Paper to be presented at the

35th DRUID Celebration Conference 2013, Barcelona, Spain, June 17-19

Drivers and Effects of Eco-innovations Using Data on Eco-patents

Giovanni Marin
CNR
CERIS
g.marin@ceris.cnr.it

Francesca Lotti
Bank of Italy
Structural Studies Department
francesca.lotti@bancaditalia.it

Abstract

We investigate drivers and productivity effect 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. Results show a substantial bias of polluting firms toward eco-innovations relative to other firms. 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 which substantially affect their innovation strategies and their performance.

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Abstract

We investigate drivers and productivity effect of eco-innovations at the firm level using a modified version of the CDM model (Crépon 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. Results show a substantial bias of polluting firms toward eco-innovations relative to other firms. 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 which substantially affect their innovation strategies and their performance.

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

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., 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 products. 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, innovation and productivity at the firm level, based on the well known model developed by Crépon et al. (1998), assessing both the drivers of environmental innovations and their effect on firm-level productivity. The modeling framework is borrowed from the Crépon et al. model (CDM hereinafter), modified to account for eco-innovation patterns: the element of novelty of our approach consists in assessing the drivers of environmental innovations and their effect on firm-level productivity, distinguishing between eco- and 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 they may hamper firms' productivity.

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-innovations, we match those firms with the EPO and PCT-WIPO patent applications database.

We find that eco-innovations tend to be less R&D intensive than other innovations while polluting firms are substantially biased towards eco-innovations relative to other firms. When considering the effect of innovation output on productivity, we observe a strong and positive effect of patent intensity and likelihood 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 briefly discusses the definition of eco-innovation and the extent to which patent data are a useful source of information. Section 4 focuses on the description of the empirical model and of the data; Section 5 discusses the results, while Section 6 concludes.

2 Are eco-innovation special?

2.1 Drivers of eco-innovation

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 and even scarcer comprehensive analysis of both drivers and effects. Due to data availability, most of the empirical works are based on German firms: Rennings and Ziegler (2004) using a firm level database developed at the ZEW find a significant positive effect of environmental organizational measures (EMAS and ISO 14001), market opportunities and R&D intensity on process and product environmental innovations. Wagner (2007) uses both data on environmental patent applications and self-reported measures of eco-innovation to investigate the effect of environmental management on environmental innovations. Results for German firms show positive effect of environmental management systems (EMS) adoption on self-reported process environmental innovations and a negative effect on firms' general patenting activity. Using a discrete choice model for German manufacturing firms, Horbach (2008) finds a strong, positive effects of technology push, demand pull and environmental policy (either mandatory or voluntary through environmental management tools) factors on environmental innovations. Horbach et al. (2012) is the first relevant study investigating the determinants of different fields of environmental innovations. Their analysis, based on the German Community Innovation Survey (CIS) for 2009, shows that the introduction of innovations aimed at reducing by-products of production activities - such as the release of air, water and noise emissions - are strongly related to government regulations (current and expected). On the other hand, innovations aimed at reducing material and energy use are driven by cost-savings and resource and energy taxes due to the direct appropriability of the returns from innovation through reductions in production costs. Rave et al. (2011) look at German firms and their patenting behavior: the results highlight the relevance of a clear and strict environmental regulatory framework, of possible cost savings due to environmental innovations and of the possibility of creating new markets. Results from a survey conducted by Cainelli et al. (2011) show that different types of environmental innovations introduced and adopted by manufacturing firms located in the Emilia-Romagna region in Italy are very strongly correlated to foreign ownership, export propensity and networking abilities. Finally, Kesidou and Demirel (2012) go beyond dichotomous indicators of environmental innovations and investigate the drivers of environmental R&D level for British industrial firms. By applying a Heckman sample selection model and quantile regression they find that while demand-side drivers have an effect on the extensive margin (probability of performing environmental R&D) only, other factors, such as the stringency of environmental regulation, cost savings and firms' organizational capabilities, have an effect both on the extensive and the intensive (level of environmental R&D) margins.

2.2 Eco-innovation and firm's performance

While environmental innovations are expected to have, by definition, a beneficial effect on the environment, their effect on firms' performance productivity is less straightforward. The conventional wisdom suggests that any policy aimed at limiting environmental by-products of firms will result in a reduction in observed productivity that could, in principle, be kept down by environmental innovations. However, since these productivity losses cannot be fully recovered, optimizing firms might divert resources devoted to generate or adopt environmental innovations to other more profitable research projects with higher expected returns (crowding out). In this respect, Popp and Newell (2009) find significant crowding out of energy R&D expenditures on general R&D in those US industries characterized by more than 5 percent of energy R&D. However, when they consider energy patents at the firm level, evidence is more mixed, with relevant, but statistically non significant, crowding out effect.

An alternative view, claimed by Porter and van der Linde (1995)[1], allows for the possibility of "win-win" outcomes. They argue that if one country adopts stricter environmental regulations than its competitors, the resulting increase in innovation will enable that country to become a net exporter of the newly developed environmental technologies, with long run positive effects on competitiveness and, eventually, on productivity. In other words, properly designed regulation may induce innovation that more than compensate for the cost of compliance. This view of the relationship between environmental regulation and economic performance is known as the "Porter hypothesis" (strong version). Instead, a "weaker" version of Porter hypothesis states that environmental regulation will stimulate certain kinds of environmental innovations, although there is no guarantee that the direction or rate of this increased innovation is socially beneficial (Jaffe and Palmer, 1997). Despite the stress on the role of (eco-) innovation in the discussion on the "Porter Hypotesis", most of the empirical analysis directly estimate the relationship between environmental regulatory stringency (or actual environmental performance) on firm's financial or productivity performance [2] with no room for the "innovation" channel. Moreover, the empirical evidence of the relationship between environmental regulatory stringency and firm's performance is mixed with no clear prevalence of either a support or a rejection of the "Porter Hypothesis".

Marin (2012), using a large panel of Italian firms, finds that innovation efforts of polluting firms and sectors is significantly biased towards environmental innovations and that eco-innovations tend to crowd out other more profitable innovations, at least in the short run. However, the analysis does not consider explicitly the role of environmental regulatory stringency on eco-innovation and productivity performance. Lanoie et al. (2011) specifically accounts for environmental R&D driven by environmental regulation: they estimate the effect on firms profitability of both the stringency of environmental regulation

[1]For a recent discussion and review of the relevant literature on the "Porter Hypotesis" refer to Ambec et al. (2011).

[2]See Horváthová (2012) for a review of the empirical literature on the subject.

(compliance cost - direct effect) and the part of environmental R&D driven by environmental regulation (offset of compliance costs, as posited by the "Porter Hypothesis" - indirect effect). They find a positive effect of environmental R&D on profitability. However, this positive effect is more than offset by the cost of compliance. Finally, Rexhauser and Rammer (2011) consider explicitly the role of regulation-induced innovation. Using the German CIS 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.

3 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. On the one hand, survey are better able to describe qualitatively the whole spectrum of eco-innovation strategies of innovative firms. On the other, the broad definition of eco-innovation is likely to result in ambiguous questions in the questionnaires which are prone to misleading interpretations by surveyed people.

As a consequence, patent data could represent an objective and viable alternative to measure eco-innovation (Oltra et al., 2010). Patents contain rich information about the technological field of the underlying innovation, through the reported 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 and they cover long time spans (Oltra et al., 2010).

Nevertheless, the use of patent data as a measure of innovation[3] and in particular as a proxy for environmental innovation output within the definition elaborated by Kemp and Pearson (2007) 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 patented[4] or because firms prefer to use alternative means to protect their innovations (secrecy, lead time, etc.). Moreover, the propensity to use patents as a mean of protecting innovations varies substantially across sectors and across technologies. In general, process innovations, which are very relevant when considering environmental innovations, are under-represented as opposed to product innovations within the patent universe. Also, patent data consider only those innovations which are "new to the market" while they ignore those innovations which are just "new to the firm" because of the novelty requirement for patented innovations.

Information on the ownership and actual use of patented innovations is generally lost after the patent has been granted. 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 (embodied or disembodied) knowledge to other firms which are the true adopters. In fact, a recent paper by Calel and Dechezlepretre (2012), dealing with the assessment of the effect on climate-related patenting of the European Emission Trading Scheme for EU firms, briefly discusses the issue of the possible separation between adoption and creation of climate-related innovations. They argue that "*economic theory predicts that environmental regulations would produce greater incentive to develop new technologies for directly regulated firms than for third-party technology suppliers*" because "*the latter are not discharging emissions themselves and receive no private benefit from the new technology*" (Calel and Dechezlepretre, 2012).

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). Last, but not least, patenting firms represent a very small fraction of innovative firms, leading to possibly low robustness of the results and to econometric problems when dealing with excess zeros of patent count indicators.

Nevertheless, due to their availability and the objective definition, many recent analysis on environmental innovations are based on patent statistics (Lan-

[3]See Griliches (1990).

[4]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).

jouw and Mody, 1996; Popp, 2002; 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" (www.oecd.org/environment/innovation), 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 classification, eco-innovations have been identified and classified according to their technological class.[5] 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 some 200 topics that are directly relevant to environmentally sound technologies, and each topic is linked with the most relevant IPC symbols, chosen by experts from around the world. 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 The modified "CDM framework"

The so-called "CDM framework" 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. The framework thus 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,

[5]Air, Water, and Waste Related Technologies; Electric & Hybrid Motor Vehicle Technologies; Energy-Efficiency in Buildings and Lighting; Renewable Energy Generation Technologies.

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 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 $\varepsilon_i$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 level of investment, and z_i is a set of determinants of the expenditure intensity. We measure expenditure intensity as the logarithm of 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:

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

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, as in Marin (2012) we use the number of European Patent Office (EPO) and PCT-WIPO patent applications as a measure of innovation output. In this second step, we estimate a knowledge production function with the number of patent applications as dependent variable. 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 applications, but classified according two broad categories: eco-patents, as defined in Section 2, and non eco-patents (throughout the paper we will refer to this second category just as patents).

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

where RD_i^* is the latent R&D effort, which is proxied by the predicted value of R&D 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 Σ. 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:

$$y_i = \pi_1 k_i + \pi_2 l_i + INNO_i^* \pi_3 + m_i \pi_4 + \nu_i \tag{5}$$

where y_i is the labor productivity (sales per employee, in logs), k is the log of capital stock[6] per worker, l is the log of employment (headcounts), $INNO^*$ is the predicted probability (or the predicted number) of innovation from the second step, and the m are the controls.

4.4 Data

We use firm-level data from the 7^{th}, 8^{th}, 9^{th}, and 10^{th} 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.[7] We obtained balance sheet information from the Company Accounts Data Service (CADS) database at the Bank of Italy and we built an unbalanced panel of 47,928 observations on 11,929 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

[6] Capital stock has been computed by means of the perpetual inventory method.

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

105 employees, but with a median of 33 only. In our sample, only 29% invest in R&D, with an average of 3,770 euros per employee, but only 6.3% have filed at least one patent application and even less (around 0.8%) have filed an eco-patent. Interestingly, on average, patenting firms have 3.2 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.

Figures 2 and 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, sectoral 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 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 tan 500 employees) have lower propensity to perform R&D (about 48 percent).

Finally, 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). Moreover, the share of patenting firms also performing and reporting formal R&D tends to be higher for medium-high technology sectors[8] than for medium-low technology sectors, reflecting heterogeneity in the complexity of technologies across sectors.

5 Results

All of the equations in the model are projected on a list of "exogenous" variables that include a quadratic in the log of firm size, a quadratic in the log of firm age, year dummies, survey wave dummies, industry dummies (13 industries), and regional dummies (4 regions)[9]. The survey wave dummies are a set of indicators for the firm's presence or absence in the four waves of the survey.[10] 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. 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 does not have any effect of R&D intensity. This assumption is verified by comparing the 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 5). Exporting firms are substantially more likely to perform formal R&D than non-exporting firms, with the difference (0.1972) being significantly different from zero. However, conditional on performing R&D, no statistically significant difference is found between exporting and non-exporting firms.

[8]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 fibres.

[9]Table 2 reports the distribution of observations by industry and by region together with the list and definition of industries and regions.

[10]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).

The results confirm the presence of selection, with a significant correlation coefficient of 0.23. 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), R&D intensity has a U-shaped relationship with size, falls with size, reaching its minimum at about 390 employees[11] and then rising again. It also falls with age, but this is barely significant. Firms facing international competitors have much higher R&D intensities (by 22%), as do firms that are members of a group or who receive subsidies of some kind. As 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. The innovation outcome is estimated for three classes of patents: all patent applications, non eco-patents and eco-patents (in the tables *No_env* and *Env*, respectively). As patents are typically a count measure, the equation is estimated with a Negative Binomial regression as in Hausman et al. (1984), the NB2 version with the variance of the disturbance expressed as a quadratic function of the conditional mean.[12] Table 6 reports the estimated coefficients which can be interpreted as semi-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 value of R&D intensity affects positively any kind of innovation output, the effect being slightly stronger (in magnitude and statistical power) for non eco-innovations. Firm size is positively and linearly (as the quadratic term is not significant) related

[11]The log of employee count has been centred at zero at the sample mean.

[12]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.

to patent counts for all classes of patent. However, the semi-elasticity is smaller than unity, meaning that larger firms have on average a relatively lower patent intensity (per employee) than smaller firms. While age does not seem to have an effect on firms' patenting activity, international competition seems to be positively correlated with the number of patents, even though the levels of significance are below any acceptable level, while having local competitors negatively and significantly correlates to patenting activity. Interestingly, those firms whose competitors are mainly small firms, have a clear dis-incentive to apply for eco-patents, maybe because they do not fear their competition or simply because they seek intellectual property protection in alternative ways.

Regional patent stock per capita (reg_pat_stock_pc), a proxy for the stock of knowledge locally available, seems not having, on average, any effect on patenting activity. Being involved in a "market for technology" (Arora et al., 2001), i.e. having bought or sold a patent in the past, is a strong predictor of patenting activity for all classes of patent applications. Human capital turns out to have no direct effect on innovative output (for either type of patent applications), once its effect on R&D intensity is taken into account. Polluting firms[13] are expected to show a significant and 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 not significant at this stage.

In addition to estimates using patent count as dependent variable, we estimate the same specification as in Table 6 but with the dependent variable being the likelihood of having at least one patent, reflecting how the drivers of innovation output affect the extensive margin. Table 7 reports the results: the first column shows the results of probit estimate, while the others a bivariate probit. Results from Table 6 are largely confirmed. R&D intensity, firm size and the involvement in them market for technologies positively affect the likelihood of applying for any of the classes of patent applications. Having international competitors has now a positive and significant effect on patent propensity even though this effect is not significant for eco-patents. Finally, being a pollut-

[13]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 starting from the year 2007 onwards. Differently from the EPER, the E-PRTR includes waste-intensive plants.

ing firm positively and significantly affects the propensity to file environmental patents.

5.3 Productivity analysis

Following the structure of the CDM model, we use the predicted number of patents coming from the second step as an explanatory variable in the productivity equation. Productivity is measured as real value added per employee (Tables 8 and 10) or turnover per employee (Tables 9 and 11). Looking at Table 8, one can see that innovation success has a generally positive impact on productivity (column (a)). 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.

When one comes to the partition on eco- and non eco-patents (columns (b) and (c)) there is evidence of a lower (although non statistically different) return in terms of productivity from eco-innovations relative to other innovations. The differential effect for polluting firms is negative but not statistically different from zero.

These results are reversed when considering turnover instead of value added as measure of firms' productivity. Results reported in Table 9 show a higher return of eco-innovations relative to other innovations when productivity is measured in terms of turnover per employee. Moreover, no statistically significant differential effect for polluting firms is found. This result should be interpreted in the light of the difference between turnover and value added as measures of productivity. Basically, value added is given by the difference between turnover and the cost of material inputs (i.e. intermediate inputs, materials, energy), meaning that eco-innovations have the effect of increasing the difference between turnover and value added more than other innovations, either by means of a greater increase in revenues or, more likely, by means of a greater reduction of material inputs.

When considering the probability of patenting instead of the expected intensity of patent applications (Tables 10 and 11) we find a strong positive effect of the likelihood of applying for a patent on productivity. Applying for a patent increases productivity by about 70 percent when considering value added per employee and by about 110 percent when considering turnover per employee. This time, environmental innovations are characterized by an expected lower return relative to other innovations for both measures of productivity (value added and turnover), with the effect being generally statistically insignificant. Another evident difference with respect to our baseline results (Table 8) regards the differential effect of eco-innovations for polluting firms. Now, the differential effect is such that an increase in the likelihood of filing for eco-patent for polluting firms has a negative and significant effect on productivity. This result, combined with the positive effect on productivity of the intensity of eco-patents, implies that the returns from eco-innovations for polluting firms are positive only if the polluting firm is able to become the technological leader for environmental technologies.

In accordance with the literature reviewed in the first part of the paper, 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-innovation are likely do 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 determinants and 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. Focusing on environmental innovations, there is evidence of a systematic difference in the effect of usual drivers of innovation output relative to other innovations and a significant bias for environmental innovations for polluting firms. Moreover, 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 the extensive margin. 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 innovations. 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) will 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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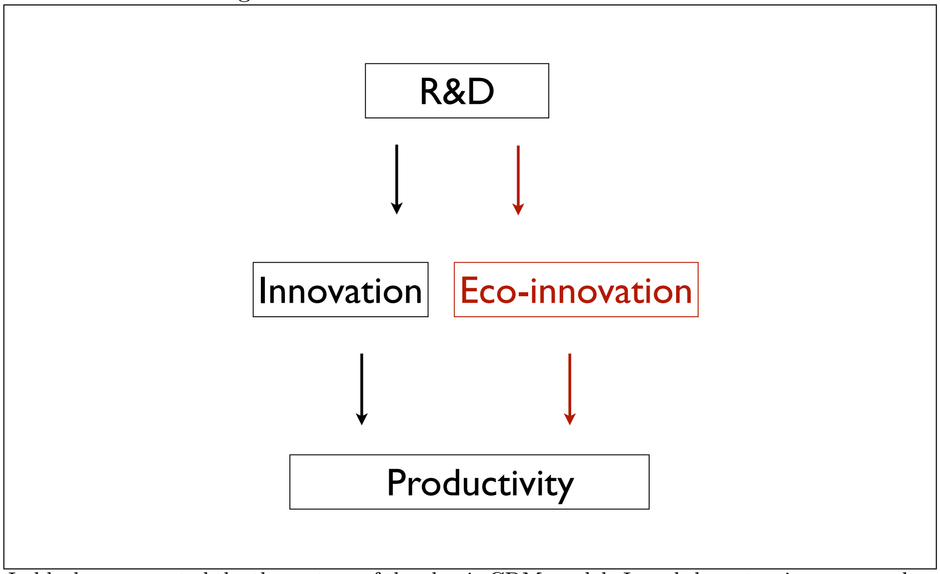
Figure 1: Basic and modified CDM model.



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

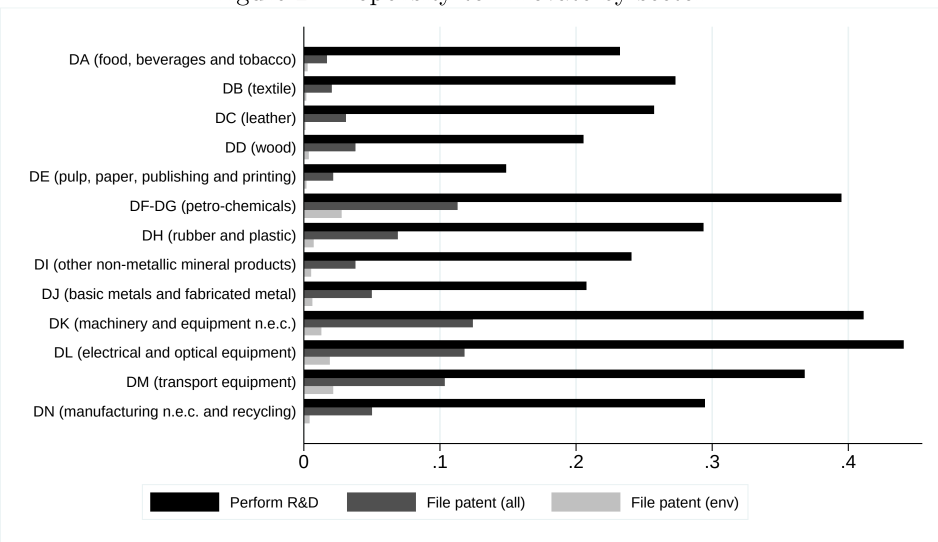


Figure 3: Propensity to innovate by firm size (# employees)

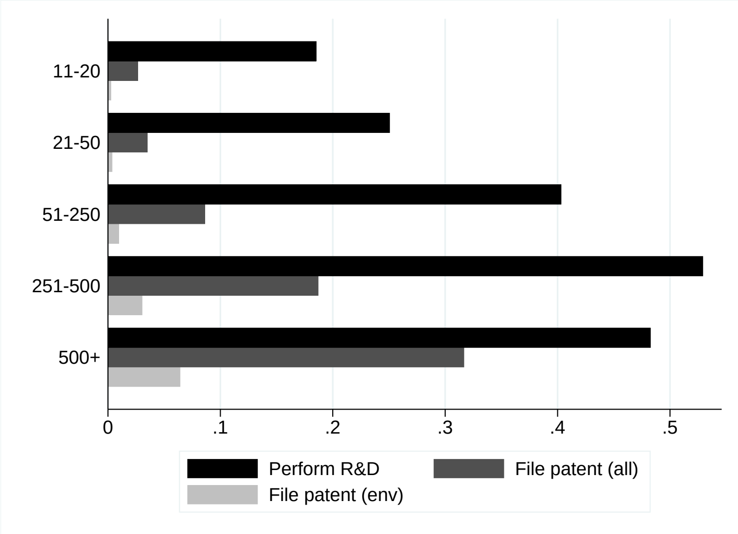


Table 1: Descriptive statistics

Period: 1995-2006			
Number of observations (firms)	47,928 (11,929)	Firms with national competitors	62%
Number of employees (mean/median)	105.5 (33)	Firms with international competitors	27.2%
Age (mean/median)	24.9 (21)	Exporting firms	69.3%
Firms with R&D	29.2%	Firms within a group	23.5%
Share of white-collar workers in employees (mean/median)	33.9% (29.3%)	Firms subsidies recipients	37.7%
R&D intensity[a] for R&D doers (mean/median)	3.77 (1.62)	Observations with patents	6.3%
Average capital intensity[a] (mean/median)	76.6 (51.6)	Observations with eco-patents	0.83%
Labor productivity[a] (VA - mean/median)	48.2 (42.3)	Observations with both eco- and non-eco- patents	0.47%
Labor productivity[a] (revenues - mean/median)	206.7 (155.2)	Count of patents (for firms with patents - mean/median)	3.2 (1)
Firms with large firms as competitors	37.8%	Count of eco-patents (for firms with eco-patents - mean/median)	1.84 (1)
Firms with regional competitors	59.2%	Observations with polluting plants (firms)	4.53% (4.02%)

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

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

	North-West	North-East	Central Italy	Southern Italy	Total
DA	1,070	1,188	536	1,433	4,227
DB	2,258	974	1,551	660	5,443
DC	153	511	975	278	1,917
DD	397	582	280	173	1,432
DE	1,200	707	735	254	2,896
DF-DG	1,268	507	411	385	2,571
DH	1,279	691	342	373	2,685
DI	797	963	660	652	3,072
DJ	3,803	2,376	1,009	1,006	8,194
DK	3,276	2,854	753	349	7,232
DL	1,916	1,229	473	343	3,961
DM	615	325	187	227	1,354
DN	703	1,240	709	292	2,944
Total	18,735	14,147	8,621	6,425	47,928

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 fibres. 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	29%	21%	40%	40%	40%	31%
DB	20%	37%	50%	64%	60%	44%
DC	44%	38%	39%	90%	0%	47%
DD	7%	30%	50%	100%	50%	31%
DE	18%	11%	46%	50%	33%	27%
DF-DG	27%	63%	52%	73%	43%	53%
DH	15%	45%	69%	67%	56%	54%
DI	11%	40%	55%	65%	48%	45%
DJ	9%	34%	51%	51%	57%	41%
DK	37%	36%	70%	69%	57%	58%
DL	34%	49%	63%	88%	69%	63%
DM	10%	55%	42%	46%	79%	56%
DN	19%	45%	54%	45%	67%	47%
Total	23%	40%	60%	68%	59%	52%

Table 4: R&D equation

Dep: log(R&D/L)	OLS	Heckman Selection	Heckman Intensity
log(L)	-0.267***	0.288***	-0.205***
	(0.0272)	(0.0167)	(0.0366)
$\log^2$(L)	0.0595***	-0.0572***	0.0466***
	(0.0112)	(0.00637)	(0.0124)
Competitors (local)	-0.108***	-0.0417*	-0.118***
	(0.0350)	(0.0231)	(0.0355)
Competitors (national)	-0.130***	0.0625***	-0.115***
	(0.0362)	(0.0227)	(0.0368)
Competitor (foreign)	0.166***	0.275***	0.226***
	(0.0357)	(0.0244)	(0.0418)
Share white collar	1.200***	0.628***	1.320***
	(0.0940)	(0.0541)	(0.103)
Firms is part of a group	0.164***	0.0647**	0.174***
	(0.0413)	(0.0281)	(0.0414)
log(age)	-0.0381	0.00962	-0.0361
	(0.0245)	(0.0158)	(0.0246)
$\log^2$(age)	-0.0177	-0.00331	-0.0179
	(0.0176)	(0.0118)	(0.0176)
Firm receives subsidies	0.264***	0.318***	0.325***
	(0.0352)	(0.0225)	(0.0419)
Firm exports		0.308***	
		(0.0275)	
Constant	-0.433***	-1.295***	-0.882***
	(0.133)	(0.0845)	(0.209)
ρ		0.233***	
λ		0.286***	
σ		1.226***	
F	22.56***		
χ^2		1163***	
log likelihood		-47647.6	
Sector d. (F or χ^2)	10.19***	257.2***	119.04***
Region d. (F or χ^2)	8.285***	63.56***	31.01***
Year d. (F or χ^2)	20.73***	228***	231.6***
Wave d. (F or χ^2)	1.354	52.07***	21.18*
N	14008	47928	

Standard errors clustered by firm in parentheses
* p< 0.1, ** p< 0.05, *** p< 0.01

Table 5: Exclusion restriction: firm exports

	Exp=1	Exp=0	Diff.	N	t-stat	p-value
Perform R&D	0.3528	0.1556	.1972	47928	44.68	0.000
ln(R&D/L)	0.4568	0.4560	0.0008	14008	0.03	0.977

Table 6: Knowledge production function (negative binomial on application count)

Dep: patent count	All patents	No_env	Env
$\log(\widehat{R\&D}/L)$	0.896***	0.949***	0.758*
	(0.217)	(0.228)	(0.425)
log(L)	0.746***	0.759***	0.698***
	(0.0644)	(0.0657)	(0.137)
$\log^2$(L)	0.0305	0.0277	0.000721
	(0.0212)	(0.0219)	(0.0337)
log(reg_pat_stock_pc)	0.106	0.151	-0.235
	(0.132)	(0.134)	(0.231)
Share white collars	-0.418	-0.536	0.194
	(0.345)	(0.364)	(0.679)
Firm sold or bought patents	0.968***	0.972***	0.679**
	(0.145)	(0.148)	(0.277)
Competitors (local)	-0.163**	-0.163**	-0.146
	(0.0829)	(0.0812)	(0.168)
Competitors (national)	0.0220	-0.000227	0.178
	(0.0691)	(0.0697)	(0.176)
Competitor (foreign)	0.0995	0.0923	0.0859
	(0.0835)	(0.0842)	(0.232)
Competitors (small)	-0.138	-0.117	-0.473***
	(0.0846)	(0.0871)	(0.182)
Competitors (medium)	0.0154	0.0104	0.145
	(0.0840)	(0.0838)	(0.177)
Competitors (big)	0.0397	0.0355	-0.000759
	(0.0868)	(0.0818)	(0.203)
log(age)	-0.0223	-0.000170	-0.0711
	(0.0554)	(0.0557)	(0.112)
$\log^2$(age)	0.0158	0.0199	0.00114
	(0.0323)	(0.0328)	(0.0932)
Polluting plants			0.334
			(0.264)
Constant	-2.542**	-2.137*	-8.470***
	(1.244)	(1.237)	(2.329)
α	8.628***	8.793***	20.45***
Pseudo R squared	0.133	0.135	0.151
χ^2	3302.1***	2953.4***	1207.5***
log likelihood	-14343.3	-13595.1	-2350.6
Sector d. (χ^2)	159.3***	170.5***	22.09**
Region d. (χ^2)	1.108	1.093	1.224
Year d. (χ^2)	24.44**	28.17***	13.21
Wave d. (χ^2)	44.75***	46.60***	16.09
N	47928	47928	47928

Bootstrap standard errors (100 repetitions)
* p< 0.1, ** p< 0.05, *** p< 0.01

Table 7: Knowledge production function (probit and bivariate probit on the probability of filing a patent application)

	Probit	Multivariate probit	
Dep: patent count	All patents	No_env	Env
$\log(\widehat{R\&D}/L)$	0.447***	0.454***	0.262**
	(0.0797)	(0.0828)	(0.122)
log(L)	0.354***	0.356***	0.229***
	(0.0222)	(0.0231)	(0.0419)
$\log^2$(L)	-0.00126	-0.00226	0.0118
	(0.00813)	(0.00846)	(0.0118)
log(reg_pat_stock_pc)	0.0415	0.0526	-0.0550
	(0.0488)	(0.0494)	(0.0790)
Share white collars	-0.259**	-0.296**	0.0649
	(0.125)	(0.131)	(0.188)
Firm sold or bought patents	0.438***	0.438***	0.209**
	(0.0769)	(0.0762)	(0.0963)
Competitors (local)	-0.0724**	-0.0642**	-0.103*
	(0.0313)	(0.0305)	(0.0567)
Competitors (national)	-0.0208	-0.0294	0.00338
	(0.0296)	(0.0296)	(0.0573)
Competitor (foreign)	0.0771**	0.0758**	0.0804
	(0.0336)	(0.0336)	(0.0627)
Competitors (small)	-0.0282	-0.0174	-0.149**
	(0.0297)	(0.0306)	(0.0630)
Competitors (medium)	0.0180	0.0201	0.0454
	(0.0315)	(0.0307)	(0.0600)
Competitors (big)	0.0228	0.0238	-0.0290
	(0.0311)	(0.0303)	(0.0583)
log(age)	-0.0188	-0.0105	-0.0425
	(0.0210)	(0.0211)	(0.0388)
$\log^2$(age)	0.0109	0.0117	-0.0109
	(0.0141)	(0.0143)	(0.0308)
Polluting plants			0.158*
			(0.0873)
Constant	-1.648***	-1.579***	-3.481***
	(0.455)	(0.464)	(0.761)
ρ		0.477	
χ^2	3250.7***		
log likelihood	-9229.6	-10544.0	
Sector d. (χ^2)	180.0***	185.2***	
Region d. (χ^2)	2.677	2.557	
Year d. (χ^2)	50.34***	41.86***	
Wave d. (χ^2)	35.31***	37.73***	
N	47928	47928	

Bootstrap standard errors (100 repetitions)
* p< 0.1, ** p< 0.05, *** p< 0.01

Table 8: Productivity equation (VA/L, predicted application count)

Dep: log(VA/L)	(a)	(b)	(c)
log(K/L)	0.241***	0.240***	0.239***
	(0.00493)	(0.00495)	(0.00496)
$\log(\widehat{\text{all\_patent}}/L)$	0.157***		
	(0.00852)		
$\log(\widehat{\text{no\_env}}/L)$		0.0777***	0.0881***
		(0.0163)	(0.0161)
$\log(\widehat{\text{env}}/L)$		0.0738***	0.0645***
		(0.0129)	(0.0128)
$\log(\widehat{\text{env}}/L) \times$ Polluting_plants			-0.0186
			(0.0136)
Polluting_plants			-0.0422
			(0.0754)
log(L)	0.00853	0.00711	0.00517
	(0.00611)	(0.00607)	(0.00616)
$\log^2$(L)	0.00419*	0.00740***	0.00604**
	(0.00228)	(0.00232)	(0.00236)
log(age)	0.00985*	0.0110**	0.0104**
	(0.00507)	(0.00493)	(0.00495)
$\log^2$(age)	0.000854	0.00133	0.00101
	(0.00417)	(0.00413)	(0.00412)
Constant	3.456***	3.634***	3.616***
	(0.0511)	(0.0595)	(0.0595)
R squared	0.328	0.329	0.330
χ^2	14971.0	16409.5	16508.4
Sector d. (χ^2)	528.8***	374.7***	377.4***
Region d. (χ^2)	194.7***	221.6***	211.3***
Year d. (χ^2)	1077.1***	1025.5***	1010.1***
Wave d. (χ^2)	345.0***	369.6***	358.7***
N	47928	47928	47928

Bootstrap standard errors (100 repetitions)
* $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$

Table 9: Productivity equation (Y/L, predicted application count)

Dep: log(Y/L)	(a)	(b)	(c)
log(K/L)	0.269***	0.267***	0.266***
	(0.00595)	(0.00596)	(0.00594)
$\log(\widehat{\text{all\_patent}/L})$	0.269***		
	(0.0142)		
$\log(\widehat{\text{no\_env}/L})$		0.0501**	0.0572**
		(0.0226)	(0.0228)
$\log(\widehat{\text{env}}/L)$		0.202***	0.196***
		(0.0168)	(0.0178)
$\log(\widehat{\text{env}}/L) \times$ Polluting_plants			-0.00683
			(0.0228)
Polluting_plants			0.00414
			(0.129)
log(L)	-0.0556***	-0.0592***	-0.0606***
	(0.00820)	(0.00818)	(0.00821)
$\log^2$(L)	0.0280***	0.0369***	0.0360***
	(0.00360)	(0.00362)	(0.00364)
log(age)	-0.0522***	-0.0461***	-0.0465***
	(0.00782)	(0.00762)	(0.00765)
$\log^2$(age)	-0.00215	-0.000416	-0.000623
	(0.00507)	(0.00510)	(0.00511)
Constant	5.479***	5.949***	5.935***
	(0.0742)	(0.0858)	(0.0866)
R squared	0.321	0.326	0.326
χ^2	14353.8***	16149.3***	16192.8***
Sector d. (χ^2)	916.1***	952.4***	964.4***
Region d. (χ^2)	37.77***	119.4***	112.4***
Year d. (χ^2)	688.9***	909.8***	845.3***
Wave d. (χ^2)	893.9***	1044.5***	1035.5***
N	47926	47926	47926

Bootstrap standard errors (100 repetitions)
* p< 0.1, ** p< 0.05, *** p< 0.01

Table 10: Productivity equation (VA/L, predicted probability of filing for a patent application)

Dep: log(VA/L)	(a)	(b)	(c)
log(K/L)	0.245***	0.245***	0.243***
	(0.00486)	(0.00486)	(0.00488)
$\widehat{\text{pr\_all\_patents}}$	0.692***		
	(0.0980)		
$\widehat{\text{pr\_no\_env}}$		0.772***	0.755***
		(0.118)	(0.125)
$\widehat{\text{pr\_env}}$		0.374	0.770*
		(0.321)	(0.454)
$\widehat{\text{pr\_env}} \times$ polluting_plants			-1.013**
			(0.464)
Polluting_plants			0.112***
			(0.0213)
log(L)	-0.0677***	-0.0691***	-0.0732***
	(0.00583)	(0.00589)	(0.00603)
$\log^2$(L)	0.00566*	0.00626**	0.00555*
	(0.00289)	(0.00304)	(0.00305)
log(age)	0.00354	0.00301	0.00332
	(0.00508)	(0.00510)	(0.00507)
$\log^2$(age)	0.00117	0.00103	0.000687
	(0.00421)	(0.00423)	(0.00420)
Constant	2.806***	2.804***	2.809***
	(0.0295)	(0.0299)	(0.0299)
R squared	0.319	0.319	0.321
χ^2	13977.1***	13923.4***	14449.9***
Sector d. (χ^2)	402.0***	399.9***	383.1***
Region d. (χ^2)	423.3***	428.3***	418.6***
Year d. (χ^2)	849.0***	858.0***	819.3***
Wave d. (χ^2)	268.5***	273.5***	271.0***
N	47928	47928	47928

Bootstrap standard errors (100 repetitions)
* p< 0.1, ** p< 0.05, *** p< 0.01

Table 11: Productivity equation (Y/L, predicted probability of filing for a patent application)

Dep: log(Y/L)	(a)	(b)	(c)
log(K/L)	0.277***	0.277***	0.274***
	(0.00599)	(0.00599)	(0.00598)
$\widehat{\text{pr\_all\_patents}}$	1.120***		
	(0.135)		
$\widehat{\text{pr\_no\_env}}$		1.401***	1.447***
		(0.182)	(0.172)
$\widehat{\text{pr\_env}}$		-0.00657	0.0749
		(0.561)	(0.565)
$\widehat{\text{pr\_env}}$ × polluting_plants			-0.647
			(0.806)
Polluting_plants			0.136***
			(0.0304)
log(L)	-0.184***	-0.189***	-0.195***
	(0.00868)	(0.00899)	(0.00877)
$\log^2$(L)	0.0316***	0.0340***	0.0329***
	(0.00400)	(0.00415)	(0.00412)
log(age)	-0.0633***	-0.0645***	-0.0643***
	(0.00790)	(0.00788)	(0.00781)
$\log^2$(age)	-0.00159	-0.00230	-0.00285
	(0.00496)	(0.00497)	(0.00494)
Constant	4.365***	4.358***	4.363***
	(0.0404)	(0.0403)	(0.0400)
R squared	0.305	0.305	0.307
χ^2	14520.5***	14462.1***	14789.4***
Sector d. (χ^2)	616.4***	615.6***	623.1***
Region d. (χ^2)	187.7***	172.1***	169.5***
Year d. (χ^2)	335.8***	362.4***	363.9***
Wave d. (χ^2)	826.5***	829.0***	863.2***
N	47926	47926	47926

Bootstrap standard errors (100 repetitions)
* p< 0.1, ** p< 0.05, *** p< 0.01