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Green technologies, complementarities, and policy

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Abstract

The present study explores the technological complementarities between green and non-green inventions. First, we look at whether inventive activities in climate-friendly domains depend on patenting in related technological domains that are not green. Based on patent data filed over the 1978–2014 period, we estimate a spatial autoregressive model using co-occurrence matrices to capture technological interdependencies. Our first finding highlights that the development of green technologies strongly relies on advances in other green and in particular non-green technological domains, whose relevance for the green economy is usually neglected. Building on this insight, we detect the non-green complementary technologies that co-occur with green ones and assess whether environmental policies affect this particular instantiation of technologies at the country level. The results of the instrumental variable approach confirm that while environmental policies spur green patenting, they do not displace the development of the non-green technological pillars upon which green inventions develop.

Keywords:
Green technology, patent data, environmental policy, network-dependent innovation
JEL: H23, O31, Q58, Q55

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1. Introduction

Over the past decades, the policy and scientific communities have acknowledged that the achievement of long-term climate objectives is contingent upon the ability of environmental policy to trigger technology improvements (Hoffert et al., 2002; Popp, 2002). In the policy arena, the deployment of environmental innovations is put to the fore in the action plan foreseen by the European Green Deal (COM(2019) 640 final) (EC, 2019) and in various policy packages such as the European Emissions Trading Scheme (Directive 2003/87/EC) and the American Recovery and Reinvestment Act (Public Law 111–5). By providing the economic incentives to internalise the social cost of environmental degradation, regulatory stringency spurs technological advances aimed at tackling greenhouse gas emissions, improving the efficient use of natural resource, minimising resource depletion, etc. (Jaffe et al., 2003). Whereas stringent policies induce technological efforts in the green technological domain (see, among others, Popp, 2002; Johnstone et al., 2010b; Nesta et al., 2014)[1], they further accelerate technological change by contextually decreasing the incentives to develop carbon-intensive technologies (Gray and Shadbegian, 1998).

In this context, exploring the nature of technological change is pivotal to assess the effectiveness of environmental regulation (Fischer and Newell, 2008). The extant literature suggests that technology does not develop in isolation (Pistorius and Utterback, 1997; Sandén and Hillman, 2011). In fact, it benefits from heterogeneous sources of externalities that arise from spatial closeness (Keller, 2001; Ertur and Koch, 2007), as well as technological relatedness. On this latter element, recent contributions indicate that technology advances through network-dependent dynamics in which technological progress in one field propels technological development in other linked domains. For instance, Acemoglu et al. (2016) show that knowledge flows neither in a local manner, i.e. with each field drawing only from its previous advancement, nor in a global way, i.e. with all fields sharing a collective pool of knowledge. There are key classes upon which each technological field builds upon; hence, the future rate of inventive activity in a given technology crucially depends on the development of upstream technological domains it draws upon. Similar results are obtained by Taalbi (2020), who makes use of a network structure built upon innovation counts and innovation use across industries, rather than patent data. The recent work by Pichler et al. (2020) further corroborates the idea that technological domains that combine components drawn from fast-growing fields grow faster. Based on these premises, a clear policy implication arises: the impact on a given technological field may depend on the effects that policy has on the technological landscape from which the targeted technology emerges.

How can these insights be applied to the case of climate-friendly technologies? At the outset, environmentally related innovations mirror other inventions: they 'often cannot fulfil anything like [their] potential unless other inventions are made relaxing or bypassing constraints which would otherwise hamper its diffusion and expansion' (Rosenberg, 1976, p. 201). Relatedly, we can expect that environmental technologies stem from the recombination of heterogeneous pieces of knowledge in new ways (Schumpeter and Backhaus, 2003; Kauffman et al., 1993; Weitzman, 1998; Fleming, 2001; Olsson and Frey, 2002; Tsur and Zemel, 2007; Marchese et al., 2019). In fact, recent evidence highlights that green technology—compared to similar non-green counterparts—tends to introduce new combinations of knowledge and to combine a greater number of technological domains from more diverse fields (Barbieri et al., 2020a). However, these underlying technologies do not necessarily provide environmental benefits but, instead, configure themselves as pillars for green technological advances via the recombination process. The extent

[1] See Barbieri et al. (2016) and Popp (2019) for a systematic review of these studies.

to which the development of green technologies depends on advances in non-green fields makes the exploration of the impact of environmental policies of particular interest. More specifically, by adopting this new network-based perspective it becomes important to assess whether and to what extent policy interventions impact the development of non-green technologies that trigger technological progress in environmentally related domains (complementary non-green technologies, hereafter). Accordingly, we ask the following question: What is the impact of environmental policies on complementary non-green technologies? Our contention is that the displacement of complementary non-green technologies may hamper the greening of the economy. A few studies from outside the economics debate directly delve into this issue. Markard and Hoffmann (2016) emphasise the dynamic nature of complementarities and highlight that some technologies may compete and complement each other at the same time, as in the case of electricity generation—in which a portfolio of technologies is required to satisfy the internal energy demand—or the co-evolution of Li-Ion batteries and photovoltaic panels. Policy intervention is required to overcome potential barriers and facilitate the creation of technological and sector-level complementarities. Sinsel et al. (2020) investigate how policymaker intervention shapes the interaction between technologies. They find that feed-in tariffs deploy renewable energy technologies but also affect technological advances in battery systems: specifically, environmental policies disincentivise consumer battery innovation whereas they have no effects on grid-connected batteries. However, the approach found in these studies is mainly qualitative and focuses on specific flagship green technologies (e.g. renewable energy, batteries, etc.).

Based on these premises, to address the aforementioned issues we move in two directions. The first step in our study is to investigate the interdependencies between green and other technologies that contribute to green technological change via knowledge-combination processes.[2] Based on patents filed over the 1978–2014 period, we borrow from the spatial econometrics literature and estimate a spatial autoregressive (SAR) model in which green and non-green technology classification codes[3] are the units of analysis and the co-occurrence of these codes within the same patent populate the cells of a cognitive distance weight matrix. This first analysis allows us to create a network structure across technology codes through which we capture when and which complementary technologies contribute to the development of green ones.

In a second step, we focus on the impact that environmental policy may exert on complementary non-green technologies. We exploit the Environmental Policy Stringency Indicator (EPSI) (OECD, 2020) that captures a wide set of environmental policies at the country level, embracing both market-based instruments (e.g. taxes, trading schemes, etc.) and non-market ones (e.g. emission standards) and is measured at the country level. This measure also allows us to exploit within-country variation, while we account for cross-country unobservable heterogeneity through fixed effects. We further address endogeneity concerns by adopting an instrumental variable approach. We use an index of democratic competition (Vanhanen, 2000) as an instrument for the EPSI. The rationale is that countries with fiercer political competition may be characterised by a shorter horizon of decision making and hence lower environmental policy stringency

[2]For example, developments in light-sensitive devices are interdependent with developments in photovoltaic panels; rotors are connected to wind turbines and vice versa, advances in batteries and in electric/hybrid vehicles are strictly related, etc.

[3]Patents are assigned to technology classes that describe the technicalities of the inventions and provide information on the technological domains the patent contributes to. These codes are organised in a hierarchical structure. That is, a low number of digits refers to general technological domains (e.g. mechanical engineering, physics, etc.) whereas a high number of digits, such as the full-digit level, implies narrow technological fields (e.g. aliphatic saturated hydrocarbons with one to four atoms, etc.).

(Nesta et al., 2014).

Our results indicate that the development of green technologies depends on advances in complementary technological areas that do not necessarily provide environmental benefits. That is, green technological change intensifies when progress in non-green technologies—previously combined with green knowledge—shows a growing trend. When comparing the magnitude of non-green and green knowledge-base contributions, the latter appears to be lower. When we directly test the effect of environmental policies, we find that despite the expected positive impact on green patents, the effect on complementary non-green technologies is not significant. Hence, we exclude the presence of a displacement effect of environmental policy on the technological pillars upon which green inventions emerge.

We contribute to two strands of the literature looking into the relation between technological change and the environment. The first focuses on how technological change can be directed towards the reduction of environmental pressure and solutions to the climate change crisis. Our contribution to this area involves new insight into the possible relation and complementarity—rather than orthogonality—between green and non-green technologies. This literature is aligned with the seminal contribution of (Hicks, 1932) and builds on the tenet that the increasing costs associated with environmental regulation induce firms to deviate away from polluting technologies to develop and adopt alternative environmentally friendly technologies. For instance, Goulder and Schneider (1999) provide an early analysis of the technological change induced by a carbon emissions abatement policy, showing that a carbon tax discourages R&D in conventional carbon-based energy while stimulating innovation in alternative energy industries, an element that relates to the crowding-out effect of environmental policies, to which we shall return later. Van der Zwaan et al. (2002) investigate the effect of technological change and the optimal path of tax and subsidies over time. They employ a model that incorporates technological change in two separate energy areas, i.e. carbon-intensive energy and carbon-neutral energy, and a learning-by-doing mechanism through which technological performance increases. Another theoretical treatment of the matter can be found in Popp (2004), who develops a model in which energy requirements are met either by fossil fuels or by technological advances that substitute these and depend on dedicated research efforts. His results suggest that optimal carbon policy induces technical change that reduces the cost of compliance. Building on Popp (2004), Coram and Katzner (2018) further elaborate on the optimal path to replace fossil fuels with green technologies and find that given a set emission-reduction targets, research efforts should be at least as strong at the beginning of a substitution path as at the end. Acemoglu et al. (2012) develop a framework in which goods are produced using substitutable dirty and clean inputs, depending on successful achievements in the betterment of dirty or clean technologies. They draw conclusions on the optimal policy, which involves carbon taxes and research incentives to steer technical change and avoid environmental collapse.

Other works provide an empirical account of the directed technological change. Popp (2002) finds that energy prices as well as the stock of existing knowledge positively influence inventive activities in the field of energy efficiency. Focusing on the automotive sector, Aghion et al. (2016) employ a firm-level analysis to investigate the effect of fuel price, a firm's own knowledge stock, and country-based knowledge spillovers on the development of clean technologies. They show that firms invent more in clean technologies when they face higher fuel prices. Moreover, prior knowledge on clean technologies as well as knowledge externalities from green patents trigger the development of environmentally sustainable inventions. As far as dirty technologies are concerned, they find that a firm's own stock of dirty patents positively influences the generation of clean technologies, although with a much lower impact than the stock of clean inventions.

Spillovers from dirty technologies have a negative impact on the generation of clean technologies. Their analysis also includes grey patents, which aim to improve fuel efficiency, the stock of which is positively associated with green patenting. Calel and Dechezleprêtre (2016) provide another analysis built upon a difference-in-difference matching procedure. They estimate the impact of the European Union Emissions Trading System (ETS) on firm patenting behaviour, finding a positive impact on low-carbon technologies. The effect of the ETS on (British) regulated firms' inventive activities is further investigated by Calel (2020), who finds this cap-and-trade policy spurs investment and generation of green inventions rather than the adoption of already-existing clean technologies.

We complement this literature by avoiding a strict dichotomous relation between green and non-green technologies: in our framework, the latter do not necessarily substitute the former and we instead directly consider the complementarity between these two groups of inventions. In this sense, expanding on the idea that green technological solutions may build upon technologies that are not sustainable per se, we contribute to the debate on the direction of technological change, which may not necessarily be away from non-green technologies.

We also contribute to the very related and partially overlapping literature that investigates the extent to which the development of environmentally related technologies comes at the expense of other technological domains. For instance, the analysis offered Popp and Newell (2012) shows that patenting in the alternative energy field results in a decrease in inventive activities in other areas. Other studies look more closely at whether this crowding-out mechanism is facilitated by the implementation of policy actions. Some studies directly investigate the role played by environmental policy and provide evidence of a crowding-out process. Barbieri (2016) finds that environmental policies—mainly in the form of tax-inclusive fuel prices—redirect technological change towards green technological fields in the automotive sector. In addition, he finds evidence that advances in one environmentally related domain crowd out inventive efforts in other green domains, pointing out that technological competition also affects the green technology realm. Noailly and Smeets (2015) investigate the effect of fossil fuel prices and renewables market size on technological change. The latter is found to trigger innovation in renewable energy both at the intensive and extensive margin and to reduce the fossil fuel–renewable technology gap by favouring entry dynamics. Fossil fuel prices instead affect innovation in renewable energy and fossil fuel technologies at the intensive margin, in addition to reducing the entry into fossil fuel innovation. Stronger evidence in support of the crowding-out effect is provided by Aghion et al. (2016), who show that while R&D subsidies only affect grey innovation, fossil fuel prices induce innovation in clean technologies at the expense of advancement in dirty ones. Contrary to these pieces of evidence are the insights emerging from Calel and Dechezleprêtre (2016), who find that the ETS has had a positive effect on carbon-intensive technologies—which could be complementary to green inventions—although the impact is higher when low-carbon solutions are considered. Similar insights come from Calel (2020), who suggests that the cap-and-trade scheme may have a positive effect even on overall firm patenting while disproportionately spurring low-carbon technologies. All in all, the extant contributions have mainly developed from the recognition of a short-term opportunity cost of moving away from technological domains that could be more profitable than green ones. We complement the extant literature by shedding some light on environmentally friendly technical change and directly focusing on the possible rootes that may be found in non-green yet complementary technologies. We contend that another undesirable effect of environmental policy could paradoxically be that of hampering the development of environmentally sustainable solutions through the displacement of inventive efforts directed towards their non-green technological pillars. In turn, we are concerned with a more dynamic relation between green and non-green technologies, which may be particularly pivotal to facilitate the transition towards greener forms of production.

The paper proceeds as follows. Section 2 presents the data and how we measure non-green interdependent technologies. Section 3 describes the empirical strategy, and Section 4 reports and discusses the results. Finally, Section 5 offers some concluding remarks.

2. Data and measures

2.1. Data

The empirical analysis builds on an original dataset that gathers data from different sources. Our primary source is the wealth of information provided by patents. We collect all patent documents included in the Worldwide Patent Statistical Database (Patstat, version Spring 2019)[4] and retrieve the patent family identification number. Patent families include patent applications that refer to the same invention and are filed in different patent offices to seek intellectual property rights protection in multiple countries.[5] For each patent family, we obtain (i) the earliest priority year to capture when the first patent application was filed with any patent office; (ii) the Cooperative Patent Classification (CPC) codes that describe the technical content of the inventions,[6] and (iii) the inventor identification number in order to geolocalise the patenting activity.

Following previous studies (e.g. Calel, 2020) we detect green technological efforts through a patent classification-based search using the CPC Y02 code: an additional code that is assigned to 'Technologies or applications for mitigation or adaptation against climate change'. The three-digit CPC Y02 code spans the spectrum of green technologies, ranging from renewable energy technologies to transportation technologies.[7]

To obtain the geographical dimension of the patent families, we retrieve the latitude and longitude of each inventor from De Rassenfosse et al. (2019). This dataset offers the geolocalisation of inventors and applicants for more than 18 million patent documents. Following the extensive literature on the geography of inventive efforts (see for example Rigby, 2015; Aghion et al., 2019), we employ the location of each inventor within a patent family to measure countries' invention performance.

[4]In order to collect a homogeneous set of patents, our dataset relies on all patent of inventions listed in Patstat and excludes documents that refer to utility models or design patents.

[5]Patent families refer to inventions for which patent protection is sought across different countries and group together patent applications that share at least one priority filing with at least one other member of the family. In the analysis, we employ INPADOC patent families. This implies that the technical content of the inventions within patent families is similar but not necessary the same. https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/patent-families/inpadoc.html

[6]The CPC is a classification system used by the European Patent Office and the United States Patent and Trademark Office. Therein, technology classification codes are provided in a hierarchical structure that captures very specific technologies depending on the digit level under analysis. A low number of digits captures broad technological fields, whereas a high number (such as the full-digit level) corresponds to narrow technological domains. The value added of the CPC with respect to other patent classification systems is that it has an ad hoc code that refers to 'Technologies or applications for mitigation or adaptation against climate change' (CPC Y02).

[7]The full list of green technologies included in the CPC Y02 class encompasses technologies related to adaptation to climate change (CPC Y02A); buildings (CPC Y02B), carbon capture and storage (CPC Y02C), energy-use reduction (CPC Y02D), energy generation (CPC Y02E), production of goods (CPC Y02P), transportation (CPC Y02T), and waste management (CPC Y02W).

2.2. Measuring complementary non-green technologies

The first step in our empirical analysis is to define complementary non-green technologies. To this aim, we resort to a network analysis that identifies the strength of the relation between green and other technological fields. In our innovation network, the full-digit classification codes are the nodes and the co-occurrences of these codes within patent families represent the links between the nodes. Although we rely on the universe of full-digit codes over the 1978–2014 period, our main interest is in the full-digit codes that co-occur with the green ones. Our final network is made up of more than 45 thousand full-digit codes with more than 13 million connections. However, the green subnetwork is relatively small, i.e. 235,500 connections among 186 green nodes and between these and almost 30,000 non-green full-digit codes, highlighting that environmentally related technological change is still in its early phase compared to other innovations (Barbieri et al., 2020b). Figure 1 shows the co-occurrence network between environmental (green dots) and complementary non-green technologies (orange dots). We can observe that it is composed of a dense number of green codes that co-occur with other green and non-green technologies. It is worth noting that some complementary technologies co-occur only with specific green technologies (those located at the external border of the network) while others are fundamental for the development of a variety of green technologies, i.e. the internal orange dots. In addition, knowledge spillovers occur also within the green technological domain, as demonstrated by the green nodes that are located close to each other in the centre of the network.

FIGURE 1 ABOUT HERE

We define as complementary non-green technologies those with full-digit codes that co-occur with green classification codes. We label as complementary technologies the full-digit codes from the year in which they co-occur for the first time with green ones onwards. The rationale for this measure is found in the recombinant innovation literature that emphasises the role of the first co-occurrence of two technologies as the premise of subsequent, persistent interactions (Verhoeven et al., 2016).[8]

Figure 2 shows the number and cumulative number (right-axis) of new full-digit code connections with green technologies per year. While there is a peak of new connections between the end of the seventies and the beginning of the eighties, there is a steadier and more limited increase in new connections from 1985 onwards.

Finally, Figure 3 provides a picture of the main technological domains (at the one-digit level) that are connected to green technologies (defined at four digits within the Y02 CPC code). In general, we can observe that green technologies tend to be connected to a few main macro-technological domains that are not directed towards sustainable solutions. The figure shows that some green technological domains co-occur with multiple supporting domains whereas others strongly rely on certain fields in an uneven way, showing an idiosyncratic pattern. Inventions belonging to the macro realm CPC F ‘Mechanical engineering; lighting; heating; weapons; blasting engines or pumps’ and CPC B ‘Performing operations; transporting’ are those that seems to be more relevant across the spectrum of green technologies. CPC F seems to represent a main pillar for adaptation, buildings, energy production, and transportation. CPC B is particularly relevant for carbon capture and storage, energy production, transportation, and waste management

[8]As robustness checks, we also define complementary technologies on a yearly basis, that is, we assume that the full-digit code supports the development of green technologies only in the year it actually co-occurs with the green codes. In Section 4.3, we show that the main results do not change when we employ this alternative measure.

technologies. Finally, CPC C, related to chemistry, is particularly relevant for green technologies such as the generation of green products, energy production, and adaptation technologies. Clearly, this is a very broad depiction of the technological pillars of green technologies that does not consider the heterogeneity within the macro-technological domains.

FIGURES 2 AND 3 ABOUT HERE

3. Empirical strategy

3.1. The effect of complementary non-green technologies on green patents

Having defined how to operationalise and measure non-green complementary technologies, we now move to the identification of a suitable econometric approach to investigate their impact on green technological change. A straightforward specification whereby environmentally sustainable technologies are regressed on non-green complementary technologies would be flawed by a relevant omitted-variable bias due to the fact that we would not be controlling for the confounding effect of other green technologies. Indeed, green technologies are expected to benefit from non-green complementary technologies as well as from other green ones (Noailly and Shestalova, 2017). Nevertheless, the inclusion of green technologies on the right-hand side of the econometric specification poses a further issue: the endogeneity arising from the inclusion of an autoregressive component (Anselin, 2003) that captures, in our case, the effect of 'neighbouring' green technologies. Given these premises, we borrow from economic geography studies a spatial econometric approach appropriate for our setting. Following recent developments in the literature (see Elhorst, 2003, 2014), we adopt a fixed effect spatial autoregressive model (SAR) based on quasi-maximum likelihood estimation (Belotti et al., 2017) with Driscoll and Kraay (1998) standard errors. Specifically, we estimate the following model:

$$g_{it} = \alpha + \rho \sum_{j=1}^{N} \frac{C_{ijt_0}\left(1-\delta_{ij}\right)\left(1-\varphi_j\right)}{\sum_k C_{ikt_0}\left(1-\delta_{ij}\right)\left(1-\varphi_j\right)} g_{jt} + \beta \sum_{j=1}^{N} \frac{C_{ijt_0}\left(1-\delta_{ij}\right)\left(\varphi_j\right)}{\sum_k C_{ikt_0}\left(1-\delta_{ij}\right)\left(\varphi_j\right)} g_{jt} + Stock_{it} + \tau_t + \mu_i + \epsilon_{it} \tag{1}$$

where g_{it} is the growth rate of green technology i over a five-year period; $\varphi_j = 1$ if j is one of the N complementary non-green full-digit CPC codes; C_{ij} is the co-occurrence of i with j at the beginning of the period of analysis, t_0, where k represents the row of the co-occurrence matrix and δ is the Kronecker delta indicating that we are excluding the diagonal elements of the co-occurrence matrix C; τ_t and μ_i are time (year) and green technology fixed effects. In order to take into account the changing nature of CPC co-occurrences over time, we estimate a set of 22 panel regressions, each focusing on a period of 10 years, with the first one covering the 1979–1988 period and the last one 2000–2009,[9] where the matrix of co-occurrences is calculated in the year before the beginning of the period under analysis (t_0). Despite accounting for idiosyncratic characteristics that may affect growth with technology-level fixed effects, following Pichler et al. (2020) we also control for the stock of patents in a given green technology class to capture the effect that a consolidated knowledge and the maturity of the field may have on the dynamic under consideration.[10]

[9] This time window is dictated by the availability of patent data from 1978 to 2014.

[10] This is computed with the usual perpetual inventory method, $K_t = K_{t-1}(1-\delta) + P_t$, where K_{t-1} is the stock of patents

3.2. The effect of environmental policy on complementary non-green technologies

The second part of our analysis investigates the impact that environmental policies exert on the development of non-green complementary technologies. The effect of environmental policies on inventive activity is scrutinised at the country level by exploiting information on patenting in different fields and the stringency of policy interventions. The chosen level of analysis is justified by the fact that most environmental policies are implemented at the national level. Thus, we exploit country-level variation using the OECD's Environmental Policy Stringency Index (EPSI) (Botta and Koźluk, 2014). The advantage of this proxy is that (i) it captures a wide range of flexible and regulatory instruments such as subsidies, taxes, and emission standards in a single indicator, (ii) it does not focus on just a few flagship sectors but, instead, covers the whole spectrum of the economy, and (iii) it is correlated to other proxies retrieved in the extant literature, such as the perceived stringency (Schwab, 2009; Johnstone et al., 2010a). The country-level analysis is conducted on 23 OECD countries[11] over the 1990–2012 period for which the EPSI is available. The estimation equation is the following:

$$Y^L_{ct} = \beta EPSI_{ct} + \gamma X_{ct} + \tau_t + \sigma_c + \epsilon_{ct} \tag{2}$$

where the dependent variable is the number of technologies—captured by the number of patent families—in country c at time t. L captures the type of technology, that is, while our interest is on testing the effect of environmental policies on complementary non-green technologies (COMPAT), we also make sure that the empirical approach we implement provides results that are aligned with prior evidence on the impact of environmental regulations on green patenting (GREENPAT) (e.g. Popp, 2002; Johnstone et al., 2010b; Nesta et al., 2014).

EPSI is an OECD indicator of environmental policy stringency, i.e. our key explanatory variable, and β is the parameter of interest. X represents a set of control variables that is inspired by the literature on the knowledge production function (Griliches, 1979; Pakes and Griliches, 1984) and includes the following variables. We capture the stock of available knowledge and the patenting propensity of a country through the stock of total patents (PATSTOCK). We further add a measure of human capital (HC), which reflects the average schooling of the population and is collected from the Penn World Table (Feenstra et al., 2015). We employ two additional variables retrieved from OECD data. We control for the fact that the stringency of regulations as well as patenting activities in green or complementary technologies may be related to the intensity of greenhouse gas emissions relative to the value added, i.e. environmental efficiency (ENVEFF). Lastly, we add GDP in constant prices (in US$ 1995) in order to capture the size of the economy. All variables are taken in log form. Table 1 reports the descriptive statistics.

TABLE 1 ABOUT HERE

The relation of interest may not only be confounded by observable characteristics but also by unobservable heterogeneity, which is constant over time and varies across countries. Similarly, certain shocks may have simultaneously affected all countries in our sample due to common

at year $t-1$, δ is the depreciation rate, assumed constant at 15% (Hall et al., 2005), and P_t is the number of new patents in year t.

[11] Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Netherlands, Norway, Poland, Portugal, Republic of Korea, Spain, Sweden, United Kingdom, United States.

circumstances that change over time (e.g. macroeconomic conditions, etc.). To address these issues, we add country (σ) and time fixed effects (τ). Finally, ϵ is the error term.

The relationship between environmental policy and our dependent variables may suffer from endogeneity issues, however. First, we cannot exclude a reverse causality issue in which the number of patents influences policy stringency. We may suppose different configurations for such a relation. Let us focus first on the case of green patents and their relation to policy stringency. Extensive patenting in green technologies within the national industrial system may induce policymakers to increase stringency to promote internal industries and to create a barrier to foreign competitors (e.g. Rodrik, 2014). We cannot exclude the opposite direction, however, which would lead to a downward-biased estimation. A high level of green patents may lead to a lower EPSI level. From a normative point of view, we may expect that policymakers support technologies only in the initial phase of their development, rather than in their maturity (Acemoglu et al., 2012). This has some empirical evidence in the relaxation of market-based instruments in leading countries like Germany and Denmark (Nesta et al., 2018). In fact, the possible existence of lower levels of the EPSI in light of extensive patenting in green technologies may also be explained by the way in which our policy variable is created. Lower levels of the EPSI do not necessarily mean an absolute reduction in stringency. Indeed, EPSI is ultimately a relative score of stringency given the use of in-sample distribution to create the bands of stringency for each item in the composite indicator. In other terms, a given country may be assigned a score that changes (e.g. reduces) due to the (stricter) implementation of policies in other countries across years.

Let us now discuss the potential reverse causality affecting the relation between non-green, complementary patents and the EPSI. Mirroring what was reported above, we can see two directions. Considering that complementary patents are essentially non-green technologies, one may argue that extensive patenting in non-environmental technologies may lead policymakers to reduce environmental stringency to avoid an excessive burden on national industries. But the other direction cannot be excluded either: substantial inventive activities in non-environmentally friendly technologies may lead regulators to seek to steer technological change towards a greener path, thus increasing the stringency of regulations. If that is the case, we would be observing an upward-biased estimation.

Endogeneity may also emerge from an omitted variable bias that persists also after the inclusion of our controls. Our data do not allow us to recover information on the presence and intensity of policy supporting non-green technologies, such as those associated with fossil fuel or carbon-intensive activities, for instance. Once again, we may advance some hypotheses on the likely effect this omission may have on our estimates. If we assume that strict environmental regulations may be implemented to compensate the support to non-green technologies via direct (e.g. general R&D subsidies) and indirect (e.g. through the stimulation of demand or investment in infrastructure) actions, we can have two opposite signs of the bias depending on what kind of patenting we have on the left-hand side of our estimation. When focusing on green patenting, given the negative correlation with non-green policy we expect a downward bias of the estimation. When looking at non-green, complementary technologies that support environmental patents, we cannot exclude a positive correlation with non-environmental policy and hence an overall upward-biased estimation of our coefficient of interest.

In order to solve these biases, we instrument EPSI using information on the political framework in which policies are devised. Specifically, our identification strategy relies on an index of democratic competition (POLCOM) that is calculated by subtracting from 100 the percentage of votes received by the largest party in the elections (Vanhanen, 2000). As such, the indicator captures the relevance of smaller parties and hence the extent to which a government is stable to political challenges posed by parties within the ruling majority (if any) or by the opposition parties. Our contention is that elections that produce stable results with a clear ruling party reduce the risk that the governing majority is contended. This, in turn, allows the executive to implement policies, such as stringent environmental regulations, that do not have an immediate and short-term political pay-off (Nesta et al., 2014). At the same time, the stability of the government—due to the greater political power of the largest party—does not directly impact patenting in green and complementary activities.

4. Results

4.1. The role of complementary non-green technologies in the growth of environmental patents

The first part of the empirical exercise focuses on the contribution of technological domains to the development of green technologies. Specifically, we are interested in the role played by (other) green and complementary non-green technologies. To do so, we focus on two main coefficients and on their difference. First we look at ρ, which captures the impact of growth in all other green patents on the growth of the focal green technology to which they are connected through a CPC co-occurrence matrix as described in Section 2. Second, we are interested in the effect of the growth of complementary technologies on that of green patents (LeSage, 2008; Belotti et al., 2017). The overall impact of a given observable explanatory variable can be decomposed into two effects: a direct effect that captures the extent to which growth in a given technological domain affects patenting growth in the same unit of analysis and an indirect effect that captures the spillover from other 'neighbouring' units. In our case, advancements in complementary non-green technologies affect a given green technology (direct effect) but they also exert an impact through the feedback effect of 'neighbouring' green inventions (indirect effect). Table 2 reports the results of the spatial regressions. We create repeated panels of 10 years each, and we use as dependent variable the five-year growth of green patents. We notice that over the entire period, the growth of both other green and complementary non-green technologies affect the growth of green patents. This result confirms that green technologies do not develop in isolation; instead, they benefit from knowledge spillovers arising from a range of technological domains, independent of the environmental benefit provided from these. Moreover, we can observe that the size of the impact of non-green complementary patents is always larger—approximately three times higher—than the effect of other green technologies. Indeed, in order to compare similar impacts, we investigate whether the direct effect of growth in complementary non-green technologies differs from the coefficient of the spatially lagged variable that captures growth in other green technological domains. The difference is statistically significant at the 1% level, suggesting that green technologies develop significantly more from the recombination of technological components that are not strictly green but are complementary to them. In addition, the data at our disposal covers a rather long time period, allowing us to consider possible differences in the contribution of green and non-green technologies to the generation of environmental patents. We observe a rather stable pattern, however; since the early years, non-green complementary patents have always played a significant role as building blocks for environmental technologies, regardless of the likely growing maturity of green technologies through the observed period. Overall, this suggests that environmental technologies combine technological knowledge that is not necessarily green in nature, so their development is based on 'borrowing' ideas that have been developed without a clear environmental objective.

TABLE 2 ABOUT HERE

4.2. The impact of green policy on complementary non-green patents

Our analysis has so far provided evidence on the importance of non-green innovation in the form of non-green technologies that are complementary to green ones. That is, the previous empirical exercise highlights that technologies not directly designed as environmentally sustainable are necessary to trigger environmentally related technological change. We now turn our attention to the investigation of the effect that environmental policy has on complementary non-green technologies. This is to ascertain whether the implementation of policy actions in support of a green transformation of the economy endangers the development of those non-green pillars upon which sustainable inventions are built.

To address this issue, we first assess whether the policy indicator has a positive effect on the development of green technologies, an extensively explored relationship on which the extant literature provides a rather conclusive evidence (Barbieri et al., 2016). Then, we substitute the dependent variable and explore the relationship between environmental policy and non-green complementary technologies.

Table 3 shows the results of the econometric estimation.[12] In Column 1, we present the specification that employs green patenting as the dependent variable. In panels A and B, we present the results of the panel estimation that employs country and time fixed effects and the IV model, respectively. We can observe that the coefficient of the EPSI is not statistically significant in panel A, whereas when we account for endogeneity and employ political competition as an instrumental variable the coefficient is positive and significant, pointing to a downwardly biased estimation that results from the combination of time-variable unobservables and reverse causality. The results highlight that a 1% increase in environmental policy stringency leads to a 0.7% increase in green patents.[13] A look at the first-stage estimation confirms the validity of our approach.[14] The usual Stock and Yogo (2005) approach to testing for the presence of a weak instrument is not applicable in our case due to the lack of homoscedastic errors (see Andrews et al. (2019) for a discussion of weak IV testing). We thus resort to the procedure proposed by Olea and Pflueger (2013). We observe that the Kleibergen–Paap F statistics (29.71) exceed the critical value of 23.1. Hence, we conclude that our instrument is not weak. The coefficient of our instrument is negative (and significant). Recalling the way in which the instrument is computed (100 – the percentage of votes gone to the first party), it is easy to see how this result is consistent with expectations. Countries where the governing majority can potentially be challenged by runner-up and also-ran parties, and hence where the government may be less prone to pursuing longer-term policy objectives, are characterised by a less stringent environmental policy.

When we replicate the estimation of the model using as dependent variable the patenting in non-green complementary technologies, the coefficient of the EPSI is insignificant also in panel B, in which we control for endogeneity sources. The insights provided by the model

[12] In the regression reported in Column (1) three observations out of 529 have zero patents which result in missing values when we log-transform the variable GREENPAT. In unreported estimates we have replaced these values with one (so to have zeros after the log-transformation). The results do not differ and are available upon request.

[13] The first-stage regression is shown in Appendix Table A1. The coefficient of the instrument (i.e. political competition) is reported in panel C of Table 3. We report the Kleibergen–Paap F statistic, whose value is above the critical value of 23.1 (Olea and Pflueger, 2013).

[14] Table A1 in the Appendix reports the entire estimation of the first-stage regression.

estimation emphasise that environmental policy stringency does not lead to a displacement of complementary non-green technologies. In other terms, environmental policies do not trigger green technological change at the expense of inventions that may work as technological pillars for green technologies. Given the constraints of our empirical setting, we cannot advance definitive conclusions as to whether this absence of effectiveness will result in a reduced pace of green patenting compared to a counterfactual scenario also characterised by a positive effect on complementary non-green technologies. Similarly, we cannot provide a full assessment of the entire policy framework of a given country.

TABLE 3 ABOUT HERE

4.3. Robustness checks

We test the robustness of our results in a number of ways. Let us first concentrate on the part of our analysis that concerns the extent to which green and complementary non-green technologies contribute to the development of environmentally sound inventions. The first robustness check we implement concerns the way in which we capture complementary non-green technologies. Our main results adopt an inclusive approach to identify complementary non-green patents: we include families with at least one technology class that has been connected with green ones, and we weight the invention for the share of non-green CPC classes. In other terms, we measure complementary non-green technologies by excluding the fraction of knowledge connected to green technological domains. An example may elucidate: if a patent family is assigned to one green and nine non-green complementary full-digit codes, the contribution of the patent to the latter group is 90%. The adoption of fractional counting allows us to consider the non-green technological component of each invention; however, we also implement a stricter definition of complementary non-green technologies. In what we label as *stricto sensu*, we measure complementary non-green technologies excluding the contribution of these patents. With this alternative definition of complementary non-green technologies, we find unchanged results for both the first part of our analysis and the second alike. From Table 4, we continue to observe a larger contribution to environmentally sustainable technological change from complementary technologies that are not green, compared to green ones (with the exception of the first panel, which goes from 1979 to 1988, for which no difference is found).

We further corroborate our results by changing the time period over which we observe the growth of patenting in green technologies. The results obtained when using the 5-year growth of green patenting could be driven by the fact that it could take longer for novel and early-stage green technologies to be absorbed into subsequent recombination processes and used as seeds for future technological inbreeding. To this aim, we employ the 10-year growth of green patenting as the dependent variable. Table 5 shows results are stable.

We also test the robustness of our results to alternative specifications of the dependent variable that we use in the second part of our analysis, where we look at the effect of environmental policies on the development of complementary non-green technologies. The results are reported in Table 6. First, we use a *stricto sensu* (see above) definition of complementary non-green technologies to keep only inventions that do not include (even if partially) an environmentally related component. Second, we allow the definition of complementary non-green technologies to change over time. While our baseline definition is based on the assumption that once a connection between green and non-green technologies is established, it remains available for—and could potentially benefit—future recombinations, with this alternative (time-varying) approach we redefine the relevant complementary technologies that are not green on a yearly basis. Finally, we check whether the results are robust to applying a yearly and *stricto sensu* definition of complementary technologies. In all of these attempts, we continue to find a non-significant effect of environmental policies on complementary non-green technologies.

TABLES 4, 5 and 6 ABOUT HERE

5. Conclusions

Green technology development is pivotal to the decarbonisation of economies and to their green transformation. Contributing to a recent stream of studies that explore how innovation networks affect the direction of technological change (Acemoglu et al., 2016), this paper goes beyond the conceptualisation of green technologies as stand-alone inventions in favour of a systemic view. In so doing, the empirical analysis offers two main conclusions. First, the development of green technology is driven by growth in non-green complementary technologies. That is, we provide evidence that non-green technologies are a fundamental and measurable determinant of the pace and direction of green inventive activity. Second, we observe that environmental policies do not affect the generation of non-green complementary technologies, so we discard the possibility of a policy paradox for which environmental policies, instead of triggering green inventions, risk displacing them by hampering the development of the knowledge base required for their advancement.

We apply an original approach to identifying non-green complementary technologies using patent data and exploiting the co-occurrence of technological classification codes with green ones. This approach enables us to measure the intensity at which these technologies—not directly seen as providing environmental benefits—co-occur with green technological classification codes. We employ this co-occurrence matrix in a spatial-autoregressive model in which the growth of green technologies is explained by both the growth of other green technologies and growth in non-green complementary technologies, which is weighted by the co-occurrence matrix. Our first set of findings reveals that the growth in patenting activities in non-green complementary domains generates externalities that benefit green technological fields. In particular, growth in non-green complementary inventions is responsible for the growth of green technologies to a greater extent compared to how much green technologies affect each other: the magnitude of the coefficient of non-green complementary technologies is approximately three times higher than the coefficient for other green technologies.

These results add to the recent stream of literature that focuses on the role of technological interdependencies (Acemoglu et al., 2016; Pichler et al., 2020; Taalbi, 2020) by explicitly looking at the interdependencies behind green technological change. In so doing, we have provided a more nuanced conception of the relation between green and non-green technologies, which is far from being strictly dichotomous at least from a technological point of view. Applying this framework to green technologies is particularly relevant given that green technologies generate higher knowledge spillovers than non-green ones, and this justifies the implementation of ad hoc supporting actions (Dechezleprêtre et al., 2014; Barbieri et al., 2020a). Disentangling the dynamics at the heart of the generation of green technologies provides insight into how to better frame policy interventions. In particular, our results imply the need to transfer technological capabilities developed in non-green but complementary fields to support the generation of environmentally sustainable inventions. To this aim, policymakers may select particular recipients, such as (teams of) inventors and firms with previous experience in non-green complementary technologies, and provide them with incentives to develop green applications associated with their technological competencies.

Moreover, we explore the role of policy intervention in this framework. Our findings point to an absent effect of environmental policies on the generation of non-green complementary technologies, indicating both the avoidance of a policy paradox that would present an obstacle to green technological development and an absence of a driving effect of policies on non-green inventions that are fundamental for the generation of green inventions. The implications of this work point to the efficiency of environmental policy interventions and warn about the unexpected bottlenecks that can arise in framing 'moonshot policies' towards the decarbonisation of the economy (Bloom et al., 2019). Although environmental policies do not displace the generation of non-green complementary technologies, they also do not favour them. This means that policy intervention in the green field should be corroborated by policy intervention in other complementary (to green) technological domains. In fact, limited R&D investment in certain technologies that are not strictly green but are complementary to them could imply the slackening of green technology development years later. In other words, the long-term dynamics of green technological development also depend on the availability of non-green complementary technologies: a shortage of such related knowledge could hamper the creation of new green innovations. Further research is required to assess whether environmental policies interact with other policy interventions that support complementary fields in order to speed up the technological transition.

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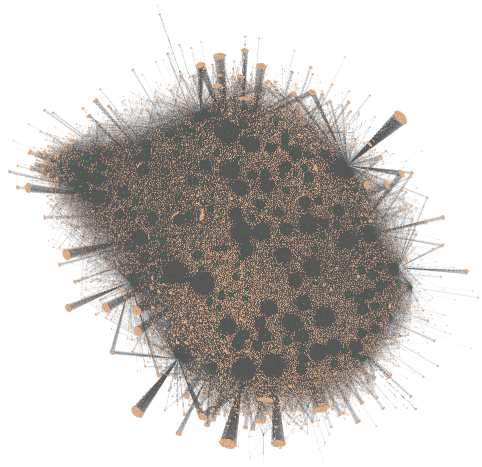
Tables and Figures

Figure 1: Technology co-occurrence network



Notes: CPC full-digit co-occurrence network over the entire period. Green nodes refer to green technological classification codes whereas orange nodes represent complementary non-green full-digit codes

Figure 2: Number of technology classification codes that connect for the first time with green technologies

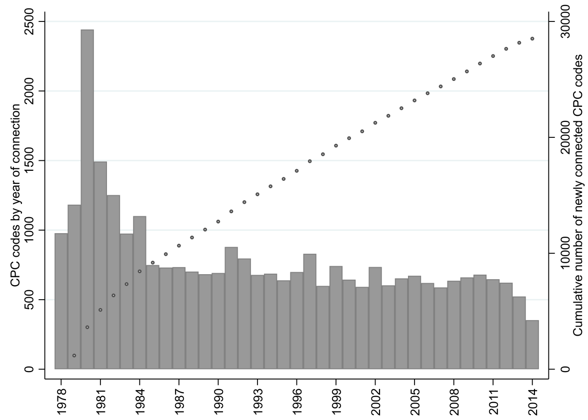
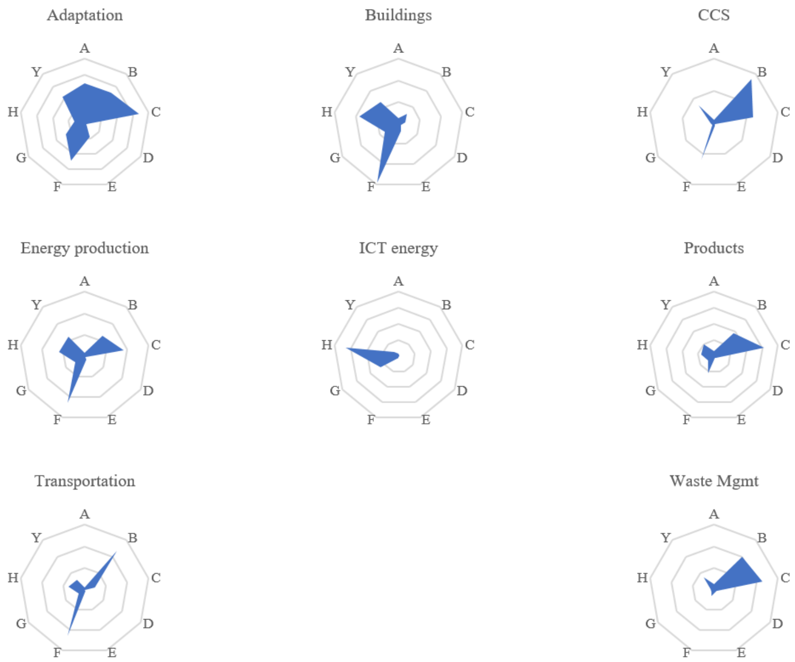


Figure 3: Technological domains that support green inventive activities



Notes: Each graph corresponds to a Y02 subclass and measures the intensity of the co-occurrence with other one-digit codes. A=Human necessities; B=Performing operations; transporting; C=Chemistry; metallurgy; D=Textiles; paper; E=Fixed constructions; F=Mechanical engineering; lighting; heating; weapons; blasting engines or pumps; G=Physics; H=Electricity; Y=General tagging of new technological developments; general tagging of cross-sectional technologies spanning over several sections of the IPC; technical subjects covered by former USPC cross-reference art collections [XRACs] and digests

Table 1: Descriptive statistics

	Obs	Mean	Std Dev	Min	Max
Green vs NonGreen					
Green patents (5-year growth)	1,750	0.34	0.58	-1.95	2.89
Green patents (5-year growth) (*strictu sensu*)	1,750	0.35	0.80	-2.83	3.63
Green patents (10-year growth)	1,750	0.36	0.66	-1.93	2.99
Complementary Non-Green patents (5-year growth)	1,750	0.19	0.29	-1.89	2.39
Complementary Non-Green patents (10-year growth)	1,750	0.22	0.40	-1.54	2.77
Patent Stock	1,750	954.33	2,160.66	1.25	24,884.77
The effect of policy					
Dependent variables					
GREENPAT	526	993.21	2,778.24	0	15,141
COMPAT (Since 1st connection)	529	8,232.84	17,230.49	3.33	84,398.8
COMPAT (Since 1st connection *strictu sensu*)	529	7,664.54	16,038.17	3.33	77,292.8
COMPAT (Yearly connection)	529	6,440.4	13,962.67	2.42	73,277.46
COMPAT (Yearly connection *strictu sensu*)	529	5,872.1	12,754.82	1.42	66,171.45
Explanatory variables					
EPSI	529	1.77	0.90	0,35	4.13
PATSTOCK	529	49,032.55	107,824.90	23.75	484,656.7
HC	529	3.14	0.36	1.94	3.72
ENVEFF	529	0.04	0.02	0.01	0.10
GDP (millions)	529	1,492,230	2,668,601	82,139.21	15,900,000
Instrumental variable					
POLCOMP	529	60.53	6.59	39.50	70

Table 2: SAR model estimation

	Complementary non-green (β)	Other green (ρ)	Patent Stock (*Stock*)	Obs	R^2	Matrix year	Direct effect	Direct effect vs ρ
Panel 1 (1979-1988)	0.434*** (0.0518)	0.148*** (0.0398)	-0.000365*** (5.02e-05)	750	0.196	1978	0.440*** (0.0535)	19.17***
Panel 2 (1980-1989)	0.470*** (0.0471)	0.115*** (0.0374)	-0.000323*** (4.80e-05)	880	0.109	1979	0.474*** (0.0484)	34.43***
Panel 3 (1981-1990)	0.457*** (0.042)	0.136*** (0.035)	-0.000482*** (5.91e-05)	1,260	0.078	1980	0.461*** (0.0432)	34.07***
Panel 4 (1982-1991)	0.453*** (0.0425)	0.192*** (0.0346)	-0.000659*** (6.59e-05)	1,310	0.054	1981	0.459*** (0.0437)	22.87***
Panel 5 (1983-1992)	0.471*** (0.0433)	0.168*** (0.0354)	-0.000825*** (7.02e-05)	1,410	0.038	1982	0.476*** (0.0446)	29.25***
Panel 6 (1984-1993)	0.491*** (0.047)	0.131*** (0.0333)	-0.000837*** (7.42e-05)	1,460	0.036	1983	0.495*** (0.0484)	38.43***
Panel 7 (1985-1994)	0.509*** (0.0497)	0.109*** (0.0366)	-0.000685*** (7.48e-05)	1,490	0.038	1984	0.513*** (0.0512)	41.32***
Panel 8 (1986-1995)	0.561*** (0.0513)	0.149*** (0.0393)	-0.000494*** (7.28e-05)	1,470	0.049	1985	0.566*** (0.0529)	40.06***
Panel 9 (1987-1996)	0.559*** (0.0502)	0.178*** (0.0338)	-0.000292*** (6.52e-05)	1,420	0.077	1986	0.566*** (0.0518)	39.29***
Panel 10 (1988-1997)	0.647*** (0.0544)	0.165*** (0.0393)	-0.000241*** (6.09e-05)	1,470	0.081	1987	0.653*** (0.0561)	50.71***
Panel 11 (1989-1998)	0.671*** (0.0556)	0.198*** (0.039)	-0.000168*** (5.34e-05)	1,470	0.117	1988	0.680*** (0.0574)	48.16***
Panel 12 (1990-1999)	0.593*** (0.0565)	0.195*** (0.0387)	-0.000102** (4.81e-05)	1,480	0.121	1989	0.600*** (0.0584)	33.55***
Panel 13 (1991-2000)	0.546*** (0.0551)	0.192*** (0.0365)	-9.18e-05** (4.29e-05)	1,610	0.109	1990	0.553*** (0.057)	28.52***
Panel 14 (1992-2001)	0.535*** (0.0512)	0.137*** (0.0374)	-0.000119*** (3.76e-05)	1,650	0.102	1991	0.539*** (0.0527)	38.59***
Panel 15 (1993-2002)	0.533*** (0.0489)	0.186*** (0.0384)	-0.000123*** (3.40e-05)	1,600	0.102	1992	0.539*** (0.0505)	30.97***
Panel 16 (1994-2003)	0.543*** (0.0452)	0.166*** (0.0334)	-0.000103*** (3.04e-05)	1,590	0.118	1993	0.549*** (0.0466)	44.59***
Panel 17 (1995-2004)	0.531*** (0.0443)	0.237*** (0.0322)	-0.000123*** (2.81e-05)	1,630	0.103	1994	0.541*** (0.0458)	29.38***
Panel 18 (1996-2005)	0.599*** (0.0436)	0.190*** (0.0332)	-0.000115*** (2.71e-05)	1,670	0.108	1995	0.606*** (0.0448)	55.48***
Panel 19 (1997-2006)	0.641*** (0.0429)	0.239*** (0.0343)	-0.000106*** (2.47e-05)	1,640	0.127	1996	0.651*** (0.0441)	54.17***
Panel 20 (1998-2007)	0.701*** (0.0429)	0.140*** (0.0334)	-9.89e-05*** (2.25e-05)	1,690	0.141	1997	0.706*** (0.0439)	105.1***
Panel 21 (1999-2008)	0.666*** (0.0428)	0.206*** (0.0364)	-7.48e-05*** (1.99e-05)	1,730	0.153	1998	0.673*** (0.0439)	67.16***
Panel 22 (2000-2009)	0.633*** (0.042)	0.174*** (0.0361)	-5.70e-05*** (1.75e-05)	1,750	0.181	1999	0.638*** (0.0431)	68.11***

Notes: The dependent variable is the 5-year growth of green patents. Driscoll and Kraay's (1998) standard errors, robust to heteroskedasticity and serial and cross-sectional correlation, in parentheses
** p < 0.1, ** p < 0.05, *** p < 0.01*

Table 3: Country-level regression results

	GREENPAT	COMPAT Since 1st connection
Panel A - Country and time fixed effects included		
EPSI	-0.058	0.044
	(0.048)	(0.034)
PATSTOCK	0.775***	0.728***
	(0.054)	(0.047)
HC	-0.139	2.590***
	(0.954)	(0.671)
ENVEFF	0.177	0.234**
	(0.141)	(0.102)
GDP	-0.113	0.315
	(0.256)	(0.257)
R^2	0.851	0.936
F	558.1	229.9
Panel B - IV with country and time fixed effects included		
EPSI	0.714**	0.233
	(0.316)	(0.326)
PATSTOCK	0.777***	0.726***
	(0.076)	(0.056)
HC	0.370	2.711***
	(0.996)	(0.758)
ENVEFF	0.140	0.228*
	(0.185)	(0.115)
GDP	-0.874**	0.138
	(0.387)	(0.423)
Observations	526	529
R^2	0.296	0.734
Panel C - First Stage		
POLCOMP -0.011***	-0.011***	
	(0.002)	
Kleibergen-Paap F	31.45	29.71

Notes: The sample includes 23 countries (see Section 3.2) observed over the period 1990-2012 (23 years). Driscoll and Kraay (1998) standard errors, robust to heteroskedasticity and serial and cross-sectional correlation, in parentheses.
** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 4: SAR model estimation (complementarity in *stricto sensu*)

	Complementary non-green (β)	Other green (ρ)	Patent Stock (*Stock*)	Obs	R^2	Matrix year	Direct effect	Direct effect vs ρ
Panel 1 (1979-1988)	0.385*** (0.0683)	0.261*** (0.0374)	-0.0000857 (0.0000567)	750	0.162	1978	0.399*** (0.0717)	2.896
Panel 2 (1980-1989)	0.612*** (0.0669)	0.142*** (0.0371)	-0.000130** (0.0000594)	880	0.099	1979	0.619*** (0.0689)	37.10***
Panel 3 (1981-1990)	0.519*** (0.0485)	0.201*** (0.0309)	-0.000231*** (0.0000619)	1260	0.059	1980	0.526*** (0.0501)	30.40***
Panel 4 (1982-1991)	0.414*** (0.0491)	0.239*** (0.0322)	-0.000294*** (0.0000678)	1310	0.021	1981	0.422*** (0.0509)	9.283***
Panel 5 (1983-1992)	0.471*** (0.049)	0.243*** (0.0306)	-0.000393*** (0.0000715)	1410	0.008	1982	0.479*** (0.051)	15.82***
Panel 6 (1984-1993)	0.521*** (0.0543)	0.229*** (0.0299)	-0.000443*** (0.0000761)	1460	0.006	1983	0.531*** (0.0564)	22.33***
Panel 7 (1985-1994)	0.437*** (0.0555)	0.216*** (0.0313)	-0.000457*** (0.0000766)	1490	0.001	1984	0.445*** (0.0575)	12.18***
Panel 8 (1986-1995)	0.490*** (0.059)	0.239*** (0.0335)	-0.000409*** (0.0000762)	1470	0.002	1985	0.498*** (0.0613)	13.80***
Panel 9 (1987-1996)	0.455*** (0.0592)	0.246*** (0.0313)	-0.000312*** (0.0000736)	1420	0.006	1986	0.465*** (0.0617)	10.03***
Panel 10 (1988-1997)	0.473*** (0.0585)	0.277*** (0.033)	-0.000200*** (0.0000641)	1470	0.009	1987	0.483*** (0.0611)	8.830***
Panel 11 (1989-1998)	0.536*** (0.0603)	0.286*** (0.0346)	-0.000110* (0.000057)	1470	0.048	1988	0.549*** (0.063)	13.35***
Panel 12 (1990-1999)	0.491*** (0.0628)	0.260*** (0.035)	-0.0000189 (0.0000513)	1480	0.09	1989	0.501*** (0.0653)	10.63***
Panel 13 (1991-2000)	0.521*** (0.06)	0.210*** (0.0334)	-0.0000353 (0.0000453)	1610	0.093	1990	0.529*** (0.0621)	20.38***
Panel 14 (1992-2001)	0.454*** (0.0569)	0.200*** (0.0339)	-8.80e-05** (0.0000411)	1650	0.056	1991	0.460*** (0.0589)	14.62***
Panel 15 (1993-2002)	0.455*** (0.0594)	0.247*** (0.0351)	-0.000135*** (0.0000386)	1600	0.042	1992	0.463*** (0.0616)	9.325***
Panel 16 (1994-2003)	0.420*** (0.0558)	0.260*** (0.0318)	-0.000135*** (0.0000354)	1590	0.035	1993	0.430*** (0.0582)	6.574**
Panel 17 (1995-2004)	0.421*** (0.0553)	0.260*** (0.0315)	-0.000143*** (0.0000333)	1630	0.033	1994	0.430*** (0.0575)	6.790***
Panel 18 (1996-2005)	0.441*** (0.0537)	0.324*** (0.0313)	-0.000130*** (0.0000316)	1670	0.035	1995	0.455*** (0.0562)	4.157**
Panel 19 (1997-2006)	0.515*** (0.053)	0.336*** (0.033)	-0.000104*** (0.0000294)	1640	0.056	1996	0.530*** (0.0553)	9.090***
Panel 20 (1998-2007)	0.542*** (0.0543)	0.302*** (0.0331)	-8.23e-05*** (0.0000273)	1690	0.081	1997	0.555*** (0.0564)	14.98***
Panel 21 (1999-2008)	0.571*** (0.0551)	0.318*** (0.036)	-5.95e-05** (0.0000246)	1730	0.104	1998	0.583*** (0.057)	15.51***
Panel 22 (2000-2009)	0.551*** (0.0536)	0.270*** (0.0351)	-5.24e-05** (0.0000219)	1750	0.123	1999	0.560*** (0.0554)	19.61***

Notes: The dependent variable is the 5-year growth of green patents. Driscoll and Kraay's (1998) standard errors, robust to heteroskedasticity and serial and cross-sectional correlation, in parentheses
** p < 0.1, ** p < 0.05, *** p < 0.01*

Table 5: SAR model estimation (10-year growth)

	Complementary non-green (β)	Other green (ρ)	Patent Stock (*Stock*)	Obs	R^2	Matrix year	Direct effect	Direct effect vs ρ
Panel 1 (1979-1988)	0.408*** (0.0626)	0.213*** (0.0382)	-0.000456*** (0.0000567)	750	0.143	1978	0.418*** (0.0652)	7.347***
Panel 2 (1980-1989)	0.439*** (0.0544)	0.210*** (0.0342)	-0.000408*** (0.0000542)	880	0.115	1979	0.448*** (0.0563)	12.98***
Panel 3 (1981-1990)	0.448*** (0.0479)	0.178*** (0.0344)	-0.000590*** (0.0000674)	1260	0.114	1980	0.453*** (0.0495)	20.83***
Panel 4 (1982-1991)	0.478*** (0.0467)	0.231*** (0.0341)	-0.000706*** (0.0000723)	1310	0.096	1981	0.486*** (0.0483)	18.63***
Panel 5 (1983-1992)	0.493*** (0.0467)	0.184*** (0.0352)	-0.000748*** (0.0000773)	1410	0.084	1982	0.499*** (0.0483)	27.88***
Panel 6 (1984-1993)	0.509*** (0.0483)	0.130*** (0.0344)	-0.000729*** (0.0000786)	1460	0.082	1983	0.513*** (0.0498)	39.98***
Panel 7 (1985-1994)	0.506*** (0.0504)	0.102*** (0.0361)	-0.000600*** (0.0000819)	1490	0.094	1984	0.510*** (0.0518)	41.55***
Panel 8 (1986-1995)	0.568*** (0.053)	0.0861** (0.0387)	-0.000428*** (0.000083)	1470	0.113	1985	0.571*** (0.0545)	52.66***
Panel 9 (1987-1996)	0.536*** (0.0517)	0.173*** (0.0348)	-0.000332*** (0.0000765)	1420	0.132	1986	0.542*** (0.0533)	33.71***
Panel 10 (1988-1997)	0.569*** (0.0532)	0.110*** (0.0391)	-0.000328*** (0.0000695)	1470	0.125	1987	0.573*** (0.0547)	47.53***
Panel 11 (1989-1998)	0.452*** (0.0517)	0.164*** (0.0398)	-0.000264*** (0.0000604)	1470	0.129	1988	0.457*** (0.0534)	19.37***
Panel 12 (1990-1999)	0.385*** (0.049)	0.205*** (0.0391)	-0.000202*** (0.0000529)	1480	0.121	1989	0.391*** (0.0508)	8.415***
Panel 13 (1991-2000)	0.379*** (0.0447)	0.205*** (0.0354)	-0.000209*** (0.0000481)	1610	0.104	1990	0.385*** (0.0463)	9.463***
Panel 14 (1992-2001)	0.481*** (0.0428)	0.230*** (0.0351)	-0.000193*** (0.0000431)	1650	0.136	1991	0.488*** (0.0443)	20.85***
Panel 15 (1993-2002)	0.545*** (0.0394)	0.321*** (0.0335)	-0.000181*** (0.0000382)	1600	0.158	1992	0.558*** (0.0409)	20.19***
Panel 16 (1994-2003)	0.639*** (0.0385)	0.172*** (0.0313)	-0.000153*** (0.0000353)	1590	0.196	1993	0.645*** (0.0396)	87.91***
Panel 17 (1995-2004)	0.583*** (0.0395)	0.268*** (0.0305)	-0.000169*** (0.0000328)	1630	0.191	1994	0.595*** (0.0409)	41.23***
Panel 18 (1996-2005)	0.584*** (0.0392)	0.271*** (0.0313)	-0.000107*** (0.0000311)	1670	0.25	1995	0.597*** (0.0407)	40.39***

Notes: The dependent variable is the 10-year growth of green patents. Driscoll and Kraay's (1998) standard errors, robust to heteroskedasticity and serial and cross-sectional correlation, in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Country-level results with alternative measures of complementary non-green technologies

	COMPAT Since 1st connection *strictu sensu*	COMPAT Yearly connection	COMPAT Yearly connection *Strictu sensu*
Panel A - Country and time fixed effects included			
EPSI	0.065*	0.024	0.05
	(0.033)	(0.037)	(0.035)
PATSTOCK	0.719***	0.740***	0.731***
	(0.047)	(0.048)	(0.048)
HC	2.731***	1.980***	2.180***
	(0.685)	(0.583)	(0.598)
ENVEFF	0.253**	0.237**	0.269***
	(0.1)	(0.099)	(0.095)
GDP	0.352	0.384	0.429*
	(0.256)	(0.245)	(0.248)
R^2	0.931	0.948	0.942
F	156	376.9	386.7
Panel B - IV with country and time fixed effects			
EPSI	0.233	0.206	0.19
	(0.346)	(0.303)	(0.325)
PATSTOCK	0.716***	0.738***	0.729***
	(0.056)	(0.056)	(0.056)
HC	2.839***	2.097***	2.269***
	(0.764)	(0.684)	(0.699)
ENVEFF	0.248**	0.231**	0.264**
	(0.113)	(0.111)	(0.105)
GDP	0.195	0.213	0.297
	(0.431)	(0.451)	(0.474)
Observations	529	529	529
R^2	0.726	0.735	0.721
Panel C - First Stage			
POLCOMP	-0.011***		
	(0.002)		
Kleibergen-Paap F	29.71		

Notes: The sample includes 23 countries (see Section 3.2) observed over the period 1990-2012 (23 years). 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*

Appendix

Table A1: First-stage regression results

	(GREENPAT) EPSI	(COMPAT) EPSI
POLCOMP	-0.011***	-0.011***
	(0.002)	(0.002)
PATSTOCK	0.015	0.032
	(0.046)	(0.041)
HC	-1.157**	-1.089**
	(0.491)	(0.518)
ENVEFF	0.038	0.023
	(0.082)	(0.076)
GDP	0.895***	0.839***
	(0.214)	(0.223)
R^2	0.836	0.836
Kleibergen-Paap F	31.45	29.71
Obs.	526	529

Driscoll and Kraay's (1998) standard errors in parentheses
** p < 0.1, ** p < 0.05, *** p < 0.01*