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Specialisation, diversification and the ladder of green technology development

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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 1970-2012 we identify key drivers of cross-country diversification and specialization. Our first finding is that countries diversify towards green technologies that are related to their existing competences. Notably, the maturity of the green technology matters more than the level of development of each country. The second main result is that countries move along cumulative paths of specialization, and towards more complex 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 specific country 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's 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 involuntary migration.

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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). 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 to adapt to climate change is stronger in poorer countries (Mendelsohn et al., 2006; Bathiany et al., 2018)[1]. In turn, unequal 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 environmen-

[1]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).

tal 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 disregard the influence of country-specific characteristics. 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 specialization in panel of 63 countries over the period 1970-2012 (the list of countries is available in Appendix B). Our empirical approach replicates the methodology proposed by Petralia et al. (2017) and extends it to green technology using disaggregated data of patenting activity. In particular, we set out to uncover the general trends of green technological specialization, 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 two. First, countries are more likely to diversify into domains of green technology that are related to their portfolio of competences. This is coherent with prior literature (e.g. Petralia et al., 2017), with the exception that our result does 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 are a bigger obstacle than gaps in wealth. Second, we find that countries move along cumulative paths of specialization, and towards more complex technologies. At the same time, and contrary to prior studies, the complexity of green technologies per se is not an obstacle to further specialisation. Notably, this holds true even for developing countries.

The paper is structured as follows. After a review of the relevant literature in Section 2, we detail the main data sources and the procedure for the construction of the main variables. In 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, policies for green innovation confront a diverse array of barriers. The first is that uncertainty on the appropriability of the prospective environmental benefits (Jaffe et al., 2005; Newell, 2010) due to clean technologies adds to the classic underinvestment due to free riding on R&D (Arrow, 1962; Nelson, 1959), thus creating a 'double externality'. 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).

The complexity associated with these generic 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 mitigate GHG emissions 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 matters 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), and such a distinctiveness is shaped by 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 facilitate the growth of knowledge and increase 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 system 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 shaped 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 subjected to endogenous barriers, and replicating the characteristics that granted leadership in early stages may simply not suffice (Nelson, 2008). Indeed, the notion of technical change based on mere adoption of machinery produced elsewhere has long been deemed as inadequate on the grounds that it overlooks the investments in intangible capital that are necessary not just to operate machines but to select and integrate them in the extant production infrastructure (Rosenberg, 1970; Bell and Pavitt, 1993).

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). A 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 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. Innovation studies have employed a variety of data sources to measure environmentally-related innovative activities (Haščič and Migotto, 2015). R&D expenditures can be used to track the input of the innovation process but they lack fine-grained information to identify precisely environmental technologies. This data source is usually available at state-level and for a limited number of countries (see e.g. Komen et al., 1997). Moreover, R&D expenditures do not allow discerning between different types of green technologies (e.g. renewable energy, alternative transportation, etc.) since they are generally provided at an aggregate level. Another source of information can be obtained from ad-hoc innovation surveys (see e.g. Cainelli and Mazzanti, 2013). Instances of these are the Community Innovation Survey or Innovation survey in Japan or Canada. However, they are available for some countries at short time series making comparison between countries unfeasible.

In the present study we follow previous country-level empirical works and exploit the wealth of information provided by patent data (Nesta et al., 2014; Miao and Popp, 2014). Patents provide highly disaggregated information on each invention, in particular the location of the inventor and the characteristics of the invention (e.g. the type of technology, citations received, etc.) which are essential for our purposes. Since patents provide a good indicator of R&D activities, as applications are usually filed early in the research process (Griliches, 1990) they have been employed in different studies to track overall inventive activities (see, among others, Castaldi et al., 2015;) as well as green ones (see, among others, Gagliardi et al., 2016; Barbieri et al., 2018a; Barbieri et al., 2018b). As for green inventions, patent data enable us to identify specific climate change adaptation and mitigation technologies (as discussed below) discerning between the type of technology and where the invention has been developed (Popp, 2005). In addition, while we acknowledge that not all inventions are patented, the characteristics of intellectual property rights 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). Overall, it is important to stress that using patent data enables us focusing only on the technological side of the transition towards sustainable societies (Kemp and Pearson, 2007).

Our main source is the PATSTAT dataset (2016 spring version, source: European Patent Office, EPO). To build this dataset, EPO relies on EPO's master bibliographic database DOCDB and INPADOC Legal Status databases. It contains worldwide information on more than 80 millions patent applications provided by more than 170 patent offices and compiled by EPO, from 1782 to 2016. We identify in this database patent applications related to green technologies using the OECD Env-Tech classification (2016), which lists International Patent Classification (IPC) and Cooperative Patent Classification (CPC)[2] codes concerning 95 green technologies, grouped into 8 families and 36 subgroups[3]. From this, we identify 1,262,281 patent families (2,730,236 patent applications) from 1970 to 2012 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 information on inventors' addresses to geocode each patent family at city level using fractional counting (i.e. if a patent family

[2]The IPC and CPC are two technology classification systems employed by patent offices to classify patent documents relatively to their technicalities. These classification systems are characterised by a hierarchical structure that describes the technical content of the patents through classification codes. At the lowest level of this hierarchy, i.e. full-digit, the codes are very specific and refer to narrow technological fields, 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 domains, e.g. IPC 1-digit C - "Chemistry, Metallurgy".

[3]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.

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). Information on the location of inventors from PATSTAT is parsed through GeoNames[4] 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 929,829 patent families (with at least 1 inventor geolocalized - 57.2% patent families have more than half of their inventors geolocalized), in 146 countries.

Complexity of green technologies. The second key dimension in our analysis is the complexity of green technologies. For this we employ the methodology of Petralia et al. (2017) built on the seminal work of Hidalgo et al. (2007). In our study, technologies are the 36 items identified by means of OECD Env-Tech classification (2016) 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:

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

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

[4]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.

Where c stands for country, j for Env-Tech subgroup, t for the year between 1970 and 2012, and I[.] represents the indicator function. This measure provides information on country's specialization in each technology, comparing the share of that technology in country's technology production with the worldwide average share of that technology for each year. 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 year 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 $t = 1970$).

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 year, 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) demonstrates that the measure of complexity for countries and technologies can be calculated 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 year 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 help us understand the specialization 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 Petralia et al., 2017. 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, etc...) 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 Petralia et al. (2017), 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:

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

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 we have a measure to estimate the proximity of green technologies between them, we can calculate how close is a 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 year t. This variable illustrates the capacities of country c to produce patents in technologies related to technology j in year t, which help to understand if capacities in the production of related technologies are linked to diversification in other technologies.

Other variables. We calculate for each Env-Tech class and each year, the number of patent families produced (Size), and the Herfindhal Index. The size will be used to control for scale effects. As is common in the literature, the Herfindhal Index is used here as an indicator of competition among countries in each technology[5]. We also control for the level of development of each country's economy over time through proxied by GDP (Source: Green Growth Knowledge Platform[6]).

[5] Given the specificities of the OECD Env-Tech classification (2016), we do not use technology value added like Petralia et al. (2017). 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.

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

4. Empirical Analysis

4.1. Descriptive Statistics

Table 1 shows descriptive statistics of our variables. To facilitate comparability with Petralia et al. (2017) we limit the dataset to 63 (our 146) countries, covering 35 green technologies, from 1970 to 2012. About 28% of countries specialized in a technology at year t ($S_{cjt} = 1$) were not specialized in the same technology a year before (identified in the column NPA_{cjt-1}), which we define as a diversification event. On the other hand, 22% of the observations were having a patent activity in year $t-1$ (identified in the column PA_{cjt-1}) and lost their technological advantages on year t ($S_{cjt} = 0$). These proportions are respectively higher and lower than those reported by Petralia et al. (2017), in that we find stronger frequency of specialisation in green technologies but, 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 specialization 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 (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 $t = 1970$) and, second, by accounting only for the cases in which there was no patenting activity in the prior year ($RTA_{cjt-1} < 0.1$). Contrary to what Petralia et al. (2017) 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 (patent production depending on firm strategies and rate of patenting varying over time and space could lead to a misrepresentation of the real knowledge production) apply.

We estimate two different linear probability models, one for diversification and the other for specialization. Both models include dummies for green technologies, countries and years in order to control for potential biases introduced by peculiarities of certain green technologies, countries or years. We specify two models as follows:

- Diversification equation

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

- Specialization equation

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

Where c, j, and t identify respectively countries, green technologies and years, S_{cjt} takes the value of unity when a country c has an RTA above unity in a technology j in year t, GDP_{ct} is the GDP per capita for country c and year t, $Density_{cjt}$ is the proximity of surrounding green technologies in country c to technology j in year 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 seeks to capture the effect of a country possessing competences in proximate technologies on diversification, and to further assess if the effect is higher when the diversification is recent or if it dates back to the beginning of the sample. The second equation aims at identifying the patterns of specialization 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. When we run regressions for this model, we interact all the variables with GDP to assess if there are patterns according to the level of development. Last but not least, we extend the framework of Petralia et al. (2017) by estimating diversification and specialization in a model adding a variable called maturity, which represents green technology life cycle stage (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

Table 2 & 4 show the results obtained from the regressions. Both tables report the results of three models: in columns (1) and (2) are the diversification models, the difference being the sample selection, and column (3) shows results from the specialisation model. Our benchmark for the interpretation of results are the findings of Petralia et al. (2017) with the proviso that we focus on green technologies.

The specification of Table 2 shows a positive and significant correlation between density and diversification. This result holds if we consider diversification with respect to the previous year as well as diversification with respect to the first year at the beginning country time-series. This positive relationship suggests that having technological capabilities in cognitive related technologies increases the likelihood of entering into a new-to-the-country green technological domain. The result is in line with previous studies that emphasise 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). Similar results have been provided by Noailly and Shestalova (2017) who point out that renewable energy technologies benefit, among other factors, from intra and inter-technology spillovers.

The positive correlation between density and diversification indicates that the finding of Petralia et al. (2017) holds for green technologies. However, in our study the interaction between Density and GDP is not statistically different from zero (Column 1 and 2). Petralia et al. (2017) find a negative coefficient, meaning 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. We ascribe the lack of a significant relationship in our results to a the peculiarity of green technologies, namely that they are altogether at an 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 positive and significant coefficients for the technology-level variables (i.e. Size and ITC) with the exception of a negative and significant coefficient for the Herfindhal index. This suggests that diversification is higher when patenting activities are spread across different countries, i.e. diversification in new green technological fields is favoured by worldwide distribution of green technological advances. The main difference with respect to Petralia et al. (2017) is the effect of technology complexity: whereas their reported coefficient is negative and significant ours is positive and significant. This implies that in the case of green technologies the likelihood of diversification and specialisation increases with technological complexity. To support this finding we recall the intrinsic features of green technologies. In a recent paper, Barbieri et al. (2018a) compare green and non-green technologies across different knowledge dimensions. It has been observed that green technologies are more complex, radical and exert higher impacts on subsequent technologies with respect to non-green ones. In particular, the authors find that green technical knowledge emerges from a variety of knowledge sources that spans a wide spectrum of cognitively distant knowledge fields. Moreover, environmental-related technologies recombine a higher amount of technological components that are drawn from different domains. That is, directing technological change towards a sustainable path requires substantial efforts in bringing together different knowledge sources, more so than in established technological domains.

Results from the specialization equation are shown in the third column of Table 2. Therein the coefficient of technology density is positive and significant in line with Petralia et al. (2017). This corroborates the idea that, even in the domain of green technologies, operating in proximate fields increases the likelihood of specialisation. Size is also positive and significant while the Herfindhal index is not. We also find that technology complexity has a positive and significant association with specialisation, in contrast with Petralia et al. (2017). However when we interact these variables with GDP, our findings suggest that the likelihood of specialising in a given green technological field decreases as far as complexity and GDP increase. Although the size of the coefficient is low, important non-linearities arising from this interaction will be discussed below. The coefficient indicates that there is a moderating effect of technological complexity in the technological specialisation of low-mid and high income countries. As discussed in details below, this result suggests that for low-mid income countries the complexity of green technologies does not represent a barrier to specialisation. As for high income countries the likelihood of specialising in a green technology is higher for less complex technologies (with respect to more complex ones). However, it is worth noting that the capacity of low-mid income countries is not only linked to the number of patent families they produce, but also with their internal capabilities. For example, Estonia produces more patent than Colombia or Venezuela but its Complexity Index is lower, meaning that Estonian portfolio of technologies is less complex on average than the Colombian or Venezuelian ones. Moreover, as shown in 2 high income countries have higher probability of specialising in more complex technologies with respect to less developed countries. However, whereas for low-mid income countries the likelihood of specialising in green technologies increases as far as the complexity grows, high income countries experience the opposite trend, i.e. the probability of specialisation is higher for less complex technologies.

Given the idiosyncratic features of our domain of analysis, we investigate whether and to what extent the degree of maturity of green technologies affects our results. To this end we refer to 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 other domains such as i.e. "Environmental or Waste management" (Env-Tech 1-2) are at a more mature stage (Barbieri et al., 2018b).[7]

Table 4 shows results of the regressions articulated according to this life-cycle classification. Therein,

[7] It is worth noting that the level of maturity is calculated relative to the stage of development of all green technologies.

the coefficient of technological maturity (i.e. TLC) is positive and significant in all specifications. That is, high levels of technological maturity are associated with an increased probability to diversify in green technological fields that had not previously been explored by the country. The result holds if we focus on 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 likelihood of specialising in mature technologies.

Figure 1 summarizes the probability of diversification taking into account the margins at different levels of GDP (left panel) and technological complexity (right panel) with darker colors showing a higher probability and isolines indicating probability values.

On the left-hand panel, the probability of diversification increases when both the country's capabilities in producing inventions in related green technologies and the GDP increase. However, the presence of related capabilities is more important for developed countries since their probability of diversification increases from 8% at low values of Density to 14% for high values of Density. Also developing and emerging countries experience a similar trend, although they move from almost 7% at low level of relatedness to less than 10% at high levels of Density. On the right-hand panel of figure 1, we focus on the relationship between Density and technological complexity and the probability of diversification. In Table 2 we observe that Density and technological complexity have a positive relationship with diversification. That is, having technological capabilities in neighboring green technologies increases diversification. The same result holds when we consider technological complexity. At a constant level of related capabilities (i.e. Density) the probability of diversification increases at high values of complexity meaning that the latter does not represent a barrier for diversification. In comparison, Petralia et al. (2017) report a negative relationship: the more complex is a technology, the lower is the probability of diversification with a similar level of density. Our reading of this difference is that diversifying into new green technological domains entails operating in a more complex system due to less advanced specific know-how. From this it follows that possessing capabilities in related domains enables diversification, even towards more complex green technologies. This resonates with the tenet that emphasises the centrality of human capital for generating and managing change beyond mere technology adoption (Rosenberg, 1970; Bell and Pavitt, 1993). Indeed, dealing with environmental pressures raises issues beyond the issue of acquiring access to clean technologies developed elsewhere. Under the proviso that the effects of climate change are strongly tied to the specificities of place, standardisation that exploits the replication of existing blueprints only goes so far. Rather, local innovation and innovation capabilities are centrally important for adapting technology to the local needs for environmental sustainability.

Figure 2 illustrates how the probability of specialization in new green technologies depends on the characteristics of the technology and on the economic performances.

The left-hand panel shows the extent to which the probability of specialization changes according to green technologies density and the complexity. These results confirm the finding associated with diversification. That is, the probability of specialisation tends to be higher when complex green technologies (usually associated with a higher economical value) are concerned and when countries have inventive capabilities in surrounding green technologies (density) in the country increases. Conversely, the right-hand panel of Figure 2 represents the effects of the technology complexity and the economic performances of the countries (proxied through GDP per capita) on the probability of specialization. We observe two main trends. First, when GDP is high the probability of specialising in green technological fields is higher for low values of technological complexity. In other words, as expected, more developed countries specialise in less complex technologies. Second, however, also countries with low levels of GDP are more likely to specialise into more complex technological fields. In this case the probability of specialisation is clearly lower compared to developed countries', but it increases together with technology complexity. The non-linearities emerging from Figure 2 (right panel) therefore indicate that the complexity of green technologies is not per se a barrier to specialisation for countries in the middle of the income distribution.

This, other than adding to previous literature, including but not limited to Petralia et al. (2017), 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.

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 entail 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 specialization in environmental technology development, and on their drivers. This exercise yields two 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. While this is coherent with prior literature, our results are peculiar in that the observed effect does not exhibit strong association with the stage of development of a country – as in Petralia et al. (2017) – but, rather, with the maturity of the green technology. In particular, differences in competences are a bigger obstacle than differences in wealth. Second, in line with prior studies, we find that countries move along cumulative paths of specialization, and towards more complex technologies. At the same time, and contrary to other studies the complexity of green technologies is not an obstacle to specialisation.

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. 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.

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Tables and Figures

Table 1. Main Descriptive Statistics

	Obs	Mean	SD	Min	Max
Specialization	95976	0.179	0.384	0	1
Log Size	95976	4.983	2.022	0	9.231
Herfindhal Index	95294	0.300	0.180	0	1
ITC	95294	12.338	3.266	3.556	23.5
Density	94550	0.416	0.404	0	1
GDP Per Capita	77065	12822.7	15636.0	97.2	113239.6

Correlation Table						
Specialization	1					
Log Size	0.213	1				
Herfindhal Index	-0.100	0.036	1			
ITC	-0.113	-0.562	-0.098	1		
Density	0.398	0.163	-0.070	0.042	1	
GDP	0.232	0.240	-0.120	0.038	0.484	1

Specialization	PA_{cjt-1}	NPA_{cjt-1}	Total
$S_{cjt} = 1$	0.723	0.277	1
$S_{cjt} = 0$	0.217	0.783	1

Number of countries: 63
Number of technologies: 35
Coverage: 1970 – 2012

Table 2. Results of the Econometric Model

	Diversification Equation (RTA < 0.1 in the previous period)	Diversification Equation (RTA < 0.1 at the beginning of the sample)	Specialization Equation
Density	0.02746***	0.11723***	0.13949***
	(0.01)	(0.01)	(0.01)
Density × GDP	0.00049	0.00030	
	(0.00)	(0.00)	
Technological-level Variables			
Log Size	0.00497**	0.00658***	0.01495***
	(0.00)	(0.00)	(0.00)
Herfindahl Index	-0.01898***	-0.04997***	0.01416*
	(0.01)	(0.01)	(0.01)
ITC	0.00169***	0.00389***	0.00484***
	(0.00)	(0.00)	(0.00)
GDP	0.00012	0.00016	0.00736***
	(0.00)	(0.00)	(0.00)
GDP × Log Size			-0.00049***
			(0.00)
GDP × Herfindahl Index			-0.01453***
			(0.00)
GDP × ITC			-0.00012**
			(0.00)
R^2	0.098	0.209	0.228
Tech Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Obs	51149	70547	77065

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

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. Ranking is based on the results of the paper Barbieri et al. (2018b) and increases with maturity.

Table 4. Regression results with technology life cycle

	Diversification Equation (RTA < 0.1 in the previous period)	Diversification Equation (RTA < 0.1 at the beginning of the sample)	Specialization Equation
Density	0.02746***	0.11723***	0.13872***
	(0.01)	(0.01)	(0.01)
Density × GDP	0.00049	0.00030	
	(0.00)	(0.00)	
Technological-level Variables			
Log Size	0.00497**	0.00658***	0.01555***
	(0.00)	(0.00)	(0.00)
Herfindahl Index	-0.01898***	-0.04997***	0.00558
	(0.01)	(0.01)	(0.01)
ITC	0.00169***	0.00389***	0.00464***
	(0.00)	(0.00)	(0.00)
Maturity	0.02568***	0.04474***	0.04034***
	(0.00)	(0.00)	(0.00)
GDP	0.00012	0.00016	0.00523***
	(0.00)	(0.00)	(0.00)
GDP× Log Size			-0.00053***
			(0.00)
GDP × HHI			-0.01311***
			(0.00)
GDP × ITC			-0.00008
			(0.00)
GDP × Maturity			0.00037***
			(0.00)
R^2	0.09796	0.20889	0.22834
Tech Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Obs	51149	70547	77065

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

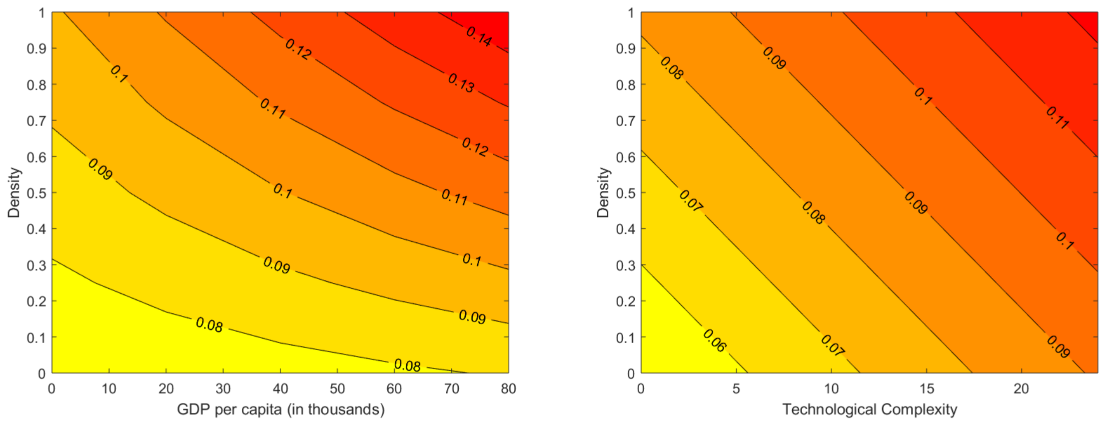

Figure 1. Diversification probabilities according to the characterics of technologies and countries.

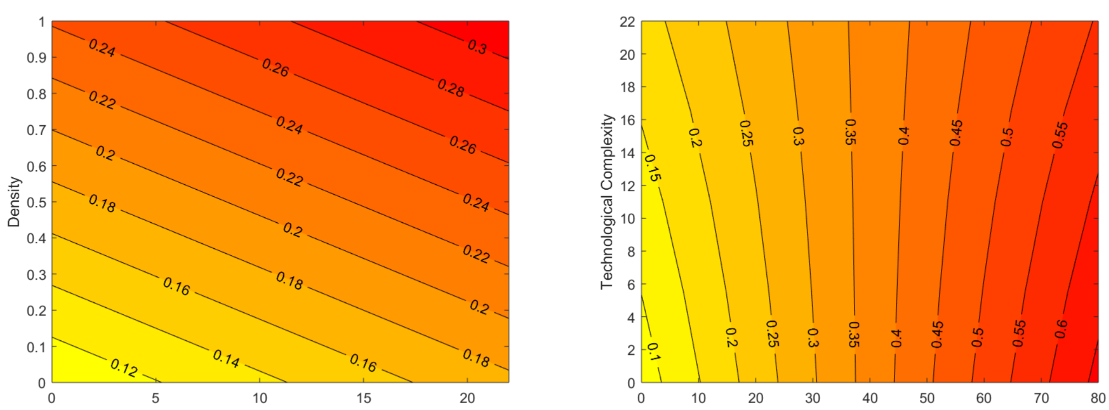

Figure 2. Specialization probabilities according to the characterics of technologies and countries.

Appendix A. Measuring life cycle stages

Different methodologies to assess the stage of development of technologies through patent data have been retrieved in the literature. Haupt et al. (2007) rely on patent indicators and empirically test their difference along the technology life cycle stages. Although they do not directly use patent indicators to detect the stage of development of technologies, the authors show that these indicators follow specific patterns depending on the stage of development of the technology – whose life cycle stages are defined a priori by a pool of experts and literature review. Other studies directly employ patent indicators to identify the life cycle stages of technologies (Gao et al., 2013; Chang and Fan, 2016). These works define life cycle stages of a benchmark technology through expert interviews 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.

In our work we could not apply these methodologies because they strongly rely on benchmark technologies from which the life cycle stages are derived or focus just on the number of patents as in the case of Hidden Markov Models. In fact, we study here a broad number of heterogeneous environmental-related technologies for which a benchmark technology is hard to identify – even with the contribution of a pool of experts. In addition, we acknowledge that the stage of development of green technologies should take into account how technologies diffuse over time and not just the intensity of patenting. Moreover, 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 not just single patents.

To identify the maturity of green technologies, we develop a measure of technology life cycle based on two indicators: the geographical ubiquity and the intensity of patenting. We calculate these using worldwide patent families for each macro-technology reported in the Env-Tech classification[8]. This enables us to measure the overall stage of development of green technologies to which all worldwide inventors contributed to.

The ubiquity indicator captures the extent to which innovative activities are geographically spread relative to countries' specialisation in green technologies. Following Balland and Rigby (2017), the geographical scope of inventions is calculated using 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 captures the efforts spent by a country in developing a specific green technology (numerator) with respect to global efforts in developing the same technology (denominator). The ubiquity of each Env-Tech technological domain is given by the number of countries that exhibit a given RTA in a particular green technology at time t:

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

Where $M_{cj} = 1$ if $RTA > 1$. Therefore, 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, the indicator is a proxy for diffusion of green innovative activities. The advantage of this measure with respect to 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

[8]The OECD Env-Tech classification (2016) groups green 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 6 reports the list of green technological domains employed to define technology life cycle stages.

their global counterparts.

We calculate a second indicator based on the number of patent families in Env-Tech Technologies at country level. This is a proxy of patenting intensity of each country in the development of green technologies. Finally, we measure the average growth rate over four years of both patenting intensity and the ubiquity indicator. This enables us to smooth the trends in both indicators and capture their dynamics over time.

Table 5. Life cycle stages

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

Combining ubiquity and patenting intensity allows us to define the life cycle stages of each Env-Tech technological domain at the worldwide level. Table 5 shows that the *emergence* phase is characterised by a low level of technological diffusion and intensity. It represents the lowest level of maturity of the technology where inventive activities are highly concentrated in few countries and the number of patents is relatively low. To reach the maturity stage we have identified two (non-exclusive) main strategies. The first implies moving from the emergence to a *development* phase in which technological advances are still geographically concentrated and characterised by intense patenting activity that favours the development of the green technology. Otherwise, technologies may be in a *diffusion* phase, wherein a growing number of countries specialise in the same green technology but patenting intensity increases at a lower 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. On the whole, this approach affords a dynamic view of technological evolution in that not all stages are always achieved, and maturity may be an intermediate stage before the appearance of further developments.

We assign green technologies to a particular stage of development by standardising the indicators and defining the low (high) values shown in 5 if the technology exhibits ubiquity or patenting intensity below (above) the average value. 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 6 reports the life cycle stages of green technology in 1980, 1990, 2000 and 2010. The indications emerging from this exercise resonate with insights that can be gathered in specialised literature or policy reports. To illustrate, "Air pollution abatement" (Env-Tech 1.1), "Renewable energy generation" (Env-Tech 4.1), etc., is found in the maturity stage since the 1980s. Conversely, "Environmental monitoring" (Env-Tech 1.5) or "Rail transport" (Env-Tech 6.2) remain in the emergence phase with respect to other green technologies. Table 6 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). Importantly, reaching maturity does not imply passing through all the life cycle stages. Development (high patenting and low ubiquity) and diffusion (low patenting and high ubiquity) seem alternative pathways to achieve maturity.

Table 6. 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 IN-DUSTRIAL 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 CONTRIBU-TION 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 5). Dark colours are associated to higher stages of the technology life cycle.

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