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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/

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 eff 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 ‘Tfe ‘Tfe‘Ta1PCTd ditional code7"hewihn(in)1313-11.2414(alel,)-242oisecode thatt45lel,acti˝ieeneti˝ieenetii.n313-2611aa

*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]

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:

$$g_{it} = \alpha + \rho \sum_{j=1} C_{ijt_0} \; 1 - \delta_{ij} \;\; 1 - \varphi_j$$

### 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 $\beta$ 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 $t-1$, $\delta$ 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 ($\sigma$) and time fixed effects ($\tau$). Finally, $\epsilon$ 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 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 $\rho$, 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 eff

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 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

## 6. Acknowledgements

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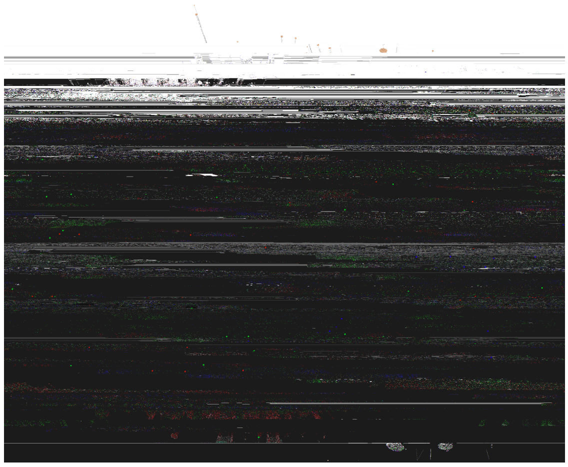
## Tables and Figures

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

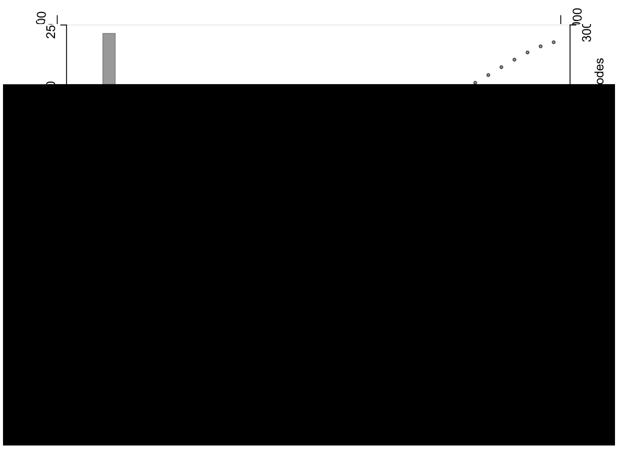
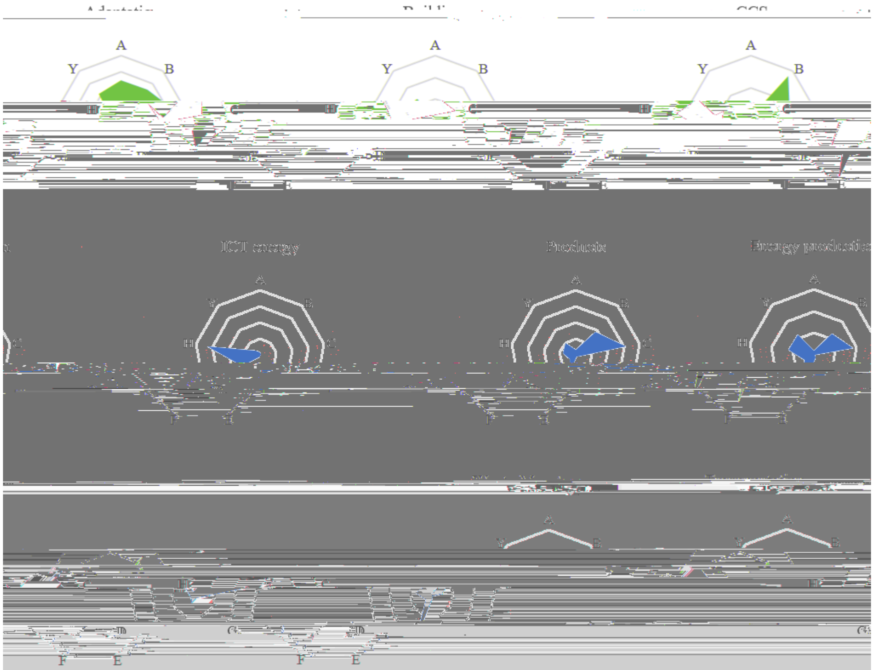


Figure 3: Technological domains that support green inventive activities



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 |
|---|---|---|---|---|---|

Table 2: SAR model estimation

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

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 e ects 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 e ects 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

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

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

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 e ects 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 e ects* | | | |
| 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)<br>EPSI | (COMPAT)<br>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*

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