ISSN: 2282-4189

LUISS

Institute for European
Analysis and Policy

The Role of Green Networks for Environmental Innovation in European Regions

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Working Paper 14/2024

July 30, 2024

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Abstract

This paper investigates the role of green research networks in green innovation capabilities (proxied by green patents) in European regions. Our hypothesis is based on the idea that cross-border collaboration facilitates the diffusion of knowledge, thereby favouring the green innovation of the regions belonging to the network. We exploit information contained in the European Framework Programmes by looking at the role of intra and extra-regional collaborations and at the diversity of institutional partners. We find that both intra and extra regional collaborations matter for green innovation, although external knowledge appears to be more relevant. We also find a positive effect of both firms and universities and a non-linear effect of network heterogeneity. We discuss the implications of the results for green innovation policies.

Keywords: green innovation; green patents; knowledge diffusion; networks; European regions

JEL classification: O33; Q55; R11; C2

1. Introduction

In an era of unprecedented environmental crises, environmental (or green) innovation (EI) plays a critical role in sustaining the green transition. The European Union has responded to this emergency by taking massive measures to decrease its carbon footprint and enhance sustainability through the European Green Deal.

One of the core components of the Green Deal is the 'Fit for 55%' package, a set of proposals introduced following the Paris Agreement. The package aims to reduce CO2 emissions by 55% compared to 1990 levels by the end of 2030 and to achieve climate neutrality, or net zero emissions, by 2050. The ultimate goal of the Fit for 55% package is to make Europe the world's first climate-neutral continent by 2050. Two key elements of the renewed EU strategy to fight climate change are the extension and revision of the European Emissions Trading System (EU ETS) and the introduction of the Carbon Border Adjustment Mechanism (CBAM). The EU ETS cap reduction aims to decrease the number of emission allowances available, while the CBAM is designed to prevent carbon leakage by applying a carbon price on imports of certain goods from outside the EU, ensuring that European companies are not disadvantaged by climate policies (Böning *et al.*, 2023).

In the short term, these measures are likely to increase production costs for firms as they should internalize the external costs of pollution. This internalization process means that firms will have to pay for the environmental damage they cause, which can initially result in higher costs and reduced profitability. In the long term, to maintain international competitiveness, companies should focus on improving their innovation capabilities and increasing R&D investments. By enhancing their ability to innovate, firms can develop new technologies and processes that reduce emissions and improve efficiency, thereby mitigating the negative impacts of the greening measures. This emphasis on innovation is critical for the green transition, as it enables companies to adapt to new regulations and avoid the transition costs.

Given the unique nature of green technologies and the specialised knowledge required for environmental innovation (EI), literature emphasises that firms cannot act in isolation (Cisneros *et al.*, 2023). They need to seek new knowledge and expertise beyond their own boundaries by collaborating with other actors. Such a transition can be achieved through innovation and cooperation among EU members. To facilitate this, the European Commission has been actively promoting and supporting cooperative initiatives in research and innovation through multi-annual and multi-thematic Framework Programmes (FP). These programmes involve significant public investments aimed at generating and diffusing knowledge, thus fostering economic growth and convergence (Balland *et al.*, 2018; Meliciani *et al.,* 2022). They finance joint projects that aim to create networks among all institutional research sectors, including firms, universities, and public research centers. The core objective of this strategy is to generate new knowledge and implement it in business practices and production processes, thereby enhancing the performance of firms, regions, and countries, and making them more competitive in the global market.

Although there is a growing body of literature examining the impact of participation in the EU FPs on knowledge transfer (Maggioni *et al.* 2007; Hoekman *et al.* 2013; Di Cagno *et al.* 2014), to the best of our knowledge there is no empirical evidence on how green networks may affect the green innovation capacity at the regional level. We try to fill this gap by investigating the role of green research networks in enhancing green innovation capabilities within European regions. First, we test the hypothesis that collaboration within these networks promotes green innovation in the regions involved. We also explore whether collaboration beyond regional boundaries facilitates the diffusion of knowledge, thus promoting EI. Our hypothesis is based on the idea that collaboration beyond boundaries facilitates the spread of knowledge in EI, favouring the green technological transition of regions that belong to the network. Then, we assess whether private companies, public research institutions, and universities contribute differently to increasing knowledge, leading to a heterogeneous impact on green innovation. Finally, we look at the role of the diversification degree of network composition. The synergies among various actors in the network are critical for enhancing innovation capacity (Ghisetti *et al.* 2015). However, these interactions might also present challenges due to the diverse knowledge bases and objectives of each actor, as highlighted by Foray and Lissoni (2010).

Our results show that collaboration within the green research network contributes significantly to green innovation. By participating in networks, firms can benefit from external collaboration and thus increase their innovative capacity. Both internal and external collaboration are beneficial for EI. However, interregional cooperation appears to be more important because it supports the hypothesis that transregional networks can bridge the knowledge gap even when regions are not geographically close. Furthermore, we find that the participation of universities and private firms is particularly important in driving green innovation and that there is a positive effect from the heterogeneity of the participants that make up the network and the synergies they generate. However, the impact of heterogeneity is non-linear: research groups that are too heterogeneous risk having a negative impact on green innovation.

This study contributes with original insights to the literature on green innovation dynamics within European regions. By examining the role of green networks and the effectiveness of policies aimed at enhancing knowledge diffusion, this paper offers a novel perspective on strategies facilitating the green transition. It introduces several key innovations compared to previous literature. First, we utilize an extensive and up-to-date dataset on green patents at the regional level, allowing for a more detailed and accurate analysis of green innovation across different areas. Second, we highlight the distinct roles played by universities, firms, and public research centers in fostering knowledge exchange. While existing studies focus on the differing green innovation capacities of institutional sectors at the country level, our research examines these differences at the regional level. Third, we look at whether the heterogeneity of the actors involved in the network helps generate new green knowledge proxied by green patents.

The paper is structured as follows. Section 2 discusses the relevant literature and proposes some testable hypotheses. Section 3 describes the methodology and data. A discussion of the econometric results is presented in Section 4, and it is followed by the conclusions in Section 5.

2. Literature review

A large body of literature has looked at the importance of networks as drivers of innovation (see Powell and Grodal, 2006 for a review of the literature). By facilitating knowledge sharing, networks increase the innovative capacity of individual firms, which alone would not have access to all the knowledge needed to innovate, especially when knowledge is highly complex.

With respect to the standard networks, EI requires multidisciplinary knowledge and large investments in physical and human capital (Cainelli *et al.*, 2015). The literature emphasizes that firms cannot achieve green innovation in isolation. Firms need to seek new knowledge and external expertise by collaborating with other actors (Cisneros *et al.*, 2023).

Empirical analyses support the idea that environmentally innovative firms cooperate more with external partners if compared to other innovative firms (de Marchi and Grandinetti, 2013; Cainelli *et al.*, 2015; Ghisetti *et al.*, 2015). This collaboration is essential for enhancing overall green innovation knowledge and capabilities (Tang *et al.*, 2020). It draws on the idea that environmental innovations require more heterogeneous sources of knowledge with respect to other innovations (Horbach *et al.*, 2013). Consequently, firms are inclined to engage in collaborative efforts with external partners, leveraging shared knowledge, resources, and expertise (Fabrizi *et al.*, 2024).

Ghisetti *et al.* (2015) argued that the open innovation mode (Chesbrough, 2003; Chesbrough *et al.*, 2006) may also be applied in the context of environmental innovation. Given the high and multidisciplinary skills (including technical and scientific skills, legislative skills, and managerial and economic competencies) required for implementing or developing green innovations, external knowledge sourcing and networking becomes crucial for firms (Fabrizi *et al.*, 2018). The first dimension of the open innovation mode is represented by the way firms search for external knowledge in order to innovate and it accounts for the breadth of the firm's knowledge search. The greater the number of external parties with which a firm cooperates, the more likely it is to compensate for the lack of some specific internal competence. Moreover, implementing green technologies aims to achieve several goals, including enhancing production efficiency and meeting market and regulatory quality standards (Oltra and Saint Jean, 2005). The extensive networks address these multiple objectives related to EI by leveraging potential economies of scope.

In addition, physical proximity encourages knowledge transfer, as underlined by Boschma (2005). This is particularly relevant because knowledge tends to be geographically concentrated, thus making location a critical factor for efficient knowledge sharing (Eugster *et al.,* 2022). Indeed, the literature highlights that knowledge spillovers from foreign sources can significantly enhance a region's innovative capacity. Spatial knowledge spillovers, especially from neighboring regions, improve the ability to innovate a specific area (see for instance, Charlot *et al.*, 2015; Kijek and Kijek, 2019).

However, when there is no geographical proximity, transnational networks can also fill this gap as noted by Autant-Bernard *et al.* (2007) and Maggioni and Uberti (2011). This is based on the idea that regions involved in transregional networks are more likely to participate in innovation activities. These transregional networks guarantee that a region could still connect to external knowledge flows even in the event of not being close to each other, hence enhancing green innovation activities in such a region. Interaction between local and transregional knowledge networks offers a strong environment for innovation; it is able to draw from both local and foreign knowledge. Given the importance of networks and open innovation for the creation of green knowledge, we use data on European FPs in green fields to investigate their contribution to generating green patents at the regional level. In particular, we pose the following research questions:

1. *Does collaboration within green research networks promote the green innovation of the regions involved?*

2. *Does collaboration beyond regional boundaries facilitate the diffusion of knowledge, thus promoting EI?*

The use of information on green FPs allows us not only to assess the importance of regional and transregional research networks, but also to consider the role of the different institutional sectors involved in the networks and of their synergies. Empirical and theoretical literature highlight the numerous benefits that can be gained from participating in mixed partnerships (Paier and Scherngell 2011; Bettina 2015; Fabrizi *et al.* 2016). These partnerships offer a set of advantages for all parties involved, such as access to complementary skills, access to larger financial resources, and the reduction of risks. Thus, synergies among different actors (private and public) in the network become crucial for driving innovation. In the context of green innovation, the interaction and hybridisation between three institutional spheres - 'industry', 'university' and 'government' (Triple Helix, Etzkowitz and Leydesdorff, 2000) - is particularly important due to the heterogeneity of knowledge required for finding green solutions, the role of regulation in directing green efforts and the necessity of adopting a systemic approach. Nevertheless, as highlighted by Foray and Lissoni (2010), the interaction might also present challenges due to the diverse knowledge bases and objectives of each actor, which could potentially reduce the innovation capacity.

In this context, we investigate which characteristics of network participants are more important for EI at the local level, studying the contribution of different institutional sectors to the innovation capacity. Moreover, we look at the diversification degree of network actors by using the entropy concept. Specifically, we formulate the last research question:

3. *Do institutional sectors contribute differently to increasing green knowledge? Does a high diversification lead to a greater innovation? Is the relationship linear?*

On the one hand, different actors can bring different knowledge and skills to the table; on the other hand, different objectives and knowledge bases can create frictions in innovation capacity. The heterogeneity of objectives and approaches, in particular between public institutions focused on broader societal impacts and private companies focused on market-driven applications, can hinder coherent progress and reduce innovation efficiency. Initially, increased diversification can enhance innovation by fostering a rich exchange of ideas and resources. However, as diversification increases, the complexity and potential conflicts between actors may reduce the ability to innovate effectively.

3. Methodology and data

3.1 Data

We collect data covering the period 2003-2021 for 282 European regions[1] on individual green patent applications to account for green innovation, and data on collaborative research projects funded under the FPs to represent green research networks within and between regions.

[1] We use the 2016 version of the NUTS2 classification.

Green patents in European regions

We rely on microdata from the OECD REGPAT database, focusing on the number of green patents as an indicator of innovative activity. The database collects data held by the European Patent Office (EPO), which contains information on individual patent applications worldwide. We focus on the application filed to the EPO rather than using data on applications filed via the Patent Cooperation Treaty (the PCT). To regionalize individual applications, the address of the inventor is used as it is considered to be a better proxy of the location where the focal technology was developed (Bello *et al.*, 2023). We consider the priority year for each application.

As underlined in Favot *et al.* (2023), there are different methodologies developed by international organisations to identify patents on environmental-related technologies. In this paper, we apply the "Y02/Y04S tagging scheme" developed by the EPO in collaboration with the United Nations Environmental Programme (UNEP) and the International Centre on Trade and Sustainable Development (ICTSD) to find low-carbon, sustainable, and climate change mitigation technologies (CCMTs).[2] This methodology adds the Y sections to the 8 pre-existing standard sections (A-H) of the Cooperative Patent Classification (CPC). The tagging scheme was introduced to facilitate the identification of mitigation technologies in the energy sector (Veefkind *et al.* 2012). Later, the scheme was expanded to include all CCMTs covering several categories such as energy, greenhouse gases (GHG) capture, buildings, industry, transport, and waste and wastewater management (Angelucci *et al.*, 2018). Table 1 reports the subclasses that allow us to identify the technologies relevant to environmental issues.

[2] Y02/Y04S tagging scheme is only applicable to patents with CPC codes.

Table 1: Y02/Y04S Tagging scheme (Favot et al., 2023).

Code	Description
Y02	Technologies or applications for mitigation or adaptation against climate change
Y02A	Technologies for adaptation of climate change
Y02B	Climate change mitigation technologies related to buildings, e.g. housing, house appliances or related end-user applications
Y02C	Capture, storage, sequestration or disposal of greenhouse gases
Y02D	Climate change mitigation technologies in information and communication technologies, i.e. information and communication technologies aiming at the reduction of their own energy use
Y02E	Reduction of greenhouse gas emissions, related to energy generation, transmission or distribution
Y02P	Climate change mitigation technologies in the production or processing of goods
Y02T	Climate change mitigation technologies related to transportation
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management
Y04	Information or communication technologies having an impact on other technology areas
Y04S	Systems integrating technologies related to power network operation, communication or information technologies for improving the electrical power generation, transmission, distribution, management or usage, i.e. smart grids

We count more than 100,000 green patent applications in European regions over the period 2003-2021. Figure 1 reports the geographical distribution of the number of patents. The map shows a clear clustering of the data. Core regions are characterised by a higher range of distribution (light red), suggesting a concentration of green innovation in central parts of Europe. Conversely, the peripheries, especially towards the north and some southern regions, show lower activity (light and dark green), indicating fewer patents within these areas.

To check the strength of our analysis, we also employ the ENV-TECH classification ("Series of patent search strategies for the identification of selected environmental-related technologies") developed by OECD (Haščič and Migotto, 2015). This methodology is based on the International Patent Classification (IPC) and the CPC codes and provides an alternative identification scheme for measuring innovation in environmental-related technologies. We follow the previous strategy for regionalizing the individual green patent applications.[3]

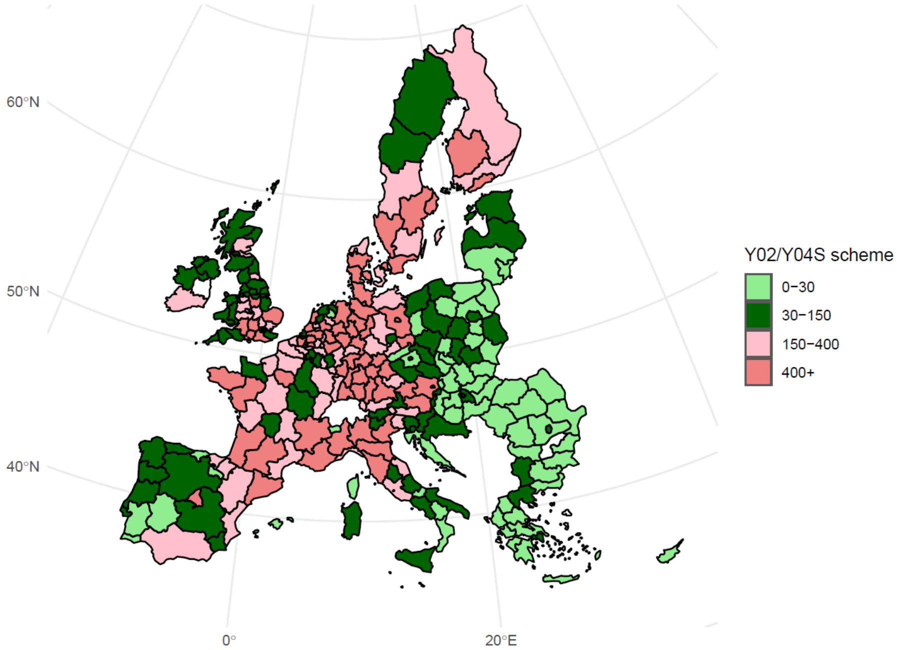

Figure 1: Distribution of green patents at NUTS2 level. Sum over the period 2003-2021. Authors' calculation is based on the Y02/Y04S scheme.

Green research networks

The second variable of interest accounts for the green networks. To construct and measure the network, we use data on EU-funded research projects that support the formation of transnational collaborations on topics related to the green transition to measure green networks. The EU OPEN DATA PORTAL provides data on joint research projects funded under the Framework Programme (FP) for Research and Technology Development (RTD). We have selected projects with green aspects according to the following thematic priority (Table 2): FP6-SUSTDEV (2002–2006), FP7-ENERGY FP7-ENVIRONMENT FP7-TRANSPORT (2007–2012), and Horizon 2020 - SOCIETAL CHALLENGES (2014-2020). These programmes were selected according to

[3] Figure 1A in the Appendix shows the geographical distribution of green patents according the ENV-TECH classification.

their close connection to the environmental objective and their focus on the role of technological advancement in meeting these goals.[4]

These data provide important insights as they include the geographical dimension and the sectoral affiliation of the participants, allowing us to examine the collaboration between countries and across different sectors.

Green network variables are derived from the information on projects funded by FPs. Specifically, we consider the total number of collaborative links within and between regions, represented by the variable *LINKS*. In Figure 2, we show the total number of collaborations (*LINKS*) for each region. The figure underlines that most of the European regions are more inclined to create networks and some of them, especially in the centre of Europe, are able to pursue environmental innovation. The clusterization is less evident with respect to the patent distribution.

Table 2: Thematic priority of FP programmes

Thematic priority	
FP6 - (2002-2006) FP7 – (2007-2013)	SUSTDEV: Sustainable development, global change and ecosystems ENERGY ENVIRONMENT TRANSPORT
Horizon 2020 (2014-2020)	H2020-EU.3.2. - SOCIETAL CHALLENGES - Food security, sustainable agriculture and forestry, marine, maritime and inland water research, and the bioeconomy H2020-EU.3.3. - SOCIETAL CHALLENGES - Secure, clean and efficient energy H2020-EU.3.4. - SOCIETAL CHALLENGES - Smart, Green and Integrated Transport H2020-EU.3.5. - SOCIETAL CHALLENGES - Climate action, Environment, Resource Efficiency and Raw Materials

[4] For details, see Meliciani *et al.* (2022).

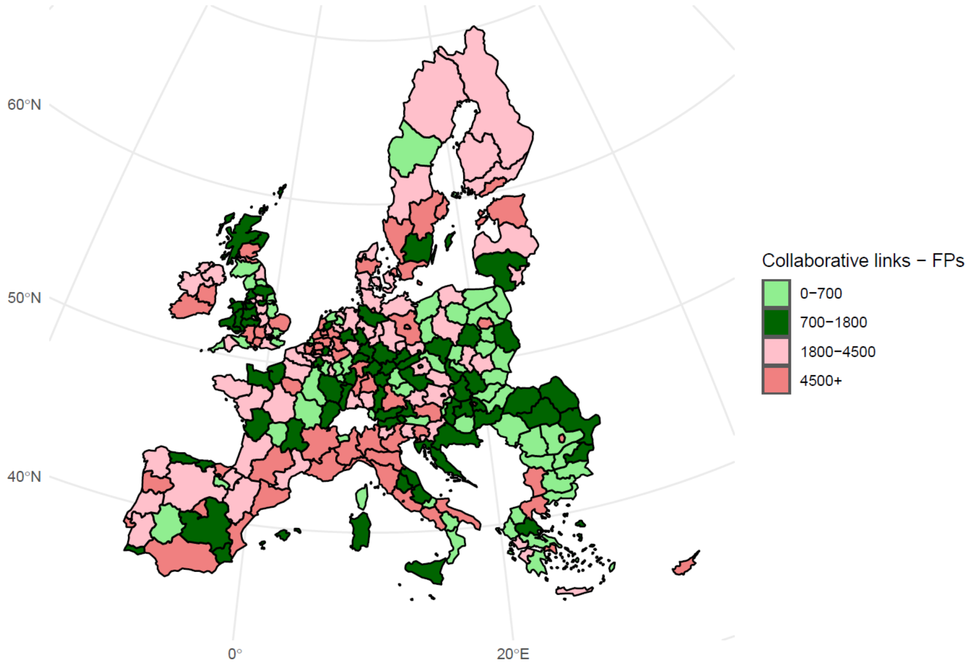

Figure 2: Number of total collaborations at NUTS2 level. Authors' calculation based on FP-RTD data.

The variable *LINKS* is then subdivided into collaborative links among residents within the same region (*INTRALINKS*) and collaborations between residents and external partners (*EXTRALINKS*). Additionally, we gather data on the number of green project participants, categorized by four institutional sectors to account for the composition of private and/or public networks. The variables *PRC*, *HES*, *REC*, and *OTH* correspond to the number of participants from private for-profit entities, higher or secondary education institutions, research centres or organizations, and other sectors, respectively. See Table 3 for details.

Table 3: Variable description and sources.

Variable	Description	Source
PAT	Total number of green patent applications	OECD REGPAT database; own elaboration
LINKS	Total number of region's collaboration links (internal and outer) with other regions	EU OPEN DATA PORTAL; own elaboration
INTRALINKS	Total number of region's internal links	EU OPEN DATA PORTAL; own elaboration
EXTRALINKS	Total number of region's outer (interregional) links	EU OPEN DATA PORTAL; own elaboration
PART	Number of project participants per region	EU OPEN DATA PORTAL; own elaboration
PRC	Number of participants belonging to private for-profit entities	EU OPEN DATA PORTAL; own elaboration
HES	Number of participants belonging to higher or secondary education institutions	EU OPEN DATA PORTAL; own elaboration
REC	Number of participants belonging to research centres or organizations	EU OPEN DATA PORTAL; own elaboration
OTH	Number of participants belonging to other	EU OPEN DATA PORTAL; own elaboration
RD	R&D total expenditure on GDP	Eurostat regional database
EDU	Ratio of population with tertiary education and total population	Eurostat regional database
POP	Population in thousands	Eurostat regional database

3.2 Empirical approach

To study the relationship between green innovation and networks, we estimate a knowledge production function as in Meliciani *et al.* (2022) and Di Cagno *et al.* (2014) at NUTS2 level. The first research question presented in Section 2 has been assessed by means of the following econometric model:

$$\ln PAT_{i,t} = \beta_0 + \beta_1 \ln LINKS_{i,t} + \beta_2 RD_{i,t} + \beta_3 EDU_{i,t} + \beta_4 POP_{i,t} + \theta_{m,t} + u_{i,t} \quad (1)$$

In Eq. (1), the dependent variable PAT is equal to $(patents + 1)$[5], where *patents* is the total number of green patent applications identified according the "Y02/Y04S tagging scheme" in each region i at time t. For

[5] We follow Berkes and Nencka (2024) for the transformation of the dependent and network variables. We show results using the inverse hyperbolic sine of patents as an alternative transformation in Tables 4A and 5A in Appendix. The results are consistent with our baseline estimates.

robustness, we also use the "ENV-TECH classification" to construct the dependent variable. The results are shown in Table 6A in the Appendix. The parameter β_1 captures the correlation between the green innovation and the independent variable *LINKS* that accounts for the green networks, expressed in logarithm. We add a set of controls to account for R&D expenditure, human capital, and size. Specifically, *RD* measures the expenditure on general R&D as a percentage of GDP, *EDU* is a proxy for human capital calculated as the population with tertiary education and the total population, while *POP* accounts for the regional population. The data are taken from the Eurostat regional database (Table 3). The error term is denoted by $u_{i,t}$.

We further control for time-invariant unobservables by considering local specific characteristics that are not captured by other regressors. We include several types of fixed effects in the equation. Specifically, the model in Eq. (1) includes NUTS1 fixed effects by year ($\theta_{m,t}$). This allows us to better account for cross-sectional and temporal heterogeneity and to control for unobservables that may vary over time. In addition, we estimate the model by separately adding country fixed effects and NUTS1 fixed effects. In both estimations, year fixed effects are included to account for time shocks that affect regions simultaneously in a given year. Finally, the model was estimated including country fixed effects by year. However, the more comprehensive approach in Eq. (1) takes into account not only the specific economic characteristics of the macro area, but also the idiosyncratic shocks that affect the specific NUTS1 region in a given year, thereby increasing the accuracy and robustness of the estimated relationships between variables.

Furthermore, we examine the role of domestic and external collaborations in Eq. (2), where the variable *NET* represents both *INTRALINKS* and *EXTRALINKS*. To better study the contribution of external collaboration to EI, we introduce *EX_INTRA* (Eq. 3), which is calculated as the ratio of *EXTRALINKS* to *INTRALINKS*. The network variables, except *EX_INTRA*, are expressed in logarithms.

$$\ln PAT_{i,t} = \beta_0 + \beta_1 \ln NET_{i,t} + \beta_2 RD_{i,t} + \beta_3 EDU_{i,t} + \beta_4 POP_{i,t} + \theta_{m,t} + u_{i,t} \quad (2)$$

$$\ln PAT_{i,t} = \beta_0 + \beta_1 EX\_INTRA_{i,t} + \beta_2 RD_{i,t} + \beta_3 EDU_{i,t} + \beta_4 POP_{i,t} + \theta_{m,t} + u_{i,t} \quad (3)$$

$$\ln PAT_{i,t} = \beta_0 + \beta_1 \ln PRC_{i,t} + \beta_2 \ln HES_{i,t} + \beta_3 \ln REC_{i,t} + \beta_4 \ln OTH_{i,t-1} + \beta_5 RD_{i,t} + \beta_6 EDU_{i,t} + \beta_7 POP_{i,t} + \theta_{m,t} + u_{i,t} \quad (4)$$

$$\ln PAT_{i,t} = \beta_0 + \beta_1 entropy_t + \beta_2 entropy_t^2 + \beta_3 \ln PART_{i,t} + \beta_4 RD_{i,t} + \beta_5 EDU_{i,t} + \beta_6 POP_{i,t} + \theta_{m,t} + u_{i,t} \quad (5)$$

Finally, to respond to the third research question, we study the contribution of different institutional sectors to EI. First, we estimate Eq. (4), trying to understand the role of *PRC*, *HES*, *REC*, and *OTH*. Second, in Eq. (5) we consider the diversification degree of network components by using the entropy index. The entropy or Shannon's index (H) is defined as:

$$H = -\sum_{i=1}^{n} p_i \, ln(p_i) \quad (6)$$

where p_i represents the probability that the network is composed of participants belonging to sector *i* (PRC, HES, REC, OTH). This entropy, which can be used to measure the dispersion degree in a distribution, reaches its maximum when events are equiprobable (or uniformly distributed). If the value of the index is near zero, the degree of dispersion is lower. The higher the value of *H*, the greater the diversity. In our setup, an entropy equal to zero corresponds to a concentration of network composition in one of the four modes (*PRC, HES, REC, OTH*). To check the presence of nonlinearities, we add the squared value of entropy index. The number of total network participants (*PART*) is added as a control.

The analysis uses an unbalanced panel dataset. With respect to the original dataset described in Section 3.1, observations for which control variables were not available were dropped. This adjustment results in the final sample of the 235 NUTS2 regions observed, on average, for 12.2 years.

4. Results

In this section, we present the findings from our empirical investigation, which attempts to understand the role of green research networks in enhancing EI in European regions.

Table 4 shows the estimates of the relationship between green patents and the number of internal and external collaborative links of regions (*LINKS*). In column (1), the model is estimated by including country and year fixed effects, while NUTS1 and year fixed effects are included in column (3). Moreover, to control for unobservables over time, we report the results including country fixed effects by year in column (2) and NUTS1 fixed effects by year in column (4). By examining the values of R-squared and Within R-squared, the last specification, which we have identified as the baseline, shows an appropriate compromise in explaining a significant portion of the overall variance and the variance within individual entities over time. We find a positive and significant coefficient of *LINKS* across all specifications (1)-(4). This indicates that the collaboration within the green research network significantly contributes to enhance the green innovation of the concerned areas. This result is consistent with the literature, which identifies networks as key drivers of innovation by enabling the sharing of knowledge and resources that individual firms may lack (Ghisetti *et al.* 2015; Fabrizi *et al.* 2016; 2024). By participating in green research networks, firms can benefit from external collaboration, as such innovations require multidisciplinary knowledge and investment in physical and human capital, as well as access to a wider range of resources and markets, thereby enhancing the innovative capacity of firms within the regions. This is in line with the open innovation mode, which emphasises outsourcing knowledge to fill the gap in technical characteristics that are essential for environmental innovation. Moreover, the control variables for R&D

expenditure (*RD*), education level (*EDU*), and population size (*POP*) also have significant and positive coefficients, indicating that these factors are crucial for green innovation alongside network collaboration. In Table 6A in the Appendix, we present the model's estimates using the "ENV-TECH classification" to identify the dependent variable. The results are quite similar and confirm the strength of our initial analysis.

We then address the second research question about whether collaboration beyond regional boundaries promotes EI, providing further insights by distinguishing between the numbers of a region's internal and external links. In columns (5)-(7), Table 4 reports the estimates of the model with NUTS1 fixed effects by year.[6] We find positive and significant coefficients for *INTRALINKS* and for extra-regional links (*EXTRALINKS*) in column (5) and (6) respectively. This suggests that both types of collaboration are beneficial for green innovation. Intraregional collaboration enhances local knowledge sharing and innovation capacity, supporting the idea that proximity fosters knowledge transfer. Interregional collaborations, on the other hand, broaden knowledge diffusion and access to diverse expertise and resources. When two or more regions are not geographically close, transregional networks can fill the gap in terms of knowledge sharing (Autant-Bernard *et al.*, 2007; Maggioni and Uberti, 2011). Moreover, improving knowledge diffusion can reduce the problem of knowledge concentration in specific advanced areas (Eugster *et al.*, 2022).

[6] Table 2A in the Appendix shows the model's estimates with country and year fixed effects, NUTS1 and year fixed effects, and country fixed effects by year. The estimates confirm the results of the baseline model.

Table 4: Estimates of the relationship between EI and green networks: total, intra, and extra links.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(LINKS_t)$	0.098***	0.107***	0.075***	0.100***			
	(0.017)	(0.020)	(0.013)	(0.019)			
$\ln(INTRALINKS_t)$					0.224***		
					(0.041)		
$\ln(EXTRALINKS_t)$						0.101***	
						(0.019)	
EX_INTRA_t							0.005***
							(0.002)
RD_t	22.959***	23.809***	15.616***	16.071***	15.201***	16.065***	17.703***
	(5.729)	(6.032)	(4.038)	(4.761)	(4.298)	(4.756)	(5.516)
EDU_t	0.023***	0.021***	0.022***	0.018***	0.011**	0.018***	0.029***
	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
POP_t	0.029***	0.028***	0.031***	0.030***	0.027***	0.030***	0.035***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Constant	-0.102	-0.060	0.068	0.090	0.337***	0.095	-0.001
	(0.114)	(0.130)	(0.104)	(0.125)	(0.123)	(0.125)	(0.142)
Country FE	YES	-	-	-	-	-	-
Time FE	YES	-	YES	-	-	-	-
Country*Time FE	-	YES	-	-	-	-	-
NUTS1 FE	-	-	YES	-	-	-	-
NUTS1*Time FE	-	-	-	YES	YES	YES	YES
Observations	2,863	2,740	2,858	2,521	2,521	2,521	2,521
R-squared	0.814	0.833	0.859	0.893	0.894	0.893	0.887
Within R-squared	0.534	0.559	0.453	0.557	0.562	0.557	0.535

Note: The model was estimated by means of a linear regression with multiple fixed effects. Dropped singleton observations: 123 (2), 5 (3), and 342 (4-7). Standard errors clustered at the regional level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Due to collinearity issues, we cannot estimate the model with both intra and extra links simultaneously. Therefore, we compare the contribution of the two types of collaboration on EI by examining the ratio between the number of external links and internal links. The results are presented in column (7), where *EX_INTRA* shows a positive and significant coefficient. Given the total number of collaborations, an increase in the number of external collaborations relative to internal collaborations may contribute positively to enhance the green innovation capabilities of the regions. These results emphasize the importance of the transregional geographical dimension of networks and the idea that cultural proximity, created through the networks, can compensate the geographical proximity for knowledge sharing (Boschma 2005).

For what concerns the composition dimension, we have highlighted how the literature points to the combination of complementary skills of different network participants for creating significant synergies that can lead to stronger innovation. However, the heterogeneity of network participants can create frictions in the ability to innovate due to different knowledge bases and the *dual use* (business and academic) of new technologies. We address this point by studying first the differential contributions of institutional sectors to EI. Table 5 reports the baseline model's estimates.[7]

The coefficient for private for-profit entities (*PRC*) is positive and significant (column 1), suggesting that private sector participation is particularly significant in driving green innovation. In contrast, we do not find significant coefficients for other institutional sectors. When considering the sectors separately however, the higher education sector (*HES*) also shows a positive and significant coefficient (column 3). While the model that includes all sectors together appears to be more suitable for describing the phenomenon, both in terms of overall R-squared and within R-squared, we cannot exclude that the insignificant coefficient of *HES* may be due to the presence of collinearity.[8] The strong capability of the private sector in driving green innovation is not surprising since private companies are more interested in patenting for commercialisation than public bodies, and, therefore, it is expected that networks composed of private firms would show a higher propensity for innovation.

[7] The results of the model with country and year fixed effects, NUTS1 and year fixed effects, and country fixed effects by year in Table 3A in the Appendix are consistent with the baseline model.

[8] The correlation coefficient between PRC and HES is 0.69.

Table 5: Estimates of the relationship between EI and green networks: institutional sectors and diversification.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(PRC_t)$	0.204***	0.203***					
	(0.044)	(0.047)					
$\ln(HES_t)$	0.067		0.117**				
	(0.046)		(0.052)				
$\ln(REC_t)$	0.017			0.076			
	(0.047)			(0.049)			
$\ln(OTH_t)$	-0.026				0.068		
	(0.046)				(0.052)		
$entropy_t$						0.040	0.360**
						(0.077)	(0.168)
$entropy_t^2$							-0.285**
							(0.131)
$\ln(PART_t)$						0.222***	0.234***
						(0.066)	(0.065)
RD_t	14.773***	15.370***	14.780***	16.251***	16.928***	14.773***	14.690***
	(4.298)	(4.530)	(5.182)	(5.219)	(5.437)	(4.342)	(4.353)
EDU_t	0.014**	0.013**	0.021***	0.021***	0.022***	0.007	0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
POP_t	0.027***	0.026***	0.030***	0.030***	0.031***	0.024***	0.025***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Constant	0.354***	0.556***	0.464***	0.487***	0.434***	0.538***	0.460***
	(0.135)	(0.142)	(0.153)	(0.160)	(0.149)	(0.133)	(0.136)
NUTS1*Time FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,916	1,916	1,916	1,916	1,916	1,916	1,916
R-squared	0.893	0.896	0.893	0.892	0.892	0.897	0.898
Within R-squared	0.557	0.522	0.508	0.505	0.503	0.528	0.531

Note: The model was estimated by means of a linear regression with multiple fixed effects. 377 dropped singleton observations. Standard errors clustered at the regional level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Then, we consider the diversification degree of network actors. In column (6), the estimates suggest a non-significant coefficient of the entropy index. On the contrary, column (7) shows a nonlinear effect with a positive and significant coefficient for the entropy index and a negative and significant coefficient for its squared term. This suggests that the diversification is positively correlated with innovation, but the relationship is nonlinear. The interaction between an overly large number of actors belonging to different sectors increases the complexity and leads to potential conflicts between them, reducing the ability to innovate effectively. Foray and Lissoni (2010) highlight that this issue stems from the differing knowledge bases and objectives of each actor. Therefore, while private actors are the primary drivers of green innovation, there is still a positive effect from the heterogeneity of the participants that make up the network and the synergies they generate. However, given the non-linear nature of the relationship, overly heterogeneous groups risk negatively impacting green patent creation.

5. Conclusions

In this paper we provide empirical evidence of how green research networks promoted by EU FPs enhance the capacity of environmental innovation in European regions.

We start from the hypothesis that firms need to seek new knowledge and expertise beyond their own boundaries by collaborating with other actors for innovating, given the unique nature of green technologies and the specialised knowledge required for EI. In particular, we ask whether the collaborations in and between regions are positively related to EI and assess whether private companies, public research institutions, and universities contribute differently to increasing knowledge, leading to a heterogeneous impact on green innovation. Additionally, we examine the role of network diversification on innovation, considering the synergies and challenges of the interaction among different actors.

Our findings support the role of collaboration in green research networks as a driving force for EI in European regions, thus supporting the role of the open eco-innovation mode (Ghisetti *et al.*, 2015) also at the regional level. By participating in networks, regions can benefit from external collaboration and thus increase their innovative capacity. Both internal and external collaborations are beneficial for EI. However, interregional cooperation broadens knowledge diffusion and access to different expertise and resources. Transregional networks can bridge the knowledge sharing gap even when regions are not geographically close, supporting the view that knowledge sharing can be facilitated not only by geographical proximity but also by cultural proximity (Boschma, 2005). This proximity can be facilitated also through the collaboration of heterogeneous actors with different types of knowledge, integrating the fundamental research carried out in universities with the applied research and development activities of private companies (Etzkowitz and Leydesdorff, 2000). However, while the diversity of participants within a network fosters synergies that eventually lead to an enhanced innovative capacity, in cases of extreme heterogeneity, these are likely to lead to conflicts and lower innovation efficiency (Foray and Lissoni, 2010).

This paper contributes to an already existent stream of literature in this area by empirically testing the influence of green networks on regional innovation capacity. It emphasizes the role EU-supported cooperative initiatives and policies can play in boosting innovation and in contributing to the EU's achievement of climate neutrality by 2050 through green innovation.

While FPs are an important instrument for fostering green innovation, Europe is lagging behind the US and China in terms of industrial green policies. The proposal to introduce a European sovereign fund for financing investments for the twin transition is still far from being realised. The experience of European Framework Programmes where universities, firms and research centres from different European regions collaborate in projects funded by common European resources is a model that can be adapted also to the implementation of green industrial policies.

In most European countries and regions, the main problem still appears to be the low propensity of academic institutions to collaborate with firms and to transform new knowledge into new processes and products. The formation of networks is an important tool for fostering private-public collaborations and stimulating the applicability of new ideas in the commercial sphere.

While this paper sheds light on the role played by green networks in green innovation, further studies could identify the characteristics of the networks that are more beneficial to green innovation by exploring not only the heterogeneity of institutional participants but also of the regions involved in the network. Moreover, the heterogeneity of effects across regions with different levels of technological intensity and absorptive capacity could be investigated also with the purpose of identifying the impact of green research networks on the evolution of regional green innovation disparities in the attempt to study the coherence between R&D and regional cohesion policies.

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Appendix

Table 1A: Variable descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
PAT	19.99	42.38	0.00	499.00
LINKS	195.25	348.90	0.00	4264.00
INTRALINK	13.40	28.92	0.00	444.00
EXTRALINKS	181.85	321.18	0.00	3820.00
PRC	5.57	12.66	0.00	197.00
HES	2.80	4.77	0.00	45.00
REC	3.00	9.05	0.00	145.00
OTH	1.94	6.73	0.00	146.00
RD	0.01	0.01	0.00	0.13
EDU	27.15	10.11	6.10	74.70
POP	18.23	15.14	0.26	123.49

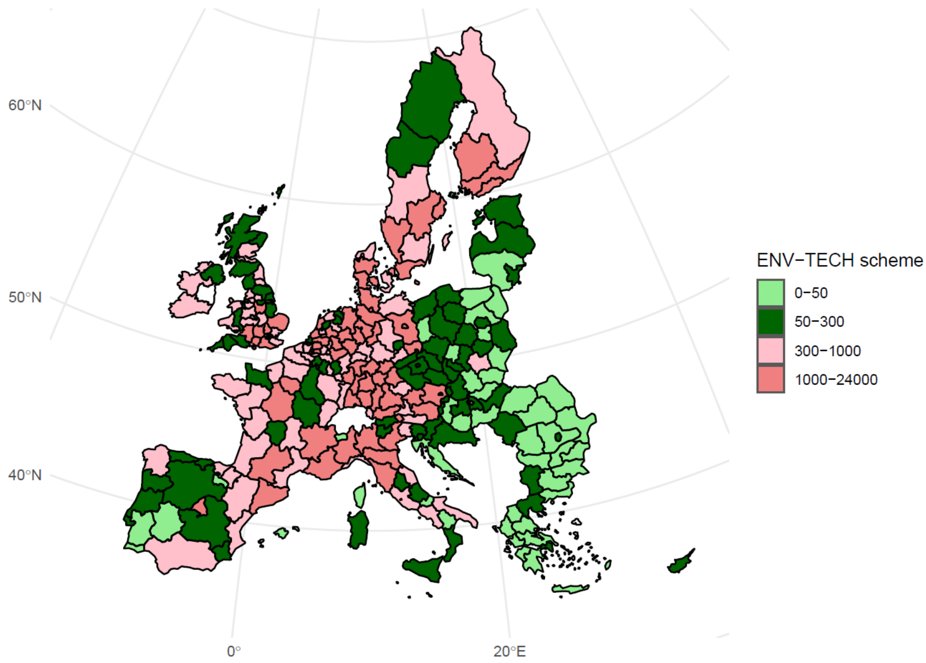

Figure 1A: Distribution of green patents at NUTS2 level. Sum over the period 2003-2021. Authors' calculation based on the ENV-TECH classification.

Table 2A: Estimates of the relationship between EI and green networks: intra and extra links.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\ln(INTRALINKS_t)$	0.209***	0.239***	0.154***						
	(0.038)	(0.046)	(0.027)						
$\ln(EXTRALINKS_t)$				0.099***	0.108***	0.076***			
				(0.018)	(0.020)	(0.013)			
EX_INTRA_t							0.004***	0.004**	0.004***
							(0.002)	(0.002)	(0.001)
RD_t	22.513***	23.278***	15.123***	22.956***	23.810***	15.602***	24.910***	25.877***	16.964***
	(5.382)	(5.602)	(3.822)	(5.730)	(6.035)	(4.033)	(6.475)	(6.865)	(4.482)
EDU_t	0.016***	0.011*	0.018***	0.023***	0.021***	0.022***	0.033***	0.033***	0.029***
	(0.005)	(0.007)	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)
POP_t	0.026***	0.025***	0.029***	0.029***	0.028***	0.031***	0.034***	0.034***	0.035***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Constant	0.143	0.236*	0.228**	-0.099	-0.057	0.071	-0.163	-0.155	0.024
	(0.118)	(0.141)	(0.103)	(0.114)	(0.130)	(0.104)	(0.122)	(0.139)	(0.114)
Country FE	YES	-	-	YES	-	-	YES	-	-
Time FE	YES	-	YES	YES	-	YES	YES	-	YES
Country*Time FE	-	YES	-	-	YES	-	-	YES	-
NUTS1 FE	-	-	YES	-	-	YES	-	-	YES
Observations	2,863	2,740	2,858	2,863	2,740	2,858	2,863	2,740	2,858
R-squared	0.815	0.835	0.860	0.814	0.833	0.859	0.806	0.824	0.856
Within R-squared	0.539	0.565	0.454	0.534	0.559	0.454	0.515	0.536	0.439

Note: The model was estimated by means of a linear regression with multiple fixed effects. Dropped singleton observations: 123 (2)-(5)-(8) and 5 (3)-(6)-(9). Standard errors clustered at the regional level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3A: Estimates of the relationship between EI and green networks: institutional sectors and diversification.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\ln(PRC_t)$	0.222***	0.268***	0.112***						
	(0.039)	(0.046)	(0.029)						
$\ln(HES_t)$	0.014	0.027	0.037						
	(0.041)	(0.048)	(0.032)						
$\ln(REC_t)$	0.012	0.006	0.035						
	(0.044)	(0.049)	(0.034)						
$\ln(OTH_t)$	-0.017	-0.032	-0.019						
	(0.033)	(0.039)	(0.029)						
$entropy_t$				-0.002	-0.028	0.074	0.213	0.274*	0.186
				(0.062)	(0.068)	(0.051)	(0.142)	(0.155)	(0.117)
$entropy_t^2$							-0.187*	-0.262**	-0.098
							(0.115)	(0.127)	(0.091)
$\ln(PART_t)$				0.209***	0.263***	0.120***	0.215***	0.271***	0.123***
				(0.055)	(0.066)	(0.042)	(0.055)	(0.065)	(0.042)
RD_t	22.388***	22.721***	15.186***	18.929***	19.627***	14.082***	18.782***	19.450***	14.038***
	(5.548)	(5.720)	(3.906)	(4.843)	(4.928)	(3.918)	(4.878)	(4.985)	(3.927)
EDU_t	0.018***	0.014**	0.020***	0.017***	0.011	0.018***	0.018***	0.012*	0.018***
	(0.006)	(0.007)	(0.004)	(0.006)	(0.007)	(0.004)	(0.006)	(0.007)	(0.004)
POP_t	0.026***	0.025***	0.030***	0.025***	0.023***	0.028***	0.025***	0.024***	0.028***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Constant	0.172	0.263	0.249**	0.216*	0.339**	0.357***	0.161	0.260*	0.330***
	(0.134)	(0.164)	(0.108)	(0.121)	(0.141)	(0.114)	(0.129)	(0.154)	(0.112)
Country FE	YES	-	-	YES	-	-	YES	-	-
Time FE	YES	-	YES	YES	-	YES	YES	-	YES
Country*Time FE	-	YES	-	-	YES	-	-	YES	-
NUTS1 FE	-	-	YES	-	-	YES	-	-	YES
Observations	2,293	2,174	2,287	2,293	2,174	2,287	2,293	2,174	2,287
R-squared	0.815	0.835	0.858	0.814	0.838	0.859	0.815	0.839	0.859
Within R-squared	0.538	0.566	0.449	0.507	0.536	0.419	0.508	0.538	0.419

Note: The model was estimated by means of a linear regression with multiple fixed effects. Dropped singleton observations: 119 (2)-(5)-(8) and 6 (3)-(6)-(9). Standard errors clustered at the regional level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4A: Estimates of the relationship between EI and green networks: inverse hyperbolic transformation.

	(1)	(2)	(3)	(4)
$LINKS_t$	0.106***			
	(0.020)			
$INTRALINKS_t$		0.225***		
		(0.040)		
$EXTRALINKS_t$			0.107***	
			(0.020)	
EX_INTRA_t				0.007***
				(0.002)
RD_t	16.458***	15.401***	16.447***	18.327***
	(5.179)	(4.637)	(5.172)	(6.028)
EDU_t	0.024***	0.016***	0.024***	0.037***
	(0.006)	(0.006)	(0.006)	(0.006)
POP_t	0.035***	0.031***	0.035***	0.041***
	(0.004)	(0.004)	(0.004)	(0.005)
Constant	0.127	0.406***	0.132	0.045
	(0.150)	(0.146)	(0.150)	(0.171)
NUTS1*Time FE	YES	YES	YES	YES
Observations	2,521	2,521	2,521	2,521
R-squared	0.887	0.888	0.887	0.881
Within R-squared	0.538	0.543	0.538	0.514

Note: The model was estimated by means of a linear regression with multiple fixed effects. The results obtained with country and year fixed effects, NUTS1 and year fixed effects, and country fixed effects by year are available upon request. 342 dropped singleton observations. Standard errors clustered at the regional level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5A: Estimates of the relationship between EI and green networks: institutional sectors and diversification. Inverse hyperbolic transformation.

	(1)	(2)	(3)
PRC_t	0.192***		
	(0.042)		
HES_t	0.063		
	(0.040)		
REC_t	0.024		
	(0.043)		
OTH_t	-0.017		
	(0.041)		
$entropy_t$		0.046	0.347*
		(0.093)	(0.201)
$entropy_t^2$			-0.264*
			(0.157)
$PART_t$		0.226***	0.232***
		(0.067)	(0.066)
RD_t	14.959***	14.981***	14.931***
	(4.595)	(4.683)	(4.705)
EDU_t	0.018***	0.011	0.013*
	(0.007)	(0.007)	(0.007)
POP_t	0.031***	0.028***	0.028***
	(0.004)	(0.004)	(0.004)
Constant	0.472***	0.647***	0.570***
	(0.160)	(0.158)	(0.161)
NUTS1*Time FE	YES	YES	YES
Observations	1,916	1,916	1,916
R-squared	0.886	0.891	0.892
Within R-squared	0.537	0.507	0.509

Note: The model was estimated by means of a linear regression with multiple fixed effects. The results obtained with country and year fixed effects, NUTS1 and year fixed effects, and country fixed effects by year are available upon request. 377 dropped singleton observations. Standard errors clustered at the regional level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6A: Estimates of the relationship between EI and green networks: ENV-TECH classification.

	(1)	(2)	(3)	(4)
$\ln(LINKS_t)$	0.118***	0.129***	0.091***	0.122***
	(0.021)	(0.025)	(0.017)	(0.024)
RD_t	25.551***	26.252***	15.967***	15.949***
	(6.543)	(6.788)	(4.345)	(5.011)
EDU_t	0.023***	0.021***	0.022***	0.019***
	(0.006)	(0.007)	(0.005)	(0.007)
POP_t	0.036***	0.036***	0.040***	0.038***
	(0.004)	(0.004)	(0.004)	(0.005)
Constant	0.238*	0.264*	0.413***	0.418**
	(0.141)	(0.158)	(0.136)	(0.165)
Country FE	YES	-	-	-
Time FE	YES	-	YES	-
Country*Time FE	-	YES	-	-
NUTS1 FE	-	-	YES	-
NUTS1*Time FE	-	-	-	YES
Observations	2,863	2,740	2,858	2,521
R-squared	0.773	0.794	0.818	0.862
Within R-squared	0.474	0.498	0.387	0.491

Note: The model was estimated by means of a linear regression with multiple fixed effects. Dropped singleton observations: 123 (2), 5 (3), and 342 (4). Standard errors clustered at the regional level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.