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The ability of European regions to diversify in renewable energies: The role of technological relatedness

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ABSTRACT

Despite the global consensus about the growing significance of renewables, the regional drivers of innovation in these unique and novel technologies have been widely neglected in the literature. In this paper, we show that renewable energy (RE) inventions differ from other green inventions in the knowledge recombination processes leading to their generation as well as in their impact on subsequent inventions. The evidence on these specificities of RE technologies allows us hypothesizing that regional branching in renewables may rely on relatedness differently than other non-RE green technologies. In checking this hypothesis, we use a data set spanning the period 1981-2015 covering 277 European NUTS2 regions in the EU28 countries plus Norway. We obtain that relatedness is highly relevant in explaining regional specialization in RE, and more relevant than for other green technologies, which we associate to the lower generality in their impact and the narrower scope of the knowledge from which they nurture. This conclusion is maintained when considering separately regions with high and low development levels. However, the impact of relatedness increases for RE as the regional economic development decreases, signalling that a low endowment of resources and capabilities does not allow the region to break from its past technological specialization, depending more on relatedness. This would not be the case for other green technologies, probably due to their higher level of generality and wider scope.

1. Introduction

Current climate change scenario poses new challenges to society (Fankhauser and Tol, 2005; Ronson and Van der Mensbrugghe, 2012) and failing to enter a sustainable growth path would put at risk future growth and development (Hayter, 2008). Being the energy sector the principal source of greenhouse gas emissions (IEA, 2018), advances in RE technologies are needed. RE sources can meet the present world energy demand but cannot compete with conventional fuels on cost (Turkenburg and Faaij, 2000). Further technology development and diffusion of RE technologies are required to get considerable cost reductions for making renewables more competitive. Thus, climate change mitigation compels new technological solutions in renewables to break the present supremacy of fossil fuels. Our paper tries to get empirical evidence on the role of technological relatedness on regional diversification into renewables as a path to transform the current energy systems towards a new low-carbon paradigm.

The study of economic geography can help to provide theories, lessons and policy recommendations on how to spur further innovation in RE. Specifically, the regional technological branching literature analyses the main drivers for a region to specialize into a new technology. Among other factors, several recent papers signal the relevance of relatedness in explaining regional technological diversification (Boschma, 2017; Hidalgo et al., 2018; Montresor and Quatraro, 2017; Tanner, 2015), with relatedness referring to the cognitive proximity between a new technology in the region and its pre-existing knowledge domains. A general conclusion is that path dependence explains the emergence of new technologies or new industries in the sense that they tend to be closely related to those that already exist in the region.

Constructing on the above, the present paper bases on the subfield of environmental economic geography and delve into the connection between RE technologies generation and their relatedness with the local competences (Tanner, 2014; Montresor and Quatraro, 2019; Santoalha and Boschma, 2020). We aim at providing evidence to understand how RE technologies are introduced and adopted across regions and why this occurs in some places rather than in others. When analysing the role of relatedness in the case of the regional specialization in RE technologies, we contribute in several ways.

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First, we focus on renewable energies, which will allow for more specific and targeted policy recommendations for governments aiming to incorporate efficient energy generation to tackle climate change. The literature thus far has been either general by focusing on green technologies (Ghisetti et al., 2015; Colombelli and Quatraro, 2018; Van den Berge and Weterings, 2014; Fabrizi et al., 2018; Montresor and Quatraro, 2019; Barbieri et al., 2020a, 2020b; Perruchas et al., 2020) or too specific to be applicable to general climate change mitigation policy (Tanner, 2015; Li et al., 2020). The work by Johnstone et al. (2009) is one of the few analysing renewables, but their analysis focuses on the impact of regulation at a countrywide scale. We hypothesize that RE inventions may differ from other green inventions, since they have been found in a maturity stage (Barbieri et al., 2020b), in contrast to many other green technologies (e.g. Environmental management, Water management, Capture and storage of greenhouse gases, Waste treatment and management, among others). To identify distinctive features of RE technologies with respect to non-RE green technologies, we compute a set of established indicators (Vehoeven et al., 2016; Barbieri et al., 2020a) that allow considering the ex-ante and the ex-post perspectives of the invention process. The ex-ante analysis seeks to identify the knowledge components on which the invention is built upon; while the ex-post approach seeks to identify how the invention allows the creation of new subsequent knowledge. Our evidence concludes that RE technologies are different from non-RE green technologies in most of the characteristics of their invention process.

Second, this evidence on the specificities of RE technologies allows us hypothesizing that regional branching in renewables may rely on relatedness differently than other non-RE green technologies. In checking this hypothesis, we use a data set spanning the period 1981-2015 covering 277 European NUTS2 regions in the EU28 countries plus Norway. This contrasts with some of the previous papers analysing the role of relatedness in green technologies, which limit the sample to all or some pre-2004 access countries in order to consider a relatively more homogeneous set of innovation systems than the EU28 in terms of patenting (Montresor and Quatraro, 2019; Boschma and Santoalha, 2020). Our sample includes the whole of Europe[1] and focus on RE technologies, which we show to behave differently than non-RE green technologies in their nature and impact. Consequently, the particularities of RE technologies make us investigate whether their regional branching relies differently on relatedness than the bulk of green technologies. Specifically, we find that RE technologies are more novel and radical and use more scientific knowledge than other green technologies; at the same time, they present a narrower technological scope and a lower generality in its impact. We expect that their higher level of novelty and radicalness and their higher use of scientific knowledge would downplay the role of relatedness. Whereas the narrower scope of the knowledge from which RE nurtures as well as the lower generality in their impact would work in the other direction: relatedness would be highly relevant in explaining regional specialization in RE. According to our regression results, the latter seems to prevail.

Finally, we go deeper into our argument by relating to recent existing literature about the differential role of relatedness on industrial diversification for different levels of regional development and innovation (Boschma and Capone, 2016; Xiao et al., 2018). They provide evidence that relatedness is more crucial for the appearance of new industrial specialization in regions with lower levels of resources and capabilities (Boschma and Capone, 2016) and weaker innovative capacity (Xiao et al., 2018) compared with leading regions. In our paper, we do not only analyse whether relatedness is a more relevant driver of technological diversification into renewables in regions with a weaker level of resources and capabilities but we also study whether this works differently in the case of RE technologies compared to other green ones. We hypothesize that the influence of relatedness in the emergence of green technologies would be higher in regions with a low level of resources and capabilities and this would be especially true in the case of RE given their lower generality and higher specificity in scope. These two characteristics would make regions with low endowments of resources and capabilities highly dependent on existing knowledge within the same technological domain of renewables. This would imply a higher role of relatedness with pre-existing technologies in the case of RE technologies if compared to other green technologies, the latter with a broader technological scope and higher generality.

The paper is structured as follows. The next section reviews the related literature and states our main research questions. Section three discusses the data and the variables under consideration and section four sets out the empirical strategy. The main results are in the fifth section as well as some tests of robustness. We end with the conclusion.

2. Background literature and conceptual framework

The importance of geographical proximity in fostering innovation and diversification has been widely noted (Boschma, 2005, 2011; Moreno et al., 2005) and economic geographers have argued that the regional scale is greatly important in the process of diversification. Regions have localised capabilities, a high degree of tacitness and consist of intangible assets that are difficult to replicate, even within a country. We must recognise the crucial role of the local spatial context when looking at the determinants of eco-innovation (Fabrizi et al., 2018; Colombelli and Quatraro, 2018). The pressure posed by climate change requires technological solutions and regions are settings where transitions towards sustainability can take place through the combination and recombination of technologies (Gibbs and O'Neill, 2018). Indeed, innovation is an evolutionary process where creation of new knowledge is incremental and is the result of deepening and re-combining existing knowledge stock (Dosi, 1982). Rationality, risk and high switching costs provide bounds for firms and prevent the creation of new technologies from scratch (Boschma et al., 2014). As a result, new technologies often do not emerge from virgin markets but are a path dependent incremental process where new capabilities relate to pre-existing ones (Neffke et al., 2011). This paper focuses on the process of knowledge recombination at the basis of the inventive activity that generates new technologies. We follow the reasoning that technological change is a cumulative process, so that each invention builds on the body of knowledge that preceded it (Boschma and Frenken, 2010). Following this foundation, we focus on RE technological specialisation and study regional factors that enable or hinder it. Specifically, we analyse whether and to what extent local competences play a role in the emergence of RE technologies across regions.

There exists a vast literature on the importance of having related technologies within a region for the creation of new industries. Neffke et al. (2011) was the first paper, on a regional scale, to show that relatedness with existing industries in a given region increases the entry probability of a new industry. Other studies followed from this, emphasising the important role that related technologies play in enabling regions to diversify into new industries and technologies (among others, Kogler et al., 2013; Rigby, 2013; Feldman et al., 2014). In these papers, relatedness refers to the cognitive similarity between the new introduced technology and the pre-existing regional knowledge base, arguing that such a proximity is crucial for getting the new technology thanks to the recombination of the pre-existing domains. The review made by Content and Frenken (2016) points to relatedness being an important driver of regional diversification across technologies (in addition to products and industries) but concludes that the evidence is still mixed. Similarly, despite recognising the role of relatedness in the emergence of new technologies, Boschma and Frenken (2006) claim that

[1] Recently, Santoalha et al (2021) elaborate an empirical analysis of the relationships between ICTs, digital skills and green diversification in European regions, considering a panel of 142 regions in 22 European countries for the period 2006-2013. They consider the EU-28 plus Norway, except Croatia, Denmark, Germany, Greece, Malta, Netherlands and Poland.

determinism is not always the rule and point to spatial eventualities as being less important at early stages of an industry's development because of the gaps between the necessities of the new knowledge and the established one.

There is a consensus in the literature that environmental innovations require access to a variety of external sources and economic agents for recombinant innovation (Cooke, 2010; Tanner, 2015) due to i) their complex and codified knowledge bases (Rennings and Rammer, 2009; Zeppini and Van Den Bergh, 2011; De Marchi, 2012; Cainelli et al., 2015; Barbieri et al., 2020a), ii) that they are more heterogeneous and novel relative to the standard technology and thus iii) require a greater diversity of knowledge sources (Horbach et al., 2013; Li et al., 2020).

Among the reasons of the higher level of complexity of environmental technologies, previous works obtain that they involve a wider range of knowledge inputs and competences, require skills that are usually beyond the firm's knowledge domain (De Marchi, 2012), present multiple objectives (Ghisetti et al., 2013) and their development embrace several dimensions from design to user-involvement and product-service delivery (Ghisetti and Montresor, 2019; Ghisetti et al., 2021). This is probably related to the result obtained in previous literature that green jobs present a greater intensity of non-routine skills (Consoli et al., 2016), which the authors associate to the continuous reconfiguration of green occupations, or that workforce e-skills are positively related to the specialization in new technological domains, this effect being stronger for green than non-green specializations (Santoalha et al., 2021). Second, with respect to the higher degree of novelty of green technologies, Cainelli et al (2015) describe them as representing a technological frontier, which imply radical change due to the lack of instituted eco-friendly best practice and technological trajectories. According to Marzucchi and Montresor (2017), eco-innovators differ from standard innovators in the management of their portfolio of knowledge drivers and are more reliant on analytical knowledge inputs from scientific partners, a conclusion also obtained in 1Ocampo et al. (2021) for the specific case of RE. Third, as for environmental innovation requiring a greater diversity of knowledge sources, previous works show that green inventions seem to rely on unique combinations of knowledge, which differ from extant knowledge bases (Barbieri et al., 2020a), and associated to broad and deep sourcing strategies (Ghisetti et al., 2015), and alternative production processes and inputs largely linked to rather new technological solutions (Horbach et al., 2013).

All in all, these distinctive features of green technologies could result in difficulties associated to their knowledge recombination process. However, prior recent research identifies relatedness as a key driver of new specializations in the domain of green technologies. Montresor and Quatraro (2019) and Santoalha and Boschma (2020), both of them focusing on regions in some specific countries in the EU, show that a high endowment of regional green-related knowledge is a driver of green technological development, and Perruchas et al. (2020) for the case of 63 countries find that countries are more likely to diversify into domains of green technology that are related to their portfolio of competences. Additionally, Santoalha et al. (2021) show that workforce skills associated with the use and development of ICT technologies in 142 European regions negatively moderate the effect of relatedness on technological diversification, both for green and non-green diversification. Consequently, despite green technologies have particularities with respect to non-green ones, cognitive proximity favours technological specialization in both domains.

However, Barbieri et al. (2020b) show that not all green technologies behave equally, but they present different levels of maturity which may condition the role of relatedness for the development of new green technologies. With our main interest focused on the analysis on how regions diversify in RE, we first analyse to what extent this technology present distinctive features with respect to other green technologies.[2] We compute a battery of indicators that allows us comparing the ex-ante and the ex-post perspectives of the invention process in both cases: the knowledge components on which the invention is built upon, and how the invention allows the creation of new subsequent knowledge, respectively. The evidence we will provide in this paper concludes that RE inventions differ from other green inventions with respect to their complexity, novelty, impact and generality.

We aim at analysing to what extent this differentiation may shape the role of relatedness. The higher level of novelty and radicalness we obtain for RE patents (if compared to other green patents) would imply that they require a break from the past, downplaying the role of relatedness in technological diversification in RE. In the same direction, their higher use of scientific knowledge would allow RE invention to nurture from sources of knowledge that would depart from the technological specialization already existing in the local knowledge base, downplaying again the role of relatedness in the case of RE if compared to non-RE green technologies. On the other hand, we observe that RE inventions are more specialized than other green inventions, as they present a narrower technological scope of the knowledge from which RE nurtures, and at the same time are less general in its forward impact. This higher level of specialization of RE technologies would make them more strongly path-dependent than in the case of non-RE green technologies, working in the other direction: relatedness would be more relevant in explaining regional specialization in RE, since they are less general technologies with a more limited scope, than in the case of non-RE green technologies. The regression analysis will allow us to provide evidence on which of the two arguments above prevail in the case of the RE diversification of European regions.

Finally, Xiao et al. (2018) argue that the role of relatedness on industrial diversification tends to be an average effect across many different regions/territories and obtain that the influence of relatedness is higher in regions with a weaker innovative capacity. This is consistent with the claim that there exist important differences between regions due to their different institutional quality (Cortinovis et al., 2017) or lower resources and capabilities (referring not only to technological knowledge but also institutions and entrepreneurship, among others) to diversify in products that are not very related to their productive structure (Boschma and Capone, 2016). This last study obtains that the effect of relatedness density on the diversification into new industries is much stronger in the case of the European Neighbourhood Policy (ENP) countries, which rely much deeply on the relatedness between products and the specific capabilities needed to produce them. Whereas EU countries tend to be able to diversify into less related industries because of the presence of more general resources in them. Specifically considering the different innovation levels of the regions, Xiao et al. (2018)

[2] Green or Environmental technologies are designed to reduce pressure on natural resources and improve adaptation to the changing environment. As such, they encompass a broad spectrum of domains, including Environmental management, Energy production, Water management, Capture and storage of greenhouse gases, Transportation, Buildings, Waste treatment and management and Production of goods. Renewable energy generation falls into the Energy production group. Examples of non-RE green technologies would be Environmental monitoring, Energy efficiency in buildings, Wastewater treatment, Climate change mitigation tech for sector-wide applications, or Enabling tech with a potential contribution to GHG emissions mitigation, among others.

argue that the impact of relatedness decreases as the innovation capacity of a local economy increases, since a high innovation level "allows an economy to break from its past and to develop, for the economy, truly new industry specializations" (p. 514). Among other findings, they observe that the importance of relatedness density in developing new industrial specialization is higher in eastern European countries relative to other European countries. Following the papers reviewed in this paragraph, we aim at analysing whether relatedness is a more relevant driver of diversification in renewables in regions with low resources and capabilities, although we depart from them since we focus on technological diversification while they study industrial diversification. Despite the abundance of empirical literature showing the relevance of relatedness on regional branching, as far as we know, there is little evidence of under what regional development levels relatedness is more needed for technological diversification to happen; and even less for diversification into RE.

Following the arguments above, we expect that the influence of relatedness in the development of RE technologies can be higher in regions with a low level of resources and capabilities because this low level of resources would not allow them to break from their past in order to develop new RE technologies; unless they are related to the pre-existing knowledge base. This would be especially true in the case of RE if compared to other non-RE green technologies, since, as we will show later in this paper, RE technologies are less general and more specific in scope. This higher specificity of renewables would make regions with low endowments of resources more dependent on existing knowledge within the same technological domain. This would imply a higher role of relatedness with pre-existing technologies in order to diversify into RE technologies. On the contrary, for non-RE green technologies, given their more general scope, low-endowed regions would find less difficulties to diversify into non-RE green technologies. Their general scope would allow low-endowed regions to feed from knowledge coming from technologies cognitively distant to them, therefore reducing the relevance that technological relatedness plays in the process of specialization in other green technologies in regions with low levels of resources and capabilities.[3]

3. Data and descriptive statistics

3.1. Dataset and dependent variable

Our data cover 277 NUTS2 regions from the EU28 plus Norway for the period of 1981-2015. We use the OECD REGPAT database (January 2020 edition) for the computation of the dependent variable as well as the relatedness indicators. Our dependent variable measures the entry of technologies in the RE technological field through patent applications filed to the European Patent Office (EPO). Patent statistics are widely used in the literature to measure technological innovation since they focus on the outputs of the inventive process. Despite their weaknesses, such as their potential inability to capture all knowledge production in an economy (Griliches, 1990) or the variations in quality between patented innovations, they are the most useful measure for our purposes. Output measures date back a very long time and have a discrete nature, allowing statistical analysis as well as the development of indicators. They are very detailed, providing a wealth of information on the nature of the innovation and the geographical location (addresses) of the inventors involved. In particular, they easily disaggregate into specific technological fields and allow us to define what we consider 'renewable energy' invention as well as its related technologies. In order to classify what we consider as RE, we take patented technologies with the International Patent Classification (IPC) system code 'Y02E10', under the title 'Renewable Energy Generation.' This consists of wind, solar thermal, solar photovoltaic (PV), solar thermal-PV hybrids, geothermal, marine energy and hydro energies. Patent statistics in the REGPAT database incorporate fractional counting when there are multiple inventors residing in different regions. However, knowledge is arguably a non-divisible asset and since we are interested in knowledge production at the regional level, full counting is used. Therefore, if there exist several inventors from different regions in the same patent document, we assign the same patent application to each region involved (Tanner, 2015).

Our dependent variable measures the entry of new RE technological specialization in a NUTS2 region, denoted as *Spec_RE*, in time windows of five years starting from 1981 and lasting until 2015, summing the data over non-overlapping five-year periods. This creates a total of seven periods. We do this in order to smooth the yearly lumpiness of patent data[4]. Following other studies on regional diversification (Kogler et al., 2013; Boschma and Capone, 2015; Rigby, 2015), to decide if a region r is specialized in RE technologies, we compute the revealed technological advantage index for the RE domain in each region r and time period t (Balland et al., 2019) and construct the dependent variable, *Spec_RE*, as follows:

$$Spec\_RE_{rt} = 1 \quad if\ \frac{patents_{REr t}/\sum_i patents_{irt}}{\sum_r patents_{REt}/\sum_r\sum_i patents_{irt}} > 1 \tag{1}$$

and 0 otherwise where $patents_{irt}$ represents the total number of patents in technology i, region r and time period t, and $patents_{REr t}$ represents the total number of patents in renewable energy technologies in region r and time period t. Having revealed technological advantage in RE technologies would mean that the region is more specialized in those technologies than the EU average. However, given that we aim at focusing on the entry of RE technologies specialization in a region r in a time period t, the dependent variable is a dummy variable that takes the value 1 if region r, which did not have a specialization in RE technologies at time t-1, acquires that specialization at time t. Otherwise, it takes the value 0, which implies that region r has not been able to get a new specialization in RE technologies between t-1 and t.

Analogously to Eq. (1), we compute the entry, at time t, of non-RE green technologies (via specialization) in a region r that did not present such specialization in t-1 ($Spec\_nonREgreen_{rt}$). To identify the set of non-RE green technologies we follow the classification of Hascik and Migotto (2015), which is also used to identify RE technologies.[5]

[3] As pointed out by a reviewer, less developed regions may have a less mature knowledge base and, consequently, a higher degree of cognitive freedom in developing new technologies in an explorative way. This could be especially true in the case of non-RE green technologies, with a higher level of generality and a wider scope, so that less developed regions would be less affected by relatedness in their process to specialize in non-RE green technologies. We thank the reviewer for raising this argument.

[4] The use of windows of data in five-year periods is common practice in empirical analyses using patent data. See Montresor & Quatraro (2019) and Santoalha & Boschma (2020) for the specific case of regional diversification into new green technologies.

[5] The subset of environment-related patents is identified through the OECD Env-Tech classification (Hascic and Migotto, 2015), which lists 95 environmental-related technologies, grouped into eight technology groups and thirty-six subgroups. The eight green groups refer to Environmental management, Water management, Capture and storage of greenhouse gases, Energy production, Transportation, Buildings, Waste treatment and management and Production of goods. Renewable energy generation lies within the Energy production group. Other technologies within the same group refer to Energy generation from fuels of non-fossil origin, Combustion tech with mitigation potential, Nuclear energy, Efficiency in electrical power generation, transmission or distribution, Enabling tech in energy sector and Other energy conversion or management systems reducing GHG emissions.

3.2. Key explanatory variables

Relatedness. Patent data have long been used to construct indicators of knowledge proximity/similarity. However, there is not a unique method to assess relatedness through similarity measures. On the one hand, Boschma et al. (2013), Colombelli et al. (2014) and Montresor and Quatraro (2019), among others, employ a measure to capture the degree of relatedness between any two technologies based on the revealed technological advantage of regions in these two technologies at a time (RTA co-occurance). Taking another approach, Balland et al. (2019) and Boschma et al. (2014), among others, use measures based on patent level technological co-classification (or co-occurrence in the terms of our study). The main difference between these two approaches is that in the first one the key figure is the number of times a region presents revealed technological advantage in two technologies at the same time (the co-occurrence of RTA at the regional level); while in the second approach the key figure to define relatedness or knowledge proximity is the number of times two technologies appear in the same patent document (the co-occurrence of technologies at the patent level). There are arguments in favour of each option, as shown below.

On the one hand, using RTA co-occurrence implies embracing the fact that two technologies are not necessarily close in cognitive terms, but in terms of other capabilities of the region. As Hidalgo et al. (2007) posed for the case of industrial relatedness and correspondingly to RTA at the industry level, this measure implies proximity or relatedness in terms of logistics, institutions, human capital and other capabilities along with knowledge that could allow the jump from one technology to another. This reasoning can be transferred to the technological realm, and relatedness based on RTA would imply having shared knowledge between two technologies and at the same time, institutions and other capabilities that allow the development of such technologies.

On the other hand, using the co-occurrence of any two technologies in the same patent document would provide a better description of the intellectual structure of the technology (van Raan and Peters, 1989; Engelsman and Van Raan, 1994; Tijssen, 2001). This will depict better the region's technology map, which could be acknowledged as more abstract representation of technological relations, leaving aside the effect of other factors. It is afterwards in a second step, as we will show afterwards, that to translate this relatedness to the regional level, the RTA of the region is considered, accounting for the region's own particularities.

In this paper, we follow the second approach.[6] We first create a measure of relatedness between technologies with the co-occurrence of two different IPC classification codes in the same patent document. We take the four-digit disaggregation of IPC in order to get a total number of 616 technological classes in which they were present for the whole period from 1981 to 2015. We are interested in technological co-location, hence, we count in how many patents a RE technology appears with any other technology (co-occurrence). More specifically, we compose the technology space network by computing the degree of relatedness between the IPC class for renewables (Y02E10) with every other IPC class *i*.

In addition, a second specificity of our measure is that, following the paper by van Eck and Waltman (2009), we use a probabilistic similarity measure which is superior to other types of similarity measures also based on co-occurrence, as explained next. Our measure of relatedness controls for the fact that this co-occurrence can be random through a probabilistic measure (or a normalized co-occurrence measure) between a RE technology and any other technology *i*:

$$\varphi_{REit} = \frac{o_{REit}}{e_{REit}} \tag{2}$$

where φ_{REit} stands for relatedness between the *RE* technology and any other technology *i*, o_{REit} is the raw co-occurrence of those two technologies and e_{REit} is the expected co-occurrence. The expected co-occurrences are computed by taking into account the number of times technology *RE* and technology *i* occur in the REGPAT database during the period *t* (s_{REt} and s_{it}, respectively), relative to the total number of patents in the same period ($patents_t$). This yields the final formula: $\varphi_{REit} = \left(\frac{o_{REit}}{s_{REt}s_{it}}\right) * patents_t$. In this case, if *RE* occurrences double, as well as the co-occurrences, the measure of similarity remains unchanged. This kind of indicator has been used before by Boschma et al. (2014) and by Balland et al. (2019).[7] We compute one co-occurrence matrix for each of the seven time windows under consideration.

To analyse how relatedness influences RE technological development at the regional level, we have to construct a regional level variable that indicates how close RE technologies are to the existing portfolio of a given region. To translate the measure of co-occurrence of technologies provided above to the regional European NUTS2 level and to calculate the relatedness density, we first construct the revealed technological advantage (RTA) index (Balland et al., 2019):

$$If \ \frac{patents_{irt} / \sum_i patents_{irt}}{\sum_r patents_{irt} / \sum_r \sum_i patents_{irt}} > 1 \text{ , } then RTA_{irt} = 1 and 0 otherwise \tag{3}$$

Having a RTA in technology *i* would mean that the region is more specialized in that technology than the EU average. We combine it with the co-occurrence matrix obtained above to know the degree of relatedness that the RE technology has with the technologies in which region *r* presents RTA through the following density index (Balland et al., 2015):

$$Relatedness\_RE_{rt} = \frac{\sum_{i \in r, i \neq RE} \varphi_{REit} RTA_{irt}}{\sum_{i, i \neq RE} \varphi_{REit}} \quad x100 \tag{4}$$

This density index computes how related is the technological base of a region *r* at time *t* with respect to RE technologies. It has all the desired properties of normalized co-occurrence data according to Van Eck and Waltman (2009). The intuition behind is that two technologies are highly related to each other when they are frequently observed at the same time in a region. This way, they share highly related local innovation capabilities (Boschma et al., 2013), once discounted how often these two technologies appear.

Analogously to Eq. (4), we compute the relatedness density index with respect to non-RE green technologies. It measures how related is the technological base of a region *r* at time *t* with respect to non-RE green technologies ($Relatedness\_noREgreen_{rt}$).

[6] In section 5.2 we test the robustness of the relationship of interest using the alternative measure of technological relatedness, that is, the one based on RTA co-occurrence as in Quatraro & Montresor (2019).

[7] Following van Eck and Waltman (2009), the use of a probabilistic similarity measure at the patent level, as we do in our study, responds to the fact that this kind of method is superior to other types of similarity measures also based on co-occurrences. The co-occurrence of two objects can be driven by two independent effects: the similarity effect and the size effect. The similarity effect is the one in which two objects co-occur because they are related to each other. The size effect is the one in which a high frequency of co-occurrence of two objects can be due to the fact that one of them occurs a lot. van Eck and Waltman (2009) offer a detailed discussion of why the type of measure used in our paper and the alternative ones in Boschma et al., (2013), Colombelli et al. (2014) and Montresor & Quatraro (2019), among others, have different implications in this respect. Basically, in our measure, if the occurrence of an object doubles, as well as the co-occurrences, similarity remains unchanged. This is not the case in the other type of measure which fails to capture the size effect in co-occurrence.

3.3. Characterization of RE vs non-RE green technologies

For the comparison between RE and non-RE green technologies, we compute a set of established indicators using patent data (Vehoeven et al., 2016; Barbieri et al., 2020a). As done in previous literature (Barbieri et al., 2020a), the analysis distinguishes between the ex-ante and the ex-post perspectives of the invention process. The ex-ante analysis seeks to identify the knowledge components on which the invention is built upon; while the ex-post approach seeks to identify how the invention allows the creation of new subsequent knowledge.

We use five indicators to proxy for the ex-ante recombination of knowledge in the invention process. First, the *scope* of the innovation measures the number of knowledge components required for the invention. It is measured as the number of different four-digit IPC codes to which the patent belongs. Second, the *originality* index measures the extent to which an invention draws on previous inventions that are dispersed across different technological fields. It is measured using the number of different four-digit IPC codes from the backward cited patents of an invention. Third, the indicator on the *novelty in recombination* captures the uniqueness of a knowledge recombination process, with an invention considered novel if it presents for the first time the combination of two knowledge components (measured with the four-digit IPC codes). Fourth, the *radicalness* index measures how much the technological classes in an invention depart from those in the patents it cites. Fifth, following Ocampo-Corrales et al. (2021) we consider to what extent the invention nurtures from scientific knowledge, and measure it as the number of non-patent literature (backward) citations (*NPL citations*).

Regarding the ex-post indicators, we aim at assessing the impacts of inventive activities on subsequent technological developments. We use two main indicators. First, we compute the number of *forward citations* received by a patent. Cutting the time period of the forward citations at five and seven years allows the comparison between old and new patents, as older patents would be more subject to be cited than more recent ones. Finally, the *generality* index of a patent reflects the extent to which the subsequent technological advances are spread across different technological fields, rather than being concentrated in few of them. The generality index captures the variety of technological fields to which the citing patents belong.[8]

3.4. Control Variables

In order to obtain information for the control variables, we merge the REGPAT database with other data primarily derived from Cambridge Econometrics and EUROSTAT. As control variables, we include first the GDP per million inhabitants (*GDPpc*) to control for the economic wealth in the region and because it has been argued that places with higher income tend to be more concerned about environmental issues (Kruize et al., 2007; Santoalha and Boschma, 2020). We control for the industrial structure of the region with the introduction of the share of manufacturing to total employment (*Industry share*), since the industrial sector tends to present a higher propensity to patent than services (Blind et al., 2003). Also, we include a measure of the overall patents produced in a region in a period of time (*Total patent*) to proxy for the overall innovativeness capacity of a region in general terms. All the independent variables are defined using their five-year average and have a time lag of one period (t-1) in order to dampen potential endogeneity issues (Boschma et al., 2014). The variable description of the dependent and explanatory variables as well as the sources and formal definition of these variables are presented in Table A1 of the Appendix online together with the correlation matrix of the variables (Table A2).

[8] For a detailed explanation of the ex-ante and ex-post patent indicators, see Barbieri et al. (2020a).

4. Empirical strategy

4.1. Characterization of RE vs non-RE green inventions

We characterize RE inventions with respect to non-RE green inventions in the European case. The end of this comparison is to show to what extent RE inventions differ from other green inventions with respect to their scope, originality, novelty, radicalness, generality and impact. We run a t-test for the mean difference of each of the continuous indicators and a contingency table with a chi-square test for the dichotomous indicator (novelty in recombination). Table 1 shows that RE inventions and non-RE green inventions are different in almost all the indicators, both ex-ante and ex-post. However, it is interesting to comment on the direction of such difference.

Particularly, RE patents are more novel and radical than other green patents, and they use scientific knowledge to a higher extent (a result also obtained in Ocampo-Corrales et al., 2021). The scope of RE patents is narrower than the one of non-RE green ones, meaning that RE would need more specialized knowledge, whereas in terms of the originality, we do not get any significant difference, implying that both of them feed from a similar number of distinct technological fields. The other set of indicators, related to the impact of the invention, point to RE patents having a higher impact on subsequent technological developments (they are characterized by a higher number of forward citations) although they seem to affect a lower variety of technological domains (as depicted by the lower and significant value of the generality indicator). That is, knowledge in the RE domain would be less spread across different technological fields than the knowledge in non-RE green technologies.

To what extent the above-mentioned characteristics of the RE inventions versus non-RE green inventions may have an effect on the role of relatedness on regional technological branching? The regression analysis will allow us to conclude which of the two arguments given in Section 2 prevails in the case of the RE diversification of European regions.

4.2. Model and estimation strategy

The main goal of this paper is to test whether, in the case of European regions, the entry of RE technological specialization in a region depends on the degree of relatedness with the pre-existing technologies in the region. To test this hypothesis, we regress the entry, at time *t*, of RE technologies (via specialization) in a region *r* that did not present such specialization in *t-1,* on its degree of relatedness with respect to already present technologies, which is captured by the relatedness density index. The econometric equation can be written as follows:

Table 1
Comparison between RE patents and non-RE green patents

	Mean RE	Mean Non-RE Green	Test of the difference	Significance level
Scope	2.01	2.11	-11.592	***
Originality	0.72	0.72	0.436	
Novelty in recombination	4.37%	3.75%	4.72	***
Radicalness	0.36	0.32	26.206	***
NPL citations	1.89	0.59	21.43	***
Forward citations (5 years)	0.95	0.8	8.51	***
Forward citations (7 years)	1.24	1.04	8.35	***
Generality	0.35	0.37	-4.52	***

Note: We compute all the indicators following the explanations in sub-section 3.2. T-tests for the difference of the mean of the indicators in both groups. In the case of the indicator on the *Novelty in recombination*, we have also computed a contingency table (Chi2 (1)=23.75***), confirming that RE and non-RE green technologies are significantly different in this respect. *NPL* refer to non-patent literature, * $p < .10$, ** $p < .05$, *** $p < .01$.

$$Spec\_RE_{rt} = \beta_0 + \beta_1 Relatedness\_RE_{rt-1} + Z_{rt-1} + \delta_r + \delta_t + \varepsilon_{rt} \quad (5)$$

where all the control variables are contained in vector Z and are lagged one period. We control both for regional and time fixed effects, δ_r and δ_t, respectively. The inclusion of these fixed effects allows us to capture the time-invariant unobserved heterogeneity as well as any time-varying shock constant across regions. Given the binary nature of our dependent variable, the method of estimation is not so evident. We will estimate both a LPM and a logit model, in both cases introducing regional and time fixed effects, to check the robustness of the results to the method of estimation.

Analogously to Eq. (5), given the different characteristics observed in the case of RE with respect to non-RE green technologies, we will consider a new dependent variable ($Spec\_nonREgreen_{rt}$), which refers to the entry, at time t, of non-RE green technologies (via specialization) in a region *r* that did not present such specialization in *t-1*. We will regress it on the degree of relatedness with respect to already present non-RE green technologies, which is captured by the relatedness density index (*Relatedness_nonREgreen*).

5. Results

5.1. Main results

We estimate a panel of seven time windows between 1981 and 2015.[9] Table 2 provides the estimates from the regressions where in the first three columns we use the entry of new RE technological specialization in a NUTS2 region as the dependent variable. Standard errors are robust and clustered at the regional level. The OLS estimation of the Linear Probability Model in column one allows us to observe the highly significant positive relationship between the relatedness density and the entry of RE technological specialization without taking into account any fixed effects. In the second column, we include the two-way fixed effects estimates. The coefficient increases and remains significant at the 1% level. The third column presents the estimation of a logit model with fixed effects. As commented in the methodological section, although it is more consistent with the binary nature of the dependent variable, the fact of introducing dummies to control for fixed effects in such a non-linear model can generate an incidental parameter problem. In any case, the coefficient continues being highly significant, so that we can conclude that the conclusion of a positive role of relatedness on the entry of RE technological specialization in the European regions is consistent to the use of different methods of estimation.

While some of the controls are significant in the OLS estimation of the Linear Probability model, they are no longer significant when the fixed effects are included. This seems to indicate that there are some regional characteristics that are influencing the entry of renewables specialization which go beyond the control variables that we have included. In this respect, as signalled by Santoalha and Boschma (2020), the non-significance they also obtain for the controls they introduce in their regressions (GDP per capita, R&D, human capital, share of elderly population, unemployment rate, population density, share of green specialization and environmental policy)[10] can be due to the fact that the literature on regional green technological diversification is quite recent and requires a wide-ranging framework of reference. The same happens in other few existing empirical studies on green diversification of regions, in which most of the control variables are either weakly or non-significant (Montresor and Quatraro, 2019; Corradini, 2019). With respect to the controls, we must note that we have limited the inclusion of controls due to the very limited availability of regional data for the big sample of regions we are considering (EU28+Norway) and the long period of time (1980-2015) as well as for attenuating the effects on our estimates of incidental parameter problems.[11]

The results from the first three columns confirm that the general finding of the relevance of relatedness in explaining regional technological diversification in green technologies also holds in the case of RE. However, as obtained in Section 4.1, RE inventions are different from other non-RE green inventions in that they are more novel and radical and feed from scientific knowledge to a higher degree, whereas they present a narrower technological scope of the knowledge from which RE nurtures and at the same time are less general in its forward impact. Consequently, in the last 3 columns in Table 2, we reproduce the same regressions for the case of the entry of non-RE green technologies specialization as a function of the degree of relatedness with respect to already existing non-RE green technologies in the region. As it can be observed, the coefficient of the relatedness density variable is not significant in the OLS estimation but turns out to be significant and positive in the case of the models including fixed effects. However, the parameter obtained is of a lower magnitude now, 47% lower when using the linear probability model, and 38% lower for the logit if compared with the case of RE technologies (3 first columns). As hypothesized in Section 2, this would indicate that the narrower scope as well as the lower generality of RE make them more strongly path-dependent than in the case of non-RE green technologies, thus, relatedness would be more relevant in explaining regional specialization for RE technologies. Our findings also point to the fact that, despite the idiosyncratic features of RE technologies in the sense of higher novelty, radicalness and higher use of scientific knowledge that would downplay the role of relatedness, this has not been found in the European case.

We also check whether the impact shown by the relatedness to RE technologies depends on the level of such technological relatedness. To test it, we include the squared term of the relatedness index (see Table B1 in appendix). We observe that it is clearly significant and negative, while the relatedness index remains clearly significant and positive. This finding seems to indicate that regions having a knowledge portfolio that is cognitively related to renewable energies is relevant to understand why such region specializes in renewables but points to the idea that cognitive proximity enables effective learning only until a certain point. After such point, having a knowledge base that is highly proximate to RE technologies would imply being locked-in. We observe the same finding for other green technologies. Indeed, previous geography of innovation literature has acknowledged that relatedness has a sort of side-effect in enhancing the regional specialization of new technological fields, that of directing regions to end up in lock-in situations (Boschma, 2005), as confirmed by our results.[12]

All in all, we can conclude that what determines specialization in RE technologies in European regions seems to be relatedness to this technological field without requiring much cross-fertilization with technologies that are cognitively distant from the RE technological domain. Whereas for the rest of green technologies, this is also the case but to a lower extent.

Since our sample consists of the regions in all EU28 countries, with very different characteristics, we turn now to explore the heterogeneity in the role of relatedness when explaining technological diversification in renewables across European regions. Indeed, for the general case of all green technologies, some recent works show relatedness as a driver of the regions' green-tech development. This is the case of the research by Montresor and Quatraro (2019), who focus on the sample of NUTS-2

[9] 1981-1985, 1986-1990, 1991-1995, 1996-2000, 2001-2005, 2006-2010, 2011-2015.

[10] They have data available for all these variables because they only consider regions in 7 European countries.

[11] As pointed out by a reviewer, instead of considering GDP in per capita terms, as a robustness analysis we considered GDP in levels to proxy for the size of the region, with the idea of controlling for regional economic heterogeneity in terms of economic size. This control variable resulted to be non-significant and the results on our key variables were maintained.

[12] We thank a reviewer for pointing this issue.

Table 2
Regression results for EU28.

	RE technologies (1) LPM-OLS	(2) LPM	(3) LOGIT	Non-RE green technologies (4) LPM-OLS	(5) LPM	(6) LOGIT
Relatedness_RE	0.00605***	0.0110***	0.0998***			
	(0.00113)	(0.00196)	(0.0179)			
Relatedness_nonREgreen				-0.00000287	0.00586**	0.0622***
				(0.00101)	(0.00230)	(0.0223)
GDPpc	-0.0298**	-0.0120	-0.114	-0.0327*	-0.0724	-0.808
	(0.0151)	(0.0872)	(0.740)	(0.0176)	(0.0726)	(0.624)
Indust Share	-0.0663	0.0763	0.422	0.0470	-0.138	-0.984
	(0.108)	(0.389)	(3.469)	(0.112)	(0.371)	(3.104)
Total Patents	-0.0242***	-0.00268	-0.00211	-0.0179***	-0.0468**	-0.290**
	(0.00532)	(0.0195)	(0.158)	(0.00604)	(0.0218)	(0.144)
Constant	0.305***	-0.0955	-2.901	0.360***	0.591**	1.687
	(0.0535)	(0.321)	(2.696)	(0.0615)	(0.253)	(2.101)
Regional Fixed Effects	No	Yes	Yes	No	Yes	Yes
Time Fixed Effects	No	Yes	Yes	No	Yes	Yes
N	1559	1559	1112	1559	1559	1023

All Columns: Entry of specialization as dependent variable. Robust standard errors in parentheses. Clustered at the regional level. * $p < .10$, ** $p < .05$, *** $p < .01$.

regions in the EU-15 as well as Santoalha and Boschma (2020) for a set of regions in seven European countries.[13] In both cases, they limit the sample to all or some pre-2004 access countries in order to consider a relatively more homogeneous set of innovation systems than the EU28 in terms of patenting. In our case, with the consideration of regions of countries with very different levels of resources and capabilities, we plan to study to what extent these different levels may imply different magnitudes of the impact of relatedness when explaining technological diversification. With this aim, in Table 3 we introduce a cross-term between the relatedness density index and the level of GDP per capita, with the idea that this variable tends to be a good indicator of the level of resources and capabilities in an economy. As observed in the first three columns referring to RE technologies, the interaction term has a statistically negative coefficient in all the columns, pointing to an impact of relatedness which is higher in regions with low levels of economic development, as predicted by previous literature in the case of industrial diversification (Boschma and Capone, 2016). This finding would imply that regions with a low level of resources and capabilities find it difficult to break from their past; these low-endowed regions would depend on the existence of a knowledge base highly related to RE in order to develop new RE technologies. On the contrary, the last three columns show that the parameter of this same cross-term in the case of non-RE green technologies is either not significant or only at a 10% significance level.

In any case, to further confirm this different role of relatedness according to different regional economic levels, Table 4 offers separately the estimation for regions with economic levels above and below the average. Following Xiao et al. (2018), we have replicated the same regressions for regions with innovative levels above and below the average, as a proxy of the level of capabilities to generate new ideas (in the Appendix). In the case of RE technologies, the results for both subsamples corroborate the significant impact of relatedness, although with a remarkable higher coefficient observed for relatedness in the case of low-income regions. This indicates that relatedness to the existing knowledge base is more relevant in low-income regions than in high-income regions to specialize into renewable energies. However, this result does not hold in the case of non-RE green technologies, for which low-income regions present a lower role of technological relatedness if compared with highly endowed regions. This result could be explained by the higher level of generality and less specific scope of non-RE green technologies (if compared to RE), which would make it easier for low-income regions to recombine pieces of knowledge that may be less cognitively proximate. The same evidence is obtained when the proxy used to account for the level of resources and capabilities is the level of innovation (see Table B2 in the Appendix).

In conclusion, the role of relatedness when studying the incorporation of renewable energy generation technologies to tackle climate change is robust to the consideration of regions with very different levels of economic development. However, we observe an important heterogeneity in the sense that the impact of relatedness decreases as the level of resources and capabilities of a regional economy increases.

5.2. Robustness analysis

We perform a number of robustness checks in order to confirm that our findings regarding the role of relatedness still holds. Firstly, given the nature of the RE technology, within the green-tech domain, prior literature has considered environmental regulation in pushing/pulling the development of green technologies, highlighting the relevance of policies for sustainable transitions (Barbieri et al., 2016; Lindberg et al., 2019). The lack of homogeneous data, though, makes it difficult to measure policy support at the regional scale in Europe. In any case, we tried to measure environmental regulation with the OECD environmental policy stringency index at the country level[14], as in Montresor

[13] Although not being the main objective in their paper, Santoalha et al. (2021) also obtain a significant role of relatedness as a key driver of new specializations in the domain of green technologies in the case of 142 European regions. In addition, they obtain that e-skills endowment negatively moderates the effect of relatedness.

[14] "The OECD Environmental Policy Stringency Index (EPS) is a country-specific and internationally-comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviour. The index ranges from 0 (not stringent) to 6 (highest degree of stringency). The index covers 28 OECD and 6 BRIICS countries for the period 1990-2012. The index is based on the degree of stringency of 14 environmental policy instruments, primarily related to climate and air pollution" (https://stats.oecd.org/Index.aspx?DataSetCode=EPS)

Table 3
Regression results with cross effect relatedness-economic development

	RE technologies			Non-RE green technologies		
	(1) LPM -OLS	(2) LPM	(3) LOGIT	(1) LPM -OLS	(2) LPM	(3) LOGIT
Relatedness_RE	0.0270*** (0.00484)	0.0427*** (0.00993)	0.337*** (0.0910)			
Relatedness*GDPpc	-0.00546*** (0.00118)	-0.00859*** (0.00254)	-0.0648*** (0.0233)			
Relatedness_nonREgreen				0.000727 (0.00136)	0.00785*** (0.00273)	0.0890*** (0.0286)
Relatedness_nonREgreen*GDPpc				-0.000421 (0.000316)	-0.000724 (0.000463)	-0.00983* (0.00567)
Indust Share	-0.158 (0.101)	-0.0735 (0.377)	-0.0800 (3.558)	0.107 (0.101)	-0.182 (0.368)	-1.379 (2.996)
Total Patents	-0.0239*** (0.00528)	-0.0328 (0.0215)	-0.245 (0.193)	-0.0202*** (0.00584)	-0.0519** (0.0216)	-0.355** (0.147)
Constant	0.213*** (0.0282)	0.121 (0.158)	-1.712 (1.282)	0.261*** (0.0317)	0.379*** (0.130)	-0.706 (0.888)
Regional Fixed Effects	No	Yes	Yes	No	Yes	Yes
Time Fixed Effects	No	Yes	Yes	No	Yes	Yes
N	1559	1559	1112	1559	1559	1023

All Columns: Entry specialization as dependent variable. Robust standard errors in parentheses. Clustered at the regional level.
* $p < .10$** p < .05, *** p < .01.

Table 4
Regression results for two subsamples: Regions with high- and low-economic development levels.

	RE technologies				Non-RE green technologies			
	(1) LPM-High GDP	(2) LOGIT-High GDP	(3) LPM-Low GDP	(4) LOGIT-Low GDP	(1) LPM-High GDP	(2) LOGIT-High GDP	(3) LPM-Low GDP	(4) LOGIT-Low GDP
Relatedness_RE	0.0245*** (0.00573)	0.258*** (0.0684)	0.0502*** (0.00861)	0.453*** (0.0902)				
Relatedness_RE^2	-0.000279*** (0.000104)	-0.00293** (0.00118)	-0.00101*** (0.000224)	-0.00956*** (0.00242)				
Relatedness_nonRE green					0.0306*** (0.00729)	0.357*** (0.0880)	0.0237** (0.0108)	0.185** (0.0851)
Relatedness_nonRE Green^2					-0.000474*** (0.000130)	-0.00547*** (0.00167)	-0.000527* (0.000276)	-0.00451* (0.00248)
GDPpc	-0.0209 (0.190)	-0.272 (1.897)	-0.0902 (0.102)	-0.867 (1.115)	-0.0239 (0.131)	-1.172 (1.631)	-0.0511 (0.0854)	-0.472 (0.710)
Indust Share	-1.003 (0.644)	-10.02 (6.486)	0.857* (0.499)	8.271* (4.663)	0.241 (0.532)	0.991 (5.939)	-0.650 (0.496)	-4.726 (3.741)
Total Patents	-0.0835* (0.0471)	-0.840** (0.400)	-0.0226 (0.0237)	-0.155 (0.221)	-0.106*** (0.0404)	-0.910** (0.379)	-0.0678** (0.0327)	-0.422** (0.199)
Constant	0.525 (0.763)	2.371 (7.419)	-0.0468 (0.317)	-3.426 (4.071)	0.494 (0.544)	4.789 (6.029)	0.618** (0.242)	1.406 (2.457)
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	999	667	999	667	999	544	999	544

All Columns: Entry of specialization as dependent variable. Robust standard errors in parentheses. Clustered at the regional level.
* $p < .10$, ** p < .05, *** p < .01

and Quatraro (2019), despite we are aware of several limitations. First, the consideration of this index, given its national scope, implies that all the regions within a country in our sample are considered equally. Second, some countries in our sample do not display data for such an index, with the consequent reduction in the number of observations in the estimations that include this indicator. Despite these limitations, we decided to include it to check whether the consideration of environmental regulation could result in the role of relatedness loosing significance. Columns one and two in Table 5 show that the conclusions obtained so far are maintained when controlling for environmental regulation, although the coefficient of the environmental policy stringency index is not significant. In general terms, this result goes in line

Table 5
Robustness analyses.

	RE technologies				Non-RE green technologies			
	(1) LPM	(2) LOGIT	(3) LPM	(4) LOGIT	(5) LPM	(6) LOGIT	(7) LPM	(8) LOGIT
Relatedness_RE	0.0322*** (0.00497)	0.284*** (0.0533)	0.0226*** (0.00871)	0.202*** (0.0703)	0.0249*** (0.00820)	0.232*** (0.0777)	0.0204** (0.00810)	0.159** (0.0698)
Relatedness_RE^2	-0.000403*** (0.0000955)	-0.00340*** (0.000998)	-0.000383** (0.000173)	-0.00361** (0.00163)	-0.000371** (0.000146)	-0.00334** (0.00156)	-0.000102 (0.000167)	-0.000136 (0.00149)
Environmental Policy	-0.0657 (0.0464)	-0.557 (0.506)			0.0107 (0.0437)	0.0728 (0.446)		
GDPpc	0.100 (0.153)	0.326 (1.354)	-0.0765 (0.0707)	-0.902 (0.627)	0.0135 (0.144)	-0.497 (1.201)	-0.0111 (0.0860)	-0.188 (0.742)
Indust Share	0.243 (0.544)	2.638 (5.661)	-0.179 (0.364)	-1.280 (3.071)	0.490 (0.534)	3.976 (4.792)	0.00645 (0.385)	0.300 (3.424)
Total Patents	-0.0667** (0.0269)	-0.518** (0.232)	-0.0685** (0.0265)	-0.447** (0.176)	-0.106*** (0.0312)	-0.720*** (0.230)	-0.0272 (0.0251)	-0.200 (0.202)
Constant	-0.186 (0.576)	-2.180 (5.007)	0.620** (0.245)	1.948 (2.143)	0.323 (0.551)	-12.89*** (4.699)	-0.0540 (0.317)	-2.021 (2.703)
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1239	796	1259	786	1239	713	1559	1023

All Columns: Entry of renewable energy specialization as dependent variable. Columns (3), (4), (7) and (8): Relatedness index as in Montresor and Quatraro (2019). Robust standard errors in parentheses. Clustered at the regional level
* $p < .10$, ** $p < .05$, *** $p < .01$.

with the one in Santoalha and Boschma (2020) who found little evidence of a direct effect of political support on the likelihood of regions to develop new green specialization. The same happens in the case of other green technologies.

As a final robustness check, columns three and four of Table 5 offer the results of the main estimations using the density index computed as in Montresor and Quatraro (2019), that is, capturing the degree of relatedness between any two technologies based on the revealed technological advantage of a region in these two technologies at a time. The main conclusions of our paper are maintained. The robustness analyses are also carried out in the case of non-RE green technologies (columns 5 to 8 in Table 5), and again the main conclusions of the paper are maintained.

6. Conclusion and discussion

We aim at analysing the role of technological relatedness on the regions' specialization in RE technologies. Prior evidence has shown the importance of the regional dimension of green-tech specialization for a limited number of European countries obtaining, among others, a significant impact of relatedness (Montresor and Quatraro, 2019; Santoalha and Boschma, 2020; Santoalha et al., 2021). In this paper, we show that RE inventions differ from non-RE green inventions both in the knowledge components on which the invention is built upon and how the invention allows the creation of new subsequent knowledge. Consequently, we argue that because of these idiosyncratic features of RE technologies, the role of technological relatedness may be differently relevant to understand how RE technologies are adopted across regions. On the one hand, we obtain that RE technologies are more novel and radical, which may require an exploratory search in other technological domains, for instance, in the form of boundary spanning and cross fertilization activities (Barbieri et al., 2020a). In addition, RE technologies are obtained to rely more intensively on scientific knowledge coming from members outside the business world, such as universities and research centres. Such characteristics could make that relatedness had a subtler role on the diversification of regions in RE technologies. Contrarily, we obtain that RE technologies are less general, both with respect to the technologies they nurture from as well as with respect to their forward impact. This would imply that RE technologies require less diverse knowledge inputs and competences, so that the knowledge obtained from related technological domain would matter importantly. Using a sample of 277 NUTS2 European regions in the period 1981-2015, we find strong evidence that relatedness is a significant driver for the specialization of regions in RE technologies, with a higher relevance than in the case of other green technologies. This would indicate that the narrower scope of the knowledge from which RE nurtures as well as the lower generality in their impact seems to make them more strongly path-dependent than in the case of non-RE green technologies.

This conclusion is maintained when considering separately regions with high income and low-income levels, since in both of them density plays a critical role in developing renewable technology specialization. However, the impact of relatedness density increases as the regional economic development decreases, signalling that a low regional economic development level and the corresponding low levels of resources and capabilities seem not to allow a region to break from its past technological specialization and to develop specialization in RE technologies. This is not the case, though, for non-RE green technologies, where relatedness is less relevant in low-income regions. This result could be explained by the higher level of generality and less specific scope of such technologies.

Our findings provide some interesting policy implications in relation to the European Union's Smart Specialisation Strategy (S3), and its recent evolution to Smart Specialisation Strategies for Sustainable and Inclusive Growth (S4+). The European Commission has made sustainable development, as well as the digital agenda, the main component of its overall growth strategy for the current decade. The European Green Deal represents an innovation-led strategy for Europe (European Commission, 2020; McCann and Soete, 2020) and sets out the direction for the EU to become climate-neutral by 2050. Our results have provided evidence that the principles of regional *embeddedness* and *relatedness* (European Commission, 2012) also support regions that aim at adapting to general climate change mitigation and try to diversify in technologies that allow to incorporate renewable energy generation to face climate change. Our paper provides policy support for the deliberate development of a region's existing strengths to stimulate innovation and thus advocates the appropriates of relatedness (Balland et al., 2019; Boschma and Giannelle, 2014) when following regional societal challenges which imply encompassing the sustainability dimension. Indeed, we confirm that having technologies cognitively proximate to renewables is important for their development and consequently this paper offers directions on how to foster the regional move towards the greening of the economy and more specifically towards renewable energies as a path to transform the current energy systems towards a new low-carbon paradigm. Since a high endowment of regional RE-related knowledge is a driver of renewables, policy interventions directed at RE technologies that are beyond the regions' knowledge bases may entail the progress of a larger scope of technologies from which RE innovation stems. Therefore, regions should have the scope to approach environmental sustainability by a context-specific environmental recombination of existing technologies.

CRediT authorship contribution statement

Rosina Moreno: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing – review & editing, Supervision, Funding acquisition. **Diego Ocampo-Corrales:** Data curation, Formal analysis, Investigation, Software.

Declaration of Competing Interest

Rosina Moreno and Diego Ocampo-Corrales declare not having any conflict of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.respol.2022.104508.

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