European Commission

SCIENCE FOR POLICY BRIEF

Industrial Innovation & Dynamics series

THE REGIONAL GREEN POTENTIAL OF THE EUROPEAN INNOVATION SYSTEM

HIGHLIGHTS

This brief provides an overview of green technological development across European regions employing the Economic Fitness and Complexity approach in order to establish a green technology space.

On one hand, the study explores the associations between comparative advantage in specific technological domains and a region's capacity to develop green technologies, i.e., its **Green Fitness**. On the other hand, it addresses the interaction between the green and non-green knowledge bases, with a particular focus on whether regional know-how in the non-green technological realm can be exploited in the green domain and vice versa. To this aim, a metric of regional **Green Potential** is proposed.

The analysis highlights a higher propensity to develop technologies connected with green technologies for regions specialised in a wide range of green technological domains spanning the whole spectrum of technological complexity.

Green technologies are linked mostly to technologies related to the production or transformation of materials; with engines and pumps; and with construction methods. In general, nearly 60% of non-green technologies are potential early signals of the future development of innovative capabilites in green technologies.

The regions with the highest Green Potential are not necessarily those with the highest Green Fitness. At the same time, regions that are highly diversified and competitive in many technologies do not necessarily also have the highest green potential.

The results suggest that there is a potential for green and non-green technological advances to generate positive spillovers in terms of capabilities to produce innovations across the spectrum of technological complexity.

Overall, we find that only a few regions have the necessary capabilities to patent at the highest level in all green technologies, thus reaffirming that local capabilities are important for fostering or hampering their development. Furthermore, we find a significant association between Green Technological Fitness and Green Potential. This suggests 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 can therefore capture the potential for green technologies in regions that have not yet developed a focus on them.

Current Policy Challenges

The fight against climate change is arguably at an unprecedented critical phase. Experts concur that we now have enough capital, technology, policy instruments and scientific knowledge to cut carbon emissions by half by 2030. 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 & Patz, 2004; McMichael, Woodruff, & Hales, 2006). 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, such as low-carbon technologies as well as sustainable production and consumption practices (Stern, 2007). According to Ayres & 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".

Against this backdrop, the present brief provides an overview of green technological development in European 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 their technological capabilities.

Second, we **elaborate a metric to capture regions' green innovation potential**.

Third, we check whether **regional comparative advantages in specific technological domains are associated with subsequent innovation in 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) emphasises that regions and cities are responsible for implementing as much as 70%

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Box: What is Economic Complexity?

Economic Complexity is a framework that builds on earlier evolutionary and institutional literature (Hirschman, 1958; Cimoli & Dosi, 1995; Teece, Rumelt, Dosi, & Winter, 1994) to tackle the complexity of economic systems. It describes the economy as an evolutionary process of globally interconnected ecosystems. The main recent advance with respect to the earlier literature is the use of newly developed *network science* and other methods to investigate *complex and dynamical systems* (Hausmann & Klinger, 2006; Hidalgo & Hausmann, 2009; Tacchella, Cristelli, Caldarelli, Gabrielli, & Pietronero, 2012) to separate the random noise from the underlying signal. The Economic Complexity framework shifts the focus from aggregate quantities (*What is the GDP of the country? How many patents are published?*) to a more disaggregated view (*In which industrial sectors do countries (or regions) specialise? In which technologies do they patent?*), with the aim of providing information that is complementary to more traditional analysis. This shift creates the opportunity to create a consistent framework that allows several cross-cutting themes to be addressed and provides a quantitative answer to several policy relevant questions that could otherwise only be answered qualitatively or by ad hoc metrics.

of green action plans. Of course, not all territories are equally proactive or capable and some will have higher innovation potential than others. This is due to differences in the availability of competences, natural resources, institutions, and infrastructures. However, regions also differ in terms of exposure to environmental impacts. As a result, green technologies may well emerge in more developed areas, while the urgency to deploy those technologies is stronger in poorer regions (Mendelsohn, Dinar, & Williams, 2006; Bathiany, Dakos, Scheffer, & Lenton, 2018).

The second relevant issue is that achieving zero Green-House Gas (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. This calls for analytical instruments that are consistent with the uncertainty of a scenario, which 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

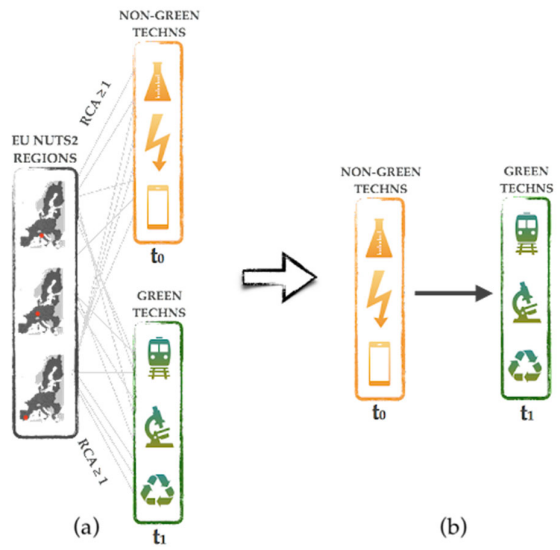

Figure 1. (a) The binary networks that connect European NUTS2 regions to the green and non-green classes in which they have a comparative advantage, and (b) the derived non-green – green network.

transformations needed to meet new criteria of environmental sustainability (see box).

Economic Complexity methods capture the underlying capabilities embedded in productive systems in different domains of human activities and have proven effective in quantifying information on technological capabilities at various levels of aggregation, recently also in relation to environmental technologies and products (Sbardella, Perruchas, Napolitano, Barbieri, & Consoli, 2018; Mealy & Teytelboym, 2020; Napolitano, Sbardella, Consoli, Barbieri, & Perruchas, 2020). We focus on the connection between 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, Marzucchi, & Rizzo, 2020). 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 & Hoffman, 2016; Sinsel, Markard, & Hoffmann, 2020), and vice versa (Noially & Shestalova, 2017).

Innovation Capacity of European Regions

The first step is to profile European regions (NUTS2-level) based on their green innovation capacity calculated using the Economic Fitness and Complexity (EFC) approach (Tacchella, Cristelli, Caldarelli, Gabrielli, & Pietronero, 2012) to geo-localised green and non-green patent data drawn from the

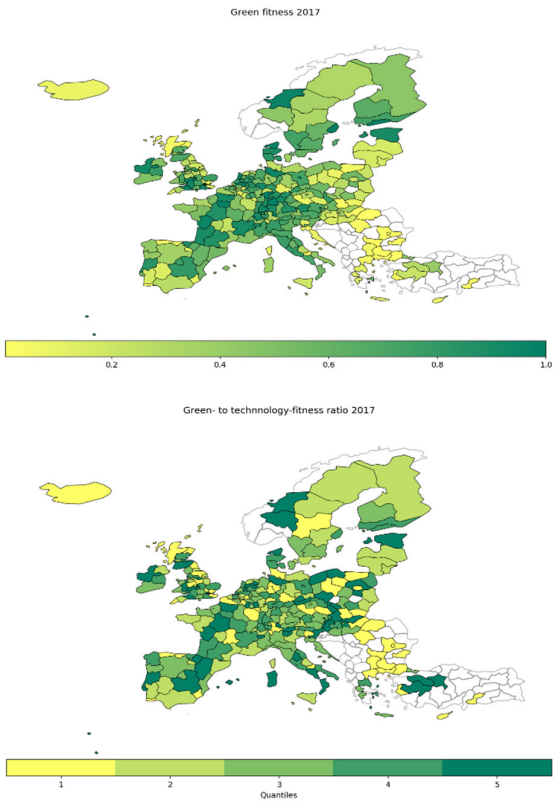

Figure 2. Green Technological Fitness of NUTS2 regions in 2017, in absolute terms (above) and relative to their overall technological capabilities (below).

Spring Edition of the PATSTAT 2020 database (European Patent Office, 2020). To this aim, we rely on previous measures of local complexity (Balland & Rigby, 2017; Sbardella, Pugliese, & Pietronero, 2017). Our methodology builds on the regional technological fitness of European regions introduced by Pugliese and Tübke (2019) and the Green Technological Fitness (GTF) defined at country-level by Napolitano, Sbardella, Consoli, Barbieri & Perruchas (2020).

The EFC algorithm extracts information about the capabilities underlying a region's knowledge base from the technologies in which it exhibits a competitive advantage in terms of patenting activity. The resulting indicator of regional technological fitness captures the composition of regional (green or non-green) capabilities as proxied by the region's portfolio of technologies. Accordingly, higher fitness signals that a region has a portfolio of technologies, some more complex than others. Comparing each region's green technological fitness with its non-green technological fitness allows us to explore the relationship between its green and non-green knowledge base. In doing this we identify not only the regions that are most proactive in green technologies, but also the relative standing of each European region in terms of breadth of capabilities.

As illustrated in Figure 1, the input to the algorithm is a binary bipartite network in which a link exists between a region and a technology if the former has a sufficiently high Revealed Comparative Advantage (RCA; see Balassa, 1965) in patents innovating in the latter. The rationale 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 regional technological portfolios. The results suggest that regions with a more advanced set of capabilities, i.e., a higher fitness, tend to have a diversified portfolio of technologies, spanning from the most to the least complex ones. In turn, complex technologies are rare and appear mostly 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.

Once the complexity of technologies is determined, we can compute the GTF index of each NUTS2 region as the sum of the complexities of the green technologies (i.e. the codes belonging to group Y02 under the Cooperative Patent Classification, henceforth CPC) linked to each region. Figure 2 displays the computed GTF for all European NUTS2 regions (top panel), as well as the ratio between regional GTF and global technological fitness (bottom panel). The top panel shows a heterogeneous green fitness landscape across countries, and we observe a divide between Central and Eastern European regions.

The map in the bottom panel, which displays how focused the region is in green technologies with respect to overall technologies, tells a different story: While absolute levels of GTF concentrate mainly in the wealthier European countries, the *focus* on green is spread throughout the continent.

Green Potential of the regional knowledge space

The second step in our analysis is to define a measure of green potential of the non-green regional knowledge space. To this aim, we identify the non-green technological classes whose presence in a regional portfolio is an early signal of the emergence of competitiveness in green technologies; the number of such early-warning technologies in which a region has a high RTA is indicative of its green potential. This sheds light on the strengths and weaknesses of green regional specialisation and is therefore relevant for the design of European policies addressing climate change or regional development.

The inspiration for the above analysis comes in part from recent studies that explore the role of spatial knowledge spillovers in the transition towards sustainable economies (Barbieri, Perruchas, & Consoli, 2020; Cheng & Jin, 2020; Nomaler & Verspagen, 2021). Therein, the distribution of patents across technological fields also captures the shape of the regional knowledge base (Castaldi, Frenken, & Los, 2015; Balland & Rigby, 2017) and allows assessing where

green technologies are more likely to emerge. Further relevant literature studies the green product space or the knowledge space (Fankhauser, et al., 2013; Mealy & Teytelboym, 2020; Hamwey, Pacini, & Assuncão, 2013; Nesta & Saviotti, 2005; Boschma, Minondo, & Navarro, 2013; Rigby, 2015) as well as the multilayer network analysis of Pugliese et al. (2019).

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 the regional patent portfolios. We start by constructing a "time-augmented" technology space that links green technologies (GTs) and non-green technologies (NGTs). This consists in 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 a given point in time also have high RCA in the GT after a fixed number of years (five, for the current analysis). Intuitively, patent codes that share similar inputs will be close to each other in the technology space. Therefore, the statistically validated NGT-GT network suggests that acquiring a competitive advantage in a NGT predicts a competitive advantage in a connected GT. Figure 3 shows the strength of the association of 3-digit non-green CPC classes (sections A-H) with green technologies, i.e. the share of 99% statistically significant NGT–GT links over the total possible links in the technology space. For ease of visualization, each colour corresponds to a 1-digit CPC section. 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. We find that **59% of non-green technologies display shares higher than that threshold.** This confirms that eco-innovative fields are inextricably interconnected with other types of technologies, and embedded into different production contexts. In the time frame under analysis, green technologies appear linked mostly to technologies related with the production or transformation of materials, with engines and pumps, and with construction methods.

After identifying the set of NGTs that have a significant association with GTs, we build our index of regional green potential (GP) by projecting the information of the NGT-GT network onto regional patent portfolios. The resulting green potential index allows us to detect the extent to which the non-green knowledge base of each NUTS2 region has the potential to prompt the development of green technologies in the future. Figure 4 displays the green potential (GP) of each NUTS2 region at different points in time. Comparing the map for 2002 (top) with the map for 2017 (bottom), we observe several differences in the colour patterns. On one hand, the path taken by regional efforts to innovate changes direction over time. On the other hand, the innovative efforts of each region rewire the technological space over time, giving way to new connections between non-green technologies and green technologies. We notice that the regions in the highest quintiles of green potential are not necessarily those with the highest green fitness. As we show in detail in the next section, this suggests that the green potential index provides different information to that of (green) 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.

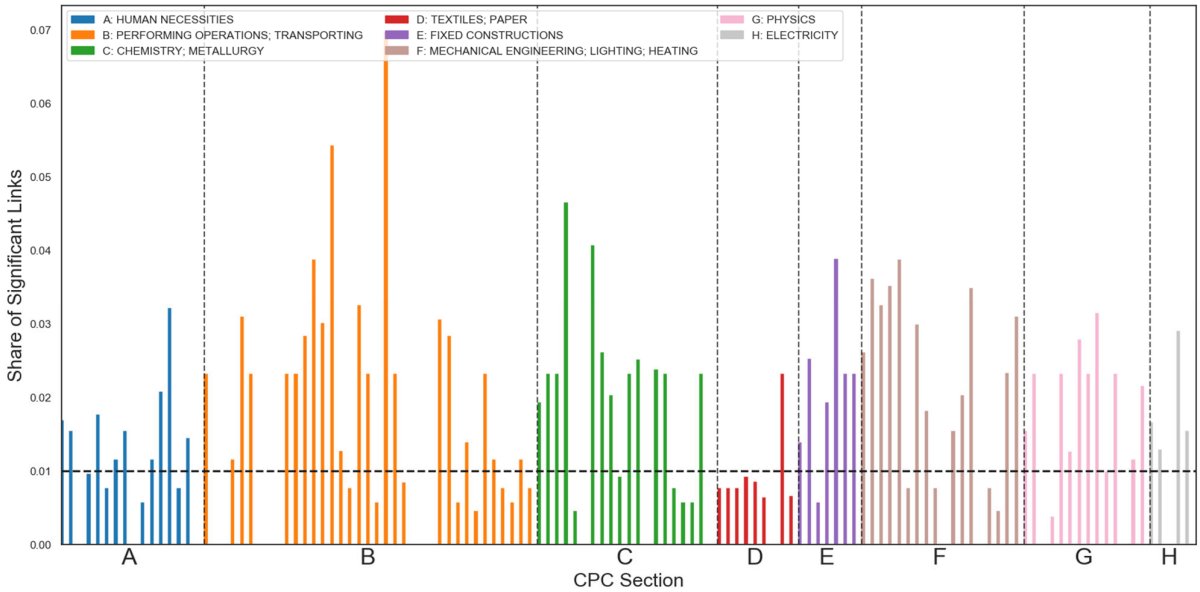

Figure 3. Share of 99% statistically significant links in the non-green–green technology space of each A-H CPC non-green technology at 4-digit aggregation level to all Y02 green technologies at 8-digit aggregation level.

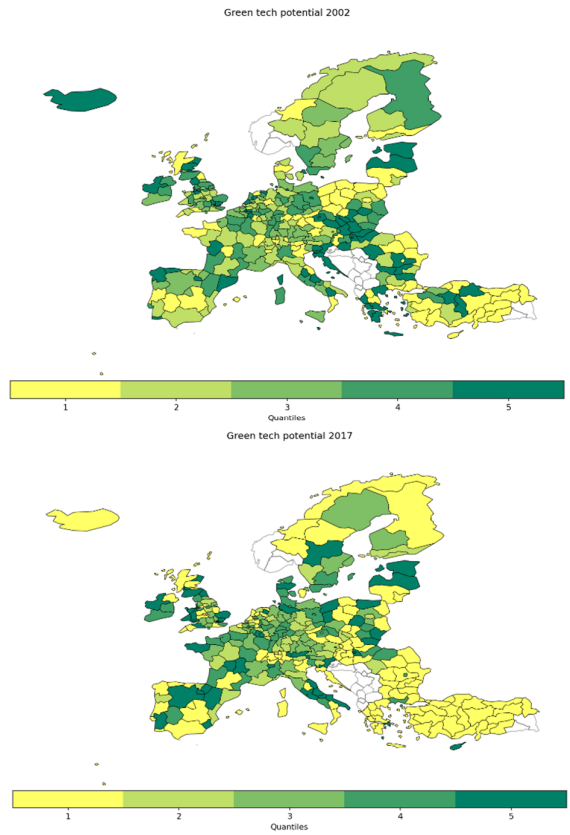

Figure 4. The Green Potential of NUTS2 regions' knowledge bases respectively in 2002 and 2017.

Regional Green Potential and future green capabilities

To capture the connection between green and non-green knowledge, we explore the relationship between the regional GTF and the GP indicator illustrated above. In other words, we look for the connection between current regional green capabilities and the non-green capabilities that predict the emergence of future green capabilities.

Figure 5 provides descriptive insight into the relationship between regional green and non-green technological fitness with GP. In both panels, regions are grouped into quintiles based on their GP. The top panel of Figure 5 shows that regions with similar GP scores are similar both in terms of their green (blue bars) and non-green (red bars) fitness rankings of regions with similar GP scores. Moreover, the same panel shows that when the GP of a region is low, it also, on average, ranks worse along both fitness dimensions. At the same time, moving from bottom to top quintiles of green potential, we find regions that are characterised by higher levels of green and non-green fitness (lower values in the ranking). Notice, in fact, that we adopt the convention to assign a lower rank number to regions with a higher fitness; hence, a higher bar in the top graph means a poorer score.

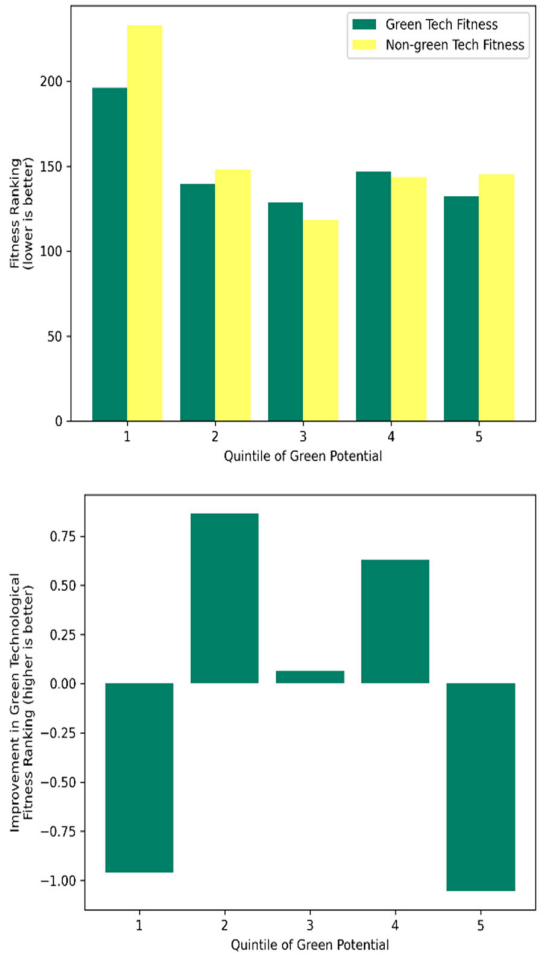

Figure 5. Green potential VS Technological Fitness. Top panel: quintiles of the GP index VS average fitness ranking of the regions within the same quintile (lower ranking number corresponds to higher fitness). Bottom panel: quintiles of Green Potential (x-axis) VS average within quintile improvement of the regional Green Fitness ranking (y-axis; positive values correspond to improvements in the fitness ranking).

The bottom panel of figure 5 puts the GP-fitness relation in a dynamic perspective by cutting the sample into two time-windows and plotting the change in the GTF ranking of regions against the distribution of GP scores in the less recent time-window. The graphs show that regions in the bottom and top quintiles lose positions in the ranking of green regional fitness, whereas regions in the middle of the green potential distribution gain positions on average. Note that the deterioration, on average, of the GTF ranking of regions in the top quintile does not necessarily suggest the existence of an inverted-u shaped relation between GP and the complexity of the existing knowledge base. Rather, it is likely that the result is driven, at least in part, by the relative nature of the GTF ranking; the closer a region ranks to the top, the less space it has for further improvement.

The relationship between GP and technological fitness is further investigated in Table 1, which reports the estimates

by means of an econometric model in which the key explanatory variable is GP. When we include regional and time fixed effects, the coefficient of GP 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. Such a connection relies on the potential of green and non-green technological advances to generate positive spillovers in terms of capabilities to produce innovations that rely on more complex green technologies.

Discussion

The Green Deal stipulates Europe's commitment to be climate neutral by 2050. Such an ambitious target requires significant effort on all parts: policy makers, firms, and consumers. Given the scale and the complexity of the environmental transition, a top-down approach would likely 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 of adapting 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. We explore the geographical distribution of innovative activities and profile EU regions based on 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. Overall, we find that only a few regions have capacity to patent at the highest level in all green technologies, thus reaffirming that local capabilities are important for fostering or hampering their development. Furthermore, we find a significant association between GTF and GP. 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 can therefore capture the potential for green technologies in regions that have not yet developed a focus on them.

Let us conclude by offering some policy implications stemming from these findings. The Green Deal is a necessary economic policy for its environmental effects, but it can also represent an economic opportunity. While the environmental effects will have global impact through the channels of international cooperation, the economic impact will be decided on a region-by-region basis, depending on pre-existing local technological capabilities. The Green deal may potentially exacerbate centre-periphery tensions and polarization between EU economies (Lucchese & 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, and an emphasis towards measuring how much absorptive capacity a region has, can distract policy makers from looking at what a region is able to do. Our analysis tries to fix this gap, identifying which regions show potential in green technology by looking at the

Table 1. Notes: The dependent variable is the (log) regional green technological fitness in Column (1)-(4) and non-green technological fitness in Column (5). Control variables include the total patenting activity in the region, the population, and the 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 reported in parentheses for each column; notice that Column (4) employs Driscoll & Kraay (1998) standard errors, robust to heteroskedasticity and serial and spatial correlation. Legend: * p< 0.1 ** p< 0.05 *** p< 0.01

	GTF				NGTF
	(1)	(2)	(3)	(4)	(5)
Green Potential	-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

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 – such as the European Innovation Scoreboard (Hollanders, 2009) and the Regional Innovation Scoreboard (Merkelbach, Hollanders, & Es-Sadki, 2019). This could inform regional industrial policy while defining long-term objectives for each 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 & Soete, 2020; Balland, Boschma, Crespo, & Rigby, 2019). This holistic way of looking both at regional and sustainability policies has been recently declined into the novel Partnership for Regional Innovation[1] (PRI) of JRC. The framework is based on the same foundational idea behind this policy brief: the need not only to acknowledge at the same time the relevance of local characteristics and the specificities of each activity, but also to qualify growth and look at it both in a quantitative and qualitative sense. This shift will require both novel scientific results and novel metrics to inform policies and strategies, some of which are covered in this policy brief.

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DATA SOURCES AND METHODOLOGY

The general workflow in Economic Complexity employs micro-data at the level of industrial agents (e.g. firms) to build a binary network connecting countries and regions to the activities in which the agents they host excel. This network, which connects technological, scientific or production activities to a geographical location, is the basic element of analysis. This map is used to infer information on the hidden layer of unobservable capabilities that shape its dynamical evolution.

In this work, the only data source is patent data, localised through the available applicant information at the country and region level, extracted from OECD REGPAT (Maraut, Dernis, Webb, Spiezia, & Guellec, 2008) and from *Geocoding of worldwide patent data* (De Rassenfosse, Kozak, & Florian, 2019; De Rassenfosse, Kozak, & Florian, 2019).

The analysis in Section 2 adapts the methodology recently developed for export products called Exogenous Fitness (Operti, Pugliese, Andreade Jr, Pietronero, & Gabrielli, 2018) to technologies. The idea of Exogenous Fitness is to run the Fitness-Complexity algorithm in one setting in which there is an abundance of information (all world countries) to extract the complexity of products, and then use those complexities to infer the Fitness of geographical entities in a different setting where there is not as much information (subnational regions). The idea of adapting techniques developed for products to be used with patents and technological classes is not new (Breschi, Lissoni, & Malerba, 2003; Balland, Boschma, Crespo, & Rigby, 2019), as there are many similarities in the data structure.

Section 3 also builds on previous academic work (Pugliese, et al., 2019); the interested reader is referred to such work for more information. The methodology introduced in that article allows determining whether activities in specific technological fields in a country are early signals of the potential capabilities to export a specific (advanced) product in the future. The connection between this and the regional analysis performed in Section 3 is introduced in Pugliese & Tübke (2019). While it is founded on well-tested scientific work, from the policy perspective, the methodology is still at testing stage and the conclusions drawn from it require further validation.

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