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Abstract

This paper examines how R&D investment enhances absorptive capacity, facilitating effective knowledge transfer within green innovation networks in European regions. Analyzing data from 2003 to 2021, the study finds that higher R&D investment significantly enhances the positive impact of network collaborations on green patenting.

Keywords: green patents; networks; absorption capacity; NUTS2
JEL classification: O33; Q55; R11; C2

1. Introduction

Green innovation has become a primary focus for policymakers. 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 finance joint projects that aim to create networks among all institutional research sectors. This approach is essential because green innovation often demands the integration of diverse types of knowledge and capabilities (Tang *et al.*, 2020). Consequently, through networks, knowledge, resources and skills can be shared with external partners, fostering green innovation (Fabrizi *et al.*, 2024).

The literature on open innovation emphasizes that external collaboration can significantly enhance innovation performance (Chesbrough, 2003; Chesbrough et al. 2006). However, collaboration with external partners requires a certain degree of depth, meaning the extent to which firms draw intensively on external knowledge providers. Unlike standard technological innovations, environmental innovations demand a more intensive and deeper engagement with external knowledge sources (Ghisetti et al. 2015). Due to the knowledge being specific to a particular actor or national context, cooperation in the network may present difficulties in communication and mutual understanding. In fact, when knowledge contains a significant tacit component, the transfer becomes difficult and costly (Powell and Grodal, 2006). The uncertainty of the expected gains from such knowledge, due to the high costs of obtaining it, suggests that the benefits derived from knowledge transfer are greatest when the knowledge involved has a moderate level of complexity.

This issue can be mitigated by the absorptive capacity, which is defined as the ability of an organization to capture the value of external knowledge and apply it (Cohen and Levinthal 1990). Absorptive capacity is not a static capability but rather one that evolves with a firm's R&D efforts. Firms that invest in R&D are better equipped to understand and integrate new information because they have developed related knowledge and skills (Cohen and Levinthal, 1989, 1990). Thus, the literature suggests investing resources in order to absorb knowledge spillovers, recognizing the role of R&D in making external knowledge more accessible (Lim, 2009). In this paper we provide empirical evidence on how R&D improves the absorptive capacity within European regions from 2003 to 2021. Specifically, the paper examines how different levels of R&D expenditure impact the ability of European regions to leverage collaborative networks for green innovation. We test the hypothesis that R&D expenditure positively moderates knowledge creation via networks.

This study contributes to broadening the debate on the role of R&D as a determinant of absorptive capacity, particularly in contexts requiring multidisciplinary knowledge, such as green innovation.

The remainder of the paper is structured as follows: Section 2 presents the data and methodology, Section 3 shows the results and Section 4 concludes the paper.

2. Methodology and data

To test our hypothesis, we estimate a knowledge production function (KPF), as proposed by Griliches (1979). We modify the standard KPF to incorporate potential nonlinear effects of networks on green innovation at changes of R&D, as illustrated in Eq. (1).

$$\ln PAT_{i,t} = \beta_0 + \beta_1 \ln NET_{i,t} + \sum_{j=1}^{9} \gamma_j (\ln NET_{i,t} * decile\_RD_{i,j,t}) + \beta_2 RD_{i,t} + \beta_3 EDU_{i,t} + \beta_4 POP_{i,t} + \theta_{m,t} + u_{i,t} \tag{1}$$

The dependent variable PAT is the total number of green patent applications in each NUTS2 region i at time t. We utilize an extensive and up-to-date dataset on green patents, starting from the OECD REGPAT database, which contains data on individual patent applications held by the European Patent Office (EPO), and regionalize individual applications based on the inventor's address. To identify patents on environmental-related technologies, we apply the "Y02/Y04S tagging scheme" (Favot *et al.*, 2023). *NET* takes into account green network variables derived from information on FP-funded projects with green aspects. The projects are selected according to the following thematic priorities: FP6-SUSTDEV (2002–2006), FP7-ENERGY FP7-ENVIRONMENT FP7-TRANSPORT (2007–2012), and Horizon 2020 - SOCIETAL CHALLENGES (2014-2020). We consider the number of collaborative links within and between regions (*LINKS*), the number of collaborative links between residents within the same region (*INTRA*), and collaborations with external partners (*EXTRA*). Following Berkes and Nencka (2024), the dependent and network variables are transformed by adding 1 to each observation and expressed in logarithm.[1]

We include the interactions between the networks and R&D expenditure on GDP (*RD*) to measure the moderating effect of R&D expenditure on the elasticity of patents to the variation in green network variables (γ_j). Given the nonlinearities in the effects of R&D, we consider the deciles of *RD*.

We add as controls *EDU*, which is a proxy for human capital calculated as the population with tertiary education and the total population, and *POP* that accounts for the regional population, as a measure of size. The data are taken from the Eurostat regional database. Table 1A in the Appendix provides the description and sources of data, while Table 2A presents the descriptive statistics.

We further control for NUTS1 fixed effects by year ($\theta_{m,t}$). This allows us to better account for specific economic characteristics of the macro area and also idiosyncratic shocks affecting the specific NUTS1 region in a given year. Several robustness checks are performed by considering different types of fixed effects in Eq. (1). We estimate the model separately, adding country fixed effects and NUTS1 fixed effects. In both estimations, year

[1] We verify the results by using the inverse hyperbolic sine of patents as an alternative transformation. The results presented in Table 4A and Figure 4A in Appendix are consistent with our baseline estimates.

fixed effects are included to account for time shocks that affect regions simultaneously in a given year. Finally, the model is estimated including country fixed effects by year. The error term is denoted by $u_{i,t}$.

We consider an unbalanced panel dataset that covers the period 2003-2021. Observations lacking data for control variables were excluded, leading to a final sample comprising 235 NUTS2 regions (based on the 2016 classification) with an average coverage of 12.2 years per region. The model was estimated by means of a linear regression with multiple fixed effects with 342 dropped singleton observations, resulting in 2,521 final observations.

3. Empirical results

In this section, we discuss the findings from our empirical investigation. Table 1 shows the estimates of the interactions between green research networks and decile of *RD*.[2] In column (1), we present the elasticity of green patents with respect to the number of internal and external collaborative links of regions (*LINKS*) at different deciles of R&D distribution. The coefficients become statistically significant starting from the third decile onwards. This suggests that at lower levels of R&D investment, the positive effect of networks on innovation capability is negligible. As the level of R&D investment increases, the benefits of participating in networks become more pronounced and statistically significant. This indicates that investments in R&D can improve the absorptive capacity of knowledge, even when this knowledge is tacit and comes from diverse contexts. This is typical of green networks, which are composed of actors with multidisciplinary skills necessary for innovation in the environmental sector. Therefore, the positive moderating effect of R&D expenditure is confirmed. However, there is a threshold level of R&D investment required before the advantages of network effects can be realized in terms of enhanced innovation capability.

[2] As a robustness check, we estimate the model by including country and year fixed effects, country fixed effects by year, and NUTS1 and year fixed effects and report the results in Table 3A in Appendix. By examining the values of R-squared and Within R-squared, the baseline model shows an appropriate compromise in explaining a significant portion of the overall variance and the variance within individual entities over time. Figures 1A, 2A, and 3A display the marginal effects.

In columns (2) and (3), we conduct a similar analysis, distinguishing between the number of links within the region (*INTRA*) and the number of collaborations outside the region (*EXTRA*). Qualitatively, the results are consistent with those of total collaborations.

The non-linearity of the effects of networks becomes more evident when calculating the marginal effects. Marginal effects provide a measure of the effect of the dependent variable modified by the presence of the variable with which it interacts. In Figure 1, we show the marginal effects of *LINKS* at each decile of R&D. For lower levels of R&D expenditure (deciles 1 to 3), the coefficients are not statistically significant, indicating that network effects do not substantially impact green innovation.

Table 1: Estimates of the model

	(1)	(2)	(3)
	$\ln(LINKS_t)$	$\ln(INTRA_t)$	$\ln(EXTRA_t)$
$\ln(NET_t)$	-0.006	-0.037	-0.006
	(0.026)	(0.070)	(0.026)
$\ln(NET_t) * decile\_RD_2$	0.019	0.044	0.020
	(0.024)	(0.068)	(0.025)
$\ln(NET_t) * decile\_RD_3$	0.057**	0.158**	0.057**
	(0.025)	(0.066)	(0.026)
$\ln(NET_t) * decile\_RD_4$	0.106***	0.252***	0.107***
	(0.028)	(0.073)	(0.029)
$\ln(NET_t) * decile\_RD_5$	0.109***	0.242***	0.110***
	(0.031)	(0.078)	(0.031)
$\ln(NET_t) * decile\_RD_6$	0.138***	0.288***	0.139***
	(0.032)	(0.077)	(0.033)
$\ln(NET_t) * decile\_RD_7$	0.140***	0.274***	0.140***
	(0.036)	(0.082)	(0.036)
$\ln(NET_t) * decile\_RD_8$	0.158***	0.293***	0.158***
	(0.041)	(0.094)	(0.041)
$\ln(NET_t) * decile\_RD_9$	0.192***	0.336***	0.193***
	(0.040)	(0.087)	(0.040)
$\ln(NET_t) * decile\_RD_{10}$	0.223***	0.329***	0.224***
	(0.046)	(0.091)	(0.046)
RD_t	7.325*	12.372***	7.458*
	(4.360)	(4.354)	(4.371)
EDU_t	0.009*	0.006	0.009*
	(0.005)	(0.005)	(0.005)
POP_t	0.027***	0.025***	0.027***
	(0.004)	(0.003)	(0.004)
Constant	0.383***	0.515***	0.384***
	(0.129)	(0.128)	(0.129)
NUTS1*Time FE	YES	YES	YES
Observations	2,521	2,521	2,521
R-squared	0.898	0.897	0.898
Within R-squared	0.580	0.574	0.580

Note: The model was estimated by means of linear regression with multiple fixed effects. 342 dropped singleton observations. Standard errors clustered at the regional level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

However, as R&D expenditure increases, the positive contribution of collaborations to green innovation becomes positive. In fact, from the fifth decile onwards, the elasticity of patents with respect to network links becomes statistically significant. This means that for regions with median or higher levels of R&D investment, the benefits of networks in fostering green innovation are more pronounced and statistically different from the lower deciles. The trend continues to strengthen with higher deciles, highlighting the importance of substantial R&D investment to fully leverage the advantages of network collaborations in promoting green innovation.

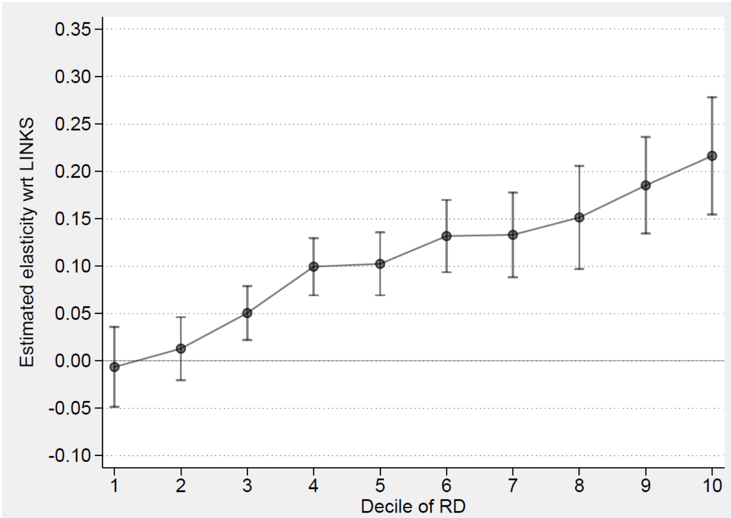

Figure 1: Marginal effects of LINKS at each decile of R&D. Confidence interval at 90%

Furthermore, in Figure 2 we report the marginal effects distinguishing between internal and external links. For internal links, an R&D level around the median is sufficient to enhance absorptive capacity, as the coefficients from the fourth decile onwards are not significantly different from each other. In contrast, for external links, high levels of R&D expenditure significantly improve the performance of networks in fostering green innovation. This indicates that while moderate R&D investment can optimize the benefits of internal collaborations, substantial R&D investment is necessary to maximize the advantages of external collaborations for green innovation.

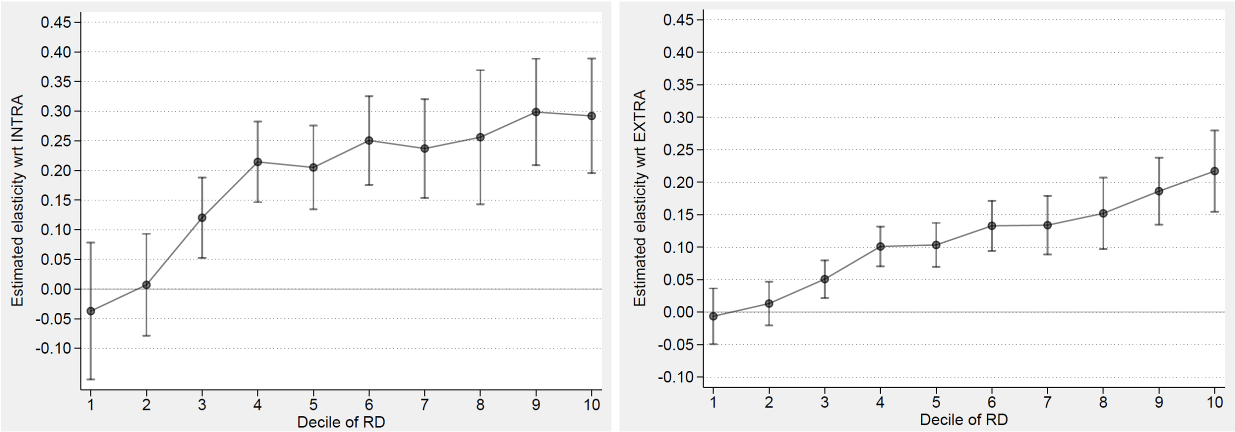

Figure 2: Marginal effects of INTRA (left) and EXTRA (right) at each decile of R&D. Confidence interval at 90%

4. Conclusions

This paper has examined the role of R&D in improving the absorptive capacity of European regions over the period 2003-2021. Using an interaction model, we try to show how participation in a network has different effects on green innovation at each level of R&D expenditure. Our results confirm that R&D expenditure increases the absorptive capacity of regions to use knowledge from the outside. The positive effect of the network on innovation is minimal at low levels of R&D, but significant from the third decile onwards. While a moderate level of R&D investment is sufficient for internal linkages, a high level of R&D is required for external linkages in order to maximize the benefits of green networks on environmental innovation.

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Appendix

Table 1A: 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	EU OPEN DATA PORTAL; own elaboration
INTRA	Total number of region's internal links	EU OPEN DATA PORTAL; own elaboration
EXTRA	Total number of region's interregional links	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

Table 2A: 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
INTRA	13.40	28.92	0.00	444.00
EXTRA	181.85	321.18	0.00	3820.00
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

Table 3A: Estimates of the model: robustness

	$\ln(LINKS_t)$			$\ln(INTRA_t)$			$\ln(EXTRA_t)$		
$\ln(NET_t)$	-0.010	-0.018	-0.009	-0.040	-0.066	-0.039	-0.009	-0.018	-0.008
	(0.020)	(0.023)	(0.019)	(0.053)	(0.059)	(0.051)	(0.020)	(0.023)	(0.019)
$\ln(NET_t) * decile\_RD_2$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln(NET_t) * decile\_RD_3$	0.033	0.041*	0.019	0.068	0.098	0.034	0.033	0.041*	0.019
	(0.023)	(0.023)	(0.022)	(0.064)	(0.063)	(0.061)	(0.023)	(0.023)	(0.022)
$\ln(NET_t) * decile\_RD_4$	0.065***	0.070***	0.054***	0.163***	0.187***	0.139***	0.064***	0.070***	0.054***
	(0.020)	(0.022)	(0.019)	(0.051)	(0.057)	(0.049)	(0.020)	(0.023)	(0.019)
$\ln(NET_t) * decile\_RD_5$	0.091***	0.102***	0.093***	0.218***	0.256***	0.213***	0.091***	0.102***	0.093***
	(0.024)	(0.027)	(0.020)	(0.058)	(0.064)	(0.053)	(0.024)	(0.027)	(0.021)
$\ln(NET_t) * decile\_RD_6$	0.097***	0.104***	0.103***	0.210***	0.247***	0.209***	0.097***	0.104***	0.103***
	(0.026)	(0.030)	(0.021)	(0.063)	(0.072)	(0.054)	(0.026)	(0.030)	(0.022)
$\ln(NET_t) * decile\_RD_7$	0.136***	0.154***	0.115***	0.268***	0.318***	0.231***	0.136***	0.155***	0.115***
	(0.026)	(0.030)	(0.023)	(0.061)	(0.070)	(0.055)	(0.026)	(0.031)	(0.023)
$\ln(NET_t) * decile\_RD_8$	0.155***	0.177***	0.113***	0.279***	0.335***	0.212***	0.155***	0.177***	0.113***
	(0.029)	(0.035)	(0.024)	(0.064)	(0.074)	(0.056)	(0.030)	(0.035)	(0.025)
$\ln(NET_t) * decile\_RD_9$	0.176***	0.199***	0.125***	0.306***	0.361***	0.223***	0.176***	0.199***	0.124***
	(0.032)	(0.037)	(0.027)	(0.069)	(0.080)	(0.062)	(0.032)	(0.038)	(0.027)
$\ln(NET_t) * decile\_RD_{10}$	0.187***	0.222***	0.139***	0.311***	0.385***	0.238***	0.187***	0.223***	0.138***
	(0.036)	(0.042)	(0.027)	(0.072)	(0.084)	(0.058)	(0.037)	(0.043)	(0.028)
Constant	0.199*	0.315**	0.259**	0.322**	0.453***	0.353***	0.198*	0.314**	0.259**
	(0.115)	(0.135)	(0.104)	(0.125)	(0.150)	(0.102)	(0.115)	(0.135)	(0.104)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	-	-	YES	-	-	YES	-	-
Time FE	YES	-	YES	YES	-	YES	YES	-	YES
Country*Time FE	-	YES	-	-	YES	-	-	YES	-
NUTS1	-	-	YES	-	-	YES	-	-	YES
Observations	2,863	2,740	2,858	2,863	2,740	2,858	2,863	2,740	2,858
R-squared	0.822	0.842	0.863	0.820	0.840	0.862	0.822	0.842	0.863
Within R-squared	0.555	0.584	0.468	0.550	0.578	0.463	0.555	0.584	0.468

Note: The model was estimated by means of 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.

Figure 1A: Marginal effects of green network variables at each decile of R&D. Confidence interval at 90%. Country and year FE

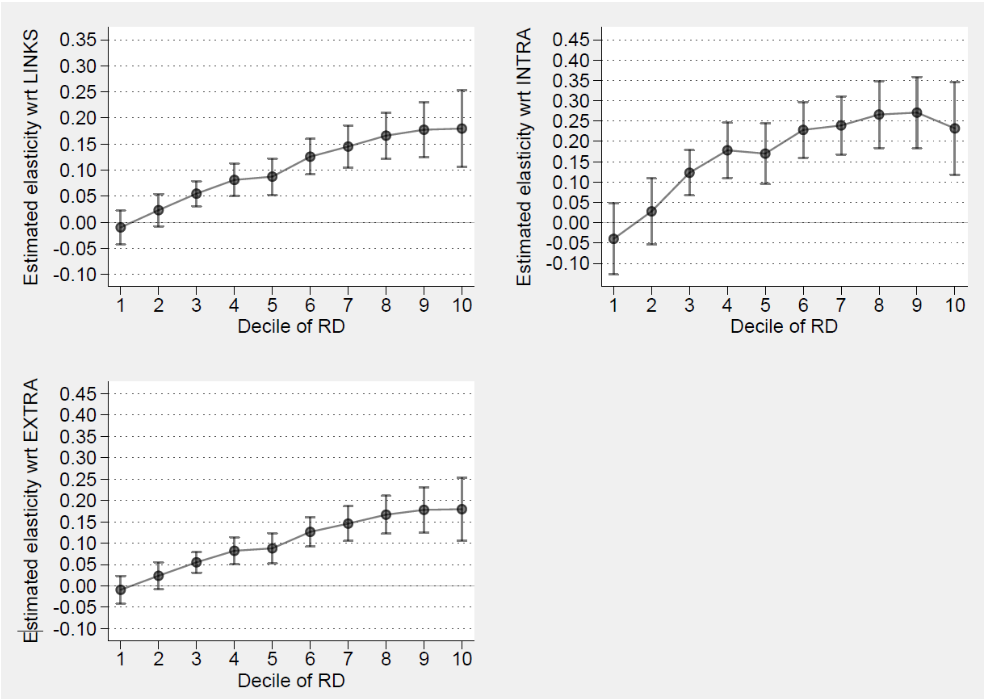

Figure 2A: Marginal effects of green network variables at each decile of R&D. Confidence interval at 90%. Country FE by year

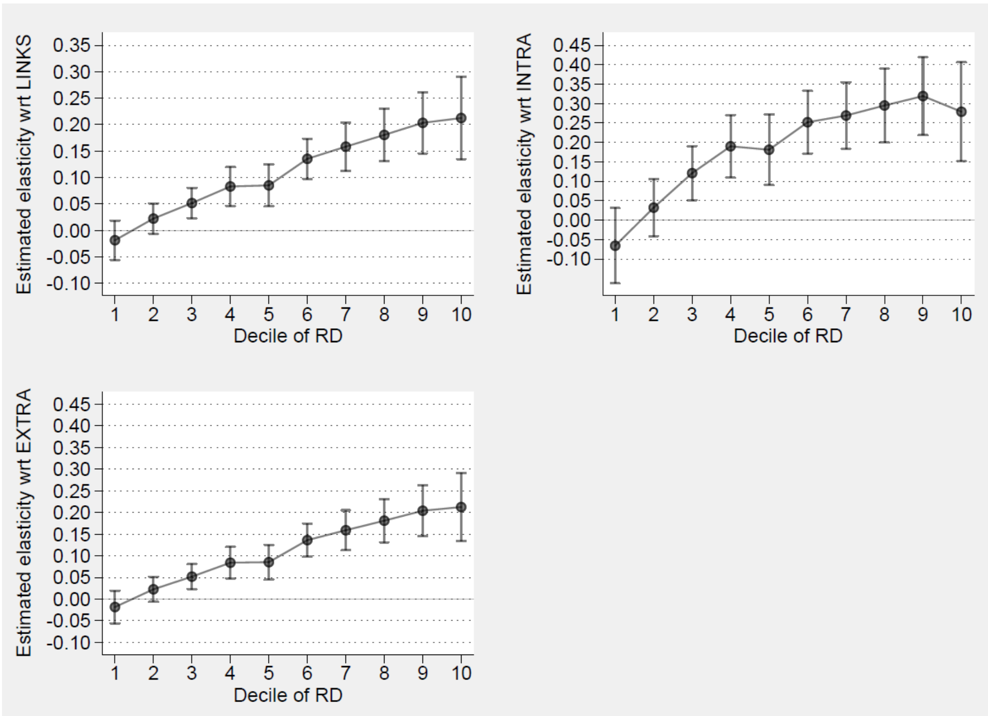

Figure 3A: Marginal effects of green network variables at each decile of R&D. Confidence interval at 90%. NUTS1 and year FE

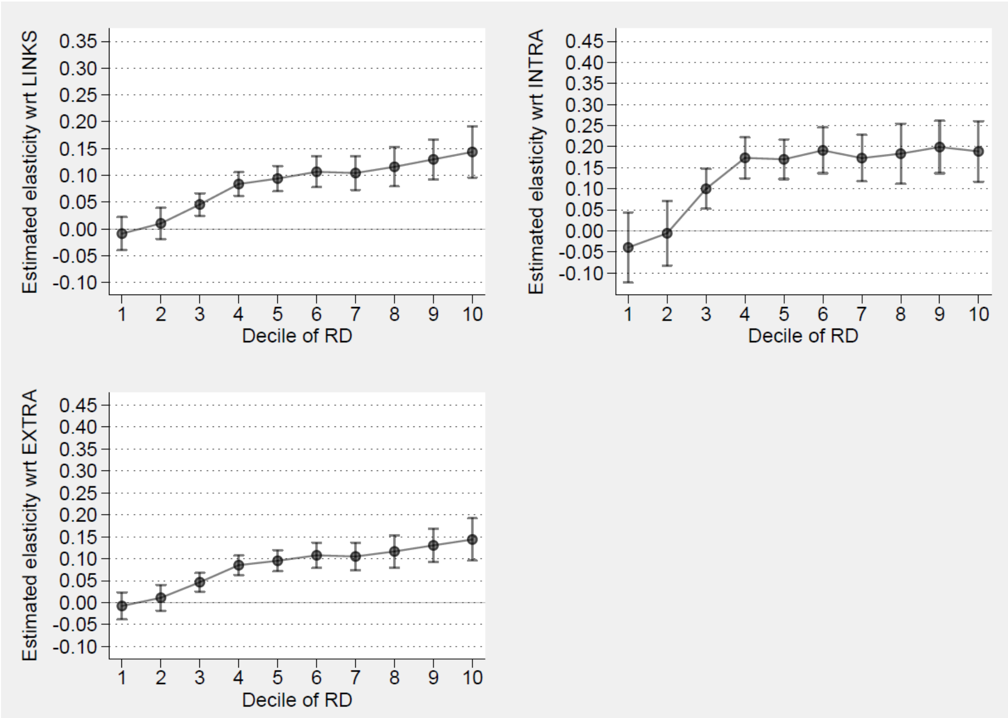

Table 4A: Estimates of the model: robustness with inverse hyperbolic transformation

	(1)	(2)	(3)
	$LINKS_t$	$INTRA_t$	$EXTRA_t$
NET_t	-0.009	-0.040	-0.009
	(0.028)	(0.069)	(0.028)
$NET_t * decile\_RD_2$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
$NET_t * decile\_RD_3$	0.023	0.051	0.023
	(0.026)	(0.067)	(0.027)
$NET_t * decile\_RD_4$	0.065**	0.166**	0.065**
	(0.027)	(0.066)	(0.028)
$NET_t * decile\_RD_5$	0.119***	0.266***	0.121***
	(0.030)	(0.072)	(0.031)
$NET_t * decile\_RD_6$	0.127***	0.267***	0.128***
	(0.033)	(0.077)	(0.033)
$NET_t * decile\_RD_7$	0.157***	0.312***	0.159***
	(0.034)	(0.076)	(0.035)
$NET_t * decile\_RD_8$	0.155***	0.292***	0.156***
	(0.038)	(0.081)	(0.038)
$NET_t * decile\_RD_9$	0.176***	0.316***	0.177***
	(0.043)	(0.091)	(0.043)
$NET_t * decile\_RD_{10}$	0.201***	0.339***	0.202***
	(0.042)	(0.086)	(0.042)
RD_t	8.568*	13.540***	8.696*
	(4.961)	(4.852)	(4.971)
EDU_t	0.012**	0.008	0.012**
	(0.006)	(0.006)	(0.006)
POP_t	0.031***	0.029***	0.031***
	(0.004)	(0.004)	(0.004)
Constant	0.472***	0.642***	0.473***
	(0.152)	(0.151)	(0.152)
NUTS1*Time FE	YES	YES	YES
Observations	2,521	2,521	2,521
R-squared	0.892	0.891	0.892
Within R-squared	0.561	0.557	0.561

Note: The model was estimated by means of linear regression with multiple fixed effects. The results obtained with country and year fixed effects, country fixed effects by year, and NUTS1 and year fixed effects 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.

Figure 4A: Marginal effects of green network variables at each decile of R&D. Confidence interval at 90%. Inverse hyperbolic transformation