PAPER

Title: Location Determinants of Eco-Innovative Firms: Evidence from French Departments

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Abstract: *This paper analyses the location determinants of eco-innovative firms in France. The analysis is based on a dataset obtained after merging firm-level microdata on the location of new firms from DIANE Mercantil Register (Bureau van Dijk) and patents information from the OECD REGPAT (2018) database for the period 2003 and 2013. This paper departs from previous contributions in three main ways. First, it analyses the effects of the regional technological knowledge base and its composition focusing on environmental-based innovations. Second, it introduces spatial econometrics techniques to capture any potential spatial spillovers arising from the location of eco-innovative firms. And third, it focuses on the French case which is of special interest in view of the relevance of regional eco-innovation policies. Main results show that unrelated knowledge variety for environmental technologies and the political support in terms of investments for the protection of the environment are the main factors explaining the location of eco-innovative firms. Indeed, by applying spatial econometrics we found that there is a clear spatial dependence on the creation. However, our results also show that the impact of the knowledge composition is quite local. These results may have many implications for French departments' environmental performance and sustainable growth.*

Keywords: *eco-innovative firms' entry, industrial location, knowledge spillovers, environmental technologies, France*
JEL codes: L26, M13, R11, O33

1. Introduction

Since the 1990s, environmental issues have become a major concern for policy makers. Faced with the threat of global warming, it was essential to reduce energy consumption, limit the use of fossil fuels, and promote the development of low-carbon energies. This requires a radical technological transformation of the global energy system, and the rapid establishment of policies encouraging the development of innovation with the aim of reducing the environmental impact and a more efficient use of natural resources.

The implementation of national and sector policies promoting eco-innovation has become a key issue to Europe's future competitiveness. In addition, to ensure a positive effect on environment, these policies must also foster economic growth from the emergence of new green activities. Europe's ambition is to be the worldwide leader in developing the technologies required to tackle climate change. It is with this mind that, the European Commission set up the Eco-innovation Action Plan (2011) whose aim is to integrate eco-innovation in environmental and industrial policies by focussing on its contribution to economic growth, job creation and the European Union (UE)'s industry competitiveness.

With the Act of 17 August 2015 on Energy Transition for Green growth, France has displayed its ambition to be an exemplary nation in terms of reducing its greenhouse gas emissions, diversifying its energy system and increasing the deployment of renewable energy sources. The Act sets out many quantitative goals, in particular, a commitment to reduce greenhouse gas emissions by 40% by 2030, compared to 1990 levels, and divide it by four by 2050 as well as to increase the share of renewables in final energy consumption up to 32% by 2030. And it is in this context where the creation of innovative start-ups may have a key role on this transition process (OECD 2011, 2016; French Government 2017). In this regard, France accounts for a specific program that supports the creation of eco-innovative firms with a special focus on the development of innovation (ADEME 2018). It seems clear, then, that the set-up of policies encouraging the creation of environmental technologies and their sustainable application in firms' activity may have many implications for French departments' environmental performance and sustainable growth.

Despite the increasing interest on the development of eco-innovation, the number of contributions analysing the regional factors that may explain the location of eco-innovative activities is still scarce. Most contributions have focused on the analysis of the determinants of environmental innovation (i.e., Horbach 2008; Demirel and Kesidou 2011; Kesidou and Demirel

2012; Ghisetti et al. 2015). Among the few studies that have analysed the creation of eco-innovative firms, they do that from a green entrepreneurship perspective, even most of them are mostly focused on sustainable entrepreneurship (Hockerts and Wüstenhagen 2010; OECD 2011; Meyskens and Carsrud 2013). In particular, previous studies provide evidence from selected regions and technologies highlighting the importance of the regional economy for the emergence of this new industry (Smith 2007; Madsen and Andersen 2010; Tanner 2015).[1]

Therefore, with this paper we aim to contribute to the literature on the location determinants of eco-innovative firms and shed light on the relationship between knowledge spillovers and the creation of new innovative firms specialised in the environmental field. Concretely, we try to give answer to three specific questions. First, is the regional amount of accumulated knowledge (in terms of patents) positively associated with the creation of eco-innovative firms? Second, how relevant is the technological relatedness and variety in fostering the creation of eco-innovative firms? And third, is the creation of eco-innovative firms positively influenced by the local knowledge base and firm creation in neighbouring regions? The answers to these questions are important both for eco-innovative firms' location decisions and for the setting up of regional policies encouraging the spatial concentration of environmental knowledge creation that to some extent may boost regional disparities in terms of environmental performance and knowledge creation or, on the contrary, reduce them. Moreover, the understanding of the dynamics of the eco-innovative firms' entry can provide useful information on how to boost local development through their direct and indirect spatial spillovers arising from the formation of eco-innovative activities in neighbouring regions.

Only two comparable works have analysed these issues: Corradini (2019) and Colombelli and Quatraro (2019). As far as we know, Corradini (2019) was the first paper to analyse the location determinants of new green technology-based firms across European regions by using the characteristics of patent applications to define them as eco-innovative. Their results show that the geographical distribution of green technology entry across European regions is not evenly distributed, giving evidence of the significant role played by the characteristics of the regional innovation system. With regard to Colombelli and Quatraro (2019), they provide evidence of the effects of the technological composition of local stocks in the creation of green start-ups across

[1] See, for instance, Barbieri et al. (2016) or Dechezleprêtre and Sato (2017) for a detailed literature review on environmental innovation.

Italian NUTS3 regions. Their findings also highlight the relevance of diverse and heterogeneous knowledge sources in related and complementary technological fields.

Against this background, the present paper departs from previous contributions in three main ways. First, we propose for the first time in this literature, as far as we know, a set of knowledge indicators capturing the degree of variety defining the local knowledge base focusing on environmental based patents' technological combinations. By doing so, we are able to disentangle the degree of diversity of the local knowledge base in terms of the interaction between environmental and non-environmental technologies as well as the interaction between the diverse environmental technological classes making up environmental patents that cannot be captured when using the traditional knowledge variety indicators. Second, we introduce spatial dependence effects by using spatial autocorrelation techniques. Even previous contributions Colombelli and Quatraro (2019) and Corradini (2019) argue that spatial path dependence and regional dynamics are important to foster eco-innovation, they do not account for the fact that the environmental local knowledge technological base generated in neighbouring regions may spill over regions and that eco-innovative firm creation may be clearly influenced by the development and creation of environmental technologies in neighbouring regions (Rennings and Rammer 2009; Horbach et al. 2013; Ghisetti et al. 2015). Thus, by using spatial econometrics we are able to identify spatial spillovers associated with the accumulated endowments of knowledge in the environmental technologies and eco-innovative firms' creation. And third, we provide evidence on the location determinants of new eco-innovative firms' entry for the French case which is subject of increasing interest as we aforementioned argued.

By using firm-level microdata on the location of new firms from DIANE Mercantil Register (Bureau van Dijk) and patent information from the OECD REGPAT (2018) database, we analyse the location determinants of new eco-innovative firms in France over the period 2003-2013. Main results show that unrelated knowledge variety for environmental technologies and the political support in terms of investments for the protection of the environment are the main factors explaining the location of eco-innovative firms. Indeed, by applying spatial econometrics we found that there is a clear spatial dependence on their creation. However, our results also show that the impact of the knowledge composition is quite local.

The paper is organized as follows. Section 2 reviews previous contributions analysing the location determinants of eco-innovative firms and the role of knowledge spillovers in this process. In Section 3, we describe data set and the variables used. In Section 4, we present the methodology and the econometric specification. Section 5 reports main results. Finally, Section 6 offers some concluding remarks and policy implications.

1. Local knowledge composition and eco-innovative firm creation

Eco-innovation is a recent concept, developed in the 1990s (Fussler and James 1996). Since then, several definitions have been proposed in the literature by national and international institutions. However, the definition of eco-innovation is still under construction. In order to better understand this concept, the European Commission set up two projects to measure eco-innovation: Measuring Eco-Innovation (MEI) and Eco-Drive. The definition adopted in the Eco-drive project emphasizes the improvement of economic and environmental performance: "eco-innovation is a change in economic activities that improves both economic performance and the environmental performance of society" (Huppes et al. 2008, p.29). While the MEI report defines eco-innovation as follows: "Eco-innovation is 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 alternative alternatives" (Kemp and Pearson, 2008).

The interest on eco-innovation stems from its environmental and economic benefits to the society (Horbach 2008). These potential benefits of eco-innovations can easily spill over the society through the creation of new firms specialised in environmental technologies. In this regard, there is a wide consensus on the key role of start-ups on this transmission process over the economy (Audretsch et al. 2006; European Comission 2011; OECD 2016). In this regard, understanding firm location decisions is becoming more and more relevant to provide evidence on the regional characteristics that may boost the creation of new innovative firms in the environmental domain. However, there are not several contributions analysing the location determinants of eco-innovative firms. Most related literature focuses on the location of innovation and the importance of knowledge spillovers (Acs et al. 2009).

According to this literature, one of the main factors explaining the creation of new innovative firms is the local available stock of knowledge (Acs et al. 2009; Audretsch et al. 2015). The main idea behind this association is the fact that the uncertain and asymmetric nature of new knowledge leads to new recombinations that may spill over to other agents stimulating the creation of new ventures when this knowledge has not been recognised or valued by incumbent

firms. For the case of environmental technologies, given their complex and specific nature, the availability of local knowledge is expected to have a more important role on the creation of eco-innovative firms. Still, the benefits stemming from the available local knowledge base may differ according to the dominant technologies being developed on the region. In this direction, some authors found that eco-innovative start-ups benefit more from knowledge spillovers coming from 'clean' technologies than from 'dirty' technologies because of (Colombelli and Quatraro 2019). On the contrary, Quatraro and Scandura (2019) consider that the creation of green technological activity substantially depends upon the stock of non-green technologies. While some others found that both environmental and non-environmental knowledge are positively associated to the emergence of environmental technologies specialisation (Montresor and Quatraro 2018). Despite this mixed evidence, we consider that both kinds of knowledge should be relevant on the formation of eco-innovative firms due to the wider scope of application of environmental technologies regards to other technologies (Dechezleprêtre et al. 2013).

H1. *The creation of new eco-innovation firms is affected by the local availability of knowledge spillovers coming from both environmental and non-environmental technologies.*

Besides the available local stock of knowledge, some authors argue that the domains over which local knowledge spans are also important when it comes to explain the location patterns of (eco)-innovative start-ups (Colombelli and Quatraro 2018). In this regard, there is ample empirical confirmation for the fact that knowledge base dimensions such as variety or/and relatedness affect the knowledge recombination effectiveness and firm formation dynamics (Bae and Koo 2009; Colombelli 2016). Regional technological heterogeneity is characterized by the presence of actors with different technological competencies and then a broader set of combinatorial opportunities leading to the creation of new innovative firms (Castaldi et al., 2013; Corradini and De Propris, 2015). Even the complementarity degree of regional knowledge configuration is important, increasing similarity may lead to negative effects. Thus, an excessive level of relatedness is likely to engender technological lock-in (Boschma 2005; Colombelli and Quatraro 2013). The most favourable configuration for the emergence of knowledge-based entrepreneurship is characterized by high levels of both relatedness and variety. In fact, a high degree of relatedness is associated to reduced knowledge asymmetries and uncertainty and an improvement in the entrepreneurial absorptive capacity. While a high degree of variety is associated to more technological opportunities (Colombelli and Quatraro 2018).

Among the few contributions analysing the impact of knowledge spillovers on the creation eco-innovative firms, Colombelli and Quatraro (2019) and Corradini (2019) stand out. On the one hand, Corradini (2019) found an inverted-U relationship between regional technological relatedness and green technological entry. In this regard, technological activities related to environmental technologies available in regions trigger the development of green technologies. However, an excessive level of relatedness may have a negative effect by limiting the set of opportunities for recombinations with other technological domains, leading to a decrease of green technological entries. On the other hand, Colombelli and Quatraro (2019) pointed out the importance of technological variety for the generation of green innovative start-ups as well as the historical process of knowledge accumulation in which the combination of related and highly complementary technological fields is relevant for the effective exploitation of technological opportunities in the green domain.

In practical terms, different strategies can be followed by regions in order to foster eco-innovative firms' entry. Some regions could follow a strategy based on unrelated diversification by investing in technologies different from the pre-existing ones (e.g., the production of electric cars in absence of a consolidated experience in the automobile sector). Others regions may exploit and combine the existing non-environmental innovations with eco-innovations into new hybrid solutions (e.g., the hybrid car combining an internal combustion engine with an electric propulsion one and photovoltaic films combining thin layer technologies with solar technologies). These strategies are examples of the wider scope of application of environmental technologies due to their complexity and specific nature (Quatraro and Scandura 2019; Santoalha and Boschma 2019).

Therefore, the understanding of the recombination of the different technologies leading to eco-innovations is of vital importance for the set up of regional policies encouraging the development of eco-innovative activities. Nevertheless, previous contributions were not able to capture the specific recombinations of knowledge that make up environmental technologies. This lack of evidence on this issue hampers the setting-up of clear policies to promote the creation of eco-innovative firms. So, this paper aims to fill this gap by analysing the importance of the interaction between non-environmental and environmental knowledge bases and by considering the interaction between the diverse technological classes within green technologies.[2]

[2] For further details in our approach to measure diversity for environmental technologies, please, see Section 3.2.

H2. *Departments that feature high levels of knowledge variety and relatedness, particularly based on the environmental innovations' knowledge combinations needs, are expected to show a higher likelihood to have eco-innovative firms' entry.*

2. Empirical specification

3.1. Data

To analyse the location determinants of eco-innovative firms, we make use of patent, firm-level data and regional economic statistics for the 96 NUTS3 metropolitan regions (Departments) across France between 2003 and 2013. Patent data are obtained from the OECD REGPAT (2018) database, which derives from two complementary sources of data: the European Patent Office's (EPO) Worldwide Statistical Patent Database (PATSTAT) and the EPO's *epoline* Database. Concretely, patent priority date, Cooperative Patent Classification (CPC) indicating the specific technological class of the patent and applicant details are the most relevant information to our study. Still, to complete this information we make use of DIANE database (Bureau van Dijk) that contains comprehensive information on firms in France, detailed by firms' geographical information and their date of creation. Finally, the dataset of the local characteristics of French Departments (96) is taken from different sources such as INSEE, French Government and Eurostat.

3.2. Variables

Dependent variable

As the main aim of this paper is to understand the entry of new innovative-based firms specialised in environmental technologies, we define eco-innovative firm entry as the entry of a new innovative firm to the environmental technology industry. This approach is based on studies in evolutionary economics focusing on real technological-based firm entry rather than traditional approach that identifies new firm creation through the date of incorporation of firms to the market (Malerba and Orsenigo 1999; Corradini and De Propris 2015; Corradini 2019).

With this purpose, we rely on OECD REGPAT (2018) patents database that have been linked to departments according to the addresses of the applicants.[3] This database provides detailed

[3] The use of patent applications is quite widespread in the literature of innovation geography since they represent reliable proxies of knowledge and innovation (Acs et al. 2002; Breschi et al. 2010; Tanner 2015). Indeed, as Corradini (2019) argues, patent applications are shown "to better capture the moment of knowledge creation allowing to be closer to the entry of new green technology-based companies".

information on firms' innovative activity over time which allows us identifying the firms who apply for a patent for the first time, and whose innovations are mostly in environmental technologies. To be considered environmental patents, we follow the CPC system of the European Patent Office (EPO), an international patent classification that assigns each patent a green tag, depending on the environmental aim of each patent. In this paper, are considered as environmental patents which main aim is the adaptation and mitigation to climate changes (Y02), in terms of buildings (Y02B), the capturing, storage sequestration and disposal of GHG (Y02C), energy (Y02E), climate change mitigation technologies related to the production of goods (Y02P), smart grids (Y04S), transportation (Y02T) and water waste and treatment (Y02W).

To identify eco-innovative firms' entry we amend the proposal of Corradini (2019) so as to retain only highly specialised firms in eco-innovation.[4] According to that, environmental-based firms are those to have at least 50% of their inventions in the period of time observed classified as environmental technologies and that have applied for the first eco-patent within the first 5 years after their creation.

By retaining only those firms that have been created not earlier than 5 years from the first patent application we are more ascertain to capture the entry of new firms since the date of the first patent and the date of firms' creation may not coincide (Breschi et al. 2010). To obtain the date of incorporation of these firms, REGPAT data was merged with DIANE database through the ID codes of applicants.[5] Then, to identify the year of entry of the firm to the environmental technology-based industry, we consider the year in which they applied for an environmental-based patent for the first time since we consider the creation of firms in terms of their innovative activity.

[INSERT FIGURE 1 ABOUT HERE]

Figure 1 shows the distribution of the number of eco-innovative firms' entry across the 96 French Departments between 2003 and 2013. From this figure stands out a non-homogenous spatial distribution on eco-innovative firms' entry throughout French departments, being that

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[4] Alternative eco-innovation firm entries definitions (i.e., at least 1, more than 75% or 100% of patents in environmental technologies) have been applied, but results do not significantly vary. Still, results are available upon request.

[5] Despite the fact that most contributions assign patent data to regions on the basis of the address of inventors (see for instance, Henderson et al. (2005), Breschi and Lissoni (2009) or Colombelli and Quatraro (2018), among others), the present paper is based on applicants' addresses. The choice of applicants' addresses is justified by the fact that we consider that applicants' addresses may capture technological-based firms' entry rather than inventors' addresses since they may live in other departments than that of the firm or may move to other firms once they have applied for the patent. This approach is also supported Antonelli et al. (2010) and Quatraro (2010) who consider it as viable alternative.

roughly 75% of innovative firms locate in and around Île-de-France and in the most populated departments such as Rhône (69) or Gironde (3). Thus, it seems clear that one of the most essential determinants of location decision are agglomeration economies arising by dense populated areas that are expected to provide some advantages that increase their attractiveness (e.g., specialised labour markets, availability of suppliers and knowledge spillovers). However, there are some less populated departments that concentrate a significant number of eco-innovative entries. Thus, there are alternative factors a part from those of the traditional industrial location that seem to significantly matter for these environmental technological-based activities.

Key explanatory variables: *knowledge indicators* and *environmental political support*

Because of the specific and complex nature that characterises the knowledge base of eco-innovative activities (Colombelli and Quatraro 2019), using the typical pool of covariates used mainly for manufacturing entries may imply some bias on the analysis of the location determinants of environmental technology-based firms. Because of that, a set of specific factors that are found to foster innovation related to environmental technologies should be considered (see for instance, Corradini 2019, Colombelli and Quatraro 2019 or Quatraro and Scandura 2019).

Among them, one of the most important factors encouraging the location of eco-innovative activity is knowledge spillovers from the innovative activities of incumbent firms (Acs et al. 2009; 2013). To capture the capacity of regions to generate and accumulate knowledge, we add a knowledge stock indicators defined as the cumulated number of patent applications (STOCK_ALL) relying on the permanent inventory method (see Appendix 1 for further details). The same variable has been built for environmental-based patents (STOCK_ENV) as well as for its complement, that is, for non-environmental-based patents (STOCK_NENV) as they may differently affect the entry of eco-innovative firms (Colombelli and Quatraro 2019). Figure 2 shows the evolution of the environmental based patents stock over time. In this figure we observe a similar distribution than that we found for eco-innovative firms' entry (Figure 1), giving evidence of the relationship between these two elements (Acs et al. 2009; Corradini and De Propris 2015).

Besides of the accumulation of knowledge, when assessing the regional factors that may incentive the formation of eco-innovation it is important to consider the nature of the local knowledge base (Colombelli and Quatraro 2018, 2019). In this regard, we calculate a set of variables measuring the complementarity and variety degree that characterise the local knowledge based on the information provided in patents documents (see Appendix for further details on their computation).

In this regard, we calculate the following measures capturing the characteristics of the knowledge base of French departments. First, knowledge coherence indicator (COH) measures the average degree of relatedness of the technologies that makes up the knowledge base of departments. Second, knowledge variety measures the degree of technological diversification of the knowledge base. It is based on the informational entropy index and it can be decomposed into related and unrelated knowledge variety. Nevertheless, in this paper we propose for the first time in this literature, as far as we know, a set of knowledge indicators capturing the degree of variety defining the local knowledge base of departments focusing on environmental based patents (KV_Y, RKV_Y and UKV_Y). While for the elaboration of the traditional variety indicators we consider all technological classes and their degree of association among them, for the KV_Y, RKV_Y and UKV_Y we focus on the association of environmental patents with other technologies. In that way, we are able to capture the degree of diversity of the local knowledge base in terms of eco-innovations that cannot be appreciated when using the former.

To control for the impact of environmental political support and the environmental sensitiveness and engagement of local population, we also include the total amount of investments for the protection of the environment (ECO_INVEST)[6] and for the share of votes for the ecologist vote at the French national elections (VOTE_ECO).[7]

Control variables

Socioeconomic characteristics such as unemployment (UNEMP), population density (POP_DEN) or specialised human capital (SCITECH) should be controlled for. Regarding the impact of unemployment on the creation of innovative firms, unemployment may be rather associated to a Schumpeter (pull) effect than a refugee (push) effect as Aubrey et al. (2015) found

[6] ECO_INVEST is not available at NUTS3 level, for this reason we corrected the same variable at NUTS2 (regional) level by applying the contribution of each department of its region GDP.

[7] Other variables proxying the environmental political support and the local sensitiveness and quality of life at the departmental level were also considered such as a dummy that takes into account whether the department has received a Cit'ergie prize that rewards communities for implementing a policy ambitious climate-air-energy; the ratio of the population under an Agenda21; or the number of highly polluting firms. However, they were not finally added to the model because they were highly correlated with other key knowledge and socioeconomic indicators.

for French regions. According to the Schumpeter effect, the creation of new firms is mainly driven by innovative ideas or market opportunities such as the case of technological-based firms. Thus, the conditions leading to higher unemployment rates may deter new eco-innovative firms' creation (Storey 1991; Fritsch 2008). While the refugee effect implies that the creation of firms may be a strategy to escape from unemployment when the individual is in bad conditions in the labour market (Oxendfelt 1943).[8] Densely populated areas can be associated to more intensive interaction and higher productivity as well as to a higher potential demand. In line with previous studies (Audretsch et al. 2010; Rodriguez-Pose and Hardy 2015), this measure serves as a proxy for agglomeration and urbanisation economies not directly related to technological activity. The role of different kinds of university knowledge in the creation of new ventures has been highlighted in previous studies (Woodward et al. 2006; Kirchhoff et al. 2007; Acosta et al. 2011; Bergmann et al. 2016) such as the knowledge embedded in university graduates that are employed in Science and Technology industries. Geography and institutional issues also matter (Guimarães et al. 2000), as firms need good accessibility to services provided in cores, so it is necessary to control for accessibility to main cities as Paris (*dist_paris*). Moreover, proximity to the most important city of the country may capture on the one hand, a potential competition effect in view of agglomeration of firms in that area and, on the other hand, a competitive advantage in terms of the services and amenities located in and around Paris.

[INSERT TABLE 1 ABOUT HERE]

A summary of definitions, sources and descriptive statistics can be found in Table 1.

4. Methods

To analyse the determinants of the location decisions of eco-innovative firms and their relationship with the knowledge technological base and composition of the departments, we estimated the eco-innovative firms' entry as a function of the set of technology indicators controlling for local characteristics. The specification to be estimated is formally defined as follows:

[8] Since the effects of unemployment on firm creation should differ for the case of innovative and technological firms who may require high-skilled workers, we have also used unemployment with tertiary education instead of the global unemployment measure. However, this measure leads to multicollinearity problems because it is high correlated with knowledge indicators, employment in Science and Technology and population density.

$$ECO\_ENTRY_{it} = \alpha + \beta_1 STOCK\_PT_{it-1} + \beta_2 STOCK\_ENV\_PT_{t-1} + \beta_3 STOCK\_NENV\_PT_{t-1} + \beta_4 COH_{t-1} + \beta_5 KV\_Y_{t-1} + \beta_6 RKV\_Y_{it-1} + \beta_7 UKV\_Y_{i_{t-1}} + \beta_{10} UNEMP_{t-1} + \beta_{11} POP\_DEN_{t-1} + \beta_{12} SCITECH_{t-1} + \beta_{13} DIST\_PARIS_t + \beta_{14} ECO\_INVEST_{t-1} + \beta_{15} VOTE\_ECO + \delta_{it} + \varepsilon$$

where δ represents the time and department dummies and ε is the disturbance. The dependent variable, ECO_ENTRY_{it}, is defined as a dichotomous variable being equal to 1 for those departments that experienced at least one eco-innovative entry in year *t*, and 0 otherwise since less than 1% of the departments experienced a multiple entry per year. The set of independent variables are one period lagged to avoid simultaneity problems. Moreover, the set of knowledge variables are not simultaneously included in the model in order to avoid multicollinearity problems.

Taking into account the nature of our dependent variable, we estimate this model by a GLM (Generalised Linear Model) following a binomial distribution and logit link function via maximum likelihood.[9] The model includes time and department fixed effects. Indeed, as the fixed-effects logit estimator is potentially inconsistent in the presence of serial correlation and heteroscedasticity (Wooldridge 2010). To deal with that cluster robust standard errors are included in the GLM regression to account for potential heterogeneity and serial dependence over time.

The effects of the determinants of firm location decisions may extend beyond departments limits and if this potential spatial dependence is not taken into account, results may be biased and inconsistent (Anselin, 1988). To account for spatial dependence, we estimate the eco-innovative entries by applying spatial econometrics for panel data (Elhorst, 2010; 2014). Concretely, a Spatial Durbin Model (SDM) was adopted through a row-standardised contiguity weighting matrix according to previous contributions for the case of French metropolitan departments (see for instance, Elhorst and Fréret (2009)).[10]

The SDM includes the spatial lag of the dependent variable as well as the spatial lag of one or more exogenous variables in the model. Thus, in this paper we include to the SDM the spatial lag for the key variables capturing the local knowledge structure and its nature for both all technologies and environmental ones. The choice of the SDM is justified for two main reasons. First, it is considered the best performant estimator among the set of spatial dependence models

[9] See Cameron and Trivedi (2010, pp. 321-322) for more details.

[10] Other spatial weighting definitions where considered such as 5 nearest neighbours or an inversed distance-based matrix. Even so, since results slightly vary, we rely on a row-standardised contiguity weighting matrix according to previous contributions for the case of French metropolitan departments (see for instance, Elhorst and Fréret (2009).

for panel data (i.e., Spatial Lag Model, Spatial Autoregressive Model and the Spatial Autocorrelation Model). Moreover, it allows for the estimation of the direct and indirect effects of the lagged variables on the dependent variable (i.e., the effects in the main region and in the neighbouring ones) (Elhorst, 2014). And second, the SDM is considered to be the most appropriate spatial model for the purposes of this paper since it allows capturing any source of spatial dependence in terms of knowledge spillovers and entrepreneurial decisions in the environmental domain spreading beyond geographical limits (Colombelli and Quatraro, 2018).

5. Results

The GLM results for the location determinants of eco-innovative firms' entries are reported in Table 2. As aforementioned, all variables are one period lagged in order to avoid simultaneity problems and all regressions include region and time fixed effects.

We first discuss the results for our key variables, that is, knowledge indicators. It is important to notice that the set of knowledge variables are not simultaneously included in the model in order to avoid multicollinearity problems. The first three specifications, shown in columns 1, 2 and 3, are the results for the estimation including the knowledge stock of patents in all technologies, environmental and non-environmental, respectively. According to our results, differences in the accumulated knowledge capital stock are positive but not significant for the creation of new eco-innovative firms. These results hold without adding population density into the model due to the high correlation with these variables. This means that the knowledge local base is not enough to characterise the knowledge generation capacity at a regional level. In this regard, we account for the nature behind the local knowledge base in the following models. The creation of eco-innovative firms may be affected for the diversity knowledge combinations specially associated to environmental technologies. This is what we do by adding the KV_Y, RKV_Y and UKV_Y indicators shown in columns 4, 5, 6 and 7.[11] In this case, even the estimates for all these variables are positive, only those of unrelated knowledge variety for environmental technologies are significant, result that holds when is jointly added to the model with related knowledge variety for environmental technologies. This result may imply that the creation of eco-innovative firms is favoured by the possibility to combine novel pieces of knowledge coming from other technologies than that of environmental ones rather than new combinations of existing knowledge in the environmental field. The fact that only unrelated knowledge for environmental

[11] The same models have been estimated by adding the knowledge variety indicators counterparts including all technological classes. Results were not significant for these indicators. The results are available upon request.

technologies is significant suggests that the more diverse are the technologies carried out within the department the higher likelihood to have an eco-innovative entry in the department. Still, the average coherence (COH) of the local knowledge base shows a positive but non-significant coefficient (see column 8).

Other important factors that may explain regional differences on the creation of eco-innovative firms are the environmental political support and local sensitiveness to environmental issues. This fact is supported for the positive and significant effect of total amount of investments for the protection of the environment (ECO_INVEST) on the likelihood to create an eco-innovative firm across all specifications. The share of the vote for ecological parties is also positive, but just significant in the last specification (column 8).

In regards to the control variables, we observe positive and significant effect for population density and distance to Paris across the different model specifications. These results support the fact that densely populated areas facilitate the entry of eco-innovative firms due to the agglomeration advantages arising from the concentration of a diverse range of economic and innovative activities (Audretsch et al. 2010; Rodriguez-Pose and Hardy 2015). According to these results, the larger distance to Paris, the higher would be the likelihood of eco-innovative firm entry. Even if we should expect that this effect is negative since they may have more difficulties to establish networking and access to specialised research and development centres which are highly concentrated in and around the French capital, a larger distance to Paris may also capture a potential competition effect in view of agglomeration of firms in that area. Instead, the estimates for unemployment are negative and significant across all model specifications. This result is consistent with the fact that for eco-innovative firms, unemployment may be rather associated to a Schumpeter (pull) effect than a refugee (push) effect as Aubrey et al. (2015) found for French regions. Finally, the estimates for employment in Science and Technology sectors with tertiary education are not statistically significant. According to that, the importance of specialised employment may be probably blurred by the influence of other variables capturing agglomeration economies such as population density as well as knowledge base indicators.

[INSERT TABLE 2 ABOUT HERE]

5.1. Spatial econometrics analysis

These results provided interesting evidence about the effects of the local knowledge base on the creation of eco-innovative firms' entry. However, it is important to take into account the spatial dimension of these effects (Elhorst 2014). Thus, we implemented an SDM with the aim to understand the effects of the spatial lag of the set of knowledge base indicators as well as the dependent variable. The estimation of the SDM was estimated using the version 1.4-11 *splm* free package for R, which allows for the maximum likelihood estimation of spatial panel models (Millo and Piras 2012).

[INSERT TABLE 3 ABOUT HERE]

The spatial econometrics results are shown in Table 3.[12] The sign and significance of the control variables are pretty consistent with the previous estimations, except for unemployment. Such result may be explained by the fact that it may coexist both a positive and negative effect on firms' creation and this result is in line with previous findings (Storey 1991). When we look at the spatial lag of the dependent variable, that is the entry of eco-innovative firms in neighbouring departments, we found a positive and significant effect on the entry of eco-innovative firms in the department of reference and this result remains stable across almost all specifications. In other words, this result implies that any increase in the creation of eco-innovative firms in neighbouring departments will have positive effects on the likelihood of eco-innovative entry in the local department. This can be interpreted as a positive contagious effect according to which the entrepreneurial dynamics in environmental technologies in neighbouring regions may encourage the entry to eco-innovative markets in the local department. Besides that, when taking into account any source of spatial dependence in the model we found interesting results. All the coefficients of each of the local stock of knowledge capital (see columns 1, 2, 3); knowledge diversity (see columns 4-6) and coherence (see column 7) turn to be positive and significant when their spatial lags are included. The larger effect is still for the unrelated variety for environmental technologies which is consistent with our previous results. However, the estimates for their spatial lagged counterparts are non-significant. These results suggest two main facts. First, important spatial dynamics across French departments exist on the creation of new eco-innovative firms, but they are mainly explained by the development of these technological activities in neighbouring regions. Second, the development of a diverse but specialised local knowledge base on environmental technologies is a relevant factor for the creation of these activities.

6. Discussion and conclusions

[12] The baseline models were also run using ordinary least squares (OLS) panel model with fixed effects in order to apply the tests for spatial autocorrelation. Results were confirmed and are available upon request.

This paper contributes to the literature on the relationship between local features and new firm formation by analysing the location determinants of new eco-innovative firms in the 96 French metropolitan departments over the period 2003-2013. In particular, we study the role played by the features of the local knowledge base on the creation of new eco-innovative firms as well as the spatial dependence on this process by computing specific knowledge indicators of relatedness and variety for environmental technologies.

Main results show that the level of local knowledge stock is not enough to explain a higher likelihood of eco-innovative firms' entry. In this direction, we found that unrelated knowledge variety for environmental technologies and the political support in terms of investments for the protection of the environment are the most important factors explaining the location of eco-innovative firms. When accounting for spatial dependence in our model, we found that the creation of eco-innovative firms in neighbouring departments may incentive the eco-innovative entry in the local department. Finally, the effects of the accumulated stock, relatedness and variety are more appreciable when spatial dependence is accounted for.

In terms of previous empirical contributions, on the one hand, these results are in line with previous findings and support the fact that the entry of environmental technology-based firms is clearly associated with the available knowledge in unrelated domains in the region (Barbieri et al. 2018; Barbieri and Consoli 2019; Quatraro and Scandura 2019). On the other hand, they do not corroborate those contributions finding a significant effect of relatedness and related variety on the entry of eco-innovative firms (Colombelli and Quatraro 2019; Corradini 2019) in their works for all European and Italian regions. In fact, the greater significance of unrelated variety for environmental technologies suggests that due to the specific nature of environmental technologies they may require a greater recombination of different pieces of knowledge that are cognitively distant, compared to non-environmental technologies (Orsatti et al. 2017; Quatraro and Scandura 2019). Indeed, the results of this paper also support and confirm those contributions suggesting the role of spatial dependence in the creation of environmental innovations (Tanner 2014, 2015; Corradini 2019; Quatraro and Scandura 2019).

Such results have important policy implications in terms of innovation and environmental policies. First, the significant and robust effect of unrelated variety for environmental technologies on eco-innovative firms' entry suggests that policies should account for the specific interdependencies of environmental technologies with other technologies rather than pursuing competitive advantage through the specialisation in the environmental domain. Second, our results highlight the importance of the environmental political support. In this regard, the set up of policies aiming to regulate environmental performance and to promote the environmental sensitiveness of local population may encourage eco-innovative firm entry. Finally, the positive neighbouring effect in terms of entrepreneurial dynamics in environmental technologies appears to be consistent with the idea behind the current French policy giving support to eco-innovative entrepreneurship at regional level (ADEME 2018). However, given that the spatial scope of knowledge indicators is quite local, the effectiveness of policies aimed at enhancing knowledge spillovers for environmental technologies should carefully assess the local specificities rather than be designed at a regional or national level. These implications are consistent with the smart specialisation strategies highlighting the importance of the path-dependent process of accumulation of local knowledge promoted by the European Union over the last years.

Despite all this, this study does have some limitations. By relying on patents data to capture eco-innovative firms' entry we are not able to encompass the whole set of firms that innovate in the environmental domain since not all innovative firms may be able to apply for patents. Nevertheless, with this approach we are able to focus on the most technological-intensive firms operating in the environmental domain. In this this regard, the use of survey data on entrepreneurs working on the environmental domain would provide additional evidence to support our findings. Furthermore, even the analysis at regional level provides remarkable results in terms of policy implications, any future research should focus on analysing this issue at more local scale in order to account for the impact of local innovation ecosystems on the creation of eco-innovative firms.

Appendix A. The implementation of knowledge spillovers[13]

a. Knowledge stock

To measure the local knowledge stock (STOCK_ALL) based on patent applications we calculate the cumulated stock of past patent applications applying the permanent inventory method as follows:

$$STOCK\_ALL_{it} = h_{it} + (1-\delta)STOCK_{it-1} \qquad \text{(A0)}$$

where h_{it} is the flow of patent applications, δ is the rate of obsolescence of 10%[14], i is the region and t is the time period. This measure has also been calculated for both non-environmental (STOCK_NENV) and environmental technologies (STOCK_ENV).

b. Knowledge variety

Our measure of knowledge variety is based on the information entropy index by following a multidimensional approach.[15] Unlike previous studies using one-dimensional entropy (Frenken et al. 2007), the analysis based on co-occurrences of technological classes allows us to identify the degree of variety of knowledge combinations (Colombelli and Quatraro 2018). Indeed, as we argued in Section 2 and 3, we focus on the association of environmental technologies with other technologies. In that way, we are able to capture the degree of diversity of the local knowledge base in terms of eco-innovations that cannot be appreciated when using the traditional knowledge indicators as we argued in Section 2 and 3.

Let us consider a pair of events (X_l, Y_l), and the probability of their co-occurrence p_{ij}. A two-dimensional total variety (*KV_Y*) measure can be expressed as follows:

$$KV\_Y = H(X,Y) = \sum_l \sum_j p_{ij} log_2(\frac{1}{p_{ij}}) \qquad \text{(A1)}$$

Let the events X_l *and* Y_l be citations in a patent document of technological classes *l* and *k*, respectively. Then, p_{ij} is the probability that two technological classes *l* and *k* co-occur within the same patent. The measure of multidimensional entropy focuses on the variety of co-occurrences

[13] This section builds on Quattraro (2010) and Colombelli and Quattraro (2017; 2019).

[14] See Soete and Patel (1985) for similar approaches. Alternative rates of obsolescence have been applied with no significant variations on the final calculations.

[15] See Saviotti (1988), Frenken and Nuvolari (2004) and Stirling (2007) for further details on the definition and properties of this index.

or pairs of technological classes in patent applications, and provides an index of how much the creation of new knowledge is focused in a narrower set of possible combinations.

The total index can be decomposed into 'within' and 'between' parts, whenever the events under study can be aggregated into smaller number of subsets. Within-group entropy measures the average degree of variety within the subsets; between-group entropy focuses on the subsets and measures the average degree of variety across them.

Let the technologies *i* and *j* belong to the subsets *g* and *z* of the classification scheme, respectively. If one allows $l \in S_g$ and $j \in S_z$, it is possible to write:

$$P_{gz} = \sum_{l \in S_g} \sum_{j \in S_z} p_{ij} \tag{A2}$$

Which is the probability of observing the couple lj in the subsets *g* and *z*, while the intra subsets variety can be measured as follows:

$$H_{gz} = \sum_{l \in S_g} \sum_{j \in S_z} \frac{p_{ij}}{P_{gz}} log_2\left(\frac{1}{p_{ij}/P_{gz}}\right) \tag{A3}$$

The weighted within-group entropy or related variety (*RKV_Y*) can therefore be written as follows:

$$RKV\_Y = \sum_{g=1}^{G} \sum_{z=1}^{Z} P_{gz} \tag{A4}$$

Between group or unrelated variety (*UKV_Y*) can instead be calculated using the following equation:

$$UKV\_Y \equiv H_Q = \sum_{g=1}^{G} \sum_{z=1}^{Z} P_{gz}\, log_2\left(\frac{1}{P_{gz}}\right) \tag{A5}$$

According to the decomposition theorem, the total entropy H(X,Y) can be re-written as follows:

$$KV\_Y = H_Q + \sum_{g=1}^{G} \sum_{z=1}^{Z} P_{gz} H_{gz} \tag{A6}$$

The first term on the right-hand-side of Eq. (A6) is the between-entropy and the second term is the weighted within entropy. Concretely, *RKV_Y* measures the degree of technological differentiation within the macro-field or, in other words, the average variety within the technological classes belonging to the Environmental class. *UKV_Y* measures the degree of technological differentiation across macro-fields, that is the average variety between environmental technologies class with the other subsets of technologies.

c. *Knowledge coherence or relatedness*

To account for the degree of complementarity among the technological classes composing the local patent's portfolio we have calculated the coherence of the 96 French Departments (Nesta and Saviotti 2006; Nesta 2008; Quatraro 2010). This measure is calculated in different steps.
Following Teece et al. (1994), the weighted average relatedness (WAR_l) is defined as the degree to which technology l is related to all other technologies $j \neq l$ in the regions'patent portfolio, weighted by patent count P_{jt}.

$$WAR_{lt} = \frac{\sum_{j \neq l} \tau_{lj} P_{jt}}{\sum_{j \neq l} P_{jt}} \qquad \text{(A7)}$$

Finally, the coherence of the region's knowledge base at time t is defined as the weighted average of the WAR_{lt} measure:

$$COH_t = \sum_l WAR_{lt} \times \frac{P_{lt}}{\sum_l P_{lt}} \qquad \text{(A8)}$$

This index is computed by analysing the co-occurrence of technological classes within patent applications, it measures the degree of complementariety of the co-occurring technologies, and it is based on how frequently technological classes are combined in used.
The technological relatedness measure τ_{lj} indicates that the utilisation of technology l also implies the use of technology j, in order to perform specific functions that are not reducible to their independent use.
To set the τ parameter first we built a relatedness matrix as follows (Nesta, 2008). Let the technological universe consist of k patent applications. Let $P_{jk} = 1$, if the patent k is assigned to technology j $[j = 1, \ldots, n]$, and 0 otherwise. The total number of patents assigned to technology j is $O_j = \sum_k P_{jk}$. Similarly, the total number of patents assigned to technology m is $O_m = \sum_m P_{mk}$. Since two technologies may be present within the same patent, $O_j \cap O_m \neq \emptyset$, the number of observed co-occurrences of technologies j and m is $J_{jm} = \sum_k P_{jk} P_{mk}$. By applying this relationship to all the possible pairs, we obtain a square matrix Ω $(n \times n)$ where the generic cell is the observed number of co-occurrences:

$$\Omega = \begin{pmatrix} J_{11} & \cdots & J_{n1} \\ \vdots & \ddots & \vdots \\ J_{1n} & \cdots & J_{nn} \end{pmatrix} \qquad \text{(A9)}$$

We can assume that the number x_{jm} of patents assigned to both the j and m technologies is a hypergeometric random mean and variance variable:

$$\mu_{jm} = E\left(X_{jm} = x\right) = \frac{O_j O_m}{K} \qquad \text{(A10)}$$

$$\sigma_{jm}^2 = \mu_{jm} \left(\frac{K - O_j}{K}\right) \left(\frac{K - O_m}{K - 1}\right) \qquad \text{(A11)}$$

If the observed number of co-occurrences J_{jm} is larger than the expected number of random co-occurrences μ_{jm}, then the two technologies are closely related: the fact that the two technologies occur together in the number of patents x_{jm} is not random. Thus, the measure of relatedness is given by the difference between the observed and the expected number of co-occurrences, weighted by their standard deviation:

$$\tau_{jm} = \frac{J_{jm} - \mu_{jm}}{\sigma_{jm}} \qquad \text{(A12)}$$

It should be noted that this measure of relatedness has lower and upper bounds: $\tau_{jm} \in]-\infty; +\infty[$. Moreover, the index shows a similar distribution to a t-student distribution; so, if $\tau_{jm} \in]-1.96; +1.96[$, one can assume the null hypothesis of non-relatedness of the and technologies. Therefore, the technological relatedness matrix Ω can be considered a weighting scheme to evaluate the technological portfolio of regions.

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Tables

Table 1. Summary Statistics

Variable	Description	Source	Obs.	Mean	Std. Dev.	Min.	Max.
ECO_ENTRY	Eco-innovative entry	Own elaboration (DIANE & OECD REGPAT 2018)	1056	0.055	0.228	0.000	1.000
UNEMP	Unemployment Rate at 31st December (%)	Eurostat	1056	8.366	1.766	4.000	14.800
POP_DEN	Inhabitants per Km^2	Eurostat	1056	551.129	2420.114	14.600	21317.9
SCITECH	Share of persons with tertiary education and employed in Science and Technology.	Eurostat	1056	0.177	0.037	0.086	0.276
DIST_PARIS	Distance to Paris from the capital of the Department in minutes	Own elaboration	1056	4.395	2.751	0.000	15.580
ECO_INVEST	Total amount of investments for the protection of the environment (millions euros)	Eurostat	1056	16.598	18.109	0.000	139.799
VOTE_ECO	Share of votes for the ecological party in the 2002, 2007 and 2012 French national elections.	French Government	1056	0.925	0.645	0.000	2.940
STOCK_ALL	Department-level stock of patents	Own elaboration (OECD REGPAT 2018)	1056	1009.875	3977.194	0.000	37493.84
STOCK_ENV	Department-level stock of patents in environmental technologies	Own elaboration (OECD REGPAT 2018)	1056	95.580	375.473	0.000	3420.506
STOCK_NENV	Department-level stock of patents in non-environmental technologies	Own elaboration (OECD REGPAT 2018)	1056	914.295	3604.062	0.000	34073.33
COH	Knowledge coherence	Own elaboration (OECD REGPAT 2018)	1056	-0.314	0.371	-2.810	0.959
KV_Y	Knowledge variety (entropy index) only for environmental technologies	Own elaboration (OECD REGPAT 2018)	1056	0.144	0.211	0.000	2.000
RKV_Y	Related knowledge variety only for environmental technologies	Own elaboration (OECD REGPAT 2018)	1056	0.038	0.114	0.000	2.000
UKV_Y	Unrelated knowledge variety only for environmental technologies	Own elaboration (OECD REGPAT 2018)	1056	0.106	0.127	0.000	0.531

Table 2. GLM logit regression estimates

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Socioeconomic factors	POP_DEN	-	-	-	0.013**	0.013**	0.013**	0.013**	0.013**
					(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
	UNEMP	-1.804***	-1.829***	-1.801***	-1.559***	-1.594***	-1.572***	-1.613***	-1.679***
		(0.578)	(0.588)	(0.576)	(0.542)	(0.542)	(0.544)	(0.554)	(0.526)
	SCITECH	-3.049	-3.234	-3.029	-2.213	-2.308	-1.644	-1.038	-1.438
		(11.51)	(11.56)	(11.50)	(11.42)	(11.39)	(11.48)	(11.50)	(11.32)
	DIST_PARIS	0.577***	0.578***	0.578**	0.602**	0.608	0.612***	0.628***	0.637**
		(0.217)	(0.202)	(0.232)	(0.247)	(0.187)	(0.142)	(0.171)	(0.324)
Environmental political support	ECO_INVEST	0.030*	0.029*	0.030*	0.037**	0.037**	0.037**	0.038**	0.037**
		(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
	VOTE_ECO	0.745	0.734	0.747	0.744	0.765	0.758	0.789	0.806*
		(0.482)	(0.482)	(0.482)	(0.486)	(0.489)	(0.482)	(0.483)	(0.479)
Knowledge indicators	STOCK_ALL	0.000	-	-	-	-	-	-	-
		(0.000)							
	STOCK_ENV	-	0.001	-	-	-	-	-	-
			(0.002)						
	STOCK_NENV	-	-	0.0002	-	-	-	-	-
				(0.0003)					
	KV_Y	-	-	-	1.008	-	-	-	-
					(0.764)				
	RKV_Y	-	-	-	-	1.171	-	-1.117	-
						(1.423)		(1.890)	
	UKV_Y	-	-	-	-	-	2.211*	2.928*	-
							(1.342)	(1.684)	
	COH	-	-	-	-	-	-	-	0.241
									(0.790)
	Constant	-14.84***	-13.87***	-14.87***	-17.72***	-17.50	-17.89	-17.93***	-17.32***
		(2.604)	(2.632)	(1.380)	(3.066)	(2.975)	(2.017)	(1.974)	(3.834)
N		960	960	960	960	960	960	960	960
Departments		96	96	96	96	96	96	96	96
Time and Department FE		Y	Y	Y	Y	Y	Y	Y	Y
Log-pseudolikelihood		-147.236	-147.266	-147.082	-145.666	-146.104	-145.313	-145.202	-146.314

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Spatial Durbin Model Estimates

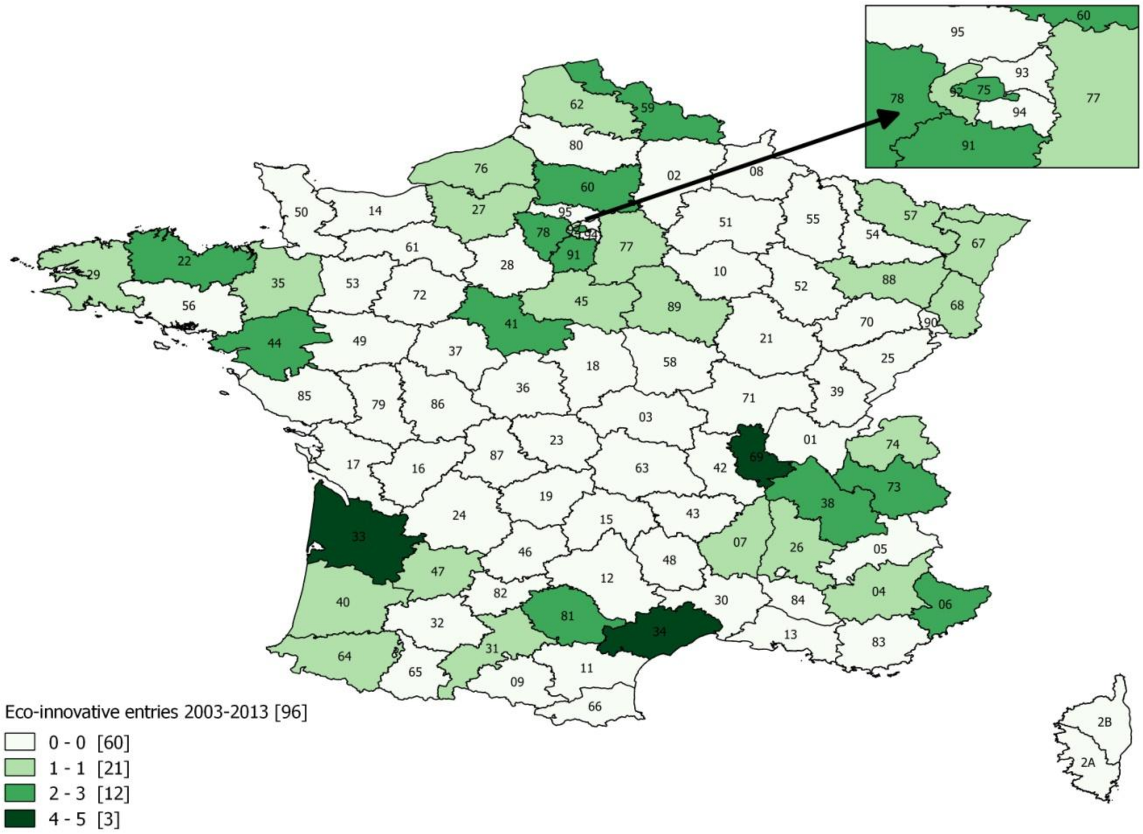
DEP. VAR. : ECO_ENTRY	(1)	(2)	(3)	(4)	(5)	(6)	(7)
W_ECO_ENTRY	0.073	0.073	0.073	0.084*	0.084*	0.082*	0.08*
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
POP_DEN	-	-	-	0.001***	0.001***	0.001***	0.001***
				(0.000)	(0.001)	(0.01)	(0.000)
UNEMP	0.017*	0.017*	0.017*	0.015	0.015	0.015	0.014
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
SCITECH	0.154	0.138	0.158	0.102	0.154	0.133	0.233
	(0.336)	(0.336)	(0.336)	(0.339)	(0.339)	(0.339)	(0.34)
DIST_PARIS	-	-	-	-	-	-	-
ECO_INVEST	0.002*	0.002*	0.002*	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
VOTE_ECO	0.037	0.037	0.036	0.032	0.028	0.032	0.025
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
STOCK_ALL	0.000***	-	-	-	-	-	-
	(0.000)						
STOCK_ENV	-	0.0008***	-	-	-	-	-
		(0.0001)					
STOCK_NENV	-	-	0.000***	-	-	-	-
			(0.000)				
KV_Y	-	-	-	0.132***	-	-	-
				(0.000)			
RKV_Y	-	-	-	-	0.182**	-	-
					(0.062)		
UKV_Y	-	-	-	-	-	0.208***	-
						(0.061)	
COH	-	-	-	-	-	-	0.024
							(0.028)
WX[16]	0.000	0.000	0.000	-0.092	-0.149	-0.134	-0.032
	(0.000)	(0.000)	(0.000)	(0.066)	(0.116)	(0.114)	(0.042)
N	960	960	960	960	960	960	960
Time FE	Y	Y	Y	Y	Y	Y	Y
Department FE	Y	Y	Y	Y	Y	Y	Y
F-Test	1.469**	1.469**	1.469**	1.309**	1.349**	1.327**	1.408***

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

[16] WX refers to the spatial lagged variable for each of the key knowledge variable introduced in each of the specifications. Concretely, STOCK_SH_ALL, STOCK_SH_ENV, STOCK_SH_NENV, KV, RKV, UKV, KV_Y, RKV_Y, UKV_Y and COH variables.

Figures

Figure 1. Geographical distribution of eco-innovative firms' entry (2003-2013)



Source: Authors with DIANE and OECD REGPAT 2018 data