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Abstract

This study explores the regional diversification processes into green technologies (2000-2017) and their implications for regional inequalities. Utilizing patent and Eurostat data, we analyze these processes along the economic strength of regions and the nature of their knowledge base. Our findings reveal that both structurally strong and weak regions can successfully diversify into green technologies if they possess related technological capabilities. However, brown regions cannot do so. Already existing patterns of divergence between these two types of regions are unlikely to be exacerbated by a green transition, but new regional disparities between brown regions and other regions could emerge.

Keywords: dark side of innovation, inequality, regional diversification, regional inequality, green innovation, green transition

JEL Classification: O32, O33, R11

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1 Introduction

The usage of fossil and non-renewable resources is nowadays still, the base for many economic activities. Climate change is one of the biggest challenges that such economic systems must face. Population growth and resource scarcity put these challenges at the top of the policy agendas of all national and supranational entities (Imbert et al., 2017; Morone, 2016). Fundamental structural adjustments need to be made (e.g. in the existing production and consumption systems) to address these challenges. The possibility to create new industrial sectors and economic opportunities through a sustainable transformation is real even if it is not without challenges. This is even more true at the regional level (Blažek et al., 2020; Hermans, 2018; Trippl et al., 2019). For example, some regions specialized in polluting activities are facing the difficult task of transforming their industrial structure (Grillitsch & Hansen, 2019). However, successful regional diversification is anything but simple. Not all regions have the same resources and skills to adapt their regional structures to meet these challenges (Binz et al., 2016; Boschma, 2017). Consequently, the restructuring processes required in the course of a green transition will likely offer new opportunities for advancement but also for relegation (Blažek et al., 2020).

However, while there is growing awareness about the potential drivers of green diversification of regions (e.g. Santoalha & Boschma, 2021; van den Berge et al., 2020), the socio-economic impacts of such process remain so far rather unclear, despite some prominent exceptions (e.g. Basilico & Grashof, 2023; Bringezu et al., 2021). This applies also especially to another (societal) challenge, the regional economic divergence (Lucchese & Pianta, 2020). In advanced economies, the real GDP per capita in structurally strong regions is now on average 70 percent higher than in structurally weak regions (Floerkemeier et al., 2021). The divergence is challenging political stability, social cohesion and economic progress in Europe (Iammarino et al., 2019; Lucchese & Pianta, 2020). Despite the relevance, it is, however, still unclear whether and to what extent the green transformation will affect these regional inequalities (Köhler et al., 2019; Lucchese & Pianta, 2020). Given the rather policy-oriented approach of *Just Transition*, which is a central component of the Green Deal (European Commission, 2021), this research gap seems particularly worthwhile to investigate it further.

Following the suggestions of Köhler et al. (2019), the paper therefore investigates who "wins" and who "loses" from this green transformation by analysing the diversification processes into green technologies along two dimensions. First, the economic strength of regions. There is evidence that innovation exacerbates inequality (e.g. Aghion et al., 2019). Higher-income regions may disproportionally profit from innovation as they own resources and capabilities on a large scale that are beneficial for innovation, because they have greater access to different resources like for example knowledge infrastructures, diversity of economic activities and human capital (Feldman, 1994). The question now arises whether this holds true for the green transition or whether, due to its particularities (e.g. Barbieri et al., 2020a), the green transition offers particularly development opportunities for structurally weak regions. Especially policy makers have a rather optimistic perspective in this context, highlighting the promising opportunities for structurally weak regions (e.g. BMBF, 2020). In view of possible differences in regional capacities, these expectations could also be more wishful thinking, as already existing regional inequalities could rather be manifested (Høst et al., 2020; Lucchese & Pianta, 2020). Second, following the framework of Grillitsch & Hansen (2019), also the nature of the regional knowledge base should be considered. Particularly interesting in this regard is the case of regions specialized in or highly related to a dirty industry (e.g. coal regions) which we call "brown" regions. In the sustainability transition literature exist several case studies showing that the existing socio-technical regime in such brown regions hampers the development of new clean technologies (e.g. Smink et al., 2015). However, by taking a more systematic perspective, recent evidence from quantitative analyses indicates that these regions are also able to diversify into green technologies (e.g. Santoalha & Boschma, 2021; van den Berge et al., 2020). The two dimensions of economic strength and the nature of the regional knowledge base can be considered together. This allows for a more accurate identification of possible differences in green diversification opportunities of regions as well as better insights into possible new and/or increased regional disparities. For example, it may be that it may be that particularly high-income regions, whether or not they have a specialized green or brown knowledge base, are able to diversify into new green technologies. This process will also bring greater economic benefits to these already economically strong regions, thereby exacerbating pre-existing regional divergence patterns. Alternatively, low-income regions with a green knowledge base may be able to diversify into new green technologies. This process would then bring economic benefits of the green transition to these more structurally weak regions offering the possibility of convergence.

The paper uses patent data from the OECD REGPAT database for the period from 1996 to 2017 to assess how different typologies of regions are able to diversify. For the identification of green technologies in European NUTS-2 regions, similar to previous studies (e.g. Santoalha & Boschma, 2021) the classification of environment-related technologies proposed by the WIPO Green Inventory is applied (WIPO, 2021). For the classification of brown technologies, we use the methodology developed by the EPO, the OECD and the International Energy Agency (EPO & IEA, 2021). Following the classification of Iammarino et al. (2019), the economic strength of the NUTS-2 regions is based on the GDP per head. Accordingly, regions with less than 75% of the EU or national averages are regarded as structural weak regions.

By empirically investigating the regional diversification processes into green technologies along the two dimensions of economic strength and the nature of the knowledge base, this paper can derive important insights about the potential dark side of green innovation in terms of regional inequality. Thereby, this paper enriches the regional diversification and sustainability transition literature. Besides contributing to broadening our knowledge about the relationship between regional diversification into green technologies and regional inequality, this paper also offers a rather pragmatic value, by highlighting possible undesirable developments that require policy intervention in order to ensure that the regional transition is not only green, but also socially sustainable (Høst et al., 2020).

The remainder of this article is structured as follows: Section 2 provides an overview over the literature and presents the underlying theoretical background. Section 3 then introduces the underlying data and the methodological approach. Thereafter, section 4 presents and discusses the empirical findings. The article ends with a conclusion in section 5, including limitations as well as promising avenues for further research.

2 Theoretical background: regional diversification, greening and inequality

In general, the study of structural change is not a new topic in science. History shows that all economies - at the states, regional, and city levels - must constantly adapt to new circumstances in order to remain competitive (Cantner, 2017; Xiao et al., 2018). In other words, regions must constantly innovate and develop new activities in order to prevent economic decline (Chapman & Walker, 1991; Walker & Storper, 1989). In this context, it is widely accepted that new industries and technologies emerge in regions where the existing regional structure and the underlying local capabilities[1] are technologically related to the new activity (e.g. Boschma, 2017; Rigby, 2015; van den Berge et al., 2020).

In view of the grand societal challenge of climate change, there is a growing interest in examining the (regional) diversification processes into green activities (e.g. Belmartino, 2022; Montresor & Quatraro, 2020; Santoalha & Boschma, 2021). Although climate change is a global issue, the relevance of green technologies to reduce, eliminate or reverse the environmental damage caused by local economic activities (Gibbs, 2006; Murphy, 2015), and the associated economic opportunities of this growing market (Belmartino, 2022; Cooke, 2010), make it worthwhile to explore the regional level. Based on the notion that diversification into green activities is not a random event, but rather an evolutionary branching process in which these new activities draw on and combine cognitively related activities in a region (Boschma, 2017; Boschma & Frenken, 2011; Frenken & Boschma, 2007), recent studies tend to find empirical evidence for the driving role of technological relatedness (e.g. Montresor & Quatraro, 2020; Santoalha & Boschma, 2021; van den Berge et al., 2020).[2] These studies show how past and place dependency make regions more likely to diversify into new technologies or industries that are closely related to those that already exist (Hidalgo et al., 2018; Neffke et al., 2011; Rigby, 2015). We follow this argumentation and therefore propose the following hypothesis:

Hypothesis 1a *Regions specialized in related technologies are more likely to diversify into green technologies.*

Unlike in the case of hypothesis 1a, the literature is relatively discordant when it comes to regions that are specialized in "dirty" technologies. Brown regions are less capable of diversifying into green technologies, unless they have technologies that are strongly related to green technologies (Santoalha & Boschma, 2021). This goes in line with the underlying idea of one prominent theoretical concept in the sustainability transition literature - the multi-level perspective (MLP). In the MLP sustainability transitions are conceptualized through the dynamic processes within and between three levels of analysis: (i.) Niches provide sheltered spaces where radically new knowledge and innovations can be created, tested and deployed; (ii.) Socio-technical regimes constitute institutional structures of existing systems following an already established technological trajectory thereby characterised by rather incremental change processes; (iii.) Socio-technical

[1] In line with (Maskell & Malmberg, 1999), local capabilities encompass the region's infrastructure and built environment, natural resources, institutional endowment as well as the knowledge and skills available in the region.

[2] As indicated in Boschma (2017), there are different forms of relatedness. However, in the case of the regional diversification into green activities, most empirical studies focus on technological relatedness so far, despite some recent exceptions (Belmartino, 2022).

landscape, which encompass exogenous (societal) events and developments, such as demographic change or rapid shocks through wars for instance (Basilico & Grashof, 2023; Geels, 2002; Geels & Schot, 2007; Rip & Kemp, 1998). The process of alignment of a novelty from the niche to the mainstream structures is thereby not simple, but instead several constraints need to be overcome, for instance due to lack of compatibility and/or resistance of the regime (Basilico & Grashof, 2023; Elzen et al., 2012; Santner, 2017). Indeed, there are several case studies in the sustainability transitions literature that show how challenging it is to change the existing socio-technical regime (e.g. Negro et al., 2012; Smink et al., 2015).

Nevertheless, other studies find no empirical evidence that current specializations in "dirty" technologies hinder diversification into green technologies (van den Berge et al., 2020). In addition, it has recently been emphasized that non-green regions can actually also diversify into green technologies by recombining their non-green technologies with green ones (e.g. Montresor & Quatraro, 2020; Santoalha et al., 2021). Following the recombinant innovation approach (Weitzman, 1998), this stream of literature stresses that regions that are better capable of recombining different knowledge domains, potentially formerly unconnected and unrelated ones, are also more likely to diversify into new green specializations (Barbieri et al., 2020b; Orsatti et al., 2023). This might also explain why green technologies are on average more complex and novel than non-green technologies (Barbieri et al., 2020a).

However, as previous research has shown (e.g. Castaldi et al., 2015; Fleming, 2001; Grashof et al., 2019) these (novel) recombinations are rather rare and also not equally distributed among regions. Hence, it appears that the effectiveness of the recombination process, i.e. how easily two technologies can be recombined (Zeppini & van Den Bergh, 2011), is not necessarily high enough to prevent a lock-in situation (Santoalha & Boschma, 2021). Brown regions that are highly specialized in "dirty" technologies might be unable to recombine other technological domains to achieve a green transformation. Instead, it is reasonable to assume that these highly specialized brown regions rather continue following already well-defined trajectories (Dosi, 1982) and engage in exploitative search processes (March, 1991). This is especially true when regional interest groups, such as local politicians or associations, use their influence to hamper initiatives for the development of new green paths (Gardt et al., 2021; Geels, 2014). In line with the argumentation proposed by Santoalha & Boschma (2021), we therefore propose the following hypothesis:

Hypothesis 1b *Brown regions, i.e. regions with existing specializations highly related to "dirty" technologies, are less likely to diversify into green technologies*

If these hypotheses are confirmed, this would result in implications for regional disparities. Especially when the cost of (unrelated) diversification, as in the case of brown regions, may be so high that very few, if any, of them can bear this financial burden (Boschma et al., 2017; Simmie, 2012). Hence, it is reasonable to expect that structurally strong regions with sufficient resources and capabilities have an advantage in coping with the necessary structural adjustment processes (Pinheiro et al., 2022). In general, recent studies have documented widening income disparities across and within regions in many developed countries, threatening economic progress, social cohesion and political stability (Boschma et al., 2023; Feldman et al., 2021; Iammarino et al., 2019; Lucchese & Pianta, 2020). Traditionally, externalities, cumulative effects and structural factors, such as institutions are regarded as factors for enhancing (national) inequalities (Hartmann & Pinheiro, 2022; Pinheiro et al., 2022). For example, Kuznets (1955) argued that countries would experience a rise in income inequality, in particular between urban and rural areas, at the initial stages of economic development, while at later stages inequality would fall again due to knowledge diffusion and associated developments of a welfare state (e.g. redistribution policies). However, the empirical evidence for this assumption is rather mixed (Fields, 2002; Hartmann & Pinheiro, 2022; Palma, 2011). In addition, the notion that counterbalancing market forces would "lift all boats" was also conceptually criticized (Hartmann & Pinheiro, 2022). For example, Myrdal (1957) suggested that the free play of market forces may not necessarily result in a process of economic convergence, but rather in a core-periphery structure of the economy. This is explained by the fact that potential spread effects, such as remittances and technology diffusion, are outweighed by backwash effects, like externalities of infrastructure for commerce, the movement of (financial) capital and the selective migration of young and highly educated human capital to more economically advanced regions(Myrdal, 1957; Pinheiro et al., 2022).

Besides these potential backwash and spread effects, innovation processes and their nature provide another (rather recent) explanation for inter-regional inequalities, often summarized under the expression "dark side of innovation" (Coad et al., 2021; Pinheiro et al., 2022). There is strong evidence that innovation processes agglomerate in space (Asheim & Gertler, 2006; Audretsch & Feldman, 1996). Knowledge does not easily spill over large geographical distances, but is geographically restricted and spatially concentrated (Jaffe et al., 1993). Especially the transfer of tacit knowledge requires face-to-face contacts for an effective transmission (Daft & Lengel, 1986). As a consequence, in line with evolutionary economic geography, regions tend to accumulate knowledge and specialize over time (Boschma & Lambooy, 1999). These highly agglomerated hotpots, most famously the Silicon Valley, pull in high-skilled workforce from other regions, since they offer a large number of high-paid and skilled-based jobs, thereby reinforcing the tendency of regional knowledge concentration embedded in the human capital (Boschma et al., 2023; Diamond, 2016; Iammarino et al., 2019). Moreover, these regions typically form also hubs in research networks, providing them with access to new knowledge sources, which again can reinforce regional disparities with respect to innovation (Maggioni et al., 2007; Moreno et al., 2005). In this regard, due to the existing agglomeration economies, among other reasons, these regions are able to a larger extent to produce radical innovations (Grashof et al., 2019; Kemeny et al., 2022). High-income regions have therefore particular resources and capabilities, such as human capital, a diverse and large knowledge pool as well as infrastructure, through which they can more easily innovate and develop new activities in order to avoid economic decline (Feldman, 1994; Pinheiro et al., 2022). Since green technologies are on average more complex and novel than non-green technologies (Barbieri et al., 2020a), it is reasonable to assume that due to their previously described characteristics, structurally strong regions have more beneficial conditions to engage in green innovation processes. We therefore propose the following hypothesis:

Hypothesis 2 *Structurally strong regions are more likely than structurally weak regions to diversify into green technologies.*

Furthermore, it is also important to take a closer look at the type of new green activities that are being created in a region (Pinheiro et al., 2022), since not all green technologies are

Nature of knowledge base/ Economic strength	„Green“ H1a: Positive	„Brown“ H1b: Negative
Strong H2 & H3: Positive	Best chances	Mixed chances
Weak H2 & H3: Negative	Mixed chances	Worst chances

Figure 1: Theoretical framework for regional diversification into green technologies

also alike, despite some common characteristics (Barbieri et al., 2020a). According to interdisciplinary research on economic complexity, regions should engage in more complex activities because of the associated economic benefits (Balland et al., 2019, 2022; Hidalgo, 2021). These economic benefits rely on the idea that complex knowledge is hard to imitate by competitors, thereby providing a competitive advantage that ultimately leads to a higher economic performance (Hidalgo & Hausmann, 2009; Kogut & Zander, 1992; Mewes & Broekel, 2022; Rigby et al., 2022). Consequently, since technologies that encompass such complex knowledge cannot be diffused so easily (Fleming & Sorenson, 2001), they are more geographically concentrated in large knowledge-intensive cities than simple technologies (Balland et al., 2020; Mewes & Broekel, 2022). This has of course also implications for regional disparities, especially because related capabilities seem to matter for the diversification into more complex activities (Balland et al., 2019). In their pioneering study, Pinheiro et al. (2022) showed that high-income regions diversify into more complex technologies and industries, while low-income regions rather move into simple technologies, implying that regional disparities are likely reinforced. Based on their empirical results and our previous hypotheses, it is therefore reasonable to assume that structurally strong regions have better capabilities not only to diversify into green technologies, but also to diversify in more complex green technologies. This multiplying effect would result to a even higher potential for economic benefits for these regions and would ultimately exacerbate the inter-regional inequality patterns (Pinheiro et al., 2022). We therefore propose the following hypothesis:

Hypothesis 3 *Structurally strong regions are more likely than structurally weak regions to diversify into highly complex green technologies.*

Figure 1 summarizes our assumptions regarding the nature of the regional knowledge base, the regional economic strength and the diversification into green technologies (additionally considering the complexity of these technologies).

3 Data and methodological approach

3.1 Data

To test our hypotheses, we use the OECD Regpat (February 2022) database to successfully detect innovative activities. We include all patents filed between 1996 and 2017 with 5 year moving windows (for example the period identified as 2000 contains patents filed between 1996 and 2000). To identify brown patents we use the taxonomy developed by (EPO & IEA, 2021). The WIPO green inventory has been used to identify the green patents (WIPO, 2021). A specific patent is classified to a green or brown technology if one of its full-digits CPC classes is belonging to either one of the two aforementioned inventories. For developing the main indicators utilized in this paper we use the CPC 4-digit classification.

Many innovation studies rely on patent data because they provide valuable information on the technological domains (e.g Boschma et al., 2014; Balland et al., 2019). However, it has been demonstrated that patents embed some limitations (Griliches, 1990). For example, based on their nature, some inventions cannot be patented (e.g. softwares and services). Thus, all the analyses (including ours) focusing on patents have a limited view on the total number of inventions. Furthermore, the analysis is based on the patent classification scheme which assumes that patents in the same CPC class are at the same time similar and different from those in other classes. This assumption might not hold true since the technological classification has been established for other purposes rather than distinguishing patents based on their technological domain (Basilico et al., 2023).

A patent is assigned to a specific region if at least one inventor resides there (Cantner & Graf, 2006). Large companies are usually patenting in their headquarters, a place where the invention was not actually originated (Graf, 2017). This effect must be considered, if not, the geographical allocation would be biased by a concentration of patents around large cities.

We consider the NUTS 2 classification as regional boundaries. Usually this geographical delimitation correspond to the regions in which regional governments are directly responsible for policies with regard to environmental protection (Giudici et al., 2019; Santoalha et al., 2021). There are in total 242 NUTS 2 regions in Europe. We consider only the regions that have at least 5% of the distribution of patents (corresponding to 40 patents) in the whole considered period. This threshold is important since applying specialization indexes to regions with very few patents would result in a overestimation for these specific regions. In other words, regions would be regarded as specialized in a specific technologies only because the number of technologies in which they are active is very low. As a result, our final sample consists of 203 NUTS 2 regions from 17 different countries.[3]

3.2 Dependent and independent variables

3.2.1 Regional specialization index: RCA

To identify the specialization patterns of regions in green and brown technologies we follow other studies about technological diversification in regions (Kogler et al., 2013; Rigby, 2015). Firstly, we divide the number of patents identified in each CPC 4 digits class in three categories. The

[3] These countries encompass the EU-15, without UK and Ireland due to data limitations, Switzerland, Poland, Czech Republic, Norway and Sweden.

first, contains the patents identified as green. The second, contains the patents identified as brown. The last category contains the patents identified as neither brown nor green. Secondly, we compute for each year, each region and each CPC 4 digit class present in the sample a revealed comparative advantage (RCA) weighting it by the number of patents identified as green and brown:

$$brown/green = \frac{patents^t_{r,z} / \sum_i patents^t_{r,i}}{\sum_r patents^t_{r,z} / \sum_r \sum_i patents^t_{r,i}} > 1 \tag{1}$$

Where $patents^t_{r,z}$ is the amount of patents in a region r in a specific CPC 4 digits class z identified as green or brown in time t, $\sum_i patents^t_{r,i}$ is the total number of patents in a region r in time t, $\sum_r patents^t_{r,z}$ is the sum of all patents in every region r in a specific CPC 4 digit class z and identified as green or brown in time t. Finally, $\sum_r \sum_i patents^t_{r,i}$ is the sum of the total amount of patents for each region in time t.

Regions r are regarded as specialized in a specific brown or green technology if there is a revealed comparative advantage in a specific technology at a period t. In other words, for being classified as specialized in a specific brown or green technology the region has a higher share of green or brown patents compared to the share of green or brown patents in the same CPC 4 digits class over all regions ($brown/green \geq 1$).

In line with previous studies (e.g. Rigby, 2015; Montresor & Quatraro, 2020; Santoalha & Boschma, 2021), we use this information ($green > 1$) in order to create our dependent variable $NewRCAgreen$. This dichotomous variable is defined in the following way:

$$NewRCAgreen_{r,t} = 1, if RCAgreen_{r,t-5} \leq 1 \wedge RCAgreen_{r,t} > 1 \wedge PatGreen_{r,t} = 10 \tag{2}$$

where $NewRCAgreen_{r,t}$ equals one, if region r had not an RCA in green technologies at time $t-5$, but develops an RCA in green technologies in t. Following Pinheiro et al. (2022), we apply a threshold of at least 10 green patents per region in order to prevent that the new RCA, being a relative measure, is based on very small absolute numbers of green patents. If a region has an amount of patents lower than 10 in a time period t this region would be removed from the sample.

3.2.2 Relatedness density

As showed by Hidalgo et al. (2007) regions tend to develop comparative advantages in technologies related to the ones which they are already specialized. We assess the relatedness between technologies using the distribution of patents in different CPC 4 digit classes this time without any geographical delimitation (the whole Europe is considered as a unique entity). For each pair of 4-digit CPC class (i and j) we check the amount of patents that co-classify them. Moreover, we apply a standardization measure using the total count of the number of patents in CPC classes i and j. Therefore, we obtain a standardized measure accounting for how many patents appear in a couple of CPC 4 digits classes i and j. We perform as standardization procedure the so-called *Cosine similarity* index using the *EconGeo* R package by Balland (2017). The Knowledge Space is actually how scientists in evolutionary economic geography such matrices (Kogler et al., 2013) which is a an n by n matrix where the nodes i ($i = 1, ..., n$) are the 4 digits

CPC classes and the edges represent the degree of relatedness between them. The estimation of the relatedness for each pair of technologies (i and j) is performed for all the periods included in the sample (from 2000 to 2017).

Moving forward it is possible to correctly identify the *green* and *brown* technological structure of each region within the EU. Drawing from other research which investigates how regional knowledge tends to cluster around specific technological fields we calculate the so-called *Relatedness Density* for both technologies identified as *green* and *brown* (Hidalgo et al., 2007; Balland et al., 2019). This indicator permits us to understand how in each region the knowledge tends to cluster around *green* and *brown* technologies. The *Relatedness Density* of *green* or *brown* technologies in region r and in time t is derived by calculating the sum of technological relatedness $\phi_{i,j,t}$ of technology i to all the other technologies j with a regional relative comparative advantage (RCA), divided by the sum of relatedness of technology i to all the other technologies j in Europe at time t:

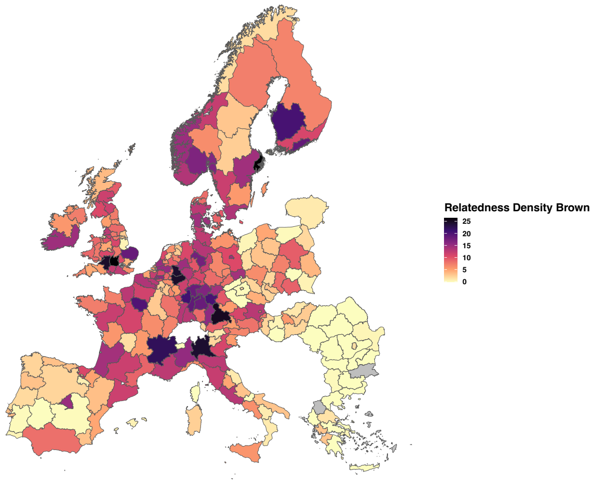
$$Relatedness\ Density_{i,r,t} = \frac{\sum\limits_{j \in r, j \neq i} \phi_{i,j}}{\sum\limits_{j \neq i} \phi_{i,j}} * 100 \tag{3}$$

Figure 2 shows the relatedness density for both *brown* (2a) and *green* (2b) technologies in the European regions for the year 2017. In general, the highest income areas are the ones which show both a high green and brown relatedness density.

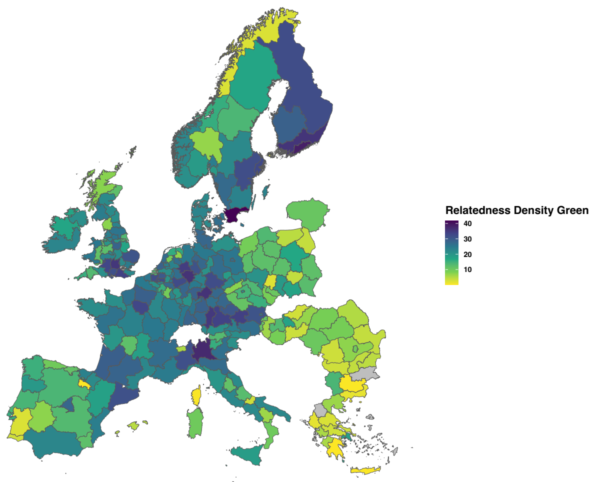
3.2.3 Technological complexity

Not all knowledge has the same value. There are some bits of knowledge which are more difficult to access than others (Hidalgo & Hausmann, 2009). These particular forms of knowledge are for most part tacit and difficult to be transmitted over long distances (Fleming & Frenken, 2007). Literature working with patent data uses forward citations or composite indicators (based still on citations with a mix between backward and forward citations) to assess the quality and the impact of the produced knowledge (Jaffe et al., 1993; Castaldi et al., 2015). Nevertheless, these measures deal with the influence of knowledge on subsequent inventions not with the characteristics and the value of knowledge stocks. Polanyi (1966) affirms that tacit knowledge consists of procedures permitting to identify bottlenecks and possible solutions in the production process. In line with this thought, Maskell & Malmberg (1999) propose that tacit knowledge is valuable because it is difficult to replicate. In fact, how people solve and react to problems is a specific knowledge embedded within individuals which is difficult to be explained or taught. Kogut & Zander (1992) show that complexity is a fundamental part composing tacit knowledge. Therefore, they propose complexity as an indicator for measuring this specific typology of knowledge.

Complexity can be measured on the level of individual patents as showed by Fleming & Sorenson (2001) through a measure which captures the difficulty to combine knowledge subsets using the technological classification of patents. Hidalgo & Hausmann (2009) propose a different measure of complexity in their product-country export analysis. The complexity of a product is mirrored by the difficulty of mastering capabilities that a country might need to export it, the diverse capabilities that each country has and how related the products are to each other. In



(a) Brown relatedness density



(b) Green relatedness density

Figure 2: Relatedness density for brown and green technologies in European regions in 2017

line with other studies in the field of economic geography we use this specific approach applying it to regions instead of countries and to patent data instead of trade data (e.g. Balland et al., 2019; Santoalha & Boschma, 2021).

In our case we assess the complexity for both *green* technologies and *brown* technologies in each region and period. We do that to assess which are the regions that produce (on average) the most complex technologies both in *brown* and *green*. We use a bipartite matrix that represent the regions and the technologies in which they are active. We represent this matrix using an adjacency matrix $M_{r,i}$ where $M_{r,i} = 1$ if a region r has an $RCA_{r,i} > 1$, otherwise $M_{r,i} = 0$.

We use the so-called *method of reflections* of Hidalgo & Hausmann (2009) due to the bipartite nature of the network. In this sense, we produce two different sets of variables based on the two types of nodes in the network (regions and technologies), we measure both the regional *diversity* of technologies and the technological *ubiquity*. The *diversity* (D) represents the number of *green* or *brown* technologies in which a region shows a specialization:

$$D_{r,0} = \sum_t M_{r,i} \tag{4}$$

On the other hand the ubiquity (U) represents the number of regions in which a technology has a comparative advantage and it is derived as follows:

$$U_{i,0} = \sum_r M_{r,i} \tag{5}$$

Putting together the diversity (D) and the ubiquity (U) we derive the complexity index (CI) for both *green* and *brown* technologies as follows:

$$CI_{r,1} = \sum_i \frac{1}{D_r} U_{r,0} M_{r,i} \tag{6}$$

The complexity index represents how rare are the *green* and *brown* technologies produced by the EU regions. Based on this information, we also calculate our second dependent variable $NewRCA\_green\_complex$, which considers the degree of complexity of new specializations in green technologies. $NewRCA\_green\_complex$ equals 1 if the corresponding region has a new specialization in green technologies (as described in Section 3.2.1) and if the respective green complexity is equal or above 75% of the national average.

3.2.4 Identification of structurally strong and weak regions

For the identification of structurally strong and weak regions, we follow previous studies using GDP per capita (e.g. Iammarino et al., 2019; Kopka & Grashof, 2022). Despite some drawbacks (e.g. Fleurbaey, 2009), this variable has been frequently used as a proxy for the economic wealth. For the specific classification into structurally strong and weak regions, we use a similar approach as Pinheiro et al. (2022). We use as threshold the 75% of the EU average of GDP per capita. This leads to the following two groups:

(1.) Structurally weak regions (regions with a GDP per capita below 75% of the EU average)

(2.) Structurally strong regions (regions with a GDP per capita equal or above 75% of the EU average[4]

Based on this classification we create the dichotomous variable GDP_strong_EU, indicating whether a regions belongs to the group structurally strong regions or not.

3.3 Control variables

Furthermore, we control for several regional characteristics that might influence the likelihood to diversify into green technologies. First, in line with previous studies (Basilico & Grashof, 2023), we include the population density in a region (*Popdensity*), as highly urbanized regions might have a higher propensity for a non-optimal distribution of resources and for producing polluting activities (Lu et al., 2021). In this sense, regions are affected by potential negative effects with a

[4]As a further robustness check, we also used the classification by Kopka & Grashof (2022) that is based on the same threshold but on the national average of GDP per capita. The corresponding results remain robust and are presented in Table 5 in the Appendix.

higher attitude to diversify into green technologies offering a solution to these issues. Moreover, if the urban agglomeration is high, highly-qualified people can be attracted, which is necessary to develop green technologies, requiring specific high-level skills (Bacolod et al., 2009). Related to the second aspect, we also control for the educational and labour market structure in regions, since green technologies are on average more complex and novel (Barbieri et al., 2020a). Based on Eurostat data, we use the share of population with tertiary education (ISCED levels 5 to 8) to control for the educational structure ($ShareTertiary$) as well as the share of employment in technology and knowledge-intensive sectors to control for the employment structure within regions ($ShareEmployKnowledge$). In both cases, we assume that high qualified human capital fosters the likelihood to enter new specializations in green technologies, because these regions have embedded the high-level skills to do so (Consoli et al., 2016). Finally, following previous studies (e.g. Montresor & Quatraro, 2020; Santoalha & Boschma, 2021), we account for the stringency of national environmental policies including the OECD Environmental Policy Stringency Index (*EnvStringency*). An overview of all variables used, including summary statistics, is presented in Table 1.[5]

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Data source
NewRCA_green	3845	0.044	0.205	0	1	OECD Regpat
NewRCA_green_complex	3845	0.042	0.200	0	1	OECD Regpat
rel_dens_brown	3209	0.064	0.048	0	0.284	OECD Regpat
rel_dens_green	3826	0.156	0.094	0	0.417	OECD Regpat
GDP_strong_EU	3715	0.724	0.447	0	1	Eurostat
Popdensity	3719	317.828	791.521	0	22469.6	Eurostat
ShareTertiary	3667	29.222	11.582	4.5	63.3	Eurostat
ShareEmployKnowlege	3501	3.741	1.825	0.5	10.9	Eurostat
EnvStringency	3618	2.786	0.707	1.139	4.222	OECD

3.4 Methodological approach

Since our database has a (unbalanced) panel structure of 203 Nuts-2 regions in 17 countries from 2000 to 2017, we conduct a panel regression analysis on the regional level in order to test our proposed hypotheses (see Section 2). In line with previous studies (e.g. Montresor & Quatraro, 2020), we choose to implement a conditional fixed-effects logistic estimation with region and time-fixed effects, as it does fit better with the binary nature of our dependent variables than a linear probability model (LPM). The stylized model has thereby the following form:

$$NewRCA\_green_{i,t} = \beta_0 + \beta_1 rel\_dens\_green/brown_{i,t} + \beta_2 GDP\_strong\_EU_{i,t} + \beta_3 Controls_{i,t} + \omega_i + \alpha_t + \mu_{i,t} \quad (7)$$

where $NewRCA\_green_{i,t}$ equals 1 if a new green specialization in region i at time t is developed, which was absent in time *t-5* (moving window). $rel\_dens\_green/brown_{i,t}$ denotes

[5] As shown in the pairwise correlation matrix (see Table 4 in the Appendix), the correlation between our variables is rather low. Thus, multicollinearity is not detected.

Table 2: Relative frequencies of no and new green specialization across structurally weak and strong regions

	Structurally weak region	**Structurally strong region**
No new green specialization	96.59%	95.24%
New green specialization	3.41%	4.76%

either the relatedness density to green or brown technologies as described in Section 3.2.2. $GDP\_strong\_EU_{i,t}$ represents a dummy variable that takes value 1 if region i at time t belongs to the group of structurally strong regions as defined in Section 3.2.4. $Controls_{i,t}$ encompasses a set of control variables (see previous section). Moreover, ω_i refers to regional fixed-effects and α_t to time fixed-effects, which are included in order to control for unobserved heterogeneity at these two dimensions. Finally, $\mu_{i,t}$ represents the residuals.

However, since previous empirical studies have also used a LPM (e.g. Santoalha & Boschma, 2021) and because we lose some observations due to perfect prediction in the case of the conditional fixed-effects logistic regression[6], as a robustness-check we also estimate a LPM with region and time-fixed effects as well as clustered standard errors.[7]

4 Empirical results: The dark side of green innovation?

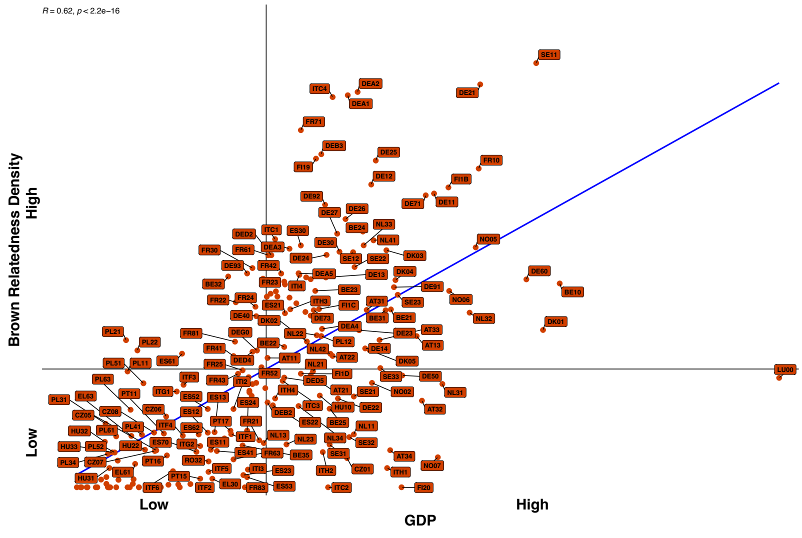
4.1 Descriptive results

Before moving towards the econometric results, we investigate potential differences between structurally strong and weak regions in a descriptive way. In this context, Figure 3 shows the relation between green (figure 3b) and brown (figure 3a) relatedness density and GDP for all the European regions included in the sample. In general, a positive trend is observed. Thus, both green and brown relatedness are positively related with the GDP. In other words, in both cases high-income regions are better equipped with related technological capabilities than low-income regions. In light of previous empirical results about regional diversification processes (e.g. Boschma, 2017; Rigby, 2015), it is therefore more likely that structurally strong regions develop new specializations in green technologies than structurally weak regions. Nevertheless, when we look at the actual entries in new specializations in green technologies, the difference between structurally strong and weak regions is relatively small (see Table 2). While 4.76% of all structurally strong regions successfully diversified into new green specializations between 2000 and 2017, with 3.41% this percentage is only slightly lower in the case of structurally weak regions. However, this rather descriptive evidence is not enough to draw some meaningful conclusions, an empirical approach controlling the elements influencing the process of knowledge accumulation in regions surely shows more robust results.

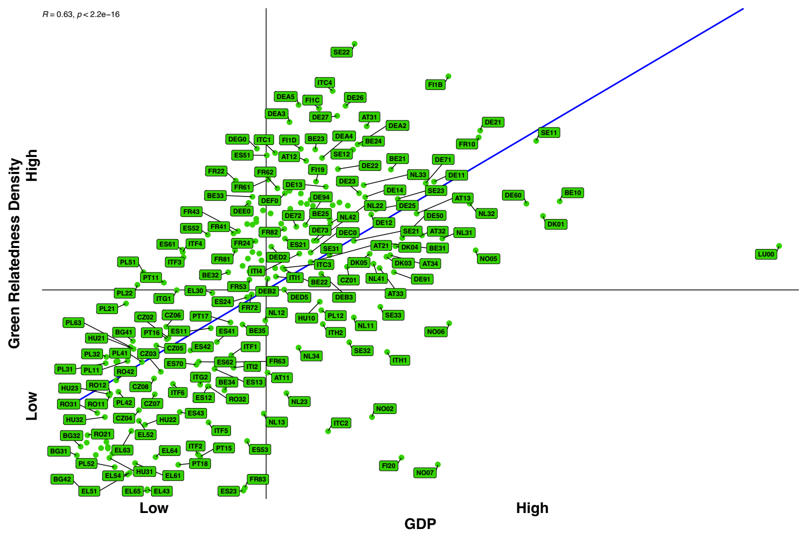
In addition to analysing whether or not a region developed a new green specialization,

[6]In some cases, up to 1,463 observations were automatically omitted in the conditional fixed-effects logistic regression because of all positive or all negative outcomes, which might create a sample selection bias.

[7]The corresponding results remain relatively stable, apart from *rel_dens_brown* which turns to be slightly insignificant. However, when we reduce the possibility that regions also have a high relatedness density to green technologies, by generating a dummy variable that takes the value 1 if *rel_dens_brown* is above the median and *rel_dens_green* is below the lowest quartile, we do find a highly significant negative influence again.



(a) Brown relatedness density vs GDP



(b) Green relatedness density vs GDP

Figure 3: Relation between relatedness density for brown and green technologies and GDP in European regions in 2017

we also consider the average complexity of these green activities. Figure 4 shows the mean difference of the average complexity of new green specializations between structurally strong and weak regions.[8] As can be seen, the average complexity of the new green specializations differs significantly between both types of regions. On average, structurally weak regions diversify into more complex green technologies than structurally strong regions. The general pattern that low-income regions tend to diversify into simpler technologies (Pinheiro et al., 2022) therefore does not seem to apply to the specific case of green technologies.

Nevertheless, despite being informative these descriptive results cannot provide the full picture of the potential dark side of green innovation, as they do not allow to draw any statistically meaningful conclusions. To deliver more reliable insights, we therefore proceed by using an econometric approach (see section 3.4) introducing variables to control for regional and national characteristics that may influence the likelihood to diversify into green technologies.

[8]The two outliers are Andalucía (in Spain) in the case of structurally weak regions and Innlandet (in Norway) in the case of structurally strong regions. Removing them does not change the corresponding results.

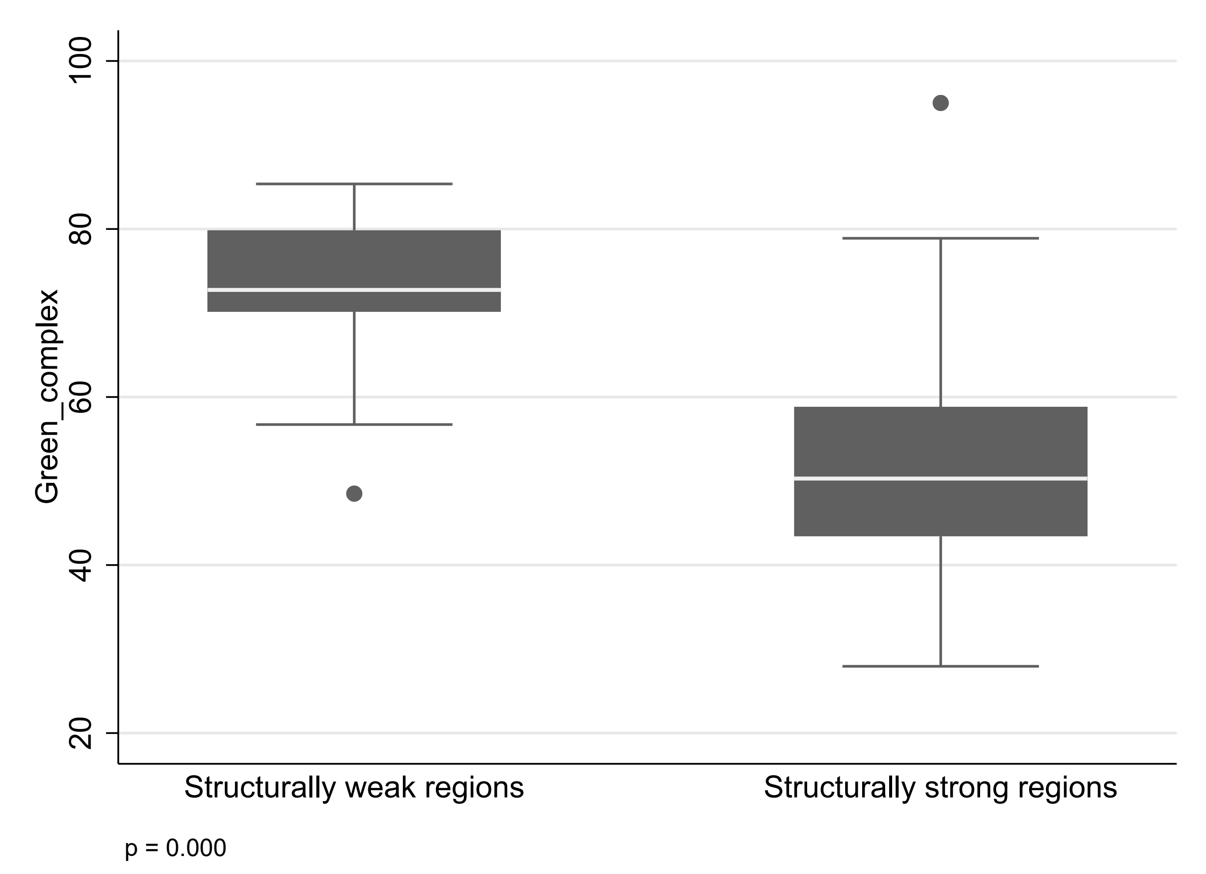


Figure 4: Boxplot representing mean difference of the average complexity of new green specializations between structurally strong and weak regions

4.2 Econometric results

Table 3 presents the regression results with respect to the influence of the regional base and the economic strength on diversification into green technologies. Looking first at our control variables used in all models, similar to previous studies (e.g. Santoalha & Boschma, 2021), only some of our control variables turn out to be statistically significant. We find evidence for a significant positive influence of the share of population with tertiary education (*ShareTertiary*). The regional educational structure therefore seem to play a promising role for the regional diversification into green technologies, which can be explained by the on average higher complexity of these technologies (e.g. Barbieri et al., 2020a) requiring highly educated human capital in the corresponding regions.

In Model 1 and Model 2, the influence of the nature of the regional base is tested by analysing green and brown relatedness density. As indicated by the positive and significant coefficient of *rel_dens_green*, the relatedness to green technologies promotes the likelihood to diversify into green technologies. This result is in line with previous studies (e.g. Santoalha & Boschma, 2021; van den Berge et al., 2020) showing that regions can more easily create new specializations in green technologies if they have already related technological capabilities. Regarding the influence of the relatedness to brown technologies (see Model 2), we do find a slightly significant and negative association with the new specializations in green technologies. Hence, regions that rather follow a path of brown technologies (i.e. fossil fuel technologies) are less likely to come up with a new specializations in green technologies.[9] This result goes rather in line with Santoalha & Boschma (2021) suggesting that pre-existing specializations in dirty technologies hamper the emergence of new specializations in green technologies. While recombinations might still be possible (Montresor & Quatraro, 2020; van den Berge et al., 2020) - at least to some extent, it seems that regions need to have some relevant amount of green capabilities to be combined with.[10] Instead, regions that are highly specialized in technologies related to brown technologies seem, on average, to have problems developing new specializations in (rather unrelated) green technologies. Therefore, we can confirm both Hypothesis 1a as well as Hypothesis 1b, indicating that the nature of the regional knowledge base plays a predominant role in the regional diversification process into green technologies.

By introducing the variable *GDP_strong_EU* (see Section 3.2.4) in Model 3, we test whether there exist regional disparities between structurally strong and weak regions with respect to the actual entries into new green technologies (see Hypothesis 2). Contrary to what was assumed, we find an insignificant and negative coefficient of *GDP_strong_EU*. Hence, we do not find evidence for a statistically significant association between the economic strength of regions and the regional diversification into green technologies. We therefore have to reject Hypothesis 2. However, what we do observe is a significant negative interaction term between *rel_dens_green* and *GDP_strong_EU* (see Model 4), despite their positive correlation (see Figure 3b). While on average the relatedness density in green technologies fosters the regional diversification in these technologies, it is especially important for structurally weak regions to have these related technological capabilities. Structurally strong regions can apparently afford to build up new green specializations that are unrelated to the existing technological portfolio, while structurally weak regions need related capabilities because they are unlikely to be able to bear the costs associated with an unrelated diversification (Boschma, 2017; Santoalha & Boschma, 2021; Simmie, 2012).

So far, the empirical evidence suggests that successful green diversification seems to be possible for both structurally strong and weak regions, but they, especially the latter, need to have related capabilities to do so. However, since not all green technologies are alike, it is also important to investigate the type of new green activities that are created in a region (Pinheiro et al., 2022). As indicated in Section 2, regions should develop more complex activities due to the associated economic benefits (e.g. limited possibility for imitation) (e.g. Balland et al., 2019). Consequently, we consider the technological complexity of the green technologies and use our second dependent variable: *NewRCA_green_complex* (see Section 3). In Model 5, we can see that the influence of *GDP_strong_EU* is negative and insignificant. Likewise in the case of the overall diversification into green technologies irrespective of the complexity (see Model 3), we find no empirical evidence for significant differences between structurally strong and weak regions. Hence, we have to reject Hypothesis 3 which suggested that structurally strong regions are more likely to diversify into highly complex green technologies. However, we do find evidence that the new entries of structurally weak regions are on average significantly more complex than

[9] In the case of the LPM with fixed effects (see Appendix 6), this coefficient turns to be insignificant. However, when we reduce the possibility that regions also have a high relatedness density to green technologies, i.e. completely focused on brown technologies, we do find a highly significant negative influence again.

[10] In fact, when excluding the potential for recombination with green technologies even further, we do not find any new green specialization of these brown regions anymore. In other words, from the 818 regions that had an RCA in green technologies below 1 and relatedness density to brown technologies above the median, none could actually develop a new green specialization.

in the case of structurally strong regions as indicated in Figure 4. Contrary to previous research emphasizing that low-income regions tend to diversify into simpler technologies (Pinheiro et al., 2022), in the specific case of green technologies we cannot confirm this general pattern. Instead, also structurally weak regions can develop new specializations in rather complex green technologies, given that they have the related technological capabilities to do so. One potential explanation for this deviating pattern may refer to the willingness of structurally weak regions to change its current situation and to exploit the chances of developing a new growth path based on green technologies. Structurally strong regions, on the other hand, are maybe more cautious due to their established and economically successful structures which they do not want to harm. This goes in line with the argument of an protective environment for experimentation and radical new ideas that peripheral regions can offer (e.g. Eder & Trippl, 2019). Linked to this, of course, increased political support could also play a role, as policy makers tend to have a rather optimistic perspective about the development opportunities of a green transition for structurally weak regions (e.g. BMBF, 2020).

Table 3: Regression results

VARIABLES	(1) NewRCA_green	(2) NewRCA_green	(3) NewRCA_green	(4) NewRCA_green	(5) NewRCA_green_complex
rel_dens_green	7.416*** (3.349)			18.381*** (6.170)	
rel_dens_brown		-8.401* (5.072)			
GDP_strong_EU			-0.535 (0.599)	1.020 (0.992)	-0.452 (0.603)
rel_dens_green#GDP_strong_EU				-12.247** (5.904)	
Popdensity	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)
ShareTertiary	0.038* (0.020)	0.035 (0.022)	0.044** (0.021)	0.043** (0.021)	0.038* (0.021)
ShareEmployKnowledge	0.210 (0.147)	0.238 (0.157)	0.183 (0.150)	0.128 (0.152)	0.179 (0.153)
EnvStringency	0.057 (0.336)	0.230 (0.364)	-0.097 (0.358)	-0.104 (0.360)	-0.017 (0.365)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Region Fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,754	1,496	1,655	1,655	1,565
Number of groups	102	92	99	99	94
Pseudo R-squared	0.091	0.111	0.088	0.102	0.094
Note:					*p<0.1; **p<0.05; ***p<0.01

5 Conclusion

The challenge posed by a growing world population and finite natural resources requires structural changes, in which green innovations play a key role (Barbieri et al., 2020b; Imbert et al., 2017; Montresor & Quatraro, 2020). Even if, there are huge ecological and economic opportunities, this sustainable transformation also poses some challenges, especially at the regional level (Blažek et al., 2020; Hermans, 2018; Trippl et al., 2019). Not all regions have the same resources and capabilities to adapt their regional economies in an environmentally sound way (Binz et al., 2016; Boschma et al., 2017). It is therefore likely that the restructuring processes required in the course of a green transition will offer new opportunities for advancement as well as for relegation (Blažek et al., 2020). However, who "wins" and who "loses" from such a green transition and how this may affect regional inequalities, remains so far rather unclear (Köhler et al., 2019; Lucchese & Pianta, 2020), which is surprising given the rather policy-oriented approach of *Just Transition* (European Commission, 2021). This paper has made an attempt to address this research gap by empirically investigating the regional diversification processes into green technologies between 2000 and 2017 along two dimensions: the nature of the regional knowledge base and the economic strength of regions.

Overall, the findings of our study imply that both structurally strong and weak regions can diversify into green technologies. Although structurally strong regions are on average more specialized in technologies highly related to green technologies (see for instance Figure 3b) and therefore have actually a better basis for diversification, they do not translate this into significantly more entries in green technologies. Instead of the economic strength, related technological capabilities matter for green diversification in regions, which is in line with previous findings (e.g. Santoalha & Boschma, 2021). This holds particularly true for structurally weak regions. While structurally strong regions may have the (financial) resources to build up new specializations that are unrelated to their existing technological regime, structural weak regions appear to be incapable to do so and therefore rely more intensively on related technological capabilities (Boschma et al., 2017; Simmie, 2012). On the other side, we find evidence that strong specialization in technologies that are highly related to "dirty" technologies hinders the development of new green technological specializations. Taken together, the nature of the regional knowledge base therefore seems to be more important for successful green diversification than the already existing economic strength of regions. Hence, in general structurally strong as well as structurally weak regions can both diverse into green technologies given that they have the related technological capabilities. This implies that already existing regional divergence patterns between these two types of regions are rather unlikely to be increased as a result of a green transition. Instead, we find evidence that particularly low-income regions with a high relatedness to green technologies can successfully diversify into green technologies. In addition, our results indicate that these new entries of structurally weak regions are on average significantly more complex than in the case of structurally strong regions, which tend to relax the general observed pattern in recent studies of low-income regions diversifying more likely into simpler technologies (Pinheiro et al., 2022).

Of course, there are political implications to these findings as well, especially with respect to the policy-oriented approach *Just Transition*, being a central component of the European Green Deal (European Commission, 2021). The underlying idea of this approach is to leave no one behind, meaning that the (regional) transition should not only be green but also socially sustainable (Høst et al., 2020). Based on our results, it would make sense that the *Just Transition* approach moves beyond "standard" cohesion policy thinking that normally differentiates between structurally strong and weak regions. Instead, it should take the actual regional capabilities into account, since structural weak regions with technological specializations related to green technologies can actually diversify into green activities without policy support. Unlike regions, that are highly specialized in technologies related to brown technologies. These regions, whether or not they are structurally strong or weak regions, are likely in need for policy support in order to overcome their lock-in situation and move to a new (green) trajectory. One pioneering example for such large-scale support programs is the Structural Strengthening Act Coal Regions in Germany, which aims at enabling and accelerating the sustainability transition in coal regions irrespective of their current economic strength (Basilico & Grashof, 2023).[11]

When considering our results, some limitations have to be discussed. First, as already described in Section 3, patent data has some drawbacks (Griliches, 1990). Second and related to the former point, patent data might bias the results towards structurally strong regions, as patent activity in structurally weak regions is rather low (Pinheiro et al., 2022), although we already excluded extreme cases to address this issue. Ideally we would follow previous studies (e.g. Pinheiro et al., 2022; Xiao et al., 2018) and extend our analysis with industry data. However, due to data limitations and rather imprecise identification of green industries, we could not follow such an approach and leave this open for future research. Third, our measurement of green diversification, although in line with previous studies (e.g. Montresor & Quatraro, 2020; Santoalha & Boschma, 2021), is rather "simple" in the sense that the actual network structure of the regional knowledge space is not considered. Following recent advancements (e.g. Basilico & Grashof, 2023), future studies should therefore also consider the change of the embeddedness of green technologies in the regional knowledge space. Fourth, we found that although structurally strong regions have more related capabilities that should promote their diversification into green technologies, they do not translate these into actual more entries into green technologies. This may be attributed to their cautiousness to keep their existing (successful) structure giving less room for experimentation, but the exact mechanisms still need to be investigated. Finally, while we tried to find an adequate trade off between the largest number possible of regions and a sufficiently large number of patents (needed for a robust empirical analysis), in general we focus only on developed regions in Europe. For future studies it may be particularly interesting to investigate developing regions, in which core-periphery structures might be more pronounced.

Despite these limitations, this paper makes a valuable contribution to the recent debate about the dark side of innovation (e.g. Coad et al., 2021; Pinheiro et al., 2022) by providing empirical evidence on the specifics of a green transition in terms of regional inequality. Deviating from previous cross-technology results (e.g. Pinheiro et al., 2022), for the concrete case of green technologies we show that both structurally strong and weak regions can successfully diversify into these technologies given that they are sufficiently equipped with related technological capabilities. On average, these new entries additionally appear to be more complex in the case of structurally weak regions, thereby providing them with the basis for future economic growth. Thus, our findings suggest that already existing patterns of divergence between these two types of regions are unlikely to be exacerbated by a green transition, but new regional disparities between brown regions and other regions could emerge, especially in the absence of adequate policy support. All in all, we can therefore conclude that there is a potential dark side of green innovation, but it is actually brighter than expected.

[11] For more information about the program, see https://www.bundesregierung.de/breg-en/service/archive/kohleregionen-foerderung-1665150.

Appendices

Table 4: Pairwise correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) NewRCA_green	1.000								
(2) rel_dens_brown	-0.037**	1.000							
(3) rel_dens_green	0.032**	0.717***	1.000						
(4) GDP_strong_EU	0.029*	0.387***	0.634***	1.000					
(5) Popdensity	0.028*	0.107***	0.173***	0.136***	1.000				
(6) ShareTertiary	0.019	0.277***	0.342***	0.352***	0.164***	1.000			
(7) ShareEmployKnowledge	0.041**	0.353***	0.458***	0.344***	0.343***	0.300***	1.000		
(8) EnvStringency	-0.055***	0.337***	0.396***	0.210***	-0.025	0.288***	-0.003	1.000	
(9) NewRCA_green_compex	0.975***	-0.050***	0.027*	0.023	0.028*	0.010	0.025	-0.052***	1.000

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

Table 5: Regression results with alternative identification of structurally strong and weak regions

VARIABLES	(1) NewRTA_green	(2) NewRTA_green	(3) NewRTA_green_complex
rel_dens_green		34.655***	
		(9.408)	
GDP_strong_National	-15.181	-12.901	-14.042
	(836.274)	(985.348)	(475.305)
rel_dens_green#GDP_strong_EU		-28.372***	
		(8.911)	
Popdensity	0.001	0.002	0.001
	(0.001)	(0.001)	(0.001)
ShareTertiary	0.043**	0.051**	0.037*
	(0.020)	(0.021)	(0.021)
ShareEmployKnowledge	0.204	0.185	0.200
	(0.151)	(0.153)	(0.154)
EnvStringency	-0.012	-0.298	0.069
	(0.356)	(0.370)	(0.363)
Year Fixed Effects	Yes	Yes	Yes
Region Fixed effects	Yes	Yes	Yes
Observations	1,655	1,655	1,565
Number of groups	99	99	94
Pseudo R-squared	0.097	0.121	0.103

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Regression results with LPM with fixed effects and clustered standard errors

VARIABLES	(1) NewRCA_green	(2) NewRCA_green	(3) NewRCA_green	(4) NewRCA_green	(5) NewRCA_green	(6) NewRCA_green_complex
rel_dens_green	0.320**				0.740***	
	(0.153)				(0.215)	
rel_dens_brown		-0.242				
		(0.188)				
only_brown			-0.042***			
			(0.010)			
GDP_strong_EU				-0.016	0.042	-0.013
				(0.025)	(0.992)	(0.025)
rel_dens_green#GDP_strong_EU					-0.507**	
					(0.248)	
Popdensity	3.22e-06	3.97e-06	3.29e-06	3.56e-06	3.85e-06	3.54e-06
	(3.19e-06)	(3.66e-06)	(3.27e-06)	(3.32e-06)	(3.46e-06)	(3.41e-06)
ShareTertiary	0.002*	0.001	0.002*	0.002**	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ShareEmployKnowledge	0.010	0.010	0.011*	0.008	0.006	0.008
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
EnvStringency	0.001	0.008	0.003	-0.003	-0.001	0.001
	(0.014)	(0.013)	(0.014)	(0.014)	(0.015)	(0.014)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,217	2,871	3,219	3,096	3,094	3,096
Number of groups	203	195	203	203	203	203
R-squared (within)	0.033	0.041	0.031	0.031	0.034	0.031

Note: Clustered standard errors, *p<0.1; **p<0.05; ***p<0.01

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