysis, robustness tests are carried out to ensure the validity of the results. Although explained in more detail in the later section of the results dedicated to robustness tests (section 4.3.3), five models using NB regression are included. These models differ from the main models in that new variables are added or the way of calculating them is altered. In addition, several models are re-estimated, but using Quasi-Poisson regression instead of NB regression. In the same way as NB regression, Quasi-Poisson regression is suitable for treating the overdispersed count data of our analysis (Hoef et al., 2007). Furthermore, it is verified that each model does not suffer from multicollinearity problems among the independent variables. For this purpose, we calculate the variance inflation factor (VIF) of each variable in each model. This is a very common measure to check the amount of multicollinearity in regression analysis. (Innocenti et al., 2020; Yan & Guan, 2018; Yang et al., 2020). In this way, those models in which any of its independent variables exceeds a VIF value of 4 have been discarded (Hoef et al., 2007).

4. Results

Split into three main parts, this section reports the results of the analysis. The first part consists of a descriptive-explorative data analysis of RE inventions. The focus is on describing RE innovation in Europe and finding evidence of its relationship with regional RE production. The following subsection describes the statistical characteristics of the variables under study. Finally, we conclude this section with regression analysis where we try to find out if the hypotheses (section 2.3), which relate different characteristics of the regional network (structural, proximity and actor-specific characteristics) with its innovative performance in RE, are met.

4.1 Descriptive-explorative data analysis of RE inventions

In this section, a description of innovation in RE in Europe is presented. For this purpose, several diagrams and maps based on renewable energy patents are shown. We point out that this description is framed within the geographic scope of this analysis, which are 270 regions of the EU countries (except the Republic of Cyprus) and Switzerland, Norway and UK. First, the approach is generic, in order to understand how RE innovation has evolved over the years, and what types of energy predominate. Subsequently, some maps are shown aiming to discover how RE innovation is distributed across Europe, seeing which regions are frontrunners and which are lagging behind. In addition, throughout the section we try to see what relationship exists between regional innovation and current sustainable energy performance.

[8] This function tests the null hypothesis of equidispersion in a Poisson model against the alternative of overdispersion (Cameron & Trivedi, 1990). The following formula summarizes the logic under the test.

$$Var(Y) = \mu + c * \mu \quad (7)$$

$$\mathrm{H0: c = 0; Ha: c \neq 0}$$

$Var(Y)$ corresponds to the variance of the model dependent variable, μ is its mean and c is a constant and the result of the dispersiontest(). If the test result gives a value of c equal to zero, it means that the variance and the mean of the dependent variable are equal, thus fulfilling the null hypothesis, and therefore the appropriate model would be the Poisson model. case c is different from 0, the alternative hypothesis would be fulfilled and an alternative to the Poisson model would need to be used.

Starting by looking at the number of patents in RE can count we count 2,296 patents from 1977, when the first one was registered in the OECD REGPAT database, until 2019. However, in the following bar chart (Figure 3), we can observe that the distribution of number of patents per year in RE is very uneven, with the vast majority concentrated from 2000 onwards.

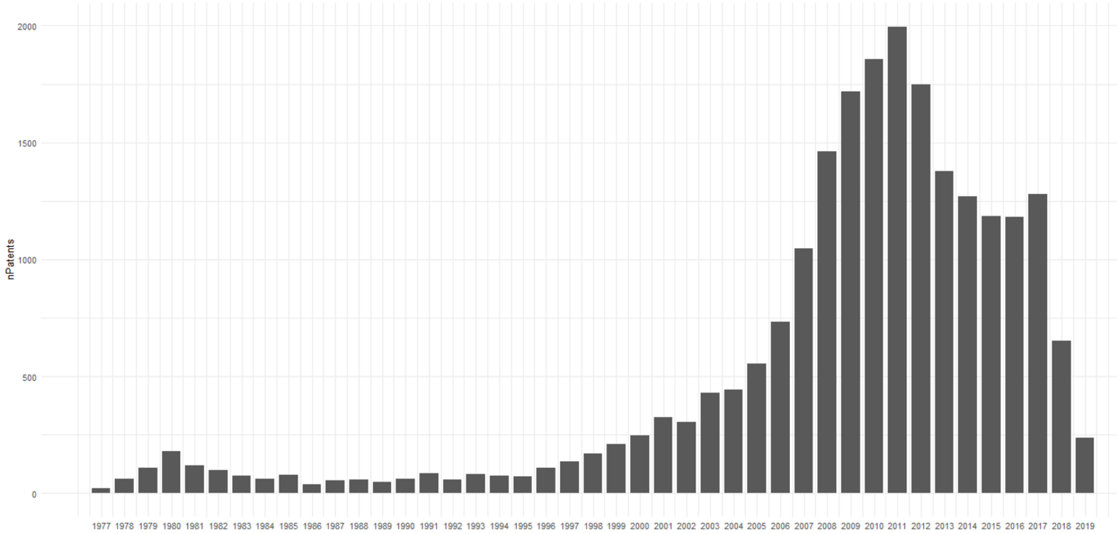

Figure 3. Bar chart with the number of patents per priority year in renewable energy according to the REGPAT database in the analysed countries (EU countries except the Republic of Cyprus plus UK, Norway, and Switzerland)

This surge in total RE inventions is in line with the growth in the share of renewable energy in total gross consumption that the EU has experienced in recent years, from 9.6% in 2004 to 22.1% in 2020 (Eurostat, 2022b), suggesting a connection between RE inventions and the shift towards cleaner, renewable energy consumption.

Furthermore, as explained in the methodology section, the time window of analysis of this study is from 2003 to 2017 in order to have enough data to construct the variables and assess the characteristics of the regional networks in a satisfactory way. This period alone agglomerates 82.73% of all patents registered. Taking a look at the pie chart below (Figure 4) we find that the vast majority of RE energy patents belong to solar energy (51.1%), especially photovoltaic (35.6%), and wind energy (37.5%). The two combined account for 88.6% of total patents.

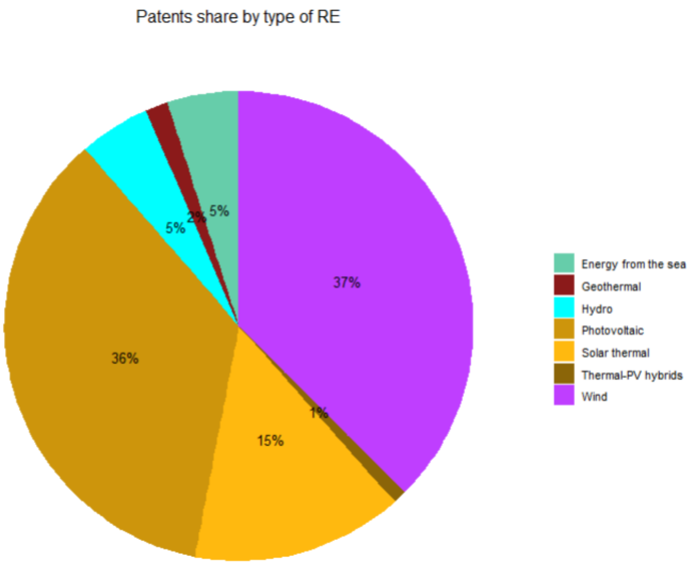

Figure 4. Pie chart of the share of RE patents per type from 2003 to 2017

The following graph (Figure 5) shows the number of patents by sub-period of analysis (Period 1: 2003 – 2007, Period 2: 2008 – 2012, Period 3: 2013 – 2017) and type of renewable energy. We can easily see how the second period is the one that accumulates the most patents in RE. Furthermore, in all three cases, solar and wind energy remain the most patented by far. This makes sense, since as mentioned in the theory (section 2.1), these are the two types of energy that have experienced the greatest growth in the last two decades (European Commission & IRENA, 2018; Schremmer et al., 2018). In 2020, wind and hydro clearly lead the ranking of electricity generated from renewable sources with 36% and 33%, respectively, followed by solar energy (14%). However, the latter has been growing the fastest in recent years, accounting for only 1% in 2008 (Eurostat, 2022b). As we discussed, the fact that hydro energy has such a low percentage of patents compared to the other two, despite the large amount of electricity it generates, might be due to the fact that the technology has been used for this purpose for many years already, a, specifically since the late 19th century, (Hydropower Facts and Information, 2019). Compared to solar and wind, for instance, it is a much more mature form of energy generation with less room for innovation.

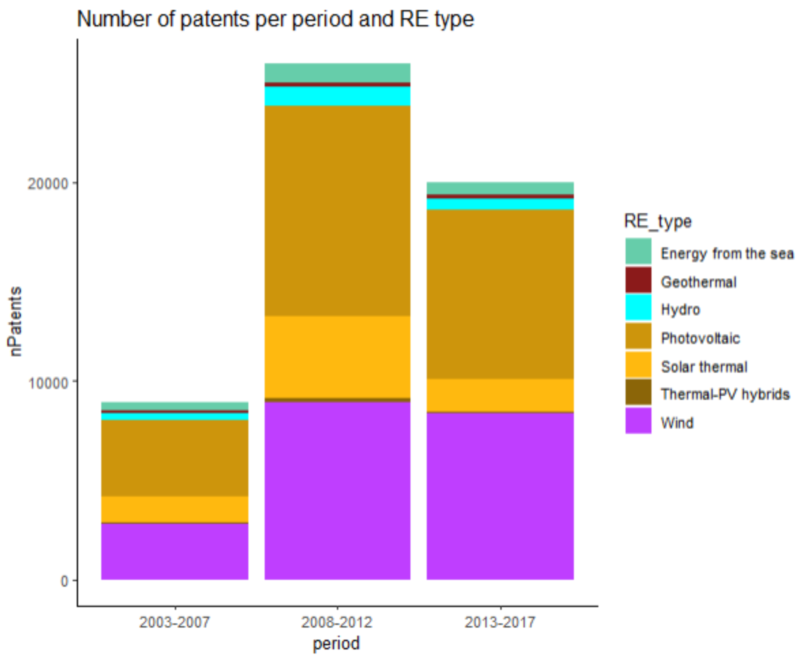

Figure 5. Number of RE patents by period and type of energy

In section 2.1 of the theory, we showed a graph (Figure 1) comparing the cumulative growth of solar PV and wind power installed capacity. Making an estimation of seven years from the priority date of the patent until its approval (Jones, 2021) and until it starts to be commercialized (Svensson, 2007), the following graph (Figure 6) compares the number of patents per year also for solar PV and wind energy. Saving the distances because the first graph was at global level and this one at European level, we can see how the growth of both energies is also very similar here, again reflecting the fact that they are at a similar stage of development. We can also deduce that this growth in solar PV and wind power installations generation is partly related to this increased innovation in both technologies.

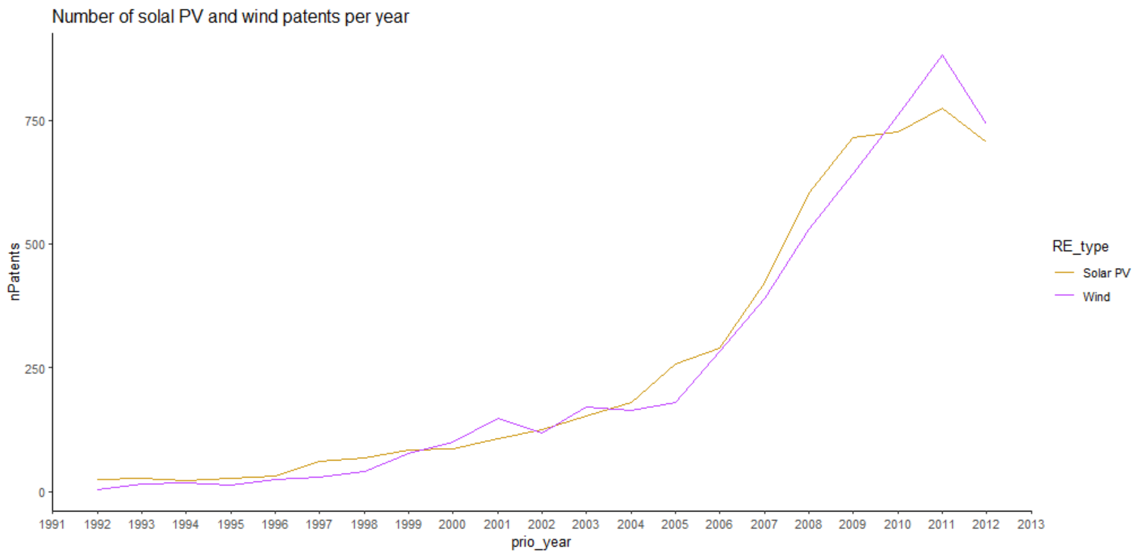

Figure 6. Number of solar PV and wind patents per priority year in Europe between 1993 and 2012.

Our attention now turns to the regions under analysis. For this purpose, a series of maps are shown (Figure 7 and Figure 8) to find out how renewable energy innovation has been distributed across Europe's regions (NUTS 2). The objective is to discover which regional differences exist in Europe in terms of innovation in renewable energies. In this way, it is possible to see whether there are major differences and, if so, which regions are hotspots in this field, and which are lagging behind. In addition, we identify which type of renewable energy is most patented in each region. This allow to determine whether there is a relationship between the innovativeness of the region and the type of energy mostly generated in the region.

With Figure 7, we start by looking at the overall distribution of the number of RE patents in Europe. The map in the top left corner reflects the distribution of patents over the entire time window (2003 - 2017), while the other three maps focus on each of the three periods of analysis. The five ranges defining the level, by colour intensity, of regional innovation in RE in each map have been created on the basis of which quintile the region is in terms of number of patents in RE in each period. Looking at these ranges we can see that the last one is the widest in all four maps. This shows that a few regions lead by a significant margin in the number of renewable energy patents. Focusing on this in more detail, we can observe that Germany is the leading country, with 24,255 patents between 2003 and 2017. It is followed by Denmark (6,779) and France (6,476). Consequently, it is not surprising that of the ten regions with the most patents, five are German (Darmstadt, Weser-Ems, Stuttgart, Oberbayern, Freiburg), two are from Denmark (Central Jutland and Southern Denmark) and two are French (Rhône-Alpes and Île de France). The ranking is closed by the Spanish region of Navarra. In addition, it can be observed that, with some exceptions, western and northern Europe concentrate most patents to the detriment of southern Europe and especially eastern Europe[9].

[9] Classification of macro regions in Europe by the United Nations (UN).

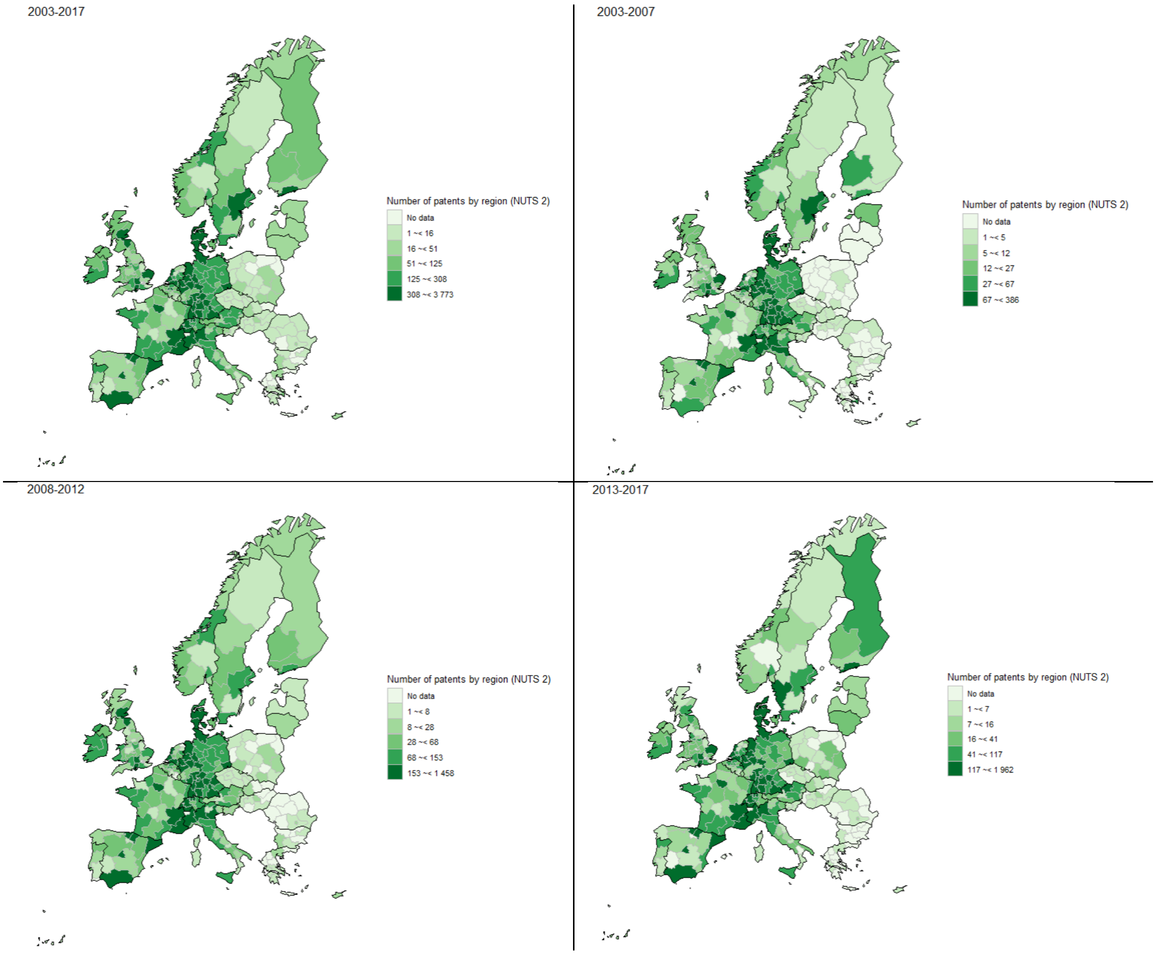

Figure 7. Distribution of the number of RE energy patents across Europe[10]

If we focus on the three analysis periods separately, we can see how the ranges increase considerably in periods 2 and 3 compared to period 1. For instance, the highest rank goes from 67-386 patents in period 1 to 153-1458 and 117-1962 in periods 2 and 3 respectively. This is in line with the global growth in the number of patents that we saw in the bar chart at the beginning (Figure 2). With this we can see that growth in innovation in RE is occurring across the board in most regions. Furthermore, we can note that, with minor exceptions, most regions remain in the same quintile, suggesting that the improvement is more or less homogeneous across Europe, with Western and Northern Europe remaining the most innovative macro-areas in RE.

The map below (Figure 8) shows which type of RE is the most patented by region. For that purpose, of the total number of patents in each region, the percentage of each of the seven renewable energies considered (energy from the sea, geothermal, hydro, photovoltaic, solar thermal, solar-thermal hybrids, and wind) has been calculated. The colour corresponds with the energy form for which the region registered the highest share. As can be noticed, the map is dominated by solar energy, primarily photovoltaic, and wind energy. It is interesting to note that the most patented region in the region is also the most, or one of the most, generated RE type in the region. For instance, in Denmark, where its three regions have mostly patents in wind

[10] The maps only differ in the period of analysis, with the top left one referring to the entire analysis window (2003-2017), and the rest each referring to each of the three analysis periods individually (2003 - 2007, 2008 - 2012, 2013 - 2017).

power, the most generated type of RE energy is also wind power (48% of the total energy generated in 2021) (Statista, 2022). In Italy, hydroelectric power has dominated the production of RE since last century, mainly thanks to its geological characteristics (Enel, 2021)

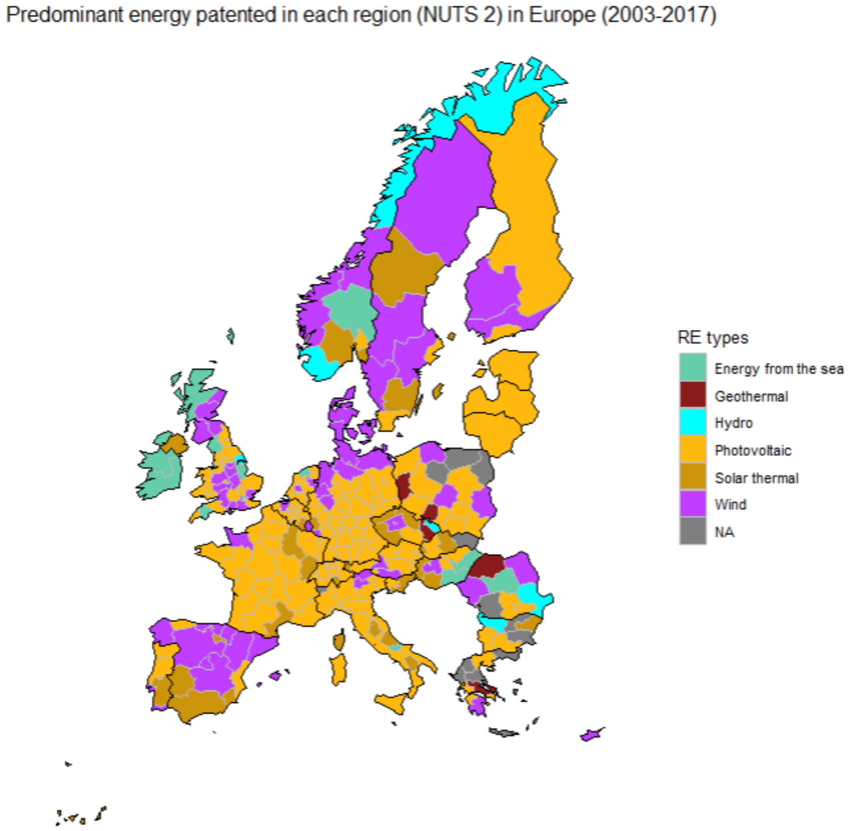

Figure 8. Most patented RE type by region in the period 2003 to 2017

In summary, we can highlight several points in this section. Firstly, it is important to note the growth in RE innovation that has been experienced in the last two decades, and especially how this goes hand in hand with renewable energy generation. This fact confirms what was already mentioned in the introduction, which is the importance of innovation in this field for the long-awaited expansion of renewable energies. On the other hand, it has been seen how a few regions are far ahead of the rest in RE innovation, and how, in general, Western and Northern Europe is several steps ahead of Southern and especially Eastern Europe. Germany and Denmark top the ranking with the most patents in the RE energies analysed. The historical commitment of both countries to this sector seems to be key, always maintaining an ambitious sustainable energy programme and high levels of public funding (Curry, 2019; Danish Ministry of Energy, 2018).

4.2. Descriptive statistics of the variables under analysis

This section of the thesis shows the results from the descriptive statistics of the variables (Table 2), outliers are flagged by calculating their boxplots (Figure 9). These correspond to the baseline model variables, thus data from the seven SRs under analysis are included[11].

Table 2. Descriptive statistics of the dependent variable and the independent variables of the baseline model dataset between 2003 and 2017. Note: The results have been rounded to two significant figures.

Variables	Mean	Median	Min.	Max.	SD
Number of patents in RE (DV)	56	29	2	760	85
Density (IV)	0.083	0.052	0	0.67	0.098
Transitivity (IV)	0.83	0.93	0	1	0.27
Geographical proximity (IV)	0.0043	0.0036	0.00041	0.019	0.0029
Technological proximity (IV)	0.66	0.68	0.18	0.89	0.13
Brokers (IV)	0.029	0.0084	0	0.32	0.042
Gatekeepers (IV)	0.87	0.11	0	26.59	0.13

[11] The statistics and boxplots of the variables in the solar and wind models are similar and therefore have not been included. They can be consulted in appendix A.

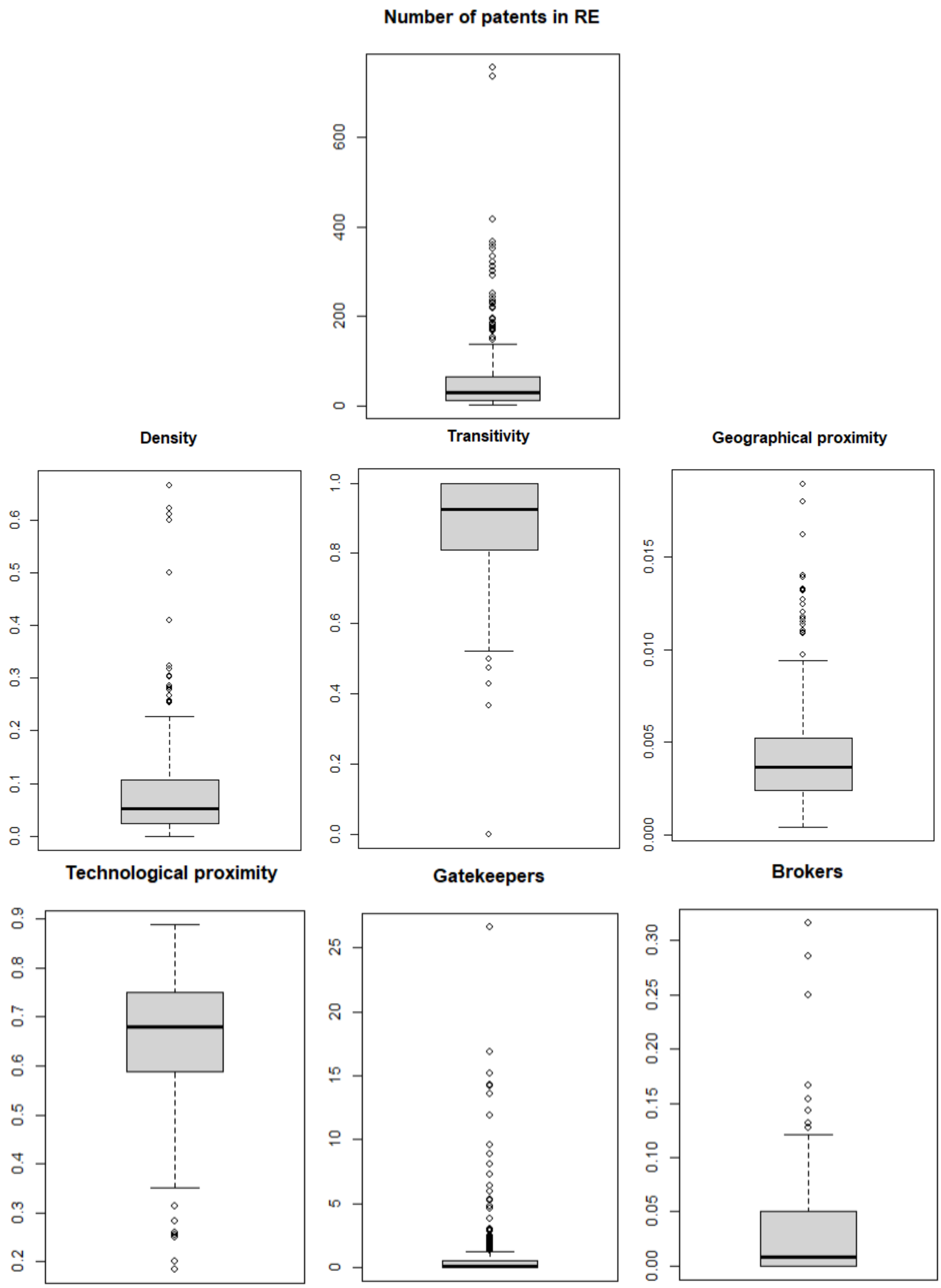

Figure 9. Boxplots of the dependent and independent variables of the baseline model dataset in the period 2003 - 2017.

From table 2 and the boxplots of the variables in figure 9 we can determine their distribution. The number of RE patents per region presents a median of 28.5, and we can see that the upper 50% of observations – which fall in the 3rd and 4th quartile – are more dispersed towards a higher number of patents. Hence, we can find a skewed distribution in the number of RE energy patents towards lower numbers. We can also confirm that there are outliers in the data which have many more patents than the average, being these mainly regions in Germany and Denmark and some more in central and northern Europe as mentioned in the previous section. As already discussed, to control for the skewed distribution we use negative binomial models.

Regarding the independent variables we can see the same pattern in four of the independent variables: density, geographical proximity, the gatekeeper index by the number of inventors and the share of brokers. These four variables have a median closer to the bottom, and all outliers on the opposite side. This is notably pronounced in the case of the variables relating to network brokers and gatekeepers, especially the latter. On the other hand, transitivity and technological proximity are skewed in the opposite direction.

Starting with density we can see that most regions have a low density, with an average of 0.08 ties per total possible ties. If we look at which regions are outliers, there is no clear pattern of a high network density geographical area. However, we can observe that most outliers have fewer patents than the European average, suggesting that a high density may be detrimental to their innovative capacity in RE. In contrast, transitivity, which reflects how cohesive the network is, shows the opposite pattern. Most regions show a high cohesion, with an average transitivity of 0.83. The outliers do not belong either to a specific geographical area in Europe but are related to low innovation rates. Regarding inter-regional proximity variables, we can notice that most regions collaborate with technologically similar regions, with median (0.68), much closer to the third quartile than to the first quartile. As for their outliers, they have a low, below-average patent production. On the contrary, most regions tend to have low values of geographical proximity but in this case looking at the outliers we cannot establish a clear relationship with RE patent production at regional level, finding values both above and below the average. Finally, we can observe the highly skewed distribution of the brokers and gatekeepers' variables. From this we can deduce that a large number of regions do not have in their network these types of actors. Focusing on the outliers, we can see that several of these also correspond to regions with a large number of patents in RE, such as DE25 (Mittelfranken), which has the most gatekeepers, producing 153 patents in RE, which is well above the average. Or DK04 (Midtjylland), the region with more patents in a single period (756 between 2008 and 2012), which has 0.13% of brokers in the same period.

4.3. Regression analysis

This section presents the estimation of the results to identify the relationship between the selected characteristics of the regional knowledge network of inventors in the field of RE and the region's capacity to innovate in this domain. We begin by presenting the correlation matrix of the variables of the analysis. Next, the results of the chosen model are presented by using the negative binomial regression. Finally, a series of robustness tests are conducted in order to check if the findings are reliable.

As specified in the methodology section (3.1), with the objective of testing whether there are differences between the characteristics of the regional network taking into account all renewable energies and focusing on a single type of renewable energy, three main models have been created. First, the baseline model includes all RE patents to construct both the dependent and independent variables. The solar model considers only patents belonging to groups related to solar energy: Y02E-10/4 (Photovoltaic), Y02E-10/5 (Solar-thermal), Y02E-10/6 (Thermal-PV hybrids). Finally, a third model (wind model) was specified to analyse wind energy (Y02E-7) separately. The number of patents for the remaining types of renewable energy is insufficient to carry out a comprehensive regression analysis.

4.3.1. Correlation analysis

The correlation matrix of all the variables from the databases of the baseline model, solar model and wind model can be found in the Appendix B.

Regarding the correlation between the dependent variable and the independent variables, particularly surprising is the high negative correlation between the number of RE patents per region and network density in the three variable databases (-0.29 in the baseline model, -0.29 in the solar model and -0.16 in the wind model). This result is in line with what was deduced from the statistical description of density (section 4.2). Contrary to the corresponding hypothesis (Hypothesis 1), it seems to confirm that high network density is counterproductive for regional innovation in RE. The rest of the independent variables show correlations in line with the corresponding hypotheses (technological proximity, gatekeeper index by number of inventors, and share of brokers) or their correlations are too low to make predictions (transitivity and geographical proximity).

Among the other variables, we can observe significant correlation coefficients between some of them. Particularly high, in all three cases, is the correlation between the control variables, population and the CDD index (-0.42 in the baseline model, 0.43 in the solar model and 0.32 in the wind model), which may lead to multicollinearity problems in our models. As mentioned, this issue is checked by measuring the variance inflation factor (VIF) of each variable in each model, making sure that is below the threshold of 4 (O'Brien, 2007).

4.3.2. Negative-binomial regression results

In this section we present the results obtained in several models based on negative-binomial regression. In the following table (Table 3), Models 1 to 4 are baseline models, i.e., the total number of patents of the seven REs considered in the study have been taken into account to create them. More specifically, models 1 to 3 show the effect of each group of network characteristics separately, together with the control variables. Thus model 1 includes the variables referring to the structural characteristics of the network (density and transitivity), model 2 focuses on the inter-regional proximity characteristics (geographical and technological proximity) and model 3 on the actor-specific characteristics (gatekeeper index by the number of inventors and the share of brokers). Finally, model 4 is the most complete model, including all three types of network characteristics in a single model[12].

Moreover, models 5 and 6 are specific models for solar and wind energy respectively. Both include the variables of the three groups of network characteristics, plus the control variables. With the difference that the solar model does not include the control variable CDD index because it causes multicollinearity (VIF = 5.37).

[12] Note that the population density control variable is not included in the first four models because they present multicollinearity problems if all control variables were included (VIF > 4 in all four models). By omitting this variable this problem ceased.

Table 3. Results of the negative regression models with period fixed effects and country dummy variables.

	(1) All RE	(2) All RE	(3) All RE	(4) All RE	(5) Solar	(6) Wind
Model	Negative binomial model					
Dependent variable	Number of patents in RE					
Density	-2.044 ***			-1.670***	-1.376 ***	-2.179 ***
	(0.463)			(0.451)	(0.362)	(0.413)
Transitivity	0.009			0.357 **	0.373 ***	0.563 ***
	(0.151)			(0.150)	(0.143)	(0.155)
Geographical proximity		-6.685***		-4.820***	-2.537*	-8.869
		(1.513)		(1.446)	(1.309)	(1.821)
Technological proximity		0.9297 ***		0.439	0.243	0.744 **
		(3.367e-01)		(0.326)	(0.336)	(0.320)
Gatekeepers			0.063 ***	0.069***	0.094 ***	0.114
			(0.014)	(0.014)	(0.012)	(0.098)
Brokers			5.005 ***	4.184 ***	1.564*	4.514 ***
			(0.912)	(0.904)	(0.873)	(0.930)
CDD	-0.002***	-0.003 ***	-0.002 ***	-0.002 ***		-0.003 **
	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)
Human capital	0.033 ***	0.035 ***	0.040 ***	0.023***	0.038 ***	0.024
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.012)
Population	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density					-0.000 ***	0.000
					(0.000)	(0.000)
R&D by GDP	4.722	2.291	3.896	2.003	1.342 ***	-1.351 **
	(3.948)	(4.020)	(3.918)	(3.776)	(4.013)	(6.161)
Theta	2.533	2.508	2.670	2.934	3.255	1.621
Observations	360	360	360	360	332	324
Nr of Regions	180	180	180	180	166	162
Period dummy	Yes	Yes	Yes	Yes	Yes	Yes
Country dummy	Yes	Yes	Yes	Yes	Yes	Yes

Note: *Significant at 0.1, **Significant at 0.05 and ***Significant at 0.01. Numbers in parenthesis are standard errors of coefficients. Numbers in parenthesis are standard errors of coefficients Numbers in parenthesis are standard errors of the variables' coefficients. Theta refers to the overdispersion parameter for negative binomial models.

Structural characteristics

Starting with the network *overall connectedness* variable, we can observe that the *density* variable coefficient is negative and highly significant in the baseline models (1 and 4) as well as in the solar (5) and wind (6) models. This goes against the hypothesis that a higher network density is positively associated with regional innovation in RE. Hence, we need to reject our hypothesis (Hypothesis 1) and assume that a high regional density is, instead, detrimental to a region's innovation performance in RE. These results are in line with those found by Innocenti et al., (2020). Considering in this case regional innovation in general, they found evidence from Italian regions that a higher network density would favour the circulation of knowledge that already exists and is redundant, but hinder development and exchange of new knowledge and thus the development of innovation capacity (e.g., new inventions) in regions. These results could also mean that the renewable energy sector is more mature than initially thought. As seen in the theory section, according to several authors, the more mature the technological sector, the more fragmented the networks should be in order to avoid technological overspecialization (Crespo et al., 2014; Fritsch & Kauffeld-Monz, 2009).

As for the *transitivity* of the network, we see that its coefficient is positive and significant in all the models in which it appears. This result is in line with what was expected and implies that the greater the cohesion of the sub-groups of the regional network, the greater their innovation in RE. Confirming the hypothesis (Hypothesis 2), it seems key that there are well-connected sub-groups of the network as this is a sign that intense collaborations exist, where knowledge is recombined for the generation of new inventions in RE. Group collaboration is claimed to be especially important in RE energy technologies, which due to their complexity require the cooperation of different experts with different backgrounds and provenance (e.g. private companies, research centers, universities...) (IEA, 2019; Laimon et al., 2020). In addition, these results also seem to confirm the importance of trust in the development of innovations, a characteristic of network sub-groups. Trust would ease risk, resource and information sharing (Crespo et al., 2014).

In neither of the two variables do we find particularly different results for solar and wind energy. In fact, both technologies have been expanding practically simultaneously in Europe. Therefore, we can deduce that they do not have a very different maturity difference, as it can happen with hydropower, which can lead to noticeable differences in terms of network connectedness.

Proximity characteristics

Concerning the effects of *geographical* and *technological proximity*, we obtain opposite results depending on the type of proximity. Firstly, in the baseline models, the geographical proximity coefficient is negative and highly significant in both the model focused on proximity variables (2) and the most complete model (4). Comparing them with the models for solar and wind energy, we see that the geographical proximity coefficient remains negative, although it loses significance. Given these results, we can reject the corresponding hypothesis (Hypothesis 3) that stated that closer collaboration between regions would be helpful for their innovation performance in RE as it reduces the costs of transmitting information and knowledge, making communication between inventors more efficient (Kalapouti & Varsakelis, 2015; Marrocu et al., 2013). In contrast, our results imply that the regions collaborating with more distant regions are also more innovative in renewable energy than those collaborating with closer ones. From this finding it can be deduced that the nature of renewable energy might be more universal or codified, and therefore communication barriers for collaboration over distance might be less rigid. In addition, we can expect that the knowledge transmitted from the distant regions is more novel. In other words, it may be easier for their knowledge bases to be more similar, which facilitates redundant knowledge sharing.

Contrary to geographical proximity, the coefficient of technological proximity is positive in both, baseline models and RE specific models. However, their significance varies, being high in model 2, which focuses on the proximity variables, and moderate in the wind model. Meanwhile, in the baseline model with all variables (4) and in the solar one (5) it loses significance. We can thus confirm hypothesis 4, whereby collaboration between regions with a certain technological similarity in RE is beneficial for their innovativeness in this field. Hence, we can assume and as discussed in the theory section (section 2.3.2), knowledge spillovers are more likely to take place across regions with a similar knowledge base that facilitates the recombination of ideas (Kalapouti & Varsakelis, 2015; Marrocu et al., 2013; Pan et al., 2020). However, it is also important to stress that this is not one of the most influential variables considered in this analysis, except for the case of wind energy. It should be recalled that in the case of the baseline models (2 and 4), the percentage in number of patents in each type of renewable energy was used to define the relationship between regions. Whereas for models specific to an ER type, the subtypes of each of the renewable energies in question, solar or wind, were used to determine them.

As for the comparison between the solar and wind model, in both cases we found some differences in the two types of proximities. The fact that the coefficient of geographic proximity is smaller and more significant for solar energy than for wind energy may be due to the differences in geographic location between the two. If we look again at Figure 8, we see that the regions where wind energy innovation predominates are mostly located in coastal areas and at high latitudes, characterized by being windy. Furthermore, an important part of wind energy is offshore[13], which by definition can only be found in coastal regions. In contrast, a bit more concentrated in Southern and Western Europe but predominant solar energy regions are found all over the map. This is also true for the energy generated. As already mentioned (Section 2.1), countries with fewer sunshine hours, such as Germany and Belgium, also have a high deployment of solar energy installations, while wind power generation is mainly located in windy areas of northern Europe. Although location affects the efficiency of both technologies, it is true that solar energy is somewhat more versatile and can be found both on large solar farms in rural areas and on rooftops in urban areas for local use. It is also capable of generating electricity even with clouds. Consequently, it may be that the fact that wind energy is a little more geographically concentrated in Europe, led to the fact that these relationships are not as distant as they can be in the case of solar energy.

Regarding technological proximity, we can observe that it is more significant in wind energy than in solar energy. The explanation for this may be due to differences in the complexity of the two technologies. The choice of the type of wind turbine to build a wind farm depends to a large extent on the wind conditions (direction and strength) and the chosen terrain (Estruga, 2020). Hence, we may think that regions specialize in certain types of wind turbines according to their conditions. It thus seems logical that regions would benefit from collaborating with technologically similar regions that can provide specific knowledge to optimize the potential of their own conditions.

We now turn our attention to the influence of brokers and gatekeepers in regional innovation. Starting with brokers, its coefficient is positive and significant in both baseline models (3,4) and renewable energy specific models (5,6). Hence, we can confirm Hypothesis 5 and affirm that a higher presence of brokers in the network is associated with more capacity of the region to innovate in RE. In line with other results in the literature, it seems that brokers help in the diffusion of knowledge through the regional network (Kauffeld-Monz & Fritsch, 2013; Piazza et al., 2019; Winch & Courtney, 2007). Thus, its function as mediator and translator between unconnected actors also appears to be effective in the renewable energy sector. This role may improve the efficiency of information transfer, which eventually could lead to its recombination into new inventions (Fritsch & Kauffeld-Monz, 2009).

Similarly, the coefficient of the gatekeeper index is positive in the four models and significant in three of them except for the wind energy model. Therefore, hypothesis 6 is also confirmed. This implies that regional RE networks that have actors with connections both inside and outside the region seem to perform better in RE. This result seems to underline the importance of having access to global knowledge pipelines for boosting regional innovation. Something that has already been emphasized by several authors (R. Boschma & Frenken, 2009; de Noni et al., 2017; Miguelez & Moreno, 2018) and in particular concerning the energy sector (Li et al., 2020). It is possible that, like brokers, gatekeepers improve the efficiency and speed of this knowledge transmission, facilitating the dissemination of new ideas in the network and thus its overall

[13] In 2021, almost 20% of new wind energy installations Europe were offshore and in total represent 12% of the wind energy generated.(Iberdrola, 2022)

innovation capacity. Their experience collaborating with both groups of inventors would enhance their ability to reinterpret the information received and make it easily comprehensible to local actors (Gallo & Plunket, 2020).

Lastly, in the comparison between the solar and wind models we can observe some difference between the results of brokers and gatekeepers' variables. As we have already noted, in both models the respective coefficients of these variables are positive, suggesting the presence of both types of actors is beneficial for the regional innovation in both RE technologies. However, looking at the significance level of each coefficient, it seems that its relevance varies depending on the type of ER. On the one hand, the broker variable coefficient is highly significant in the wind model and to a lesser extent in the solar model. On the other hand, the one concerning the gatekeepers is the opposite, highly significant in the solar model and not at all in the wind model. As with the differences between the two SRs in the case of proximity, this may perhaps be due to the technological particularities of each. As mentioned above, the choice of the type of wind energy and turbine model is more tailored to the settlement where it is to be installed than in the case of solar energy. This can make the inventors of a region look more among their own network, to adapt to their geographic circumstances. Therefore, it would be more logical that brokers, focused on intra-regional knowledge diffusion, would be more relevant than gatekeepers that bring external knowledge.

4.3.3. Robustness checks of the model

Several complementary analyses were performed in order to check the robustness of our findings. Firstly, additional models using the negative binomial regression are presented in Table 4. These five models correspond to the main database, which is built up from patents covering the seven renewable energies under consideration. The first one includes the control variable *population density*, which was previously removed because it caused multicollinearity problems. In its place, the control variable R&D per GDP has been dropped to ensure that this is not a problem either. Subsequently, models 2 and 3 present the results of a complete model but focusing on periods 1 and 2 respectively. Finally, models 4 and 5 focus on the variables relating to the presence of gatekeepers and brokers in the regional network respectively. The difference with its equivalent model in the previous section (Model 3 of table 3) is that the variables relating to brokers and gatekeepers are categorical. Specifically, 4 levels have been created according to the presence of gatekeepers and brokers in each region. Level 0 corresponds to regions without any gatekeeper/broker in the network. The following three levels have been defined according to the tercile to which the original variables belong, with the first being the one with the lowest share of these actors, and the third the one with the highest share. The reason why a model has been created for each variable is that together they provide multicollinearity problems.

Table 4. Negative binomial robustness regression models

	(7)	(8)	(9)	(10)	(11)
Model	Negative Binomial				
Dependent variable	Number of patents in RE				
Density	-1.649***	-1.634***	-4.955***		
	(0.449)	(0.447)	(1.464)		
Transitivity	0.356**	0.649***	0.328		
	(0.150)	(0.169)	(0.328)		
Geographical proximity	-4.816***	-6.785***	-2.103		
	(1.441)	(1.733)	(2.668)		
Technological proximity	0.427	0.497	0.130		
	(0.324)	(0.392)	(0.575)		
Gatekeepers	0.069***	0.104	0.0491***		
	(0.0137)	(0.0315)	(0.01702)		
Gatekeeper1				0.370***	
				(0.108)	
Gatekeeper2				0.400***	
				(0.113)	
Gatekeeper3				0.708***	
				(0.129)	
Brokers	4.222***	4.186***	2.664*		
	(0.897)	(1.101)	(1.442)		
Broker1					0.623 ***
					(0.107)
Broker2					0.685***
					(0.109)
Broker3					0.805***
					(1.085e-01)
CDD	-0.002***	-0.001	-0.001	-0.003***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	0.000)
Human capital	0.034***	0.017*	0.038***	0.035***	0.028***
	(0.008)	(0.010)	(0.011)	(0.008)	(0.008)
Population	0.000***	0.000***	0.000***	0.000***	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density	-0.000				
	(0.000)				
R&D by GDP		0.704	3.664	2.142	5.666
		(5.076)	(5.707)	(3.962)	(3.808)
Theta	2.961	3.862	2.713	2.585	2.823
Observations	360	180	180	360	360
Nr of Regions	180	180	180	180	180
Period dummy	Yes	No	No	Yes	Yes
Country dummy	Yes	Yes	Yes	Yes	Yes

Note: *Significant at 0.1, **Significant at 0.05 and ***Significant at 0.01. Numbers in parenthesis are standard errors of coefficients. Numbers in parenthesis are standard errors of coefficients Numbers in parenthesis are standard errors of the variables' coefficients. Theta refers to the overdispersion parameter for negative binomial models.

Starting with the first of these models (1), we can see that the results are very similar to those of the original model (Model 4 of Table 3). Indeed, all coefficients of the variables have the same sign, close values and the same level of significance. Secondly, the objective with models 2 and 3 is to test how the density variable varies from period to period. In the theory section, it was argued that over time the level of density beneficial to the innovativeness of the RE region would decrease. The reason being that the more mature the sector becomes, the greater the circulation of existing knowledge if the density of the region remains unchanged or increases, which hampers innovation. If we look at models 2 and 3 we see that the coefficient of this variable in the second period (-4.955) is indeed lower than in the first (-1.634), which confirms this effect and reinforces the robustness of the model. Lastly, with models 4 and 5 we found that changing the way the gatekeepers and brokers variables are calculated does not change the results either. In both cases, the coefficients of the variables are positive and significant in all categories, and their value increases as the share of brokers and gatekeepers increases. Thus, the greater the presence of gatekeepers and brokers in the network, the greater the innovation in RE, as seen in model 3 (Table 3).

Additionally, in table 5 the three initial models are calculated using the Quasi-Poisson regression instead of the negative binomial regression. As it was mentioned, like the negative binomial, the Quasi-Poisson regression is suitable for dealing with over-dispersed count data of our analysis (Hoef et al., 2007). Model 12 corresponds to the baseline database while model 13 corresponds to solar and model 14 to wind. In all three cases, the same variables are included as in the equivalent model of the negative regression analysis.

Table 5. Quasi-Poisson robustness regression models

	(12)	(13)	(14)
Model	Quasi-Poisson		
Dependent variable	Number of patents in RE		
Density	-6.026***	-3.196***	-5.153***
	(1.210)	(0.637)	(1.021)
Transitivity	0.129	0.486**	5.586e-01**
	(2.257e-01)	(2.3465e-01)	(2.463e-01)
Geographical proximity	-8.416***	-5.056**	-9.210***
	(2.591)	(2.001)	(3.069)
Technological proximity	0.560	0.434	1.094**
	(0.481)	(0.493)	(0.448)
Gatekeepers	0.052***	0.0797***	0.062
	(0.012)	(0.008)	(0.103)
Brokers	1.076	1.498	0.576
	(0.953)	(1.039)	(1.039)
CDD	-0.001		-0.004*
	(0.001)		(0.002)
Human capital	-0.005	0.012	-0.018
	(0.010)	(0.009)	(0.017)
Population	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Population density		-0.000**	0.000
		(0.000)	(0.000)
R&D by GDP	2.607e+00	16.554***	-19.882**
	(4.392)	(3.766)	(8.374)
Observations	360	332	324
Nr of Regions	180	166	162
Period dummy	Yes	Yes	Yes
Country dummy	Yes	Yes	Yes

Note: *Significant at 0.1, **Significant at 0.05 and ***Significant at 0.01. Numbers in parenthesis are standard errors of coefficients. Numbers in parenthesis are standard errors of coefficients Numbers in parenthesis are standard errors of the variables' coefficients. Theta refers to the overdispersion parameter for negative binomial models.

While it is true that some coefficients lose significance with the Quasi-Poisson regression, such as the transitivity coefficient, which is significant in the baseline model (4), or the share of brokers in the wind one (6), none of the coefficients change their sign. Overall, the results of the various sensitivity analyses support our findings.

5. Summary and conclusions

Innovation in RE is crucial to combat climate change and accelerate the energy transition. In this thesis, we examined how the structural, geographical, and actor-specific characteristics of a region´s renewable energy knowledge network influences its innovation performance in this sector, being this our main research question. The analysis covers 270 NUTS 2 regions of the EU countries (except the Republic of Cyprus) and UK, Norway and Switzerland, between 2003 to 2017.

We started by conducting a descriptive analysis of RE innovation in Europe. From this analysis we have been able to deepen the relationship between RE innovation and the region's current performance in the sector. In particular, we found empirical evidence supporting the idea that innovation favours RE production. Comparing the regions´ number of patents in RE and their generation of energy from RE sources, it has been found that in general the most inventive regions are also the ones that generate more RE. The growth in the number of solar PV solar and wind energy patents over the years also coincides with the boom they have experienced in Europe over the last two decades. In addition, it was observed that in general, the most patented source of renewable energy in the region is also the most or one of the most produced in the region, reinforcing the idea that RE energy generation and innovation are closely related.

Following the descriptive analysis, the regression analysis was conducted, with the aim of contrasting our hypotheses on the relation between different characteristics of regional RE knowledge networks and the region's innovation performance in this sector. Each network characteristic is linked to a hypothesis, and in turn each hypothesis is linked to one of the three sub-research questions of the thesis.

The first sub-research question addresses how the structural characteristics of a regional knowledge network impact on its performance in RE. Specifically, the characteristics analysed are the overall connectedness of the network and the cohesion of its subgroups, measured through the density and transitivity of the network respectively. The results of the regression analysis indicate that both characteristics affect the innovative performance of the European regions in RE, albeit in opposite ways. From what has been described in previous studies (R. A. Boschma, 2005; Innocenti et al., 2020) and contrary to predictions (Hypothesis 1), it can be deduced that an overconnected network may lead to technological lock-in in the region due to the recirculation of redundant knowledge. In addition, some studies (Crespo et al., 2014; Kauffeld-Monz & Fritsch, 2013) suggested that its negative impact may be accentuated by the passing of time, as the technology matures and often requires new knowledge flows to reinvent itself. Our results also point in this direction, where from one period to another the density favouring a higher number of patents in RE is lower. In contrast, greater connectedness of the network subgroups appears to foster innovation in RE. Hence, it is important to stress that a region can be highly connected and exhibit a low presence of cohesive groups, and vice versa. These findings are in line with theories claiming that the existence of subgroups in the network facilitates innovation (Fritsch & Kauffeld-Monz, 2009; Innocenti et al., 2020). These subgroups tend to be characterized by a more recurrent collaboration, where the actors know each other better and there is more trust. This allows the transmission of information to be more efficient and facilitates its recombination in new innovations.

With the second sub-research question we explore how the proximity of cross-regional collaborations, in terms of geographical and technological proximity, influences a region's RE innovation performance. On the one hand, contrary to predictions (Hypothesis 3), it has been found that those regions where collaboration with other more distant regions prevails have turned out to be more innovative in RE. Some authors point out that differences in the social and economic environment can lead to semantic differences in referring to a technology that complicate collaborations between distant regions (Kalapouti & Varsakelis, 2015; Marrocu et al., 2013). Therefore, we suggest that the reason why collaboration between distant regions is preferable in the particular case of RE may be because the global scope of RE energies has led to a more standardized and codified language, which minimizes or eliminates semantic barriers, facilitating the transfer of tacit knowledge. Once communication is easier, collaborating with distant regions can be beneficial to the region by bringing new refreshing ideas for the generation of new innovations. Regarding technological proximity, although with less significance than the other characteristics analysed, the sharing of certain knowledge base in RE among actors when they collaborate seems to foster regional innovation in the sector (Hyptothesis 4). In this case, our prediction is correct, and technological proximity seems to help cooperation between actors to develop more smoothly (Marrocu et al., 2013; Pan et al., 2020; Verdolini & Galeotti, 2011).

Finally, our third sub-research question concerns the actors who are assumed to be key in the circulation of knowledge spillovers in the regional network, namely brokers and gatekeepers. With this question we have tried to determine how their presence influence the performance of the regions in RE. Consistent with previous studies, by transmitting knowledge between groups, brokers may prevent groups of inventors from becoming too isolated in their own knowledge base, (R. A. Boschma, 2005). Intermediaries, such as brokers, but among actors internal and external to the region, the presence of gatekeepers has also resulted to be favourable for the region's innovativeness in RE. Their role as a supplier of external knowledge within the regional network seems to be critical for the renewal of the regions' knowledge base (Gallo & Plunket, 2020). Moreover, in both cases, their experience as mediators can help to ensure that information is conveyed in an effective and understandable way (Gallo & Plunket, 2020; Kauffeld-Monz & Fritsch, 2013).

In addition, by means of specific models for solar and wind energy, we have been able to verify whether an approach focused on one technology reveals differences in the influence of the network characteristics. According to our results we can say that there are no major changes in the case of wind and solar energy. What we have observed is a difference in the relevance of some variables with respect to others. Our results showed that in wind energy innovation, technological proximity gains relevance to the detriment of collaborating with distant regions. Moreover, brokers are also more significant than gatekeepers. In the case of solar energy, the exact opposite is true. We associate it with the technical peculiarities of each technology as both are in a similar stage of development. Wind energy is somewhat more dependent on geographical and climatic conditions to function properly than solar energy. Furthermore, it requires further modification of its components to adapt to a given environment (Estruga, 2020). Thus, we believe that wind energy innovation can benefit more from knowledge within its own network and from collaborations with closer and more technologically similar regions, which have more experience in what technology to deploy in order to be as efficient as possible in the region.

In conclusion, this thesis provides a new perspective from which to face the great challenge of innovating in renewable energy, which is key to achieving the ambitious climate targets that lie ahead in the coming years. When it comes to explaining the innovative performance of European regions in the renewable sector, regional knowledge networks have proven to play a fundamental role. Thus, we hope that our findings have served to expand the factors to be taken into account when addressing innovation in renewable energy, and that they inspire future studies to continue exploring this avenue of research.

6. Discussions

6.1. Contributions

We believe that this thesis provides several contributions to the extant literature on regional knowledge networks and regional policy aiming to improve the region performance on the RE sector.

Starting with the literature contributions. To the best of our knowledge, most empirical studies on regional knowledge networks are focused on a particular type of characteristics of the network. Although it has been demonstrated that several of them influence the technological innovativeness of the network, the different types of characteristics analysed in this study have not been studied together before. Then, it may happen that some of them are no longer as relevant as expected when evaluated in combination. What we have done is bringing together in a single analysis several of these characteristics assessed by different authors, grouping them into structural (Innocenti et al., 2020), proximity (Marrocu et al., 2013; Pan et al., 2020) and actor-specific (Gallo & Plunket, 2020; Kauffeld-Monz & Fritsch, 2013). Interestingly, all the variables considered show some kind of significance in one of the three full models considered (general baseline model, solar model and wind model). This reveals, on the one hand, the important role of the network in the innovative performance of the region, but also its complexity, where multiple of its characteristics have an influence.

Second, despite it has been already emphasised the importance of regions (IEA, 2019; Larruscain et al., 2017) and collaboration to foster innovation in RE (IEA, 2020), this is one of the few studies to investigate regional RE innovation from a knowledge network perspective. As a result, we have been able to find some contradictions with previous studies investigating the effect of networks on innovation in general or in a particular sector other than the energy sector. In particular, while authors such as Marrocu et al. (2013) and Pan et al. (2020), found that collaborations between actors from neighbouring regions facilitated knowledge transfer and thus innovation, in our case we have observed the opposite. This highlights the global nature of RE innovations. Our findings also diverge from studies that have found it beneficial for the network to be highly connected (Kauffeld-Monz & Fritsch, 2013; Tseng et al., 2016), suggesting that this favours the accumulation of redundant knowledge in RE that can lead to technological lock-in in the region (Innocenti et al., 2020).

In addition to contributions to the literature, we believe that our results may also be useful to regional policy makers seeking to improve their region's performance in RE. In relation to the importance of external knowledge circulating in the region, we can think of several measures. First, given the potential benefits of external knowledge spillovers in the regional network, we advise regional policy makers to promote the region's integration into international networks. One option for regions is to take advantage of the many instruments offered by the European Commission (EC) to facilitate international collaborations to jointly plan R&D programs and promote knowledge sharing among RE actors (IEA, 2020). These include several industrial alliances open to European stakeholders in the renewables sector. The aim of these alliances is to bring together actors across the European Union and from different fields (academic, research institutes, industry and SMEs etc...) to enhance the development of RE technologies

(IEA, 2020). One example is the Clean Hydrogen Alliance, focused on promoting the growth of technologies based on the use of hydrogen as RE source (European Commission, n.d.-a). Second, we recommend identifying other regions whose knowledge base in RE is similar, especially in the case of wind energy is, and take measures to facilitate cooperation with them. For example, by removing possible bottlenecks that hinder these cooperations or by funding or restructuring R&D programmes in RE to incentivise more collaboration with their external actors. Third, given the importance of gatekeepers in the dissemination of external knowledge in the region, We encourage policy makers to identify organizations or individuals that show frequent inter-regional cooperation in RE and attempt to integrate those into networking activities of the region.

Within the region, we advise creating policies that encourage the formation of dense sub-networks in which collaborations are more frequent, and where high trust among members prevails. One possibility is to establish industry platforms where actors specialized in a given RE can share their knowledge and expertise. Moreover, these platforms make it easier to find other stakeholders with common interests with whom to initiate new projects together (Marrocu et al., 2013). Finally, to enhance knowledge spillovers within the regional network, public organizations can be created for the specific purpose of acting as brokers. One example is the IMDEA Energy Institute, created by the Madrid Regional Government. In collaboration with other research centers and universities, it aims to join efforts in the development of R&D activities in the sustainable energy sector and also acts as a link in the transfer of R&D findings to the productive sector (IMDEA Energy Institute, n.d.).

With this study we have seen the relevance of collaborations and the way in which they are produced in order to diffuse knowledge throughout the regional network and thereby stimulate innovation in renewable energy. This is why, generally speaking, we urge regions to invest in policies aimed at investing in the diffusion of knowledge throughout the region, rather than just investing in R&D in RE.

6.2. Limitations and further research

At this point it is necessary to underline the limits of the present research. Some of them are commonly found in innovation studies based on patent data. To begin with, the links in our networks are based solely on co-inventions. The reality is more complex, and there are many personal and professional ties that are not reflected in patents collaborations. Moreover, these collaborations can be oriented towards other innovative activities such as the improvement of RE products and processes that are not reflected in patents. Another limitation related to the use of patents in the analysis is that there are fewer patents RE at the regional level (NUTS 2) in Europe than originally thought. This has prevented us from having a larger time window of analysis to better understand the evolution over time of the network's characteristics. We suggest for further conducting a similar research but with an approach at NUTS 3 regional level or at the national level, with the objective of accumulating more patents per unit of analysis, which could solve this problem. In addition, this broader approach may allow to get a better grasp of how the maturing of the technology influences the network characteristics. This limitation in the number of patents has also impeded a broader comparative analysis of network characteristics between RE types. It has only been possible to make a comparison between wind and solar energy, both of which are experiencing their expansion in recent years. The fact that both technologies are at a similar stage of development allows us to explore in depth how technological differences affect the characteristics of regional knowledge networks. However, it would have been interesting to also compare with technologies such as hydro energy, which had their innovation boom many more years ago but still have an important share in the generation of renewable energy in Europe, and to see how the maturity of technology influences the network.

Our dependent variable is also a limitation in itself. As we have already discussed, not all patents have the same relevance and not all innovations are patented. To solve the first problem, we suggest using patents weighted by family size (Guan & Liu, 2016) or number of citations (Miguelez & Moreno, 2018). As for the second, it would be interesting to use an alternative to the use of patents for the creation of regional knowledge networks in order to corroborate our results. A different option could be the use of R&D research projects in RE, which have already been used in other studies using SNA (Larruscain et al., 2017).

Furthermore, when analysing inter-regional collaboration through proximity and gatekeepers we have not differentiated whether the collaborations have taken place within the country or outside its boundaries. For future studies it would be interesting to include this distinction, for example by adding a categorical variable that distinguishes between external collaborations within the NUTS 1 region level boundaries, within the same country and at the international level. This would allow us to more precisely narrow down the distance at which inter-regional collaborations benefit regional innovation in RE, adding a layer of complexity to our results. Future research could also examine the dynamics of regional knowledge networks in RE using not only intra- and inter-regional EU collaborations, but also interactions with countries outside the EU, such as the regions of North America, Asia or developing countries.

Moreover, for this analysis we have tried to include several control variables that have been demonstrated to influence both RE innovation and especially innovation in general. We believe that the availability of more comprehensive datasets oriented towards the RE could improve the results. Some of these may be regional R&D expenditures in RE or number of regional projects in this field. Additionally, there are aspects such as the legislative framework for the promotion of renewable energies at the national or regional level which presumably also influence their innovative performance in the sector, and which are very difficult to transfer into an empirical study.

Finally, although we have tried to combine several types of network characteristics in the same study, there are still more which have been relevant in other studies that have not been considered. For instance, Miguelez et al. (2018) found direct external ties boost the innovative capacity of regions. From our results, where collaborating with distant regions is a positive factor, it seems that it is be beneficial for the region. However, it would be interesting to compare this with the indirect connections to the external regions mediated by the gatekeepers and see what is most worthwhile for the region.

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Appendix A: Descriptive statistics of the variables in the solar and wind models.

Descriptive statistics

Table 6. Descriptive statistics of the variables in the solar model. Note: The results have been rounded to two significant figures.

Variables	Mean	Median	Min.	Max.	SD
Number of patents in RE (DV)	32	15	0	320	46
Density (IV)	0.12		0	0.78	0.13
Transitivity (IV)	0.80	0.93	0	1	0.31
Geographical proximity (IV)	0.0045	0.0037	0.00029	0.020	0.032
Technological proximity (IV)	0.75	0.76	0	1	0.12
Brokers (IV)	0.026	0	0	0.29	0.040
Gatekeepers (IV)	1	0	0	28	3.0

Table 7. Descriptive statistics of the variables in the wind model. Note: The results have been rounded to two significant figures.

Variables	Mean	Median	Min.	Max.	SD
Number of patents in RE (DV)	25.81	9	0	740	71
Density (IV)	0.13	0.078	0	0.90	0.15
Transitivity (IV)	0.77	0.92	0	1	0.34
Geographical proximity (IV)	0.0047	0.0040	0	0.00043	0.0022
Technological proximity (IV)	0.66	0.71	0	1	0.21
Share of brokers(IV)	0.025	0	0	0.50	0.059
Gatekeepers index by number of inventors (IV)	0.18	0	0	6.94	0.54

Boxplots

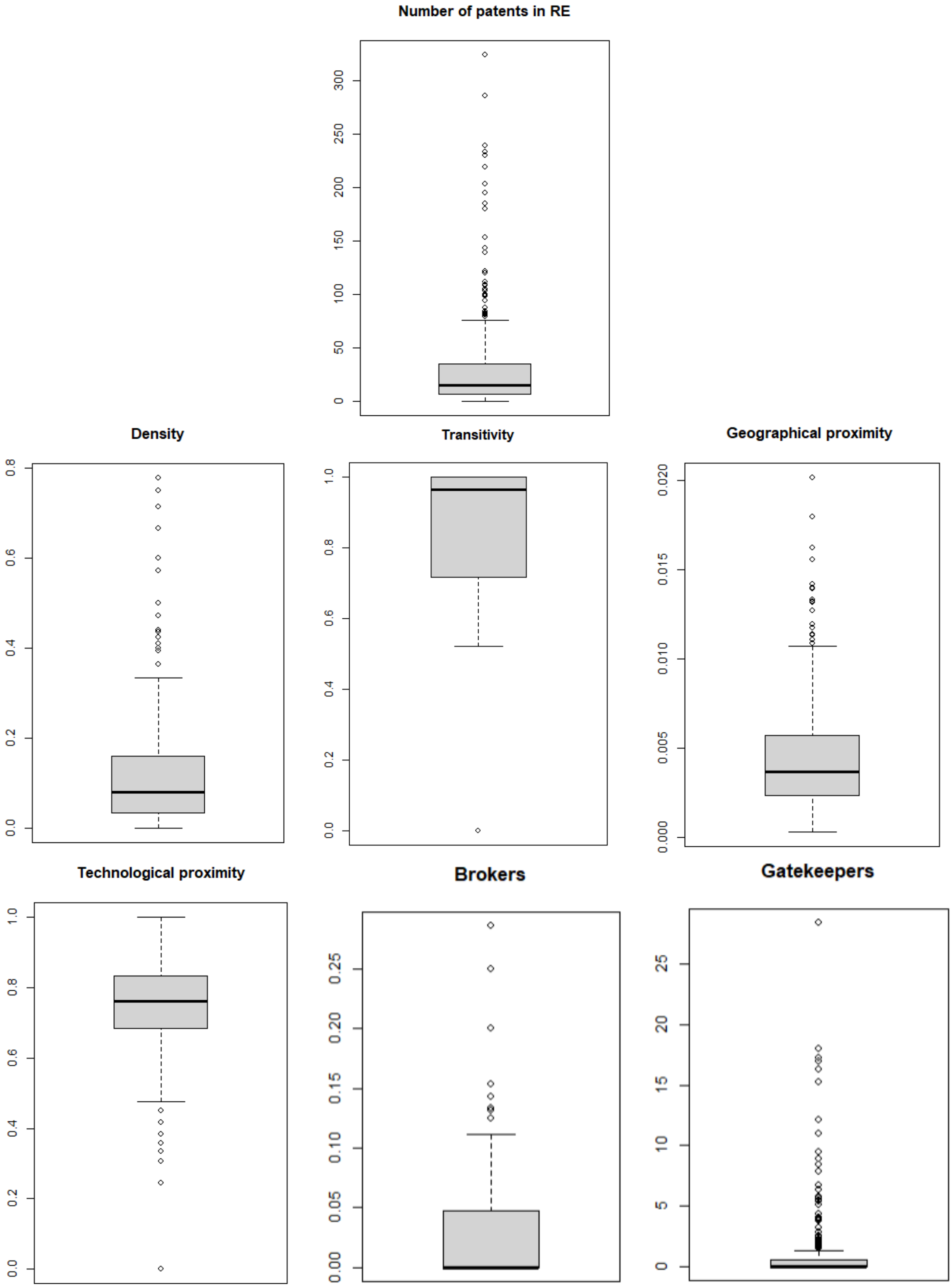

Figure 10. Boxplots of the dependent and independent variables of the solar model dataset in the period 2003 - 2017.

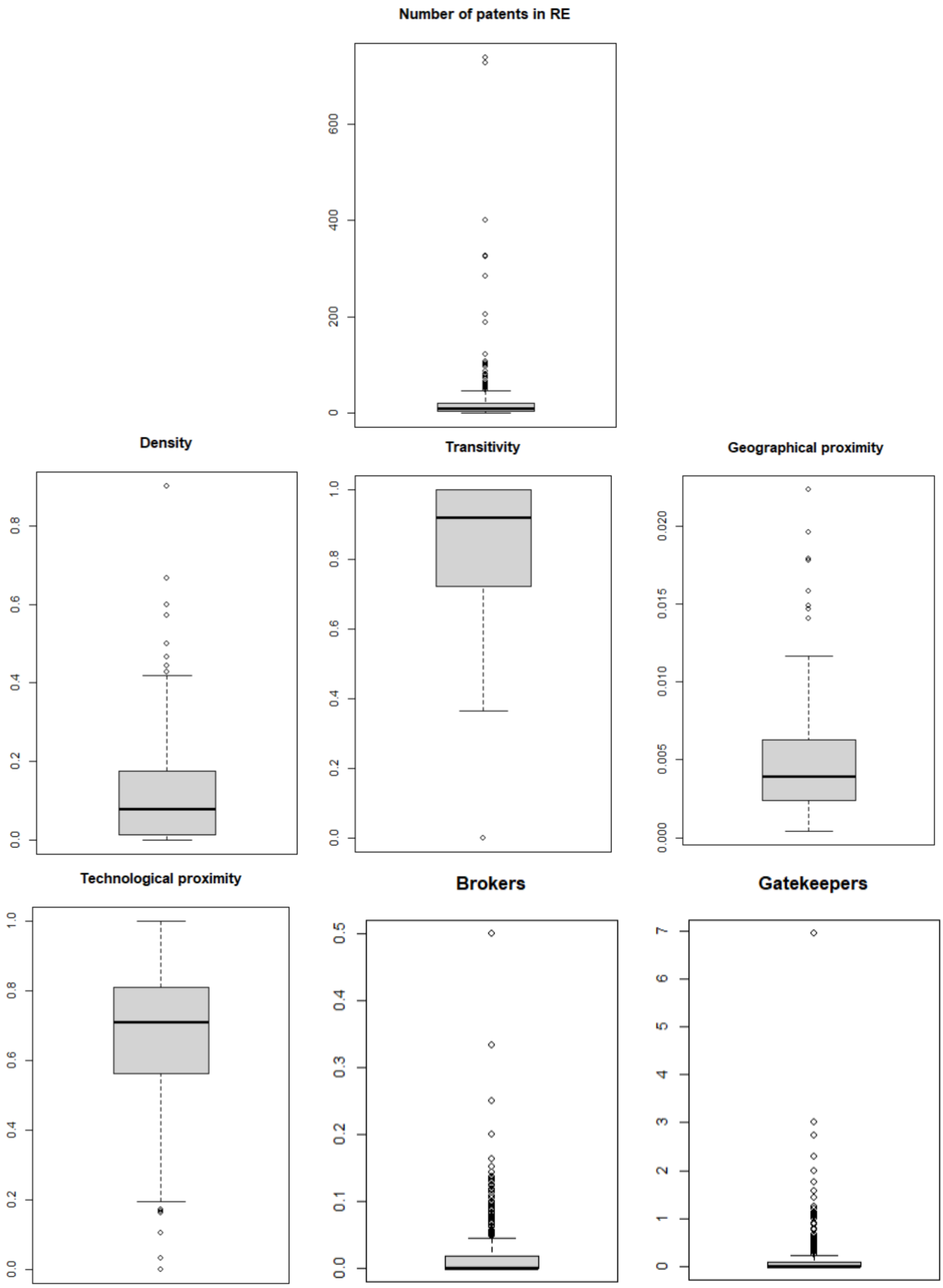

Figure 11. Boxplots of the dependent and independent variables of the wind model dataset in the period 2003 - 2017.

Appendix B: Correlation tables

Table 8. Correlation matrix of the baseline model database variables

	nPatents	Density	Transitivity	Geo prox	Tec prox	Gatekeeper	Brokers	CDD index	Human capital	Population	Population density	R&D/GDP
nPatents	1											
Density	-0.29	1										
Transitivity	-0.04	-0.2	1									
Geo prox	-0.06	0.14	0.09	1								
Tec prox	0.27	-0.32	0.11	0.06	1							
Gatekeepers	0.23	-0.15	-0.2	0.01	0.25	1						
Brokers	0.3	-0.28	-0.28	0	0.28	0.2	1					
CDD index	-0.14	0.16	0.03	-0.25	-0.07	-0.1	-0.24	1				
Human capital	0.06	-0.23	0.06	-0.01	0.01	0.04	0.05	-0.27	1			
Population	0.26	-0.14	0.06	-0.27	0.06	-0.01	0	0.42	-0.1	1		
Population density	0.03	-0.1	0.07	0.01	0.06	0.01	0.05	0.01	0.27	0.14	1	
R&D/GDP	0.19	-0.22	0.05	-0.05	0.11	0.09	0.07	0.09	0.2	0.02	-0.05	1

Table 9. Correlation matrix of the solar model database variables

	nPatents	Density	Transitivity	Geo prox	Tec prox	GK index	Brokers share	CDD index	Human capital	Population	Population density	R&D/GDP
nPatents	1											
Density	-0.29	1										
Transitivity	0.015	0.24	1									
Geo prox	-0.039	-0.02	-0.03	1								
Tec prox	0.26	-0.21	0.04	0.13	1							
Gatekeepers	0.43	-0.15	-0.15	0.03	0.30	1						
Brokers	0.22	-0.22	0.01	-0.02	0.10	0.18	1					
CDD index	-0.09	0.09	-0.01	-0.22	-0.15	-0.08	-0.18	1				
Human capital	0.05	-0.13	0.01	0.11	-0.25	0.06	0.13	-0.26	1			
Population	0.37	-0.17	0.10	-0.25	0.04	-0.01	0.05	0.42	-0.12	1		
Population density	0.01	-0.09	0.06	0.09	0.13	0.01	0.07	0.02	0.29	0.11	1	
R&D/GDP	0.33	-0.21	0.08	-0.10	0.03	0.09	0.15	-0.28	0.16	0.04	-0.01	1

Table 10. Table 3. Correlation matrix of the wind model database variables

	nPatents	Density	Transitivity	Geo prox	Tec prox	GK index	Brokers share	CDD index	Human capital	Population	Population density	R&D/GDP
nPatents	1											
Density	-016	1										
Transitivity	0.10	0.30	1									
Geo prox	-0.06	0.03	-0.03	1								
Tec prox	0.13	-0.01	0.34	-0.05	1							
Gatekeepers	0.18	-0.10	0.08	-0.05	0.22	1						
Brokers	0.22	0.02	0.04	-0.01	0.15	0.36	1					
CDD index	-0.10	0.06	-0.13	-0.16	-0.15	-0.12	-0.14	1				
Human capital	0.01	-0.04	0.20	-0.07	0.15	0	-0.08	-0.13	1			
Population	0.03	-0.01	0.13	-0.16	0.05	-0.03	-0.01	0.32	-0.11	1		
Population density	0.01	-0.06	0.03	0.05	-0.05	0.08	0.02	-0.04	0.26	0.15	1	
R&D/GDP	0.02	-0.05	0.17	-0.07	0.26	0.05	-0.04	-0.25	0.15	0.05	-0.03	1