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Abstract

We investigate the productivity effects of eco-innovations at the firm level using a modified version of the CDM model (Crepon et al., 1998). The peculiar nature of environmental innovations, especially as regards the need of government intervention to create market opportunities, is likely to affect the way they are pursued and their effect on productivity.

The analysis is based on an unbalanced panel sample of Italian manufacturing firms merged with data on patent applications and balance sheet information. When looking at the returns of innovations in terms of productivity, we observe that eco-innovations exhibit a generally lower return relative to other innovations, at least in the short run. This differential effect is more pronounced for polluting firms, which are likely to face higher compliance costs for environmental regulations than other firms. This result holds for both the extensive (probability of patenting) and intensive (patent count) margin.

Keywords: R&D, innovation, productivity, patents, eco-patents.
JEL: L60; Q55

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1 Introduction

Structural change, technological progress and changes in consumers' preferences, have largely been acknowledged as crucial factors in achieving environmental sustainability (Jaffe et al., 1995 and 2002; Popp et al., 2009; Popp, 2010). Technological progress might improve environmental performance through different channels: a more efficient use of natural resources and lower emission intensity in production activities and through the supply of new more "sustainable" products as substitutes to other less efficient productions. Indeed, firms are key actors in the creation, adoption, diffusion of - and sometimes resistance to - environmental innovations. In this light, the paper is aimed at exploring the links between R&D, environmental (or eco-) innovation and productivity at the firm level, assessing the effect of eco-innovations on firm-level productivity. The modeling framework is borrowed from the Crépon et al. model (CDM hereinafter), modified to account for differential effects of eco-innovation with respect to non-eco-innovation. The underlying hypothesis is that while the "public" returns to eco-innovation are clearly positive, the "private" returns are often ambiguous, as eco-innovations can depress firms' productivity, at least in the short run. Needless to say, this represents a clear disincentive for firms to pursue eco-innovation and leave some room for government intervention. This argument stems directly from the "Porter hypothesis", namely the fact that "strict environmental regulations can induce efficiency and encourage innovations that help improve commercial competitiveness" (Porter, 1991). The hypothesis suggests that strict environmental regulation triggers the discovery and introduction of cleaner technologies and environmental improvements, making production processes more efficient. The cost savings that can be achieved can be sufficient to (over)compensate for both the compliance costs of the new regulations and the innovation costs.

We use four consecutive waves (7^{th}, 8^{th}, 9^{th} and 10^{th}) of the Unicredit survey on Italian manufacturing firms for the periods 1995-1997, 1998-2000, 2001-2003, and 2004-2006. Moreover, in order to recover information on eco- and non-eco-innovation, we match those firms with the EPO and PCT-WIPO patent applications database.

We find a strong and positive effect of patenting activity, while we observe a generally lower return in terms of productivity for eco-innovations relative to other innovations, the difference being greater for polluting firms.

The paper is organized as follows. Section 2 reviews the relevant literature about the drivers of eco-innovation and its effect on firm's performance; Section 3 contains the description of the data used and discusses the definition of eco-innovation. Section 4 focuses on the description of the empirical model; Section 5 discusses the results, while Section 6 concludes.

2 Are eco-innovation special?

Most of the literature on eco-innovation patterns at the firm level focuses on the identification of the drivers of eco-innovation, with little attention devoted to the effects of eco-innovation on firms' performance. Recent contributions in this field agreed on a taxonomy of three different sets of drivers of eco-innovation (Horbach, 2008; Horbach et al., 2012). Market pull factors mostly refer to demand conditions, such as the demand of more environmentally friendly products exerted by consumer (including public procurement). Technology push drivers and other firm-specific factors refer to supplyside factors such as the availability of capabilities to develop eco-innovations in terms of knowledge stock and skills needed to develop and adopt eco-innovations. Finally, regulation aimed at reducing environmental pressures plays a crucial role for eco-innovation due to the "public good" nature of improvements in environmental performance generated by eco-innovation. This latter component is the one that really characterizes eco-innovation as opposed to other innovations.

While eco-innovations are expected to have, by definition, a beneficial effect on the environment, their effect on firms' productivity performance can be negative. This market failure underlines the necessity of government intervention, by means of the so-called Porter's hypothesis (Porter, 1991): well designed and stringent environmental regulation can stimulate innovations, which in turn increase the productivity of firms or the value of the product for end users (Porter, 1991; Porter and van der Linde, 1995). Environmental regulation would be beneficial for both society and regulated firms by triggering dynamic efficiency of firms and these benefits may offset the compliance costs of environmental restrictions. However, this view has been criticized on the ground that any policy aimed at limiting environmental by-products of firms will result in a reduction in observed productivity, at least in the short run due to the fact that policies impose additional constraints to firms (Palmer et al., 1995). Since these productivity losses cannot be fully recovered, firms might divert resources devoted to generate or adopt environmental innovations from other more profitable research projects with higher expected returns (crowding out effect) in order to offset regulatory compliance costs. The result would be that those innovations that were induced by environmental regulation will have a smaller return in terms of profitability and productivity when compared to other "autonomous' innovations"

Ambec et al. (2013) provides a systematic overview of the theoretical foundations of the Porter Hypothesis that emerged from the literature. A first group of studies has motivated the possibility of a positive link between environmental regulation and competitiveness by departing from the paradigm of profit maximization by firms and by introducing behavioral aspects. Sub-optimal behaviors include the lock-in into established routines, bounded rationality and risk aversion of managers. In this framework, environmental regulation forces firms to change established routines or may signal the presence of inefficiency that were not accounted for by bounded rational managers. A second theoretical aspects that may explain the Porter Hypothesis is the presence of market failures in the form of market power, asymmetric information and R&D spillovers. In presence of imperfect competition, regulation may strategically favor domestic firms by granting them a first-mover advantage vis-a-vis competitors abroad that will follow in adopting stringent regulations. Regulation can also introduce barriers to entry thus favoring incumbent firms and may help to reduce asymmetric information between firms and customers by sorting out 'green' and 'brown' firms.

The existing empirical evidence on the extent to which environmental regulation affects economic performance seems to go in the direction of refusing the Porter Hypothesis even though some case of win-win outcome are found. Christiansen and Haveman (1981) review early investigations that looked at the contribution of environmental regulation to the reduction in productivity in the US for the period 1965-1979. Environmental regulation, as compared to other factors (e.g. reduction in capital deepening), accounted for about ten percent of the overall slowdown in productivity that was observed in that period. A negative relationship between environmental regulatory stringency and measured productivity is also found, for the US, by Gray and

Shadbegian (1993) (in the paper, oil and steel industries) and Gollop and Roberts (1983, in telectric power industry) while no effect was found in the food industry (Alpay et al., 2002) and a positive effect for refineries in the Los Angeles Air Basin was found by Berman and Bui (2001). More recently, Greenstone et al. (2012) evaluated the role played by the enforcement of the Clean Air Act on nonattainment counties for a sample of 1.2 million of establishment in the US, finding a negative effect of increased stringency on total factor productivity. It should be noted, however, that most of these studies are based on the evaluation of the Clean Air Act that is a command-and-control regulation, while the Porter Hypothesis emphasizes the need for market-based instruments that are more likely to reward innovative response to regulatory stringency rather than simple compliance to standards. Lanoie et al. (2011) evaluate the effect of environmental regulatory stringency on (eco-) innovation and firm performance for a sample of 4200 firms in 7 OECD countries. They conclude that regulation stimulates eco-innovation but they show that the positive effect of eco-innovation on firm performance does not fully offset the compliance costs. From a more theoretical viewpoint, Acemoglu et al (2012) point out that changes in the relative price of energy inputs have an important effect on the types of technologies that are developed and adopted. Energy intensive, or polluting, firms are likely to have different incentives with respect to other firms, to develop or to adopt eco-innovations. Moreover, the authors argue that without a government intervention, the economy would rapidly go towards an environmental disaster, because the initial productivity advantage would direct innovation and production to the sector of using "dirty" inputs, contributing to environmental degradation. However, an environmental regulation would be sufficient to redirect technical change and avoid an environmental disaster. In the same spirit, Aghion et al (2014) show that firms belonging to the automotive industry innovate relatively more in clean technologies when they face higher tax-inclusive fuel prices, as a proxy of carbon tax.

More recent analyses look empirically at the link between environmental innovation and firm performance: Marin (2014), using a large panel of Italian firms, finds that innovation efforts of polluting firms are significantly biased towards environmental innovations and that eco-innovations tend to crowd out other more profitable innovations, at least in the short run. Rexhäuser and Rammer (2014) consider the role of regulation-induced innovation: using the German CIS (Mannheim Innovation Panel 2009), they find that cost-reducing innovations aimed at reducing energy and material input have a positive effect on firms' profitability while regulation-induced environmental innovations, mainly aimed at reducing environmental pressures, have a negative but weak effect on profitability. van Leeuwen and Mohnen (2013) investigate the extent to which eco-innovation and other innovations are characterized by complementarity or substitutability in their effect on productivity. Their analysis, based on a panel of Dutch firms, finds no effect of eco-innovation on productivity. Finally, Ghisetti and Rennings (2014) show that for German firms there exists a positive relationship between eco-innovation aimed at improving resource and energy efficiency and financial performance (returns on sales) while a negative relationship emerges for eco-innovations aimed at reducing environmental externalities (e.g. environmental abatement).

A recent contribution by Dechezlepretre et al. (2013) has investigated whether technologies in the "green" fields differ from technologies in other fields in terms of generation of knowledge spillovers. They show that knowledge spillovers generated by patents that belong to four green technology domains (energy production, automobiles, fuel and lighting) are substantially larger than the ones generated by patents pertaining to the four corresponding substitute brown technologies. Moreover, knowledge spillovers from green patents are greater in magnitude than the ones flowing from other recent breakthrough technology fields such as biotechnology, nanotechnology, robotics and 3D printing while they are only slightly (but significantly) smaller than for information technologies.

Summing up, a large part the literature has investigated a sort of "reduced form" relationship between environmental regulation and productivity, finding a negative relationship, some more recent work have focused on the contribution of eco-innovation to productivity and, more generally, on firms' performance, with more mixed results. We contribute to this latter field of literature by providing evidence on the return of environmental patents (as opposed to other patents) in terms of productivity for a large sample of Italian firms.

3 Data

3.1 How to measure environmental innovations

First of all, an unambiguous definition of eco-innovation is needed. There has been a rich debate in the economic literature about the distinctive features of environmental innovations as opposed to general innovations (Rennings, 2000). Environmental innovation (or eco-innovation) has been defined by Kemp and Pearson (2007) within the project 'Measuring Eco Innovation' as "*the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organization (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives*".

Indeed, this is a broad definition, that makes even more difficult to measure environmental innovation in a comprehensive way, even by means of ad hoc surveys.

As a consequence, patent data could represent an objective and viable alternative to measure eco-innovation (Popp, 2002; Oltra et al., 2010). Patents contain rich information about the technological field of the underlying innovation, through the international patent classification (IPC) classes and the text contained in the patent or in the abstract. This information is generally exploited through the identification of relevant "environmental" IPC classes or through the systematic search of "environmental" keywords. Moreover, patent data are publicly available, they cover long time spans and do not suffer from sample selection.

Nevertheless, the use of patent data as a measure of innovation[1] and in particular as a proxy for environmental innovation is characterized by some limitations.

As largely documented in the empirical literature, patents cover only a part of the innovation output, as many innovations are not patented either because they cannot be

[1] See Griliches (1990).

patented[2] or because firms prefer to use alternative means to protect their innovations (secrecy, lead time, etc.).

Moreover, patent data ignore the whole phase of 'adoption' of innovations; thus, it is plausible that a share of patented innovations is not adopted by applicant firms which could act as specialized suppliers of knowledge to other firms (Calel and Dechezleprêtre, 2014). Finally, common to all the patent studies, the distribution of the value of patents is very skewed, with a tiny proportion of extremely valuable patents and a great majority of patents with little or even no commercial value (Hall et al., 2007).

Nevertheless, due to their availability and the objective definition, many recent analysis on environmental innovations are based on patent statistics (Lanjouw and Mody, 1996; Brunnermeier and Cohen, 2003; Wagner, 2007; Johnstone et al., 2010).

In order to identify eco-innovations, we rely on the results provided by the OECD project on "Environmental Policy and Technological Innovation" (ENV-TECH Indicator)[3], aimed at evaluating the effects of public environmental policy on technological innovation. As a prerequisite for such work, appropriate indicators of eco-innovation based on patent data have been constructed. Based on selected IPC and ECLA classifications, eco-innovations have been identified and classified according to their technological class. A second source of relevant information was provided by the World Intellectual Property Organization (WIPO). In 2010 the WIPO launched the "IPC Green Inventory", with the aim of highlighting environmentally sound technologies within the IPC Classification. The IPC Green Inventory contains nearly 200 topics that are directly relevant to environmentally sound technologies, and each topic is linked with the most relevant IPC class chosen by experts. For this paper, we define eco-innovation those patents with at least one IPC code belonging to the groups selected by the OECD or by the WIPO[4] (see Table 11 and Table 12 for a list of the selected IPC codes). Even though it is acknowledged by the same creators of the IPC Green Inventory that their definition of 'environmentally sound technologies' could be too

[2] An innovation can be patented if it is novel, non-obvious and commercially viable. Moreover, specific patent offices do not allow to patent specific technologies (e.g. living organisms).

[3] http://www.oecd.org/env/consumption-innovation/indicator.htm

[4] We decided to exclude some of the technology fields identified in the Green Inventory. The rationale was that many technologies in these fields were not striclty related to environmental improvements, differently from more established technology fields such as, for example, renewable energy generation technologies and pollution control technologies. We excluded four macro-categories. Costantini et al., (2012) suggest that just a small proportion of patents in the biofuel technology field of the Green Inventory is related to technologies with potential environmentally benign effects. Second, given our focus on manufacturing firms, we excluded patents in the field of agriculture and forestry. The exclusion of the field 'Administrative, regulatory and design aspects' is motivated by the fact that these aspects, although potentially relevant for environmental issues, are too generic (e.g. the actual description of the IPC class in the field labeled as '*Carbon/emissions trading, e.g. pollution credits*' is '*Data processing systems or methods, specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes; systems or methods specially adapted for administrative, commercial, financial, managerial, supervisory or forecasting purposes, not otherwise provided for*'). Finally, patents in the field of nuclear power generation have not been included in the category of environmental patents for two reasons, one related to the choice of Italy to stop the generation of energy with nuclear technologies with a referendum in 1987 following the Chernobyl disaster, the other one linked to the potentially harmful environmental effects of the diffusion of these technologies.

broad[5], we decided to included most of the technology fields in the IPC Green Inventory for two reasons. First, this approach reduces the risk of excluding potential environmental patents, leaving them in the 'non-environmental' category, thus further reducing the (already small) number of environmental patents. Second, the fact that we also consider PCT (non-EPO) patents could be a limitation because they do not report ECLA classes, crucial to identify some specific technologies in the ENV-TECH Indicator (Y02* ECLA classes). The IPC Green Inventory complements the absence of ECLA classes in PCT patents.

Example of environmental technologies are capture, storage, sequestration or disposal of greenhouse gases, renewable energy generation, pollution abatement and waste management.

We further split environment-related technologies into two separate categories, based on their relative content of 'public good'[6]. From the point of view of the generator (i.e. the patent applicant), new environmental technologies could be seen as an impure public good[7]. New environmental technologies improve the performance of the firm in terms of more innovative turnover or improved production efficiency (private component) while they also provide a joint public component in terms of reduced environmental externalities (public component). This is relevant for our purposes because, as a consequence of the presence of some public content of the eco-innovations, they can have different returns and differential impacts on firms' productivity. The assignment of technology fields to the 'private' or 'public' category is based on the expected relative role played by 'private' returns in each technology field. In the category 'private' environmental innovations we include transport technologies (mainly directed to improve overall energy efficiency), technologies to improve energy efficiency of specific devices (e.g. lighting) or services (e.g. heating), technologies for improved input and output energy efficiency and, finally, various technologies with potential or indirect contribution to emissions mitigation The primary aim of innovations in these technology fields is to improve energy efficiency (with clear private benefits). The category 'public' environmental innovations, on the other hand, includes those technologies explicitly aimed at dealing with environmental externalities (polluting emissions, waste generation and treatment, climate change), for which most of the benefits consist in the reduction of negative externalities, or to develop alternative energy production technologies (mainly renewables) that are not ready to compete in production costs with traditiona fossil fuel technologies.

In order to link patent applicants to firm-level data, we apply the procedure described in Lotti and Marin (2013). After cleaning and harmonizing firm and applicant names and addresses, we identified both exact matches as well as score matches (based on measures of string similarity). Score matches have been checked one-by-one to minimize false matches.

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[5] The creators of the IPC Green Inventory state that '*search results may additionally include irrelevant results not relating to ESTs*' (http://www.wipo.int/classifications/ipc/en/est/).

[6] We thank an anonymous referee for the suggestion.

[7] Refer to Kotchen (2006) for a theoretical formalization of green markets as providers of impure public goods.

3.2 Firm-level data

We use firm-level data from the 7th, 8th, 9th and 10th waves of the "Survey on Manufacturing Firms" conducted by Unicredit (an Italian commercial bank, formerly known as Mediocredito-Capitalia). These four surveys were carried out in 1998, 2001, 2004, and 2007, respectively, using questionnaires administered to a representative sample of Italian manufacturing firms. Each survey covered the three years immediately prior (1995-1997, 1998-2000, 2001-2003, and 2004-2006) and although the survey questionnaires were not identical in all four of the surveys, they were very similar in the sections used in this work. All firms with more than 500 employees were included in the surveys, whereas smaller firms were selected using a sampling design stratified by geographical area, industry, and firm size. We merged the data from these four surveys, excluding firms with incomplete information or with extreme observations for the variables of interest.[8] We obtained balance sheet information from the Company Accounts Data Service (CADS) database at the Bank of Italy and we built an unbalanced panel[9] of 47,990 observations on 11,938 firms throughout the period 1995-2006.

Table 1 contains some descriptive statistics for the unbalanced panel: not surprisingly, the firm size distribution is skewed to the right, with an average of 106 employees, but with a median of 33 only. In our sample, only 29% of the firms invest in R&D, with an average of 3,770 euros per employee, but only 6.1% have filed at least one patent application and even less (around 0.7%) have filed an eco-patent. Even though the proportion of eco-patents in our sample (6.2 percent) is low, it is somewhat in line with the average share of eco-patents by Italian applicants as a whole (7.9 percent) and by EU15 applicants (8.7 percent) in the same period[10]. Interestingly, on average, patenting firms have 3 patents each. Nearly 30% of the employees at the median firm are white-collar workers. Turning to the other variables used in the empirical analysis, 62% of the firms in the sample report that they have national competitors, while 27% have international competitors. Nearly a quarter of the firms belong to an industrial group and 38% of the firms in our sample received a subsidy of some kind (mainly for investment and R&D; we do not have more detailed information on the subsidies received). Table 2 shows the distribution of observations by sector and macro-region.

Figure 2 and Figure 3 show the propensity to innovate expressed as share of observation performing R&D expenditure, applying for a patent and applying for environmental patent with, respectively, sectorial and size class breakdowns. The propensity to innovate varies substantially across sectors, with medium-high technology sectors such as electrical and optical equipment (DL), machinery and equipment (DK), petro-chemicals (DF-DG) transport equipment (DM) having very high shares of firms performing formal R&D (about 40 percent) and of firms applying for patents (more than

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[8] When identifying extreme observations we consider the following variables: log value added per employee and log R&D per employee. An observation is considered to be extreme if its value (for any of the variables) is more than three interquartile ranges greater than the third quartile or smaller than the first quartile. We identify 620 extreme observations (1.28 percent).

[9] We did not exploit the panel dimension of our dataset due to instability of the panel across waves. In fact, we a balanced panel for only 150 firms (1.26 percent of firms), while 7,360 (61.65 percent) firms were available for one wave (three consecutive years) only.

[10] Own calculation based on the OECD REG-PAT Database (edition July 2013).

10 percent). Also the propensity to apply for eco-patents tend to be substantially higher in medium-high technology sectors. Looking at the size class breakdown of innovation propensity, we observe that patent propensity and eco-patent propensity monotonically increase with firms size while the share of R&D-doing firms reaches its peak for the category of firms with 251-500 employees (about 52 percent) while very big firms (more than 500 employees) have lower propensity to perform R&D (about 48 percent).

Table 3 reports the share of observations (with a sector and size class breakdown) for which, despite observing at least one patent application, no R&D is reported by the firm. This phenomenon has been also highlighted by Bugamelli et al (2012) and Hall et al (2009) who stress the fact that non-R&D doers innovators tend to focus on rather marginal improvements to existing technologies. On average, about half of the patenting firms do not report or perform formal R&D even though this evidence is very heterogeneous across sectors and size classes. More specifically, the share of patenting firms with formal R&D activities belonging to the class of medium-big firms (between 251 and 500 employees) is three times as bigger than the share of patenting firms with formal R&D activities belonging to the class of small firms (between 11 and 20 employees). Moreover, it is interesting to note that in most sectors the size class of very big firms (more than 500 employees) applying for at least a patent has a lower propensity to perform formal R&D than medium-big firms (between 251 and 500 employees). Finally, the share of patenting firms also performing and reporting formal R&D tends to be higher for medium-high technology sectors[11] than for medium-low technology sectors, reflecting heterogeneity in the complexity of technologies across sectors.

Before moving to the description of the CDM framework, it is worth discussing some preliminary descriptive evidence on the relationship between productivity and patents, both environmental and non-environmental. Table 4 shows the average and median labor productivity (real value added per employee, in thousand euro,) by size class and patenting status. It is evident that patenting firms (second column) are more productive than non-patenting firms (first column), for all size classes. The difference tends to be larger for average than for median values, meaning that, for patenting firms, the average is particularly influenced by few firms with very high levels of productivity. With the only exception of small firms (less than 20 employees), firms with at least one environmental patent (column 4) are characterized by larger productivity (average and median) than patenting firms with no environmental patents (column 3). Conditional on size only, firms involved in the development of environmental technologies tend to be more productive than firms that innovate in other fields. Also in this case, differences in median values are substantially smaller than differences in average values. Table 5 shows pairwise correlations between productivity and patents (simple count and count per employee), both for the full sample and the sub sample of observations with at least one patent. We observe a positive correlation between all patenting indicators and productivity. However, correlation coefficients tend to be rather small (ranging from 0.16 and basically zero) and systematically greater when considering total patents than patents alone. The unconditional correlation does not seem to highlight strong links

[11] DL - electrical and optical equipment, DK - machinery and equipment n.e.c., DM - transport equipment, DH - rubber and plastic products, DF-DG - coke, refined petroleum products, nuclear fuel, chemicals, chemical products and man-made fibers.

between patenting and productivity. However, many confounding factors are expected to influence these relationships and motivate the use of a more "structural" approach to evaluate these links.

4 The modified "CDM framework"

The so-called "CDM framework" (Crépon et al., 1998) intends to shed some light in the black box of the innovation process at the firm level, by linking innovation inputs to innovation outputs and innovation outputs to productivity, and not only by considering a reduced form relation from innovation inputs to productivity. The CDM framework follows the logic of firms' decisions by distinguishing three types of equations (or groups of equations) for respectively investment in innovation inputs, the production of innovation outputs (or knowledge production function) and the traditional production function augmented to include innovation outputs as additional factors of productivity. We extend the CDM model to include eco-innovations as possible output and to evaluate their impact on productivity, similarly to van Leeuwen and Mohnen (2013) and Marin (2014). The framework encompasses three groups of relations as shown in Figure 1. The first consists of the decision whether to invest in R&D or not and how much to spend. The second step is an equation for innovation outcomes (in several versions of the CDM models are dummy variables for the introduction of a new or significantly improved process, introduction of a new or significantly improved product, organizational change associated with process innovation, or organizational change associated with product innovation). The final equation is a conventional labor productivity regression that includes the innovation outcomes as well.

Summing up, productivity is assumed to depend on innovation, and innovation to depend on investment choices. Of necessity, our estimation is cross-sectional only, for two reasons: first, we have few firms cases with more than one year of observation. Second, the timing of some of the questions of the survey is such that we cannot really assume a direct causal relationship since they are measured over the preceding three years in the questionnaire. Therefore, the results that we report should be viewed as associations rather than as causal relationships.

4.1 R&D decision

In the first stage, as in the standard CDM model, we consider the decision to invest in R&D. A firm must decide whether to perform R&D or not; then, given that the firm chooses to do R&D, it must choose its intensity. This statement of the problem can be modeled in a standard sample selection framework. We use RD_i to denote R&D investment of firm i, and define this decision as follows:

$$D\_RD_i = \begin{cases} 1 & \text{if } RD_i^* = w_i\alpha + \varepsilon_i > \hat{c} \\ 0 & \text{if } RD_i^* = w_i\alpha + \varepsilon_i \leq \hat{c} \end{cases} \tag{1}$$

where D_RD_i is an (observable) indicator function that takes the value 1 if firm i has - or reports - positive expenditures on RD, RD_i^* is a latent indicator variable such that firm i decides to perform - or to report - expenditures if it is above a given threshold $\hat{c}$, w_i is a set of explanatory variables affecting the decision, and ε_i is the error term. For those firms performing R&D, we observe the intensity of resources spent for these activities:

$$RD_i = \begin{cases} RD_i^* = z_i\beta + e_i & \text{if } D\_RD_i = 1 \\ 0 & \text{if } D\_RD_i = 0 \end{cases} \tag{2}$$

where RD_i* is the unobserved latent variable corresponding to the firm's intensity of investment, and z_i is a set of determinants of the expenditure intensity. We measure expenditure intensity as the logarithm of real R&D spending per employee. Moreover, we assume that the error terms in Equations (1) and (2) are bivariate normal with zero mean and covariance matrix given by:

$$\Sigma = \begin{pmatrix} 1 & \\ \rho\sigma_\varepsilon & \sigma_\varepsilon^2 \end{pmatrix} \tag{3}$$

The system of Equations (1) and (2) can be estimated by maximum likelihood methods: in the literature, this model is sometimes referred to as a Heckman selection model (Heckman, 1979) or Tobit type II model (Amemiya, 1984).

4.2 Knowledge production function

The combination of innovation inputs (R&D) with internal and external resources may result in the introduction of innovations. Successful innovations have been measured in CDM models in several ways, depending on data availability. Crépon et al (1998) use patent applications count and share of innovative sales as indicators of successful innovations, while other authors (e.g. Hall et al (2009) for Italy and Griffith et al (2006), for France, Germany, Spain and the UK) use survey-based dummy variables describing the introduction of innovations, generally distinguishing between process and product innovations. In this paper, we use the number of European Patent Office (EPO) and PCT-WIPO patent families[12] sorted by priority year as a measure of innovation output. In this second step, we estimate a knowledge production function with the probability of filing a patent and, alternatively, the number of patent applications as dependent variables. In order to account for that part of innovation activity that has not been formalized, we do not restrict estimation to R&D performing firms only. This is likely to be especially important for small and medium-sized enterprises, which represent nearly 90% of our sample. The outcomes of the knowledge production function are EPO and PCT-WIPO patent families, but classified according two broad categories: eco-patents, as defined in Section 2, and non-eco patents.

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[12] A simple patent family is defined by the European Patent Office as follows: "*All documents having exactly the same priority or combination of priorities belong to one patent family*"
http://www.epo.org/searching/essentials/patent-families/definitions.html
The use of patent families count instead of row count of patents allows to avoid double counting of inventions covered by different documents.

$$\begin{cases} PAT_i = RD_i^*\gamma_1 + x_{1,i}\delta_1 + u_{1,i} \\ ECOPAT_i = RD_i^*\gamma_2 + x_{2,i}\delta_2 + u_{2,i} \end{cases} \tag{4}$$

where RD_i* is the latent R&D effort, which is proxied by the predicted value of R&D intensity from the model in the first step, $x_{1,i}$ and $x_{2,i}$ are set of covariates and the error terms $u_{1,i}$ and $u_{2,i}$ are distributed normally with covariance matrix. Moreover, using the predicted value instead of the realized value is a sensible way to instrument the innovative effort in the knowledge production function in order to deal with simultaneity problem between R&D and the expectation of innovative success. However, given the fact that the model is estimated in sequential stages, conventional standard error estimates will be biased and we present bootstrapped standard errors.

4.3 Productivity equation

In the third and final step of the model, production is modeled by means of a simple Cobb-Douglas technology with labor, capital, and knowledge as inputs:

$$y_i = k_i\pi_1 + l_i\pi_2 + INNO_i^*\pi_3 + m_i\pi_4 + v_{1,i} \tag{5}$$

where y_i is the labor productivity (real value added per employee , in logs), k_i is the log of capital stock[13] per worker, l_i is the log of employment (headcounts), $INNO_i$* is the predicted number (or the predicted probability) of innovation from the second step, and the m_i are the controls.

5 Results

All of the equations in the model are projected on a list of "exogenous" variables that include a the log of firm size, the log of firm age, year dummies, survey wave dummies, industry dummies (13 industries), and regional dummies (4 regions)[14]. The survey wave dummies are a set of indicators for the firm's presence or absence in the four waves of the survey.[15] The left-out categories for the control dummies in all equations are: sector DA (food and beverage), Central Italy region, year 1995 and the indicator for firms included in the last wave only.

5.1 R&D decision

We estimate the first step by means of a Heckman sample selection model (Table 6). To test for selection in R&D reporting, we first estimated a probit model in which the presence of positive R&D expenditures is regressed on the set of firm characteristics and whether the firm exported at least part of its production. We use this latter variable as an exclusion restriction: with no assumption on the causality link, we assume that being involved in international trade may affect the likelihood of doing R&D, but it

[13] Capital stock has been computed by means of the perpetual inventory method.
[14] Table 2 reports the distribution of observations by industry and by region together with the list and definition of industries and regions.
[15] For example, a firm present in all the four waves will have a '1111' code, '1000' if present in the first only, '1100' if in the first and in the second only, and so forth. These codes are transformed into a set of 14 dummies (24 = 16 minus the 0000 case and the exclusion restriction).

does not have any effect of R&D intensity. It is very difficult to identify those variables that could affect the R&D choice, but not the subsequent R&D expenditures conditional on the decision to perform R&D, since both phenomena are quite similar. As a consequence, our assumption is, inevitably, empirically grounded: we compare the average likelihood of performing R&D and, for positive R&D, the log of its intensity (per employee) between exporting and non-exporting firms (Table 7). Exporting firms are substantially more likely to perform formal R&D than non-exporting firms, with the difference (0.1973) being significantly different from zero. However, conditional on performing R&D, no statistically significant difference is found between exporting and non-exporting firms in terms of R&D intensity.

Unlike van Leeuwen and Mohnen (2013), we do not have data to separate green R&D from traditional R&D, and this is the reason why, in this step, we model R&D decision as a whole. Nevertheless, in our view, this first stage of the CDM model is necessary to avoid simultaneity problems in the subsequent knowledge production functions.

The results confirm the presence of selection, with a significant correlation coefficient of 0.31. The interpretation of this result is that if we observe R&D for a firm for whom R&D was not expected, its R&D intensity will be relatively high given its characteristics. Conversely, if we fail to observe R&D, its R&D intensity is likely to have been low conditional on its characteristics. In line with the results provided by Hall et al (2012), conditional on investing, R&D intensity decreases with size. It also falls with age, but this is barely significant. Firms facing international competitors have much higher R&D intensities, as do firms that are members of a group or who receive subsidies of some kind. These last two results suggest that financial constraints may be relevant for these firms when dealing with R&D investments. Finally, human capital (in terms of share of "white collars" on total employees) is, as expected, positively related to both the probability of performing R&D and its intensity.

5.2 The knowledge production function

The second step of this modified version of the CDM model has been performed by including in the knowledge production function the predicted log of R&D intensity coming from the first step, mainly to address simultaneity issues. The innovation outcome is estimated for three classes of patents: all patent applications (*Total patents*), non-eco patents (*Non environmental patents*) and eco-patents (*Environmental patents*).

As before, we try to separate the extensive margin from the intensive margin, estimating first a class of models with the probability of having a patent and then, since patents are typically a count measure, another class of models with a Negative Binomial regression as in Hall et al (1984), namely the NB2 version with the variance of the disturbance expressed as a quadratic function of the conditional mean.[16]

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[16] Overdispersion in our count variables are mainly driven by excess zeros. An alternative way to deal with excess zeros is to assume that part of the observed zeros is the result of a different data generation process than the one for positive counts and hence to employ zero inflated (Poisson or Negative Binomial) models (Cameron and Trivedi, 1998). We experienced some problems of convergence of the likelihood function when computing bootstrapped standard errors. Point parameters were in line with the results obtained for the negative binomial while standard errors were substantially higher. Results remain available upon request.

The first three columns of Table 8 reports the coefficients of a probit model for the probability of having at least one patent (col. 1), and of a bivariate probit for the likelihood of having a non environmental patent and an environmental patent (col 2a and 2b, respectively). The same structure can be found in Table 9, that reports the estimated coefficients of the count data model, which can be interpreted as elasticities for logarithmic independent variables (expected relative changes in patent applications count for a relative change in the independent variable) and, for dummy variables as relative change in patent applications count when the variable switches from zero to one (Cameron and Trivedi, 1998). The predicted R&D intensity is positively related both to the probability of having any patent and to the number of patents. Firm size is correlated to patent propensity, less so if it is an environmental patent, suggesting the existence of smaller firms specializing in green innovations; the same results hold for the count of patent families. However, in the latter case, the elasticity is smaller than unity, meaning that larger firms have on average a relatively lower patent intensity (per employee) than smaller firms. The regional patent stock per capita (as a proxy for the stock of knowledge locally available) has no effect on the likelihood of having patents; human capital turns out to have no direct effect (or negative but weak) on innovative output (for either type of patent applications), once its effect on R&D intensity is taken into account. The extent of competition has no relation with the probability of patenting nor with the number of patent families.

Being involved in a "market for technology" (Arora et al., 2001), i.e. having bought a patent in the past, is a strong predictor of current patenting activity for all classes of patent applications. Polluting firms[17] are expected to show a systematic bias towards environmental innovations relative to other firms. Firms at least one big polluting plant are expected to be more affected by environmental regulations and more likely to be inspected in order to enforce environmental standards, thus triggering the likelihood of improving their environmental performance by means of environmental innovations. This fact is partly reflected in the patent equation, with polluting firms applying for a greater number of environmental patents even though the effect is barely significant.

Results are largely confirmed using forward citations count[18] instead of raw families count (Table 10). The count of forward citations has been acknowledged to be a good proxy for the technological importance and the economic value of the patent (Squicciarini et al., 2013), thus allowing to account for the heterogeneity of patents in that respect.

[17] A firm is considered "polluting" if it is the owner of a plant included into the EPER (European Pollutant Emission Register) or the E-PRTR (European Pollutant Release and Transfer Register) registers. EPER includes all facilities and plants above a certain threshold of air or water pollution. The E-PRTR substituted the EPER register (in place for 2001 and 2004) starting from the year 2007 onwards. Differently from the EPER, the E-PRTR includes waste-intensive plants. Plants have been assigned to firms in our sample by matching firm name and address with the parent company name and address reported in the EPER and E-PRTR database. We employed name harmonization procedures similar to the ones described in Lotti and Marin (2013).

[18] We retrieve patent forward citations from the OECD EPO Indicators Database (Squicciarini et al., 2013). We use the indicator counting forward citations received by the patent in the five years after its publication (variable *fwd_cits5_xy* in the OECD EPO Indicators Database).

5.3 Productivity analysis

Following the structure of the CDM model, we use the predicted probabilities and the predicted number of patents coming from the second step as explanatory variables in the productivity equations. Productivity is measured as real value added per employee. Looking at the last three columns of Table 8, Table 9 and Table 10, one can see that innovation success has a generally positive impact on productivity. This effect, very strong both in economic and statistical terms, is in line with expectations and highlights the relevance of indicators of innovation output based on patents.

Exploiting the partition on eco- and non-eco-patents (col. 4 of Table 8) there is evidence of a nihil return in terms of productivity from eco-innovations, while the returns for non-eco-patents are positive and significant. The differential effect for polluting firms is negative and statistically different from zero. When considering the number of patent families (Table 9, our baseline model) and the number of forward citations (Table 10) we still find a strong positive effect of patenting activity on productivity. Again, environmental innovations are characterized by an expected lower return relative to other innovations, although this difference is significant in the case of patent citations only; moreover, it is confirmed the negative effect on productivity of eco-innovations for polluting firms. An increase in the likelihood of filing for eco-patents for polluting firms has a negative and significant effect on productivity.

As a further robustness check, we split the broader set of environmental patents into ‘private’ and ‘public’ environmental patents, as described in section 3.1. We adopt the same specifications of our baseline model, with the count of patent families as a dependent variable. Results, displayed on , show that the productivity returns of ‘public’ eco patents are negative and significant, while those of ‘private’ eco-patents are sizeable and positive. This gap is in line with expectations: environmental innovations with a relatively more pronounced ‘public’ component (within a mixed good framework) tend to generate private losses in the short run while ‘private’ environmental innovations tend to be more similar to other innovations in terms of productivity gains.

In accordance with the literature reviewed in the first part of the paper (van Leeuwen and Mohnen, 2013; Marin, 2014; Rexhäuser and Rammer, 2014), the generally lower return of environmental innovations relative to other innovations could depend on two, possibly combined, factors. First, the expected positive link between compliance costs of environmental regulations and environmental innovations is likely to divert innovation inputs from general innovations towards eco-innovations with a loss in terms of returns from innovations if the firm, in absence of the regulation, would have chosen to focus on other more promising innovative projects. Second, eco-innovations, especially if they have a ‘public’ content, are likely to be systematically different from other innovations in terms the distribution of the returns through time due to the fact that they regard newly created markets which are small and fast growing. In this context, short run returns from eco-innovations could be negligible while medium-long run returns could be very high. When considering the differential effect of eco-innovations for polluting firms, it is important to highlight that these firms are the ones which are expected to face more stringent environmental policies than other firms. This asymmetry in the policy environment forces them to bias their innovation patterns towards innovations aimed at reducing compliance costs (eco-innovations) characterized by a low content of private (i.e. productivity-enhancing) returns.

6 Conclusions

In this paper we investigate the innovation patterns of Italian manufacturing firms, with a specific focus on the productivity effects of environmental innovations. Our modified version of the CDM model describes innovation patterns consistently with expectations, with R&D being an important input for innovation and patent applications having strong positive effects on labor productivity. Environmental innovations systematically differ from other innovations in their effect on firm's productivity, with a generally lower return than non-environmental innovations, especially so when considering those with a “public” nature. This result, coupled with the limited availability of financial resources to be devoted to R&D activities, is a possible evidence of crowding out of environmental innovations relative to non-environmental ones. It is important to stress that the evidence of crowding out refers to short term indicators of productivity. It is reasonable to assume, however, that positive effects of policy-induced environmental innovations on competitiveness (and possibly measured productivity) predicted by the “strong” version of the Porter Hypothesis (Porter and van der Linde, 1995) would eventually show up, if any, in the medium-long run due to the fact that the returns from eco-innovations mainly depend on early-mover advantages of eco-innovators and on the creation of new markets for “green” technologies.

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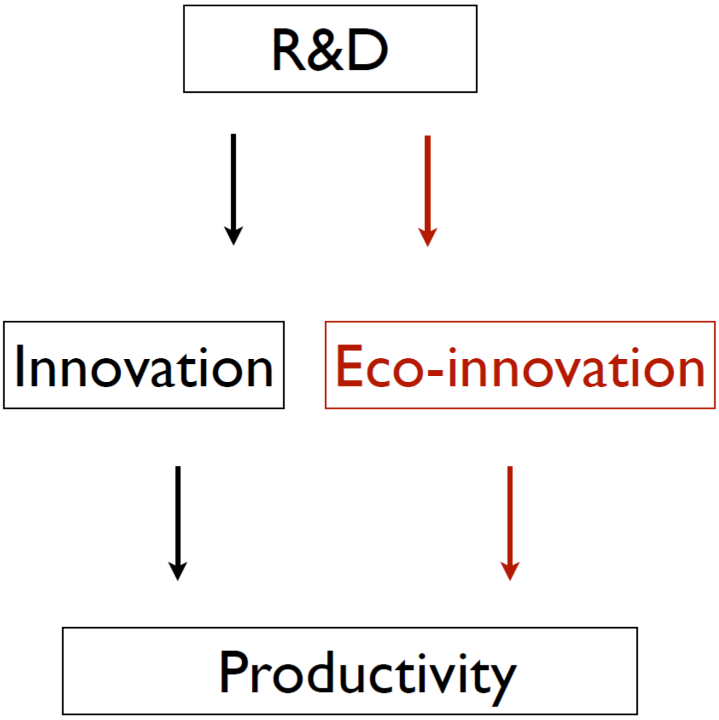
Figure 1: Basic and modified CDM model



In black are reported the three steps of the classic CDM model. In red the extension proposed, to take explicitly into account the role of eco-innovations.

Figure 2: Propensity to innovate by sector

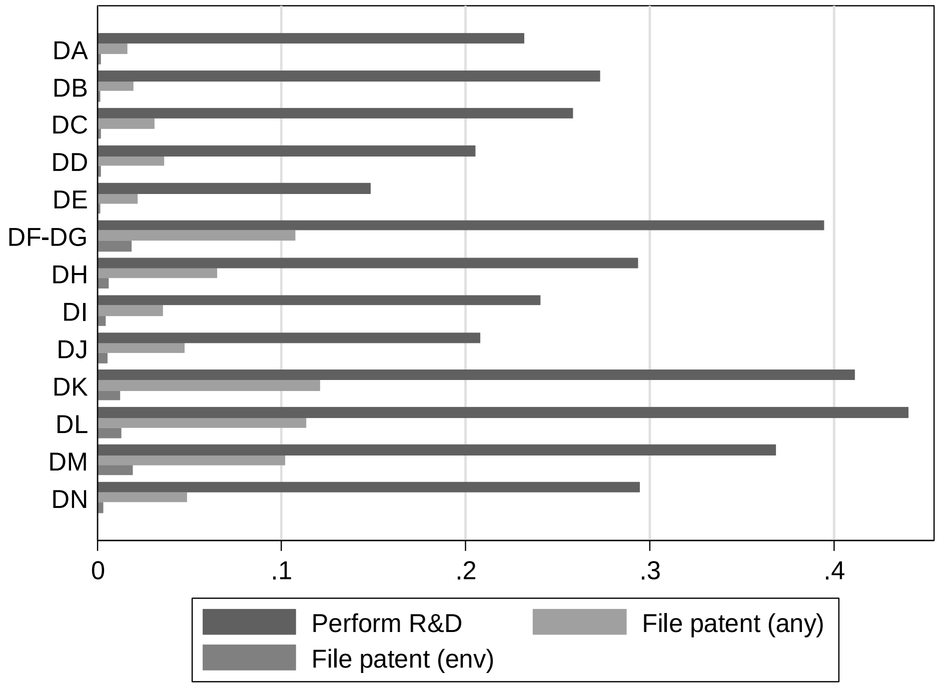


Figure 3: Propensity to innovate by firm size (# employees)

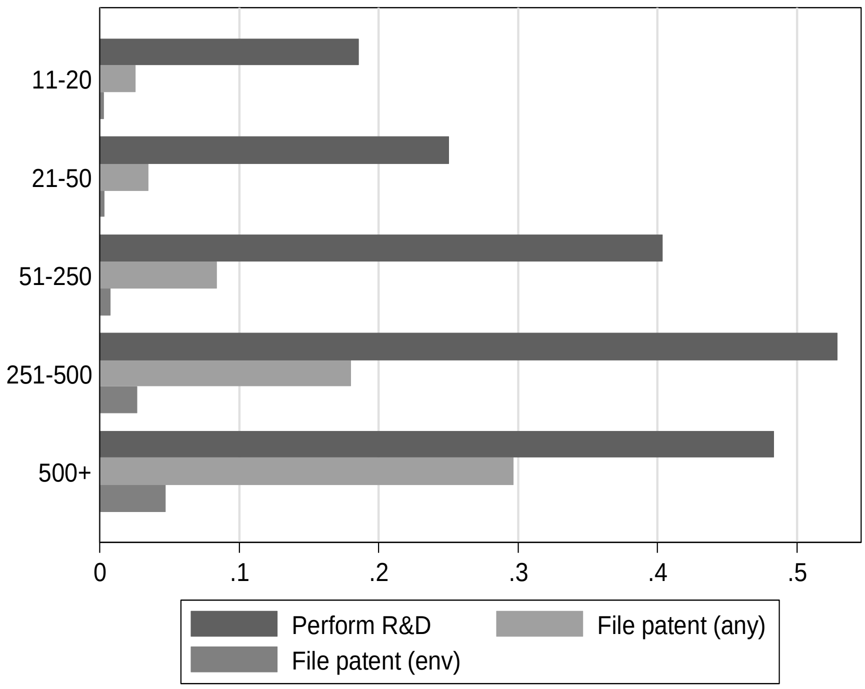


Table 1: Descriptive statistics

Period: 1995-2006			
Number of observations (firms)	47,990 (11,938)	Exporting firms	69.3%
Number of employees (mean/median)	105.7 (33)	Firms within a group	23.5%
Age (mean/median)	24.4 (20)	Firms subsidies recipients	37.7%
Firms with R&D	29.2%	Observations with patents	6.1%
Share of white-collar workers in employees (mean/median)	33.9% (29.3%)	Observations with eco-patents	0.69%
R&D intensity[a] for R&D doers (mean/median)	5.07 (1.61)	Observations with both eco- and non-eco-patents	0.39%
Average capital intensity[a] (mean/median)	76.6 (51.6)	Count of patent families (for observations with patents - mean/median)	3 (1)
Labor productivity[a] (VA - mean/median)	48.2 (42.3)	Count of eco-patent families (for observations with eco-patents - mean/median)	1.64 (1)
Firms with large firms as competitors	37.8%	Average forward citations (for observations with patents)	0.83
Firms with mid-sized firms as competitors	49.5%	Average forward citations for eco-patents (for observations with eco-patents)	0.48
Firms with national competitors	44.1%	Share of 'public' (share of 'private') eco-patents	46.8% (81.4%)
Firms with international competitors	27.2%	Observations with polluting plants (firms)	4.55% (4.03%)

[a] Units are real thousand euros per employee (base year = 2000)

Table 2: Distribution of observations by sector and macro-region

	North-West	North-East	Central Italy	Southern Italy	Total
DA	1,071	1,190	537	1,434	4,232
DB	2,261	977	1,551	661	5,450
DC	154	511	977	278	1,920
DD	397	582	280	173	1,432
DE	1,200	707	735	254	2,896
DF-DG	1,271	507	412	385	2,575
DH	1,281	691	343	373	2,688
DI	798	964	663	652	3,077
DJ	3,812	2,376	1,010	1,007	8,205
DK	3,280	2,858	754	349	7,241
DL	1,918	1,230	473	345	3,966
DM	616	325	187	227	1,355
DN	706	1,243	711	293	2,953
Total	18,765	14,161	8,633	6,431	47,990

Macro-regions. North-West: Valle d'Aosta, Piemonte, Liguria and Lombardia. North-East: Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia and Emilia-Romagna. Central Italy: Toscana, Umbria, Marche and Lazio. Southern Italy: Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia and Sardegna.
Sectors (Nace Rev. 1.1 sub-sections). DA: food products, beverages and tobacco. DB: textiles and textile products. DC: leather and leather products. DD: wood and wood products. DE: pulp, paper and paper products, publishing and printing. DF-DG: coke, refined petroleum products, nuclear fuel, chemicals, chemical products and man-made fibers. DH: rubber and plastic products. DI: other non-metallic mineral products. DJ: basic metals and fabricated metal products. DK: machinery and equipment n.e.c.. DL: electrical and optical equipment. DM: transport equipment. DN: manufacturing n.e.c.

Table 3: Probability of performing formal R&D conditional on patenting (by sector and size class – employees count)

	11-20	21-50	51-250	251-500	501+	Total
DA	20%	25%	47%	40%	40%	32%
DB	21%	35%	50%	60%	63%	44%
DC	44%	38%	39%	90%	0%	47%
DD	7%	39%	50%	100%	50%	35%
DE	14%	10%	40%	50%	33%	25%
DF-DG	27%	56%	52%	72%	43%	52%
DH	11%	50%	71%	61%	56%	54%
DI	10%	38%	53%	63%	48%	43%
DJ	9%	35%	52%	48%	57%	42%
DK	37%	38%	70%	66%	58%	58%
DL	32%	48%	63%	90%	68%	62%
DM	10%	55%	43%	46%	80%	57%
DN	17%	46%	55%	44%	69%	47%
Total	22%	40%	60%	66%	59%	52%

Table 4: Average and median labor productivity by size class (in terms of employees) and patenting status

Size class	No patent	Any patent	Only non-env patents	Also env patents	Total
11-20	47.19 (40.66)	57.18 (44.03)	58.21 (44.15)	47.47 (38.27)	47.45 (40.72)
21-50	45.33 (39.80)	55.61 (43.69)	54.40 (43.17)	66.76 (47.07)	45.68 (39.94)
51-250	48.81 (44.11)	57.85 (51.01)	57.15 (50.77)	64.49 (53.78)	49.56 (44.62)
251-500	53.45 (48.03)	60.26 (54.57)	58.53 (53.92)	70.04 (61.27)	54.67 (49.42)
500+	61.96 (53.14)	63.20 (56.03)	62.00 (55.54)	69.34 (58.78)	62.33 (54.18)
Total	47.54 (41.83)	58.56 (50.35)	57.69 (50.10)	65.27 (53.77)	48.21 (42.33)

Average (median) value added per employee in thousand euro.

Table 5: Correlations between patenting and labor productivity

Pairwise correlations with VA/L	Full sample	Sample of patenting firms
Count of non-env patents	0.0849	0.1600
Count of env patents	0.0421	0.0672
Count of non-env patents (per employee)	0.0550	0.0262
Count of env patents (per employee)	0.0194	0.0083

Table 6: R&D equation. Dependent variable: R&D per employee (col 1 and 2a) and probability of performing R&D (col 2b).

	(1) OLS	(2a) HECKMAN	(2b) Select eq
log(L)	-0.1465***	-0.0929***	0.1988***
	(0.0208)	(0.0265)	(0.0135)
National competitors	-0.0646	-0.0258	0.1161***
	(0.0458)	(0.0489)	(0.0266)
Foreign competitors	0.1461***	0.2610***	0.3637***
	(0.0478)	(0.0610)	(0.0298)
Share white collars	1.2807***	1.4278***	0.5743***
	(0.0962)	(0.1045)	(0.0542)
Part of a group	0.1639***	0.1765***	0.0573**
	(0.0430)	(0.0438)	(0.0282)
log(age)	-0.0497**	-0.0434*	0.0198
	(0.0243)	(0.0247)	(0.0152)
Receive incentives	0.2577***	0.3463***	0.3270***
	(0.0358)	(0.0459)	(0.0224)
Firm exports			0.3170***
			(0.0277)
R squared	0.1476		
Chi squared		1080.7009	
Sigma		1.2786	
Rho		0.3141	
Lambda		0.4016	
Chi sq (H0: Rho=0)		9.6950***	
Log likelihood		-48185.4	
N	14035	47990	

Table 7: Exclusion restriction: firm exports

	Exp=1	Exp=0	Diff.	N	t-stat	p-value
Perform R&D	0.353	0.1557	0.1973	47990	44.73	0.000
ln(R&D/L)	0.4548	0.4449	0.0099	14035	0.32	0.745

Table 8: Patent and productivity equations (probability model)

	Patent equation			Productivity equation		
	(1)	(2a)	(2b)	(3)	(4)	(5)
Estimator	Probit	Bivariate probit		OLS	OLS	OLS
Dependent variable	Tot patents (0/1)	Non-env (0/1)	Env (0/1)	log(VA/L)	log(VA/L)	log(VA/L)
log(R&D/L)	0.4319***	0.4147***	0.4771***			
fitted	(0.0579)	(0.0790)	(0.1360)			
log(L)	0.3430***	0.3416***	0.2596***	-0.0590***	-0.0567***	-0.0630***
	(0.0097)	(0.0148)	(0.0248)	(0.0064)	(0.0064)	(0.0065)
log(reg pat stock)	0.0213	0.0322	-0.0783			
	(0.0333)	(0.0510)	(0.0791)			
Share white	-0.2537***	-0.2486*	-0.2558			
collars	(0.0971)	(0.1342)	(0.2374)			
National	0.0056	0.0024	-0.0108			
competitors	(0.0281)	(0.0385)	(0.0724)			
Foreign	0.0853**	0.0880*	0.0173			
competitors	(0.0336)	(0.0477)	(0.0853)			
Big	-0.0375	-0.0389	0.0044			
competitors	(0.0352)	(0.0499)	(0.0938)			
Mid-sized	-0.0162	-0.0197	-0.0174			
competitors	(0.0364)	(0.0529)	(0.1006)			
log(age)	-0.0241*	-0.0175	-0.0410	0.0055	0.0049	0.0054
	(0.0144)	(0.0217)	(0.0374)	(0.0047)	(0.0046)	(0.0046)
Bought patents	0.5001***	0.5034***	0.1853			
	(0.0552)	(0.0811)	(0.1274)			
Polluter			0.1666*			0.1276***
			(0.0976)			(0.0201)
log(K/L)				0.2402***	0.2403***	0.2377***
				(0.0047)	(0.0047)	(0.0047)
Prob pat tot				0.8877***		
fitted				(0.0926)		
Prob pat no_env					0.7999***	0.8354***
fitted					(0.1416)	(0.1472)
Prob pat env					0.4955	0.7294
fitted					(0.5738)	(0.7157)
Prob pat env						-1.5938***
x Polluter						(0.6001)
Pseudo R squared	0.1712					
R squared				0.3117	0.3115	0.3133
Rho		0.5021				
Chi squared	3753.4576	1950.7822		5993.1498	5994.8668	6097.5520
Log likelihood	-9088.5	-10260.7				
N	47990	47990		47990	47990	47990

Bootstraped standard errors (500 repetitions) in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01

Table 9: Patent and productivity equations (count of patent families)

	Patent equation			Productivity equation		
	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	NB2	NB2	NB2	OLS	OLS	OLS
Dependent variable	Total patents	Non-env patents	Env patents	log(VA/L)	log(VA/L)	log(VA/L)
log(R&D/L)	0.9810***	0.9796***	1.3046***			
fitted	(0.1978)	(0.2020)	(0.4145)			
log(L)	0.8146***	0.8228***	0.7385***	0.0186***	0.0218***	0.0141***
	(0.0413)	(0.0420)	(0.0760)	(0.0043)	(0.0044)	(0.0047)
log(reg pat stock)	0.0582	0.0943	-0.3124			
	(0.1285)	(0.1290)	(0.2507)			
Share white	-0.6097*	-0.6272*	-0.8531			
collars	(0.3553)	(0.3625)	(0.7167)			
National	0.1431	0.1409	0.0643			
competitors	(0.1091)	(0.1081)	(0.2330)			
Foreign	0.1856	0.1870	0.0630			
competitors	(0.1195)	(0.1195)	(0.2610)			
Big	-0.1907	-0.2029	-0.0378			
competitors	(0.1278)	(0.1298)	(0.2689)			
Mid-sized	-0.1332	-0.1551	-0.0067			
competitors	(0.1341)	(0.1349)	(0.3030)			
log(age)	-0.0467	-0.0370	0.0039	0.0147***	0.0112**	0.0126***
	(0.0547)	(0.0553)	(0.1260)	(0.0048)	(0.0048)	(0.0048)
Bought patents	1.0342***	1.0404***	0.8047**			
	(0.1332)	(0.1387)	(0.4005)			
Polluter			0.3290			-0.0992
			(0.3108)			(0.0800)
log(K/L)				0.2365***	0.2354***	0.2339***
				(0.0047)	(0.0047)	(0.0047)
log(pat tot)				0.1618***		
fitted				(0.0099)		
log(pat no_env/L)					0.0924***	0.1309***
fitted					(0.0231)	(0.0234)
log(pat env/L)					0.0646***	0.0308
fitted					(0.0204)	(0.0210)
log(pat env/L)						-0.0335**
x Polluter						(0.0135)
Pseudo R sq	0.1254	0.1274	0.1300			
R squared				0.3178	0.3182	0.3196
Chi squared	1401.8716	1412.9564	505.1102	6373.2825	6371.6071	6522.5930
Alpha	9.0232	9.1416	26.1792			
Log likelihood	-13947.3	-13323.7	-2009.1			
N	47990	47990	47990	47990	47990	47990

Bootstraped standard errors (500 repetitions) in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01

Table 10: Patent and productivity equations (patent citations)

	Patent equation			Productivity equation		
	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	NB2	NB2	NB2	OLS	OLS	OLS
Dependent variable	Citations (total)	Citations (non-env)	Citations (env)	log(VA/L)	log(VA/L)	log(VA/L)
log(R&D/L)	1.3222***	1.3065***	1.3349			
fitted	(0.3175)	(0.3273)	(1.0642)			
log(L)	1.0897***	1.0972***	0.9615***	-0.0230***	-0.0257***	-0.0326***
	(0.0698)	(0.0726)	(0.1685)	(0.0039)	(0.0038)	(0.0039)
log(reg pat stock)	-0.0028	0.0618	-0.9468*			
	(0.2309)	(0.2381)	(0.5658)			
Share white	-0.9169*	-0.8320	-2.0553			
collars	(0.5496)	(0.5618)	(1.8996)			
National	-0.0611	-0.0210	-0.6287			
competitors	(0.1766)	(0.1770)	(0.6028)			
Foreign	-0.0711	-0.0435	-0.3016			
competitors	(0.1987)	(0.2076)	(0.5880)			
Big	-0.0394	-0.1101	0.9370			
competitors	(0.2043)	(0.2100)	(0.9089)			
Mid-sized	0.1267	0.0692	0.9320			
competitors	(0.2260)	(0.2302)	(0.9606)			
log(age)	0.0311	0.0414	0.1105	0.0049	0.0054	0.0063
	(0.0839)	(0.0837)	(0.2409)	(0.0046)	(0.0046)	(0.0046)
Bought patents	0.4970*	0.5226*	0.3323			
	(0.2626)	(0.2788)	(2.1948)			
Polluter			0.5460			0.0879***
			(0.7536)			(0.0283)
log(K/L)				0.2349***	0.2362***	0.2333***
				(0.0047)	(0.0047)	(0.0047)
log(cit tot)				0.1535***		
fitted				(0.0090)		
log(cit no_env/L)					0.1829***	0.1884***
fitted					(0.0097)	(0.0097)
log(cit env/L)					-0.0390***	-0.0468***
fitted					(0.0061)	(0.0061)
log(cit env/L)						-0.0027*
x Polluter						(0.0014)
Pseudo R sq	0.1402	0.1414	0.1902			
R squared				0.3190	0.3220	0.3244
Chi squared	868.8435	817.8438	672.1205	6370.5825	6512.9343	6667.0430
Alpha	25.4517	26.1553	118.2651			
Log likelihood	-4724.9	-4486.9	-499.1			
N	47990	47990	47990	47990	47990	47990

Bootstraped standard errors (500 repetitions) in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01

Table 11 – Environmental patent classes (source: ENV-TECH Indicator Database, OECD, 2013)

Macro-category	Sub-category	IPC (or ECLA for Y02 classes)
General environmental management	Air pollution abatement	BO1D46, B01D47, B01D49, B01D50, B01D51, B01D53/34-72, B03C3, C10L10/02, C10L10/06, C21B7/22, C21C5/38, F01N3, F01N5, F01N7, F01N9, F23B80, F23C9, F23G7/06, F23J15, F27B1/18
	Water pollution abatement	B63J4, C02F, C05F7, C09K3/32, E02B15/04-06, E02B15/10, E03B3, E03C1/12, E03F
	Solid waste collection	E01H15, B65F
	Material recovery, recycling and re-use	A23K1806-10, A43B1/12, A43B21/14, B03B9/06, B22F8, B29B7/66, B29B17, B30B9/32, B62D67, B65H73, B65D65/46, C03B1/02, C03C6/02, C03C6/08, C04B7/24-30, C04B11/26, C04B18/04-10, C04B33/132, C08J11, C09K11/01, C10M175, C22B7, C22B19/28-30, C22B25/06, D01G11, D21B1/08-10, D21B1/32, D21C5/02, D21H17/01, H01B15/00, H01J9/52, H01M6/52, H01M10/54
	Fertilizers from waste	C05F1, C05F5, C05F7, C05F9, C05F17
	Incineration and energy recovery	C10L5/46-48, F23G5, F23G7
	Waste management n.e.c.	B09B, C10G1/10, A61L11
	Soil remediation	B09C
	Environmental monitoring	F01N11, G08B21/12-14
Energy generation from renewable and non-fossil sources	Wind energy	Y02E10/7
	Solar thermal energy	Y02E10/4
	Solar photovoltaic (PV) energy	Y02E10/5
	Solar thermal-PV hybrids	Y02E10/6
	Geothermal energy	Y02E10/1
	Marine energy	Y02E10/3
	Hydro energy	Y02E10/2
	Biofuels	Y02E50/1
	Fuel from waste	Y02E50/3
Combustion technologies with mitigation potential	Technologies for improved output efficiency (combined combustion)	Y02E20/1
	Technologies for improved input efficiency	Y02E20/03
Climate change mitigation	CO2 capture or storage	Y02C10
	Capture or disposal of greenhouse gases other than CO2	Y02C20
Potential or indirect contribution to emissions mitigation	Energy storage	Y02E60/1
	Hydrogen technology	Y02E60/3
	Fuel cells	Y02E60/5
Emissions abatement and fuel efficiency in transportation	Integrated emissions control	F02B47/06, F02M3/02-055, F02M23, F02M25, F02M67, F01N9, F02D41, F02D43, F02D45, F01N11, G01M15/10, F02M39-71, F02P5, F02M27, F02M31/02-18
	Post-combustion emissions control	F01M13/02-04, F01N5, F02B47/08-10, F02D21/06-10, F02M25/07, F01N11, G01M15/10, F01N3/26, B01D53/92, B01D53/94, B01D53/96, B01J23/38-46, F01N3/08-34, B01D41, B01D46, F01N3/01, F01N3/02-035, B60, B62D
	Technologies specific to propulsion usin electric motor	B60K1, B60L7/10-20, B60L11, B60L15, B60R16/033, B60R16/04, B60S5/06, B60W10/08, B60W10/26, B60W10/28, B60K16, B60L8
	Technologies specific to hybrid propulsion	B60K6, B60W20
	Fuel efficiency-improving vehicle design	B62D35/00, B62D37/02, B60C23/00, B60T1/10, B60G13/14, B60K31/00, B60W30/10-20
Energy efficiency in buildings and lighting	Insulation	E04B1/62, 04B1/74-78, 04B1/88, E06B3/66-677, E06B3/24
	Heating	F24D3/08, F24D3/18, F24D5/12, F24D11/02, F24D15/04, F24D17/02, F24F12, F25B29, F25B30
	Lighting	H01J61, H05B33

Shaded categories: ‘public’ environmental innovations

Table 12 – Environmental patent classes (source: Green Inventory, WIPO, 2013)

Macro-category	Sub-category	IPC
Alternative energy production	Integrated gasification combined cycle (IGCC)	C10L3, F02C3/28
	Fuel cells	H01M4/86-98, H01M8/00-24, H01M12/00-08
	Pyrolysis or gasification of biomass	C10B53, C10J
	Harnessing energy from manmade waste	C10L5, C10L5/42-44, F23G7, C10J3/02, C10J3/46, F23B90, F23G5/027, B09B3, F23G7, C10L5/48, F23G5, F23G7, C21B5/06, D21C11, A62D3/02, C02F11/04, C02F11/14, F23G7, B09B3, F23G5, B09B, B01D53/02, B01D53/04, B01D53/047, B01D53/14, B01D53/22, B01D53/24, C10L5/46, F23G5
	Hydro energy	E02B9, F03B, F03C, B63H19/02, B63H19/04
	Ocean thermal energy conversion	F03G7/05
	Wind energy	F03D, H02K7/18, B63B35, E04H12, F03D11/04, B60K16, B60L8, B63H13
	Solar energy	H01L27/142, H01L31, H01G9/20, H02N6, H01L27/30, H01L21/42-48, H01L25, C01B33/02, C23C14/14, C23C16/24, C30B29/06, G05F1/67, F21L4, F21S9/03, H02J7/35, H01H9/20, H01M14, F24J2, F24D17, F24D3, F24D5, F24D11, F24D19, F24J2/42, F03D1/04, F03D9, F03D11/04, F03G6, C02F1/14, F02C1/05, H01L31/058, B60K16, B60L8, F03G6, E04D13, F22B1, F24J1, F25B27, F26B3, F24J2/06, G02B7/183, F24J2/04
	Geothermal energy	F01K, F24F5, F24J3/08, H02N10, F25B30/06, F03G4, F03G7/04
	Other production or use of heat, not derived from combutstion	F24J1, F24J3, F24D11/02, F24D15/04, F24D17/02, F24H4, F25B30
	Using waste heat	F01K27, F01K23/06-10, F01N5, F02G5, F25B27/02, F01K17, F01K23/04, F02C6/18, F25B27/02, FC02C6/18, F25B27/02, C02F1/16, D21F5/20, F22B1/02, F23G5/46, F24F12, F27D17, F28D17, F28D18, F28D19, F28D20, C10J3/86
	Devices producing mechanical power from muscle energy	F03G5
Transportation	Vehicles in general	B60K6, B60W20, F16H3, F16H48, H02K29/08, H02K49/10, B60L7/10-22, B60L8, B60L9, B60L11/18, F02B43, F02M21/02, F02M27/02, B60K16, H02J7
	Vehicles other than rail vehicles	B62D35, B63B1/34-40, B62K, B62M1, B62M3, B62M5, B62M6
	Rail vehicles	B61
	Marine vessel propulsion	B63H9, B63H13, B63H19/02-04, B63H16, B63H21/18, B64G1/44
Energy conservation	Storage of electrical energy	B60K6/28, B60W10/26, H01M10/44-46, H01G9/155, H02J3/28, H02J7, H02J15
	Power supply circuitry	H02J
	Measurement of electricity consumption	B60L3, G01R
	Storage of thermal energy	C09K5, F24H7, F28D20
	Low energy lighting	F21K99, F21L4/02, H01L33, H01L51/50, H05B33
	Thermal building insulation, in general	E04B1/62, E04B1/74-80, E04B1/88, E04B1/90, E04C1/40, E04C1/41, E04C2/284-296, E06B3/263, E04B2, E04F13/08, E04B5, E04F15/18, E04B7, E04D1/28, E04D3/35, E04D13/16, E04B9, E04F13/08
	Recovering mechanical energy	F03G7/08, B60K6/10, B60K6/30, B60L11/16
Waste management	Waste disposal	B09B, B65F
	Treatment of waste	A61L11, A62D3, A62D101, G21F9, B03B9/06, B09C, D21B1/08, D21B1/32
	Consuming waste by combustion	F23G
	Reuse of waste materials	A43B1/12, A43B21/14, B22F8, C04B7/24-30, C04B18/04-10, C05F, C08J11, C09K11/01, C11B11, C11B13, C14C3/32, C21B3/04, C25C1, D01F13, B29B17, B62D67, C08J11/04-28, C10G1/10, C10L5/46, C10L5/48, C22B7, C22B19/30, C22B25/06, D01G11, D21C5/02, H01J9/50, H01J9/52, H01M6/52, H01M10/54
	Pollution control	B01D53/14, B01D53/22, B01D53/62, B65G5, C01B31/20, E21B41, E21B43/16, E21F17/16, F25J3/02B01D53, F01N3, B01D53/92, F02B75/10, C21C5/38, C10B21/18, F23B80/02, F23C9, F23G7/06, F01N9, B01D45, B01D46, B01D47, B01D48, B01D49, B01D50, B01D51, B03C3, C21B7/22, C21C5/38, F27B1/18, F27B15/12, C10L10/02, C10L10/06, F23J7, F23J15, C09K3/22, G08B21/12, B63J4, C02F, C05F7, C09K3/32, E02B15/04, E03C1/12, C02F1, C02F3, C02F9, E03F, G21C13/10

Shaded categories: ‘public’ environmental innovations

Table 13: Patent and productivity equations (patent families – 'private' and 'public' environmental patents)

	Patent equation		Productivity equation	
	(1)	(2)	(3)	(4)
Estimator	NB2	NB2	OLS	OLS
Dependent variable	Priv env pat	Publ env pat	log(VA/L)	log(VA/L)
log(R&D/L)	1.286**	1.527***		
fitted	(0.530)	(0.482)		
log(L)	0.704***	0.813***	0.0289***	0.0208***
	(0.0860)	(0.104)	(0.00466)	(0.00504)
log(reg pat stock)	-0.364	-0.586**		
	(0.277)	(0.259)		
Share white	-0.682	-1.316		
collars	(0.863)	(0.834)		
National	0.181	0.419		
competitors	(0.259)	(0.301)		
Foreign	0.0705	0.0166		
competitors	(0.347)	(0.334)		
Big	-0.371	-0.112		
competitors	(0.287)	(0.365)		
Mid-sized	-0.319	-0.0500		
competitors	(0.324)	(0.386)		
log(age)	0.00213	-0.0755	-0.00224	0.000949
	(0.128)	(0.162)	(0.00495)	(0.00497)
Bought patents	1.289***	0.665		
	(0.313)	(0.574)		
Polluter	0.308	0.168		-0.0460
	(0.364)	(0.344)		(0.0532)
log(K/L)			0.237***	0.235***
			(0.00467)	(0.00467)
log(pat no_env/L)			0.0907***	0.139***
Fitted			(0.0265)	(0.0274)
log(pat env priv/L)			0.164***	0.108***
fitted			(0.0278)	(0.0298)
log(pat env pub/L)			-0.122***	-0.101***
fitted			(0.0172)	(0.0177)
log(pat env priv/L)				-0.0136**
x Polluter				(0.00633)
log(pat env pub/L)				-0.00621
x Polluter				(0.00582)
R squared			0.320	0.322
Chi squared	454.3	464.8	6444.0	6555.0
Alpha	28.24	32.56		
Log likelihood	-1645.0	-1395.6	-25416.5	-25376.2
N	47990	47990	47990	47990

Bootstraped standard errors (500 repetitions) in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01