An assessment of the relationships between R&D, eco-innovation and productivity: Evidence from French firms

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Abstract

Since the 1990s, environmental issues have become a major concern for policy makers. To tackle climate change, the development of new technologies compatible with sustainability issues must play a key role. A specific feature of environmental innovation is that, in addition to generating knowledge spillover, it also generates environmental spillover. Rennings (2000) called this specificity of eco-innovation "the double externality problem" and pointed out that this problem diminishes the incentives of firms to innovate. The purpose of this article is to explore both determinants and productivity effects of environmental innovation using an extended CDM model (Crépon, Duguet and Mairesse, 1998). First, we distinguish two types of R&D: environmental and non-environmental. Second, we introduce environmental regulation variables at the firm level as drivers of environmental innovation. Combining both of patents data extracted from REGPAT and HAN OECD databases with financial firm data collected from DIANE database and the firm research and development (R&D) survey, the empirical analysis is carried out for French firms over the period 2003–2015. Preliminary results show that private economic returns in terms of productivity are lower for environmental innovation than for non-environmental innovation. This validates the hypothesis according to which market incentives alone are not sufficient to allow the environmental innovation of firms to increase considerably. More efforts in terms of green promotion and environmental regulation are important for the flourishing of such innovations.

Keywords: Environmental innovation, Research and development, Patents, CDM model
JEL Classification: O30, Q55, L25

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1. Introduction

Because of the progressive degradation of the environment, policy makers insist on the importance of making changes in the use of resources, they are calling, more precisely, for a change in human interaction with the environment.

The innovations that can lead to energy transition are referred to as eco-innovations. As all innovations, eco-innovation creates knowledge spillover. Given that technological learning is a pubic good, firms encounter difficulties in appropriating their innovation. A specific feature of eco-innovation is that, in addition to generating knowledge spillover, it also generates environmental spillover. When firms adopt or develop innovations that allow for the reduction of environmental impact, they bear the costs while all of society benefits from it. Therefore, environmental innovation allows firms to avoid negative externality and to provide a positive one. Rennings (2000) has called this specificity of eco-innovation "the double externality problem", and explains how this problem diminishes the incentives of firms to innovate. This "double externality problem" is a market failure that reveals the importance of environmental regulation (ER).

The study of the impact of ER on firm's performance has attracted the attention of many researchers. For a long period, the negative effect of competitiveness has been the leading point of view for studies of ER. Indeed, when an additional constraint is imposed, firms are faced with increased cost. As a result, productive investments are discouraged due to the additional expenses incurred to reduce negative externality caused by pollution. This loss in competitiveness is followed by a decrease in exportation. In the long run, we may expect the delocalization of firms (in particular those that are more polluting) to countries where ER is less strict. This is known as the pollution haven hypothesis (Copeland and Taylor, 2004; Letchumanan and Kodama, 2000). However, over the past two decades, several authors have criticized this point of view by developing a new approach known as the Porter hypothesis. It states that a well-designed ER can stimulate innovation. It is precisely this innovation that will reduce partially or offset fully the compliance costs associated with the ER. A well-designed environmental policy leads to a win-win result: productivity gains and environmental protection (Porter, 1991; Porter and van der Linde 1995; Wagner, 2006).

In this paper, I study the relationship linking the innovation input (R&D) to the innovation output (patents) and the productivity effects of the innovation output. I make a comparison between environmental and non environmental innovation. The main contribution of this paper is that I propose an extended CDM model that includes two types of R&D: environmental and non environmental R&D for the case of French firms. I also incorporate environmental variables at the firm level as determinants of environmental innovation. My results show that Environmental innovations differ from non environmental innovations in their effect on firm's productivity, with a generally lower return than non environmental innovations.

I exploit patents data extracted from REGPAT and HAN OECD databases that I combine with financial firm data collected from DIANE database and firms R&D survey. I use patents count as a proxy for eco-innovation. Patents are essentially a measure of the output of eco-innovation. A patent is a legal document that provides for the exclusive rights of exploitation of an innovation. Generally these rights do not exceed a period of 20 years. Patents have many advantages: the availability of data for many countries over a period of many years, and the possibility of being classified into groups. They also provide detailed information about innovations. Nevertheless, this method proves limited in that: 1) patents measure invention rather than innovation; 2) there are inventions that are not patentable.

The paper is organized as follows: Section 2, provides a literature review. Section 3, outlines the data. Section 4 Shows the evolution of innovation in France over time. Section 5, introduces the model and the variables. Section 6, presents the results.

2. Literature review

The empirical literature has largely investigated the determinants of environmental innovation (Belin and al.,2011**;** Triguero and al.,2013; Brunnermeier and Cohen,2003; Horbach,2008; Horbach and al.,2012, Galliano and Nadel ,2013) and the importance of environmental regulation for stimulating eco-innovation (Kneller and Manderson, 2012, Johnstone and al.,2009, Brunnermeier and Cohen, 2003). There are fewer articles that have investigated the relationship between environmental innovation and firms' performance.

Most researchers that targeted the study of environmental innovation and firms' performance focused on macro-economic data and miso-economic data (country and industry level approaches) (De Santis and Lasinio, 2015, Soltmann and al.,2015; Yang and al., 2012; Rubashkina et al.,2015; Franco and Giovanni,2014) . Less attention has been devoted to the firm level approach.

Furthermore, the main existing empirical studies at micro-economic level are based on surveys. Doran and Ryan (2013) examine the drivers of eco-innovation and how does eco-innovation impact firm performance measured by turnover per worker. They used a simple of 2000 Irish firms extracted from the community innovation survey. They find that firms that introduce eco-innovation have higher levels of turnover per employee than firms that innovate in classical innovations and firms that do not engage in innovation activity.

Lanoie and al. (2011) analyze all the links in the causality chain from environmental regulatory stringency to eco-innovation and firm performance. The study is based on an OECD survey carried out in 2003 for a simple of 4200 facilities from 7 OECD countries. They argue that environmental regulation induces eco-innovation (environmental R&D). This latter has a positive effect on firm performance (binary variable), but it doesn't fully offset the costs of complaining with environmental regulation.

Ghisetti and Rennings (2014), using survey data for German firms, analyse the relationship between environmental regulation and firms' performance measured by returns on sales. They consider two types of eco-innovations: innovations aiming at reducing the
negative externalities (such as air, water, noise and soil pollution) and energy efficiency innovations. They point out that energy efficiency innovations impact positively the firms' performance while innovations allowing the reduction of negative externalities have a negative impact on firm performance.

Some exceptions can be found in some articles where authors have used administrative data. This data based on balance sheet and income statement, is reported in a transparent way, it is more reliable and gives more objective and standardized information (Marin 2014) .

Kruse (2016) studies the impact of green and non-green energy technologies on firm's economic performance measured by productivity. He carries out an analysis based on a panel of 8619 firms from 22 European countries over the period 2003-2010. He uses firms accounts data from Amadeus database and patent data from OEDE REGPAT and HAN databases. The study is based on a Cobb Douglas production function. He finds a negative effect of green energy innovations on firms' performance. This negative effect is more pronounced for larger firms, whereas, non-green-energy technologies have a positive effect on firms' performance. It is worth noting that the study is limited to green energy (renewable energy technologies and energy efficiency technologies) and doesn't include the other kinds of eco-innovation such as waste management and capture and storage of Green House Gases (GHG).

Marin (2014) analyses the drivers of environmental innovation and the effects of environmental innovations and non-environmental innovations on firms' performance measured by value added per employee. The study is based on a panel of 5905 Italian firms over the period 2000-2007. The main findings suggest a crowding out effect of green innovations on non-green innovations, in the short run. He compares the estimation results to a sub-sample of most polluting firms and find that the crowding out effect is more pronounced for these firms. Moreover, he shows that environmental innovations have no significant effect on firms' performance while non-environmental innovations have a positive effect.

A similar analysis was carried out by Marin and Lotti 2017. They extend the study to cover a larger sample of 11,938 Italian firms over the period 1995-2006. They conclude that both environmental and non-environmental innovations have a positive effect on firm performance measured by value added per employee. However, environmental innovations display a lower return comparing to non-environmental innovations. Furthermore, their results confirm the crowding out of environmental innovation relative to non-environmental innovation.

Colombelli, Krafft and Quatraro (2015), using a panel of 456240 firms from 5 European countries over the period 2002-2011, analyze the impact of eco-innovation on firms' growth focusing on gazelles (firms with high growth rates). They show that eco-innovation triggers firms' growth; firms that adopt eco-innovation have higher growth rates of sales than firms adopting classical innovation.

Ki-Hoon and Byung (2015), analyze the relationship between environmental innovation, measured by Green R&D and the environmental and financial performance of Japanese manufacturing firms over the period 2001-2010. The financial performance is measured by the market value of the firms using the Tobin's Q indicator. They find evidence that eco-innovation has a negative effect on environmental performance and a positive effect on firms' financial performance.

The studies described above differ considerably in the method, the geographical scope and the indicators used as proxies for the variables. The produced results are mixed and the relationship remains ambiguous.

In line with such empirical literature we analyze the effect of environmental innovation on firm performance using data on French firms. In contrast to Marin (2014), we consider that patenting activity differs from small and medium firms and large firms.

3. Data

Data comes from the Organisation for Economic Cooperation and Development (OECD) REGPAT database. This database is derived from the Worldwide Patent Statistical Database "PATSTA" maintained by the European Patent Office (EPO) (2017 Version).

A careful consideration should be given to the extraction of data. Indeed, some characteristics of patents may cause multiple counting when associating patents to a country, technology or company, for example several patents are a result of collaboration between more than one inventor or applicant. Similarly, patents can be protected in more than one country.

Many alternatives are available for patent counts according to the question we want to answer. In this study, I used simple patent counts as a proxy for innovation. The patent count is conducted using specific selection criteria. I take into consideration only the patents filled in the EPO[2] by the companies located in France. I choose applicant count rather than inventor count because environmental innovation is specific for each country and depends on the country where the firm is located. Inventor's country reflects the country of origin of inventions while the applicant country reflects the ownership of inventions and gives an idea concerning the innovative performance of firms in a given country. I use the application filling year[3] as year of reference, I suppose that it's the closest date to the invention. I take into consideration the firms that granted at least one patent in the study period. Data was extracted for classical innovations and environmental innovations.

In PATSTAT, patents are assigned to technological fields using two types of classification: the International Patent Classification (IPC) and the Cooperative Patent Classification (CPC). Until now, most of the studies are based on IPC code (Marin 2014, Kruse 2016). When using this method one should look for green patents in different classes (several authors have explained how to combine these codes to select the patents belonging to a specific technological field). This data retrieval method leads to two risks: selecting irrelevant patent applications and excluding relevant patent applications. Since 2015, the EPO has completed the CPC classification which includes a classification section called the Y section dedicated to applications related to green technologies (see table 1). A searching strategy based on CPC is

[2] It is a regional office including 38 European members in 2017. Applicants submit a patent application to this office when they want to protect their inventions in several European countries. This procedure is used when the applications are expected of high value and commercially profitable.

[3] Several dates are attributed to a patent. The filing year is the year of the application filling date. It refers to the date when an application is filled in a specific patent office.

an easier and more reliable way to select green patents (for more details see Veefkind et al. (2012)). In our study, patents are attributed to technological fields according to CPC codes. We consider the main CPC codes and all their sub-classes. It is worth mentioning that a patent can be attributed to more than one CPC code and some patents don't have a CPC code.

Table 1: CPC classification of environmental technologies

Technology	**CPC code**
Climate Change Mitigation Technologies (CCMT) related to buildings	Y02B
greenhouse gases (GHG) capture and storage	Y02C
CCMT related to energy generation, transmission or distribution	Y02E
CCMT in the production or processing of goods	Y02P
CCMT related to transportation	Y02T
CCMT related to wastewater treatment or waste management	Y02W
Smart grids	Y04S
Technical subjects covered by former USPC cross-reference art collections and digests	Y10S
Technical subjects covered by former US classification	Y10T
Technologies for adaptation to climate change	Y02A
CCMT in information and communication technologies	Y02D

Source : Elaborated by the Author based on CPC scheme and CPC definitions

Patent data is matched with financial data drawn from DIANE database maintained by the Bureau Van Dijk (BVD). We used the 2017 version. This database contains information about balance sheet of approximately 16 million French firms. Data is available for a time period of 10 years. The first available year in Diane is 2002. Our study is based on the unconsolidated statements. Unlike Marin (2014) who focuses his study on big Italian firms with a turnover above 1,5 million euros, we use the full version of DIANE which includes small, medium and large firms.

Due to the absence of a common identifier between the two databases, we use the name and the address of companies to merge the data.

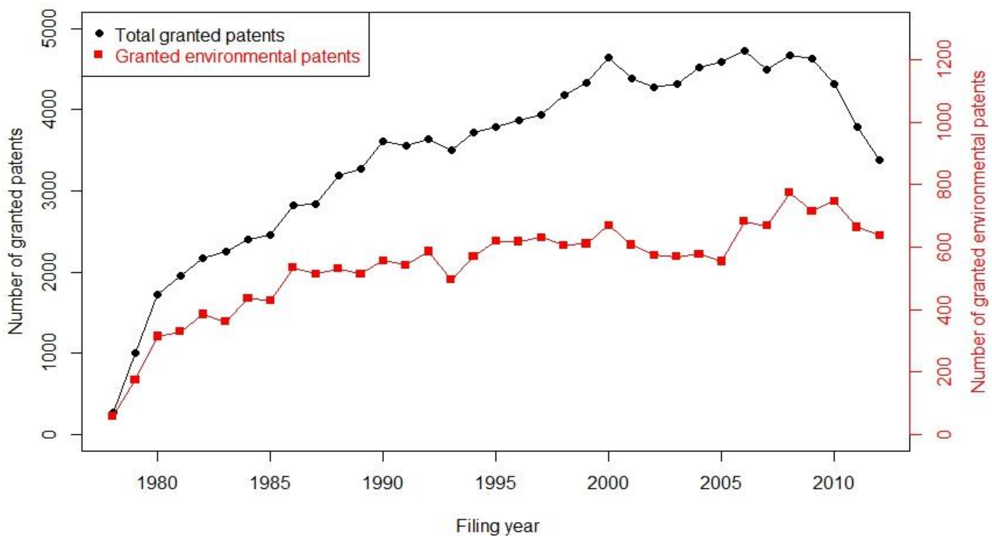
Company names and addresses are not uniform and there are spelling differences. In this case, before proceeding to the statistical analyses we need to harmonize and after that to match the data using an algorithm.

R&D data come from the annual firm research expenditures survey conducted by the French Ministry of Higher Education, Research and Innovation.

4. Evolution of the innovation activity over time in France

Figure 1 represents the trends in green and non-green technologies in French firms. The number of granted patents by French firms at the EPO has risen from 1731 in 1980 to 4634 in 2009. The number of green patent has increased from 314 in 1980 to 716 in 2009. However, we notice a decrease of the number of granted patents after 2009. This may be a consequence of the financial crisis of 2008.

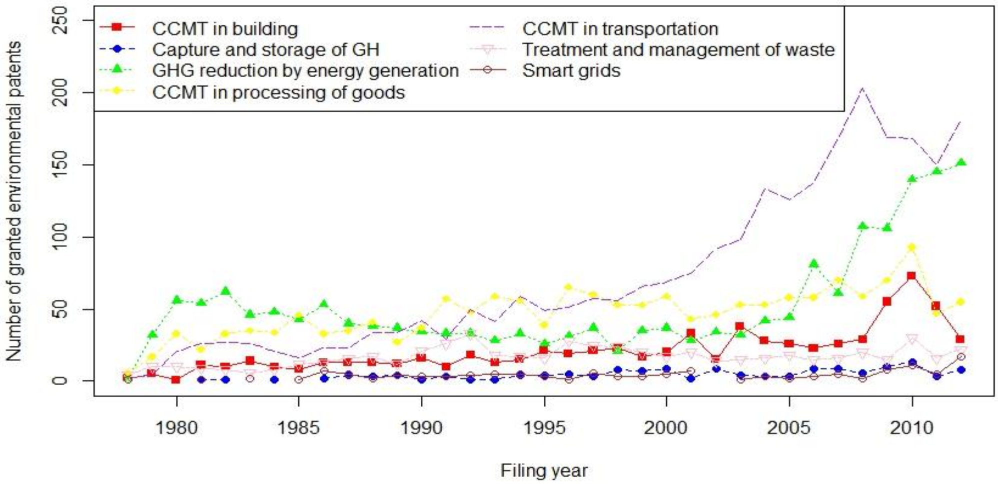
Figure 1: The evolution of green patents and total patents during 1978-2012 in France



Source: Authors' calculations from REGPAT

Figure 2 reports the trends in patenting activity by technology over time. From 1978 to 1989, the biggest number of green patents is related to GHG reduction by energy generation. We see a significant increase of the granted patents in this kind of technologies in 2008. Since 1991, the number of patents in CCMT in transportations increased considerably, and it has maintained the highest number of granted patents in the field of green technologies, over all the following years. It reached its peak of 203 patents in 2008 before going down.

Figure 2: Evolution of green patents by technology over time (1978-2012), classified by applicant's country



Source: Authors' calculations based on REGPAT

5-Estimation Model

My econometric analysis is based on a modified version of the CDM model proposed by Crepon and al (1998) to explain the relation between innovation and productivity by linking the input of innovation (R&D) to the output of innovation (patents in the present study) and innovation to productivity. The advantage of the structure of the model is that it allows to handle two problems of innovation data: selection bias and endogeneity.

The selection bias problem is due to the truncation type of innovation data. Input innovation data (research and development, cooperation…) is only reported by firms that carried out innovation activities. So it is necessary to correct the data truncation. The decision to undertake R&D activity is simultaneously determined by other factors that may in turn be affected by R&D. The CDM model is a sort of instrumental variable approach to correct these two flaws.

This approach is composed of three stages formalized by three simultaneous equations.

5-1 R&D decision and intensity

The purpose of this first stage is to model the decision of firms whether or not to undertake R&D investment and then to determine the intensity of this investment. I consider two types of R&D expenses: Environmental and Non environmental R&D.

This first equation is estimated by a two steps Heckman model that is specified as follows:

$$D\_NE_{it} = \begin{cases} 1 \; si \; RDNE_{it}^{*} = x_{it}\,\beta + \varepsilon_{it} > \; \bar{c} \\ 0 \; si \; RDNE_{it}^{*} = x_{it}\,\beta + \varepsilon_{it} \leq \bar{c} \end{cases} \qquad (1)$$

$D\_NE_{it}^{*}$: Variable latente qui renseigne sur le choix de l'entreprise d'investir ou pas dans la recherche et développement Non environnementale.

$$D\_ENV_{it} = \begin{cases} 1 \; si \; RDENV_{it}^{*} = x_{it}\,\beta + \varepsilon_{it} > \bar{c} \\ 0 \; si \; RDENV_{it}^{*} = x_{it}\,\beta + \varepsilon_{it} \leq \bar{c} \end{cases} \qquad (2)$$

Where i indexes the firm, t indexes the year.

D_NE_{it} is a dummy variable that takes the value 1 if the firm i reports a positive Non environmental R&D.

D_ENV_{it} is a dummy variable that takes the value 1 if the firm i reports a positive environmental R&D.

$RDENV_{it}^{*}$ is a latent indicator variable such as a firm decides to undertake environmental innovation if this indicator is above a given threshold $\bar{c}$ which represents an unobservable expected returns on environmental R&D.

$RDNE_{it}^{*}$ is a latent indicator variable such as a firm decides to undertake Non environmental innovation if this indicator is above a given threshold $\bar{c}$ which represents an unobservable expected returns on Non environmental R&D.

The explanatory variables x_{it} are : Market share (M_SHARE) defined as the ratio between th e firm's total sales and the total sales of the firms in the same sector (I use three digit NACE c lassification). Labor (L), defined as the number of employees. Physical capital defined as the t otal assets (TA).[4] ε_{it} is an error term.

$$I\_RDNE_{it} = \begin{cases} I\_RDNE_{it}^{*} = x_{it}\,\beta + \varepsilon_{it} & si \; D\_NE_{it} = 1 \\ 0 & si \; D\_NE_{it} = 0 \end{cases} \qquad (3)$$

$I\_RDNE_{it}^{*}$ is the unobserved latent variable representing the firm's Non environmental R&D intensity.

$$I\_RDENV_{it} = \begin{cases} I\_RDENV_{it}^{*} = x_{it}\,\beta + \varepsilon_{it} & si \; D\_ENV_{it} = 1 \\ 0 & si \; D\_ENV_{it} = 0 \end{cases} \qquad (4)$$

[4] The variables labor and total assets are expressed per employee and in logarithm

$I\_RDENV_{it}^{*}$: is the unobserved latent variable representing the firm's environmental R&D intensity.

The explanatory variables x_{it} are the same as that in equation (1) and (2). I add a dummy variable Age that denotes 1 if the firm is older than 10 years.

The predicted values of Environmental ($I\_RDENV_{it}^{*}$) and Non environmental R&D ($I\_RDNE_{it}^{*}$) are introduced in the second equation presented below.

5-2 The innovation equation

In this stage I analyze the relationship between the input of innovation and the output of innovation. I use environmental patent applications count ($ENVP_{it}$) as a proxy for environmental innovation and Non environmental patent applications (NEP_{it}) as a proxy for Non environmental innovation.

$$NEP_{it} = \alpha\, I\_RDNE_{it-2}^{*} + \beta\, I\_RDENV_{it-2}^{*} + \gamma w_{it} + \varepsilon_{it} \qquad (5)$$

$$ENVP_{it} = \alpha\, I\_RDNE_{it-2}^{*} + \beta\, I\_RDENV_{it-2}^{*} + \gamma w_{it} + \varepsilon_{it} \qquad (6)$$

$I\_RDNE_{it-2}^{*}$ and $I\_RDENV_{it-2}^{*}$ are the predicted R&D obtained from the first stage (lagged two periods). w_{it} represent a vector of explanatory variables.

Patent data counts are positive integers characterized by an excess of zeros. I use a negative binomial model to estimate the equations (5) and (6).

5-3 The productivity equation

I estimate a Cobb-Douglas production function. I extend the equation by adding the innovation variables ($NEP_{it}^{*}, ENVP_{it}^{*}$) predicted in the second stage.

$$ln\, VA_{it} = lnA + \alpha\, ln\, L_{it} + \beta lnTA_{it} + \gamma_1 ln\, NEP_{it-2}^{*} + \gamma_2\, lnENVP_{it-2}^{*} + \varepsilon_{it} \quad (7)$$

NEP_{it-2}^{*} and $ENVP_{it-2}^{*}$ are two lagged variables. I consider that there is a time delay between innovation and its impact on productivity. VA_{it} represents the value added.

6. Results

Table 2 reports the results of the equation (1) and (2) (the selection equation) and table 3 shows the results of the equation (2) and (3) (R&D intensity equation) of the first stage.

Inverse Mills ratios that I obtain are significant, showing the importance of taking the selection problem into consideration.

Firm size measured by number of employees has a positive impact on the decision of undertaking both environmental and non environmental R&D investments. Thus the larger the firm, the more likely to engage in R&D activities.

Total assets doesn't affect the decision to invest in both environmental and non environmental R&D investments. In contrast, it has a positive and significant effect on the intensity of environmental and non environmental R&D. The coefficient of Total assets is positive and statistically significant. This indicates that in case a firm choose to invest in R&D, complementarity between R&D and total assets seems to arise. The coefficient of age is positive and statistically significant meaning that older firms have higher probability to perform environmental R&D.

Market share is negatively related to the probability of performing R&D. Firms holding a dominant market position have little incentive to innovate and they prefer to defend their dominant position rather than exploring new markets or changing their production technology.

Table 2: First step: selection equation

	(1)	(2)
VARIABLES	D_NE	D_ENV
M_SHARE	-2.333***	-2.310***
	(0.453)	(0.681)
LN_TA_L	0.000594	0.0268
	(0.0238)	(0.0335)
LN_L	0.488***	0.379***
	(0.0191)	(0.0250)
Constant	-2.271***	-3.267***
	(0.156)	(0.221)
Observations	2,825	2,825

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: First step: R&D Intensity equation

VARIABLES	LN_I_RDNE	LN_I_RDENV
M_SHARE	-0.380	-2.292**
	(0.460)	(0.903)
LN_TA_L	0.227***	0.165***
	(0.0254)	(0.0424)
LN_L	0.430***	0.420***
	(0.0343)	(0.0400)
AGE_DV	0.0155	0.292***
	(0.0373)	(0.0808)
invmills	0.650**	-2.122***
	(0.263)	(0.440)
Constant	-0.395	-1.762***
	(0.241)	(0.264)
Observations	2,825	2,825
Number of Siren	433	433

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Second step: Innovation (Patent equation)

	(1)	(2)
VARIABLES	NEP	ENVP
LN_I_RDNE*	-0.437	
	(0.371)	
LN_L	0.310*	-0.0714
	(0.166)	(0.211)
LN_I_RDENV*		0.586
		(0.585)
Constant	-1.456*	0.765
	(0.822)	(1.813)
Observations	2,183	810
Number of Siren	268	90

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Third step: Productivity equation

VARIABLES	(1) LN_VA_L
LN_ NEP *	-0.308***
	(0.111)
LN_ ENVP*	0.667***
	(0.151)
LN_TA_L	0.449***
	(0.0172)
Constant	1.726***
	(0.112)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 shows the estimation results of the equations (5) and (6) of the second stage. In this step I include the predicted environmental and non environmental R&D into environmental and non environmental patent equations that I estimate with a negative binomial model.

The effect of the expected R&D intensity on environmental and non environmental patent count is insignificant this may be related to the high proportion of observations with no patent applications.

The effect of firm size on non environmental patents is positive as is the case for non environmental R&D. However, the coefficient of this variable is insignificant in the case of environmental patents.

The results of the third stage are shown in table 5. I notice that predicted non environmental patent count has a statistically significant positive impact on value added. Whereas predicted environmental innovation has a statistically negative effect on value added.

The coefficient suggests that an increase of the patent count by 1 would lead to a 3,08% decrease in productivity. In contrast, an increase of the patents count by 1 would result in a 6,67 % increase in productivity.

Indicating that private economic returns measured in terms of productivity are lower for Environmental innovation than for non environmental innovation.

This finding is in consonance with the previous results found by Marin (2014), Marin and Lotti (2016) and Kruse (2016).

Conclusion

In this paper, I studied the relationship that links the innovation output (Patents) to the innovation input (R&D) and the effects of innovation output on productivity. I distinguish the case of environmental R&D and patents from the case of non environmental R&D and patents. I based my study on an unbalanced panel of French firms over the period (2003-2015). To constitute the panel, I matched patent data drawn from REGPAT and HAN OECD databases with financial data extracted from the DIANE database and R&D data drawn from firms research and development (R&D) survey. I used a CDM model that allows me to control for selection biais and endogeneity that characterize innovation data.

My results confirm the hypothesis according to which there exists a difference in the effect of environmental and non environmental innovation on firms productivity. Environmental innovation leads to lower economic returns (measured by productivity) comparing to non environmental innovation.

Given the fact that financial ressources allocated to R&D are restricted, there may be a crowding out effect of environmental innovations relative to non environmental innovations, at least at short run. These results correspond to those found by Marin (2014), Marin and Lotti (2016) and Kruse (2016). This finding show that there exist factors (i.e., green promotion, environmental regulation, among others) other than market forces that push firms to invest in environmental innovation. This is why environmental regulation variables will be introduced at the firm level in order to answer this question in the final version of this paper.

Environmental innovation generates lower private returns for firms but, at the same time, it contributes to the increasing of the social returns, so this may not affect the total welfare of the population. Even so, the increase of the returns generated by environmental innovation is an important factor for the increasing of the total welfare. This may be an argument for policy makers to promote and encourage more this type of innovations in order to improve their private returns.

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