Measuring the effects of "green" innovations on the productivity of European regions

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ABSTRACT

Environmental innovation is considered one of the key drivers of sustainable development and economic growth. However, we still know very little about the organizational factors underling the development of this category of innovations and their relative competitive effect. In this paper, we focus on regions and we look at the specific effect of environment-related technologies and collaborative environmental inventions on the competitiveness of European regions. In fact, the complex and multidisciplinary nature of environmental innovation is expected to further strengthen the competitive advantage of regions and the strategic significance of geographical proximity. A longitudinal study of 232 European regions over the period 2000-2013 was organized using data from the RegPat, Cambridge Econometrics and Eurostat databases. Our main results confirm the positive effect of environment-related technologies and local collaborative networks on regional competitiveness with significant implications in terms of policy making.

Keywords: Green Innovation, Environment-related technologies, Clean technologies, Regional productivity

1 INTRODUCTION

Environmental innovation is receiving increasing attention form scholars and policy makers as key driver in the development of a greener and more competitive economy. The term environmental is used to classify innovation with a positive effect on the environment (Kemp et al., 2001; Beise and Rennings, 2005; Kemp 2010). Therefore, it is the effect rather than the content that defines an innovation as green. Due to its unspecific character with respect to the content of the innovation, large part of the literature on innovation has either overlooked the concept or have focused on the policy issues related to the adoption of this kind of innovations (De Marchi, 2012). In fact, differently from other types of innovations, whose effect can be directly appropriated by users, environmental innovation generate value for society as whole. Therefore, users side externalities are expected to further slowdown the adoption of this kind of innovation. Differently, little attention has been given to the process through which these innovations are developed, the resources and competences that contribute to their development, and the competitive effect of those innovations. This paper attempts to cover part of this gap by focusing on environmental innovation in regions.

There is an extensive literature highlighting that innovation is not uniformly distributed across regions and geographical proximity matters (Asheim, et al. 2011). This literature has highlighted several factors that contribute to explain the geographical advantage of some regions compare to others. Recent literature pointed out two factors that seem to matter the most in shaping the competitiveness of regions. Those are related variety (Frenken et al. 2007; Asheim, et al. 2011) and collaborative capacity (De Noni et al., 2017; De Noni et al., 2018; Sun and Cao, 2015). Both affect the extension and thickness of knowledge spill-overs and knowledge exchanges both within and across sectors as major drivers of the innovative capacity and competitiveness of a regions. Those factors are also expected to play a significant role in strengthening the capacity to generate environmental innovation. This is because environmental innovation is both complex and multidisciplinary (De Marchi, 2012; Roscoe et al. 2016). Therefore, leveraging on related variety and collaborative capacity, environmental innovation is expected to further strengthen to the competitiveness of regions and the significance of geographical proximity as distinctive source of competitive advantage. Therefore, our objective with this paper is to test whether and to which extent environmental innovation and collaborative environmental innovation strengthen the competitiveness of regions and the significance of geographical proximity as distinctive source of competitive advantage.

To achieve this objective, we apply panel regressions with time and regional effects using generalized estimating equations on a 11-year dataset of 232 European regions. The OECD RegPat database is used for measuring environment-related technologies and collaborative networks. Cambridge Econometrics data are used to operationalize our dependent variable - regional competitiveness and data from Eurostat are further collected to define the control variables more widely assumed by the literature on innovation.

Our results confirm that environmental innovation contribute to strengthen the competitiveness of regions. Furthermore, we also show that geographical proximity plays as significant as intraregional collaborative environmental innovation positively contribute to the competitiveness of regions. Differently, extra-territorial forms of collaboration negatively impact on the added value generated by the regions. These results, as we shall see, have significant implications in terms of policy making. First, they highlight that much of the externalities generated by environmental innovation are internalized at regional level. Second, they suggest that environmental innovation may widen the competitive gap between competitive regions and lagging beyond regions.

The structure of the paper is indeed the following. In the next section, we review the literature and we build up our main theoretical arguments. This section ends up with our main hypotheses. In section 3, we discuss methodology. Section 4 presents our results. Finally, the last section discusses the main results and their relative implications and provide some directions for further research.

2 BACKGROUND LITERATURE AND THEORY BUILDING

There is extensive literature looking at effect of spatial agglomeration on innovation and regional growth (Asheim, 2016). Central to this literature is the concept of agglomeration economies, which can be roughly translated into economies from which a firm can benefit from being located as the same place as one or more other firms. Three sources of agglomeration economies have been emphasized in this literature: localization economies, urbanization economies, and Jacobs externalities (Frenken et al. 2007). Localization economies refers to Marshallian externalities, which, in turn, are related to spatial specialization. Therefore, these advantages are associated to the co-localization of firms of the same industry and indeed sharing a common technological specialization: labour market pooling; the creation of specialized supplier, and the emergence of knowledge spill-overs. Urbanization economies are external economies that firms absorb from being localized into highly and densely populated locations, such as and most important deriving from the access to highly qualified knowledge infrastructures. Finally, Jacobs externalities are positive externalities associated to the interaction between firms with a different technological specialization. Therefore, according to this latter view, variety may be an additional source of knowledge spill-over, innovation, and indeed regional growth. However, as recent literature points out, it is not sufficient to be diversified to stimulate the spill-over and recombination of knowledge across sectors, but some degree of relatedness is also required (Frenken et al. 2007; Van Oort eta al., 2014; Aarstad et al., 2016). This is because the cost of establishing connection, sharing and combining knowledge across unrelated sectors are too high (Nooteboom et al. 2007). Therefore, it is not the variety per se that contribute to regional growth, but the relatedness between sectors.

The concept of related variety highlights that geographical proximity per se is not sufficient to sustain interactive and collective learning and innovation. Differently, as suggested by Boshma (2005), the concept of geographical proximity should always be examined in relation to other dimensions of proximity that may provide alternative solutions to the problem of coordination and further stimulate the process of interactive learning. In particular, high relevance is placed to the concepts of social proximity and collaboration. The term social proximity defines the extent which actors are socially connected with each other in a system. Therefore, in the case of regional systems, the extents to which people in the region are socially connected with each other. Social connectivity is important for two reasons. First, it further strengthens knowledge spill overs across sectors. Even if knowledge spill-overs may be the outcome of mutual observation. Therefore, in theory, they may not require any social relations. Knowledge spill-overs may be the result of the informal and unintentional exchange of information, such as in the case of small talks around a table. Therefore, in this case, social connectivity enhances the likelihood information about relevant innovations is spread locally. Therefore, it strengths the intensity of knowledge spill-over both across and within sectors. Second, social connectivity is also and especially important to produce trust and support collaboration. Innovation is not only the result of knowledge spill-overs. Most often, it involves the intentional exchange and combination of knowledge, which, to be possible and successful, requires mutual trust. Therefore, social connectivity strengthens innovation and regional growth by improving the efficiency of people and firms in sharing valuable knowledge through collaboration and mutual trust (De Noni et al., 2017; Sun and Cao, 2015).

The objective of this paper is to investigate whether and to which extent environmental innovation contributes to strength regional competitiveness and indeed regional growth. There are two reasons why this might be the case. First, there is increasing interest and demand for innovative solutions to the so-called environmental problem. Second, environmental innovations are often path breaking, and high impact innovations (Coenen et al. 2015; Haščič, and Migotto, 2015)). Therefore, with a high added value in terms of economic returns. However, understanding whether environmental innovation may strengthen the competitive advantage of regions requires developing a better understanding of what environmental innovation means and how the peculiarities characterizing this form of innovation interact with the factors shaping regional competitiveness.

The term environmental, green, sustainable, or eco-innovation is used to characterize products, services, or processes whose effect is to reduce or avoid environmental harms (De Marchi, 2012; Kemp et al., 2001; Beise and Rennings, 2005; Kemp 2010). Therefore, it is the effect and not the content that define innovation as environmental. Furthermore, it is not the initial intent nor its radical or incremental character that define innovation as environmental. Even if there are not substantial differences, if not for the effect, characterizing innovation as environmental, the literature has already highlighted a number of specificities that makes environmental innovation as peculiar to other forms of innovation worth to study separately. First, environmental innovation is subjected to the double externality problem (Ghisetti & Rennings, 2014). Rennings, 2000; Jaffe et al., 2005). Innovation generate positive externality as firms can only partially appropriate the value of their innovation. However, in case of environmental innovation, positive externalities are even stronger because environmental innovation, to be called as such, create social value, which can only be shared, but not entirely appropriated by the innovator. Therefore, the incentives for firms to invest in environmental innovation are even weaker and the importance of policy intervention even stronger.

The literature of environmental innovation has mainly con concentrated on the policy issues. However, there are other aspects, which are typical of environmental innovation, that have been overlooked in the literature (; Cainelli et al., 2015; De Marchi, 2012; Andersen, 1999, 2002; Foxon and Andersen, 2009).. These are the complex and multidisciplinary nature of environmental innovation. Environmental innovation is complex because is often the emergent result of the interaction between different functions and developmental trends. The typical example is that of the electric car. Reducing the environmental impact of cars through the introduction of the electric car is not sufficient to develop small sized and efficient batteries, it is also necessary to organize a widespread and efficient recharging infrastructure and adopt clean method of energy production. Therefore, collaborative capacity is strategic in the development of environmental innovation. Environmental innovation is multidisciplinary because it requires integrating the know-how available in different sectors and technological fields. For instance, in the development of the smart grids are integrated competence related to the fields of ICT, electronic and mechanical engineering, statistics and physics. Therefore, the availability of diversified, but related, competence is key resource in the development of environmental innovation. Therefore, given the factors contributing the most regional competitiveness and those required to create environmental innovation, we expect that development of environmental innovation at regional level may further strengthen the capacity of regions to leverage on those resources with positive effect for their competitiveness. Therefore, the following hypotheses should hold:

H1: The more a region produces environmental-related innovation the greater its competitive advantage;

H2: The more a region produces collaborative environmental-related innovation the greater its competitive advantage.

3 METHODOLOGY

3.1 Setting and Data

The interest of policymakers in the development and diffusion of environment-related technologies (env-tech) is motivated by their potential to render environmental policies more effective and more cost-efficient. Some governments are also motivated by the goal of creating new products, business opportunities and markets, and thereby accelerating the transition to "green" growth (Haščič and Migotto, 2015). Thus, the aim of this research is to explore the role of env-techs and collaboration in -technologies on the productivity and competitiveness of European regions. First, we have to define environmental technologies. For these reasons, patent data are best suited for identifying specifically environment-related technologies. This identification has been conducted through a search based on the Cooperative Patent Classification (CPC). The CPC system is an extension of the International Patent Classification (IPC) provided by the World Intellectual Patent Office (WIPO) and it has over 200,000 technology classes. CPC, introduced in 2013, is the result of a partnership between the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO) in their mutual effort to develop a common, internationally compatible classification scheme for technical documents, in particular patent publications (Haščič and Migotto, 2015). Consequently, patent data allow very specific "environmental" technologies to be recognized. The search strategies presented in this paper rely on the CPCY02 classes to the extent possible. This is because the Y02 scheme allows selected climate change mitigation technologies to be identified even by non-specialists. The Y02 scheme contains several sets of environment-related technologies including those directed at (a) the traditional domains of environmental management (air and water pollution, waste disposal, etc.) as well as those directed at (b) adaptation to water scarcity, (c) addressing biodiversity threats and (d) mitigating climate change (energy, greenhouse gases, transport, buildings). These sets of env-techs are directed at four major environmental policy objectives, including human health impacts of environmental pollution, addressing water scarcity, ecosystem health, and climate change mitigation.

Finally, the fractionalized number of environment-related patents per region r and per year t are counted as the sum of inventors' shares weighted for regional share, as follows:

$$Number\ of\ eco-patents_{r,t} = \sum_{r,t}\sum_{i} Inv_{share} * Reg_{share}$$

where Inv_{share} is the share that inventor i is involved in the environment-related patent creation and Reg_{share} is the regional share, if inventor i is registered in different regions1 (De Noni et al. 2017; De Noni et al. 2018). Second, env-tech collaboration is defined as collaborative network of inventors involved in the creation of environment-related technologies and measured through co-patenting activities by using data about patents granted by the European Patent Office (EPO) and relative inventors per year and region, as provided by the OECD-RegPat database (release version February 20162).

Patents in environment-related technologies represent only a small portion of the overall patenting activity in Europe, but environment-related patents and env-tech collaboration are increasing their importance over the years (see Figure 1).

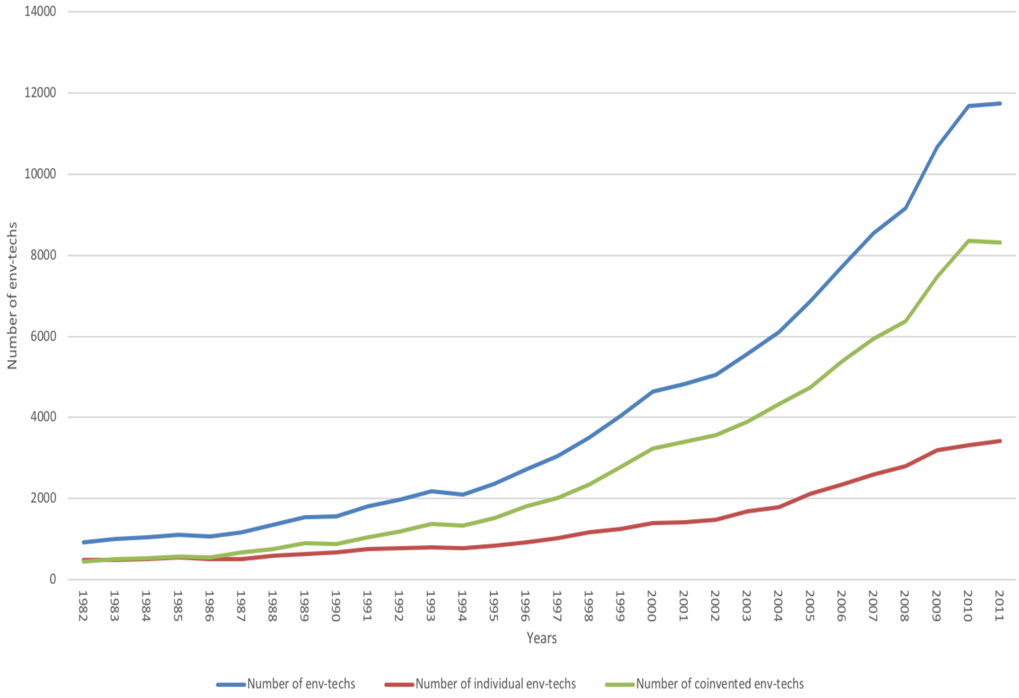

Figure 1: Distribution of environment-related technologies and env-tech collaboration in Europe over time

Due to missingness of data related to control variables and the operationalization of the dependent variable, our final sample involves 232 (starting from 284) regions in 29 countries (European Union plus Norway). NUTS2 (Nomenclature of Territorial Units for Statistics) is used to define the regional level. Data from Eurostat were further collected in order to define some typical control variables, such as R&D expenditures or human capital and. Finally, data from Cambridge Econometrics are used to operationalize our dependent variable - regional competitiveness. Cambridge Econometrics maintains the European Regional Database. It provides a complete and consistent, historical time series of data for the period 1980-2015. With regional (NUTS 2 and 3) and sectoral disaggregation, it offers a unique database relevant to academic, policy and trend analysis. The final panel dataset covers the time period from 2000 to 2013. Therefore, because of these variables' structure, the number of time series in the panel dataset is limited to T=11.

3.2 Variables

Dependent variable

[1] *Reg_share* and *Inv_share* are directly provided by the RegPat database. *Reg_share* is less than 1 if the inventor has multiple address registrations due to his mobility across regions. *Inv_share* is less than 1 when the patent is co-invented. If a patent application has more than one inventor, it is equally fractionalized based on the number of inventors.

[2] Regional Patent Data provided by OECD RegPat are updated at the end of 2011.

Regional industry GVA growth. Gross value added (GVA) is an indicator of the economic activity of a country or a region. It reflects the total value of all goods and services produced less the value of goods and services used for intermediate consumption in their production. To operationalize our dependent variable, we used the industry GVA provided by Cambridge Econometrics mainly as technological innovations have a direct impact on the industrial sector (Antonioli et al. 2016). We calculated the growth of GVA as a measure of regional productivity and competitiveness as the compound annual growth rate (CAGR) in a 3-year time moving window to capture for short/medium term trends[3] starting from the year 2001[4].

Exploratory variables

Env-tech diffusion. We used the fractionalized number of environmental-related patents generated in a region calculated as the number of env-techs generated in a region weighted by the number of inventor of the same region as a proxy of the regional capacity to produce new technological knowledge related to green and clean technologies. Higher is this capacity higher should be the ability of a region to create new "clean products" with higher mark ups or new and efficient processes to reduce energy costs, waste and pollution.

Env-tech collaboration propensity. In the patenting process, the number of collaborative links among inventors within and across regions is a proxy for regional connectivity capacity. Specifically, since technological flows among firms and inventors are favored by geographical and cultural proximity (Sun, 2016), we distinguished in three different variables 1) Env-tech local collaboration propensity as the number of env-techs involving more inventors within the same European region divided by the total number of regional env-techs, 2) Env-tech national collaboration propensity as the number of env-techs involving more inventors from different regions but within the same European country divided by the total number of regional env-techs, and 3) Env-tech international collaboration propensity as the number of env-techs involving more inventors from different regions and different European countries divided by the total number of regional env-techs.

Control variables

Gross value added. We used the level of industry GVA at time t-1 of a region as control for the value added CAGR because higher starting levels of value added may negatively influence the regional ability to continuously increase the growth in the following periods.

R&D expenditures. Research & Development (R&D) intensity is expected to have a positive impact on the productivity and competitiveness of regions and countries because of the positive relation existing between technological input and output (Gilsing et al., 2008; Castaldi et al., 2015). We operationalized R&D expenditures as Gross domestic expenditure on R&D as a percentage of gross domestic product is an indicator of the capacity to invest in the creation and production of new knowledge at the EU, national and regional levels.

Human capital. Since the attitude of a region to produce, innovate and compete may depend on the average level of human capital within the local economy (Lee et al. 2010), we used tertiary educational attainment as a proxy for human capital. The higher the educational level, the higher the potentiality of a region to generate new knowledge, produce more and compete in an effective way. This indicator, provided by Eurostat, is specifically based on the EU Labour Force Survey. It is defined as the percentage of the population aged 25-64 who have successfully completed tertiary studies.

Population density. Externalities related to the urbanization processes are proxied by population density (Mameli et al. 2012). Generally, urbanization is positively correlated with the presence of industry research laboratories, schools, associations and other knowledge-generating organizations

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[3] We also used a 5-year time moving window but the results are qualitatively similar.

[4] Thus, the first 3-year moving window is related to the period 2001-2003, the second to the period 2002-2004 until the last window 2011-2013.

(Frenken et al. 2007). Thus, urban economies may better support manufacturing productivity than non-urban economies.

Employment rate. Employment rates are defined as a measure of the extent to which available labour resources (people available to work) are being used. They are calculated as the ratio of the employed to the working age population. Despite the potential established through human capital, the regional capability to produce and compete also depends on the employees' skills and abilities, in particular their areas of competence and their creativity. We Expect that higher rate of employment should lead to higher productivity performances.

Year. Because we want to remove the influence of time trends over the study period, we controlled for the effect of all unobserved factors due to macroeconomic trends, financial crises and other factors that might affect the industry productivity by including dummies for each year of the study period into the model.

Regions. To capture time invariant country-specific effects, we included dummies for each region of the study into the model.

3.3 Model estimation

Our dependent variable measures regional productivity by computing the industry GVA growth generated by a region in a given year. Because the dependent variable - GVA growth - can take on continuous values, a Gaussian specification is recommended.

Thus, we used the following formula:

$$VGA\ CAGR_{i,t(0,1,2)} = a_i + \beta_1(Eco\ technology\ diffusion_{i,t-1}) + \beta_2(Eco\ technology\ local\ collaboration\ propensity_{i,t-1}) + \beta_3(Eco\ technology\ national\ collaboration\ propensity_{i,t-1}) + \beta_4(Eco\ technology\ international\ collaboration\ propensity_{i,t-1}) + \beta_5(GVA_{i,t-1}) + \beta_6(R\&D\ expenditures_{i,t-1}) + \beta_7(Human\ capital_{i,t-1}) + \beta_7(Population\ density_{i,t-1}) + \beta_7(Employment\ rate_{i,t-1}) + \beta_7(Year\ dummies) + \beta_7(Region\ dummies) + \varepsilon_{i,t}$$

We estimated the regression models using the generalized estimating equations (GEE) to control for heterogeneity at the regional level and the existence of any systematic difference across regions due to unobserved effects.

This methodology allows for correlation in the dependent variable across observations over time due to repeated yearly measurements by estimating the correlation structure of the error terms (Liang and Zeger, 1986). A good starting point is to choose the correlation structure that makes sense given the nature of the data. Because these are repeated measures data, an exchangeable or an autoregressive (AR(1)) structure are good choices. However, this method is robust in the sense that using it allows one to draw correct inferences from the data even if the correlation model was incorrectly specified.

We ran the model by imposing an exchangeable correlation structure, which assumes that each pair of observations in a group has the same correlation across time. We also used an AR(1) assuming the correlations between repeated measurements of the dependent variable decline from period to period, but found the results to be qualitatively similar to those reported in this paper. We report significance levels using Huber-White robust standard errors to control for any residual heteroscedasticity across panels. We obtained our results using the "geepack" package in R[5] (version 3.5.0).

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[5] R is an open source software environment for statistical computing and graphics.

4 RESULTS

Table 1 presents the results of descriptive statistics and the correlation matrix for all variables used in the regression models. The correlation values are relatively low under the cut-off point of 0.50 (O'Brien 2007). The only exception is the correlation between local collaboration propensity and national collaboration propensity. For this reason, we entered separately these explanatory variables in the regression models to avoid any kind of bias due to multicollinearity among explanatory regressors. Moreover, we checked for the existence of multicollinearity by computing the variance inflation factors (VIFs) and found multicollinearity is not a problem, as the VIFs are well below the suggested cut-off value of 5 (O'Brien 2007).

In Figure 1, we present the distribution of env-tech patents through the European regions. The top 25% of the distribution (4qrt) of environmental patents represents the leading regions related to environmental technologies, the third quartile indicates "intensive" env-tech regions, the second moderate "green" regions and the first quartile the less innovative (modest) regions.

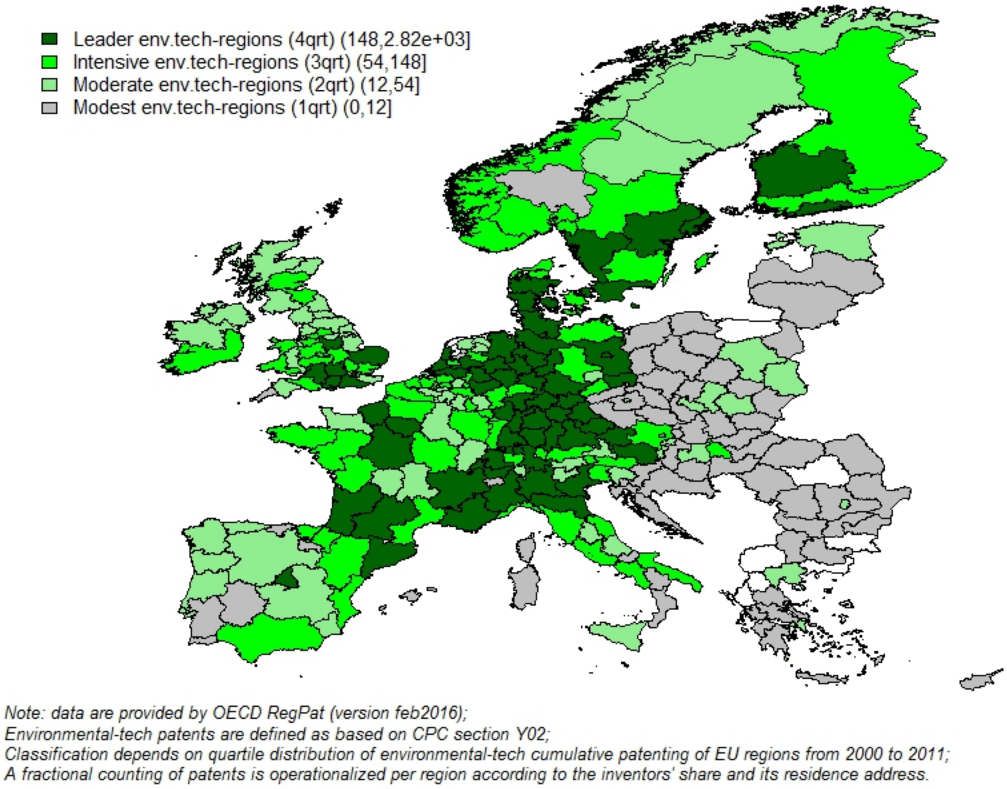

Figure 2: Distribution of the number of env-technologies through European regions over the period 2000-2011

Table 2 presents the GEE coefficient estimates for the "gaussian" regression model to explain the drivers of regional productivity growth. We estimated all models, controlling for Year dummies and Country dummies, but the coefficient estimates are not reported due to space constraints.

In Model 1, we present the outcome with only the control variables as a baseline model. Model 2 shows the results of the controls after entering the eco-technology diffusion. Model 3 introduces the results of the controls plus the eco-technology collaboration propensity. Model 4 presents the results of the controls after entering the local collaboration propensity. Finally, Model 5 introduces the last explanatory variables – eco-tech national and international collaboration propensity.

First, looking at the control variables (Model 1), the level of GVA seems to confirm that higher starting of value added may negatively influence the regional ability to continuously increase their growth. R&D intensity is confirmed to have a significant and positive effect on the productivity of European regions. Human capital, even though positive, is not statistically significant.

Population density has a negative and significant impact on the productivity of European regions. Even though urbanization economies are expected to improve the competitiveness of the regional performances, in largely populated areas negative externalities may be due to congestion costs, unskilled workers and immigrant inflows rather than talents, oversupply of labor, higher cost of living and insufficient infrastructure investments (Dijkstra et al., 2013, De Noni et al. 2018). Employment rate, even though positive through all the models, is not statistically significant on improving the regional productivity, probably due to a lack of skilled workers in some European regions.

Model 2 shows that the growth of productivity of European regions is positively influenced by the diffusion of environmental technologies ($p<0.01$), fully confirming the importance of green technologies in promoting and supporting regional growth and competitiveness because environmental innovations are often path breaking, high impact innovations and they can create new industrial processes and new markets.

Model 3 does not support the idea of a significant effect of env-tech collaboration propensity on regional growth competitiveness ($p>0.10$), which would mean that developing green-tech collaborative inventors' networks and thus increasing the regional potential to exploit socialization mechanisms for fostering knowledge transfer and creation processes is not significant to support regional competitiveness. Probably to better understand this result, we have to deepen our knowledge on green collaboration modes. In fact, this unexpected result is partially contradicted by the results of Model 4 and Model 5 which explain the non-significance of collaborative innovations on productivity as a result of the opposing and contrasting effects of the propensity in intra and extra regional collaborations.

Model 4 presents a positive and also statistically significant ($p<0.01$) impact of local env-tech collaboration on the productivity growth of European regions. Several studies underline that technological collaboration and networks are crucial for innovative and economic performances (De Noni et al. 2017, De Noni et al. 2018). A high level of intra-regional collaboration, especially in the case of new technologies and technological niches, supports the exploitation of the regional knowledge base and the creation of a robust scientific regional background that can improve the economic growth.

Model 5 indicates that a decrease of the regional propensity in national (extra region collaboration but in the same country) and international env-tech collaboration increases the growth of regional productivity contrasting the positive effect of the local collaborative networks. It is clear that regions that are able to combine local entrepreneurship innovative networks, high-grade public often university and research centers are facilitated in creating new green tech clusters (Cooke, 2008) and these clusters can leverage regional competitiveness exploiting the positive effect of environmental-related technologies.

Table 1: Descriptive statistics and Pearson correlation matrix

	Variables	Mean	St.Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1	*Industry GVA growth*	0.01	0.06	-0.47	0.58	1										
2	*Industry GVA*	8088.78	8310.53	92.79	74035.13	-0.15***	1									
3	*R&D expenditures*	415.83	470.45	1.8	2876.6	-0.08***	0.47***	1								
4	*Human capital*	30.05	15	3	84.4	-0.16***	-0.10***	-0.27***	1							
5	*Population density*	250.65	434.39	3.3	4289.3	-0.08***	0.20***	0.20***	-0.07***	1						
6	*Employment rate*	65.12	8.07	37.8	80.9	-0.14***	0.37***	0.50***	-0.27***	0.12***	1					
7	*Env-tech diffusion*	11.39	24.12	0	288.3	0.05*	0.50***	0.51***	-0.18***	0.08***	0.26***	1				
8	*Env-tech collaboration propensity*	0.05	0.09	0	1	0.00	0.05*	0.01	-0.01	-0.04*	0.03*	0.12***	1			
9	*Env-tech local collaboration propensity*	0.31	0.34	0	1	0.04*	0.21***	0.16***	0.08***	-0.06**	0.03	0.19***	0.12***	1		
10	*Env-tech national collaboration propensity*	0.32	0.35	0	1	-0.03	-0.10***	-0.10***	-0.03	0.05*	0.01	-0.10***	-0.11***	-0.73***	1	
11	*Env-tech international collaboration propensity*	0.1	0.22	0	1	0.01	-0.15***	-0.09***	-0.06**	0.01	-0.04*	-0.12***	-0.01	-0.35***	-0.38***	1

Notes: Significance levels are *** p<0.001. ** p<0.01. * p<0.10.

Table 2: Generalized Estimating Equations (GEE) results

Dependent variable - Regional Value Added Growth (industry)	*GEE model results*				
	Mod. 1	*Mod. 2*	*Mod. 3*	*Mod. 4*	*Mod. 5*
Intercept	0.024 (0.003)***	0.024 (0.003)***	0.023 (0.003)***	0.024 (0.003)***	0.024 (0.003)***
Explanatory variables					
Env-tech diffusion		0.004 (0.001)**			
Env-tech collaboration prop.			0.001 (0.001)		
Env-tech local collaboration prop.				0.003 (0.001)**	
Env-tech national collaboration prop.					-0.003 (0.001)**
Env-tech international collaboration prop.					-0.002 (0.001)*
Control variables					
Industry GVA	-0.005 (0.001)***	-0.007 (0.001)***	-0.005 (0.001)***	-0.006 (0.001)***	-0.006 (0.001)***
R&D expenditures	0.004 (0.001)***	0.003 (0.002)*	0.004 (0.001)***	0.004 (0.001)**	0.004 (0.001)**
Human capital	0.001 (0.004)	-0.001 (0.004)	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)
Population density	-0.003 (0.001)***	-0.003 (0.001)***	-0.003 (0.001)***	-0.003 (0.001)***	-0.003 (0.001)***
Employment rate	0.001 (0.002)	0.000 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
Year (dummies)	Yes	Yes	Yes	Yes	Yes
Region (dummies)	Yes	Yes	Yes	Yes	Yes
No. of observations	2552	2552	2552	2552	2552
EU NUTS-2 regions	232	232	232	232	232
No. of years	11	11	11	11	11
QIC	78.32	82.05	80.08	80.08	82.26
Quasi Likelihood	-2.34	-2.32	-2.34	-2.33	-2.33
LR test (change over Mod.1)		8.41 (1)**	0.53 (1)	7.75 (1)**	7.89 (2)*

Notes: Standard errors are heteroskedastic-consistent (“robust”). Coefficients are mean centered standardized. Significant levels are *** p<0.001. ** p<0.01. * p<0.1

5 DISCUSSION AND CONCLUSION

The objective of this paper was to investigate whether and the extent to which environmental innovation contribute to the competitiveness of regions. In this respect, we highlight that recent literature on regional innovation emphasizes then role of related variety and collaboration in strengthening the competitiveness of regions. These factors are also critical for the development of environmental innovation. Therefore, we expect that environmental innovation may further strengthen the capacity of regions to leverage on their sources of competitive advantage with positive effect for their competitiveness. Two effects were tested: the effect of environmental innovation and that of collaborative environmental innovation.

Our results confirm that green innovation positively affect regional competitiveness. Differently from what expected, the share of collaborative environmental innovation does not positively contribute to regional competitiveness. However, if the collaboration is disentangled into its constituents, we discover that intraregional collaboration positively affects regional competitiveness whether extra-territorial forms of collaboration impact negatively of the regional added value. Therefore, this confirms that spatial proximity is key strategic resource in the process of environmental innovation. This is probably due to the complex and multidisciplinary nature of this innovation, which relies extensively on face-to-face interaction to share significant cognitive and social cues.

Our paper has significant implication in terms of policy making. First, it shows that environmental innovation contributes to strengthen the competitiveness of regions. Therefore, in the distribution of public incentive to support environmental innovation policy makers should consider regional competitiveness. In fact, the risk to contribute to further widening the competitive disadvantage of lagging behind regions. Differently, policy makers should provide stronger incentives to facilitate the transfer of environmental innovation to lagging behind regions. However, they should not only support knowledge transfer, but also knowledge localization and the development of local collaborative networks. Second, it shows that positive externalities generated by environmental innovation tend to stick at regional level. Therefore, regional level may represent the most suitable level for the implementation of environmental strategy.

This is the first paper, according to our knowledge, attempting to assess the effect of environmental innovation on regional productiveness and competitiveness. Therefore, lots of work remain to be done. First, in this paper we assessed whether environmental innovation impact positively on regional competitiveness. However, we did not model specifically how environmental innovation lever on regional advantages and how environmental innovation translate into added value and indeed into regional competitiveness. Further reflection on those issues are indeed required. Second, we measure environmental innovation on the basis of patents classified as environmental. However, patents are only a proxy of the new knowledge produced in the environmental field. It tells us little about whether this knowledge is adopted and to which extent firms in the regions are adopting environmental innovation. Therefore, our analysis should be integrated with indicators related to the adoption of environmental innovation.

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