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Nicolò Barbieri, Alberto Marzucchi and Ugo Rizzo

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Knowledge sources and impacts on subsequent inventions: Do green technologies differ from non-green ones?

Nicolò Barbieri[1]

Alberto Marzucchi[2]

Ugo Rizzo[3]

Abstract

The paper contributes to our understanding of the nature and impact of green technological change. We focus on the search and impact spaces of green inventions, scrutinising the knowledge recombination processes leading to the generation of the invention and the impact of the invention on subsequent technological developments. Using a large sample of patents filed during 1980-2012, we analyse a set of established patent indicators that capture different aspects of the invention process. Technological heterogeneity is controlled for by comparing green and non-green technologies within similar narrow technological domains. Green technologies are found to be more complex and radical than non-green ones and to have a larger and more pervasive impact on subsequent inventions. However, the results show a variety of distinctive patterns with respect to the knowledge dimension considered. We derive some important policy implications.

Keywords: environmental inventions, patent data, knowledge recombination, knowledge impact

JEL Classification: O33, O34, Q55

[1] Department of Economics and Management, University of Ferrara (IT). Email: nicolo.barbieri@unife.it
[2] SPRU, Science Policy Research Unit, University of Sussex (UK). Email: a.marzucchi@sussex.ac.uk
[3] Department of Economics and Management, University of Ferrara (IT). Email: ugo.rizzo@unife.it

1. Introduction

The transition towards a greener economy revolves strongly around the role of technological change (see, among others, Smith, 2008; Pearson and Foxon, 2012; Barbieri et al., 2016). To provide new evidence on the rate and direction of "green" technological change, we reprise a recurrent question in the economics of innovation and investigate "the ways in which technological change is generated and propagated" (Griliches, 1957, p. 501). To address this question, requires a combined perspective that looks at the roots and impacts of the evolution of technologies (Rosenberg, 1976; Nelson and Winter, 1982). In other terms, both the *search* and *impact space* should be investigated. The former reflects the origins of inventions and the conditions under which new knowledge emerges (Fleming and Sorenson, 2004; Arthur, 2007). The latter reveals the mechanisms underlying the diffusion of the inventions and the potential benefits of this process (Rogers, 1983).

It is widely acknowledged that technological change is "a cumulative process, whereby each innovation builds on the body of knowledge that preceded it, and forms in turn a foundation for subsequent advances" (Trajtenberg et al., 1997, p. 20). Building on this, studies of the characteristics of technological change tend to follow one of two non-exclusive and complementary perspectives. That is, an 'ex-ante' (e.g., Verhoeven et al., 2016), or 'backward-looking' (Trajtenberg et al., 1997), approach that characterises inventions in terms of their nature by focusing on the knowledge recombination processes leading to the invention (e.g. Schumpeter, 1934; Fleming, 2001; Carnabuci and Operti, 2013); and an ex-post', or a 'forward-looking' approach which focuses on the impact on subsequent inventions (Ahuja and Lampert, 2001; Schoenmakers and Duysters, 2010).

To provide empirical insights into the shape of the technical knowledge from which technology emerges and evolves, we adopt the above ex-ante and ex-post perspectives. Following the diffused approach proposed in the seminal work by Trajtenberg et al. (1997, p. 20), we conduct an empirical analysis "using detailed information contained in patents, relying heavily on citations to other patents, since these citations provide good evidence of the links between an innovation and its technological 'antecedents' and 'descendants'". The objective is to compare green and non-green technologies across various knowledge dimensions to study the continuity between the search and impact spaces. First, technological complexity is analysed in order to investigate whether green and non-green technologies differ in the variety of their knowledge sources or number of technological components. Second, radicalness is used here to examine the structure of the recombination process from which new artefacts stem. Finally, the impact on subsequent technologies is investigated to capture knowledge spillovers from green and non-green technological domains.

The contributions of the present study to the extant literature are manifold. The paper compares green and non-green technologies by focusing on the preliminary phase of the innovation process, that is, the invention phase. A large part of the available evidence considers environmental innovation as a whole (e.g., Cainelli et al., 2015) and does not account for the fact that innovation activities are heterogeneous and result from different and interlinked phases (e.g. Kline and Rosenberg, 1986; Tidd et al., 1997), ranging from conception to market exploitation. In turn, distinctive environmental innovation traits with respect to "standard" ones can emerge in any of the different phases in the environmental innovation chain. Failing to account for this could lead to imprecise implications for policy and practice. To provide more accurate insights, we investigate the "upstream" phase of green technological development, that is, the inventive process. Specifically, we compare the characteristics of the green and non-green knowledge bases of inventions and study their differences.

The comparison is carried out across several dimensions, both ex-ante and ex-post, captured by a variety of established patent indicators (Squicciarini et al., 2013), that is, patent scope, originality, radicalness, forward citations and generality. Thus, the analysis embraces different aspects of green technologies pertaining to knowledge recombination (i.e., complexity and radicalness) and their impact on succeeding technological developments. The relatively scant literature on the difference between green and non-green technologies focuses mainly on one of these dimensions (e.g., Popp and Newell, 2012). However, ignoring one of them could lead to incomplete analyses and circumscribed policy implications. Our aim is to investigate both the technological antecedents and descendants of inventions that contribute to linking the search and impact spaces (Dahlin and Behrens, 2005).

The use of established indicators to systematically test the differences between green and non-green technologies is also an original element with respect to the extant literature on the knowledge bases of environmental innovations. This literature offers insights and argumentation related to the peculiarities of the green knowledge base (e.g., De Marchi, 2012; Ghisetti et al., 2015), but does not provide direct tests of its distinctive features.

Finally, in the empirical analysis, we control for the idiosyncratic features of each technological field considered. This allows us to mimic the matching between green and "similar" (i.e., in the same narrow technological field) non-green patents. Our approach to allow netting out of the confounding factors that can arise when comparing very different technologies, is another original contribution. Prior studies on the impact of green technologies on following inventions, generally focus on a few technological domains and/or do not provide fine-grained control of the technical specificities of inventions (e.g., Popp and Newell, 2012; Dechezleprêtre et al., 2014).

Our analysis, based on the wealth of information provided by worldwide patents filed over the period 1980-2012, reveals that green technologies differ from non-green ones across all the dimensions we investigate, although to different extents. First, green patents appear to be more complex than non-green ones, especially in relation to the breadth of knowledge components.

Second, green technologies appear to be (somewhat) more radical than their non-green counterparts. That is, green compared to non-green inventions show more distinctive traits with respect to their prior knowledge. Third, if we focus on the impact on subsequent technological developments, our results show that green inventions pervade a larger and more diverse range of technological domains. These results point to relevant implications for types of and scope of policy actions, and their rationale.

The paper is structured as follow. Section 2 reviews the literature and formulates the research questions. Section 3 identifies appropriate patent-based indicators for the empirical analysis, described in Section 4. Section 5 presents the results and Section 6 concludes.

2. Literature review

This section reviews the literature on environmental innovations in order to identify the main propositions about the differences between green and non-green technologies. To provide continuity in the analysis of the search and impact spaces, we build on the above-mentioned distinction between the ex-ante and ex-post theoretical characterization of inventions. First, we review the differences between green and non-green technologies from an ex-ante perspective, looking for patterns in the sources of knowledge leading to the generation of technologies. Next, we focus on the differences between green and non-green inventions from an ex post point of view, by describing the state of the art in the current literature on the impact of technologies on subsequent technological advances. In Section 3, we link the insights derived from this literature to appropriate indicators and proxies.

2.1 Ex-ante perspective: Knowledge recombination processes in green inventions

Inventive activity is the outcome of knowledge recombination processes (Schumpeter, 1934; Usher, 1954; Nelson and Winter, 1982; Fleming, 2001). Recent developments in the theory of invention suggest that the characteristics of the search space influence the outcome of the recombination process. Fleming and Sorenson (2001) find that the number of components and the strength of their interdependence, that is, complexity, affect the success of inventive activities. They argue, also, that local search, that is, recombination of familiar technological components (Fleming, 2001), influences the degree of novelty of the invention. Moving away from existing practices and recombining components in a new way, increases both the risk of failure and the likelihood of achieving a radical invention (Ettlie et al., 1984; Nooteboom, 2000; Fleming, 2001; D'Este et al., 2017).

A recent strand of literature dealing with the determinants of environmental innovation looks at the knowledge capabilities required by firms in order to introduce environmental innovations. While these studies do not test directly for specific features pertaining to the search space of green technologies, they provide useful insights into the recombination of knowledge components and the novelty that this recombination entails: in other words, they provide insights into the complexity and radicalness of environmental technologies (e.g., Lerner, 1994; Trajtenberg et al., 1997; Verhoeven et al., 2016).

In relation to the *complexity* of green compared to non-green technologies, previous studies show that environmental technologies encompass a broader range of objectives and knowledge inputs. In particular, De Marchi (2012) argues that the development of new and green products calls for competences that are far from the traditional industrial knowledge base. The higher complexity of green technologies is demonstrated by the multi-purpose and systemic nature of environmental innovations (Ghisetti et al., 2015). Environmental technologies are expected to satisfy different and joint objectives, related to production efficiency, and product quality, dictated, for instance, by standards (Florida, 1996; Oltra and Saint Jean, 2005). At the same time, their development encompasses several dimensions including design, user-involvement, product-service delivery – comprising new products, their related services, the supporting network and infrastructure (e.g., Mont, 2002) – as well as institutional requirements related to, for example, the regulatory framework (Carrillo-Hermosilla et al., 2010; Mazzanti and Rizzo, 2017).

Another interesting feature of green technologies is the extent to which they embody new and different recombinations of knowledge with respect to prior technologies, that is, their *radicalness.* Environmental innovations are expected to imply radical change due to the absence of established environmental best practice and technological trajectories. In addition, they are characterised by technological uncertainty and require skills, which, often, are outside the firm's knowledge domain (De Marchi, 2012). Environmental innovations are described as representing a technological frontier (Cainelli et al., 2015) where the economic actors have relatively scarce experience (Porter and van der Linde, 1995). In similar vein, Horbach et al. (2013) note that, with the exception of eco-industries whose core business is development of green technologies, environmental innovations encourage firms to master new knowledge linked to alternative production processes, and inputs that generally are associated to relatively new technological solutions. Acknowledging the diversity of environmental innovations (i.e., depending on their objective), Marzucchi and Montresor (2017) suggest that efficiency-related environmental technologies exhibit important elements of novelty, for instance, industrial design and engineering mechanisms, making them reliant on analytical knowledge inputs from scientific partners. The greater extent to which green innovations require new recombinations of existing knowledge, resonates well with the argument that they call for specific skills. In a study of the human capital and skill content of green jobs, Consoli et al. (2016) found that green jobs are characterised by greater intensity of non-routine skills and they link this finding to the boundary fluctuations and constant reconfiguration of green occupations resulting from the early stages in the life cycles of environmental technologies. While their study focuses on jobs associated to environmental practices, our paper offers a complementary view concerning the technological dynamics.

In sum, we can identify two main traits which differentiate green technologies from non-green ones: complexity and radicalness. Based on the above premises, to shed light on the search space of green inventions, we look at the different recombination processes that lead to the generation of green (and non-green) technologies. In particular, we address the following research questions:

RQ1. Are green technologies more complex recombinations of technological knowledge compared to their non-green counterparts?

RQ2. Do green technologies entail more radical recombinations of technological knowledge compared to their non-green counterparts?

2.2 Ex-post perspective: impacts of green inventions on following technological development

The characterization of an invention from an ex-post perspective is related to the capacity to trigger future technological developments and opening up a variety of new technological opportunities (Schoenmakers and Duysters, 2010). While the former characteristic refers to the extent to which an invention is considered as a source of knowledge for subsequent technologies (Griliches, 1992; Jaffe et al., 1993), the latter is close to the concept of pervasiveness and captures the variety of fields impacted by the invention (Helpman and Trajtenberg, 1994). These characteristics often are associated to General Purpose Technologies (GPTs), which are identified by their pervasiveness, continuous technical advances and wide diffusion (Bresnahan and Trajtenberg, 1995; Hall and Trajtenberg, 2004).

Some recent works have addressed related issues, when looking at the association between the green transition and past industrial revolutions or technological waves. These studies argue that green technologies exhibit the traits of GPTs, although at an early stage (Stern, 2011), and are expected to play the role, which, in the past, was played by the steam engine, electricity and the more recent Information and Communication Technologies (ICT) (Pearson and Foxon, 2012; Perez, 2016). For instance, low carbon technologies are thought to have widespread potential use, to stimulate complementary innovations and to contribute to productivity gains and economic benefits (Pearson and Foxon, 2012). Ardito et al. (2016) adopt a similar standpoint in claiming that green technologies should be considered to be GPTs. They stress the relevance of GPT developments, which, while targeting new and more sustainable pathways rather than single technological solutions, have multiple applications and spillovers in related technological domains (e.g., transportation) and have the potential to trigger micro- and macro-economic and environmental benefits.

In similar vein, studies of specific technological realms highlight that green technologies are indeed characterised by high levels of pervasiveness. For example, Cecere et al. (2014) focus on environmental technologies based on applications of ICT equipment or software (e.g., application of ICT to renewable energy and sustainable mobility) and offer evidence of the high level of pervasiveness of green ICTs that rely on a wide variety of knowledge sources and actors. Further support for the pervasiveness of green technologies comes from two studies that assess the social value of investing (public funds) in green innovations. Popp and Newell (2012) find that patents in sustainable energy domains are cited more often than other patents, and that their forward citations stem, in particular, from a variety of other technological domains. The high pervasiveness and broad applicability of these technologies in a wide set of domains are confirmed by the empirical investigation conducted by Dechezleprêtre et al. (2014) on clean (and dirty) technologies in four fields: energy production, automobiles, fuel and lighting. Their findings reveal that clean technologies receive more citations than dirty technologies, and are characterised by more general applicability outside their domain, suggesting that they are more likely to display the traits of a GPT.

Despite recent advancements, there is a lack of systematic understanding of the impact and pervasiveness across all technological fields, of green inventions. Extant studies focus on specific domains and target pivotal sectors for the green economy – such as production of green goods, air pollution abatement and water management. Furthermore, when comparing green and non-green inventions, they do not control for the idiosyncratic features of narrow technological domains (Popp and Newell, 2012; Dechezleprêtre et al., 2014). From an ex-post perspective, our study fills this gap by analysing all environmental-related technologies and taking account of the specificity of each technology (see Section 4.1). Building on these premises, we propose the following research question, which focuses on the impact space of green (and non-green) inventions:

RQ3. Do green technologies exhibit a higher impact on subsequent technological developments relative to their non-green counterparts?

3. Identifying inventions using patent data

To address our research questions, we conduct an empirical analysis based on patent data. This limits the analysis to a group of inventions whose technicalities respect the criteria of patentability. Although patent data provide a wealth of information – detailed in Section 4 – their use in empirical studies is not exempt from complications (Griliches, 1990; Lanjouw et al., 1998). Nevertheless, various works highlight the validity of patent based indicators (e.g., Arts et al., 2013).

Patents provide three main types of information: the knowledge components used to develop the invention; the knowledge base on which the invention draws; and the knowledge generated subsequently by the patent. In this work, we distinguish between ex-ante and ex-post perspectives to study the characteristics of the inventions and to address our research questions by exploiting various patent indicators. In particular, building on Section 2, we are interested in testing, from an ex-ante perspective, whether green technologies are more complex and more radical than non-green ones and, from an ex-post perspective, whether green technologies have a higher impact on future technological developments. Drawing on the patent-based empirical literature, we can identify six indicators to proxy for complexity, radicalness and impact.

Complexity captures the variety of knowledge bases, components and competences required to develop the new technology and is proxied by patent scope (Lerner, 1994; Shane, 2001) and originality (Trajtenberg et al., 1997; Hall et al., 2001). Patent scope measures the variety of the knowledge components and originality measures the variety of the knowledge sources. Radicalness captures the distance between the new technology and its knowledge sources, that is, it captures the extent to which the new technology differs from previous technologies. It is proxied by the homonymous indicator developed by Shane (2001) and refined by Squicciarini et al. (2013).

To investigate the impact of green inventions on following patents, we consider whether green inventions become the seeds for future technological developments. The most frequent indicators are number of forward citations and generality index (Trajtenberg et al., 1997; Hall et al., 2001). The former is a quantitative measure of the number of times the invention is cited as prior art in new technological advances; the latter measures the variety of technological domains in which the invention is prior art, that is, its pervasiveness across different technological domains.

3.1 Indicators to characterize ex-ante recombination processes

The ex-ante perspective characterises the invention by looking at the recombination of knowledge components processes (Schumpeter, 1934). As already mentioned, we use two proxies for complexity – originality and scope,- and one for radicalness.

3.1.1 Scope

The number of a patent's distinct International Patent Classification (IPC)[4] codes is a proxy for the technological breadth or scope of the invention (Lerner, 1994). Research shows that at firm level, higher patent scope is associated to higher firm value (Lerner, 1994) and that patent scope is a main predictor of the probability the patent will be licensed (Shane, 2001). Patent scope is measured as the number of distinct IPC 4-digit codes to which the patent belongs (Lerner, 1994; Shane, 2001; Squicciarini et al., 2013). Since it measures how many distinct knowledge components are required for the invention, patent scope is associated to invention complexity (Lerner, 1994). Higher levels of patent scope correspond to higher levels of invention protection with respect to the number of other inventions that can infringe it (Shane, 2001).

3.1.2 Originality

The originality index developed by Trajtenberg et al. (1997) and used widely in the literature (e.g., Hall et al., 2001, Hicks & Hegde, 2005), measures the extent to which a patent draws on previous inventions dispersed across different technological fields. Exploiting the information on backward citations, the originality index of the focal patent captures the variety of technological domains, proxied by the number of IPC 4-digit codes to which the cited patents

[4] International Patent Classification (IPC) and Cooperative Patent Classification (CPC) are technology classification systems that describe the technicalities of patents. Their hierarchical structure enables the assignment of patents to broad or narrow technological fields as the number of digits increases.

belong. The higher level of the patent's originality index, the greater the diversification of knowledge sources across technological fields. Originality is measured as:

$$Originality_i = 1 - \sum_{j}^{n_i} s_{ij}^2$$

where s_{ij} is the percentage of citations made by patent i in the 4-digit patent classes j among n_i patent classes. The originality index is calculated as a Herfindahl-Hirschman (HH) concentration index of patent classes and ranges from 0 to 1. High levels of the HH index indicate that the cited patents come from a wide variety of different technological classes, meaning that the focal patent is the outcome of the combination of numerous technological fields.

3.1.3 Radicalness

A radical invention is defined as a new combination of components that "depart in some deep sense from what went before" (Arthur, 2007).[5] To be characterized as radical, an invention needs to show processes of recombination that differ from those characterizing incremental inventions. Radicalness is often conceptualized at firm level and is recognised when the invention emerges from the integration in the firm's knowledge base of knowledge from outside the firm's boundaries (Rosenkopf and Nerkar, 2001; Ahuja and Lampert, 2001).

In similar vein, Shane (2001) conceptualizes radicalness at the invention level, as the knowledge distance between the focal patent's technological classes and those of its cited patents. Shane (2001, p. 210) argues that "when a patent cites previous patents in classes other than the ones it is in, that pattern suggests that the invention builds upon different technical

[5] The broad definition of a radical invention includes the capacity of the invention to affect the future generation of technological developments. In Section 3.2 we consider the impact-related aspects of inventions, thereby encompassing ex-post radicalness (see, e.g., Schoenmakers and Duysters, 2010). Therefore, in this paper, we refer to radicalness only in terms of recombinant processes.

paradigms from the one in which it is applied" (see, also, Rosenkopf and Nerkar 2001). The indicator proposed by Shane (2001) is calculated as the number of distinct IPC 4-digit codes included in the cited patents, but which are not assigned to the focal patent. Squicciarini et al. (2013) refines the indicator calculating it as follows:

$$Radicalness_P = \sum_{j}^{n_p} \frac{CT_j}{n_p}\ ; IPC_{pj} \neq IPC_p$$

where CT_j is the count of IPC codes of patent/s j (cited by patent p) which are not present in the focal patent p; n_p is the number of IPC codes in the backward citations of the focal patent p for which the indicator is calculated.

3.2 Indicators to characterize ex-post impact of inventions

From an ex post perspective, inventions are characterised by the extent to which they impact future technological developments (Ahuja and Lampert, 2001). This conceptualisation revolves around the idea that inventions can be distinguished by their ability to become the seeds for future technological developments. The literature tends to investigate the impact of technologies using two indicators: forward citations and generality index. The former is employed here to measure the number of subsequent inventions influenced by the patent under investigation; the latter is used to capture the variety of technological fields affected by the focal patent.

3.2.1 Forward citations (5 years and 7 years)

The use of forward citations is probably the most diffused measure of patent quality. Prior studies use forward citations counts to proxy for invention value (Harhoff et al., 2003; Hall et al., 2005; Sapsalis et al., 2006), diffusion and knowledge spillovers (Trajtenberg, 1990; Hall &

Helmers, 2013; Sorenson & Fleming, 2004; Bacchiocchi & Montobbio, 2009; Dechezleprêtre et al., 2014), and importance (Dahlin and Behrens, 2005; Trajtenberg et al., 1997).

In the present paper, we use patent citations to investigate the impact on subsequent inventions, indicating a knowledge flow from one invention to the other. Patent citations are commonly used to assess the role of an invention as the starting point for further inventions (e.g., Hall & Helmers, 2013). The OECD patent quality indicators report (Squicciarini et al., 2013) develops two indicators of forward citations that differ in the time intervals (5 and 7 years after the patent publication date) at which the citations are observed.

3.2.2 Generality

The generality index is the forward citations counterpart of the originality index. It measures "the extent to which the follow-up technical advances are spread across different technological fields, rather than being concentrated in just a few of them" (Trajtenberg et al., 1997, p. 27). The generality index of a focal patent characterizes the degree to which citing patents belong to a variety of technological fields. The higher the patent's generality index, the higher its impact on a variety of different technological fields.

The generality index is measured as:

$$Generality_i = 1 - \sum_{j}^{n_i} s_{ij}^2$$

where s_{ij} is the share of IPC 4-digit codes j present in patent i among the overall number of n_i patent classes to which the citing patents belong. The index ranges from 0 to 1.

The generality index is used frequently in the innovation literature. Trajtenberg et al. (1997) argue that higher levels of generality correspond to higher levels of basicness of the knowledge exploited, while Hall and Trajtenberg (2004) show that GPT tend to have higher generality indexes than the average invention.

4. Data and Methods

4.1 Data

The comparison between green and non-green patents is based on two data sources. First, from the EPO Worldwide Patent Statistical Database (PATSTAT) – Autumn 2016, we gathered information for patents filed at the European Patent Office (EPO) in the period 1980-2012,[6] on patent families, citations, technological classification codes and patent applicants' geographical information. Second, the OECD Patent Quality Indicators database (Squicciarini et al., 2013) makes available a wide array of patent indicators, which we employ to proxy for the knowledge dimensions described in Sections 2 and 3.

Merging these two data sources, results in a dataset that provides information on patent documents and indicators. Following standard practice in the literature, we exploit the former information to identify environment-related patents based on a technology classification search. Specifically, for each patent, we obtained the list of IPC and CPC assigned to it. Then, using the OECD Env-Tech classification (2016),[7] which provides a list of technological classification codes associated to selected environment-related technologies, we can define patents as green if they include an Env-Tech classification code. The OECD patent classification list enables us to focus on a greater number of green technologies compared to previous studies (e.g., Popp and Newell, 2012; Dechezleprêtre et al., 2014), in particular: environmental management, water-related adaptation technologies, climate change mitigation

[6] The EPO was established in 1978. However, during the first two years of its existence, trends in the number of patents filed at this patent office were characterised by large fluctuations. Hence, we decided to drop the first two years and focus on patents filed from 1980 onwards.
[7] See Haščič and Migotto (2015) for an exhaustive explanation of this classification.

technologies related to transportation, buildings, environmental goods, carbon capture and storage, and energy generation, transmission and distribution.

We use patent family as our unit of analysis to deal with multiple equivalents of the same invention (Hall and Helmers, 2013), that is, patents issued in more than one country, which could lead to double counting of the same patent filed at different patent offices. Although the patents pertain to the same family, this does not guarantee that their claims and disclosure conditions are identical. Patent filing procedures vary among patent offices and patent issuing authorities (Simmons, 2009).[8] This heterogeneity of information within patent families leads to slight differences in the values of the patent indicators within a family, for example, number of citations, technological classification codes, etc. To deal with this issue, we follow Verhoeven et al. (2016) and take the maximum value of each indicator within the patent family. Although this practice has been operationalised in the literature, we further tested the stability of our results using alternative values for the patent indicators (see Section 5.2).

Table 1 provides descriptive statistics of the variables employed in the empirical analysis. We observe that 8.4% of the patent families in our sample are related to environmental technologies. Note that the number of observations used in our estimates varies according to the indicator considered. This variation stems from the way the indicators are built. In particular, it is impossible to calculate originality and radicalness indicators if the focal patent does not cite any prior patents; similarly, computing the generality index if the focal patent is not cited by subsequent patents is not feasible (see Section 3).

[8] E.g., at the United States Patent and Trademark Office (USPTO) applicants are legally required to provide a list of citations during the application process, whereas at the EPO such requirement does not exist.

4.2 Methodology

To investigate the differences between green and non-green inventions, across different dimensions, such as complexity, radicalness and impact, we estimate the following model:

$$pat.indic_i^A = \alpha + \beta\ Green_i^{0,1} + \gamma\ controls_i^A + IPC.3dig_i^{0,1} + geo_i^{0,1} + time_i^{0,1} + \varepsilon_i$$

where $pat.indic_i^A$ refers to the patent indicator A, that is, scope, originality, radicalness, forward citations and generality. The nature of the indicator dictates the choice of estimation method. When focusing on indicators for originality, radicalness and generality, we are dealing with censored dependent variables (i.e., by definition, their values cannot go below 0 or exceed 1), therefore, we rely on Tobit regressions.[9] Conversely, scope and forward citation are count indicators , thus, we rely on Poisson estimations. $Green_i^{0,1}$ is the main variable of interest and is equal to 1 if at least one patent within the patent family i is green, that is, it belongs to technological fields included in the OECD Env-Tech list, and 0 otherwise. $IPC.3dig_i^{0,1}$ is a set of IPC 3-digit dummy variables that capture the specific features of each technological domain (a detailed description is provided below). $geo_i^{0,1}$ are geographical dummies employed to control for heterogeneous effects across geographical areas.[10] We also include time dummies, $time_i^{0,1}$, to control for unobservable factors related to changes in patenting patterns through time. These dummies capture whether the earliest priority year of the patent family falls within one of three time windows: 1980-1990, 1991-2001, 2002-2012.[11] This allows us to control for unobservable heterogeneity that affects patent indicators equally and varies over time (e.g., patenting intensity, etc.). Finally, ε_i is the error term.

[9] In our sample, the originality and generality indicators never reach the upper "theoretical" limit (i.e. 1) (see Table 1). Hence, in these two cases, in our regressions, we impose only the left-censoring limit at 0.
[10] We assign patents to geographical areas on the basis of country of origin of the (highest share of) applicants. Geographical dummies refer to: Europe; United States; Japan; Other OECD countries; and Non-OECD countries.
[11] As a robustness check, we use time dummies, each of which captures a 5-year period. The different lengths of the "time windows" do not influence the results (available upon request), which remain extremely stable compared to those reported in Section 5.

We also include a set of control variables. First, we control for number of applicants, which might affect the extent to which the patent can rely on a larger pool of knowledge (Staats et al., 2012) and, consequently, the complexity, radicalness and impact of the invention. In some cases, choice of the controls is dictated by the way the patent indicators are built. For patent indicators that rely on information about prior knowledge, that is, originality and radicalness, we control for backward citations (Hall et al., 2001). In addition, since backward citations are considered to proxy for invention quality (Harhoff et al., 2003), if scope, forward citations and generality are the dependent variables, we include, as a control, the variable capturing backward citations. Moreover, since the generality index relies on citations from subsequent patents, we control for the number of forward citations (Hall et al., 2001). Finally, for the scope and radicalness indicators, which are built using technological classification codes, that is, we control for the number of full digit IPC codes (e.g., Sapsalis et al., 2006).

4.2.1 Controlling for technological specificities

We include a technology dummy, $IPC.3dig_i^{0,1}$, because, unlike other related studies (e.g. Popp and Newell, 2012; Dechezleprêtre et al., 2014), we control for the invention's technical specificities by comparing green and non-green patent families within narrow technological fields. This allows us to compare green and non-green inventions that are expected to be similar,[12] that is, belong to the same technological domain. Comparison between patent families relies on the fact that patents with similar technical features are assigned to the same IPC 3-digit code.

[12] Consoli et al. (2016) employ a similar empirical setting in the context of green jobs. They compare the skill content and human capital indicators for green and non-green occupations. In our work, a similar model is applied, using technological classification structures instead of occupational categories, to compare the difference between green and similar (i.e., belonging to the same technological fields) non-green patents.

Comparing green and non-green patents within the same IPC 3-digit codes adds to the robustness of the analysis. Rather than focusing on macro-technological groups (e.g., energy production, transportation, etc.), we investigate the difference between green and non-green inventions within narrow technological fields, for example, “Basic electric elements” (H01 - IPC); “Steam generation” (F22 - IPC); “Organic chemistry” (C07 - IPC), etc. Failing to take account of the idiosyncratic features of technological domains – such as, availability of a consolidated prior art, propensity to cite or be cited by other patents, tendency to rely on a wider range of knowledge components – could bias estimation of the true difference between green and non-green patents. Indeed, without controls for technological heterogeneity, estimation of the coefficient of the *green* variable could be driven by differences in complexity, radicalness and impact across technological fields, rather than by the true particularities of green compared to non-green patents. It should be noted that including these dummies, limits the analysis to those IPC 3-digit codes which include at least one green and one non-green patent family.[13]

In order to assign an IPC 3-digit code to each patent family, we rely on use of the primary codes, that is, the main IPC code assigned to each patent (Thompson and Fox-Kean, 2005; Leydesdorff et al. 2014).[14] Since primary codes are provided only by the USPTO, where ‘Primary’ and ‘Secondary’ classification codes are mandatory for patent applications, we focus on patent families with patents filed at both the EPO and the USPTO. This results in the inclusion in our sample of high-quality patents, reduces the heterogeneity arising from differences in the patenting processes across patent offices and allows us to obtain a coherent

[13] Some environmental-related patent classification codes included in the OECD Env-Tech list are at the IPC/CPC 4-digit level. This implies that the lowest digit level at which we can find both green and non-green patent families is the 3-digit level. It follows that, in order to compare both green and non-green patent families within the same 3-digit code, we must adopt the IPC system since some of the CPC codes relate entirely to green technologies (e.g., Y02 - CPC).

[14] Verspagen (1997) points out that primary or main classification codes are good proxies for the sector in which the knowledge is produced, whereas supplementary codes can be considered as proxying for sectors to which knowledge spills over.

and homogeneous set of patent families. As an alternative approach, we exploit Breschi et al. (2003), which assumes no difference between primary and supplementary codes. Hence, we retrieve the full set of IPC 3-digit codes assigned to patent families. This alternative approach, in turn, increases the size of the patent family sample as it allows the inclusion of a set of USPTO patent applications with missing information for primary code.[15]

Both approaches retrieve multiple IPC 3-digit codes within each patent family. While this is to be expected from the alternative approach, we observe that some patent families have multiple primary codes. This is not surprising since primary codes are assigned to patents rather than to patent families. In both cases, we choose the most frequent IPC 3-digit code assigned to each patent family in order to obtain a unique code. Although, for the vast majority of patent families, we can identify a unique $IPC.3dig$, some families still have multiple IPC codes with the same frequency. In these cases, we identify the 3-digit code of the earliest dated patent document. However, this procedure failed to identify unique IPC 3-digit codes for 4.53% of patent families which, thus, are excluded from the analysis.[16]

[15] In PATSTAT, almost half of the patents include this information. Further details on the IPC position field in PATSTAT are available from the PATSTAT Data Quality Report, available at: https://www.google.it/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0ahUKEwiAqrTv7ffWAhVHKFAKHcq5CdIQFggnMAA&url=https%3A%2F%2Fcircabc.europa.eu%2Fwebdav%2FCircaBC%2FESTAT%2Finfoonstatisticsofsti%2FLibrary%2Fmethodology%2Fpatent_statistics%2FPATSTAT-DataQuality_December%25202013.pdf&usg=AOvVaw3Wuf24IJ9w5TDKzM0NP89e (last accessed January 2018)

[16] The same approach is implemented to identify a unique geographical code for each family. After collecting information on the geographical location of each applicant, we identify the most frequent applicant's geographical area within each patent family. In the case that some patent families have multiple geographical codes with the same frequency, we assign the patent family to the geographical area of the earliest patent document within the family. Since across country co-patenting is not frequent (Hagedoorn, 2003; Belderbos et al., 2014), the number of families not eventually assigned to a unique geographical area is 0.54% of the sample.

5. Results

5.1 Comparing green and non-green inventions

In this section, we present the results of our empirical analysis. First, we compare green and non-green patents without controlling for the technological specificities of each invention, that is, by calculating a simple t-test on the mean difference across the indicators presented above. Table 2 shows whether green technologies are different from non-green technologies. On average, green and non-green technologies are significantly different (at the 99.99% level) along the search and impact spaces. In particular, green patents are characterised by higher complexity in their recombination, relative to non-environmental technologies, in both scope (+14.18%) and originality (+7%). Also, green patents are characterised by higher levels of radicalness (+3.13%) than non-green inventions. In relation to impact on subsequent patents, inventions with environmental-related application are 6.25% more general and receive 12.83% (or 10.9%) more citations on average than non-green patents, within 5 (or 7) years of publication.

However, these results do not account for the different types of technologies characterising the sample. That is, the positive difference between green and non-green patent families may be driven by a subset of technological domains in which green technologies perform relatively better. Figure 1 depicts average values of each patent indicator over the IPC 3-digit codes for green and non-green patent families (respectively solid and dashed lines) and their difference (black bars). We observe that the average value of green patent indicators is higher than the value of non-green indicators across almost all IPC 3-digit codes. This finding provides heuristic evidence that, even when considering narrow technological fields, green patent families exhibit greater complexity and radicalness and have a greater impact on subsequent technologies compared to non-green patent families.

<<Table 2 around here>>

<<Figure 1 around here>>

The core of our econometric analysis is intended to test and quantify the differences between green and non-green technologies by controlling for technological characteristics and other factors that might influence the patent indicators. Table 3 includes two columns for each patent indicator, depending on the strategy used to identify the IPC 3-digit dummy variables, that is, primary code or all classification codes (see Section 4.2). A first insight is that differences between green and non-green technologies persist along all the dimensions we consider, even when controlling for patent citation patterns, number of applicants, geographical dummies, time dummies and technological fields. More precise insights emerge from inspection of the specific indicators that capture ex-ante recombination and ex-post impact patterns.

Let us focus on the first group of indicators, which measure complexity based on indicators of scope and originality, and radicalness. First, we see that the controls have the expected signs and significance. Patent families with larger pools of applicants tend to be characterised by higher originality and scope and greater radicalness. When looking at backward citations, inventions that develop upon a larger body of prior knowledge appear to be broader in scope, more original and radical. As expected, *Scope (Full-digit)* exerts a positive and significant effect on patent scope. Finally, we notice a negative coefficient of *Scope (Full-digit)* when radicalness is the dependent variable, which is in line with how the indicator is built (see Section 3.1.3).[17]

Moving to the main analysis, including environmentally-sound technological solutions in a patent increases, *ceteris paribus*, complexity in recombination in a non-homogeneous way.

[17] A higher number of IPC classes in the focal patent reduces the probability of the presence of technological classes in the cited patents which are not included in the focal patent, which is what the radicalness indicator measures (see Section 4.2).

Green inventions are more original and have a broader scope than their non-green counterparts. In other words, green technologies stem from a more dispersed search space and, at the same time, include more distinct knowledge component branches than their non-green counterparts. More specifically, belong to a green technology domain increases patent originality by around 3% (from +2.8% to +3.2%, depending on the technology dummies used, that is, $IPC.3dig_i$, see Section 4.2), and increases the scope of an invention by more than 10% (i.e., from +10% to +13%).[18] Hence, it appears that including an environmental objective in an invention increases its technological breadth (as captured by the scope indicator) more than dispersion of the different technological fields upon which this is based (as captured by the originality indicator). In other words, our results suggest that green compared to non-green patents, draw on slightly more diversified knowledge fields, but, in particular, combine a markedly higher number of technological components.[19]

The third indicator of ex-ante recombination pertains to the radicalness of the invention. In this case, we notice that the effect of including an environmentally-sound technological component is limited (although not negligible) compared to the effect of the scope and originality indicators. The evidence still points to a positive, albeit relatively small, and significant effect of the *Green* dummy on the radicalness indicator. Green patent families are more differentiated from their knowledge sources than non-green patent families. In particular, the green orientation of an invention increases its radicalness by around 1.5% (+1.3% to +1.5%).

<<Insert Table 3 here>>

[18] Table 3 presents the β-coefficients of our Tobit and Poisson regressions. In order to provide a quantification of the results, given the non-linear nature of our models, in Section 5.1 we present the marginal effects of *Green*. For the Tobit estimates, we follow Cameron and Trivedi (2005, p. 542) and compute the marginal effect $\partial E(y|x)/\partial x$ of *Green*, focusing on the partial derivative of the conditional mean of the observed dependent variable, *y*.

[19] The following examples help to explain the possible coexistence of high values for scope and more limited values for originality. Patent EP1354631(A2) covers a relatively large number (4) of IPC 4-digit classes, and its backward citations are not evenly distributed across IPC 4-digit classes, but rather are concentrated in one class (i.e., more than 50% of the IPC classes of the cited patents are related to the IPC B03C code).

Following the results for ex-ante recombination, we focus next on the characteristics of the impact space according to the ex-post indicators described in Section 3.1, that is, number of forward citations and the generality index. Again, we find the expected positive sign of the coefficients of our controls for number of applicants and backward citations patterns and, when the generality indicator is used as dependent variable, for forward citations.

In the case of green patents and their impact on future inventions, captured by the effect on forward citations in 5 (and 7) years, our estimates reveal a positive and significant effect. Green patents receive 29%-30% (27%-29%) more citations from subsequent inventions than non-green patents. This is evidence that green inventions are more likely to become the seeds for future inventions than their non-green counterparts. Our results show that green patents, on average, are more likely than their non-green counterpart to exhibit an impact on a variety of technological domains. In particular, our estimates show that, on average, the generality of a green patent increases by more than 4.5% (from +4.3% to +4.6%). In this sense, our results confirm the pervasiveness of green inventions in technological realms that are different from the original domain of the patent, thus, corroborating the idea that environmentally-sound technologies shows traits typical of GPTs (Hall and Trajtenberg, 2004).

5.2 Robustness checks

In this section we provide a series of robustness checks to test the stability of our results. The so-called "p-value problem" concerns the inverse relationship between this measure and sample size (Chatfield, 1995): p-values and standard errors decrease with increasing sample size, leading us to question whether the significance of the coefficients can be interpreted as a meaningful or only a statistical effect. This is particular relevant in the case of our analysis: our conclusions about the statistical significance of the coefficients could be driven by the large sample size (Lin et al., 2013). To deal with this issue, in Tables 2 and 3 we adapt the p-value threshold for significance to the sample size, by considering the coefficients as statistically significant if their p-value is smaller than 0.01%. Following Benjamin et al. (2018), who point to the need to adopt more stringent p-value thresholds, our claim of statistical significance is one hundred times more restrictive than the usual $p < 1\%$. Second, to reduce issues arising from the sample size, we ran the analysis using a smaller number of observations. We reran the regressions on subsamples obtained from a stratified random sampling procedure, to maintain representativeness in terms of share of patents per year and technological field, and share of green patents. Appendix Table A1 reports the results using two subsamples, that is, amounting to 5% and 10% of the original dataset. We observe that the sign and statistical significance of our results hold even with these smaller representative samples. This suggests that our findings are not driven by the relative large sample size, but, instead, capture truly significant and meaningful effects.

In Section 4.1, we follow the methodology employed in Verhoeven et al. (2016) by taking the maximum value of the patent indicators within each patent family (our unit of analysis). In order to check whether our results are robust to this choice, Appendix Table A2 presents the results obtained using the minimum values of the indicators within each patent family. We observe that the significance and sign of the key variable *green* and the control variables do not change when we use the lower bound of the indicator values within the patent families. The results confirm that, although there may be heterogeneity in patent indicator values within the same patent family, their variance is relatively low and does not affect the regression estimates.

Finally, we consider the quality of the patents included in our dataset. As an additional robustness check, we focus on triadic patent families (Dernis and Khan, 2004), that is, those patents filed at the three most important patent offices: the EPO, USPTO and Japan Patent Office. This enables us to focus on high-quality inventions, since the size of the patent families is considered to be a good proxy for high-value inventions (Lanjouw et al. 1998; Harhoff et al. 2003). Appendix Table A3 presents the results for the triadic patent family subsample. We observe that the significance and signs of the coefficients do not vary with respect to our main results.

6. Discussion and conclusions

In this paper, we focused on green technologies to assess whether they differ from their non-green counterparts. Using patent data and a set of established patent indicators provided by Squicciarini et al. (2013), we sought to link the search and impact spaces. The search space was investigated from an ex-ante perspective that captured the knowledge recombination processes leading to an invention. The impact space was explored using an ex-post approach that assessed the impacts of inventive activities on subsequent technological developments. We focused on the upstream phase of the innovation process, that is, inventive activity, to net out differences between green and non-green technologies that might relate to the adoption and commercial exploitation of innovations. Also, we accounted for possible confounding factors arising from technological heterogeneity and citations patterns to identify differences due directly to the environmental orientation of the inventions.

Our first set of findings provides an original and direct test of whether the generation of technological knowledge differs between the green and non-green realms. Our results confirm the distinctiveness of the green knowledge base found in prior studies (e.g., Cainelli et al., 2015; Ghisetti et al., 2015). Green technologies are more complex and, to a lesser extent, also more radical than non-green ones. Overall, our results for the ex-ante recombination of knowledge lead to three potential conclusions. First, green technologies combine a higher number of technological components than their non-green counterparts. Second, green patents rely on more diverse branches of knowledge for their generation compared to their non-green patent counterparts. Third, green inventions develop based on new combinations of knowledge, which are different from their knowledge sources. The size of the coefficients of our estimates suggests the first conclusion is stronger than the second and, in particular, than the third one.

Linking our analysis to the evidence from firm-level studies investigating the knowledge bases of environmental innovations, our results suggest that meeting the additional requirements of complexity and radicalness is not straightforward and requires difficult knowledge-sourcing efforts, such as, exploitation of open innovation modes and external knowledge providers (e.g., De Marchi, 2012; Ghisetti et al., 2015; Marzucchi and Montresor, 2017). However, it is important to stress two issues, which suggest caution in making a direct link between our results and the available firm-level evidence, based mainly on survey data. First, as already mentioned, in our study, we focused on the process of knowledge recombination at the basis of the inventive activity that generates new technologies. It might be that, "downstream" phases, including adoption of technologies or the economic exploitation of environmental innovations, add complexity, which needs to be dealt with, and require radically new competences, which induces firms to look for knowledge outside their boundaries. Second, compared to the firm-level evidence available in the literature, we looked at another type of difference, namely that between the knowledge content of a green patent and the knowledge base of all non-green inventions in the same technological field. Prior studies consider firms' knowledge-sourcing activities that are dictated by differences between their internal competences and those required to increase their environmental innovation performance. As a result, our findings cannot be translated directly into firm-level implications for knowledge sourcing strategies. This would require consideration of firms' actual capacities to identify, assimilate (and exploit) knowledge from the external environment, that is, their absorptive capacity (Cohen and Levinthal, 1989; Zahara and George, 2002). This is beyond the scope of the analysis in this paper, but should be addressed in future research: not considering firms' idiosyncratic capacity to access the pool of patented knowledge "underestimates" firms' challenges and reactions related to technological complexity and radicalness.

This first set of results not only provides insights into the knowledge base underlying environmental innovation, it also suggests some important policy implications. The fact that green technologies rely on more and diversified branches of knowledge resonates with the idea that these technologies are in an early stage of their life cycle (Consoli et al., 2016): the need to draw on multiple technological fields would seem to suggest that established green technological development trajectories have yet to be defined (Barbieri, 2016). This implies the need to devise technology policy interventions that support multidisciplinarity, to favour knowledge diversification rather than specialisation and ease knowledge transfer. By the same token, network-type policy actions emerge as fundamental tools to facilitate connections among actors involved in different technological arenas. These actions would seem to constitute a viable strategy to trigger the introduction of radical technical change, which is recognised as fundamental to achieve environmental sustainability (Mazzanti and Rizzo, 2017).

The second set of results relate to the impact of green technologies on future technological developments. Without restricting our analysis to specific technological domains, we contribute to previous work (e.g. Popp and Newell, 2012) by providing more general evidence of whether green patents differ from similar non-green ones in terms of forward citations and generality. We found that green technologies are characterised by more forward citations and higher generality. Our results show that, while effective for triggering subsequent patented technologies (forward citations), green inventions also affect a higher variety of technological domains as highlighted by the generality index. In other words, green inventions are characterised by higher impact and pervasiveness, a major trait of GPTs. As such, green technologies may not (yet) offer unique solutions; rather, they open opportunities for technological developments in different sectors. Moreover, their economic and environmental impact rests on the technological complementarities within application fields (Bresnahan and Trajtenberg, 1995; Cantner and Vannuccini, 2017).

This connects to two sets of technology policy implications. Given the high potential for spillovers across a variety of technological fields, public interventions (e.g., R&D subsidies) to support green technologies seem to be well justified. This is consistent with prior analyses, for example, Dechezleprêtre et al. (2014). In addition, the traits that green inventions share with GPTs call for actions to support the development of downstream technological applications. This would increase the economic and environmental returns to advances in green technologies. Direct interventions by policy makers could ease coordination problems and realign the incentives of actors that are distance in terms of sectors and technologies (Bresnahan and Trajtenberg, 1995). However, this would involve much selection of the applications to be supported. In an evolutionary approach, given the uncertainty surrounding the green technological development trajectory, excessive selection could lead to inefficient outcomes if it becomes detrimental to the variety of the alternatives (Metcalfe, 1994).

Our work sets the stage for further research. We focused on a specific phase in the innovation process: generation of inventions. It is important to ascertain whether the adoption and exploitation of green technologies represent complex and radical changes for firms. This would help to clarify whether resorting to external knowledge to augment the firm's existing knowledge, is the solution to issues that arise in one or all the different phases in the innovation process. Second, the availability of a reliable match between patent and firm level data, would allow future research to scrutinise the role of firms' absorptive capacity and prior experience of developing green technologies (or related non-green ones). Finally, our analysis is confined to the technological realm. Going beyond this scope is required to assess whether (and which) green technologies provide increasing (environmental and) economic returns to scale, which is an important trait of GPTs (Hall and Trajtenberg, 2004).

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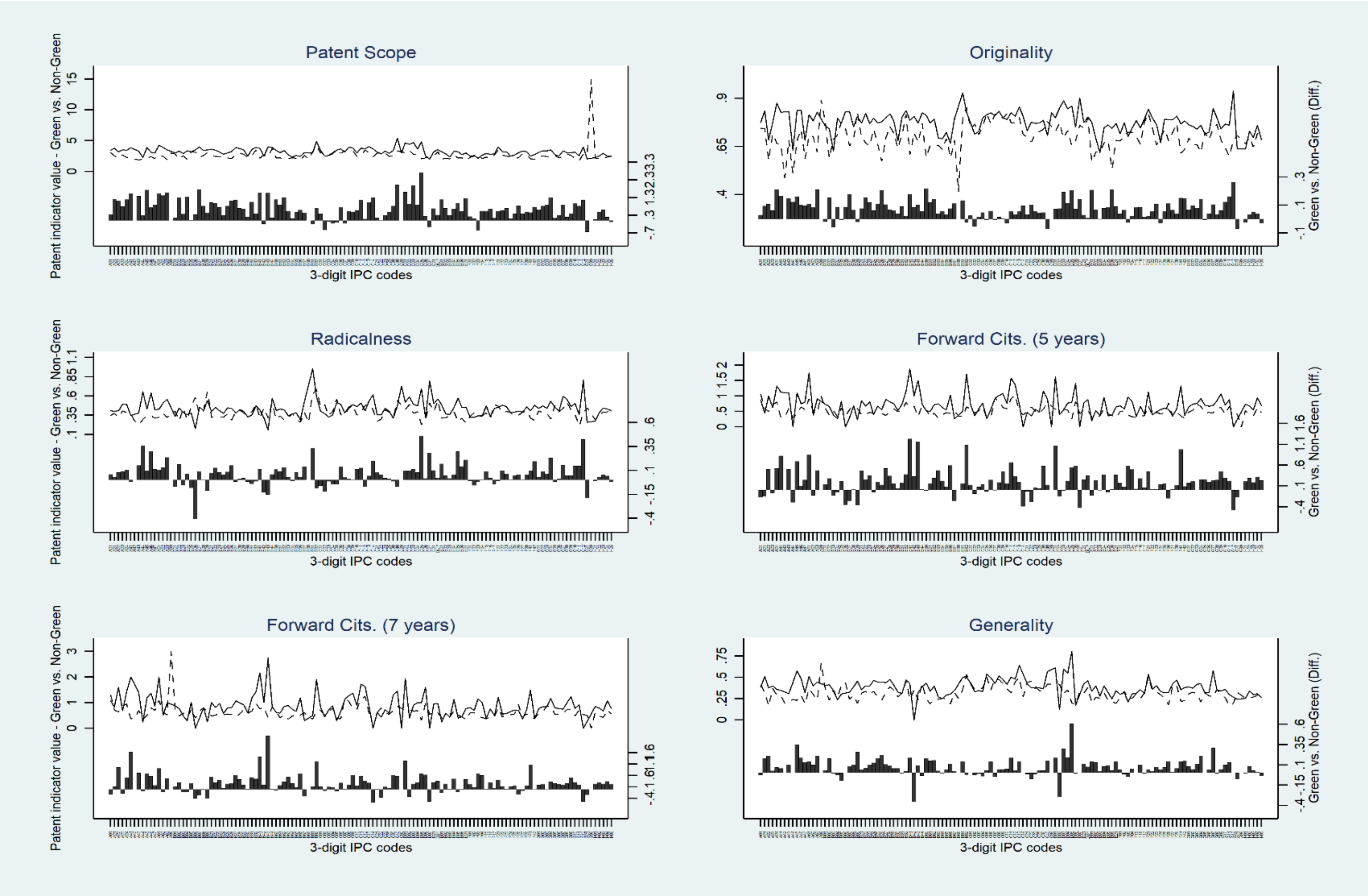
Figures

Figure 1 – Indicators within each IPC 3-digit code: mean differences between green and non-green patent families



Note: IPC 3-digit codes are listed in alphabetical order in the x-axis. Left axis reports the average value of the patent indicators within each IPC 3-digit code for green patent families (solid line) and non-green patent families (dashed line). The bar graphs (right axis) measure the difference in the mean value of the patent indicators.

Tables

Table 1 – Descriptive statistics

Variable	Variable description	Obs	Mean	Std. Dev.	Min	Max
Scope (4-digit)	*Number of IPC 4-digit codes*	1,856,311	2.411	1.380805	1	61
Originality	*Herfindahl–Hirschman Index of IPC codes in the cited patents (Trajtenberg et al., 1997)*	1,799,369	.674	.2371565	0	.987
Radicalness	*Number of IPC codes assigned to the cited patents which are not included in the citing patent (Squicciarini et al., 2013)*	1,799,808	.319	.2664022	0	1
Forward citations (5 years)	*Citation count in the 5 years after patent application*	1,856,311	.832	2.177193	0	655
Forward citations (7 years)	*Citation count in the 7 years after patent application*	1,856,311	1.051	2.546413	0	674
Generality	*Herfindahl–Hirschman Index of IPC codes in the citing patents (Trajtenberg et al., 1997)*	702,194	.350	.2817849	0	.944
Backward citations	*Count of backward citations*	1,856,311	5.52	6.957807	0	1,002
Number of applicants	*Number of applicant - team size*	1,856,311	2.646	2.114494	1	100
Scope (Full-digit)	*Number of IPC full-digit codes*	1,856,311	5.729	5.318183	1	247
Green	*Dummy variable equal to 1 if the patent is green and 0 otherwise*	1,856,311	.084	.277942	0	1

Table 2 – Statistics on patent indicators

Variable	Mean		Diff	Std. Dev.		t-test	z-test
	Green	Non-Green	Green – Non-green	Green	Non-Green	Difference	Ranksum
Scope	2.745	2.404	0,341	1.495	1.358	-89.36***	-99.62***
Originality	.719	.672	0,047	.203	.238	-87.91***	-75.43***
Radicalness	.329	.319	0,010	.257	.267	-15.38***	-21.98***
Forward citations (5 years)	.923	.818	0,105	2.353	2.135	-17.50***	-22.46***
Forward citations (7 years)	1.149	1.036	0,113	2.764	2.496	-15.98***	-18.04***
Generality	.374	.352	0,022	.280	.281	-19.56***	-19.46***

*** p< 0,01%

Table 3 – Regression results

	Complexity				Radicalness		Impact					
	Scope (4-digit) - Primary	Scope (4-digit) - All-IPC	Originality - Primary	Originality - All-IPC	Radicalness - Primary	Radicalness - All-IPC	Forward citations (5 years) - Primary	Forward citations (5 years) - All-IPC	Forward citations (7 years) - Primary	Forward citations (7 years) - All-IPC	Generality - Primary	Generality - All-IPC
Green	0.096***	0.118***	0.028***	0.032***	0.015***	0.013***	0.258***	0.266***	0.240***	0.252***	0.043***	0.046***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.014)	(0.009)	(0.013)	(0.008)	(0.003)	(0.002)
Forward citations (5 years)											0.014***	0.019***
											(0.002)	(0.002)
Number of applicants	0.011***	0.013***	0.007***	0.009***	0.004***	0.007***	0.076***	0.074***	0.074***	0.070***	0.012***	0.011***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)	(0.003)	(0.000)	(0.000)
Backward citations	0.002***	0.002***	0.004***	0.005***	0.003***	0.004***	0.006***	0.006***	0.005***	0.006***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Scope (Full-digit)	0.022***	0.024***			-0.003***	-0.004***						
	(0.001)	(0.001)			(0.000)	(0.000)						
Observations	1,013,182	1,856,311	983,528	1,799,369	983,686	1,799,808	1,013,182	1,856,311	1,013,182	1,856,311	311,534	701,802
Regional Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
IPC.3dig	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F			686.7	1607	470	1249					274.4	625.6
Chi2	136729	311621					19986	50132	24041	65676		

Robust standard errors in parentheses
*** p< 0,01

Appendix

Table A1 – Regression results using smaller samples of the patent dataset

	5% patent sample						10% patent sample					
	Complexity		**Radicalness**	**Impact**			**Complexity**		**Radicalness**	**Impact**		
	Scope (4-digit) - Primary	Originality - Primary	Radicalness - Primary	Forward citations (5 years) - Primary	Forward citations (7 years) - Primary	Generality - Primary	Scope (4-digit)- Primary	Originality - Primary	Radicalness - Primary	Forward citations (5 years) - Primary	Forward citations (7 years) - Primary	Generality - Primary
Green	0.102***	0.026***	0.010*	0.260***	0.297***	0.033***	0.091***	0.033***	0.009***	0.256***	0.259***	0.021**
	(0.008)	(0.003)	(0.005)	(0.051)	(0.044)	(0.012)	(0.008)	(0.002)	(0.004)	(0.032)	(0.031)	(0.009)
Forward citations (5 years)						0.014***						0.020***
						(0.004)						(0.002)
Number of applicants	0.009***	0.007***	0.005***	0.068***	0.106***	0.011***	0.012***	0.007***	0.004***	0.100***	0.102***	0.012***
	(0.002)	(0.000)	(0.001)	(0.012)	(0.008)	(0.001)	(0.002)	(0.000)	(0.000)	(0.005)	(0.005)	(0.001)
Backward citations	0.003***	0.005***	0.003***	0.013***	0.012***	0.001***	0.002***	0.003***	0.003***	0.006***	0.005***	0.001***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Scope (Full-digit)	0.022***		-0.004***				0.020***		-0.003***			
	(0.002)		(0.000)				(0.002)		(0.000)			
Observations	50,574	49,083	49,092	50,574	50,574	15,444	101,355	98,387	98,401	101,355	101,355	31,106
Regional Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
IPC.3dig	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F		38.84	25.81			16.94		70.34	44.83			29.77
Chi2	8643			6384	5084		16798			9473	4148	

Robust standard errors in parentheses
*** p< 0,01%

Table A2 – Regression results using the minimum indicator values within each patent family

	Complexity				Radicalness		Impact					
	Scope (4-digit) - Primary	Scope (4-digit) - All-IPC	Originality - Primary	Originality - All-IPC	Radicalness - Primary	Radicalness - All-IPC	Forward citations (5 years) - Primary	Forward citations (5 years) - All-IPC	Forward citations (7 years) - Primary	Forward citations (7 years) - All-IPC	Generality - Primary	Generality - All-IPC
Green	0.045***	0.082***	0.026***	0.029***	0.010***	0.005***	0.243***	0.221***	0.220***	0.212***	0.035***	0.038***
	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)	(0.006)	(0.009)	(0.006)	(0.003)	(0.002)
Forward citations (5 years)											0.039***	0.040***
											(0.001)	(0.001)
Number of applicants	0.019***	0.015***	0.012***	0.011***	0.028***	0.029***	-0.198***	-0.144***	-0.230***	-0.159***	0.017***	0.014***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.012)	(0.008)	(0.013)	(0.008)	(0.003)	(0.002)
Backward citations	0.000	-0.001***	0.005***	0.007***	0.004***	0.005***	0.004***	0.005***	0.003***	0.005***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Scope (Full-digit)	0.027***	0.029***			-0.015***	-0.011***						
	(0.002)	(0.001)			(0.000)	(0.000)						
Observations	1,012,249	1,856,311	982,608	1,799,369	982,766	1,799,808	1,012,249	1,856,311	1,012,249	1,856,311	310,861	701,205
Regional Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
IPC.3dig	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F			609.7	1422	506	1253					228.6	622.9
Chi2	59781	217446					23404	69477	28660	85507		

Robust standard errors in parentheses
*** p< 0,01%

Table A3 – Regression results using triadic patent families

	Complexity				**Radicalness**		**Impact**					
	Scope (4-digit) - Primary	Scope (4-digit) - All-IPC	Originality - Primary	Originality - All-IPC	Radicalness - Primary	Radicalness - All-IPC	Forward citations (5 years) - Primary	Forward citations (5 years) - All-IPC	Forward citations (7 years) - Primary	Forward citations (7 years) - All-IPC	Generality - Primary	Generality - All-IPC
Green	0.094***	0.116***	0.026***	0.031***	0.010***	0.011***	0.229***	0.257***	0.220***	0.247***	0.035***	0.039***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.018)	(0.010)	(0.017)	(0.009)	(0.003)	(0.002)
Forward citations (5 years)											0.011***	0.017***
											(0.001)	(0.002)
Number of applicants	0.008***	0.009***	0.007***	0.009***	0.004***	0.007***	0.080***	0.078***	0.078***	0.073***	0.012***	0.010***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.003)	(0.004)	(0.003)	(0.000)	(0.000)
Backward citations	0.002***	0.002***	0.003***	0.005***	0.003***	0.004***	0.006***	0.006***	0.005***	0.006***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Scope (Full-digit)	0.020***	0.023***			-0.003***	-0.003***						
	(0.000)	(0.000)			(0.000)	(0.000)						
Observations	595,028	1,246,468	580,384	1,209,152	580,469	1,209,473	595,028	1,246,468	595,028	1,246,468	201,817	517,487
Regional Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
IPC.3dig	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
F			466.9	1208	306.3	879.4					200.5	493.9
Chi2	99779	251855					15497	32113	18359	41214		

Robust standard errors in parentheses
*** p< 0,01%

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SPRU – Science Policy Research Unit
University of Sussex
Falmer, Brighton, BN1 9SL,United Kingdom
SWPS Website: www.sussex.ac.uk/spru/research/swps
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