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**Specialization, diversification and environmental technology life-cycle**

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# Specialization, diversification and environmental technology life-cycle

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**Abstract.** The paper analyses whether and to what extent regional related and unrelated variety matter for the development of green technology, and whether their influence differs over the technology life-cycle. Using patent and socio-economic data on a thirty-year (1980-2009) panel of US States, our study finds that unrelated variety is a positive predictor of green innovative activities. When unpacked over the life cycle, we find that unrelated variety is the main driver of green technology development in early stages while related variety becomes more prominent as the technology enters into maturity.

**KEYWORDS:** Green technology; Technology life-cycle; Regional Diversification

**JEL:** O33; Q55; R11

## 1 Introduction

The objective of this paper is to analyse whether and to what extent regional related and unrelated variety matter for the development of technology, and whether their influence differs along the various stages of the technology life-cycle. To address these questions, we focus on green technology, a particular instantiation of innovation consisting of standards and artefacts aimed at mitigating or reversing the negative effects of human action on the environment. We frame the analysis in the context of economic geography under the premise that climate change is a global phenomenon with markedly local manifestations, and that regions and countries differ significantly both in their exposure to climate events as well as in their ability to respond to them. From a policy perspective, the green economy is often touted as holding the potential for new growth and job creation. At the local scale, the pressure is on regions' and countries' institutions to create the adequate premises for innovation in adaptation and mitigation strategies.

Economic geographers and innovation scholars concur that the more diverse the spectrum of know-how available in a region, the greater the potential of successfully exploiting available inputs as well as unexplored interdependences between them (Rigby and Essletzbichler, 1997; Frenken and Boschma, 2007; Balland and Rigby, 2016). This rests on the premise that the composition of activities through which knowledge is channelled into productive uses affects the rate and direction of technical change in a region. In this vein, it has been argued, the more sectors are related, the easier is recombination stemming from the transfer of knowledge from one context of application to another. A thorough review of empirical studies by Content and Frenken (2016) confirms that relatedness is an important driver of regional diversification across a broad spectrum of dimensions (e.g., products, industries, technologies) and of spatial units (e.g., countries, regions, cities, labour market areas) of analysis. In particular, related diversification is observed to be a stronger driver compared to unrelated diversification. This is, to some extent, not surprising considering the nature of these constructs. Diversification is an uncertain process that can be better dealt with by relying on available local resources, and on well-tested connections across them, both trademark features of related variety. Unrelated diversification, on the other hand, entails implementing new forms of coordination across different and formerly unassociated capabilities (Desrochers and Leppälä, 2011; Boschma, 2017). At the same time, Boschma and Frenken (2006) call for caution against determinism, highlighting that spatial contingencies are of minor importance at the initial stage of development of a sector, because a gap is likely to exist between the requirements of new knowledge and the established environment.

Within this debate, the question of whether and to what extent related and unrelated variety actually affect technological innovation has been addressed only recently by Castaldi et al. (2015). Their empirical analysis on the United States (US) shows that the two forms of regional diversification are not opposite but, rather, complementary forces. In particular, radical innovations is observed more frequently in federal states with a diversified knowledge base across unrelated domains, whereas incremental innovation has a stronger association with related variety in local knowledge. The present paper aims to move this analysis forward by distinguishing between related and unrelated variety along the path of development of green technology. In so doing we take issue with the notion that either related or unrelated variety are drivers of innovation regardless of the life-cycle stage of the technology.

We propose that it is important to consider simultaneously region-specific and external factors that may trigger opportunities for new industry and technologies to emerge. To this end, we adopt a regional knowledge production function (RKP) approach that incorporates qualitative features of the local knowledge base as well as the degree of maturity of technology. So far, the analysis of regional innovation has focused mainly on the extent to which R&D and human capital interact (Charlot et al., 2015) and affect (Crescenzi et al., 2015) the innovation generation process. However, following the evolutionary tenet that innovation is the result of successful recombination of existing ideas (Schumpeter, 1939; Basalla, 1982; Weitzman, 1998; Arthur, 2007), we account for the fact that the structure of the regional knowledge base and the relatedness between its components influence the recombination process (Frenken et al., 2007; Castaldi et al., 2015). Against this backdrop, we expect the life cycle stage of technology to determine whether local diversification (or specialisation) across knowledge domains provides the highest benefits for innovation.

The study builds on the above to test two conjectures. The first is that unrelated variety of the local knowledge stock matters for innovation at early stages of the technology life-cycle while related variety has little or no effect. The second is that, as the technology approaches maturity, related variety of the local knowledge base is the major driver, while unrelated variety loses progressively prominence. The empirical analysis is on green technology development in a panel of 48 US federal states and District of Columbia

(D.C.) between 1980 and 2009. Our main data source is the catalogue of patent applications contained in PATSTAT. From this, we extract information on patent family to develop an original indicator for the stage of development of green technologies, and on the location of inventors to assign patents to states. In order to study the relationship between technology life cycle and regional knowledge structure we build entropy indicators that are decomposed at different levels of relatedness between technological domains (Jacquemin and Berry, 1979; Attaran, 1986; Frenken et al., 2007; Castaldi et al., 2015). Finally, we follow the parametric approach proposed by Charlot et al. (2015) and adopt a random growth specification of the unobservable part of the model to control for time-invariant regional characteristics, common time effects and time-varying unobservable features whose exclusion would bias the econometric estimation.

The analysis yields two main findings. First, green technology development exhibits stronger association with unrelated variety than with related variety. This is not surprising considering that, first, the transition towards environmentally sustainable production is still at early stages (OECD, 2015) and, second, that green technology, being more complex than non-green technology, requires the orchestration of diverse and cognitively distant knowledge inputs (Barbieri et al, 2018). The second key finding is that unrelated variety has stronger association with the early stages of the green technology life cycle, while related variety becomes more important as technology enters into maturity. On the whole, the paper claims novelty on three fronts. First, we operationalise the empirical connection between the technology life cycle and the knowledge base, which had so far only been approached on conceptual grounds (Vona and Consoli, 2015). The second contribution is to the debate spurred by Castaldi et al (2014) on whether and to what extent related and unrelated variety affect technological innovation, with the additional benefit of the life-cycle perspective. Third, last but not least, we add empirical evidence on the connection between environmental sustainability and regional studies on which, according Truffer and Coenen (2012), the sub-discipline of environmental economic geography has been largely silent.

The remainder of the paper is organised as follow. The next section presents the theoretical background of the article. Section 3 describes the data, variables and empirical strategy. Finally, whereas Section 4 presents the descriptive statistics and discuss the results, Section 5 concludes the paper and illustrates the policy implications.

# 2 Theoretical background

## 2.1 Industry life cycle and agglomeration economies

In economic geography, two complementary pathways are usually seen as triggers for regional development. One dates back to Marshall's (1920) idea of interaction and proximity of goals and of competences, whereas the other stems out the work of Jane Jacobs (1969) and thrives on the diversity of competences of the local economy. Glaeser et al. (1992) have further extended this framework emphasising the importance of diversification for urban growth. The question of whether industries benefit in different ways from agglomeration externalities depending on their stage of maturity has been recently explored from both empirical and theoretical perspectives.

The life cycle heuristic has been a staple of scholarly research on the opportunities and the challenges associated with innovation. Empirical evidence both from regional economics (Norton, 1979; Norton and Rise, 1979; Markusen, 1985) and industrial dynamics (e.g. Gort and Klepper, 1982; Abernathy and Clark, 1985; Audretsch and Feldman, 1996; Klepper, 1996; 1997; Agarwal and Gort, 2002) supports the conjecture that emerging industries grow at a faster pace than those locked into old, mature industries.[1] Duranton and Puga (2001) elaborate a conceptual framework that explains how diversification and specialisation favour, respectively, young and mature industries. At the beginning of the life cycle young firms need experimentation of their new products or prototypes. Diversified local environments act as the seedbed for alternative production processes that can be tried, adopted or discarded by firms. However, when firms reach maturity and need to switch to mass production, specialised cities are more suitable due to lower production costs. These findings are confirmed by empirical studies that have investigated the association between agglomeration economies and industry life cycle. Neffke et al. (2011a) confirm Henderson et al.'s (1995) insights showing that Marshallian specialisation externalities exert a positive impact as long as maturity is reached. On the contrary, young industries benefit from local diversity that becomes even negative for mature ones (Neffke et al., 2011).

[1] For instance, Norton and Rise (1979) find that the decline of the US Manufacturing Belt during the late sixties was essentially a core-periphery realignment, which has theoretical roots in the product life cycle framework. The decentralisation of production to peripheral Southern and Western states followed the dispersion of innovative capacity and the rise of new, high-tech sectors at the beginning of the life cycle.

The process that links together agglomeration externalities and industry growth along the life cycle has been studied in depth in a strand of economic geography that places diversification at the heart of the innovation process. In particular, diversification leads to regional growth due to the knowledge spillovers and learning opportunities that urban diversity brings about (Glaeser et al., 1992; Duranton and Puga, 2001; Frenken et al., 2007). In turn, empirical evidence confirms that Jacob's externalities are associated with the adoption of new production processes or the development of new product, whereas Marshall externalities are often perceived as detrimental (Harrison et al., 1996; Kelley and Helper, 1999; Feldman and Audretsch, 1999; Castaldi et al., 2015). The theoretical explanation of the positive relationship between diversification of the regional structure and the generation of innovation can be found in the recombinant innovation theory (Schumpeter, 1939; Nelson and Winter, 1982; Weitzman, 1998; Fleming, 2001). Therein, the higher the availability of pieces of knowledge the higher the likelihood of successfully recombining knowledge in an original manner that leads to innovation. In this context, local search and bounded rationality are important dimensions (March and Simon, 1958; Nelson and Winter 1982), so innovators tend to recombine bits of knowledge they are familiar with in order to decrease the risk of failure even though. In so doing, however, they reduce the chances of developing radical innovation. On the contrary, when innovators recombine cognitive distant bits of knowledge they face higher uncertainty but, if successful, the resulting innovative output exerts higher impacts.

The recent evolutionary turn in economic geography builds on tenet that Jacobs externalities do not merely lead to a more efficient division of labour within regions. Rather, in a diversified environment the opportunities for innovation increase due to the availability of different types of knowledge that is geographically close and can be recombined. Along these lines, Frenken et al. (2007) moved the debate on agglomeration economies further by acknowledging that diversification per se does not fully capture the mechanism that brings about regional economic growth. The flow of knowledge within regions requires a balance of cognitive distance to avoid lock-ins and of cognitive proximity to enable effective learning (Nooteboom, 2002; Iammarino and Boschma, 2009). The notion of related (unrelated) variety has been put forth to explain how agglomeration externalities lead to regional growth. Related industries share some cognitive structures that enhance learning opportunities and knowledge spillovers that enable regions to growth faster – a result that has been confirmed by an increasing number of studies (Frenken et al., 2007; Essletzbichler 2007; Bishop and Gripaios 2010).

These studies have directly or indirectly assumed that diversified local contexts are supportive of knowledge spillovers and recombinant innovation. Castaldi et al. (2014) have directly tested to what extent diversified regional knowledge bases trigger the generation of innovation. Their findings are in line with the recombinant nature of innovation put forward by evolutionary studies. More radical innovations seem to emerge in regions whose knowledge base is diversified across cognitive distant technological domains, whereas incremental innovation are developed in regions characterised by related variety in local knowledge.

### 2.2 Technology life cycle in the regional knowledge production function

The literature presented above emphasises the key role that technological change plays in regional development. Along the life cycle, industries rely on different types of innovation that require different sources (Norton and Rise, 1979). The birth of new industries typically follows radical innovation and the development of immature technologies, whereas once a dominant design is established, technological disruptions are less likely and the industry reaches a maturity stage in which innovation is mostly incremental (Neffke et al., 2011a). Such a mechanism implies that industries exploit different types of agglomeration externalities according to their stage of maturity. So far, we have observed that existing studies treat technology as a latent element that evolves and leads to industry maturity. Agglomeration economies are beneficial for industry and regional growth because of their indirect effect in terms of knowledge spillovers and learning opportunities. However, no study has provided a direct test to explore why agglomeration externalities should trigger industrial technology.

Like industries or products, technology evolves along a S-shaped (or double-S-shaped) life cycle moving from a period of introduction to growth, maturity and decline (Achilladelis et al., 1990; Achilladelis, 1993; Andersen, 1999; Haupt et al., 2007). In the introduction phase different pieces of knowledge are recombined to obtain a new technology that differs from what has been developed before. In this phase, a small number of firms are involved in the experimentation and aim at solving the technological problems that characterise this activity. The technology that emerges in this phase is often associated with high production costs, low penetration in the market and uncertainty in the potential use of the technology itself (Callon, 1998). In the growth phase the lower uncertainty that surrounds the new technology triggers a phase of development in which R&D risk decreases, innovation is less radical and the number of innovators increases (Haupt et al., 2007). Finally, when a dominant design is reached the technology enters a maturity phase that is mainly characterised by incremental innovation, high standardisation and widespread diffusion.

A critical issue in the diffusion literature is the implicit assumption is that neither the new technology nor the one that is being replaced change (Hall, 2004). This static view stands in sharp contrast with empirical evidence on the incremental adaptations that ultimately leads to improvement of technology (Christensen, 1997; Foster, 1986). Moreover, and closer to the goals of our analysis, central to the dynamics technology is the balance between intrinsic performance characteristics and the specific features of the selection environment (Vona and Consoli, 2015). These features can be bottlenecks – see e.g. the analysis of the American machine tool industry by Rosenberg (1976) or Hughes' (1983) account of the evolution of the electrical power system – or can be facilitating circumstances of the ecosystem – as is the case in Constant's (1980) study on aircraft piston-engine or in Henderson's (1995) analysis on optical lithography. The broader point is that acknowledging the role of the context of adoption entails shifting the focus from substitution between new and old technology to the evolution of the selection environment. This resonates with Boschma and Frenken's (2006) cautionary remark concerning deterministic accounts of regional variety: spatial contingencies, and the associated uncertainties, matter.

Building on these premises, we look at how agglomeration economies and technology life cycle interact. In the geography of innovation literature, the RKP function approach provides a suitable theoretical framework to investigate these issues (see e.g. Crescenzi et al., 2007, 2012; Ponds et al., 2010; Feldman et al., 2014; Charlot et al., 2015). Therein the regional perspective is embedded in the knowledge production function framework proposed by Griliches (1979) to observe the regional determinants of the generation of innovation. However, whether regional innovation inputs (e.g. human capital and R&D investments) and agglomeration economies exert heterogeneous effects on innovation output according to the maturity of the technology remains an unexplored question. Delving into details provides insights into the type of knowledge base structure that enables regions to intensify their innovative activities and evolve along the life cycle. To do so, we extend the RKP framework to incorporate knowledge diversification at different levels of variety (Frenken et al., 2007; Castaldi et al., 2015). Moreover, since the regional endowment of innovation inputs and given the heterogeneity of regional structural characteristics, we also test whether specific features of the local knowledge base exert different impacts on innovation output depending on the level of development of regions.

# 3 Empirical application

## 3.1 Data

The empirical analysis builds on an original dataset that incorporates information on patenting activities and socio-economic data in 49 US Federal States over the period 1980-2009. Patent data are extracted from the 2016 version of PATSTAT (source: European Patent Office, EPO). Relevant to our analysis is the subset of environmental-related patents identified through the Env-Tech classification of the OECD (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] Following prior literature, we also extract from PATSTAT information on patent families, our unit of analysis (see e.g. Hall and Helmers, 2013). To avoid double counting of inventions for which protection was sought at different national offices, we identify 1,071,869 patent families (or 2,379,464 patent applications) to which at least one Env-Tech classification code is assigned. The resulting data set includes patent families, filled between 1980 and 2009 in eight domains of green technology: environmental management, water management, energy production, capture and storage of greenhouse gases, transportation, buildings, waste management and production of goods.

## 3.2 Measuring regional knowledge base

To measure regional knowledge base, we assign patent families to US states using the inventor's address information obtained from PATSTAT. In particular, we identify the geographical coordinates of inventors' address and assign the patent families he/she developed to US states using geographical projection. To carry out this task we exploit

[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] In an intermediate step, we convert the IPC codes listed in the ENV-TECH into CPC codes using a correspondence table provided by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO). This enables us to deal with just one classification system.

GeoNames[4] a database containing worldwide geographical information on, among others, administrative borders and postal codes.

Inventor's address is geo-localised detecting the postal code within the address string and searching for it in GeoNames. When the postal code information is missing, we identify the city name in the address string using GeoNames. That is, we split addresses in several elements in order to isolate the street, city, etc. Then, since the city name is usually provided at the end of the address we search for it by browsing the address string from right to left. Our algorithm compares each element of the address with the city name information included in GeoNames. We repeat this process for all the elements of the address string moving from the end to the beginning and associate the address to the city name in case of matching.[5] In order to reduce potential noise, we limit the search to cities with at least five thousand inhabitants and manually check if the city name is far from the end of the address string. Finally, we use the Google Maps API – a programmable interface developed by Google since 2005, to assign the geographical coordinates of the remaining addresses not found in the first steps.[6]

In spite of EPO's constant updates, a non-negligible share of inventor's addresses is still missing from the PATSTAT database. Therefore, after the data cleaning process (detailed in Appendix A) we exploit the work by the Institut Francilien Recherche Innovation Société (IFRIS) where missing addresses have been filled using sources such as REGPAT and National Patent Databases.[7] This extra effort allows us to geo-localise 798,455 (74.5%) green patent families worldwide, 149,161 of which in the US (91.3 % have half or more of their inventors geo-localised and 67.1 % have all their inventors geo-localised). We then group patent families according to the state of residence of the inventor.

Figure 1 shows the geographical distribution of green and total patenting activities per million inhabitants at state level (Panel A and B, respectively). Not surprisingly, the two distributions follow a similar pattern with states such as Massachusetts, Connecticut, Alabama, Georgia, Maryland and Kansas that fall in the top quintile in both panels. It is

[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.

[5] For example, in the address: *John Smith, 1 West 72nd Street, New York, NY,* there are four elements to check: "John Smith", "1 West 72nd Street", "New York" and "NY". Starting from the right, the city will be detected in the second loop of the algorithm, i.e. New York.

[6] Daily search limits and costs did not enable us to use Google Maps API to search for the geographical coordinates of all addresses.

[7] For more details, check https://github.com/cortext/patstat

worth noting that states in the Great Lakes (e.g. Michigan, Indiana, etc.) and New England (e.g. Massachusetts, Connecticut, etc.) are particularly effective in the production of green technological knowledge, whereas states in the West (e.g. California, Oregon, Washington, etc.) perform better in total patenting over time. Another noticeable element is that some states rank high in the distribution of green patent families per million inhabitants and low in total patenting activities, for example Illinois, Michigan and Ohio.

The overall green patenting trend by groups as per Env-Tech (OECD, 2016) is reported in Figure 2. Therein we observe that patenting in most green technologies experience an acceleration after 2000. Technologies that improve the sustainability of the energy and building sector lead the trend, followed by green products and processes and transportation. The number of patent families related to water-related and carbon capture and storage technologies is relatively smaller compared to other green technologies (Panel A). However, the latter increases at a faster pace compared to 1980 levels, as showed in Panel B. Patenting on transportation and energy efficiency buildings experiences a sharp increase after 2005. Conversely, environmental management and water-related technologies exhibit lower growth rates over the period.

FIGURES ONE AND TWO ABOUT HERE

### 3.3 Measuring regional knowledge base diversification

We calculate entropy indicators to measure diversification of regional innovative activities. The advantage is that such measure can be scaled up or down at different levels of aggregation associated with specific degrees of relatedness. In the seminal paper by Frenken et al. (2007), the entropy measure is decomposed into related and unrelated variety to capture the extent to which relatedness and diversification characterise the regional cognitive structures. Recently, Castaldi et al. (2015) employ the same measure to assess diversification in technological capabilities of US federal states. In the present paper, we follow Castaldi et al. (2015) in the use of geographical information on patent families (as detailed in Section 3.2) to calculate the entropy indicators using patent data at the state level in US. To do so, we exploit the technological classification codes assigned to each patent. The hierarchical structure of the International Patent Classification (IPC) system can be used to measure variety at different code digits. We calculate related, semi-related and unrelated variety of patenting activities assuming relatedness between two patents when they share the same IPC code. Moreover, this relatedness increases when the number of IPC digits rises. Specifically, unrelated variety

(UV) is measured using the entropy of the patent family distribution over IPC 1-digit classes:

$$UV_{it} = \sum_{k=1}^{N} pf_{k,it} \ln\left(\frac{1}{pf_{k,it}}\right)$$

Where $pf_{k,it}$ is the share of patent families in technological field $k = [1 \ldots N]$ at IPC 1-digit level, with at least one inventor located in state $i$ at time $t$. Semi-related variety (SRV) is equal to the entropy at 4-digit within each IPC 1-digit level. Given the decomposition theorem developed by Theil (1972), SRV is the difference between the entropy measure calculated at 4-digit and 1-digit level (i.e. UV):

$$SRV_{it} = \sum_{l=1}^{P} pf_{l,it} \ln\left(\frac{1}{pf_{l,it}}\right) - UV_{it}$$

Where $pf_{l,it}$ represents the share of patent families in each state over technological fields $l=[1 \ldots P]$ (IPC 4-digit level). Finally, we calculate related variety (RV) at the IPC 8-digit level. As before, RV is obtained by subtracting to the entropy at 8-digit, the one at 4-digit level. In so doing, we calculate variety across narrow technological fields (i.e. IPC 8-digit level) within each broader technological field (i.e. 4-digit level):

$$RV_{it} = \sum_{m=1}^{R} pf_{m,it} \ln\left(\frac{1}{pf_{m,it}}\right) - SRV_{it}$$

Where $pf_{m,it}$ is the share of patent families in state $i$ at time $t$ over technological fields $m=[1 \ldots R]$. As far as we move from UV to RV, the cognitive distance between technological fields decreases. RV is calculated across very similar and specific technological domains compared to UV, which is measured across distant and broad technological fields.

### 3.4 Measuring life cycle stages

To identify the maturity of green technologies, we develop a measure of technology life cycle based on two indicators: the geographical ubiquity of patenting and volume of patenting intensity. We calculate these using worldwide patent families for each macro-technology reported in the Env-Tech classification.[8] It is worth noting that this empirical

[8] The Env-Tech classification OECD (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-

exercise is based on the information on all patent families and not only those filed by US applicants/inventors (the focus of our study). 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 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.

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digit) technological fields. Table 2 reports the list of green technological domains employed to define technology life cycle stages.

Combining ubiquity and patenting intensity allows us to define the life cycle stages of each Env-Tech technological domain at the worldwide level. Table 1 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, coherent with the framework of Section 2.2, 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 Table 1 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 2 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 2 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.[9]

TABLES ONE AND TWO ABOUT HERE

Finally, we obtain the regional green technological efforts at each stage of the technology life cycle as follow:

$$GP_{it}^{L} = \sum_{j} P_{ij(L)t}$$

$$for\ each\ L = [Emergence, Development, Diffusion, Maturity]$$

where the green patent families in state $i$ and time $t$ are summed according to the life cycle stage $L$ of green technology $j$ they belong to (see Table 2 and Figure A1). The resulting four variables capture the geographical distribution of green patenting activities in each stage of the technology life cycle.

Figure 3 shows the distribution of population-weighted green patenting across US states per life cycle stages, i.e. $GP_{it}^{L}$. A quick comparison across the different panels of the figure shows persistence of leading states in the top quintile of all stages of the life cycle. These states are also characterised by a medium-high patenting activity when the size of green patenting is concerned. Other states are more effective in the production of green technological knowledge just in some stages of the life cycle. Thus, for example, Washington ranks high in the development of green technologies in the developing stage, whereas New York in the development and diffusion stages. Michigan is effective especially in the production of knowledge related to developing and mature green technologies but not in those in the diffusion phase. Conversely, South Carolina falls in the top quintile in the diffusion stage.

FIGURE THREE ABOUT HERE

### 3.5 The empirical model

To test whether and what type of knowledge base diversification is associated with the generation of new environmental technical knowledge, the paper employs a Knowledge Production Function (KPF) inspired approach previously formalised by Griliches (1979) that is extended in three directions. First, following Jaffe (1989) and Crescenzi et al.

[9] An exhaustive description of the yearly patterns is provided in Appendix B.

(2007) we exploit the geographical dimension of the dataset (in our case US states), rather than focussing on firms (Jaffe, 1986), as unit of analysis to investigate the spatial organisation of innovative activities. Second, we acknowledge that local knowledge diversification plays a pivotal role in the knowledge production process (Jacobs, 1969; Glaeser et al., 1992) and that various forms of variety are associated with different degrees of relatedness between technological domains (Frenken et al., 2007; Castaldi et al., 2015). Third, we integrate the technology life-cycle heuristic into the KPF framework in order to assess which type of variety in the knowledge base is associated with knowledge production process at different the levels of technological maturity.

We estimate the following empirical model:

$$GP_{jt}^{L} = \beta_1 \mathrm{Variety_{jt}} + \beta_2\ R\&D_{jt} + \beta_3\ HC_{jt} + \mathrm{Controls_{jt}} + \mathrm{\tau_j} + \mathrm{\gamma_t} + \mathrm{\delta_{jt}} + e_{jt}$$

where the dependent variable is the number of patent families per million inhabitants in all green technologies and separately for green technologies at different stages of the technology life cycle ($L$) in state $j$ and year t. *Variety* is a proxy for regional knowledge base diversification discussed above that includes UV, SRV and RV. *R&D* are research and development expenditures and *HC* human capital. In some specifications we also include a battery of controls that capture R&D and human capital in neighbouring states and population density (*Controls*).[10] We also include time fixed effects ($\gamma_t$), state fixed effects ($\tau_j$) and region specific time trends that control for unobservable heterogeneity that varies linearly over time in each state. The latter enables us to capture, among others, state-specific time patterns that we are not able to control for due to data availability, such as policy intervention, green fiscal reforms, etc. which are usually introduced at federal state level. Finally, $e_{jst}$ captures the residual variation. Table 3 provides descriptive statistics of the variables employed in the econometric analysis.

TABLE THREE ABOUT HERE

## 4 Econometric results

Before exploring the results of the econometric analysis, Figure 4 provides a graphical indication of the extent to which green and total patenting are associated with the regional diversification of the knowledge base. There is a positive relationship between patenting

[10] Neighbour states are defined as states that share a border

activities and variety at different level of relatedness. As far as related variety is concerned, green and total patents follow an almost-overlapping pattern with a relative majority of patents that are generated where greater related variety characterises regional knowledge. However, the distribution of patenting activities over quintiles of unrelated variety shows that this type of diversification is particularly relevant at supporting the generation of green knowledge compared to all patents. At lower levels of unrelated variety, total patenting prevails over green patenting. Conversely, as far as unrelated diversification of the regional knowledge base increases, green patenting is favoured and shows a higher association with this type of variety.

FIGURE FOUR ABOUT HERE

These results are confirmed by the econometric estimation of the model detailed in Section 3.5 (Table 4). Two main specifications are proposed in order to observe the differences between green and total patent families as dependent variable. Common to all specifications is that whereas UV and RV variety are positive and statistically significant in the case of green patents, SRV and RV are positively associated with total (i.e. green plus non green) patenting. This suggests that green inventive activities emerge in states where the knowledge base is diversified across unrelated technological domains. On the other hand, total patenting activities proliferate in states characterised by semi-related and related diversification across knowledge fields. In addition, when testing the difference between the coefficients in each respective specification, we observe that while UV and RV are significantly different just at 10%, in the case of total patenting the null hypothesis of equality between SRV and RV coefficients is rejected.[11] This lends support to the notion that green technologies need both diversification across unrelated and related knowledge domains, and differ from total patenting that require more related diversification. The result is in line with studies that emphasise the different nature of green technologies. Barbieri et al. (2018) provide evidence of the higher complexity of green innovation, suggesting that the recombination process in the green field requires bits of knowledge with higher cognitive distance. Here we observe this peculiar feature of green technologies from a local perspective. Finally, looking at the innovation input we can observe that human capital is positive and slightly significant across all specifications. On the contrary, the coefficient of R&D expenditures is not statistically significant in both the green and non-green RKP functions.

[11] The null hypothesis is rejected at 5%

TABLE FOUR ABOUT HERE

Moving to the core of the analysis, Table 5 presents the estimates of the model using green patents per capita as dependent variable. First, the coefficient of UV is statistically significant for emerging technologies, thus implying that diversification across unrelated technological fields favours green technologies in the emerging phase. According to the recombinant innovation theory, in the early stage of the life cycle technological development benefits from the richness of cognitively distant bits of knowledge. Together with unrelated variety, R&D expenditures play a key role in this stage of technology evolution. In the subsequent stage of the life cycle, characterised by higher patenting intensity, all types of variety exert a positive effect on green innovative activities. In this phase human capital is positively associated with green patent production. Moving to the diffusion phase, related variety in the local knowledge base is positively correlated with the generation of environmental-related patents. In addition, both the main innovation inputs, i.e. R&D and human capital are positive and significant. Finally, when maturity is achieved, related variety becomes the main driver of green innovative activities.

These results confirm the propositions outlined in the introduction, and are coherent with the conceptual framework of section 2. The development of technology along the life cycle requires different types of regional knowledge base diversification and innovation inputs. These elements interact with the selection environment of the surrounding states, in this case, and enable technology to advance. Unrelated variety exerts more influence at the beginning of the life cycle when technologies are at an early stage. Knowledge recombination of cognitive distant knowledge is required to enable experimentation and trial and error. In these early phases also R&D and human capital are fundamental to trigger patenting activity. However, in the maturity phase, when a dominant design is established, regional diversification is the main driver of green knowledge production though at a higher level of technological relatedness.

TABLE FIVE ABOUT HERE

## 5 Conclusions

The present paper has explored empirically the relationship between local knowledge structures and the generation of environmental-related technology in the US over a thirty-year period. We framed the analysis in the life cycle heuristic to test whether the development of green technology benefits from specific types of agglomeration economies at different levels of technological relatedness. While prior literature in economic geography had acknowledged the existence of a life cycle path, ours is the first paper to operationalise the heuristic by means of an empirical framework.

The main finding is that local environment-related innovation are positively correlated with a knowledge base that is diversified across unrelated technological fields. This is coherent with the notion that green technology is on average more radical and complex than non-green technology, and that it requires a higher variety across cognitively distant domains (De Marchi, 2012; Barbieri et al., 2018). We also find that diversification across unrelated technological domains in local innovative activities favours green innovation mostly at early stages of development. On the other hand, more mature technologies benefit from a diversification across related knowledge domains. This confirms our main conjecture, and is consistent with Castaldi et al (2014) with regards to the influence of local economic variety on technological innovation.

The present paper points to issues that have relevance for policy, i.e. what are the local conditions that enable technologies to emerge, develop and mature? We contextualise this question in the broader debate on climate change adaptation and mitigation. Besides the relevance from a political and socio-economic perspective, environmental-related technologies exhibit some peculiar traits that make them different from standard technologies and, thus, worth investigating (Barbieri et al., 2018). While on the whole, green technologies can be considered at early stages of development (OECD, 2011; Barbieri and Consoli, 2017) within this assorted mix are mature technologies, such as e.g. photovoltaics panels, that compete in terms with the potential disruption of emerging technologies such as e.g. Carbon Capture and Storage. Shedding light on the regional dimension of green technologies and their evolution enables to explore how regions may contribute to tackle climate change, an issue that the current literature has substantially overlooked.

Last but not least, we reaffirm that formative and stabilizing phases in new technology need to be integral to the analysis of how regional knowledge fosters or thwarts innovation. Further, we hope that our study provides a useful input and a complement to qualitative approaches rooted in the socio-technical transition approach applied to sustainability. Given the common ground on evolutionary drivers of regional and industrial development, we believe there is scope for cross-fertilization along the lines indicated by Truffer (2011) and Boschma (2017). What is integral to both approaches is the need to account for spatial contingencies that bring to bear on the capacity of cities, regions and countries to adapt production and consumption. This paper has identified a connection between the organisation of local knowledge and the differential state of development of green technology which hopefully contributes to move forward the subfield of environmental economic geography.

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## Tables

**Table 1**. Life cycle stages

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

**Table 2**. Life cycle stages of green TECH

| ID | ENV-TECH | 1980 | 1990 | 200 0 | 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 PETROCHEMICAL 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 1). Dark colours are associated to higher stages of the technology life cycle.

**Table 3.** Descriptive statistics

| Variable | Description | Obs | Mea n | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| UV (IPC 3-dig) | *Unrelated variety at 3-digit level* | 1,470 | 3.773 | .221 | 2.832 | 4.204 |
| SRV (IPC 4-dig) | *Semi-Related Variety at 4-digit level* | 1,470 | 1.248 | .205 | .268 | 1.528 |
| RV (IPC 8-dig) | *Related Variety at 8-digit level* | 1,470 | 1.453 | .361 | .246 | 1.916 |
| GP | *Green patent families, pmi* | 1,470 | 27.69 | 26.64 | 0 | 300.94 |
| Tot Pat | *Total patent families, pmi* | 1,470 | 429.6 | 351.2 4 | 36.18 | 2810.15 |
| Emergence | *Green patents, Emergence stage, pmi* | 1,470 | 4.451 | 4.781 | 0 | 51.61 |
| Development | *Green patents, Development stage, pmi* | 1,470 | 6.821 | 9.026 | 0 | 95.21 |
| Diffusion | *Green patents, Diffusion stage, pmi* | 1,470 | 6.163 | 6.345 | 0 | 83.79 |
| Maturity | *Green patents, Maturity stage, pmi* | 1,470 | 24.08 | 25.93 | 0 | 320.18 |
| R&D | *Research and Development expenditures (w.r.t. GDP)* | 1,470 | .014 | .011 | .001 | .066 |
| HC | *% Population with bachelor degree or more* | 1,470 | .057 | .021 | .0321 | .541 |
| R&D Neighb | *Research and Development expenditures in neighbouring states (w.r.t. GDP)* | 1,470 | .015 | .007 | .002 | .047 |
| HC Neighb | *% Population with bachelor degree or more in neighbouring states* | 1,470 | .055 | .007 | .037 | .093 |
| Pop Dens | *Population Density* | 1,470 | 4.80 | 1.476 | 1.53 | 9.14 |

Number of States: 49; Coverage: 1980-2009; pmi= per million inhabitants

**Table 4.** Regression results

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | GP (log) | Tot Pat (log) | GP (log) | Tot Pat (log) | GP (log) | Tot Pat (log) |
| UV (IPC 3-digit) (log) | 1.413*** | -0.875 | 1.403*** | -0.881 | 1.386*** | -0.931* |
| | (0.460) | (0.539) | (0.445) | (0.519) | (0.421) | (0.507) |
| SRV (IPC 4-digit) (log) | 0.317* | 0.232*** | 0.301 | 0.215*** | 0.286 | 0.193*** |
| | (0.179) | (0.0655) | (0.179) | (0.0682) | (0.184) | (0.0668) |
| RV (IPC 8-digit) (log) | 0.397*** | 0.523*** | 0.394*** | 0.521*** | 0.392** | 0.515*** |
| | (0.143) | (0.0952) | (0.142) | (0.0956) | (0.154) | (0.0987) |
| R&D (log) | | | 0.0233 | 0.00806 | 0.0222 | 0.00694 |
| | | | (0.0196) | (0.0112) | (0.0181) | (0.0103) |
| HC (log) | | | 0.134** | 0.140* | 0.0960* | 0.0995* |
| | | | (0.0644) | (0.0689) | (0.0545) | (0.0532) |
| R&D Neighb (log) | | | | | 0.0427 | 0.0278 |
| | | | | | (0.0634) | (0.0280) |
| HC Neighb (log) | | | | | 0.294 | 0.224** |
| | | | | | (0.218) | (0.0829) |
| Pop Dens | | | | | -0.502 | -0.889*** |
| | | | | | (0.813) | (0.196) |
| State FE | x | x | x | x | x | X |
| Time Dummies | x | x | x | x | x | x |
| Random growth | x | x | x | x | x | x |
| Obs. | 1466 | 1470 | 1466 | 1470 | 1466 | 1470 |
| R2 | 0.856 | 0.965 | 0.857 | 0.965 | 0.857 | 0.966 |
| F | 906429.2 | 216914.8 | 52052121.7 | 225300.1 | 128242.3 | 12321.1 |

Notes: The analysis covers 48 US Federal States and the District of Columbia over 1980-2009. Driscoll and Kraay’s (1998) standard errors, robust to heteroskedasticity and serial and spatial correlation, in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

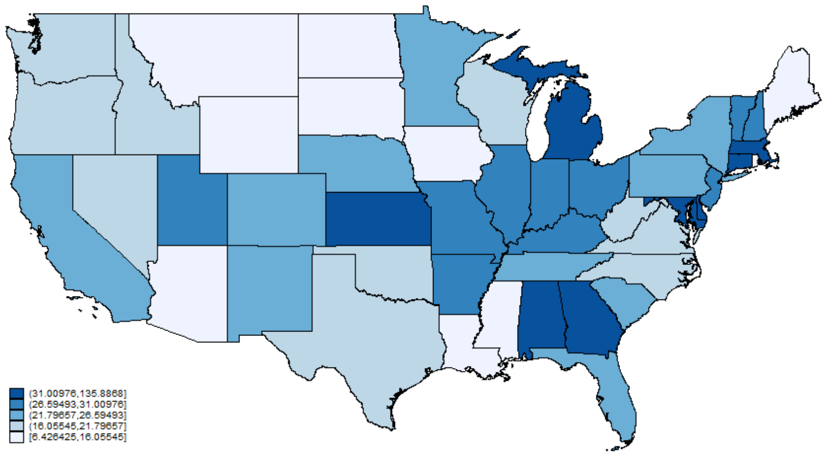
**Table 5.** Regression results over the life cycle

| | GP (log) | Emergence | Development | Diffusion | Maturity |
|---|---|---|---|---|---|
| UV (IPC 3-digit) (log) | 1.386*** | 0.958* | 1.214** | 0.597 | 0.716 |
| | (0.421) | (0.523) | (0.590) | (0.786) | (0.473) |
| SRV (IPC 4-digit) (log) | 0.286 | -0.356 | 0.783*** | 0.166 | -0.205 |
| | (0.184) | (0.338) | (0.201) | (0.249) | (0.147) |
| RV (IPC 8-digit) (log) | 0.392** | 0.421 | 0.516*** | 0.434* | 0.554*** |
| | (0.154) | (0.313) | (0.157) | (0.247) | (0.0848) |
| R&D (log) | 0.0222 | 0.0784** | 0.0192 | 0.0628** | -0.0296 |
| | (0.0181) | (0.0290) | (0.0414) | (0.0235) | (0.0217) |
| HC (log) | 0.0960* | -0.0164 | 0.333** | 0.251* | -0.000803 |
| | (0.0545) | (0.105) | (0.127) | (0.143) | (0.0578) |
| R&D Neighb (log) | 0.0427 | 0.197*** | 0.0772 | 0.137 | -0.0518 |
| | (0.0634) | (0.0517) | (0.102) | (0.0889) | (0.0482) |
| HC Neighb (log) | 0.294 | -0.00881 | 0.366 | 0.0946 | 0.860*** |
| | (0.218) | (0.375) | (0.891) | (0.358) | (0.261) |
| Pop Dens | -0.502 | 0.662 | 0.999 | -0.301 | -0.338 |
| | (0.813) | (0.828) | (0.965) | -1.210 | (0.587) |
| State FE | x | x | x | x | x |
| Time Dummies | x | x | x | x | x |
| Random growth | x | x | x | x | x |
| Obs. | 1466 | 1392 | 1371 | 1424 | 1452 |
| r2.w | 0.857 | 0.542 | 0.760 | 0.662 | 0.885 |
| F | 128242.3 | 644300.7 | 86586.6 | 168032.5 | 451319.1 |

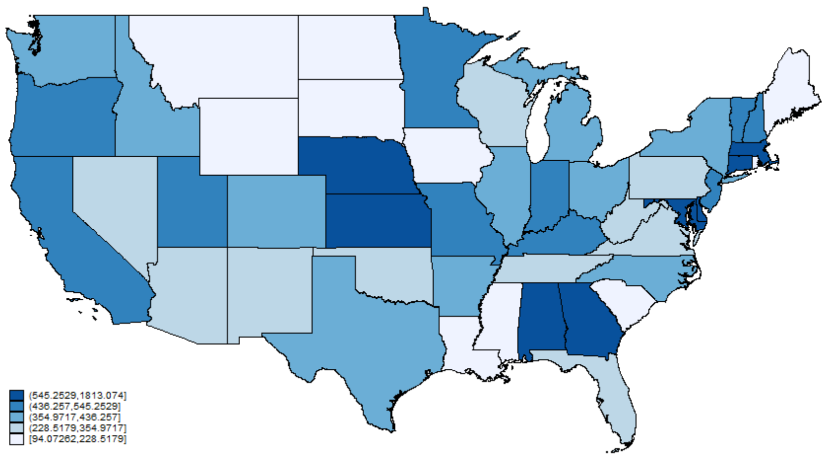
Notes: The analysis covers 48 US Federal States and the District of Columbia over 1980-2009. Driscoll and Kraay's (1998) standard errors, robust to heteroskedasticity and serial and spatial correlation, in parentheses. * p < 0.1; **p < 0.05; *** p < 0.01.

## Figures

**Figure 1.** Quintiles of green and total patent families per million inhabitants (average 1980-2010)



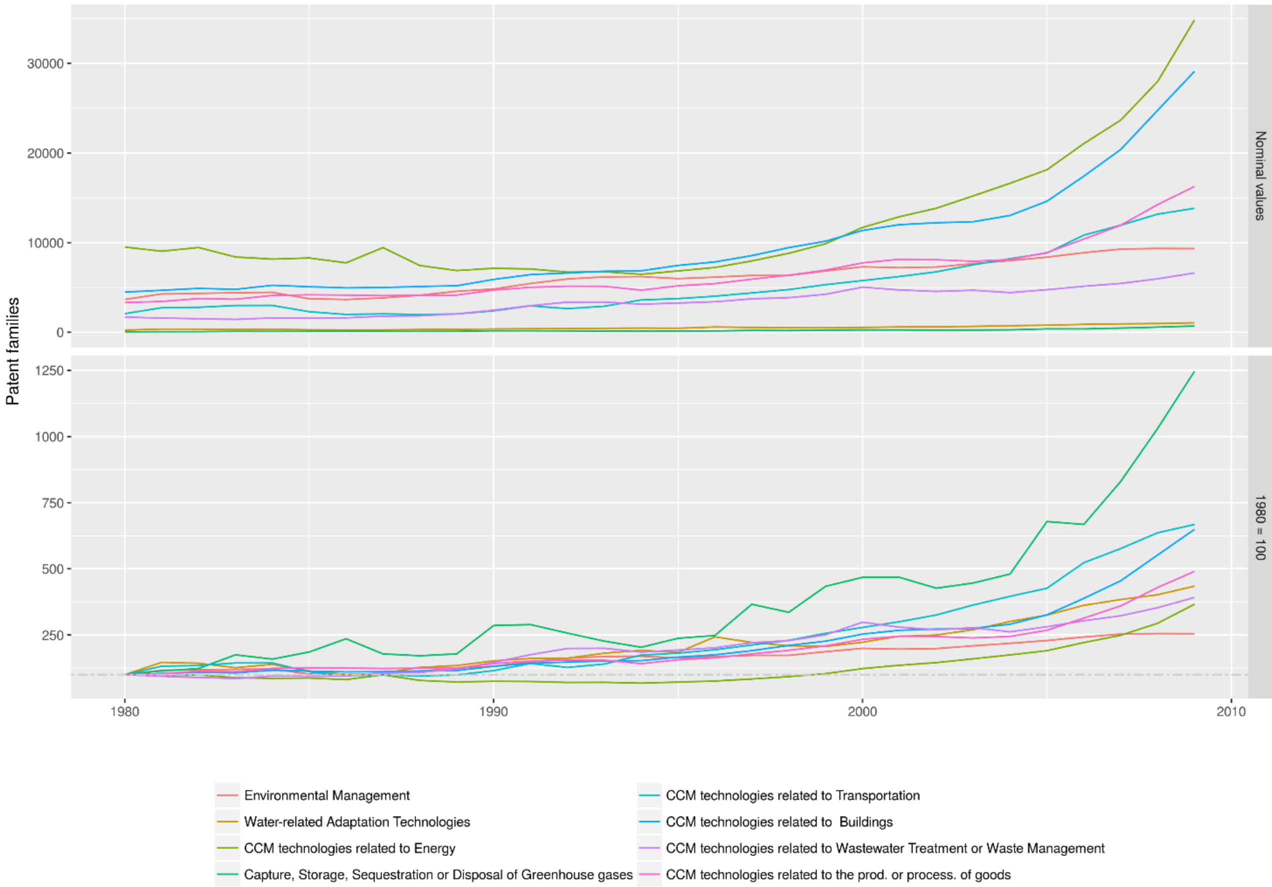

**(A) Green TECH**




**(B) All TECH**

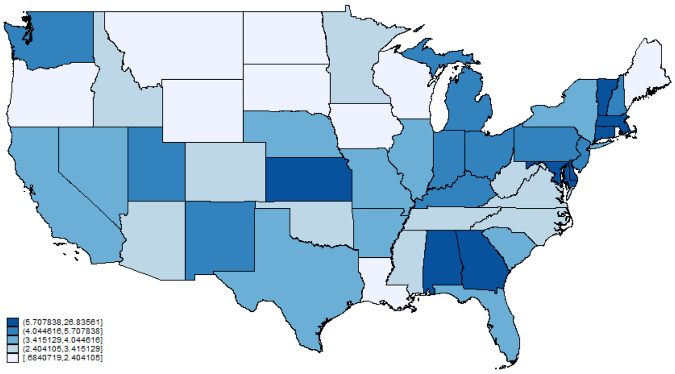
Darker colours correspond to top quintiles. 48 US federal states and District of Columbia are included in the maps. Alaska and Hawaii are left out from the analysis. The cartographic boundary shapefile is provided by the US Census Bureau (Accessed in 2018). Source: Own elaboration

**Figure 2.** Evolution of the number of green patent families by Env-Tech families, 1980 – 2009. Top panel: nominal values; bottom panel: 1980= 100.

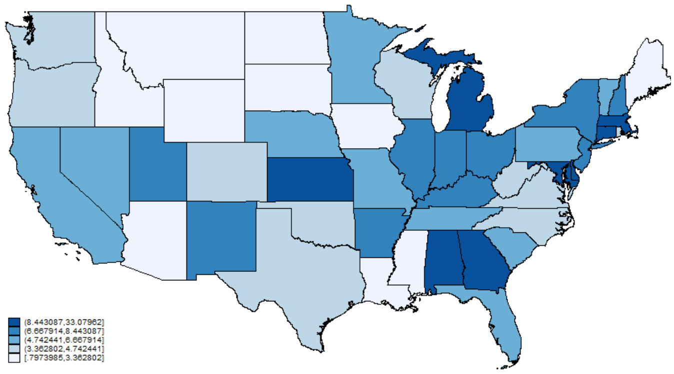



Source: Own elaboration

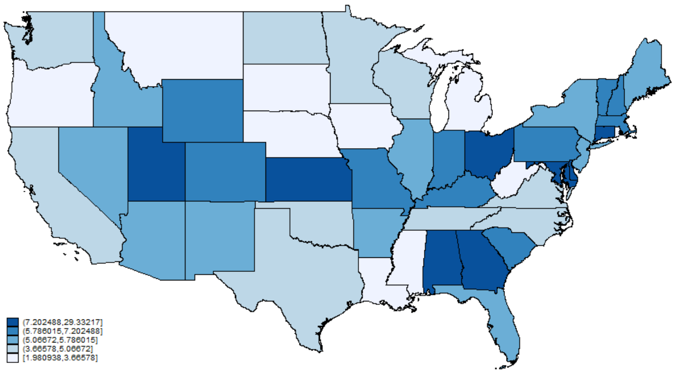
**Figure 3.** Quintiles of green patent families per million inhabitants over technology life cycle stages (average 1980-2009)



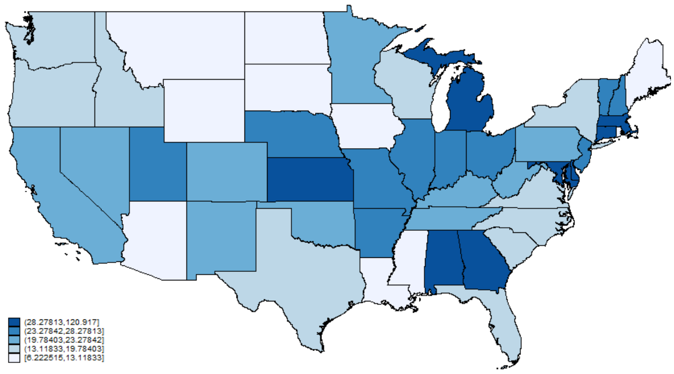

**(A) Emergence phase**




**(B) Development phase**



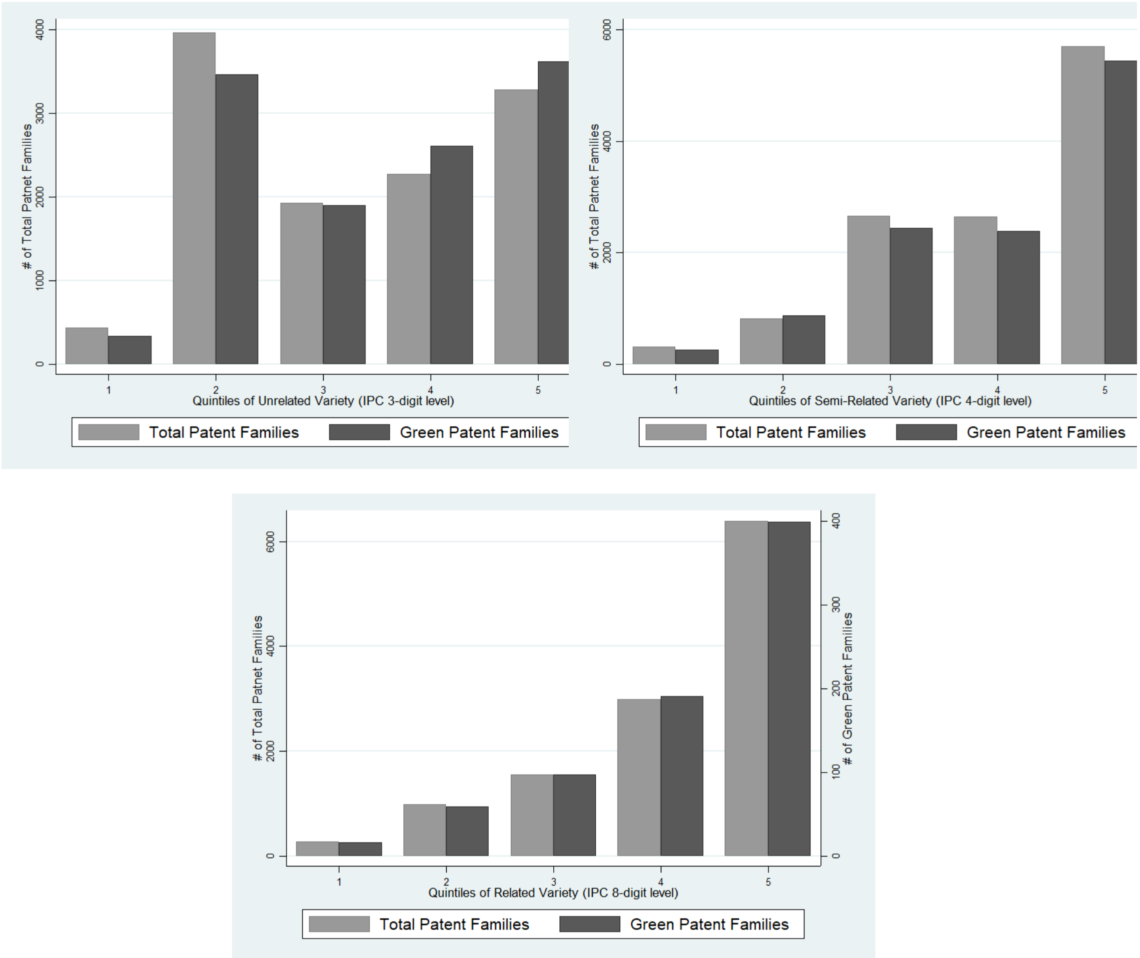

**(C) Diffusion phase**




**(D) Maturity phase**

Darker colours correspond to top quintiles. 48 US federal states and District of Columbia are included in the maps. Alaska and Hawaii are left out from the analysis. The cartographic boundary shapefile is provided by the US Census Bureau (Accessed in 2018).

**Figure 4.** Distribution of green and total patent families over quintiles of Unrelated, Semi-Related and Related variety (average 1980-2009)



## APPENDIX A (Online publication) – Missing inventor's address

Before geo-localisation we collect all the inventors' addresses from the PATSTAT database. Two main issues arise in carrying out this task. First, although the European Patent Office (EPO) assigns an unambiguous ID to each applicant or inventor, we may still find multiple IDs for the same person due to misspelling, name variations, second names, etc. For instance, the inventor's name may appear as John Paul Smith, J. Smith or J.P. Smith and be assigned to different patents. Second, address information is provided in PATSTAT for just some inventors. According to the first issue, address information for an inventor may be provided for some IDs and missing for others. For example, address information may be provided for John Paul Smith and not for J. Smith due to differences in their IDs.

To reduce the number of inventors/applicants with a missing address we exploit the information on the patent family – our unit of analysis. Within each patent family we create a link between the multiple inventors' IDs assuming that they are the same person based on a string matching indicator. We calculate the Levenshtein distance between the inventor name for which the address information is provided and all the other names with missing information within the patent family. We consider two or more inventors as the same person if the indicator is below three. This means that their full names differ for less than three characters. Then, if the address information is provided for one of these inventors we assign it also to the others IDs for which this information is not provided (even though they have different IDs). For example, we can find in the same patent family two inventors with different IDs, the first one with a complete address, the second one with a missing one: "Gehri, Martin Christian Adrian" and "GEHRI, MARTIN, CHRISTIAN, ADRIAN". As the levenshtein distance between the two names is less than 3 when both strings are converted to uppercase, we assume it is the same person and we use the complete address to fill the missing one.

## APPENDIX B (Online publication) – Technology Life Cycle indicator

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, our paper focuses on 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.

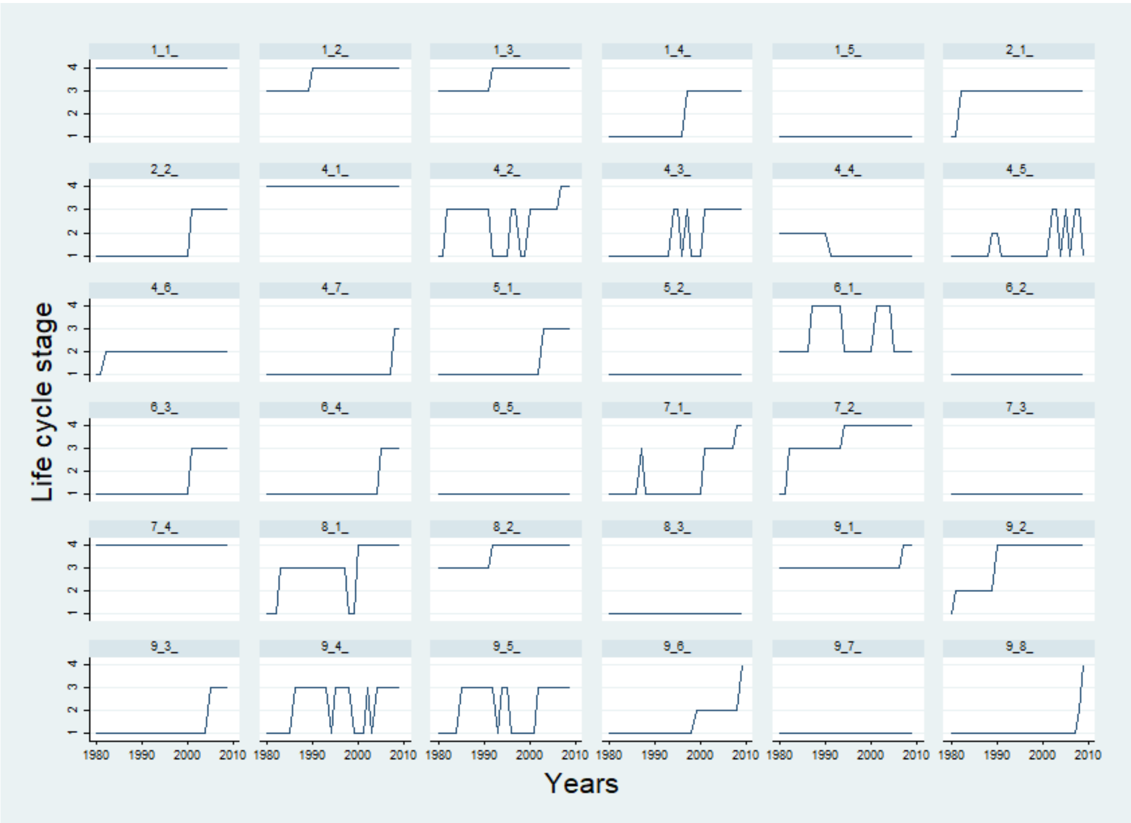
Therefore, as described in Section 3.4 we develop our measure of technology life cycle based on two indicators, i.e. the geographical ubiquity and patenting intensity. We calculate these indicators using worldwide patent families for each macro-technology reported in the Env-Tech classification.

Figure A1 shows the life cycle of green technologies over the entire period of the analysis (1980-2009). We can observe that the indicator captures the heterogeneity that characterises green technologies allowing for non-linear transition between life cycle stages. For instance, ENV-TECH 7.1 "Integration of renewable energy sources in buildings" falls in the emergence stage until 2000 moving to the diffusing phase until maturity is reached in 2008. Green technologies aimed at reducing the environmental impact of nuclear energy follow an opposite pattern starting in the development phase moving to the emergence stage from 1990 onwards.

Some illustrative examples are provided in Figure A2. Technologies related to renewable energy generation exhibit a fairly stable level of patenting activity since the period 1981-1990, while geographical ubiquity reaches the highest value among all the other technologies. This is in line with what we expect from a set of technologies in a diffusion, or mature, stage (US National Academy of Sciences, 2010). On the other hand, a small number of countries contribute to the enabling technologies in transport (application of fuel cell or hydrogen technology to transportation and charging of electric vehicle) but patenting activity is increasing over time, meaning that these technologies are not mature but still in a development phase, in line with the evidence available (i.e. US Department of Energy, 2010). The other three technologies (air pollution abatement – 1.1, CO2 capture and storage – 5.1 and technologies related to metal processing – 9.1) in Figure A2 are instances of a shift from development towards maturity in that they exhibit sustained growth in patenting during the whole period while geographical ubiquity increases only over the last two decades, and in line with prior empirical studies (Lim et al., 2009). This pattern differs from that of technologies related to efficiency and reduction of greenhouse gas emissions in metal processing (9.1): between 1981-1990 and 1991-2000 patenting is stable and spread over a higher number of countries, while in the last decade, ubiquity diminishes and patenting activity grows again. This trajectory suggests a future change in the trend of the life cycle of these technologies (The Boston Consulting Group, 2015).

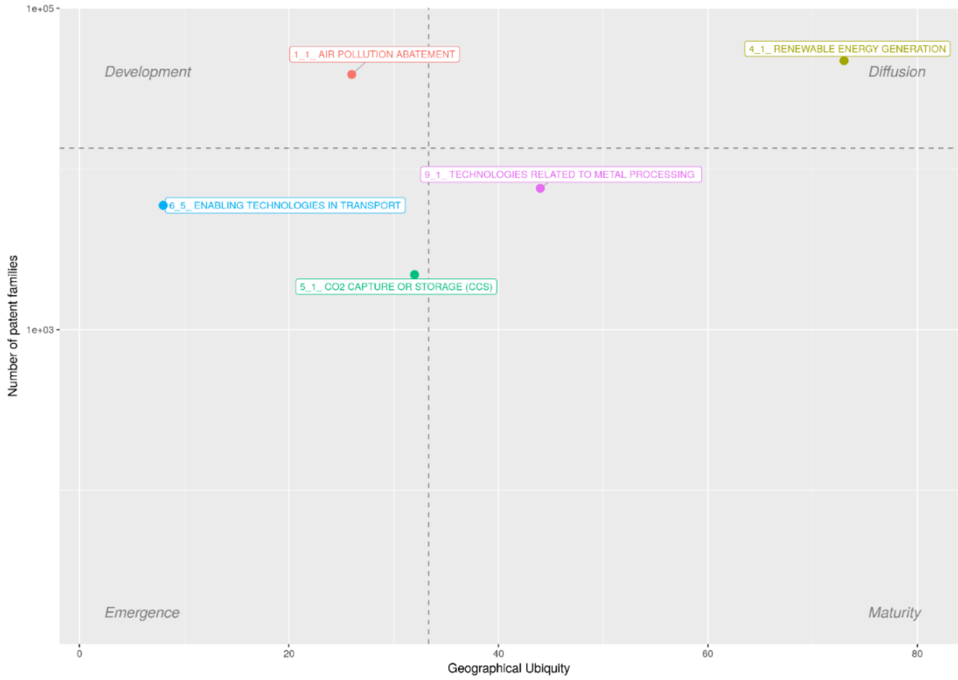
All the technologies follow a similar path, but some are more advanced in the TLC than others. For example, even if air pollution abatement and CO2 capture or storage are moving toward the diffusion stage, their movements start later compared to the average of all the other technologies. To characterize this evolution in the broader context of all green technologies, we calculate the average value of ubiquity and patenting growth rate for all the GT in each time period. The combination of these two characteristics gives rise to four different regimes (Table 1). "Emergence" technologies have patenting intensity and ubiquity below average; "development" technologies exhibit above average patenting and below average ubiquity; technologies in "diffusion" are above average in both intensity and ubiquity; in the "maturity" ubiquity is above average and patenting below the average of all the technologies in the same period. Figure A3 illustrates the 4 phases of TLC during the period 2001-2010 for the technologies shown in Figure A1 (dashed lines indicate mean values). In this example, CO2 capture or storage (5.1) and enabling technologies in transport (6.5) in the "emergence" phase, air pollution abatement (1.1) in the "development" phase, renewable energy generation (4.1) would be in the "diffusion" phase and technologies related to metal processing (9.1) in the "maturity" phase.

**Figure A1**. The life cycle of green technologies (1980-2009)



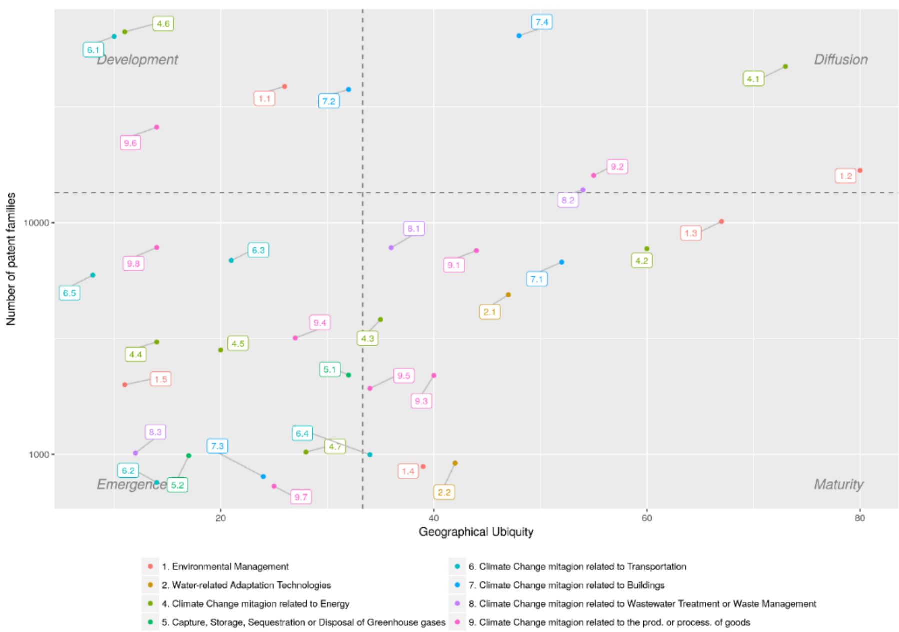

Technology names are provided in Table 2 of the paper. For the sake of space the figure reports the two-digit label of Env-Tech (OECD, 2016). Numbers in the y-axis correspond to the technology life cycle stages: 1 “Emergence”, 2 “Development”, 3 “Diffusion” and 4 “Maturity” (see Table 1 for a taxonomy).

**Figure A2**. Selected Green Technologies by stage of life-cycle, 2001-2010




Source: Own elaboration

**Figure A3.** All green technologies by stage of life cycle, 2001 – 2010



Technology names are provided in Table 2 of the paper. For the sake of space the figure reports the two-digit label of Env-Tech (OECD, 2016). Source: Own elaboration