Document downloaded from:

http://hdl.handle.net/10251/172138

This paper must be cited as:

Perruchas, FDX.; Consoli, D.; Barbieri, N. (2020). Specialisation, diversification and the ladder of green technology development. Research Policy. 49(3):1-12. https://doi.org/10.1016/j.respol.2020.103922

The final publication is available at

https://doi.org/10.1016/j.respol.2020.103922

Copyright Elsevier

Additional Information

Specialisation, diversification and the ladder of green technology development

François Perruchas[a,*], Davide Consoli[a], Nicolò Barbieri[b]

[a]INGENIO [CSIC-Universitat Politècnica de València], Spain
[b]Department of Economics and Management, University of Ferrara, Italy

Abstract

This paper elaborates an empirical analysis of the temporal and geographical distribution of green technology, and on how specific country characteristics enable or thwart environmental inventive activities. Using patent data on 63 countries over the period 1971-2012 we identify key drivers of cross-country diversification and specialisation. Our first finding is that countries diversify towards green technologies that are related to their existing competences. Notably, the maturity of the green technology seems to matter more than the level of development of each country. The second main result is that countries move along cumulative paths of specialisation, and towards more mature green technologies. Interestingly, the complexity of green technologies is not an obstacle to further specialisation. The latter holds also for developing countries that are most exposed to climate change hazards.

Keywords: Environmental Technology; Technological diversification; Technological specialisation.

JEL: O14; O33; Q55.

1. Introduction

This paper elaborates an empirical analysis of the temporal and geographical distribution of environmental inventive activities, and on how country and green technological characteristics enable or thwart the development of green technology. The backdrop to our study is the debate on climate change and the growing consensus around the urgency to build climate resilience and increased exposure to extreme weather events for preserving global stability (World Economic Forum, 2018). The prospective costs of non-action are high considering that, for example, air and water pollution pose serious threats to human health, or that loss of biodiversity and depletion of agricultural resources imperil the global supply of food (see i.e. Haines and Patz, 2004; Patz et al., 2005; McMichael et al., 2006). What is more, these risks are interconnected in ways that could trigger a chain of events with potentially higher social and economic costs – for example, water scarcity may induce large-scale in-

*Corresponding author: franperr@ingenio.upv.es

voluntary migration. Scholars and policy makers agree that multilateral and multilevel responses are required to contain the degradation of the global environment and prevent further risks. As Ayres and van den Bergh (2005) [p. 116] put it "economic growth must be accompanied by structural change, which implies continuous introduction of new products and new production technologies, and changes in [energy] efficiency and de-materialization".

Far from ignoring the limitations and the intrinsic difficulties of a 'technological fix' (Sarewitz and Nelson, 2008), accelerating the development and diffusion of new low-carbon technologies remains a staple of any strategy aimed at dealing with climate change (Stern, 2007; Johnstone et al., 2012). The presence of market failures highlights that policy intervention aimed at incentivising investments in the development of green technologies and products are required (Jaffe et al., 2005; Popp et al., 2010). According to Arrow (1972), increasing returns, knowledge inappropriability and uncertainty lead to underinvestment in R&D activities. Whereas these issues commonly affect all types of knowledge, the higher complexity, novelty and impact of environmental technologies enhances the detrimental effect of these market failures (Barbieri et al., 2018a). In addition, the loss of environmental quality brought about by production activities is borne by third parties rather than by the polluters (i.e. environmental externalities). Thus, in this complex scenario the targets and design of policy are pivotal to address these market failures and trigger green technological change.[1] Indeed, successful policy would call upon a broad portfolio of technologies and of competences, due to the wide range of activities and sectors that generate greenhouse-gas (GHG) emissions. This implies high complexity and uncertainty. For one, the ability to stay apace with the green technological frontier varies significantly across countries (Sbardella et al., 2018). Further, while environmentally-friendly technologies emerge first, and more frequently, in more developed countries the urgency of effective deployment of adaptation technologies is stronger in poorer countries (Mendelsohn et al., 2006; Bathiany et al., 2018)[2]. In turn, unequal

[1] See Barbieri et al. (2016) for a review of the studies that investigate the inducement effect of environmental policies on eco-innovation.

[2] See an overview of emissions by country: `http://www.wri.org/blog/2017/04/interactive-chart-explains-worlds-top-10-emitters-and-how-theyve-changed` (Last accessed: 1 November 2018).

distribution of innovative capacity is a global problem, because achieving or maintaining resource efficiency through innovation requires international cooperation, for example to harmonize product standards (Stern, 2007). Furthermore, this process could become self-reinforcing, as less developed countries remain trapped in high-carbon regimes that limit incentives to develop competences for emission containment and that, ultimately, increase exposure to climate change (Dessai et al., 2009; Cardona et al., 2012).

Against this backdrop, we propose an empirical study of environmental innovation that accounts for both the specificities of geography and of technological domains. As the comprehensive review by Barbieri et al. (2016) shows, existing literature falls short in at least one of these two dimensions. Prior efforts at comprehensively mapping the spatial distribution of inventive activities in environmental technologies are limited to most advanced economies (i.e. Lanjouw and Mody, 1996; Veugelers, 2012; Costantini and Mazzanti, 2012; Fankhauser et al., 2013; Calel and Dechezleprêtre, 2016) and do not delve into country-specific green technological characteristics (e.g. technological comparative advantage, technological maturity). Other scholarly work focuses on either individual countries (Calel and Dechezleprêtre, 2016; Marin, 2014; Gagliardi et al., 2016) or on specific technological domains - predominantly energy (Popp, 2002; Fischer and Newell, 2008; Nesta et al., 2014). In our view, the lack of engagement with issues concerning how countries build green innovation capabilities, and how such a capacity differs along the gradient of economic development, is a major shortcoming for both policy and scholarly debates.

The present paper fills this gap by, first, elaborating systematic and up-to-date evidence on environmental technology development and, second, by analysing patterns of diversification and specialisation in panel of 63 countries over the period 1971-2012. Our empirical approach replicates the methodology proposed by Petralia et al. (2017), hereafter PBM, and extends it to green technology using disaggregated data of patenting activity. While PBM provides an empirical framework on all technology, we apply the same approach to uncover general trends of green technological specialisation, and identify country-specific factors that enable or hinder the diversification in new areas of green technology. Such an exercise provides a clear characterization of the leaders and of the laggards in the global effort to counter climate change.

The main findings of this paper are three. First, countries are more likely to diversify into domains of green technology that are related to their portfolio of competences. This is coherent with the broad picture on the entire technological landscape that emerges from PBM. The result is also in line with the insights provided by Barbieri et al. (2018a) who point out that green technologies recombine a broad range of knowledge sources and technological components. Second, specialisation and diversification do not exhibit strong association with the stage of development of a country but, rather, with the maturity of the green technology. In fact, gaps in competences may represent a bigger obstacle than gaps in wealth. Third, we find that countries move along cumulative paths of specialisation. At the same time, and contrary to prior studies, the complexity of green technologies is not an obstacle to further specialisation. Notably, this holds true even for developing countries. Although our study is not aimed at analysing the effectiveness of policy implementation, the commitment of the political framework to address environmental harmful behaviour is crucial for spurring competitive advantage in green technological development. We expect our insights to aid the identification of effective policy design in that accounting for both the innovation capabilities a country is endowed with and for the maturity of green technologies is important to inform the course of action.

The paper is structured as follows. After a review of the relevant literature in Section 2, Section 3 details the main data sources and the procedure for the construction of the main variables. Section 4 provides information on the descriptive statistics and the empirical methods. Results are discussed in Section 5. The last section summarises and concludes.

2. Literature review

The analysis of the nature, the sources and the diffusion of eco-innovation is at the centre of an intense debate among academics and policy makers alike. The broad consensus is that accelerating the development of new low-carbon technologies and promoting their global application are crucial steps, albeit not the only ones, towards containing and preventing GHG emissions (OECD, 2011). As a vast literature shows, the development of green innovation confront a diverse array of barriers that lead to underinvestment in R&D activities. First, uncertainty in reaching the desired innovation outcome or in the market success of innovations negatively affects the propensity to engage in such activities (Arrow, 1962). Second, the public good nature of the information contained in innovation implies that innovators bear the entire cost of the knowledge generation process while externalities prevents them from reaping the full benefits (Arrow, 1962; Nelson, 1959). Third, uncertainty on the appropriability of the prospective environmental benefits and knowledge-related barriers create the so-called 'double externality' feature that hampers green technological development (Jaffe et al., 2005; Newell, 2010). Other barriers to the diffusion of green technology may arise from systemic failures – such as i.e. lack of skills, weak institutions – that hinder knowledge flows and, thus, the efficiency of R&D and innovation efforts (OECD, 2003). These market failures lead to insufficient credit to eco-innovation which deters from investing in green technologies (Ghisetti et al., 2015). The extant literature emphasise that policy maker intervention is crucial to overcome barriers to green innovation, suggesting that environmental policies are important to mobilise knowledge generation (see, among others, Popp, 2002).

The complexity associated with these broad issues increases significantly when the analysis includes the spatial dimension. Geography is, we argue, a necessary lens as climate change is a global phenomenon with marked local manifestations, which implies that confronting this grand societal challenge depends crucially on the specificities of place. For one, geographical areas differ significantly both in their exposure as well as in their ability to respond effectively to climate events (Jurgilevich et al., 2017). Further, the striking paradox is that while environmentally-friendly technologies emerge primarily in industrialized countries, the urgency to adapt to climate change is stronger in poorer countries (Mendelsohn et al., 2006; Bathiany et al., 2018). In addition, the double externality problem highlights the critical role of the attendant institutional conditions for promoting or thwarting sustainable economic growth. Governance mechanisms that are crucial to create the right mix of incentives for efficient use of natural resources and environmental conservation while minimizing prospective market failures, are spatially bound (Deacon and Mueller, 2006).

Spatial features also matter for the innovation process. It has long been established that the generation and diffusion of knowledge, prime engines of innovation, stem from the recombination of existing ideas (Romer, 1994; Weitzman, 1998) among agents that have limited access to information, and imperfect capacity to absorb, process, and respond to new information (Cohen and Levinthal, 1990). A key point is that economic development builds on existing local capabilities to generate distinctive technological and industrial profiles (Rigby and Essletzbichler, 1997). Such a distinctiveness depends on the composition of knowledge, that is, the number of underlying inputs and the interdependence between them (Frenken and Boschma, 2007; Neffke et al., 2011). The greater and more diverse the spectrum of know-how, the more complex the domains to which this knowledge is applied, be they products (Hidalgo and Hausmann, 2009; Cristelli et al., 2013), industries or technologies (Balland and Rigby, 2017). As a consequence, information exchange confronts costs that increase with the diversity of the attendant knowledge base. Put otherwise, higher coherence between activities facilitates the growth of knowledge and increases the likelihood of innovation (Atkinson and Stiglitz, 1969; Chatterjee and Wernerfelt, 1991). These characteristics point to potential weaknesses and systemic failures in the growth and diffusion of knowledge, especially when mismatches in the incentives of private and public research organisations become barriers to the diffusion of necessary competences.

The dynamics of local knowledge mirror, of course, those of physical technology. The literature has analysed the latter through the lenses of the life cycle heristic proposed by Abernathy and Utterback (1978) and further refined by Klepper (1996) and Utterback (1994). At early stages, variety is highest and each prototype technology carries a set of characteristics whose effectiveness cannot be judged ex-ante because, at least in evolutionary accounts of the story, the selection environment co-evolves together with the contestants (Adner and Kapoor, 2015; Barbieri et al., 2018a). As technology moves towards maturity, the inferior variants are selected out, industry structures consolidate and the knowledge base acquires a configuration based primarily on routine activities to the detriment of explorative ones. Underlying the dynamics of the knowledge base stands the adaptation of supporting institutional structures in the form of new training and research, regulatory regimes, government infrastructure (Nelson, 1994; Vona and Consoli, 2015).

In turn, knowledge generation and diffusion rely on the organization of the territory, and the attendant socioeconomic and cultural systems that determine the success of the local economy via entrepreneurial ability, local production factors (labour and capital) as well as capacity for decision-making that enables local economic and social actors to guide the development process (Capello, 2010). Clearly the ability to develop an effective network of institutions differs significantly among countries, and these differences significantly shape the ability to enter a technological regime, regardless of the intrinsic complexity of the technology. No matter how codified the relevant know-how may be, the global diffusion of technologies is subject to endogenous barriers, and replicating the characteristics that granted leadership in early stages may simply not suffice (Nelson, 2008).

Following on these premises, we propose to identify whether and to what extent local competences hinder or facilitate the development of green technologies across countries. Prior research leads us to expect that there are significant cross-country differences both in the ability to enter existing technological domains, as well as setting in motion new trajectories (Lanjouw and Mody, 1996; Veugelers, 2012; Costantini and Mazzanti, 2012; Fankhauser et al., 2013; Calel and Dechezleprêtre, 2016). Only few areas possess the necessary competences to invest in complex technologies, and this capacity is plausibly correlated with their long-run path of economic development (Pugliese et al., 2017; Sbardella et al., 2018). The recent study by Petralia et al. (2017) has tackled this issue by exploring the entire landscape of technologies across a large selection of countries. Their analysis disentangles the role of country-specific characteristics - namely, possessing technological competences - as well as technology-specific characteristics - namely, complexity of technology - on the paths of specialisation and diversification.

In the remainder of the paper we employ a similar approach to map the geographical distribution of environmental technology development, and to assess how specific country and technological characteristics enable or thwart the development of inventive activities. In so doing we seek to fill a gap concerning how countries build green innovation capabilities, and how such a capacity differs along the gradient of economic development.

3. Data and Variables

Data sources. We use patent data as an indirect measure of innovation capabilities in green technologies. This source of information carries benefits and shortcomings. Patents provide highly disaggregated information of each invention, in particular the location of the inventor and the characteristics of the invention which are essential to the analysis proposed here. In addition, prior research has pointed out that patents provide a good indicator of research and development activities, as applications are usually filed early in the research process (Griliches, 1990). In this study, we use groups of patent, viz. families, on related inventions that have been filed in various countries to track diffusion of knowledge across countries (e.g. Lanjouw and Mody, 1996). While we acknowledge that not all inventions are patented, the characteristics of intellectual property rights (IPR) regimes underlying patenting activities are likely to have a significant effect on the propensity to search and develop inventions (Cohen et al., 2000; Ginarte and Park, 1997). Further, compared to other domains, the regulatory framework plays a particularly important role in the case of environmental technologies (Jaffe et al., 2002; Popp et al., 2010).

The main source is the PATSTAT dataset (2016 spring version, source: European Patent Office, EPO) from which we select patent applications related to green technologies using the ENV-TECH classification (OECD, 2016). This lists International Patent Classification (IPC) and Cooperative Patent Classification (CPC)[3] codes concerning 95 green technologies, grouped into 8 families and 36 subgroups[4]. We identify a total of 1,262,281 patent families (1,032,635 patent families geolocalized

[3]The IPC and CPC are hierarchical technology classification systems that describes the technical content of the patents. At the full-digit level (i.e. the lowest level of the hierarchy) the codes refer to narrow technological domains, e.g. IPC full-digit C03C 1/02 – "Pre-treated ingredients generally applicable to manufacture of glasses, glazes or vitreous enamels". At the highest level, i.e. 1-digit, the codes refer to general, broad technological fields, e.g. IPC 1-digit C - "Chemistry, Metallurgy".

[4]The majority of ENV-TECH technologies are defined using CPC codes, but Environmental Management and Water-related Adaptation Technologies are identified also with IPC codes. In an intermediate step, we convert these IPC codes into CPC codes using a correspondence table provided by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO), in order to deal with just one classification system.

and grouped in three-year intervals from 1971 to 2012 - see below) to which at least one ENV-TECH code is assigned, in eight specific domains: environmental management, water management, energy production, capture and storage of greenhouse gases, transportation, buildings, waste management and production of goods.

Geolocalisation of green patent families. Our goal of developing a cross-country analysis calls for accurate geographical localisation of inventive activities. To this end, we use the green technology database [5], in particular information on inventors' addresses to geocode each patent family at city level. Information on the location of inventors from PATSTAT is parsed through GeoNames[6] and Google Maps API.

The procedure entails 3 steps. First, we geo-localise patent families by identifying the postal codes within the address string and searching in GeoNames. Second, for patent families in which the postal code information is missing, or for which it is not possible to detect the geographical coordinates, we identify the city name in the address using the city table of the GeoNames database (limiting the search to cities with at least 5000 inhabitants in order to reduce potential noises) and we manually check the results. To retrieve the remaining addresses for which geographical coordinates was missing, we used the Google Maps API, a programmable interface to the geographical database developed by Google since 2005 which allows obtaining for an address its coordinates and the administrative entities it belongs to.

This procedure allows us to geolocalize 1,032,635 patent families (with at least 1 inventor geolocalized - 57.2% patent families have more than half of their inventors geolocalized), in 146 countries. The allocation of green inventions to countries is done using fractional counting (i.e. if a patent family has 2 inventors living in 2 different countries, 0.5 of the patent family will be assigned to the first country and 0.5 to the second country).

[5] An online version is publicly available at `https://www.greentechdatabase.com/`

[6] GeoNames is a geographical database available under a Creative Commons attribution license which contains over 10 million geographical names corresponding to over 9 million unique features whereof 2.8 million populated places and 5.5 million alternate names. A feature can be physical (mountain, lake...), political (country, territory...), a human settlement (city, village...), etc. See http://www.geonames.org for more information.

Using geolocalisation at city level leads us to drop patent families where the inventor's localisation is not geocoded (either because his address is missing or not found). The geolocalisation rate remains almost stable across ENV-TECH families (1 digit) and patent offices: standard deviation are 0.089 and 0.118 respectively. This reduces concerns about any bias that may be due to the geolocalisation procedure.

Complexity of green technologies. The second key dimension in our analysis is the complexity of green technologies. For this we employ the methodology of PBM built on the seminal work of Hidalgo et al. (2007). In our study, technologies are the 36 items identified by means of ENV-TECH classification and countries are those of the inventors.

The first step is to calculate the Reveal Technological Advantage (RTA), to identify countries' technological trajectories and capabilities over time. To this end we calculate:

$$RTA_{cjt} = \frac{Patents_{cjt} / \sum_j Patents_{cjt}}{\sum_c Patents_{cjt} / \sum_{cj} Patents_{cjt}}$$

$$S_{cjt} = I[RTA_{cjt} > 1]$$

Where c stands for country, j for ENV-TECH subgroup, t for the 3 years time period between 1971 and 2012, and I[.] represents the indicator function. This measure provides information on country's specialisation in each technology, comparing the share of that technology in country's technology production with the worldwide average share of that technology for each time period. A country has an advantage when its share in a green technology domain is bigger than the world average, identified when S_{cjt} is equal to one. This indicator identifies the time period t in which a country c starts to diversify in a technology j ($S_{cjt-1} = 0$ and $S_{cjt} = 1$) or the circumstance in which a country had not entered a technology domain at the beginning of the period ($S_{cjt} = 0$ with $t = 1971 - 1974$).

To construct our Index of Technological Complexity (ITC), we only consider countries that are significant producers of particular green technology (GT) ($S_{cjt} = 1$). To this end, we build a two-mode matrix $M = (M_{c,j})$ for each time period, where $M_{c,j}$ reflects whether a country c has RTA in the production of GT j. Following the method of reflections, the ITC is an iteration between two variables: the diversity of countries and the ubiquity of GT. These two variables measure the degree of centrality for both sets of nodes, in the country - green technology network.

The degree of centrality of countries is given by the number of GT in which a country has an RTA (diversity):

$$k_{c,0} = \sum_{j} M_{c,j}$$

In the same manner, the degree of centrality of GT is given by the number of countries with a RTA in this technology (ubiquity):

$$k_{j,0} = \sum_{c} M_{c,j}$$

Hidalgo and Hausmann (2009) calculate the measure of complexity for countries and technologies as an iteration of these two degrees of centrality, as follows:

$$k_{c,n} = \frac{1}{k_{c,0}} \sum_{j} M_{c,j} k_{j,n-1}$$

$$k_{j,n} = \frac{1}{k_{j,0}} \sum_{c} M_{c,j} k_{c,n-1}$$

Each iteration of n provides finer-grained estimates of the knowledge complexity of technologies they produce. To llustrate, when $n = 1$, $k_{j,1}$ represents the average diversity of countries that have an RTA in technology j. In the next iteration, $k_{j,2}$ represents the average ubiquity of the green technologies produced in countries that have a RTA in GT j. ITC for technology j is defined as the value of $k_{j,n}$ with the maximum number of iterations for each period under analysis.

Green technological space. ENV-TECH defines 3 levels of classification, from the broader level which we call family to the more detailed one, called technology. Families are too broad to elucidate the specialisation patterns of countries but technologies have too few patent families to capture the contribution to green technologies of low-middle income countries, as defined in PBM (Appendix A). Moreover, some families, in particular “capture, storage, sequestration or disposal of greenhouse gases” or “climate change mitigation technologies related to transportation” are only divided into subgroups. Since using 3-digit classes of ENV-TECH would entail missing some important green technologies, we use the 2-digits level, for a total of 36 green technologies (GT).

Each ENV-TECH family aggregates a set of technologies by topic (transportation, energy, building, et cetera) and objective (climate change adaptation or mitigation), but the technologies belonging to a family can have a different gradient of relatedness, and can even be more related to other technologies outside their own family. In order to measure relatedness, we follow PBM, Hidalgo et al. (2007) and Balland and Rigby (2017) in seeing the Technological Space as a network-based representation of the production of technologies, defined as nodes, the relatedness of each couple of technologies being a tie between two nodes. Accordingly, relatedness between green technology i and j is calculated as follows:

$$R_{ijt} = \frac{C_{cjt}}{\sqrt{S_{it} S_{jt}}}$$

Where C_{cjt} counts the co-occurrences of technologies i and j, and S_i and S_j count the size of GT at period t. Therefore, the more two technologies are associated to the same patent families, the more related they are controlling for size, the higher is R_{ijt}.

Density of green technologies. Once the proximity between green technologies is estimated, we calculate how close is each technology to the country's portfolio of all technologies. This variable varies from 0 to 1, with higher values indicating a country has capacity to produce GT nearby a given technology. It is measured as follows:

$$Density_{cjt} = \frac{\sum_i R_{ijt} X_{cit}}{\sum_i R_{ijt}}$$

Where X_{cit} is a dummy variable that takes value 1 if country c is patenting in GT i during the period t. This variable captures the capacities of country c to produce patents in technologies related to technology j in time period t, which help to understand if capacities in the production of related technologies are linked to diversification in other technologies.

Other variables. For each ENV-TECH class we calculate the number of patent families produced (Size) to control for scale effects, as well as the Herfindhal Index to account for competition among countries in each technology[7]. We also control for the level of development of each country's economy over time through proxied by GDP (Source: Green Growth Knowledge Platform[8]).

4. Empirical Analysis

4.1. Descriptive Statistics

Table 1 shows descriptive statistics of our variables. Our database gather information on 63 countries and 36 green technologies, from 1971 to 2012, in 14 time periods of 3 years each. About 24% of countries specialized in a technology at time period t ($S_{cjt} = 1$) were not specialized in the same technology in the previous time period (identified in the column NPA_{cjt-1}), which we define as a diversification event. On the other hand, 33% of the observations were having a patent activity in time period $t-1$ (identified in the column PA_{cjt-1}) and lost their technological advantages on the next time period t ($S_{cjt} = 0$). These proportions are lower than those reported by PBM, but follow the same trend: once a country has started to invent, it tends to retain a technological advantage.

4.2. Regression analysis

Our objective is to characterize patterns of technological diversification and specialisation in green technologies, in relation with the intrinsic characteristics of the technology (size and complexity), but also with the characteristics of the country, in particular activity in other proximate green technologies

[7]Given the specificities of the ENV-TECH classification, we do not use technology value added like PBM. This is because, first, ENV-TECH associates various IPC and CPC codes to a technology, which makes difficult to associate an industrial sector to a specific technology, so makes inappropriate the use of manufactures surveys. Second, and in particular in the case of emergent technologies like for example CO_2 capture and sequestration, the value added could be important in the future but this kind of technology is not used enough at present to be able to estimate it.

[8]Available at http://www.greengrowthknowledge.org/

(Density) and whether there is prior technological advantage as per RTA. We characterise diversification in two ways: first, by restricting the dataset to cases in which there were no patenting activity at the beginning of the sample ($RTA_{cjt} < 0.1$ where $t = 1971 - 1974$) and, second, by accounting only for the cases in which there was no patenting activity in the prior time period ($RTA_{cjt-1} < 0.1$). As for specialisation, we account for the RTA of a country in a green technological domain disregarding if it shows a technological advantage in previous periods. Contrary to what PBM find, using patents from PATSTAT instead of USPTO mitigates the uncertainty on the detection of global knowledge production, as PATSTAT is a worldwide patent database and is not limited to the United States only. All the other limitations identified apply.

We estimate two different models, one for diversification and the other for specialisation. The former is further split by considering short-term and long-term effects, namely by accounting for period to period changes and for changes relative to the first time period of the sample. In turn, Specialisation focuses on comparative advantage in developing innovation in technological fields in each period. All models include dummies for green technologies, countries and time periods in order to control for potential biases introduced by peculiarities of certain green technologies, countries or time periods. We specify two models as follows:

- Diversification equation

$$\begin{aligned} S_{cjt} = \Theta_1 Density_{cjt-1} + \Theta_2 Density_{cjt-1} \times GDP_{ct} + \beta_1 \log Size_{jt} + \beta_2 HI_{jt} \\ + \beta_3 ITC_{jt} + \beta_4 GDP_{ct} + \delta_c D_c + \delta_j D_j + \delta_t D_t + \varepsilon_c jt \end{aligned} \quad (1)$$

- Specialisation equation

$$\begin{aligned} S_{cjt} = \Theta_1 Density_{cjt-1} + \beta_1 \log Size_{jt} + \beta_2 HI_{jt} \\ + \beta_3 ITC_{jt} + \beta_4 GDP_{ct} + \beta_5 \log Size_{jt} \times GDP_{ct} + \beta_6 HI_{jt} \times GDP_{ct} \\ + \beta_7 ITC_{jt} \times GDP_{ct} + \delta_c D_c + \delta_j D_j + \delta_t D_t + \varepsilon_c jt \end{aligned} \quad (2)$$

Where c, j, and t identify respectively countries, green technologies and time periods, S_{cjt} takes the value of unity when a country c has a RTA above unity in a technology j in time period t, GDP_{ct} is the gross domestic product per capita for country c and time period t, $Density_{cjt}$ is the proximity of surrounding green technologies in country c to technology j in time period t, HI_{jt}, ITC_{jt} and $Size_{jt}$ are the technology-related variables defined in Table 1, and $\varepsilon_c jt$ is the error term.

The first model captures the effect of a country possessing competences in proximate technologies on diversification over both short- and long-term time horizons. The second model aims at identifying the patterns of specialisation in green technologies, measuring the effects of the technology determinants themselves and those of surrounding technologies in a country, regardless of whether a country has previously produced that technology.[9] In the regressions all the variables are interacted with GDP to check for the influence of each country's level of development. Last but not least, we extend the framework of PBM by estimating diversification and specialisation in a model that accounts for the degree of maturity of the green technology along life-cycle (as defined in Appendix A). In so doing we evaluate whether green technologies behavior is homogeneous across families, or if intrinsic characteristics of ENV-TECH domains have a differential influence.

5. Results and discussion

The present section is organised in three parts. First, we present the results of the regression models specified above. Second, we extend the general framework to include the technology life-cycle. Third, we include a robustness check that accounts for the role of environmental policy. All along the benchmark for the interpretation of the results is the work of PBM, with the proviso that the present paper focuses on the domain of green technology.

5.1. Specialisation and Diversification

Table 2 shows the results of the main regressions. In columns (1) and (2) are the diversification models for, respectively, short- and long-term, while column (3) shows results from the specialisation

[9] We employ OLS with robust standard errors to estimate the two linear probability models. This enables us to compare our findings to PBM and interpret the coefficients in more effective way.

model. In all cases we find a positive and significant coefficient for density. This suggests that having technological capabilities in related domains increases the likelihood of investing in a new-to-the-country green technology. Such a finding is in line with prior work on the pivotal role of related capabilities in the green knowledge generation process (Sbardella et al., 2018). Indeed, knowledge stemming from existing capabilities reduces the costs and uncertainty that exploratory mechanisms entail and triggers technological variety across different - though related - fields (Castaldi et al., 2015). A study by Noailly and Shestalova (2017) also points out that renewable energy technologies benefit, among other factors, from intra and inter-technology spillovers. In this sense, green technologies do not differ from all other technologies.

The same goes for the negative coefficient of the interaction between Density and GDP in the short-term model (Column 1). The interpretation is that existing capabilities in related technologies are less relevant for developed countries relative to developing ones, and, thus, that the costs and uncertainty of exploring new technological domains is a major concern when the endowment of financial resources is lower. Note however that the latter only holds for the short-term while the coefficient is not significant in the long-term (Column 2). Thus, green technologies differ from other technologies in that possessing established competences matter in the immediate but not necessarily over the long haul. We ascribe this to the notion, consolidated in the literature, that green technologies are at an altogether early stage of development (OECD, 2011; Barbieri et al., 2018b). Operating in such a technological domain characterised by a high level of uncertainty, due to lack of established practices and gaps in know-how, entails that financial capacity does not influence diversification capacity.

We also find significant coefficients for two technology-level variables, namely Size and the Herfindhal index. The former is positive and significant, again only in the short-term model, thus suggesting that scale effects at country level matter. The negative sign of the Herfindhal index instead indicates that high geographical concentration of environmental technology does not favor diversification. Both findings are in line with what has been observed in the entire technology landscape by PBM. Our results, however, differ for what concerns the role of technology complexity, ITC, which is not significant. The current stage of development of green technology plausibly marks the difference with the broader landscape: because taking a sustainable path requires bringing together different knowledge sources, more so than in established technological domains (Barbieri et al., 2018a), complexity in terms of diffusion of innovation capabilities to develop GT is not necessarily a barrier.

Results from the specialisation equation are shown in the third column of Table 2. The finding that the coefficient of technology density is positive and significant corroborates the idea that operating in proximate fields increases the likelihood of specialisation. Again, the coefficients of Size and of the Herfindhal index are both significant, and in line with prior results. Also, technology complexity bear no association with specialisation. Interacting these variables with GDP instead yields negative and significant coefficients. This implies, first, that scale effects decline with the income level of the country (though the magnitude is rather low) and, second, that high geographical concentration may hinder specialisation among low-income countries more than for high-income ones.

Figures 1 and 2 provide a visual summary of the main findings. Figure 1 shows the probability of diversification taking into account the margins at different levels of GDP (left panel) and Size (right panel) with darker colors showing a higher probability and isolines indicating probability values. On the left-hand panel, we can observe that the presence of related capabilities is particularly important for countries at lower levels of GDP per capita. As far as we move to the right we notice that diversification in high income countries benefits from related capabilities along the whole spectrum of Density. The result provides evidence that the endowment of capabilities in related green technologies eases diversification especially in those countries at the beginning of the greening process for which knowledge spillovers are key to explore new-to-the-country technological domains. As for developed countries, diversification is still associated with Density but experimentation is less risky than in developing or emerging countries and thus does not represent a strong barrier. Our insight suggests, once again, that accounting for country and technological characteristics is a fundamental step to explore diversification and specialisation patterns. The right-hand panel of Figure 1 shows that diversification is favoured by high levels of related capabilities (i.e. Density) and patenting intensity (i.e. Size). That is, increasing both dimensions enhances the stock of knowledge that can be exploited by innovators.

The left-hand panel of Figure 2 shows the the probability of specialisation at different levels of GDP per capita and Density. The result confirms what has been observed in the case of diversification. The endowment of related inventive capabilities appears to be more important for low income than high income countries. The left-hand panel of Figure 2 shows the extent to which the probability of specialisation changes according to green technologies density and the size. These results confirm the finding associated with diversification. That is, the probability of specialisation tends to be higher when countries have inventive capabilities in surrounding green technologies (i.e. Density) and the stock of knowledge in that technology (i.e. Size) increases.

This, other than adding to previous literature, including but not limited to PBM, offers interesting insights for policy. Our reading is that, akin to several other societal challenges, dealing with environmental sustainability calls upon the capacity to build rich and diverse knowledge structures with the proactive participation of both firms and the attendant institutions (Nelson, 2008). The evidence provided here shows that countries that successfully develop domestic capabilities can overcome technological barriers. More than this, we find that these opportunities are not precluded to countries with lower income levels, and therefore to the places that according to many are most vulnerable to climate change hazards.

5.2. Green Technology Life-Cycle

Given the idiosyncratic features of our domain of analysis, we now enrich the indications stemming from the general analysis above by assessing whether and to what extent the maturity of green technologies plays a role. To this end we refer to the empirical constructs of a recent study by Barbieri et al. (2018b) on the relation between regional knowledge diversification and the life cycle stage of environmental technologies. Table 3 reports the macro-technological groups provided by OECD (2016) ranked in relation to their level of maturity. Therein technologies such as i.e. "Capture, storage, sequestration or disposal of GHG" (ENV-TECH 2) are at early stages of development while others, i.e. "Environmental or Waste management" (ENV-TECH 1-2), are more mature (Barbieri et al., 2018b).[10]

Table 4 shows results of the regressions articulated according to the life-cycle classification. The coefficient of technological maturity is positive and significant in all specifications, thus indicating that the more consolidated a technology the higher the probability to diversify in green domains that had not previously been explored. The result holds also in the specialisation equation (Column 3). Not surprisingly the finding suggests that countries tend to diversify and specialise, i.e. spend effort to explore new-to-the-country green domains, in more mature technological domains. This is particularly relevant as far as developed countries are concerned. Indeed, the interaction term between GDP and TLC suggests that the more a country is developed, the higher is the association between the maturity of the technology and the likelihood of specialising in that field.

5.3. The role of Environmental Policy

As stated in the introduction, environmental policies play a crucial role in the context of green growth. Policy intervention is required to address market failures with which the development of green technologies confronts. In order to deal with this issue we check the robustness of previous results by testing the correlation between diversification and specialisation patterns and environmental regulation. To do so, we employ the OECD's Environmental Policy Stringency Index (EPSI) (Botta and Koźluk, 2014) with the aim of capturing the commitment of the institutional framework to contain environmentally harmful behaviour by means of different policy instruments. The results of Table 5 confirm previous findings [11]. The coefficient of EPSI across the different specifications indicates that the diversification into previously unexplored technological fields (Columns 1 and 2) correlated with countries' technological capabilities rather than with environmental regulation. This is in line with studies that highlight the effectiveness of flexible environmental policy instruments at triggering innovation (Johnstone et al., 2010). That is, the technology-neutrality of policies may favours the

[10] Note that the level of maturity is calculated relative to the stage of development of all green technologies.

[11] The reader will appreciate that the number of observations decreases substantially from 63 to 32. This is due to data availability, as information on EPSI exists only for most of the OECD countries plus Brazil, China, India, Russia and South Africa.

development of technologies whose know-how is already present in the country. This suggests that environmental policies are positively correlated with specialisation patterns which capture the efforts in developing green technologies regardless to the endowment of innovation capabilities in the previous periods.

6. Conclusions

The new growth agenda laid out in the Sustainable Development Goals (SDGs) and the Paris Agreement states explicitly that growth, climate action and development are complementary objectives. This complementarity defines not only the nature of the goals but also that of the policies that can best facilitate achieving them. Building climate change resilience within countries entails the reorganisation of existing, and in some case the creation of new, systems for generating and using natural resources. Against this backdrop, accelerating the development and diffusion of new low-carbon technologies remains a crucial ingredient of the environmental policy mix.

Progress in recent years has been significant if uneven, not only between green technology domains but also across countries, and the concern is that imbalances on the distribution of opportunities could further exacerbate these gaps and, paradoxically, become hurdles towards sustainability. Thus, continued innovation and deployment are crucial, but so is the capacity to put in place policies that facilitate diffusion, especially towards developing countries that are most exposed to climate hazards and yet lag behind the technological frontier. Because climate change is a global phenomenon with local manifestations, we proposed an analysis that articulates green technology development across domains and across countries. Effective resource management cannot be divorced from characteristics of the institutional regime over which regulatory functions are to be undertaken. While the geographic distribution of natural resources may partially be determined by exogenous factors – such as i.e. availability of raw materials – the capacity for adaptation and mitigation stems from endogenous factors such as human capital and institutional flexibility.

The present study has tackled these questions by analysing cross-country patterns of diversification and specialisation in environmental technology development, and on their drivers. This exercise yields three main findings. First, countries are more likely to diversify into new domains of green technology that are close to the portfolio of existing competences as proxied by prior technological orientation. Second, our results are peculiar in that diversification and specialisation do not exhibit strong association with the stage of development of a country but, rather, with the maturity of the green technology. In particular, differences in competences are a bigger obstacle than differences in wealth. This insight is in line with the ongoing debate on the limits of GDP as a welfare indicator (Fleurbaey, 2009). Going beyond GDP implies accounting for other complementary indicators that capture the value of public - or extra-market - goods such as environmental quality or, as in our case, knowledge and its spillovers (Mazzanti and Gilli, 2018). Third, in line with prior studies, we find that countries move along cumulative paths of specialisation. At the same time, and contrary to other studies, the complexity of innovative capabilities is not an obstacle to specialisation.

The paper also explores the correlation between the development of green technologies and environmental policy. Although data availability reduces the sample of countries in our analysis, we have observed that environmental policy stringency is a significant predictor of specialisation patterns which is in line with the insights provided by the extensive literature that focuses on the innovation inducement effect of policy implementation. Once again the role of environmental policies to address market failures emerges and emphasises that green growth is strongly connected to the institutional framework that characterises the innovation system.

On the whole, our empirical analysis suggests that policy intervention should account for current characteristics of countries' knowledge space. This implies that triggering innovation in new-to-the-country technological domains is contingent upon existing innovation capabilities with which countries are endowed. Environmental policy that aims at increasing those capabilities out of the blue may face a serious barrier in achieving its objectives. Additionally, in line with previous studies that highlight the heterogeneous incentives provided by different types of instruments (Milliman and Prince, 1989), policies focused on the reduction of pollutant emissions should be designed carefully in order to exploit pollution abatement technologies available to the country. An effective strategy may arise from a careful assessment of existing capabilities that should be taken into account in the design of policy. Thus, policy interventions targeting green technological domains that are outside countries' knowledge bases may require the development of a broader range of technologies from which green innovation stems. This would call upon a mix of policy instruments that are designed to target a portfolio of technologies (Veugelers, 2012), highlighting the ability of policy makers at anticipating or reacting to the development of new technological opportunities (Requate, 2005). However, such an intervention should not affect the variety of technological options that are presented to the changing selective environment and the resulting adaptive flexibility of the system (Rammel and van den Bergh, 2003). Once again the role of diversification emerges as stressed by the recent stream of studies that investigate how (related and unrelated) variety of skills, practices and knowledge bases enhance economic performance (Frenken et al., 2007; Castaldi et al., 2015; Barbieri et al., 2018b; Barbieri and Consoli, 2019). These policy implications may be considered in the current debate around the new green deals that explicitly stress the role of technology to achieve long-term climate policy objectives (e.g. the Green New Deal, EU Circular Economy Strategy).

Our analysis is not free from limitations which, we suggest, may offer useful insights for future research. First, the empirical study relies on patent data which clearly represent only one dimension of green innovation. This seemed the best strategy considering that one of the goals of the present paper was to provide a global map of progress in environmental technology, an exercise that requires harmonised and comparable data. Our effort could therefore be a primer to guide country-specific analysis on the state of deployment of adaptation and mitigation activities, which may be extended by investigating non-linear relationship between development paths and technological trajectories. A second limitation is that our analysis does not account explicitly for efficiency in the use of natural resources, which a proficient literature debates in terms of a shifting balance between technological innovation and structural change. Such a debate is however narrower relative to our approach, in that it focuses mostly on energy. The analysis proposed here could therefore be be extended to explore the determinants of countries' and sectors' heterogeneity in performance, thus informing case study analysis. While we acknowledge these limitations, we hope that the empirical findings of the present paper can foster new interest in the relationship between environmental sustainability and economic development.

Acknowledgements

We are indebted to the editor and two anonymous referees for constructive feedback. DC acknowledges the financial support of Consejo Superior de Investigaciones Científicas (CSIC) "Ayuda de Incorporación para Científicos Titulares" (OEP2014) and of the Ministerio de Economia Industria y Competitividad "Programa Estatal de I+D+i Orientada a los Retos de la Sociedad, 2017" (ECO2017-86976R). FP acknowledges the financial support of European H2020 Project RISIS2 (grant agreement nº 824091). All errors and omissions are our own.

Bibliographic References

Abernathy, W. J., Utterback, J. M., 1978. Patterns of industrial innovation. Technology review 80 (7), 40–47.

Adner, R., Kapoor, R., mar 2015. Innovation ecosystems and the pace of substitution: Re-examining technology S-curves. Strategic Management Journal 37 (4), 625–648.

Arrow, K., 1962. Economic Welfare and the Allocation of Resources for Invention. Princeton University Press, pp. 609–626.

Arrow, K. J., 1972. Economic welfare and the allocation of resources for invention. In: Readings in industrial economics. Springer, pp. 219–236.

Atkinson, A. B., Stiglitz, J. E., 1969. A new view of technological change. The Economic Journal 79 (315), 573–578.

Ayres, R. U., van den Bergh, J. C. J. M., 2005. A theory of economic growth with material/energy resources and dematerialization: Interaction of three growth mechanisms. Ecological Economics 55 (1), 96–118.

Balland, P. A., Rigby, D., 2017. The Geography of Complex Knowledge. Economic Geography 93 (1), 1–23.

Barbieri, N., Consoli, D., 2019. Regional diversification and green employment in us metropolitan areas. Research Policy 48 (3), 693–705.

Barbieri, N., Ghisetti, C., Gilli, M., Marin, G., Nicolli, F., mar 2016. A survey of the literature on environmental innovation based on main path analysis. Journal of Economic Surveys 30 (3), 596–623.

Barbieri, N., Marzucchi, A., Rizzo, U., 2018a. Knowledge sources and impacts on subsequent inventions: Do green technologies differ from non-green ones? SPRU Working Paper Series 2018-11.

Barbieri, N., Perruchas, F., Consoli, D., 2018b. Specialization, diversification and environmental technology life-cycle. Papers in Evolutionary Economic Geography, Universiteit Utrecht 18-38.

Bathiany, S., Dakos, V., Scheffer, M., Lenton, T. M., may 2018. Climate models predict increasing temperature variability in poor countries. Science Advances 4 (5).

Botta, E., Koźluk, T., 2014. Measuring environmental policy stringency in oecd countries (1177). URL `https://www.oecd-ilibrary.org/content/paper/5jxrjnc45gvg-en`

Calel, R., Dechezleprêtre, A., mar 2016. Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market. Review of Economics and Statistics 98 (1), 173–191.

Capello, R., 2010. Space, growth and development. In: Capello, R., Nijkamp, P. (Eds.), Handbook of regional growth and development theories, edward elg Edition.

Cardona, O. D., van Aalst, M. K., Birkmann, J., Fordham, M., McGregor, G., Mechler, R., 2012. Determinants of risk: Exposure and vulnerability. In: Field, C. B., Barros, V., Stocker, T. F. (Eds.), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge University Press, Cambridge.

Castaldi, C., Frenken, K., Los, B., may 2015. Related Variety, Unrelated Variety and Technological Breakthroughs: An analysis of US State-Level Patenting. Regional Studies 49 (5), 767–781.

Chang, S.-H., Fan, C.-Y., apr 2016. Identification of the technology life cycle of telematics: A patent-based analytical perspective. Technological Forecasting and Social Change 105, 1–10.

Chatterjee, S., Wernerfelt, B., 1991. The link between resources and type of diversification: Theory and evidence. Strategic management journal 12 (1), 33–48.

Cohen, W., Levinthal, D. A., 1990. Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly 35, 128–152.

Cohen, W. M., Nelson, R. R., Walsh, J. P., 2000. Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not). Working Paper 7552, National Bureau of Economic Research.

Costantini, V., Mazzanti, M., feb 2012. On the green and innovative side of trade competitiveness? The impact of environmental policies and innovation on EU exports. Research Policy 41 (1), 132–153.

Cristelli, M., Gabrielli, A., Tacchella, A., Caldarelli, G., Pietronero, L., 2013. Measuring the Intangibles: A Metrics for the Economic Complexity of Countries and Products. PLoS ONE 8 (8), e70726.

Deacon, R., Mueller, B., 2006. Political Economy and Natural Resource Use. In: Ramón López, M., Toman, M. (Eds.), Economic Development and Environmental Sustainability. Oxford University Press, pp. 122–153.

Dessai, S., Hulme, M., Lempert, R., Pielke Jr, R., 2009. Climate prediction: a limit to adaptation. In: Adapting to climate change: thresholds, values, governance. Cambridge University Press Cambridge, pp. 64–78.

Fankhauser, S., Bowen, A., Calel, R., Dechezleprêtre, A., Grover, D., Rydge, J., Sato, M., oct 2013. Who will win the green race? In search of environmental competitiveness and innovation. Global Environmental Change 23 (5), 902–913.

Fischer, C., Newell, R. G., mar 2008. Environmental and technology policies for climate mitigation. Journal of Environmental Economics and Management 55 (2), 142–162.

Fleurbaey, M., 2009. Beyond gdp: The quest for a measure of social welfare. Journal of Economic literature 47 (4), 1029–75.

Frenken, K., Boschma, R. A., 2007. A theoretical framework for evolutionary economic geography: industrial dynamics and urban growth as a branching process. Journal of economic geography 7 (5), 635–649.

Frenken, K., Van Oort, F., Verburg, T., 2007. Related variety, unrelated variety and regional economic growth. Regional studies 41 (5), 685–697.

Gagliardi, L., Marin, G., Miriello, C., 2016. The greener the better? Job creation effects of environmentally-friendly technological change. Industrial and Corporate Change 25 (5), 779–807.

Gao, L., Porter, A. L., Wang, J., Fang, S., Zhang, X., Ma, T., Wang, W., Huang, L., mar 2013. Technology life cycle analysis method based on patent documents. Technological Forecasting and Social Change 80 (3), 398–407.

Ghisetti, C., Mazzanti, M., Mancinelli, S., Zoli, M., et al., 2015. Do financial constraints make the environment worse off? understanding the effects of financial barriers on environmental innovations. SEEDS Working Paper Series, 19p.

Ginarte, J. C., Park, W. G., oct 1997. Determinants of patent rights: A cross-national study. Research Policy 26 (3), 283–301.

Griliches, Z., 1990. Patent Statistics as Economic Indicators: A Survey. Working Paper 3301, National Bureau of Economic Research.

Haines, A., Patz, J. A., 2004. Health Effects of Climate Change. Journal of the American Medical Association 291 (1), 99–103.

Haupt, R., Kloyer, M., Lange, M., apr 2007. Patent indicators for the technology life cycle development. Research Policy 36 (3), 387–398.

Hidalgo, C. A., Hausmann, R., 2009. The building blocks of economic complexity. Proceedings of the National Academy of Sciences 106 (26), 10570–10575.

Hidalgo, C. A., Winger, B., Barabási, A. L., Hausmann, R., 2007. The product space conditions the development of nations. Science 317 (5837), 482–487.

Jaffe, A. B., Newell, R. G., Stavins, R. N., 2002. Environmental Policy and Technological Change. Environmental and Resource Economics 22 (1/2), 41–70.

Jaffe, A. B., Newell, R. G., Stavins, R. N., 2005. A tale of two market failures: Technology and environmental policy. Ecological Economics 54 (2-3), 164–174.

Johnstone, N., Haščič, I., Kalamova, M., 2010. Environmental policy characteristics and technological innovation. Economia Politica 27 (2), 277–302.

Johnstone, N., Haščič, I., Poirier, J., Hemar, M., Michel, C., 2012. Environmental policy stringency and technological innovation: Evidence from survey data and patent counts. Applied Economics 44 (17), 2157–2170.

Jurgilevich, A., Räsänen, A., Groundstroem, F., Juhola, S., 2017. A systematic review of dynamics in climate risk and vulnerability assessments. Environmental Research Letters 12 (1), 13002.

Klepper, S., 1996. Entry, Exit, Growth, and Innovation over the Product Life Cycle. The American Economic Review 86 (3), 562–583.

Lanjouw, J. O., Mody, A., jun 1996. Innovation and the international diffusion of environmentally responsive technology. Research Policy 25 (4), 549–571.

Lee, C., Cho, Y., Seol, H., Park, Y., jan 2012. A stochastic patent citation analysis approach to assessing future technological impacts. Technological Forecasting and Social Change 79 (1), 16–29.

Lee, C., Kim, J., Kwon, O., Woo, H.-G., may 2016. Stochastic technology life cycle analysis using multiple patent indicators. Technological Forecasting and Social Change 106, 53–64.

Marin, G., mar 2014. Do eco-innovations harm productivity growth through crowding out? Results of an extended CDM model for Italy. Research Policy 43 (2), 301–317.

Mazzanti, M., Gilli, M., 2018. Contextualising sustainability. In: Cultures of Sustainability and Well-being. Vol. 111. ROUTLEDGE in association with GSE Research, pp. 111–134.

McMichael, A. J., Woodruff, R. E., Hales, S., 2006. Climate change and human health: present and future risks. Lancet 367 (9513), 859–869.

Mendelsohn, R., Dinar, A., Williams, L., 2006. The distributional impact of climate change on rich and poor countries. Environment and Development Economics 11 (2), 159–178.

Milliman, S. R., Prince, R., 1989. Firm incentives to promote technological change in pollution control. Journal of Environmental economics and Management 17 (3), 247–265.

Neffke, F., Henning, M., Boschma, R., 2011. How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. Economic Geography 87 (3), 237–265.

Nelson, R. R., 1959. The Simple Economics of Basic Scientific Research. Journal of Political Economy 67 (3), 297–306.

Nelson, R. R., 1994. The Co-evolution of Technology, Industrial Structure, and Supporting Institutions. Industrial and Corporate Change 3 (1), 47–63.

Nelson, R. R., 2008. What enables rapid economic progress: What are the needed institutions? Research Policy 37 (1), 1–11.

Nesta, L., Vona, F., Nicolli, F., 2014. Environmental policies, competition and innovation in renewable energy. Journal of Environmental Economics and Management 67 (3), 396–411.

Newell, R. G., 2010. The role of markets and policies in delivering innovation for climate change mitigation. Oxford Review of Economic Policy 26 (2), 253–269.

Noailly, J., Shestalova, V., mar 2017. Knowledge spillovers from renewable energy technologies: Lessons from patent citations. Environmental Innovation and Societal Transitions 22, 1–14.

OECD, jun 2003. Voluntary Approaches for Environmental Policy. OECD Publishing.

OECD, may 2011. Towards Green Growth. OECD Green Growth Studies. OECD Publishing.

Patz, J. A., Campbell-Lendrum, D., Holloway, T., Foley, J. A., 2005. Impact of regional climate change on human health. Nature 438 (7066), 310–317.

Petralia, S., Balland, P. A., Morrison, A., 2017. Climbing the ladder of technological development. Research Policy 46 (5), 956–969.

Popp, D., 2002. Induced Innovation and Energy Prices. The American Economic Review 92, 160–180.

Popp, D., Newell, R., Jaffe, A., 2010. Energy, the Environment, and Technological Change. In: Rosenberg, N., Halland, B. (Eds.), Handbook of the Economics of Innovation- Vol-II. Academic Press, Burlington, USA, pp. 873–938.

Pugliese, E., Chiarotti, G. L., Zaccaria, A., Pietronero, L., 2017. Complex economies have a lateral escape from the poverty trap. PloS one 12 (1), e0168540.

Rammel, C., van den Bergh, J. C., 2003. Evolutionary policies for sustainable development: adaptive flexibility and risk minimising. Ecological economics 47 (2-3), 121–133.

Requate, T., Aug. 2005. Dynamic incentives by environmental policy instruments—a survey. Ecological Economics 54 (2-3), 175–195.
URL `https://linkinghub.elsevier.com/retrieve/pii/S0921800905000315`

Rigby, D. L., Essletzbichler, J., 1997. Evolution, process variety, and regional trajectories of technological change in US manufacturing. Economic Geography 73 (3), 269–284.

Romer, P. M., 1994. The origins of endogenous growth. Journal of Economic perspectives 8 (1), 3–22.

Sarewitz, D., Nelson, R., 2008. Three rules for technological fixes. Nature 456 (7224), 871–872.

Sbardella, A., Perruchas, F., Napolitano, L., Barbieri, N., Consoli, D., Sbardella, A., Perruchas, F., Napolitano, L., Barbieri, N., Consoli, D., oct 2018. Green Technology Fitness. Entropy 20 (10), 776.

Stern, N., 2007. The economics of climate change: the stern review. Cambridge University Press.

Utterback, J., 1994. Mastering the dynamics of innovation.

Veugelers, R., 2012. Which policy instruments to induce clean innovating? Research Policy 41 (10), 1770–1778.

Vona, F., Consoli, D., 2015. Innovation and skill dynamics: a life-cycle approach. Industrial and Corporate Change 24 (6), 1393–1415.

Weitzman, M. L., may 1998. Recombinant growth. The Quarterly Journal of Economics 113 (2), 331–360.

World Economic Forum, 2018. The global risks report 2018, 13th edition.

Tables and Figures

Table 1. Main Descriptive Statistics

	Obs	Mean	SD	Min	Max
Specialisation	31248	0.234	0.423	0	1
Log Size	31248	6.161	1.980	0.406	10.257
Herfindhal Index	31248	0.299	0.145	0.000	1
ITC	31248	12.644	3.105	4.429	22.5
Density	31248	0.535	0.400	0	1
GDP Per Capita	26604	12947.3	15595.4	112.73	107318

Correlation Table						
Specialisation	1					
Log Size	0.177	1				
Herfindhal Index	-0.134	0.175	1			
ITC	-0.086	-0.619	-0.313	1		
Density	0.357	0.145	-0.066	0.036	1	
GDP	0.202	0.225	-0.121	0.045	0.468	1

Specialisation	PA_{cjt-1}	NPA_{cjt-1}	Total
$S_{cjt} = 1$	0.758	0.242	1
$S_{cjt} = 0$	0.328	0.673	1

Number of countries: 63
Number of technologies: 36
Coverage: 1971 – 2012 (14 periods of 3 years each)

Table 2. Results of the Econometric Model

	Diversification, Short-Term (RTA $<$ 0.1 prior period)	Diversification, Long-Term (RTA $<$ 0.1 first time period)	Specialisation
Density	0.07050***	0.11723***	0.13949***
	(0.01)	(0.01)	(0.01)
Density $\times$ GDP	-0.00229**	-0.00033	
	(0.00)	(0.00)	
Technological-level Variables			
Log Size	0.00857*	0.00652	0.01912***
	(0.00)	(0.01)	(0.01)
Herfindahl Index	-0.11388***	-0.16854***	-0.09516***
	(0.02)	(0.02)	(0.03)
ITC	-0.00065	-0.00042	0.00270
	(0.00)	(0.00)	(0.00)
GDP	0.00116	-0.00036	0.00000
	(0.00)	(0.00)	(.)
GDP $\times$ Log Size			-0.00115***
			(0.00)
GDP $\times$ Herfindahl Index			-0.01439***
			(0.00)
GDP $\times$ ITC			-0.00009
			(0.00)
R^2	0.10189	0.19124	0.22482
Tech Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Obs	13902	19599	24372

* $p < .1$, ** $p < .05$, *** $p < .01$

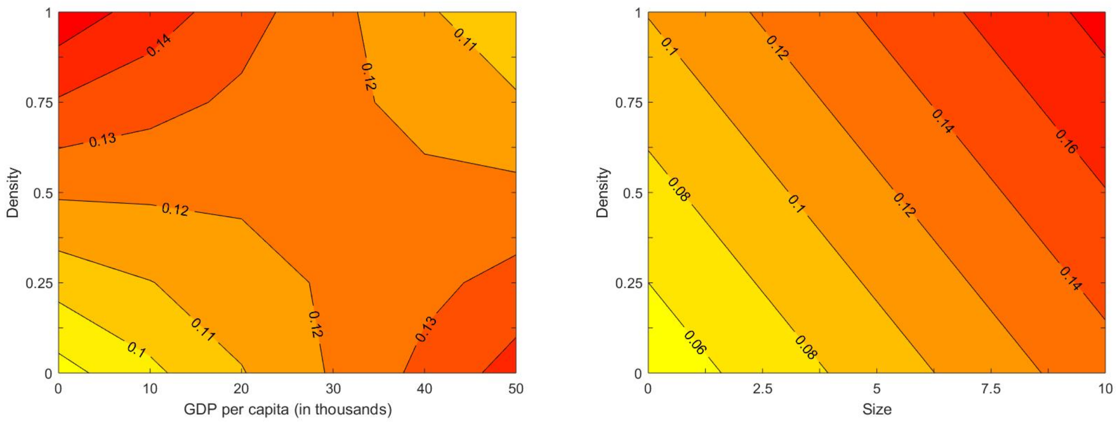

Figure 1. Diversification probabilities according to the characterics of technologies and countries.

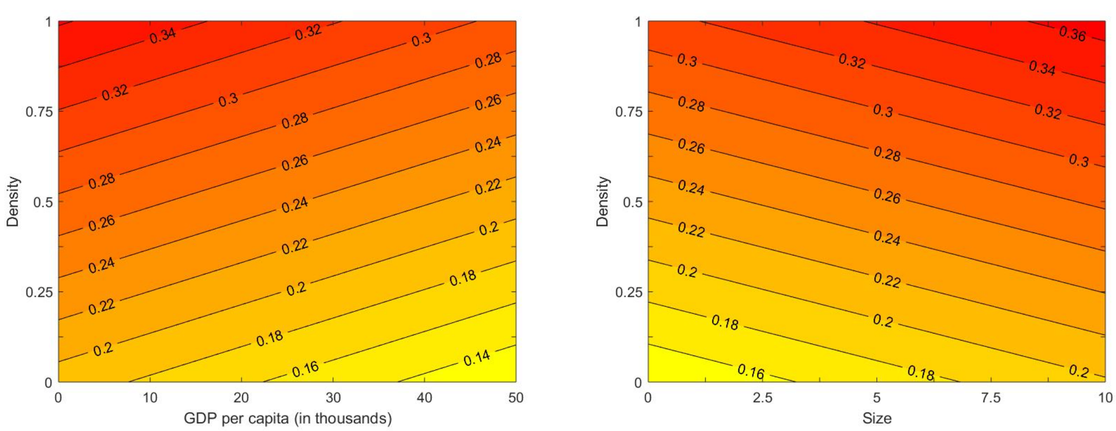

Figure 2. Specialisation probabilities according to the characterics of technologies and countries.

Table 3. Technology maturity ranking

ENV-TECH (1-DIGIT)	Technological field	Ranking
ENV-TECH 5	Capture, storage, sequestration or disposal of GHG	1 (Less mature)
ENV-TECH 6	Transportation	2
ENV-TECH 4	Energy generation, transmission or distribution	3
ENV-TECH 9	Production or processing of goods	4
ENV-TECH 2	Water-related adaptation technologies	5
ENV-TECH 8	Wastewater treatment or waste management	6
ENV-TECH 7	Buildings	7
ENV-TECH 1	Environmental management	8 (More Mature)

Note: The list of environmental-related technologies is provided by OECD (2016). ENV-TECH 3 - "Biodiversity protection and ecosystem health" does not include technological classification codes. This ranking is based on Barbieri et al. (2018b).

Table 4. Regression results with technology life cycle

	Diversification, Short-Term (RTA $<$ 0.1 prior period)	Diversification, Long-Term (RTA $<$ 0.1 first time period)	Specialisation
Density	0.07050***	0.13161***	0.17200***
	(0.01)	(0.01)	(0.01)
Density $\times$ GDP	-0.00229**	-0.00033	
	(0.00)	(0.00)	
Technological-level Variables			
Log Size	0.00857*	0.00652	0.01889***
	(0.00)	(0.01)	(0.01)
Herfindahl Index	-0.11388***	-0.16854***	-0.10849***
	(0.02)	(0.02)	(0.03)
ITC	-0.00065	-0.00042	0.00239
	(0.00)	(0.00)	(0.00)
Maturity	0.02312***	0.02586***	0.03605***
	(0.01)	(0.01)	(0.01)
GDP	0.00116	-0.00036	0.00843***
	(0.00)	(0.00)	(0.00)
GDP$\times$ Log Size			-0.00119***
			(0.00)
GDP $\times$ HHI			-0.01229***
			(0.00)
GDP $\times$ ITC			-0.00002
			(0.00)
GDP $\times$ Maturity			0.00041***
			(0.00)
R^2	0.10189	0.19124	0.22551
Tech Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Obs	13902	19599	24372

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 5. Regression results with the Environment Policy Stringency Index

	Diversification, Short-Term (RTA < 0.1 prior period)	Diversification, Long-Term (RTA < 0.1 first time period)	Specialisation
Density	0.08312	0.12386***	0.17041***
	(0.05)	(0.04)	(0.03)
Density × GDP	-0.00645*	-0.00288	
	(0.00)	(0.00)	
Technological-level Variables			
Log Size	0.02314	0.02719	0.06970***
	(0.03)	(0.02)	(0.02)
Herfindahl Index	-0.20542**	-0.21335***	-0.21122**
	(0.10)	(0.08)	(0.08)
ITC	-0.00457	0.00219	0.00484
	(0.01)	(0.01)	(0.01)
EPSI	0.02212	0.01128	0.05005**
	(0.03)	(0.02)	(0.02)
GDP	0.00105	0.00067	0.00000
	(0.00)	(0.00)	(.)
GDP× Log Size			-0.00131***
			(0.00)
GDP × HHI			-0.00412
			(0.00)
GDP × ITC			0.00002
			(0.00)
GDP × EPSI			-0.00149*
			(0.00)
R^2	0.11967	0.18250	0.17868
Tech Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Obs	2140	5225	7740

* $p < .1$, ** $p < .05$, *** $p < .01$

Appendix A. Measuring life cycle stages

Different methodologies exist in the literature to estimate the development of technologies using patent data. Haupt et al. (2007) try to identify differences in the evolution of patent indicators in relation with the technology life cycle stages. First, the authors identify using a pool of experts and literature review in which development stages are the technologies. Then, they show that patent indicators follow specific patterns depending on the stage of development of the technology. Other studies use patent indicators to identify directly the life cycle stages of technologies (Gao et al., 2013; Chang and Fan, 2016). They use interviews of experts in benchmark technology to define life cycle stages, and assess the trends of patent indicators over its technological evolution. Subsequently, they compare patent indicators of the technologies under analysis with the ones calculated on the benchmark technology assigning the life cycle stage of the latter to the former. Finally, stochastic techniques are also employed to measure technology life cycle. Lee et al. (2012; 2016) run Hidden Markov Models to analyse patent indicators time-series. This technique allows calculating the highest probability path that gives the most probable stage of development at each step of the time series.

Unfortunately, we could not use these methodologies in our research because the identification of technology life cycle stages relies either on benchmark technologies or is based only on the number of patents in the case of Hidden Markov Models. The identification of benchmark technologies to analyse 36 heterogeneous environment-related technologies is nearly impossible, even with the contribution of a wide pool of experts. Moreover, the stage of development of green technologies should not take into account only the evolution of the number of patents as the Hidden Markov Models do, but also the diffusion of technologies over time. It should also take into account that not all intermediate stages are achieved by technologies. Finally, our desired indicator should be able to provide information on the life cycle stage of broad technological domains and not just single patents.

Our methodology proposed below to identify green technologies life cycle stages is based on these two dimensions: the geographical diffusion (ubiquity) and the patenting intensity. We use worldwide patent families for each technology as identified by the OECD in the Env-Tech classification[12]. This leads us to determine the overall stage of development of green technologies to which all worldwide inventors contributed to.

The ubiquity indicator measures how geographically spread are inventive activities in green technologies, relative to country's specialisation. Following Balland and Rigby (2017), we calculate the Revealed Technological Advantage (RTA) for each green technology, country and time period as follows:

$$RTA_{jct} = \frac{Patents_{jct} / \sum_j Patents_{jct}}{\sum_c Patents_{jct} / \sum_{jc} Patents_{jct}}$$

The RTA measures the intensity of the contribution of each country c to the development of Env-Tech technology j at time t. That is, it indicates the proportion of country's patent activity is a specific technology with respect to all green technologies divided by the world's proportion in this same specific technology. A technological advantage is "revealed" for country c in technology j during the time period t if $RTA_{jct} > 1$. Therefore, the ubiquity of each Env-Tech technological domain is given by the number of countries with a Revealed Technological Advantage, as follows:

$$UBIQUITY_{jt} = \sum_c M_{cj}$$

Where $M_{cj} = 1$ if $RTA > 1$.

Consequently, the higher the number of countries specialised in the development of a particular green technology, the higher the UBIQUITY of that technology. In other words, Ubiquity is a proxy to measure the diffusion of green innovative activities. The advantage of this measure with respect to

[12]The Env-Tech classification OECD (2016) groups environmental-related technologies at different digits (up to three). In the present paper we focus the 2-digit which is a compromise between narrow (three digits) and broad (1-digit) technological fields. Table 7 reports the list of green technological domains employed to define technology life cycle stages.

other potential patent indicators of diffusion (such as i.e. citations, family size, etc.) is that it allows capturing specialisation patterns in specific green technologies relative to their global counterparts.

The second dimension is measured using the number of patent families of a green technology at country level filled during a time period. This is a proxy of patenting intensity of each country in the development of green technologies.

Table 6. Life cycle stages

		Ubiquity	
		Low	*High*
Patenting intensity	*High*	**Development**	**Diffusion**
	Low	**Emergence**	**Maturity**

Bringing together these two dimensions (ubiquity and patent intensity) leads us to define four life cycle stages for each technological at the worldwide level, as shown by table 6. The *emergence* phase is characterised by a low level of technological diffusion and intensity. It is the lowest level of maturity, where there is a low patenting activity concentrated in only few countries. We have identified two different strategies (non-exclusive) to reach the maturity stage. The first one consists in an increase of the patenting activity but still geographically concentrated, which is the *development* phase. The other one goes toward a geographical *diffusion* phase meaning an increased number of countries specialised in a technology, but the patenting activity grows at a slower pace. Finally, in the *maturity* phase standardisation in the design and knowledge-related activities is achieved, both patenting intensity and geographical diffusion of inventive activities are at relatively high levels. This approach allows a dynamic understanding of technological evolution in the sense that not all stages are always achieved, and maturity may be an intermediate stage before the appearance of further developments.

In order to assign to each green technology a stage of development, we standardise the indicators by calculating the average of ubiquity and patenting activity for each time period. Then, we attribute a life cycle stage to a technology when its exhibits a value above or below the average value of each dimension. In so doing, the technology life cycle indicator depends on both idiosyncratic features of the technology under analysis and on the stage of development of the other green technologies.

Table 7. Life cycle stages of green technologies

ID	ENV-TECH	1980	1990	2000	2010
1.1	AIR POLLUTION ABATEMENT	4	4	4	4
1.2	WATER POLLUTION ABATEMENT	3	4	4	4
1.3.	WASTE MANAGEMENT	3	3	4	4
1.4	SOIL REMEDIATION	1	1	3	3
1.5	ENVIRONMENTAL MONITORING	1	1	1	1
2.1	DEMAND-SIDE TECH (water conservation)	1	3	3	3
2.2	SUPPLY-SIDE TECH (water availability)	1	1	1	3
4.1	RENEWABLE ENERGY GENERATION	4	4	4	4
4.2	ENERGY GENERATION FROM FUELS OF NON-FOSSIL ORIGIN	1	3	3	4
4.3	COMBUSTION TECH WITH MITIGATION POTENTIAL	1	1	1	3
4.4	NUCLEAR ENERGY	2	2	1	1
4.5	EFFICIENCY IN ELECTRICAL POWER GENERATION, TRANSMISSION OR DISTRIBUTION	1	2	1	1
4.6	ENABLING TECH IN ENERGY SECTOR	1	2	2	2
4.7	OTHER ENERGY CONVERSION OR MANAGEMENT SYSTEMS REDUCING GHG EMISSIONS	1	1	1	3
5.1	CO2 CAPTURE OR STORAGE (CCS)	1	1	1	3
5.2	CAPTURE OR DISPOSAL OF GREENHOUSE GASES OTHER THAN CARBON DIOXIDE (N2O, CH4, PFC, HFC, SF6)	1	1	1	3
6.1	ROAD TRANSPORT	2	4	2	2
6.2	RAIL TRANSPORT	1	1	1	1
6.3	AIR TRANSPORT	1	1	1	3
6.4	MARITIME OR WATERWAYS TRANSPORT	1	1	1	3
6.5	ENABLING TECH IN TRANSPORT	1	1	1	2
7.1	INTEGRATION OF RENEWABLE ENERGY SOURCES IN BUILDINGS	1	1	1	4
7.2	ENERGY EFFICIENCY IN BUILDINGS	1	3	4	4
7.3	ARCHITECTURAL OR CONSTRUCTIONAL ELEMENTS IMPROVING THE THERMAL PERFORMANCE OF BUILDINGS	1	1	1	1
7.4	ENABLING TECH IN BUILDINGS	4	4	4	4
8.1	WASTEWATER TREATMENT	1	3	4	4
8.2	SOLID WASTE MANAGEMENT	3	3	4	4
8.3	ENABLING TECH OR TECH WITH A POTENTIAL OR INDIRECT CONTRIBUTION TO GHG MITIGATION	1	1	1	1
9.1	TECH RELATED TO METAL PROCESSING	3	3	3	4
9.2	TECH RELATING TO CHEMICAL INDUSTRY	1	4	4	4
9.3	TECH RELATING TO OIL REFINING AND PETRO-CHEMICAL INDUSTRY	1	1	1	3
9.4	TECH RELATING TO THE PROCESSING OF MINERALS	1	3	1	3
9.5	TECH RELATING TO AGRICULTURE, LIVESTOCK OR AGROALIMENTARY INDUSTRIES	1	3	1	3
9.6	TECH IN THE PRODUCTION PROCESS FOR FINAL INDUSTRIAL OR CONSUMER PRODUCTS	1	1	2	4
9.7	CLIMATE CHANGE MITIGATION TECH FOR SECTOR-WIDE APPLICATIONS	1	1	1	1
9.8	ENABLING TECH WITH A POTENTIAL CONTRIBUTION TO GHG EMISSIONS MITIGATION	1	1	1	4

ID and ENV-TECH correspond to green technology groups listed in OECD (2016). Numbers in the columns indicate the life cycle stage of green technologies: 1="Emergence", 2="Development", 3="Diffusion", 4="Maturity" (as per Table 6). Dark colours are associated to higher stages of the technology life cycle.

As an illustration, table 7 reports the life cycle stages of green technology in 1980, 1990, 2000 and 2010. Indications from this exercise resonate with information that can be gathered in specialised literature or policy reports. As an example, "Air pollution abatement" (ENV-TECH 1.1), "Renewable energy generation" (ENV-TECH 4.1), etc., are found in the maturity stage since the 1980s. Contrarily, "Environmental monitoring" (ENV-TECH 1.5) or "Rail transport" (ENV-TECH 6.2) remain in the emergence phase. Table 7 also shows some technologies that move from emergence to maturity stages – i.e. "Energy efficiency in buildings" (ENV-TECH 7.2), "Wastewater treatment" (ENV-TECH 8.1). It is important here to emphasise that reaching maturity does not need to go through all the life cycle stages. Moreover, as explained earlier, development and diffusion phases seem to be alternative pathways to achieve maturity.