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Regional technological capabilities and Green opportunities in Europe

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Regional technological capabilities and Green opportunities in Europe

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Abstract: The goal of the paper is to elaborate an empirical overview of green technological development in European regions. This is a timely pursuit considering the ambitious commitments stipulated in the recent European Green Deal to achieve climate neutrality by 2050. Our analysis is organised in three steps. First, we map the geographical distribution of innovative activities in Europe and profile regions in terms of technological capabilities. Second, we elaborate a metric to identify regions' green innovation potential. Third, we check whether possessing comparative advantage in specific technological domains is associated with a region's capacity to develop green technologies.

JEL classification: O32, Q01, Q55

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1. Introduction

The fight against climate change is arguably at an unprecedented critical phase. On the one hand, experts concur that we now have enough capital, technology, policy instruments and scientific knowledge to cut by half carbon emissions by 2030. On the other hand, should inaction, or insufficient action, prevail, irreversible transformations in the ecosystem could trigger a calamitous domino effect for both the environment and for society (Haines and Patz, 2004; McMichael et al., 2006). To be sure, countries and regions worldwide are actively exploring avenues to deal with the opportunities and challenges of shifting to a low-carbon regime. Such an endeavour requires policies that promote a wide spectrum of innovations, including low-carbon technologies as well as sustainable production and consumption practices (Stern, 2007). According to Ayres and van den Bergh (2005, p. 116) these policies would enact "economic growth […] accompanied by structural change, which implies continuous introduction of new products and new production technologies, and changes in [energy] efficiency and dematerialisation".

Against this backdrop, the present paper provides an overview of green technological development in European (EU) regions. Such an endeavour is timely in view of the radical commitments stipulated in the recent EU Green Deal to achieve climate neutrality by 2050. Accordingly, our goal is threefold. First, we explore the geographical distribution of innovative activities and profile EU regions in terms of technological capabilities. Second, we elaborate a metric to capture the shape of the local knowledge space and, consequently, to identify regions' green innovation potential. Third, we check whether possessing comparative advantage in specific technological domains is associated with a region's capacity to develop green technologies.

To frame these goals in the current scholarly and policy debates, we call attention to two characteristics of the transition to low-carbon societies. First, geography matters. The European Commission (2015) along with other international bodies emphasises that regions and cities are responsible for implementing as much as 70% of green action plans. Of course, not all territories are equally proactive or capable in that, some will have higher innovation potential than others. This is due to differences in availability of natural resources, infrastructures and competences and, last but not least, of institutions. However, regions also differ in terms of exposure to environmental impacts. As a result, local innovation capacity may not match the demand for environmentally-friendly solutions. Put otherwise, green technologies may well emerge in more developed areas while the urgency of deploying those technologies is stronger in poorer regions (Mendelsohn et al., 2006; Bathiany et al., 2018).

This calls for an analytical framework rooted in economic geography that accounts for spatial differences in the transition towards sustainable economies. Territorial differences provide a clear rationale for regional and local governance of environmental transitions, so that spatially differentiated transformation trajectories reflect local needs and potentials (Truffer and Coenen, 2012). Thereby, the spatial dimension is pivotal in at least two ways. The first is that it reaffirms the centrality of institutions for restructuring production and consumption, and the inherently context-specific nature of both designing and implementing environmental policies (York and Rosa, 2003; Gibbs, 2006). The second is the, perhaps most obvious, importance of co-location and territorial proximity for creating and consolidating synergies for sustainable creation and use of natural resources (Chertow, 2008). Building on these insights, Truffer and Coenen's (2012) call for cross-fertilisation between regional studies and sustainability transition studies recently paved the way to a strand of empirical work (Barbieri et al., 2020a; Corradini, 2019; Montresor and Quatraro, 2019; Perruchas et al., 2020). The present study draws on and contributes to this nascent area of research.

Yet another relevant issue is that achieving zero GreenHouse Gases (GHG) emissions requires, as per recent pronouncements by the European Commission, radical "economic and societal transformations [...], engaging all sectors of the economy and society" [European Commission, 2018, p. 5]. Put otherwise, the implementation of the Green Deal will require structural change which, inevitably, will open up opportunities but also raise challenges. Given the difficulty in separating local and global environmental aspects of climate-related hazards, benefits to some will no doubt come at a cost to others. To illustrate, decarbonizing harmful production activities might cause job losses and worker displacement. This calls for analytical instruments that are consistent with the uncertainty of a scenario that features feedback loops, multiple trade-offs and emergent behaviours.

In view of this, we turn to the interdisciplinary field of complexity economics, and in particular to a set of tools that are designed to account for the increasingly dynamic and interconnected nature of the socio-economic transformations that are needed to meet new criteria of environmental sustainability. In the complexity framework, economic systems are understood as adaptive and dynamic by virtue of collective properties that arise from the interactions among their micro-components, rather than from their individual properties (Arthur, 1999; Blume and Durlauf, 2001; Cilliers, 2001). Our goal is to extend the Economic

Complexity (EC) approach (Hidalgo and Hausmann, 2009; Tacchella et al., 2012) to the analysis of the environmental competitiveness of European regions. EC methods capture the underlying competences of productive systems in different domains of human activities, i.e. industrial, technological and scientific production, while also providing tools to analyse the interaction across these dimensions. Different measures of economic complexity have been adopted by international institutions, such as the European Commission, the World Bank, and the OECD, and by local and national governments.

EC methods have proven effective in quantifying information on technological capabilities at various levels of aggregation, recently also in relation to environmental technologies and products (Mealy and Teytelboym, 2020; Napolitano et al., 2020; Sbardella et al., 2018). A key ingredient for the success of EC in characterizing the structure of regional capabilities on a large scale is a broad-encompassing approach to account for variety in regional output rather than a narrow focus on specific areas of regional specialization. In particular, mapping the innovative capabilities of a large set of regions across multiple countries, knowing in which technologies a region is competitive, is more relevant than knowing how much it produces in any specific subset. Since the sustainable transition will entail large-scale industrial, infrastructural and spatial transformations, we envisage that an economic complexity approach holds the promise of shedding new light on the green potential of individual technological competences.

Our empirical analysis is organised in two steps. First, we connect green and non-green capabilities in developing complex technologies by assessing whether and to what extent the latter are conducive to green technological advances. Green technologies have been observed to recombine different bits of knowledge from different sources (Barbieri et al., 2020b) and the exploration of the nature of these sources is fundamental from a policy perspective. Various scholars argue that green and non-green technical knowledge exhibit complementarity, so that the development of non-green technologies generates positive externalities for the generation of green knowledge (Markard and Hoffmann, 2016; Sinsel et al., 2020), and vice versa (Noailly and Shestalova, 2016). Accordingly, the first step of the present paper is to profile European regions based on their green innovation capacity calculated using the Economic Fitness and Complexity (EFC) approach (Tacchella et al., 2012) to geo-localized green and non-green patent data. EFC is an empirical recursive algorithm that is able to extract information on the capabilities of a region's knowledge base from the technologies in which it displays a competitive advantage in terms of green or non-green patenting activity. The input to the algorithm is a binary bipartite network in which a region and a technology are linked if the former has a sufficiently high Revealed Comparative Advantage (RCA; see Balassa, 1965) in patents involving the latter. The resulting indicator of regional technological fitness captures the composition of regional (green or non-green) competences as proxied by the region's portfolio of (green or non-green) technologies. Accordingly, higher fitness scores signal both that a region has a more diversified portfolio of technologies that includes more complex technologies. Notice also that, within the EFC framework, a technology has high complexity if it does not appear in the portfolio of low-fitness regions. As a consequence, higher fitness scores indicate that a region possesses more advanced technological capabilities. This approach allows the identification not only of the regions that are most proactive in green technologies but, also, each region's standing in terms of the breadth of the competencies relative to other European regions.

In the second step of our analysis, we define a measure of green potential of the non-green regional knowledge space by drawing from recent contributions on the green product or knowledge space (see e.g. Fankhauser et al., 2013; Hamwey et al., 2013; Mealy and Teytelboym, 2020; Boschma et al., 2013; Rigby, 2015). The indicator builds on the bipartite network of regional competitive advantages in technological fields and captures the strength of the association between high regional RCA in non-green technologies at time t_1 and the subsequent development of high RCA in green technologies within the same regions at time $t_2 = t_1 + \Delta t$. This allows us to identify non-green technological classes whose presence in a regional portfolio is an early signal of the emergence of competitiveness in green technologies within the same region; the number of non-green technologies of this kind within a regional technological portfolio is indicative of the green potential of the region. In the context at hand, we map the ecosystem of regional technological competences and identify empirically the combinations of non-green know-how that are most likely to favour a region's entry in the domain of green technology. Such an exercise yields evidence on the strengths and weaknesses of green regional specialisation and is therefore relevant for the design of both climate and regional development European policy. In doing so, the paper relies on studies that explore the role of spatial knowledge spillovers in the transition towards sustainable economies (Barbieri et al., 2020a; Cheng and Jin, 2020; Nomaler and Verspagen, 2021). Therein, the distribution of patents across technological fields also captures the shape of the regional knowledge base (Castaldi et al., 2015; Rigby and Balland, 2017) and allows to assess where green technologies are more likely to emerge.

Two main findings arise from the empirical analysis. First, we provide novel insights into the connection between green and non-green technological capabilities. This highlights that regional know-how in the non-green technological realm can be exploited in the green domain – and vice versa. Second, the shape of the regional technology space matters when it comes to dealing with complex capabilities. Regional technology spaces that exhibit higher propensity to develop technologies connected with green technological fields (i.e. higher green potential) specialise in a wide range of green technological domains that span the spectrum from the less to the most diffused ones.

The reminder of the paper is organised as follows. Section 2 describes the data, measures and methods employed in the empirical analysis. Section 3 shows the geographical distribution of green innovative activities and potential in European regions. Section 4 presents the main findings of the analysis. Finally, Section 5 concludes.

2. Data and Methods

2.1 Data - Measuring Regional Patenting Activity

To analyse innovative activities of different European NUTS2 regions we employ patent data from PATSTAT 2020a (European Patent Office, 2020), a database containing information about more than 100 million patents collected from most patent offices worldwide. Although patents are widely used to measure innovative activities, they carry well-known limitations. Indeed, the commercial value of patents may differ substantially across inventions, and not all inventions are patented. In addition, some technical knowledge cannot be patented. Finally, there is a high heterogeneity across sectors and countries (Archibugi and Pianta, 1996; Griliches, 1991). However, the wealth of information contained in patents is a useful data source in innovation studies. That is, patents are the only available measure that can be accessed at reasonable costs that enables to discern between green and non-green technological fields at a very fine spatial level (Popp, 2005).

The information available in PATSTAT is particularly rich. Crucial to our purposes, it allows retrieving the Cooperative Patent Classification[1] (CPC) codes used by patent offices to

[1] https://www.cooperativepatentclassification.org/index

associate the claims contained in patent applications filed worldwide with specific areas of technology in which the applications make an innovative contribution. As we detail below, CPC codes are proxies of embedded technological competences. Furthermore, PATSTAT records the address of the majority of patent inventors and patent applicants; these can be used to map the applications and the associated codes to geographical regions. In this paper we focus the analysis on patents filed between 1997 and 2017 by Europe-based inventors. The goal of capturing regional innovative activities through patents requires some preliminary steps.

We start by geolocalizing patent applications. To this end, we assign patents to their inventors' NUTS3 2013 regions of residence by exploiting, when possible, two sources of information: PATSTAT and the patent geolocalization exercise performed by de Rassenfosse et al. (2019) – which we henceforth refer to as *Geocoding*. Whenever the information differs between the two sources (a rare event), we weigh each inventor’s location. For example, if PATSTAT has two inventors localized in regions X and Y, and Geocoding has the two inventors localized in regions X and Z for the same patent, we consider the contribution of region X to the invention to be twice as big as that of regions Y and Z. Notice that Geocoding gives longitude and latitude information for inventor addresses, and not NUTS information. We move from punctual information to NUTS3 by using GIS data from Eurostat[2] and then aggregate NUTS3 2013 information at the NUTS2 2016 level.[3] This allows us to attribute patent applications to around 300 European NUTS2 regions across 33 countries.[4]

As a second step in the data preparation procedure, we associate patents to technological fields through the CPC codes of the patents in our sample. The CPC has five hierarchical levels spanning from nine sections to more than two hundred thousand subgroups. There are two types of codes. Codes starting with letters A to H are similar to the codes used in the International Patents Classification (IPC), and represent a traditional classification of technological fields. Codes starting with Y are meant to tag cross-sectional technologies spanning over several sections of the IPC classification. In particular, the Y02 class (*Technologies or Applications for Mitigation or Adaptation against Climate Change*)

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[2] EUROSTAT NUTS - GISCO, https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/administrative-units-statistical-units/nuts

[3] If we would have started from NUTS2 2013 information it would not have been possible to move to the 2016 classification.

[4] The list of countries include not only EU27 members but also neighboring countries (e.g. Norway, Switzerland) for which a regional classification equivalent to the NUTS is defined.

includes patents related to climate change adaptation and mitigation technologies covering a wide range of technologies related to sustainability objectives, such as energy efficiency in buildings, energy generation from renewable sources, sustainable mobility etc.

Finally, we group patents in INPADOC patent families (our main unit of analysis), each of which represents a collection of patent documents covering a technology. Among those we select only those families that include at least one patent application to two patent offices, one of which belonging to the IP5 forum. The IP5 forum groups together the five largest intellectual property offices in the world – i.e. the European Patent Office (EPO), the Japan Patent Office (JPO), the Korean Intellectual Property Office (KIPO), the National Intellectual Property Administration of the People's Republic of China (CNIPA), and the United States Patent and Trademark Office (USPTO). This preliminary activity leads to a data-set of around 6 million patent families out of 63 million families in PATSTAT. In addition, it allows us both to avoid country biases and to select relevant innovations for which information is readily present. Selecting patent families in this way enables us to geolocalise more than 90% of inventors and to gather CPC classification codes for at least one patent in each geolocalised family.

We employ a fractional count to assign the innovative contribution of each geolocalised patent family into the corresponding fields of technology and geographical regions. For each family, we take the number R of NUTS2 regions of residence of the inventors, the number C of NGTs (i.e. codes belonging to sections A-H of the CPC classification), and the number of C_y of GTs (i.e. Y02 codes; this number is zero if a family has no associated GTs). We then assign a share of $1/(R*C)$ to all combinations of NGT and NUTS2 region, and a share of $1/(R*C_y)$ for all combinations of GT and NUTS2 region.

2.2 Measures

2.2.1 (Green) Technological Fitness

The Economic Fitness and Complexity framework allows studying the geographical distribution of technological capabilities across European regions (NUTS2-level) by means of a Technological Fitness index that quantifies the complexity and competitiveness of the regional knowledge base. From this measure of fitness based on the whole technology spectrum we are then able to define a Green Technological Fitness (GTF) and a Non-Green Technological Fitness (NGTF) index. To this aim, we rely on previous measures of local complexity (Balland and Rigby, 2017; Sbardella et al., 2017; Operti et al., 2018). In particular, we draw from the technological fitness of European regions introduced by Pugliese and Tübke (2019) and the GTF at the country-level defined by Napolitano et al. (2020).

[FIGURE 1 ABOUT HERE]

As outlined in Figure 1(a), the EFC algorithm is based on a binary bipartite network that connects each region to the technologies in which it displays a comparative advantage. The adjacency matrix of the network M is digitised using RCA. For each region *i* and technology *j* the element of the matrix M_{ji} is defined as follows:

$$M_{ij} = \begin{cases} 1 & \text{if } RCA_{ij} \geq 1 \\ 0 & otherwise \end{cases} \qquad \text{where} \qquad RCA_{ij} = \frac{X_{ij}}{\sum_{i'} X_{i'j}} \Big/ \frac{\sum_{j'} X_{ij'}}{\sum_{i'j'} X_{i'j'}} \tag{1}$$

and X_{ij} is the sum of the shares of patents in technology class *t* that can be traced back to region *i*.

The binary matrix is then fed to the EFC algorithm that yields a measure of fitness for each region (F_i) and of complexity for each technology (Q_j). In formulae, for region *i* and technology *j*, the recursive algorithm is defined as follows:

$$\begin{cases} \widetilde{F}_i^{(n)} = \sum_j M_{ij} Q_j^{(n-1)} \\ \widetilde{Q}_j^{(n)} = \dfrac{1}{\sum_i M_{ij} \dfrac{1}{F_i^{(n)}}} \end{cases} \qquad \begin{cases} F_i^{(n)} = \dfrac{\widetilde{F}_i^{(n)}}{< \widetilde{F}_i^{(n)} >_i} \\ Q_j^{(n)} = \dfrac{\widetilde{Q}_j^{(n)}}{< \widetilde{Q}_j^{(n)} >_j} \end{cases} \tag{2}$$

where $< \cdot >_x$ denotes the arithmetic mean with respect to the possible values assumed by the variable dependent on x, and the initial condition is $Q_j^{(0)} = 1 \; \forall j$. The fixed point of the algorithm in Equation 2 defines the non-monetary metric that quantifies F_i, the fitness of region i, and Q_j, the complexity of technology j.

Depending on the structure of the input matrix, the EFC algorithm is known to possibly converge to zero fitness and zero complexity for a subset of geographical areas and technologies respectively (Pugliese et al., 2016). However, this is not an issue because it is always possible to define a consistent ranking along both dimensions, that is why we base our analysis on the fitness ranking rather than scores.

The rationale of the algorithm is that the fitness of the analysed regions and the complexity of the technologies in which they innovate can be determined recursively by taking advantage of the information contained in the composition of the technological portfolio of the former. In particular, a region with a more advanced set of capabilities will have a diversified portfolio of technologies, spanning from the most to the least complex ones, and will have higher fitness. In turn, complex technologies are rare and appear almost exclusively in the portfolio of high-fitness regions. Consequently, a region with low fitness has a smaller endowment of capabilities and thus operates exclusively in less complex (green and non-green) technological domains. Figure 1(b) illustrates this point. It displays matrix M whose rows and columns are ordered by, respectively, the technological fitness of the regions and the complexity of technologies. The black dots identify the technologies in which regions have RCA greater than 1; fitness decreases from top the top to the bottom row; complexity increases from the leftmost to rightmost column; the vertical green stripes correspond to green technologies. This particular ordering of M brings out a peculiar nested structure wherein regions with lower fitness are competitive in a subset of activities in which higher fitness regions are competitive. Nested structures typically emerge from the implementation of the EFC algorithm to matrices like M constructed from a variety of data sources, e.g. patents, international trade, scientific publications (Cimini et al., 2014; Napolitano et al., 2020; Tacchella et al., 2012). Nestedness, in turn, points to a key feature of the EFC framework, namely the possibility to capture the capability structure of a country or region in a given domain of human activity not based on *how much* competitiveness it displays in any subset of activities but, rather, *in which* activities it is competitive.

Once the complexity of technologies is determined, it is possible to derive the GFT index employing the Sector Fitness approach: we take into consideration the full spectrum of CPC codes, and compute the GTF of each NUTS2 as the sum of the complexities of the Y02 codes in which the region has a comparative advantage. Similarly, the fitness in non-green technologies is the sum of the complexities over the set of technologies that are not considered green according to the CPC classification, i.e. all codes belonging to sections A-H.[5]

2.2.2 Green Potential of the regional knowledge space

To assess whether a region's non-green knowledge base and existing capabilities are significantly correlated with its capacity to patent in environment-related technology fields, we introduce a measure of regional *green potential* that enables us to identify which technological fields have been historically statistically significant forerunners of the development of high RCA in green technologies in the NUTS2 regions included in our sample. To this aim, we draw both from recent works on the green product space (Fankhauser et al., 2013; Hamwey et al., 2013; Mealy and Teytelboym, 2020), and the technology space (Nesta and Saviotti, 2005; Boschma et al., 2013; Rigby, 2015). We also build on Pugliese et al. (2019) who defined a multilayer network analysis to study the knowledge spillovers from the patenting activity and scientific production of countries to their exported goods, as well as on Pugliese and Tübke (2019) who applied a range of economic complexity techniques to profile the technological competitiveness of European regions. To define our indicator of regional green technological potential we adopt a three-step strategy: definition of the technology space, selection of statistically significant links in the network, projection of the technology space onto NUTS2 regional patent portfolios. Therefore, we first construct a "time-augmented" technology space that links green technologies (GTs) and non-green technologies (NGTs), i.e. a multilayer network in which a link between a NGT and a GT exists if there is a significantly higher than random probability that regions with high RCA in the NGT at time t_1 also have high RCA in the GT after a fixed number of years Δt.

[FIGURE 2 ABOUT HERE]

[5] Further details of the GTF technique can be found in Napolitano et al. (2020).

In practice, as shown in Figure 2(a), we start with two binary networks that connect respectively NUTS2 regions to NGTs at time t_1; and NUTS2 regions to GTs at time $t_2 = t_1 + \Delta t$. The adjacency matrices of the two networks $M^1(t_1)$ and $M^2(t_2)$are normalised with the same procedure displayed in Equation 1: in both networks, a link is established when a region shows a revealed comparative advantage greater than 1 in a technological class. The columns of M^1reflect the 656 CPC 4-digit codes comprising sections A-H, while the columns of M^2 reflect the 44 "green" 8-digit codes under CPC class Y02. The reason for employing different aggregations to characterize GTs and NGTs for this exercise is that there are too few 4-digit CPC codes under Y02 for a meaningful analysis, and this would get in the way of the statistical validation of links in the GT-NGT technology space.

By contracting the two binary networks over the geographical dimension as in Figure 2(b), we obtain a $NGT - GT$ network that identifies the probability of observing time-lagged empirical co-occurrences within the regions in our dataset of comparative advantages in NGTs at time t_1 and comparative advantages in GTs at time t_2. To avoid "size effects", we normalise each co-occurrence by $u_{NGT}(t_1) = \Sigma_i M^1_{i,NGT}(t_1)$, the ubiquity of NGTacross regions, and by $d_i(t_2) = \Sigma_{GT} M^2_{i,GT}(t_2)$, the green technological diversification of region i in which the co-occurrence is observed. This way, we measure the probability that having a comparative advantage in the NGT precedes having a comparative advantage also in the GT. These probabilities are contained in the "assist" matrix $B(t_1, t_2)$ (Pugliese et al., 2019), the generic element of which corresponds to the normalised $NGT - GT$ co-occurrences across all regions and is defined as follows:

$$B_{NGT,GT}(t_1, t_2) = Pr(GT, t_2 | NGT, t_1) = \Sigma_i Pr(GT, t_2 | i)\, Pr(i \mid NGT, t_1)$$

$$= \Sigma_i \frac{M^2_{i,GT}(t_2)}{d_i(t_2)} \frac{M^1_{i,NGT}(t_1)}{u_{NGT}(t_1)} \tag{3}$$

However, a co-occurrence may not be informative *per se*. A high observed probability of co-occurrence may in fact be driven by the ubiquity of technological fields or regional diversification. Therefore, to rule out spurious links we assess the statistical significance of each link in the network with a null-model called the Bipartite Configuration Model (BiCM, see Saracco et al., 2015, 2017; Straka et al., 2017), a maximum entropy algorithm designed to randomise bipartite networks. The null hypothesis of the BiCM is that NGT-NT co-occurrences are random and their probability is determined only by the ubiquity of the NGT and by the diversification of the region that shows a comparative advantage in the GT. Once we have filtered the links with our null model, we interpret the statistically significant co-occurrence of the non-green and green technology fields as a signal of an overlap between the capabilities required to achieve proficient levels in both. Intuitively, patent codes that share similar inputs will be situated close to each other in the technology space, and proximity in the statistically validated NGT-GT network is positively related to the probability that acquiring a competitive advantage in the NGT is predictive of a competitive advantage in a connected GT.

We leverage the information stored in the $NGT - GT$ network to build our index of regional *green potential*. For each non-green technology NGT we define $N_{NGT\rightarrow GTs}(t_1, t_2)$ as the number of significant time-lagged co-occurrences between NGTs and green technologies. We interpret this as a proxy for the strength of the association between non-green technologies and the green knowledge base. Finally, we project this value onto regional patent portfolios by weighing the average of $N_{NGT\rightarrow GTs}$ against the patent stock of region *i*:

$$GP_i\left(t_1, t_2\right) = \Sigma_{NGT} M^1_{i, NGT}(t_1) N_{NGT\rightarrow GTs}(t_1, t_2). \quad (4)$$

It is worth noting that in the context under analysis, i.e. complexity exercises aimed at capturing regional technological capabilities, patenting is a proxy of research activities in a technological field. We look at *how many* patents are produced by a region in each field only to determine the technological activities in *which* the region is specialized. This implies that the total number of patents is inconsequential to our analysis. In this context, many of the common issues with the analysis of patent data are not problematic for our specific analyses. For example, the fact that a country tends to patent more than another in every field because of different regulations, does not affect our analysis because we are looking only at the share of patents in each field. Moreover, the fact that the propensity to patent is higher in some fields does not affect our analysis either, because we are looking only at the relative share of a field in different countries.

2.3 - Econometric model

To provide empirical evidence on the relationship between green and non-green regional fitness and investigate the role of a region's green potential we estimate the following econometric models:

$$GTF_{i,t} = \alpha + \beta_1 NGTF_{i,t} + \beta_2 Controls_{i,t} + \sigma_i + \tau_t + \phi_{i,t} + \varepsilon_{i,t}$$

$$GTF_{i,t} = \alpha + \beta_1 GP_{i,t} + \beta_2 Controls_{i,t} + \sigma_i + \tau_t + \phi_{i,t} + \varepsilon_{i,t}$$

$$NGTF_{i,t} = \alpha + \beta_1 GP_{i,t} + \beta_2 Controls_{i,t} + \sigma_i + \tau_t + \phi_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $GTF$is the regional fitness calculated on green technologies developed in region *i* at time t. $NGTF$is the regional fitness measured using non-green technologies. GP is the green potential of the knowledge space of region i as defined in Equation 4.$Controls$is a set of variables that control for the size of the patenting activity performed in the region, population and Gross Domestic Product. Moreover, regional fixed effects (σ) control for unobservable heterogeneity, that is constant over time and varies across European regions. Regional fixed effects enable us to control for idiosyncratic features that characterise European regions (e.g. geographical characteristics, etc.), whereas time fixed effects (τ) control for unobservable variation that is common to all regions but varies over time (e.g. changes in practices at the European Patent Office, etc.). Finally, we include region-specific time trends (ϕ) that account for unobservable heterogeneity that varies linearly over time in each EU region (Barbieri et al., 2020a; Charlot et al., 2015). This enables us to capture and control for different aspects that affect regional complexity that we are not able to control due to data availability (e.g. environmental policy implementation, skills endowment, etc.).

3. Exploratory data analysis

In this section we profile European regions based on their green potential (Section 3.1), green and non-green technological fitness rankings (Section 3.2 and 3.3), and the green technological domain in which they strive to innovate (Section 3.4).

3.1 Green potential

Figure 3 shows for each 3-digit A-H CPC class $N_{NGT \to GTs}(t_1, t_2)$, the strength of its association with green technologies, i.e. the share of 99% statistically significant

$NGT\ (t_1) - GT\ (t_2)$ links over the total possible links in the technology space, where $t_1 = 2012$ and $t_2 = 2017$. For ease of visualization, each color indicates a 1-digit CPC section. First, for 3-digit CPC codes the 85% of non-green technologies has at least a significant link to a green technology, and the average link share in the plot is 0.017. At the chosen statistical significance, shares lower than 0.01 are compatible with the null hypothesis of random association. Hence, bars that are lower than the dotted horizontal line represent technologies that, according to the data, are not significant precursors of green technologies. However, 59% of non-green technologies display shares higher than that threshold, confirming that eco-innovative fields are inextricably interconnected with other types of technologies, and that they are embedded to different production contexts.

[FIGURE 3 ABOUT HERE]

In particular, in the time-frame under analysis green technologies appear linked mostly to pre-existing patents about production, transformation or working of different types of materials, engines and pumps, and technologies used in construction. More in detail, we observe the highest shares in the field B-Performing Operations; Transporting section, that populates the 40% of the top ten shares with the CPC codes B32 (Layered products, i.e. products built-up of strata of flat or non-flat, e.g. cellular or honeycomb form), B26 (Hand Cutting Tools; Cutting; Severing), B24 (Grinding; Polish), and B29 (Working of plastics). Also two technologies from the C-Chemistry section can be found in the top ten, i.e., C04 (Cements; concrete; artificial stone; ceramics; refractories) and C07 (Organic chemistry). While the predominant section is F-Mechanical Engineering; Lighting; Heating; Weapons, in particular the classes F05 (Indexing schemes relating to engines or pumps), F02 (Combustion engines; hot-gas or combustion-product engine plants), F04 (Displacement machines for liquids; pumps for liquids or elastic fluids), F25 (Refrigeration or cooling; combined heating and refrigeration systems; heat pump systems; manufacture or storage of ice; liquefaction solidification of gases), as well as E05 (Locks; keys; window or door fittings; safes) from the section E-Fixed constructions.

[FIGURE 4 ABOUT HERE]

Figure 4 displays the green potential $GP_i(t_1, t_2)$ of each NUTS2 region i; in Figure 4 (a) $t_1 = 1998$ and $t_2 = 2002$, while in Figure 4 (b) $t_1 = 2012$ and $t_2 = 2017$. GP_i projects on the geographical dimension the information observed in Figure 3. Comparing the map for 2002 with the map for 2017 we observe several differences in the color patterns. On the one hand, this is due to the fact that the direction in which efforts to innovate in every region are directed change over time. On the other hand, the technological space is rewired by the technological efforts of each region that give way to new connections between non-green technologies and green technologies. In a way, the green potential index captures to what extent the non-green part of the regional technology portfolios incorporates the pathways that characterized the network at a given point in time.

We notice that the regions in the highest quintiles of green potential are not necessarily those with the highest green fitness, or with the highest technological fitness in general. This suggests that the green potential index provides a different information than that of technological fitness, which instead is an indication of the complexity of the regional technological knowledge base. Indeed, regions that are highly diversified and competitive in many technologies do not necessarily also have the highest green potential. As shown in Section 4.2, green potential has a non-trivial relation with green technological fitness. In Figure 4(c) and (d), NUTS2 regions are colored to reflect the A-H CPC technology fields with the strongest association to the green patents that are present in their technological portfolios in 2002 and 2017 respectively. For the sake of readability, the colormap associates each region to a 1-digit CPC technology. It is interesting to notice that the relationship between these maps and the bar plot of Figure 3 is also not trivial. In fact, by looking at Figure 3 one might expect that CPC sections B and F would be overwhelmingly more represented in Figures 4(c) and (d). However, projecting on the actual technological portfolio owned by the regions, the effect of the composition of the portfolio prevails. For this reason, we find e.g. in 2017 that A (Human Necessities) contributes to regional green potential more often than B or F.

3.2 Non-green Technologies

We consider here non-green technologies, i.e. all CPC classes outside of the Y02 class. The EFC algorithm applied to these CPC classes provides for each region and each year a ranking, where the first positions are occupied by regions that patent several “uncommon” technologies, i.e. domains in which not many other regions patent.

[FIGURE 5 ABOUT HERE]

Figure 5 shows the evolution of the ranking of the non-green technological fitness of European NUTS2 regions over time. We split the fitness ranking computed at three different points in time into four equal parts, each of which is represented by a node. Hence, we have three sets of nodes and the regions belonging to the same slice of the ranking in a given year are grouped the same node. The best ranked regions in each time period are represented by the dark green node at the top of each column, followed by progressively lighter shades of green. The yellow node contains the bottom fourth of the ranking. Nodes are labelled to reflect the countries whose regions mostly lie in the corresponding part of the ranking. Label colors indicate the node to which each country is assigned in the first period to help trace the dynamics of the regions within the ranking. The links connecting the nodes represent the flow of regions within the ranking from one period to the next. The color of the link reflects the source node, while link thickness is proportional to the number of regions included in the flow. For instance, the majority of top-ranked regions in terms of non-green technological fitness in 2005 remain at the top in 2010. In general, Figure 5 indicates relatively stable rankings over time, with only a minority of regions switching between differently colored nodes at any point in time.

[TABLE 1 ABOUT HERE]

Focusing on the most complex regions in non-green technologies, we calculated the average ranking position for two time periods, 1998-2006 and 2007-2017 as shown in Table 1. The stability observed in Figure 5 is confirmed. Moreover, we notice that six regions out of ten are German in both time periods, which suggests the predominance of certain countries. Table 2 indicates the bottom ten European regions in the non-green technological fitness ranking. It is worth noting that not all regions have enough patents to allow the computation of the economic fitness index. This is why the ranking in the first period is shorter than in the second.

[TABLE 2 ABOUT HERE]

3.3 *Green Technologies*

As mentioned, green technologies contribute to mitigate greenhouse emissions as well as adapt to climate change and are classified in the CPC Y02 class (Technologies or Applications for Mitigation or Adaptation against Climate Change), which comprises eight groups; in contrast NGTs comprise a much larger set of CPC codes (over a hundred classes). Green technologies can be more complex, radical, pervasive and impactful than most non-green technologies (Barbieri et al., 2020b) and therefore require a wide range of competences that (at times) are far from established know-how (De Marchi, 2012). Accordingly, we do not expect the regions that have the highest technological fitness in NGTs to necessarily top the fitness ranking in GTs; we also expect the latter ranking to display a more turbulent evolution over time.

[FIGURE 6 ABOUT HERE]

Figure 6 summarizes the evolution of the green technological fitness of NUTS2 European regions over time. Contrary to the non-green fitness ranking, we observe a relatively turbulent evolution over time. For instance, though a relative majority of regions tends to stay in the same part of the ranking from one period to the next, the fraction of regions that move between nodes is noticeably larger. Indeed, some regions drop all the way from the top of the ranking to the bottom (and *vice versa*) in the space of just a few years. The greater turbulence in the green fitness ranking is also reflected in the country labels, whose colors are quite mixed by 2015. This implies that multiple regions within the same country can quickly rise (e.g. Lithuania) or fall (e.g. Italy) according to the metric.

[FIGURE 7 ABOUT HERE]

The maps in Figure 7 depict the green fitness of NUTS2 regions at the beginning and the end of the period under analysis. The regions with lower green fitness are colored in yellow, which turns into progressively darker shades of green as green fitness increases. To improve readability, the fitness scores in both maps are rescaled to the [0, 1] range. The green fitness landscape is quite heterogeneous across countries and relatively stable over time. In particular, we observe a persistent divide between Central and Eastern European regions. A striking element is the substantial lack of coverage in several countries, which signals no patenting activity in fields related to green technology. By 2017 the gap is almost completely closed in terms of the existence of green patents in every European region. Furthermore, the green area is far less concentrated at the end of the period than at the beginning, suggesting that in less than 20 years entire countries started innovating in green technologies, and some regions have also caught up with the leaders.

[FIGURE 8 ABOUT HERE]

Figure 8 shows two snapshots of the ratio within each region of the green fitness ranking relative to the non-green technological fitness ranking. The regions in yellow are those that rank lowest in green fitness relative to their non-green fitness, while regions in darker green ranked higher in green fitness. The left panel shows that in 2002, at the beginning of the period under analysis, most underachievers in green technology are regions with the lowest green fitness (see Figure 7). This suggests that green technology did not offer a “safe harbour” for less technologically advanced regions in this early time window. The right panel shows a more nuanced picture for 2017. Perhaps the most striking element is that several regions in Germany and France are now among the green underachievers, even though they still perform relatively well in terms of both green and non-green technological fitness. This suggests that the evolution of the areas of green technology has possibly created an avenue for the development of technological capabilities also for regions that started late in the race and are still in the process of catching up.

[TABLE 3 ABOUT HERE]

Among the top ten regions in term of complexity in green technologies in Table 3, diversity is higher than in the non-green technologies (eight countries represented instead of four) and the evolution is more turbulent (only five regions remain in the top ten between the two time periods while there are seven in the case of non-green technologies). Four regions are in the top ten during the whole time period in both non-green and green technologies fitness rankings: Oberbayern (DE21), Helsinki-Uusimaa (FI1B), Ile-de-France (FR10) and Noord-Brabant (NL41). This could indicate that the high quality knowledge and skills available in these regions to develop non-green technologies could be also used for green technologies.

[TABLE 4 ABOUT HERE]

Table 4 shows the least complex European regions in terms of green technology development. The shorter fitness ranking in green technologies (last position around 259 during 1998-2006 while it is around 305 for the non-green ones) indicates that less regions have capacity to patent in climate change adaptation and mitigation technologies. While, in the case of non-green technologies, Turkish and Greek regions were almost the only ones at the bottom of the ranking, we see here more diversity due to the presence of regions from Poland, Bulgaria, Spain and Norway, with only one region (Nord-Norge - NO07) present in both time periods.

These metrics seem to be in line with other studies about regional technological development in Europe. Among the top thirteen regions present in the non-green fitness ranking in both periods, eleven are classified as “Innovation leaders” (highest level) and two as “Strong innovators” (second highest level) in the Regional Innovation Scoreboard 2021 (European Commission, 2021). On the green technology side, despite the lack of comparative study of European Regions’ performances, some examples can be confirmed by the existing literature. The rise of Stockholm (SE11) in the green fitness ranking (Table 3) is observed in a technical report about the development of green technologies in Sweden (DTU Management Engineering, 2019), as well as the good position of the region of Noord-Brabant (NL41), located around Eindhoven (Balland et al., 2019). Finally, the presence of only two regions from the South (Lombardia - ITC4, Emilia-Romagna - ITH5) seems to be associated with an important development of supportive policies (greenER, 2018; Eco-Innovation Observatory, 2015).

3.4 Performance of regions by green technology

Green technologies are not a homogeneous body, they require a different recombination of unrelated and related knowledge (Barbieri et al., 2020a; Perruchas et al., 2020). Following Barbieri et al. (2020a) and Perruchas et al. (2020) patent data may be employed to measure the maturity of green technology. The authors exploit the intensity and the geographical diffusion of patenting activities in green technological domains to define the technology life cycle stages.[6] Some technologies are more mature than others (e.g. photovoltaic panels versus CO2 capture, sequestration and storage), hence not all the regions have a knowledge and skill base adapted to the development of all the technologies. Therefore, for each region and green technology (CPC 4 digit in the Y02 class) we calculate the fractional count of patent families.

[TABLE 5 AND TABLE 6 ABOUT HERE]

Table 5 and Table 6 represent the top five European regions for each green technology for the time periods 1998-2006 and 2007-2017 respectively. The reader will recall that even if there is a correlation between the green fitness ranking and the number of green patents, these two indicators do not capture the same phenomenon. The former measure indicates a region's capacity to develop several technologies not commonly developed by other regions, while the latter provides information on how a region performs in a specific group of technologies. Consequently, we expect to observe in the following tables regions already in the top ten ranking of the green fitness but also regions that were not previously identified.

In the first time period, Ile-de-France (FR10) is in the top five of all the green technologies except for Climate Change Mitigation Technologies (CCMTs) in Information and Communication Technologies. Oberbayern (DE21) is also predominant, lacking only two GTs: CCMTs related to Capture, Sequestration and Storage of GhG (Y02C) and CCMTs

[6] Green technologies that diffuse in few countries and are characterised by low level of patenting activities are classified as 'emerging'. Technologies that diffuse across space with overall low patenting are in the 'diffusion' phase. Vice versa when patenting intensity is high and diffusion is low, they are in the 'development' phase. Finally, high patenting intensity and high geographical diffusion indicate that technology has reached a 'mature' stage.

related to wastewater treatment or waste management (Y02W). Finally, another German region (Köln, DEA2) is also active in four GTs while the remaining regions perform well in only one or two GT domains. Once again, German areas are predominant, with at least one region in every group and four in two groups (Y02P and Y02T). France is present in all groups owing to the highly concentrated patenting activities of Ile-de-France (FR10). Thus, four technology groups – CCMTs related to energy (Y02E), production of goods (Y02P), transportation (Y02T) and waste (Y02W) –, mainly emerging technologies (Barbieri et al., 2020a; Perruchas et al., 2020), are dominated exclusively by German and one or two French regions, while the remaining groups have a more balanced portfolio. Finland is only present in CCMTs in Information and Communication Technologies with two regions, indicating a dominance in this sector, although Helsinki-Uusimaa (FI1B) is the most complex region on average in the time period. Only Hamburg (DE60) and Zentralschweiz (CH06) have a high green fitness without being present in any of the top five, illustrating the differences between the two indicators.

In the second time period (2007-2017) we find a concentration of green patenting activities in fewer regions (sixteen different regions instead of the nineteen in the previous period) and countries (all the countries remain except the United Kingdom). Interestingly, even if German regions are still prevalent, their average number per group is lower (2,75 to 2,5). Oberbayern (DE21) is now present in all technology groups while Ile-de-France (FR10) is in the top five regions for six groups. Rhône-Alpes (FRK2) and Stuttgart (DE11) improved their green patenting capacities, and are now in the top regions in five different green technologies.

Comparing both time periods, on average more than half (2,86) regions maintain their leadership over the entire time period. However, the number of regions in both time periods is lower in emerging technologies (e.g. two regions, Ile-de-France (FR10) and Rheinhessen-Pfalz (DEB3) in Y02C - CCS or Disposal of Greenhouse Gases) than in mature technologies (e.g. four regions in Y02A - Adaptation to climate change or in Y02B - CCMTs related to buildings). This may be indicative of the fact that it is more difficult for a region to keep up with all the different designs appearing at the initial phase of the technology life cycle, whilst it is easier to remain predominant in the latter phase, when the designs are mainly standardized and the knowledge associated with them is stable (Vona and Consoli, 2015).

Moreover, only half of the regions in the top ten of the green fitness ranking are among the top green inventors, thus reiterating the difference between the two indicators. To conclude this exploratory analysis, complex regions in the development of green technologies are mainly located in central and western Europe, in particular in Germany. Even if there is a correlation between the fitness ranking and the patenting activity, these indicators capture different aspects of green innovation. Few regions are capable of patenting at the highest level in all the green technologies, which indicates that local capabilities are important to fostering or hampering their development.

4. Results

In this section we present and comment on the empirical exercises based on green fitness at regional level in Europe. As discussed in Section 2, the NUTS2 level offers a compromise between data availability and the dimension of the unit of observation. Indeed, the regional unit has been adopted in various empirical works that explore the geography of green innovative activities (see e.g. Ghisetti and Quatraro, 2013; Santoalha and Boschma, 2020).

Since the goal of the study is to explore regional capacity to develop green technologies, viz. green technological fitness and the green potential of the non-green knowledge space, the analysis is organised in two steps. Firstly, we explore the relationship between regional fitness calculated on green and non-green patenting activities. This enables us to check whether there is a relationship between the capabilities to develop these two instantiations of innovation (Section 4.1). Secondly, we delve into the relationship between green and non-green technological capabilities by observing whether our measure of regional green potential is correlated with better green fitness performance (Section 4.2).

4.1. The relationship between green and non-green technological fitness of European regions

The first empirical exercise consists in exploring the association between green and non-green technological fitness at the regional level. In doing so we aim to capture the extent to which innovative capabilities in non-green technologies are conducive to the development of green, complex technologies. Indeed, regional technological fitness provides a picture of the "rareness" of technological capabilities that characterise the regional knowledge space.

[FIGURE 9 ABOUT HERE]

Figure 9 shows the relationship between green and non-green technological fitness of EU regions. The scatter plot, weighted by the intensity of the patenting activity in the region, highlights a strong correlation between the two measures. This suggests that green technologies, usually more complex, novel and impactful than other technologies (Barbieri et al., 2020b), require capabilities that are unevenly diffused across regions. Regions that are already dealing with such a complexity in the non-green realm may have a comparative advantage for developing more complex green technologies. In other words, developing non-green technologies requires know-how, skills, resources (human, financial, technological, etc.) that can be also useful for green technologies – and vice versa.

Figure 9 provides a descriptive indication of the relationship between green and non-green regional fitness, which we further investigate by estimating the econometric model in Section 2.3.

[TABLE 7 ABOUT HERE]

Table 7 reports the result of the model estimation. Column (1) shows the results of the OLS model. The other columns include both regional and time fixed effects. Finally, in Columns (4) to (6), our preferred specifications, we include regional specific time trends. Results confirm the strong correlation between non-green and green regional fitness: a one percent increase in non-green regional fitness is associated with a 0.8-0.9 percentage increase in green regional fitness – depending on the specification. These insights emphasise that although green and non-green technologies may compete especially when financial resources are constrained, they show patterns of complementarity in terms of knowledge capabilities.

4.2. The green potential of the regional knowledge space

In prior empirical exercises we find a correlation between regional green and non-green technologies fitness. Here we investigate whether green regional fitness is associated with specific shapes of the regional knowledge space. In doing so, we delve into the characteristics of the regional knowledge base with a view to identify connections with higher levels of green fitness.

[FIGURE 10 ABOUT HERE]

To capture the connection between green and non-green knowledge we develop and employ the indicator introduced in Section 2.2.2 to measure the green potential of the non-green knowledge base and investigate whether this measure is correlated with the non-green and green technological fitness of EU regions. Figure 10 shows the relationship between green regional fitness and quintiles of the green potential indicator. We observe that the fitness rankings are similar between green technologies (blue bars) and non-green technologies (red bars). This first descriptive insight emerges from the strong, positive relationship between green and non-green regional fitness as highlighted in the previous empirical exercise. In addition, it is worth noting that when the green potential of the regional knowledge space is low, on average regions have lower ranks in both green and non-green fitness. However, when we move from the bottom to the top quintiles of green potential, we can find regions that are characterised by higher levels of green and non-green fitness (lower values in the ranking). Figure 10(b) shows this relationship adopting a dynamic perspective. Therein, regions in the bottom and top quintile lose positions in the ranking of green regional fitness, whereas regions in the middle of the green potential distribution gain positions on average.

[TABLE 8 ABOUT HERE]

The relationship between the green potential of the technology space and both green and non-green fitness is further investigated in Table 8. We estimate a similar model adopted in the previous exercise in which the key explanatory variable is the green potential of non-green technologies. We observe that in Column (1) the relationship between the green potential and green technological fitness is negative and significant. However, this result is mainly driven by the fact that the pooled OLS is not able to capture the idiosyncratic features that may explain an important part of the variation in green fitness. In fact, when we include regional and time fixed effects the coefficient of GreenPotential is positive and significant. Moreover, by adding regional specific time trends (Columns 3 and 4) the coefficient is still significantly different from zero – holding other variables constant. Finally, when we look at non-green regional fitness the coefficient is positive and non-significant.

These results suggest that there is a connection between the regional knowledge space and the green fitness measure. In particular, such a connection relies on the potential of green and non-green technological advances to generate positive spillovers in terms of capabilities to deal with more complex green technologies.

5. Conclusions

The Green Deal stipulates Europe's commitment to be climate neutral by 2050. Such an ambitious target requires significant efforts on all parts: policy-makers, firms and consumers. Given the scale and the complexity of the environmental transition, a top-down approach would not go very far because action plans need to be implemented from the bottom-up, in regions and cities. Of course, not all territories are equally proactive, nor are they equally capable to adapt to new criteria of environmental sustainability that entail a radical reconfiguration of production and consumption activities.

Against this backdrop, we propose a novel methodology to help inform policy with respect to regional capabilities related to green innovation. To task we explore the geographical distribution of innovative activities and profile EU regions in terms of technological capabilities to identify regions' green innovation potential. Finally, we check the association between comparative advantage in specific technological domains and green technology capacity to validate the relevance of the metric in informing policy action.

The results indicate that regions with advanced capabilities in the development of green technologies are mainly in central and western Europe, especially in Germany. On the whole, we find that only few regions have capacity to patent at the highest level in all green technologies, which indicates that local capabilities are important to fostering or hampering their development. Further, we find a strong correlation between non-green and green regional fitness. This implies that although green and non-green technologies may compete, for example for financial or human capital resources, the underlying knowledge capabilities exhibit interesting complementarities. The methodology proposed is therefore able to capture the potential for green technologies for regions without a present focus on green technologies.

Let us conclude by offering some policy implications stemming from these findings. The Green Deal is a necessary economic policy for its environmental effects, and it can also represent an economic opportunity. While the environmental effects will have global impact driven by cooperation, the economic impact will be decided on a region by region basis, depending on their preexisting local technological capabilities. The Green deal may potentially exacerbate the center-periphery tensions and polarization between EU economies

(Lucchese and Pianta, 2020). Timely assessment of green specific regional capabilities is therefore relevant both to inform industrial policy and to project possible winners and losers with an eye towards cohesion policies. Capabilities are however field-specific and product-specific: measures focusing on *how much* absorptive capacity a region has can distract policy makers from looking at *what* a region is able to do. The analysis of this paper tried to fix this gap, identifying which regions show potential in green technology by looking at the present focus of their innovation efforts.

The analysis and metrics discussed in this work can form the basis for an organic measurement effort of regional capabilities with respect to the development of green technologies, akin to similar efforts to capture country and regional innovation capabilities in general – like the European Innovation Scoreboard (Hollanders, 2009) and the Regional Innovation Scoreboard (Markelbach et al., 2019). This could inform regional industrial policy while defining long term objectives for the region. It is indeed important to notice that the need for a quantitative approach connecting *sustainable* development with local characteristics was already in the mind of policy makers. The European Commission Joint Research Centre is moving to include Green policies into its regional cohesion policy, the Smart Specialisation Strategies — S3 (Mccann and Soete, 2020). This holistic way of looking at regional and sustainability policies at the same time, named Smart Specialisation Strategies for Sustainability — S4, is based on the same theoretical foundational idea behind this paper: the relevance of local characteristics. This shift will require both novel scientific results and novel metrics to inform policies and strategies. In this paper, we tried to do that.

The research can be extended over different directions. First, we have pointed out that patents capture only a portion of innovative activities. Corroborating our results with ad hoc innovation surveys or other data sources would be important to support the evidence that emerge from this study. Second, our explorative study aims at shedding light on the co-evolution between green and non-green knowledge bases. We hope that this initial effort will pave the way to future research on empirical designs that strives for the identification of causal, robust effects.

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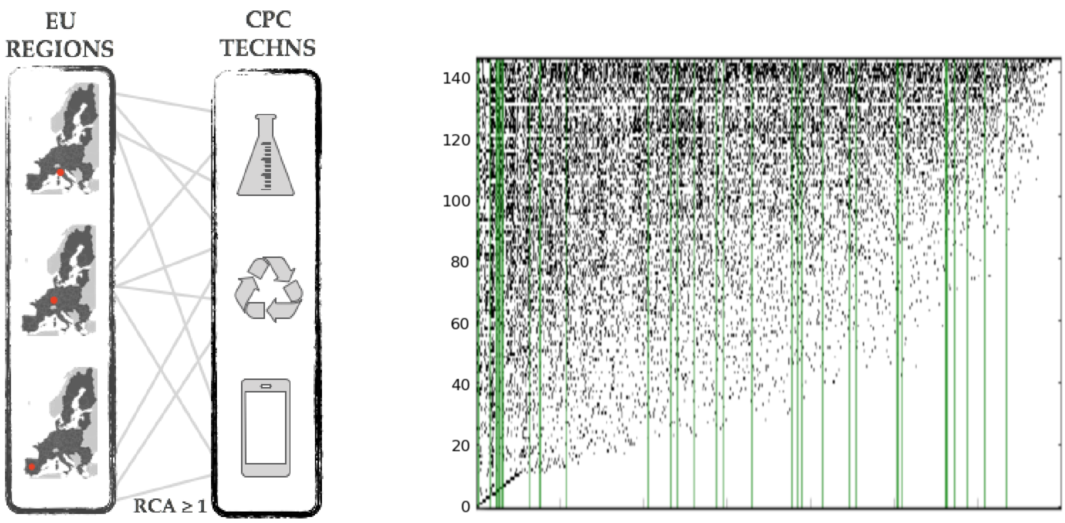
Tables and Figures

Figure 1. The binary network that connects European NUTS2 regions to the CPC classes in which they have a comparative advantage, graphical representation in (a) and adjacency matrix in (b).



(a) (b)

Figure 2. The binary network that connects A-H CPC non-green technologies at 4-digit aggregation level at time t_1 to Y02 green technologies at 8-digit aggregation level at time t_2. Each network link represents the correlation between having a comparative advantage in a NGT and a subsequent comparative advantage in a GT.

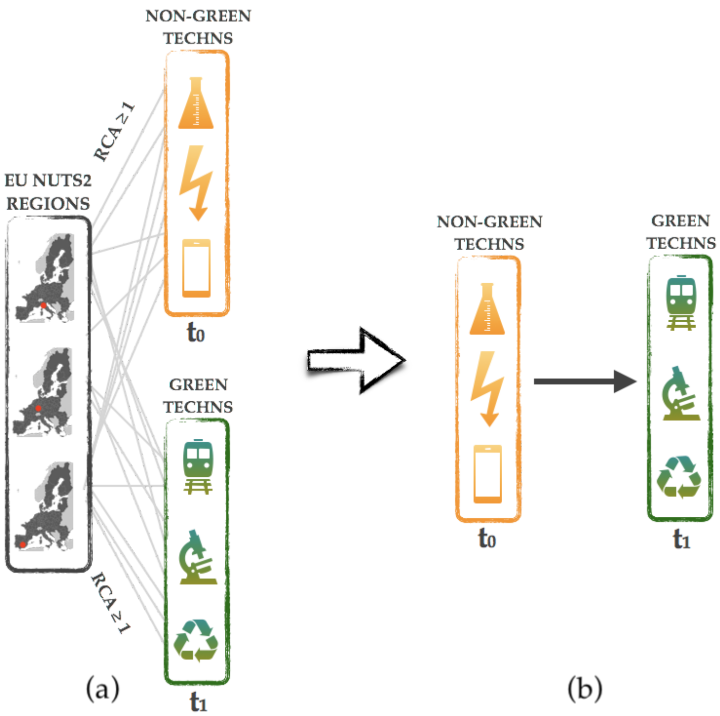


Figure 3. Share of 99% statistically significant links in the non-green – green technology space of each A-H CPC non-green technology at 4-digit aggregation level (considered at time $t_1 = 2012$) to all Y02 green technologies at 8-digit aggregation level (considered at time $t_2 = 2017$).

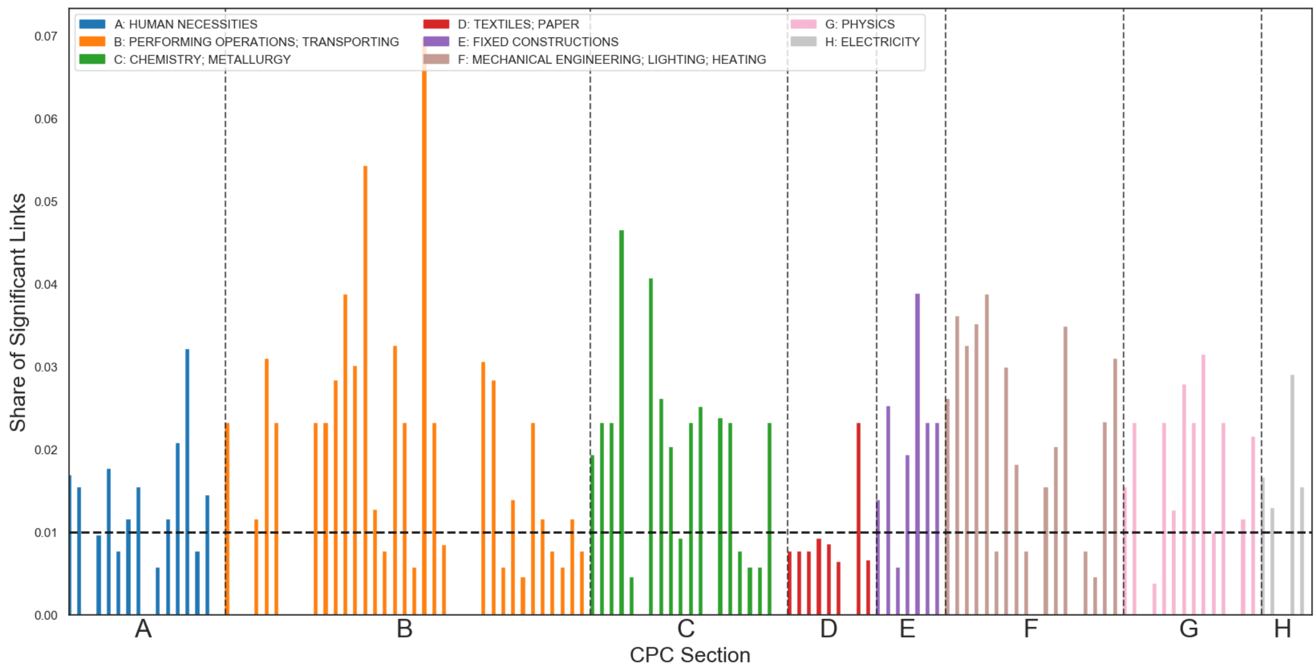
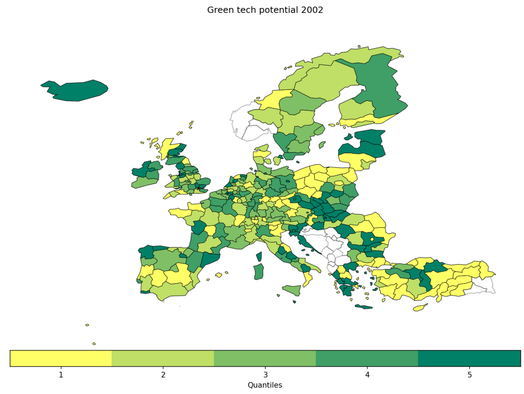
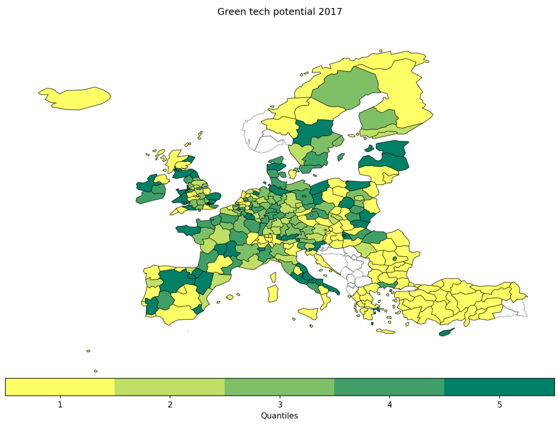


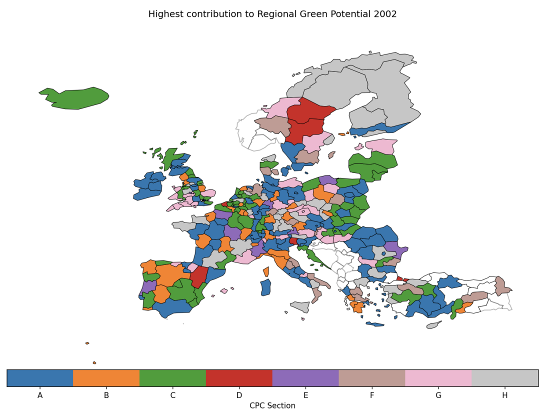
Figure 4. The Green Potential of NUTS2 regions' knowledge base in 2002 and 2017 respectively in (a) and (b), and the highest contributions to the Green Potential in terms of A-H CPC non-green technology at 4-digit aggregation level (colored according to the color-scheme in Figure 3) in 2002 and 2017 respectively in (c) and (d).



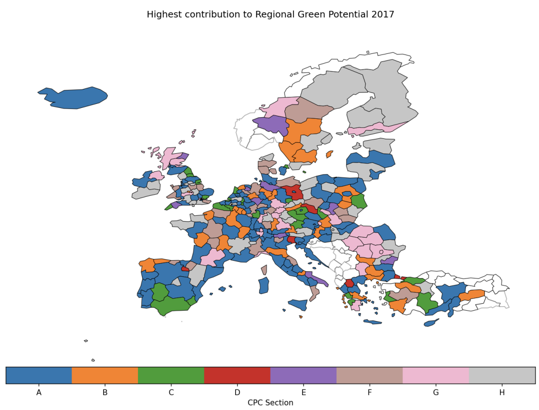
(a)



(b)



(c)



(d)

Figure 5. Evolution of the Non-green Technological Fitness ranking of EU NUTS2 regions.

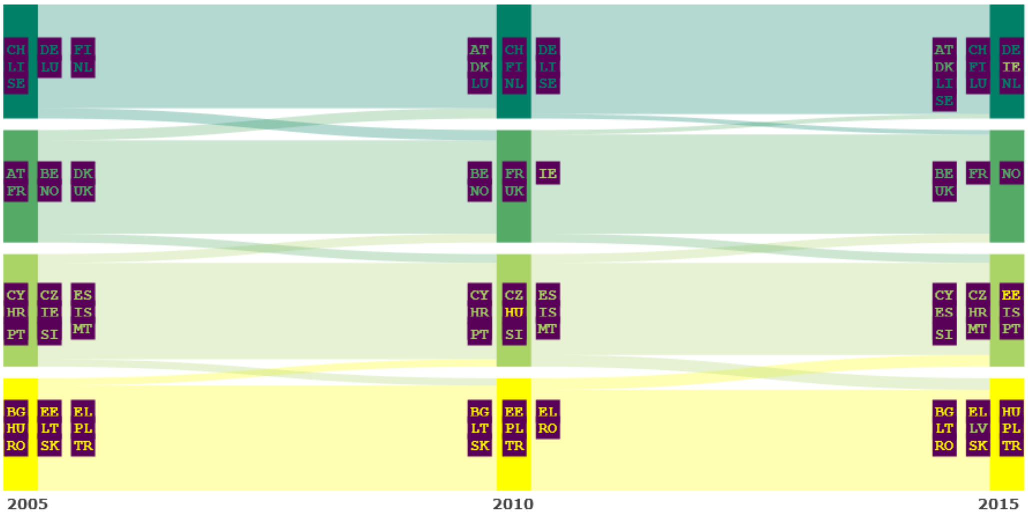


Figure 6. Evolution of the Green Technological Fitness ranking of EU NUTS2 regions.

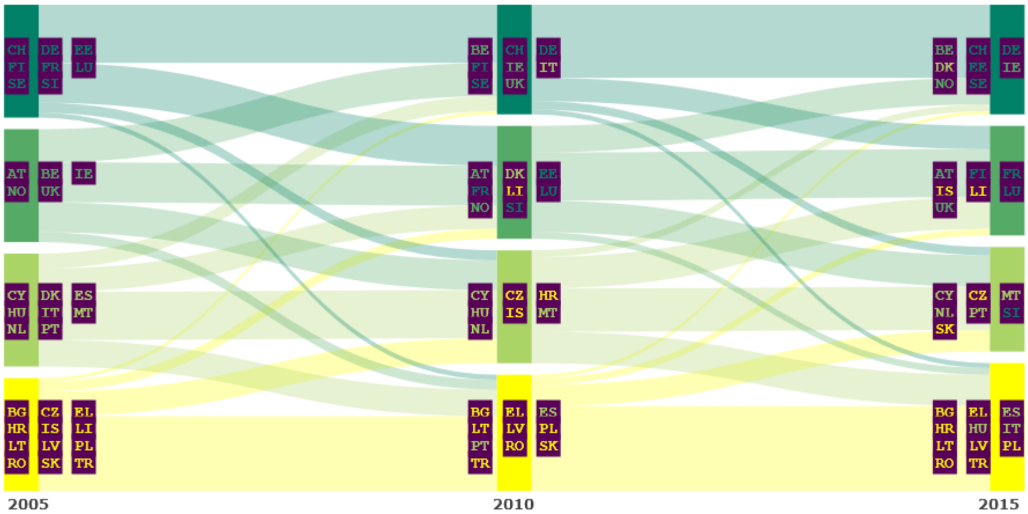
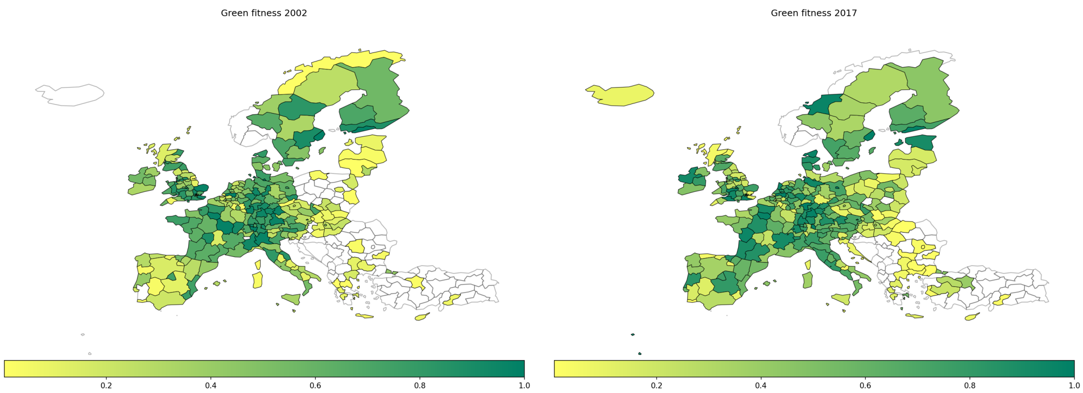
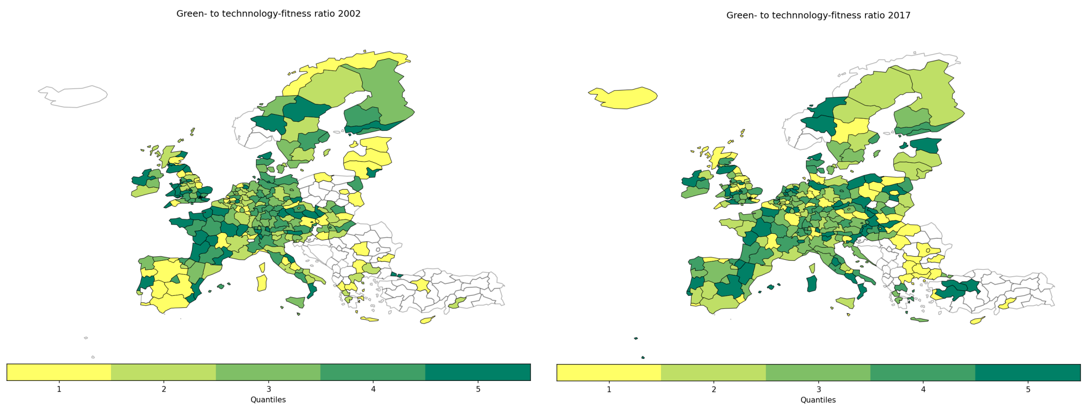


Figure 7. Green Technological Fitness of NUTS2 regions in 2002 and 2017 respectively in (a) and (b).



(a) (b)

Figure 8. Green Technological Fitness ranking relative to the overall technological ranking in 2002 and 2017 respectively in (a) and (b).



(a) (b)

Figure 9. Relationship between Green and Non-Green Technological Fitness in NUTS2 EU regions. Each point corresponds to NUTS2. Low values of the axes are associated with higher ranks. Each variable is weighted by total patenting activity (size of the circle).

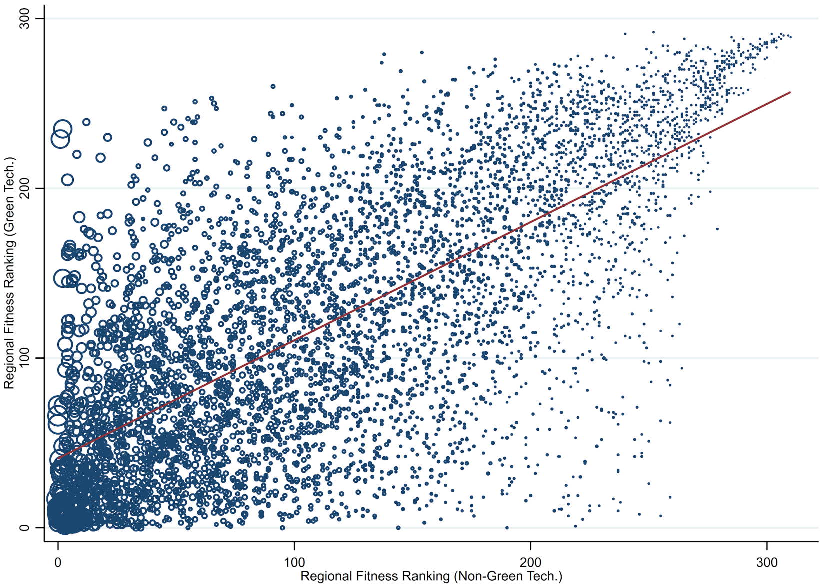


Figure 10. Regional Technological Fitness and the Green Potential of NUTS2 EU regions.

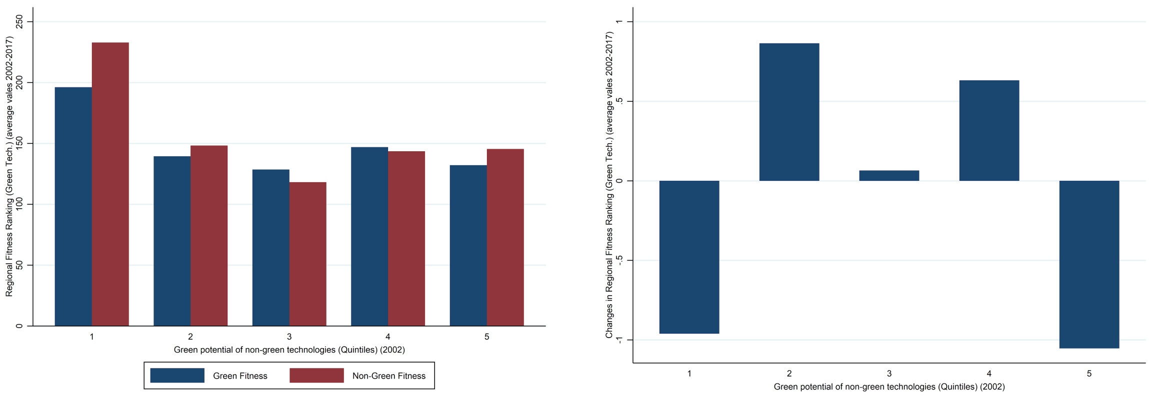


Table 1. Top 10 EU NUTS2 regions in the Non-Green Technological Fitness ranking.

1998-2006			2007-2017		
NUTS code	Region name	Average Fitness Ranking	NUTS code	Region name	Average Fitness Ranking
DE21	Oberbayern	1,2	DE21	Oberbayern	1,4
DE11	Stuttgart	2,1	FR10	Ile-de-France	2,1
FR10	Ile-de-France	2,7	DE11	Stuttgart	2,7
DEA1	Düsseldorf	4,8	DEA1	Düsseldorf	4,6
NL41	Noord-Brabant	5,6	SE11	Stockholm	5,6
DE71	Darmstadt	6,2	DE14	Tübingen	7,6
DEA2	Köln	6,9	DE71	Darmstadt	8,1
DE12	Karlsruhe	8,1	FI1B	Helsinki-Uusimaa	8,7
FI1B	Helsinki-Uusimaa	10,0	NL41	Noord-Brabant	8,8
ITC4	Lombardia	10,6	DE25	Mittelfranken	9,0

Table 2. Bottom 10 EU NUTS2 regions in the Non-Green Technological Fitness ranking.

1998-2006			2007-2017		
NUTS code	Region name	Average Fitness Ranking	NUTS code	Region name	Average Fitness Ranking
TR32	Aydin, Denizli, Mugla	294,4	TR63	Hatay, Kahramanmaras, Osmaniye	302,7
TR72	Kayseri, Sivas, Yozgat	294,7	TR22	Balikesir, Çanakkale	304,4
EL53	Δυτική Μακεδονία	294,8	TR82	Kastamonu, Çankiri, Sinop	305,4
RO31	Sud - Muntenia	295,9	TR83	Samsun, Tokat, Çorum, Amasya	305,5
TR83	Samsun, Tokat, Çorum, Amasya	296,3	EL41	Βόρειο Αιγαίο	306,5

EL41	Βόρειο Αιγαίο	300,7		TRB1	Malatya, Elazig, Bingöl, Tunceli	307,3
EL62	Ιόνια Νησιά	303,0		TRC2	Sanliurfa, Diyarbakir	308,8
RO42	Vest	304,0		TR71	Kirikkale, Aksaray, Nigde, Nevsehir, Kirsehir	311,3
TRC3	Mardin, Batman, Sirnak, Siirt	304,0		TR81	Zonguldak, Karabük, Bartin	314,4
TR63	Hatay, Kahramanmaras, Osmaniye	305,0		TR90	Trabzon	314,8

Table 3. Top 10 EU NUTS2 regions in the Green Technological Fitness ranking.

1998-2006			2007-2017		
NUTS code	Region name	Average Fitness Ranking	NUTS code	Region name	Average Fitness Ranking
FI1B	Helsinki-Uusimaa	5,4	SE11	Stockholm	4,1
DE25	Mittelfranken	10,8	DE12	Karlsruhe	14,7
SE11	Stockholm	15,0	NL41	Noord-Brabant	15,0
DE21	Oberbayern	16,7	FR10	Ile-de-France	18,3
FR10	Ile-de-France	17,1	FI1B	Helsinki-Uusimaa	19,1
DE60	Hamburg	17,7	UKK1	Gloucestershire, Wiltshire and Bristol/Bath area	22,7
CH06	Zentralschweiz	18,8	DE21	Oberbayern	23,6
ITC4	Lombardia	24,0	ITH5	Emilia-Romagna	26,3
NL41	Noord-Brabant	24,0	UKI3	Inner London - West	27,8
UKJ3	Hampshire and Isle of Wight	24,4	DE26	Unterfranken	31,3

Table 4. Bottom 10 EU regions in the Green Technological Fitness ranking.

1998-2006			2007-2017		
NUTS code	Region name	Average Fitness Ranking	NUTS code	Region name	Average Fitness Ranking
PL42	Zachodniopomorskie	250,5	BG33	Североизточен	276,7
ES13	Cantabria	250,7	RO31	Sud - Muntenia	276,8
PL61	Kujawsko-pomorskie	251,0	EL65	Πελοπόννησος	278,9
PL41	Wielkopolskie	252,0	EL62	Ióνια Νησιά	280,6
TR21	Tekirdag, Edirne, Kirklareli	252,5	EL53	Δυτική Μακεδονία	284,2
NO07	Nord-Norge	254,9	NO07	Nord-Norge	285,2
EL61	Θεσσαλία	255,8	BG31	Северозападен	285,2
TR32	Aydin, Denizli, Mugla	256,0	TR22	Balikesir, Çanakkale	287,4
EL42	Νότιο Αιγαίο	259,0	TRA1	Erzurum, Erzincan, Bayburt	288,4
RO42	Vest	266,0	TR82	Kastamonu, Çankiri, Sinop	288,8

Table 5. Top 5 EU NUTS2 regions for each group of green technologies (1998-2006).

Technology	NUTS code	Region name	Frac. count of patent families
Y02A - Technologies For Adaptation To Climate Change	FR10	Ile-de-France	107,1
	DE11	Stuttgart	62,7
	DE21	Oberbayern	48,7
	DEA2	Köln	35,4
	DK01	Hovedstaden	32,1
Y02B - CCMTs Related To Buildings	NL41	Noord-Brabant	106,9
	DE21	Oberbayern	85,8
	FR10	Ile-de-France	36,4
	DE11	Stuttgart	33,3
	ITC4	Lombardia	26,9
Y02C - Capture, Storage, Sequestration or Disposal of Greenhouse Gases [GhG]	FR10	Ile-de-France	30,3
	NL32	Noord-Holland	6,7
	UKK1	Gloucestershire, Wiltshire and Bristol/Bath area	5,7
	DE12	Karlsruhe	5,2
	DEB3	Rheinhessen-Pfalz	5,2
Y02D - CCMTs In Information and Communication Technologies [ICT]	NL41	Noord-Brabant	42,8
	DE21	Oberbayern	30,8
	FI1B	Helsinki-Uusimaa	29,6
	SE11	Stockholm	28,1
	FI19	Länsi-Suomi	23,7
Y02E - Reduction of Greenhouse Gas [GhG] Emissions, Related to Energy Generation, Transmission or Distribution	FR10	Ile-de-France	106,1
	DE21	Oberbayern	74,8
	DE25	Mittelfranken	74,7
	FRK2	Rhône-Alpes	72,5

	DEA2	Köln	58,9
Y02P - CCMTs in the Production or Processing of Goods	DE71	Darmstadt	113,6
	FR10	Ile-de-France	105,7
	DEB3	Rheinhessen-Pfalz	93,3
	DE21	Oberbayern	85,3
	DE12	Karlsruhe	75,6
Y02T - CCMTs Related to Transportation	DE11	Stuttgart	552,8
	FR10	Ile-de-France	502,1
	DE21	Oberbayern	166,0
	DE12	Karlsruhe	129,5
	DEA2	Köln	90,6
Y02W - CCMTs Related to Wastewater Treatment or Waste Management	FR10	Ile-de-France	45,6
	DE14	Tübingen	29,6
	DEA1	Düsseldorf	29,1
	FRK2	Rhône-Alpes	27,8
	DEA2	Köln	21,7

Table 6. Top 5 EU NUTS2 regions for each group of green technologies (2007-2017).

Technology	NUTS code	Region name	Frac. Count of patent families
Y02A - Technologies For Adaptation To Climate Change	FR10	Ile-de-France	91,4
	DE11	Stuttgart	63,0
	DEA2	Köln	62,1
	DE21	Oberbayern	48,8
	SE11	Stockholm	47,7
Y02B - CCMTs Related To Buildings	NL41	Noord-Brabant	169,7
	DE11	Stuttgart	120,3
	DE21	Oberbayern	120,0
	ITC4	Lombardia	108,5
	FRK2	Rhône-Alpes	81,0
Y02C - Capture, Storage, Sequestration or Disposal of Greenhouse Gases [GhG]	FR10	Ile-de-France	35,8
	DE71	Darmstadt	17,4
	FRK2	Rhône-Alpes	15,9
	DE21	Oberbayern	15,8
	DEB3	Rheinhessen-Pfalz	15,5
Y02D - CCMTs In Information and Communication Technologies [ICT]	SE11	Stockholm	143,3
	SE22	Sydsverige	80,1
	FI1B	Helsinki-Uusimaa	64,2
	DE21	Oberbayern	64,1
	FR10	Ile-de-France	52,3
Y02E - Reduction of Greenhouse Gas [GhG] Emissions, Related to Energy Generation, Transmission or Distribution	DK04	Midtjylland	411,2
	DE21	Oberbayern	346,7
	DE11	Stuttgart	242,6
	FRK2	Rhône-Alpes	236,7
	FR10	Ile-de-France	212,3

Y02P - CCMTs in the Production or Processing of Goods	DE21	Oberbayern	153,0
	FRK2	Rhône-Alpes	136,1
	DE71	Darmstadt	133,2
	DE11	Stuttgart	118,2
	NL32	Noord-Holland	117,0
Y02T - CCMTs Related to Transportation	FR10	Ile-de-France	715,0
	DE11	Stuttgart	699,9
	DE21	Oberbayern	463,7
	DE14	Tübingen	178,8
	DEA2	Köln	167,7
Y02W - CCMTs Related to Wastewater Treatment or Waste Management	FRK2	Rhône-Alpes	49,2
	FR10	Ile-de-France	39,4
	DE21	Oberbayern	32,7
	ITC4	Lombardia	29,7
	DE12	Karlsruhe	27,2

Table 7. Econometric results on the estimation of the relationship between Green and Non-Green Technological Fitness.

	Dep Variable: GTF					
	(1)	(2)	(3)	(4)	(5)	(6)
NGTF	0.932***	0.813***	0.776***	0.776***	0.776***	
	(0.009)	(0.055)	(0.083)	(0.083)	(0.055)	
TotalTech Fitness						0.771***
						(0.081)
Controls	Y	Y	Y	Y	Y	Y
Fixed Effects	N	Y	Y	Y	Y	Y
Time Dummies	N	Y	Y	Y	Y	Y
Regional Time Trends	N	N	Y	Y	Y	Y
N	2,920	2,920	2,920	2,920	2,920	2,919
R2	0.818	0.824	0.873	0.873	0.873	0.873

Notes: The dependent variable is the (log) regional green technological fitness. Control variables include the total patenting activity in the region, population and GDP (in logs). In Columns (4) and (5) we control for: green patenting, non-green patenting, population and GDP (in logs). Column (1) shows the results of the pooled OLS, whereas Columns (2)-(6) report the OLS estimation of the fixed effect model. Robust standard errors in parentheses except for Column (5), which employs Driscoll and Kraay (1998) standard errors, robust to heteroskedasticity and serial and spatial correlation, in parentheses. *** p< 0.01.

Table 8. Estimation of the relationship between Green Potential and Green and Non-Green Technological Fitness.

	Dep Variable: GTF				*Dep Variable: NGTF*
	(1)	(2)	(3)	(4)	(5)
GreenPotential	-2.798**	2.274***	1.351*	1.351***	0.278
	(1.091)	(0.664)	(0.714)	(0.419)	(1.228)
Controls	Y	Y	Y	Y	Y
Regional FE	N	Y	Y	Y	Y
Time Dummies	N	Y	Y	Y	Y
Regional Time Trends	N	N	Y	Y	Y
Observations	3,381	3,381	3,381	3,381	3,617
R-squared	0.023	0.754	0.833	0.833	0.936

Notes: The dependent variable is the (log) regional green technological fitness in Column (1)-(4) and regional non-green technological fitness in Column (5). Control variables include the total patenting activity in the region, population and GDP (in logs). Column (1) shows the results of the pooled OLS whereas Columns (2)-(5) report the OLS estimation of the fixed effect model. Robust standard errors in parentheses, except for Column (4) which employs Driscoll and Kraay (1998) standard errors, robust to heteroskedasticity and serial and spatial correlation, in parentheses. * $p< 0.1$ ** $p< 0.05$ *** $p< 0.01$.