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Abstract

Regional diversification is a process characterized by past and place dependence: new activities tend to emerge and develop in a region in technological or industrial fields closely related to existing local activities. Recently, the relatedness concept has also been applied successfully to studies on green diversification of regions, providing new insights to the transition literature that is primarily focused on disruptive change. What has received little attention is a systematic approach that assesses the role of political support for the ability of regions to diversify into new green activities. This paper makes a first attempt to test the impact of regional capabilities and political support for environmental policy at the national and regional scale on the ability of 95 regions in 7 European countries to diversify into new green technologies during the period 2000-2012. We find evidence that related capabilities rather than political support in a region is associated with green diversification of regions in Europe. However, political support tends to moderate the role of regional capabilities.

Keywords: green technologies, regional diversification, sustainability transition, political support, relatedness

JEL: O18, O44, Q55, R11

1. Introduction

Processes of regional diversification have been widely studied in Evolutionary Economic Geography. It is well accepted that relatedness plays an important role in regional diversification (Boschma 2017; Hidalgo et al. 2018). Diversification is characterized by past and place dependence, meaning that new activities emerge more easily in technological or industrial fields closely related to those that already exist in a place. The relatedness concept has also been applied successfully in studies on green diversification of regions (Tanner 2014, 2016; van den Berge and Weterings 2014; Corradini 2019), showing that relatedness appears to be crucial driver behind green diversification of regions. Doing so, they have provided new and additional insights to the transition literature that has a tendency to underestimate processes of past dependence, and to overlook the role of regional capabilities.

However, this relatedness literature has drawn little attention to the role of politics and institutions (Boschma and Capone 2015; MacKinnon et al. 2019). This is different from the transition literature that highlights the importance of policies and politics for sustainability transitions (Requate 2005; Carrión-Flores and Innes 2010; Dewald and Truffer 2012; Karnøe and Garud 2012; Barbieri et al. 2016; Lindberg et al. 2018). Studies have shown how urban and regional policies matter for sustainability transitions and have often run ahead of national and supranational policies (Hansen and Coenen 2015). What has received little attention in the transition literature is, however, the effect of regional capabilities (and relatedness) on greening of economies. Moreover, the transition literature tends to focus primarily on idiosyncratic case studies in distinct places (Markard et al. 2012). As Hansen and Coenen (2015) put it, "… the consensus is still *that* place-specificity matters while there is little generalisable knowledge and insight about *how* place-specificity matters for transitions" (p. 105). So, there is need for a systematic comparative approach to the ability of regions to diversify in green activities, in which the role of political support at various spatial scales is assessed.

The main objective of this paper is to address this gap and increase our understanding of the importance of political support (and regional capabilities) for the ability of European regions to diversify in green technologies. This is a daunting task, as it is complex to operationalize political support at the regional scale. This paper makes a first attempt and focuses on a specific set of policies that are relevant for green technologies: environmental protection policies. We test the impact of regional capabilities and political support at both the national and regional level on the ability of 95 (NUTS-1 and NUTS-2) regions in seven European countries (Austria, Belgium, France, Germany, Italy, the Netherlands, and Spain) to diversify into new green technologies during the period 2000-2012. Overall, we find evidence that regional capabilities rather than political support is associated with green diversification of regions in Europe. However, our results show that political support may indirectly influence green diversification through capabilities: political support often moderates the importance of capabilities in processes of green diversification of regions in Europe.

The paper is organized as follows. Section 2 discusses the regional diversification and sustainability transition literatures and addresses the importance of politics for regional diversification into green technologies, proposing some hypotheses. Section 3 introduces the data and discusses the construction of the variables of interest. Section 4 presents and discusses the main findings. Section 5 concludes.

2. Regional diversification, greening and politics: the missing link

Territories differ in their ability to diversify and adapt to change. This is true for their ability to develop new activities in general, and new green activities in particular. Regions present huge dissimilarities regarding their ability to create and develop new green activities. There is an uneven distribution of green specializations across regions both in Europe (Tanner 2014, 2015; Corradini 2019) and in the US (Barbieri and Consoli 2019). Although climate change is a global phenomenon, local solutions may be crucial to respond to this global challenge (Murphy 2015). This makes it important to understand what factors foster green diversification and drive inter-regional differences. This captures a key research challenge in the literature on the geography of sustainability transitions, which is to go beyond case studies, and to develop generalisable knowledge about place-specificity in processes of sustainability transitions (Coenen and Truffer 2012; Hansen and Coenen 2015).

What has received little attention so far in the sustainability literature is the effect of regional capabilities on the greening of economies. There is strong evidence that regional capabilities play a key role in processes of regional diversification (Boschma 2017). That is, new economic activities tend to develop more easily in industrial or technological fields that are closely related to those that already exist in a territory (Hidalgo et al. 2018). In other words, past and place dependence matter in regional diversification, because they bear the seeds for the development of new industrial or technological specializations in regions (Neffke et al. 2011; Kogler et al. 2013; Rigby 2015).

This tends to contrast with the transition literature which often refers to the need for transformative change to enable the greening of economies (Schot and Kanger 2018) and tends to depict new green technologies as disruptive and radical breakthroughs (Dechezleprêtre et al. 2013). So, while the regional diversification literature shows that related diversification is the rule and unrelated diversification the exception (Hidalgo et al. 2018; Pinheiro et al. 2018), the transition literature tends to suggest that unrelated diversification is more common in processes of sustainable transition.

However, empirical evidence in regional studies on greening so far is mixed. Studies applying a relatedness framework find that new green activities are more likely to be developed in a region with a local presence of activities related to green activities. Van den Berge and Weterings (2014) found that in EU-regions, the probability of developing new eco-technologies depends on pre-existing technologies in related fields in the region during the period 1982-2005. Tanner (2016) found strong evidence for the impact of relatedness on the emergence of the new fuel cell industry in European

NUTS-2 regions, besides the importance of local access to universities, research activities and user industries (Tanner 2014). Montresor and Quatraro (2018) found a positive effect of technological relatedness to local green and non-green knowledge on the emergence of new green specializations in EU-15 regions. Corradini (2019) found an inverted U-shaped relationship between the entry of regions in green technologies and the degree of relatedness to green knowledge in the region. Studies applying a recombinant approach argue that new green activities combine and draw on many local resources (Cooke 2012). As new environmental technologies are often at an early stage of development (OECD 2015), they are complex technologies that need inputs from a wide variety of sources (Barbieri and Consoli 2019). Barbieri and Consoli (2019) found that both related and unrelated variety had a positive impact on green employment growth in US Metropolitan Statistical Areas. Colombelli and Quatraro (2019) found that a local knowledge base of related technological fields had a positive effect on the creation of green start-ups in Italian regions, but did not find support for unrelated variety. Barbieri et al. (2018) showed that unrelated variety is more prominent in the early stage of the green technology life cycle, while related variety becomes more important as a green technology matures. And studies find evidence that new green technologies are special, compared to non-green technologies, in the sense that they tend to recombine different pieces of knowledge that are often cognitively distant (Orsatti et al. 2017; Fusillo 2019; Quatraro and Scandura 2019)

Based on the previous discussion, we develop the first hypothesis:

H1: new specializations in green technologies are more likely to occur in regions with related technologies

The transition literature claims that strong policy intervention is needed to meet sustainability objectives and to develop new green technologies in particular (Lindberg et al. 2018). The role of public policies in processes of transition has been widely explored (Markard et al. 2012; Rogge and Richardt 2016). There is a wide support for the idea that policies and environmental regulation enable sustainability transitions (Requate 2005; Carrion-Flores et al. 2010; Dewald and Truffer 2012; Barbieri et al. 2016; Edmondson et al. 2018): state intervention provides incentives to ease green transitions, to overcome initial lack of performance and cost competitiveness of new environmental technologies, and to mitigate barriers to their development and adoption (Karnøe and Garud 2012).

Studies on transitions often restrict their attention to environmental policy at the national level, like the ‘Energiewende’ in Germany, or national environmental regulations (Lanjouw and Mody 1996). The literature on the geography of sustainable transition (Coenen and Truffer 2012; Hansen and Coenen 2015) also looks at policy initiatives at the regional and local level. The presence and nature of environmental policies differ widely across regions within and between countries (Cooke 2010). This is likely to reflect the political attitude of regional actors towards environmental protection. Studies tend to focus on one particular case, or make a comparative analysis of a number of cases (Markard et al. 2012) but what has received little attention is a systematic approach that assesses the impact of political support at the regional scale (Ghisetti and Quatraro 2017). Cainelli et al. (2015) investigated how firms in regions with stricter waste policies are more likely to adopt environmental innovations. Giudici et al. (2019) tested systematically across 110 Italian provinces whether local environmental awareness (defined as the sensitivity to environmental issues by local governments, firms and residents) has a positive effect on clean-tech entrepreneurship. However, we have little understanding of whether regional political support for green policy affects the ability of regions to develop new green activities, when controlling for regional capabilities, as tested in hypothesis 1.

Moreover, we have little understanding at which level (national or regional) political support is relevant for regional diversification into green technologies (Markard et al. 2012). It might be that national environmental policy affects the development of new green specializations in some regions but not in other regions in a country. This may have to do with local capabilities that enable some regions to turn national support into new green activities, or it may be attributed to strong political support in these regions. Dewald and Truffer (2012) observed varying tendencies of German regions to develop a photovoltaic market, in spite of a national policy framework (the Renewable Energy Sources Act - EEG) that aimed to stimulate market development across all regions in Germany. This regional heterogeneity may be attributed to differences in regional capabilities, but an alternative explanation is differences in political support to environmental policy across regions. We test the effect of political support at the national and regional scale in the following hypothesis:

H2a: new specializations in green technologies are more likely to occur in regions with short-term political support

Another dimension that needs to be considered is the continuity and consistency of the political support to environmental policies. Cases show that enduring policy support to the development of renewable energies may have a favorable impact on sustainable transitions. For instance, in Germany, even after the federal government shifted to a conservative majority in 2009, policies to support photovoltaic market remained active. This situation contrasts with Spain, where national photovoltaic support schemes lost political support in 2009, after a short period in operation (Dewald and Truffer 2012). Another example is the development of the wind turbine industry. While in Denmark (considered a success story), this industry received policy support from the early 1970s up to 2000, in the US, the Reagan administration abandoned policy support schemes (Cooke 2010). This shows that long-term political support is more likely to be effective fostering the development of new green technological specializations in regions. Therefore, we test hypothesis 2b:

H2b: new specializations in green technologies are more likely to occur in regions with long-term political support

The transition literature has a tendency to claim that new environmental technologies are disruptive, because subject to fundamental uncertainty (and high risks of failure), as they have to confront many obstacles both at the supply and demand side. In that context, it is unlikely that incremental changes will contribute to transformations towards sustainability (Markard et al. 2012). As these required transformations are essentially about unrelated diversification that are less likely to occur spontaneously, they should be supported from its incipient stages by policy (Frenken 2016). Such view on transitions would expect that relatedness would not matter (contrary to hypothesis 1), while the political and institutional dimension would instead be perceived as absolutely crucial to develop new green technologies, because of a lack of (related) capabilities in the region. If hypothesis 1 is confirmed (relatedness matters) however, it might still be that political support is important. This comes close to Fornahl et al. (2012) who concluded that related capabilities and active policy intervention both at the national and regional scale contributed to the development of the offshore wind energy industry in northern Germany. However, political support might also relax (i.e. lower or decrease) the importance of related capabilities in the region. Conversely, it could be that the effect of political support will be less relevant, the higher the degree of relatedness in a region. To our knowledge, these possibilities of complementarities between related capabilities and political support have not yet been explored. Accordingly, we investigate the following hypothesis:

H3: the effect of relatedness on new specializations in green technologies will be less relevant, the stronger the political support

Another potential barrier to the development of new green specializations is the existence of ‘dirty’ specializations in a region. It might be more difficult to develop new green technologies in regions that are specialized in technologies that cause environmental pollution, because regional vested interests might oppose the development of green technologies that could challenge and form a threat to existing ‘dirty’ specializations in a region (Wesseling 2015; Acemoglu et al. 2016). Accordingly, we have to account for the role of power among different political and economic interests (Shove and Walker 2007), as transitions are often contested and may lead to conflicts and power struggles. The intensity of conflicts may vary across regions, resulting or not in environmental friendly policies and actions by firms and citizens (Murphy 2015). On the other hand, scholars have argued that in ‘dirty’ regions, there is more awareness of risks associated with the continuous use of non-eco-friendly activities and policies. Local actors, including political actors in ‘dirty’ regions, may regard transition to greener technologies as an opportunity worth to explore. In this case, dirty regions may evolve towards a green path through the development of new green technologies that mitigate the negative effects of dirty ones (Grillitsch and Hansen 2018). Ghisetti and Quatraro (2013) showed that local demand from polluting sectors may actually stimulate the development of new green knowledge.

So, we develop the following hypothesis:

H4: new specializations in green technologies are less likely to occur in regions with existing specializations in 'dirty' technologies

Finally, scholars have argued that regions that manage to develop new green specializations are also more likely to develop other new green specializations, because support among agents in a region (economic, political and other agents) will increase (Grillitsch and Hansen 2018). However, recent studies have shown that the presence of non-green technologies in a region may actually stimulate new green technologies in a region. Quatraro and Scandura (2019) found local knowledge spillovers from non-green technological domains generating inventions in green domains in Italian regions. Corradini (2019) showed an inverted U-shaped relationship between the entry of regions in green technologies and relatedness to local green knowledge. This result suggests that local supply of green knowledge is not sufficient for the development of green technologies. Montresor and Quatraro (2018) found that the magnitude of the impact of technological relatedness to non-green knowledge on the local emergence of new green specializations is larger than the impact of relatedness to green technologies.

So, we test the following hypothesis:

H5: new specializations in green technologies are more likely to occur in regions with existing specializations in green technologies

3. Data and Variables

This paper aims to explain the ability of regions to develop new green specializations in Europe. The analysis includes 95 regions, all of which are NUTS-2 regions, except in Belgium and Germany where the unit of analysis is NUTS-1. We calculate the entry of new green technological specializations in a region for 9 overlapping periods of five years each (2000-2012), following other studies on regional diversification (e.g. Boschma and Capone 2015; Rigby 2015). The paper only considers regions in which the average number of patents over the period 2000 -2008 is at least equal to 5.

Most explanatory variables are lagged with at least one-year to the beginning of each 5-year period. This means they cover the period 1999-2007. To measure the effect of political support, it is assumed that a given election is only relevant for a given five-year period if the year of the election is lagged with at least three-years to the start of a five-year period. For instance, if the analysis concerns the development of new green technological specializations between 2000 and 2004, only regional elections in 1997 or before are considered. Moreover, it is minimized the time difference between the year of the election and the year corresponding to the beginning of the five-year period.

Our main variables of interest are: regional capabilities, political support at the national and regional scale, and green and dirty specializations in regions. Below, we explain all main variables one by one.

3.1. Dependent variable: entry of new green technological specializations in regions

Following previous research on technological diversification in regions (Kogler et al. 2013; Rigby 2015; Balland et al. 2018), this paper focuses on the emergence of new green technological specializations in European regions, making use the OECD REGPAT patent database[1]. Our spatial unit of analysis is mainly NUTS-2 regions for which regional data are available over the period 2000-2012. NUTS-2 regions are often regions in which regional governments have direct responsibility for issues related to environmental protection, like in Italy (Giudici et al. 2019).[2]

Studies have identified green technologies and linked them to technology classes of patents. We follow the classification of *environment-related technologies* proposed by OECD ENV-TECH, in which IPC/CPC codes of patent applications have been recoded according to the search strategies for the identification of selected *environment-related technologies* (OECD 2016). It is considered the most detailed classification with 107 different 3-digit categories of environment-related technologies. Most existing research assumes that if the first digits of a given IPC code are considered environment-related, all patents that start by these digits are environment-related (van den Berge and Weterings, 2014; Montresor and Quatraro 2018). We avoid the risk of overestimating the number of green patent applications, as the recodification is based on full IPC /CPC codes (and not only on first digits).

Although it is possible to identify 107 OECD ENV-TECH 3-digit technological categories, in the OECD REGPAT database, there are only patents in 52 of these categories. This is mainly due to the absence of group 9 (*Climate change mitigation technologies in the production or processing of goods*) patent applications in the OECD REGPAT database. Appendix A shows the full list of 3-digit environment-related technological categories identified by OECD (2016), and those for which there are data on patent applications in the dataset used in this paper.

We regionalized the patent data based on assignees' addresses[3]. To determine whether a region is specialized in a green technology, we compute, for each year and each region in the sample, the Revealed Comparative Advantage (RCA) for each technology (both green and non-green):

$$RCA_{izt} = \frac{PATizt}{\sum_{z=1}^{n} PATizt} / \frac{\sum_{i=1}^{m} PATizt}{\sum_{i=1}^{m}\sum_{z=1}^{n} PATizt} \quad (1)$$

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[1] OECD REGPAT database, February 2016

[2] Regional governments in Belgium and Germany are operationalized at NUTS-1 level. This is the reason why for these two countries the unit of analysis is NUTS-1 rather than NUTS-2.

[3] Patent data regionalized based on inventors' addresses has been used as a robustness check

where RCA_{izt} represents the Revealed Comparative Advantage of region i, in technology z, at year t, while PAT_{izt} is the number of patent applications attributed to technological field z in region i and year t. This indicator assesses the relative strength of a given region, at a given time, in technology z, in comparison to all other regions. If RCA is greater than 1, that means region i is specialized in technology z, in year t.

As this paper focuses on the development of new green technological specializations, the analysis includes all pairs of regions and green technologies z in which a given region is not specialized at time t. The dependent variable represents the entry of a new green technological specializations in a region, and it is defined as follows:

$$S_{izt+4} = 1 \text{ if } RCA_{izt} \leq 1 \wedge RCA_{izt+4} > 1 \wedge \Delta PAT_{izt,t+4} > 0 \wedge \Delta RCA_{izt,t+4} \geq 0.5 \wedge RCA_{izt+5} > 1 \wedge Green_z = 1$$

$$S_{izt+4} = 0 \text{ if } ((RCA_{izt} \leq 1 \wedge RCA_{izt+4} \leq 1) \vee (\Delta PAT_{izt,t+4} \leq 0) \vee (\Delta RCA_{izt,t+4} < 0.5) \vee (RCA_{izt+5} \leq 1)) \wedge Green_z = 1 \tag{2}$$

where S_{izt+4} is a dummy variable that takes the value 1 if region i, which did not have a specialization in green technology z at time t, acquires that specialization at time t+4. Otherwise, S_{izt+4} takes the value 0, which means region i has not succeeded in acquiring a new specialization in technology z between t and t+4. In order to avoid that slight variations either in the RCA or in the regional patenting activity may lead a region to become specialized in a given green technology z, three additional conditions are imposed. The first one is that a region only acquires a new green technological specialization when there is a substantial increase in the RCA of that technology in that region (i.e. $\Delta RCA_{izt,t+4} \geq 0.5$). The second condition is that a given region should present an absolute growth in the number of patents in technology z between the beginning and the end of each period (i.e. $\Delta PAT_{izt,t+4} > 0$). The third one is that the given region remains specialized in the newly acquired technological specialization at least for 1 year after the end of each period (i.e. $RCA_{izt+5} > 1$).

3.2. Relatedness

A key objective is to assess whether the entry of a new green specialization in a region depends on the degree of relatedness with existing technologies in the regions, following previous studies (e.g. van den Berge and Weterings 2014; Tanner 2014). We capture to what extent green technologies in which the regions are not specialized in at time t are related to technological specializations existing in the region at time t. We calculate a relatedness measure similar to those that has been used in other studies on regional diversification (e.g. Rigby 2015; Balland et al. 2018). This requires computing the degree of relatedness between pairs of technologies. To do so, the paper establishes all combinations of two technological domains for which a given region, in a given year, has at least a share in a patent application. Next, we compute the relatedness between technologies composing a pair, where a and b represent two technological fields, and RCA is defined as in (1), following the formula:

$$\Omega_{ab} = \min \{P(RCA_a > 1 \mid RCA_b > 1), P(RCA_b > 1 \mid RCA_a > 1)\}, \tag{3}$$

where $P(RCA_a > 1 \mid RCA_b > 1) = \frac{P(RCAa > 1 \cap RCAb > 1)}{P(RCAb > 1)}$ (4)

In (3), Ω_{ab} indicates the relatedness between technologies a and b, while the expression $P(RCA_a > 1 \mid RCA_b > 1)$ represents the conditional probability of there being, in the sample, cases where technology a has an RCA>1 given that for technology b RCA>1. For computing Ω_{ab} and its underlying probabilities, in the sample one observation is a pair consisting of a region and a year. In total, the sample contains more than 3,000 pairs of years (2000–2013) and regions.[4] The relatedness between two technological fields is computed based on the frequency of finding the spatial co-occurrence of a specialization (RCA>1) in these fields.

Now it is possible to compute relatedness between each green technology z in which region i is not specialized at time t and the technological specializations s of region i at time t. To do so, we compute a variant of the density index as proposed by Hausmann and Klinger (2007)[5]:

$$AvgProximity_{izt\text{-}t+4} = \frac{\sum_{s=1}^{n} \Omega zs Sist}{\sum_{s=1}^{n} Sist} \tag{5}$$

such that:

$$S_{ist} = 1 \text{ if } RCA_{ist} > 1$$

(6)

$$S_{ist} = 0 \text{ if } RCA_{ist} \leq 1$$

where $AvgProximity_{izt\text{-}t+4}$ represents the average proximity (or relatedness) of a given green technology z in which the region i is not specialized at time t to the set of technologies s in which region i, at time t, is already specialized. Briefly, this indicator divides the sum of the proximities between z and the technological specializations existing in region i at time t by the total number of technological fields s in which region i has a specialization at time t.

[4] This means that proximity between technological domains is computed based on patent data from all EU regions with available data.

[5] The use of the density indicator as proposed by Hausmann and Klinger (2007) would attribute, by construction, higher relatedness to regions with more specializations at time t. To avoid such shortcoming, we have adapted it as in equation (5).

3.3. Political support to environmental protection

The biggest challenge is to come up with a good comparative indicator that measures political support to environmental protection at the scale of European regions. We propose two indicators that will be explained below: (1) political support to environmental protection policy at the regional and national scale; (2) share of votes at regional elections for Green parties.

A lot of research exists on the link between individuals' and political parties' political ideology and their policy stances regarding environmental protection. At least until recently, studies find evidence that left-wing individuals/parties are more concerned about environmental issues than right-wing individuals/parties (Neumayer 2004). Left-wing political parties tend to embrace more governmental intervention, are less pro-business and are more concerned about the welfare of the lower social classes (that might bear the highest environmental costs) than right-wing parties (Dunlap et al., 2001; Neumayer 2003; Carter 2013). Dunlap (1975) suggested that pro-environment reforms require increasing government intervention and costly innovative action and therefore are strongly favored by the left-wing electoral base but firmly opposed by business and industry (Facchini et al. 2017). Garmann (2014) stated that left-wing parties are traditionally more pro-environment than right-wing parties because promotion of environmental quality and prevention of environmental degradation implies government intervention that potentially constrains business activities (Facchini et al. 2017).

A novelty of our paper is that it proposes to measure the extent to which there is political support in a region, as proxied by the political stance of regional governments regarding environmental protection policies. To our knowledge, Le Maux et al. (2011) is the only paper that focuses on regional level data (that is, French *Départments*) to investigate the role of political ideology on policy decisions (in this case, social public expenditures per capita). They consider whether the position of political parties matters not only for policy outcomes, but also for effective political power. We follow the literature that explores the link between political ideology and environmental concerns and use the Manifesto Project Database. We construct a continuous variable Env(Reg) that measures to what extent political parties assume, in their manifestos, environmental issues as a political priority.

The first step to do so is to ascertain whether each EU country (plus Norway) has a regional government. In cases where regional governments exist, it is also verified if they are operationalized at NUTS-1, NUTS-2 or NUTS-3 level. This information is collected from the CEMR - The Council of European Municipalities and Regions (2016). This paper considers exclusively countries where regional governments exist in all regions at NUTS-1 or NUTS-2 level. To allow data comparability over time, the analysis is also restricted to countries whose regional governments operate consistently at the same regional structures since the 1990s up to now. So, we excluded countries whose regional structures used for the operationalization of sub-national governments changed over time. This leaves us with seven countries: Austria, Belgium, France, Germany, Italy, Netherlands, and Spain.

The government support to environmental policies is determined based on political parties' stance on this issue. This opens the question which political parties should be taken into account to determine the political stance of regional governments regarding green policies. We adopt the view that a given regional government is strongly influenced by the party of the government leader. For instance, Leinaweaver and Thomson (2016) consider the prime minister's party stance regarding environmental policy as the most relevant in a given government, and use this approach to measure to what extent national governments support environmental protection. They argue that in multiparty coalitions, the policy influence of the prime minister's party is preponderant.

Dandoy and Schakel (2013) and Schakel (2013) database[6] on regional elections is used to identify, among other things, the year in which regional elections have been taken place in European regions. The political affiliation of the leader of a given regional government after a given regional election was collected manually, for each region and electoral year. Different sources were used: in most cases, it was necessary to search on the web the designation of the head of regional governments in each country, either in English or in the respective national language.[7] It is assumed that the political mandate of a given regional government expires in the year when the next election takes place.

To collect data on each party political support to environmental protection, we use the Manifesto Project Dataset. This data includes a variable that reflects the share of quasi-sentences in topics related to environmental protection policies, calculated as a fraction of the total number of codes available in the political manifesto of a political party, in a given national election[8]. The quasi-sentences whose code falls into the environmental protection category include 'general policies in favor of protecting the environment, fighting climate change, and other "green" policies'. This includes a great diversity of policies with the common objective of fostering environmental protection, like the "general preservation of natural resources; preservation of countryside, forests, etc.; protection of national parks; animal rights" (Manifesto Project Dataset, 2016, p. 17).

This variable has been used in the expanding literature on the determinants of political parties' concerns regarding environmental protection and climate change. Apostoaie (2016) uses this variable to understand the determinants of environmental preference of political parties, while Facchini et al. (2017) uses the same variable to investigate the determinants of political parties' environmental concerns. Farstad (2018) departs from the same variable to study the features of political parties that explain differences in climate change salience, as expressed in manifestos of political parties. Leinaweaver and Robert Thomson (2016) go beyond these discussions and use these data to

[6] https://www.arjanschakel.nl/regelec_dat.html

[7] For instance, "Minister-President" for Austria, Belgium and Germany, "Queen's Commissioner" for Netherlands, "Présidents des Conseils Régionaux" in France, etc.

[8] Variable *per501*

investigate to what extent political parties' position regarding environment influences governmental policies in EU countries. To our knowledge, there are no studies using these data and this variable to investigate green diversification, and operationalize this variable at the regional level.

As the Manifesto Project Database has no available data on parties' political manifestos for regional elections, this paper assumes that political parties have similar positions regarding environmental protection policies at national and regional elections. In most countries, regional and national elections do not occur simultaneously. It is therefore essential determining criteria to match a given regional election to the relevant national election. The paper assumes that a given national election is relevant to determine the political support to environmental protection policies in a given region, if the national election happens at most 2 years before or at most 2 years after the regional election. Within this time window, we prioritize national elections that take place: 1) in the same year of the regional election, 2) the year immediately before and the year immediately after the regional election, 3) two years before and two years after the regional election. Applying these rules, we attribute to every regional government their policy stance regarding environmental protection, called Env (Reg).

We also constructed a variable that not only measures the effect of political support at the regional but also at the national scale: Env (Nat). To determine the policy stance of a given national government regarding environmental protection, we use the Manifesto Project database again. Since it collects data on national elections, it is only necessary to match the party that leads the executive after a given national election with the political position of that party regarding environmental policy, as expressed in its political manifesto prepared for the national election. The information on the party that leads the executive is available at the World Bank database of Political Institutions.

Finally, we constructed a variable Green votes that measures more directly the population's support to environmental protection policies: the share of votes on green parties in each regional election. This should reveal, to a considerable extent, the degree of adherence of the regional population to green and ecological ideals, reflecting a bottom-up environmental concern, rather than a top-down one, as represented by Env (Reg). We compute this variable using Schakel (2013) database, which provides information on the share of votes obtained by each party / coalition in a given regional election. We identify green parties searching for the following words / expressions in the parties' names: 'grun' (Austria); 'vert', 'groen', 'grun' or 'ecolog' (Belgium); 'vert', 'ecolog' or 'écolog' (France); 'grune' (Germany); 'verd' or 'ecolog' (Italy); 'groen' (Netherlands); and 'verd' or 'ecolog' (Spain).[9]

[9] We acknowledge that this method may underestimate the share of votes in green parties, because it might not be able to capture situations when green parties belong to broad coalitions, where these expressions are not present in the name of the coalition. Although it would be possible to identify these situations, they mean that in such cases green ideology does not dominate within the coalition. Moreover, it is impossible to disentangle the share of votes that belong to each individual party within a given coalition.

While nowadays it is almost consensual that environmental protection and climate change is an important strand of policy, this was not so evident decades ago. This means that the number and length of statements related to this topic that are present in the political parties' manifestos may have been affected by the need to raise voters' awareness. It can be the case that in the past more arguments and details were needed to convince voters about their importance. If so, this does not mean that political parties attribute less importance to environmental protection in more recent times. However, the data would reflect so. Thus, in order to mitigate this, we standardize Env (Reg) and Env (Nat) to have a zero mean and unit standard deviation by period. We apply a similar procedure to the Green votes variable, such that it is comparable to the other two variables related to environmental protection.

3.4 Green and Dirty Technological Specializations

To test hypotheses 4 and 5, we constructed dummy variables to identify the existence of green and dirty technological specializations in regions. We compute a dummy that takes the value of 1 when a region has already at least one green specialization at the beginning of each period. Within the group of non-green technologies, we make a distinction between dirty and non-dirty technologies. We follow Dechezleprêtre et al. (2017) and identify two types of dirty technologies based on two groups of IPC codes: transport and electricity production. We compute a dummy taking the value of 1 when a region has a specialization, at the beginning of each period, in at least one of the dirty technologies.

3.5 Control variables

It is important to control for several regional features that may affect the development of new green technological specializations and that simultaneously might be correlated with the political support to environmental protection policies. Existing literature suggests there are several dimensions that might influence the importance individuals / political parties attribute to environmental issues.

First, we include Gross Domestic Product per capita (GDPpc) because it has been argued that populations in richer countries are more concerned about environmental conditions. Second, we account for the technological capacity of regions (R&D percentage of GDP). Third, we control for the regional stock of human capital (share of population with higher education). Fourth, we include a variable share of elderly population, as aging population is considered to attribute less importance to environmental issues. Fifth, we control for population density in a region, as we might expect that this is likely to increase the demand for environmental improvements, as more densely populated areas are, in principle, more affected by environmental degradation than sparsely populated areas. And finally, we account for regional unemployment as high unemployment rates might decrease the population support for government spending on environmental issues.

4. Results

Table 1 shows the summary statistics of the variables used in the econometric analysis. Our data includes 39,318 observations. Each observation represents a triplet constituted by a region, a five-year period and a green technology in which the region is not specialized at the beginning of each five-year period. The acquisition of a green technological specialization by a given region, during a given five-year period, is a rare event, as it only happens in around 3% of the observations. The distribution of the success rate in the acquisition of new green technological specializations is very uneven across European regions. The average entry rate ranges between 0% in Basilicata (ITF5) and Lower-Normandy (FR25) to 12.8% in Bavaria (DE2). Regarding the variable on regional political support Env(Reg), the highest scores are observed in some Dutch, German and Spanish regions. Regions with the highest average entry rates on green technologies are not necessarily those with the highest scores in terms of political support to environmental protection policies. The correlation matrix in Table 2 confirms this: the correlation between green entry and political support is very weak.

To investigate the hypotheses developed in Section 2, we use the variables and data described above, and we estimate the following model specification:

$$S_{izt,t+4} = \alpha + \beta_1 \text{ AvgProximity}_{izt,t+4} + \beta_2 \text{ Env(Reg)}_{it,t+4} + \beta_3 \text{ Env(Nat)}_{it,t+4} + \beta_4 \text{ Green Votes}_{it,t+4} + \beta_5 \text{ Green}_{it} + \beta_6 \text{ Dirty}_{it} + \gamma^k \text{Controls}^k_{it-1} + \eta_i + \theta_t + \varepsilon_{it} \quad (7)$$

where i indicates the region, z the green technology, and t the year. S represents a dummy that is 1 if a technological specialization z enters a region i between t and t+4, and 0 otherwise. AvgProximity denotes relatedness as described in Section 3.2. The variables Env(Reg), Env(Nat) and Green Votes represent the three measures of political support to environmental protection policies. Green/Dirty represent a dummy variable that takes value 1 if region i has at least one technological specialization in a green/dirty technology at time t, 0 otherwise. Controls is the set of *k* control variables, η_i is region fixed effects, and θ_t is time fixed effects (a dummy for each of the 9 five-year periods).

Following previous research on technological diversification in regions (Balland et al. 2018), our baseline results are OLS estimates using a linear probability model (LPM)[10]. Tables 3 to 5 present the

[10] We also estimated probit and logit models to assess the robustness of the OLS regression results and to, explicitly, consider the binary nature of our dependent variables. Findings are more or less similar. Although the dependent variable has a large number of zeros, because success in the acquisition of new green technological specializations is a rare event, the fact we are using a very large sample (with more than 39,000 observations) should avoid the risk of obtaining biased estimates due to a dependent variable that represents rare events.

regression results. As shown in Table 3, our first hypothesis is confirmed. As expected, relatedness shows a positive and significant coefficient in all specifications, meaning that new specializations in green technologies are indeed more likely to occur in regions with related technologies. This replicates findings in earlier studies (e.g. van den Berge and Weterings 2014).

We find little support for hypothesis 2a on the effect of political support to environmental protection policies on the development of new green technological specializations. In Table 3, the coefficient of political support at the regional scale tends to be negative and non-significant, while the coefficient of political support at the national scale is negative and significant only at 0.1 level. The coefficient of green votes is positive, but it is not statistically significant. In specification v, we reach similar conclusions. Specifications vi to ix are similar to ii to v, with the only difference that in the former we interact relatedness with one of the three variables related to political support, to test hypothesis 3. In this case, both the coefficients of political support at national scale and votes in green parties in regional elections are positive and statistically significant, while the interaction term, as expected, is negative and statistically significant. However, the coefficient of regional political support is negative, while the coefficient of the interaction is positive, but both are non-significant. Although in specifications vii, viii and ix, we find positive and statistically significant coefficients for some of the variables related to political support, their signs and statistical significance depend on the degree of relatedness. Thus, we remain with little support for hypothesis 2a.

In Table 4, we test hypothesis 2b, to account more for the continuity and consistency of political support to environmental policies, which is captured by the Sum variable. This variable represents the sum, for each region, of its current and past observations in terms of political support to environmental protection policies. What our results show is that the coefficient of all three political support variables is again non-significant. This means we have to reject hypothesis 2b.

To quantify the importance of the interaction effects tested in Tables 3 and 4 (to assess hypothesis 3), Table 6 presents the marginal effects of relatedness for different levels of political support. Table 6 shows marginal effects of relatedness when political support is equivalent to: minimum, first quartile, second quartile, third quartile and maximum. In the first three rows of Table 6, marginal effects are computed using specifications vi, vii and viii of Table 3. The last three rows use the same specifications of Table 4. Table 6 suggests that the effect of relatedness is stronger in regions with strong political support at the regional scale. For instance, taking into account the LPM, an increase in relatedness by 0.1 may increase by 4.8 (Env (Reg) = min) to 5.3 (Env (Reg) = max) percentage points the probability a given region acquires a new green technological specialization. This result is robust to different estimation methods and both to short (Env (Reg)) and long-term political support (Sum_Lags_Env (Reg)). The only exception is the LPM with long-term political support. In this case, it seems that in the presence of strong (long-term) political support the role of relatedness on the development of new green technological specializations becomes weaker. This is similar in the presence of high levels of political support at national scale and high levels of votes in green parties in regional elections. For instance, an increase in relatedness by 0.1 may increase by 6.4 (Env (Nat) = min) to 3.4 (Env (Nat) = max) percentage points the probability a given region acquires a new green technological specialization (LPM). This differentiated role of political support on relatedness at the regional and national scales may indicate that the regional dimension strengthens relatedness, while the national one weakens it. Thus, we only find partial support for hypothesis 3 that the effect of relatedness will be less relevant, the higher the political support.

With respect to the control variables, only GDP per capita to some extent, shows a negative and significant coefficient. The other control variables like R&D, the share of elderly people, human capital, unemployment rate and population density are not statistically significant.

In Table 5, we test hypotheses 4 and 5. We find strong support for hypothesis 4: the pre-existence in the region of a specialization in dirty technologies hampers the development of new green technological specializations. This is evident in all specifications that include the dummy variable Dirty. Interestingly, we find that relatedness moderates this negative association between regions with dirty technological specializations and the development of new green technological specializations (dirty*relatedness), implying that relatedness relaxes the negative effect of the local presence of dirty technologies. This negative effect may be taken away when relatedness is very strong (see Table 7). We find no evidence that political support fulfils such moderating role. Moreover, we reject hypothesis 5. we do not find evidence that new specializations in green technologies are more likely to occur in regions with existing specializations in green technologies: the coefficient of Green is non-significant at the conventional levels.

5. Concluding remarks

Diversification into green activities is a key topic that combines the strengths of two strands of literatures that have, so far, hardly been combined (Boschma et al. 2017). Broadly speaking, the regional diversification literature has been strong in assessing the role of regional capabilities in quantitative studies, while the geography of sustainability transition literature is strong in pointing out the importance of policies and politics in processes of transformation in case studies. This paper has made an attempt to combine both literatures by investigating the roles of both regional capabilities and political support for the ability of European regions to develop new green technologies. We have made use of an unique dataset (Manifesto Project Database) that, jointly with other data, allowed us to regionalize the political support for environmental policy in a number of European countries.

A key insight derived from our analysis is that regional capabilities matter for green diversification in regions. While the transition literature often tends to underline the radical or disruptive nature of green technologies, we find strong and robust evidence that new green activities are more likely to develop in regions where related capabilities are available. This outcome replicates findings in other studies (van den Berge and Weterings 2014; Tanner 2014, 2016; Corradini 2019). Second, political support did not increase the likelihood of developing new green technologies. We found even some (weak) evidence of a negative effect of short-term political support at the national scale while we had anticipated a positive effect. We also found an interaction effect between relatedness and political support: this implies that relatedness is a key factor for green diversification in regions that is strengthened/weakened by political support at the regional/national scale. Third, we did not find evidence that pre-existing green specializations enhanced the probability of regions to develop new green specializations, but we found that the regional presence of dirty technologies hampered the development of new green technological specializations in a region. Relatedness tends to relax this negative effect of the local presence of dirty technologies, and it may even take it away.

This paper also comes with a number of limitations. First, we used as dependent variable regional diversification in green technologies, not green activities in general. As not all green activities are taken up by patent data, and green activities also concern applications of environmental technologies that contribute to greening of economies, future research should take up diversification in green economic activities, and assess more fully the role of political support. Second, we made use of an unique dataset (Manifesto Project Database) that allowed us to regionalize the political support for environmental policy, and to make a distinction between national and regional support. This has been operationalized by the extent to which political parties that lead national and regional governments defend, in their political manifestos, policies related to environmental protection and climate change. This indicator does not take up the direct impact of environmental policy: we had no information on whether the political support resulted in the implementation of environmentally friendly policies and practices in the region. In other words, we cannot draw conclusions whether environmental policy made a difference or not. Needless to say that this is a crucial issue that needs to be explored systematically in future research (see Giudici et al. 2019).

Third, we have looked at the impact of political support in the period 2000-2012. Political programs still differed a lot in terms of environmental policy during that period. We might expect this is less the case in more recent years, as environmental policy is rapidly gaining momentum in European countries, and therefore have entered by now in almost all programs of political parties. This might imply that this indicator does not take up anymore large differences between European regions with respect to their political support to environmental policy, as compared to the period that we investigated. We leave that point for further research. Fourth, we found strong evidence of a negative effect of dirty technologies on the probability of a region to develop new green technologies. This may be attributed to the local presence of regional vested interests in dirty technologies, but exactly through which mechanisms this negative effect of dirty technologies works is still unclear. Finally, we assessed the role of geography in terms of regional capabilities and at the regional and national level in terms of political support. We did not account for network linkages across regions at various spatial scales, though these are increasingly recognized as potentially relevant for (green) diversification (Binz et al. 2014). These and other questions are considered crucial to increase our understanding of the role of politics and political support in developing new green activities in regions.

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Table 1. Descriptive statistics

Variables	N	mean	max	min	std dev
Dummy Green Entry	39318	0,03	1	0	0,18
Env. (Reg)	39318	0,01	5,37	-2,14	1,00
Env. (Nat)	39318	0,12	2,09	-1,89	0,82
Share green votes in regional elections	39318	0,00	3,42	-1,33	1,00
Relatedness (AvgProximity)	39318	0,11	0,43	0	0,07
Dummy Green Specialization	39318	0,90	1	0	0,30
Dummy Dirty Specialization	39318	0,50	1	0	0,50
GDP per capita	39318	24429	57300	12000	6833
R&D	39318	1,38	12,19	0,21	0,88
Human Capital	39318	20,63	42,40	6,70	7,39
Share elderly population	39318	0,17	0,27	0,09	0,03
Population density	39318	373,42	6458,70	21,90	850,70
Unemployment rate	39318	8,60	28,10	1,20	4,93

Table 2. Correlation matrix

	Dummy Green Entry	Env. (Reg)	Env. (Nat)	Share green votes	Relatedness	Dummy Green Specialization	Dummy Dirty Specialization	GDP per capita	R&D	Human Capital	Share elderly population	Population density	Unemployment rate
Dummy Green Entry	1												
Env. (Reg)	-0.011 **	1											
Env. (Nat)	-0.033 ***	0.456 ***	1										
Share green votes	0.005	0.138 ***	0.147 ***	1									
Relatedness	0.194 ***	-0.003	-0.005	0.004	1								
Dummy Green Specialization	0.047 ***	-0.046 ***	-0.075 ***	0.098 ***	-0.011 **	1							
Dummy Dirty Specialization	0.015 ***	0.064 ***	-0.010 *	-0.133 ***	-0.013 **	0.173 ***	1						
GDP per capita	0.039 ***	0.062 ***	0.002	0.464 ***	-0.002	0.232 ***	-0.067 ***	1					
R&D	0.051 ***	0.048 ***	0.043 ***	0.408 ***	-0.003	0.243 ***	-0.013 ***	0.318 ***	1				
Human Capital	0.024 ***	0.149 ***	0.190 ***	0.230 ***	-0.005	0.156 ***	-0.109 ***	0.349 ***	0.345 ***	1			
Share elderly population	0.016 ***	-0.135 ***	-0.306 ***	-0.368 ***	0.002	-0.027 ***	0.084 ***	-0.152 ***	-0.199 ***	-0.230 ***	1		
Population density	0.017 ***	-0.051 ***	-0.108 ***	0.429 ***	0.004	0.107 ***	-0.145 ***	0.612 ***	0.265 ***	0.353 ***	-0.160 ***	1	
Unemployment rate	-0.016 ***	-0.218 ***	-0.346 ***	-0.198 ***	0.002	-0.122 ***	-0.027 ***	-0.418 ***	-0.148 ***	0.006	0.089 ***	0.130 ***	1

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

Table 3. Regression results III. Linear Probability Model (LPM) estimated by OLS. Dependent variable: Entry of new green technological specializations

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
Relatedness	0.49172***	0.49171***	0.49160***	0.49172***	0.49159***	0.49165***	0.50139***	0.48968***	0.50151***
	(0.01638)	(0.01638)	(0.01638)	(0.01638)	(0.01638)	(0.01638)	(0.01685)	(0.01631)	(0.01688)
Env. (Reg)		-0.00034			0.00029	-0.00115			-0.00510***
		(0.00120)			(0.00127)	(0.00151)			(0.00171)
Env. (Nat)			-0.00316*		-0.00353*		0.00493**		0.00653***
			(0.00174)		(0.00185)		(0.00201)		(0.00223)
Green votes				0.00019	0.00103			0.00609***	0.00631***
				(0.00182)	(0.00192)			(0.00206)	(0.00215)
GDP per capita	-0.00000	-0.00000	-0.00000*	-0.00000	-0.00000**	-0.00000	-0.00000*	-0.00000	-0.00000**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
R&D	-0.00155	-0.00151	-0.00129	-0.00157	-0.00139	-0.00150	-0.00133	-0.00159	-0.00144
	(0.00121)	(0.00121)	(0.00121)	(0.00122)	(0.00122)	(0.00122)	(0.00118)	(0.00120)	(0.00119)
Human Capital	-0.00043	-0.00040	-0.00042	-0.00043	-0.00047	-0.00040	-0.00042	-0.00043	-0.00045
	(0.00070)	(0.00070)	(0.00070)	(0.00070)	(0.00070)	(0.00070)	(0.00070)	(0.00070)	(0.00070)
Share elderly population	-0.07688	-0.07455	-0.10390	-0.07895	-0.12025	-0.07455	-0.10101	-0.07973	-0.11706
	(0.18523)	(0.18533)	(0.18444)	(0.18670)	(0.18580)	(0.18533)	(0.18440)	(0.18674)	(0.18584)
Unemployment rate	0.00020	0.00016	-0.00010	0.00020	-0.00010	0.00016	-0.00010	0.00019	-0.00012
	(0.00046)	(0.00047)	(0.00047)	(0.00046)	(0.00048)	(0.00047)	(0.00047)	(0.00046)	(0.00048)
Population density	0.00003	0.00003	0.00004	0.00003	0.00003	0.00003	0.00004	0.00003	0.00003
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Relatedness * Env. (Reg)						0.00749			0.04960***
						(0.01585)			(0.01816)
Relatedness * Env. (Nat)							-0.07480***		-0.09285***
							(0.01983)		(0.02264)
Relatedness * Green votes								-0.05359***	-0.04805***
								(0.01601)	(0.01628)
Constant	-0.01231	-0.01269	0.00157	-0.01167	0.00694	-0.01267	-0.00012	-0.01151	0.00496
	(0.04242)	(0.04241)	(0.04241)	(0.04312)	(0.04328)	(0.04241)	(0.04238)	(0.04310)	(0.04326)
Time fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Overall R-sqr	0.061	0.061	0.061	0.061	0.061	0.061	0.062	0.062	0.062
N	39318	39318	39318	39318	39318	39318	39318	39318	39318

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

Table 4. Regression results II. Linear Probability Model (LPM) estimated by OLS. Dependent variable: Entry of new green technological specializations

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
Relatedness	0.49172***	0.49173***	0.49172***	0.49173***	0.49173***	0.49172***	0.50055***	0.49040***	0.50183***
	(0.01638)	(0.01638)	(0.01638)	(0.01638)	(0.01638)	(0.01638)	(0.01678)	(0.01634)	(0.01693)
Sum_Lags_Env. (Reg)		0.00051			0.00082	0.00102**			-0.00022
		(0.00044)			(0.00054)	(0.00049)			(0.00064)
Sum_Lags_Env. (Nat)			-0.00017		-0.00074		0.00158***		0.00146*
			(0.00057)		(0.00070)		(0.00061)		(0.00078)
Sum_Lags_Green votes				-0.00004	-0.00005			0.00094**	0.00072
				(0.00040)	(0.00040)			(0.00043)	(0.00044)
GDP per capita	-0.00000	-0.00000*	-0.00000	-0.00000	-0.00000*	-0.00000*	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
R&D	-0.00155	-0.00151	-0.00158	-0.00157	-0.00165	-0.00151	-0.00162	-0.00157	-0.00169
	(0.00121)	(0.00121)	(0.00121)	(0.00121)	(0.00121)	(0.00120)	(0.00118)	(0.00120)	(0.00118)
Human Capital	-0.00043	-0.00065	-0.00036	-0.00043	-0.00052	-0.00065	-0.00036	-0.00043	-0.00052
	(0.00070)	(0.00072)	(0.00073)	(0.00070)	(0.00073)	(0.00072)	(0.00072)	(0.00070)	(0.00073)
Share elderly population	-0.07688	-0.08269	-0.09713	-0.07663	-0.17308	-0.08264	-0.09413	-0.07661	-0.17090
	(0.18523)	(0.18549)	(0.19336)	(0.18560)	(0.20246)	(0.18551)	(0.19326)	(0.18570)	(0.20245)
Unemployment rate	0.00020	0.00019	0.00021	0.00022	0.00026	0.00019	0.00020	0.00022	0.00026
	(0.00046)	(0.00046)	(0.00046)	(0.00049)	(0.00049)	(0.00046)	(0.00046)	(0.00049)	(0.00049)
Population density	0.00003	0.00004	0.00003	0.00003	0.00003	0.00004	0.00003	0.00004	0.00003
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Relatedness * Sum_Lags_Env. (Reg)						-0.00480			0.00968*
						(0.00413)			(0.00541)
Relatedness * Sum_Lags_Env. (Nat)							-0.01620***		-0.02047***
							(0.00427)		(0.00553)
Relatedness * Sum_Lags_Green votes								-0.00907***	-0.00725**
								(0.00321)	(0.00323)
Constant	-0.01231	-0.00420	-0.01026	-0.01273	0.00902	-0.00417	-0.01170	-0.01293	0.00722
	(0.04242)	(0.04345)	(0.04252)	(0.04320)	(0.04582)	(0.04346)	(0.04250)	(0.04321)	(0.04579)
Time fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Overall R-sqr	0.061	0.061	0.061	0.061	0.061	0.061	0.062	0.062	0.062
N	39318	39318	39318	39318	39318	39318	39318	39318	39318

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

Table 5. Regression results III. Linear Probability Model (LPM) estimated by OLS. Dependent variable: Entry of new green technological specializations

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)
Dirty	-0.00610***		-0.00576***	-0.00568***	-0.00566***	-0.01672***	-0.00569***	-0.00526**	-0.00565**	-0.01114***
	(0.00218)		(0.00216)	(0.00219)	(0.00219)	(0.00286)	(0.00219)	(0.00223)	(0.00220)	(0.00291)
Green		-0.00056	0.00150	0.00136	-0.04001***	0.00130	0.00137	0.00128	0.00134	-0.03865***
		(0.00233)	(0.00241)	(0.00243)	(0.00313)	(0.00243)	(0.00246)	(0.00243)	(0.00244)	(0.00311)
Relatedness			0.49159***	0.49146***	0.16612***	0.44135***	0.49146***	0.49147***	0.49146***	0.15244***
			(0.01637)	(0.01637)	(0.03027)	(0.02208)	(0.01637)	(0.01637)	(0.01637)	(0.03170)
Env. (Reg)				0.00056	0.00055	0.00057	0.00060	0.00059	0.00056	-0.00019
				(0.00128)	(0.00128)	(0.00128)	(0.00160)	(0.00128)	(0.00128)	(0.00168)
Env. (Nat)				-0.00346*	-0.00347*	-0.00344*	-0.00346*	-0.00126	-0.00347*	-0.00081
				(0.00185)	(0.00185)	(0.00185)	(0.00185)	(0.00229)	(0.00186)	(0.00239)
Green votes				0.00101	0.00099	0.00100	0.00101	0.00077	0.00084	0.00028
				(0.00192)	(0.00192)	(0.00192)	(0.00192)	(0.00192)	(0.00218)	(0.00220)
GDP per capita	-0.00000	-0.00000	-0.00000	-0.00000*	-0.00000*	-0.00000*	-0.00000*	-0.00000	-0.00000*	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
R&D	-0.00205*	-0.00176	-0.00184	-0.00171	-0.00167	-0.00172	-0.00172	-0.00206*	-0.00168	-0.00190
	(0.00117)	(0.00117)	(0.00121)	(0.00123)	(0.00124)	(0.00122)	(0.00124)	(0.00124)	(0.00124)	(0.00126)
Human Capital	-0.00064	-0.00051	-0.00055	-0.00061	-0.00061	-0.00060	-0.00061	-0.00070	-0.00060	-0.00068
	(0.00071)	(0.00071)	(0.00070)	(0.00071)	(0.00071)	(0.00071)	(0.00071)	(0.00071)	(0.00071)	(0.00071)
Share elderly population	-0.11572	-0.10347	-0.08441	-0.12918	-0.12479	-0.12722	-0.12917	-0.12893	-0.12971	-0.12507
	(0.18909)	(0.18984)	(0.18624)	(0.18672)	(0.18660)	(0.18671)	(0.18672)	(0.18675)	(0.18692)	(0.18682)
Unemployment rate	0.00010	0.00026	0.00006	-0.00021	-0.00023	-0.00021	-0.00021	-0.00018	-0.00021	-0.00022
	(0.00046)	(0.00047)	(0.00046)	(0.00048)	(0.00048)	(0.00048)	(0.00048)	(0.00048)	(0.00048)	(0.00048)
Population density	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003	0.00003
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
Green * Relatedness					0.37135***					0.35500***
					(0.03528)					(0.03599)
Dirty * Relatedness						0.10110***				0.05648*
						(0.03260)				(0.03313)
Dirty * Env. (Reg)							-0.00008			0.00152
							(0.00199)			(0.00225)
Dirty * Env. (Nat)								-0.00396		-0.00486
								(0.00261)		(0.00296)
Dirty * Green votes									0.00038	0.00097
									(0.00212)	(0.00220)
Constant	0.05115	0.04941	-0.01205	0.00728	0.04287	0.01225	0.00726	0.00668	0.00732	0.04387
	(0.04318)	(0.04347)	(0.04271)	(0.04353)	(0.04341)	(0.04353)	(0.04354)	(0.04356)	(0.04354)	(0.04345)
Time fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Overall R-sqr	0.023	0.022	0.061	0.061	0.064	0.062	0.061	0.061	0.061	0.064
N	39318	39318	39318	39318	39318	39318	39318	39318	39318	39318

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

Table 6. Marginal effects of relatedness for different levels of political support

	LPM		Probit		Logit		Interaction Variables
	0,48	***	0,43	***	0,44	***	Env (Reg) = min
	0,49	***	0,47	***	0,49	***	Env (Reg) = Q1
Relatedness	0,49	***	0,48	***	0,50	***	Env (Reg) = Q2
	0,50	***	0,50	***	0,52	***	Env (Reg) = Q3
	0,53	***	0,63	***	0,67	***	Env (Reg) = max
	0,64	***	0,50	***	0,52	***	Env (Nat) = min
	0,53	***	0,49	***	0,51	***	Env (Nat) = Q1
Relatedness	0,49	***	0,49	***	0,50	***	Env (Nat) = Q2
	0,47	***	0,48	***	0,50	***	Env (Nat) = Q3
	0,34	***	0,47	***	0,49	***	Env (Nat) = max
	0,56	***	0,56	***	0,58	***	Green votes = min
	0,53	***	0,53	***	0,54	***	Green votes = Q1
Relatedness	0,49	***	0,49	***	0,50	***	Green votes = Q2
	0,45	***	0,44	***	0,46	***	Green votes = Q3
	0,31	***	0,29	***	0,31	***	Green votes = max
	0,55	***	0,44	***	0,44	***	Sum_Lags_Env (Reg) = min
	0,50	***	0,48	***	0,49	***	Sum_Lags_Env (Reg) = Q1
Relatedness	0,49	***	0,48	***	0,50	***	Sum_Lags_Env (Reg) = Q2
	0,49	***	0,49	***	0,51	***	Sum_Lags_Env (Reg) = Q3
	0,40	***	0,56	***	0,63	***	Sum_Lags_Env (Reg) = max
	0,67	***	0,51	***	0,53	***	Sum_Lags_Env (Nat) = min
	0,53	***	0,49	***	0,51	***	Sum_Lags_Env (Nat) = Q1
Relatedness	0,50	***	0,49	***	0,50	***	Sum_Lags_Env (Nat) = Q2
	0,48	***	0,48	***	0,50	***	Sum_Lags_Env (Nat) = Q3
	0,29	***	0,46	***	0,47	***	Sum_Lags_Env (Nat) = max
	0,59	***	0,65	***	0,67	***	Sum_Lags_Green votes = min
	0,52	***	0,53	***	0,54	***	Sum_Lags_Green votes = Q1
Relatedness	0,49	***	0,49	***	0,50	***	Sum_Lags_Green votes = Q2
	0,47	***	0,45	***	0,47	***	Sum_Lags_Green votes = Q3
	0,30	***	0,22	***	0,24	***	Sum_Lags_Green votes = max

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

Table 7. Marginal effects of the presence of dirty technological specializations in regions, for different levels of relatedness and political support

	LPM		Probit		Logit		Interaction Variables
Dirty	-0,016	***	0,000	*	0,000		Relatedness = min
	-0,012	***	0,001	*	0,000		Relatedness = Q1
	-0,007	***	0,003	*	0,002		Relatedness = Q2
	0,000		0,011	*	0,009		Relatedness = Q3
	0,027	**	0,106	*	0,093		Relatedness = max
Dirty	-0,006		0,000		0,001		Env (Reg) = min
	-0,006	**	0,000		0,000		Env (Reg) = Q1
	-0,006	**	0,000		0,000		Env (Reg) = Q2
	-0,006	**	0,000		0,000		Env (Reg) = Q3
	-0,006		-0,001		-0,002		Env (Reg) = max
Dirty	0,002		0,009	*	0,009	*	Env (Nat) = min
	-0,004		0,002	*	0,002		Env (Nat) = Q1
	-0,006	***	-0,001	*	-0,001		Env (Nat) = Q2
	-0,007	***	-0,002	*	-0,002		Env (Nat) = Q3
	-0,014	**	-0,008		-0,008		Env (Nat) = max
Dirty	-0,006	*	-0,001		-0,001		Green votes = min
	-0,006	**	0,000		0,000		Green votes = Q1
	-0,006	***	0,000		0,000		Green votes = Q2
	-0,005	*	0,000		0,000		Green votes = Q3
	-0,004		0,002		0,001		Green votes = max

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

Appendix A: OECD selected environment related technologies (3-digits technological groups)

Green Technological group code	Green Technological group name	Patent Data availability (0/1)
1.1.1.	Emissions abatement from stationary sources (e.g. SOx, NOx, PM emissions from combustion plants)	0
1.1.2.	Emissions abatement from mobile sources (e.g. NOx, CO, HC, PM emissions from motor vehicles)	0
1.1.3.	Not elsewhere classified	0
1.2.1.	Water and wastewater treatment	1
1.2.2.	Fertilizers from wastewater	0
1.2.3.	Oil spill cleanup	0
1.3.1.	Solid waste collection	1
1.3.2.	Material recovery, recycling and re-use	1
1.3.3.	Fertilizers from waste	0
1.3.4.	Incineration and energy recovery	0
1.3.6.	Waste management – Not elsewhere classified	0
1.4.0.	Soil remediation	1
1.5.0.	Environmental monitoring	0
2.1.1.	Indoor water conservation	1
2.1.2.	Irrigation water conservation	0
2.1.3.	Water conservation in thermoelectric power production	0
2.1.4.	Water distribution	0
2.2.1.	Water collection (rain, surface and ground-water)	0
2.2.2.	Water storage	0
4.1.1.	Wind energy	1
4.1.2.	Solar thermal energy	1
4.1.3.	Solar photovoltaic (PV) energy	1
4.1.4.	Solar thermal-PV hybrids	1
4.1.5.	Solar thermal-PV hybrids	1
4.1.6.	Marine energy	1
4.1.7.	Hydro energy	1
4.2.1.	Biofuels	1
4.2.2.	Fuel from waste	1
4.3.1.	Technologies for improved output efficiency (Combined heat and power, combined cycles, etc.)	1
4.3.2.	Technologies for improved input efficiency (Efficient combustion or heat usage)	1
4.4.1.	Nuclear fusion reactors	1
4.4.2.	Nuclear fission reactors	1
4.5.1.	Superconducting electric elements or equipment	1
4.5.2.	Not elsewhere classified	1
4.6.1.	Energy storage	1
4.6.2.	Hydrogen technology	1
4.6.3.	Fuel cells	1
4.6.4.	Smart grids in the energy sector	1
4.7.0.	Other energy conversion or management systems reducing GHG emissions	1
5.1.0.	CO2 capture or storage (CCS)	1
5.2.0.	Capture or disposal of greenhouse gases other than CO2	1

6.1.1.	Conventional vehicles (based on internal combustion engine)	1
6.1.2.	Hybrid vehicles	1
6.1.3.	Electric vehicles	1
6.1.4.	Fuel efficiency-improving vehicle design (common to all road vehicles)	1
6.2.0.	Rail transport	1
6.3.0.	Air transport	1
6.4.0.	Maritime or waterways transport	1
6.5.1.	Electric vehicle charging	1
6.5.2.	Application of fuel cell and hydrogen technology to transportation	1
7.1.0.	Integration of renewable energy sources in buildings	1
7.2.1.	Lighting	1
7.2.2.	Heating, ventilation or air conditioning [HVAC]	1
7.2.3.	Home appliances	1
7.2.4.	Elevators, escalators and moving walkways	1
7.2.5.	Information and communication technologies	1
7.2.6.	End-user side	1
7.3.0.	Architectural or constructional elements improving the thermal performance of buildings	1
7.4.0.	Enabling technologies in buildings	1
8.1.0.	Wastewater treatment	1
8.2.1.	Waste collection, transportation, transfer or storage	1
8.2.2.	Waste processing or separation	1
8.2.3.	Landfill technologies aiming to mitigate methane emissions	1
8.2.4.	Bio-organic fraction processing; Production of fertilisers from the organic fraction of waste or refuse	1
8.2.5.	Reuse, recycling or recovery technologies	1
8.3.0.	Enabling technologies or technologies with a potential or indirect contribution to GHG mitigation	1
9.1.1.	Reduction of greenhouse gas [GHG] emissions	0
9.1.2.	Process efficiency	0
9.2.1.	General improvement of production processes causing greenhouse gases [GHG] emissions	0
9.2.2.	Improvements relating to chlorine production	0
9.2.3.	Improvements relating to adipic acid or caprolactam production	0
9.2.4.	Improvements relating to chlorodifluoromethane [HCFC-22] production	0
9.2.5.	Improvements relating to the production of other chemicals or pharmaceuticals	0
9.3.1.	Reduction of greenhouse gas [GHG] emissions during production processes	0
9.3.2.	Bio-feedstock	0
9.3.3.	Carbon capture or storage [CCS] specific to hydrogen production	0
9.3.4.	Ethylene production	0
9.4.1.	Production of cement	0
9.4.2.	Cement grinding	0
9.4.3.	Manufacturing or processing of sand or stone	0
9.4.4.	Production or processing of lime	0
9.4.5.	Glass production	0
9.4.6.	Production of ceramic materials or ceramic elements	0
9.5.1.	Agricultural machinery or equipment	0
9.5.2.	Reduction of greenhouse gas [GHG] emissions in agriculture	0
9.5.3.	Land use policy measures	0
9.5.4.	Afforestation or reforestation	0

9.5.5.	Livestock or poultry management	0
9.5.6.	Fishing and aquaculture	0
9.5.7.	Apiculture	0
9.5.8.	Food processing	0
9.6.1.	Technologies for shaping products (e.g. rolling metal, forging, hammering, pressing or riveting)	0
9.6.2.	Technologies for metal working	0
9.6.3.	Technologies for printing, lining or stamping machines	0
9.6.4.	Technologies for working on wood, veneer or plywood	0
9.6.5.	Technologies for production of paper and paper articles	0
9.6.6.	Technologies for working on or processing of plastics	0
9.6.7.	Technologies for conveying, packing or storing of goods	0
9.6.8.	Other manufacturing technologies (e.g., for mixing, separation, applying liquids, drying, etc.)	0
9.6.9.	Manufacturing of products or systems for producing renewable energy (e.g. wind turbines)	0
9.6.10.	Manufacturing of batteries and fuel cells	0
9.6.11.	Manufacturing or assembling of vehicles	0
9.6.12.	Manufacturing of electric and electronic components of products	0
9.6.13.	Technologies for production or treatment of textiles and foot wear	0
9.6.14.	Technologies for production of tobacco products	0
9.7.0.	Climate change mitigation technologies for sector-wide applications	0
9.8.0.	Enabling technologies with a potential contribution to GHG emissions mitigation	0