Harnessing artificial intelligence for regional eco-innovation: a patent-based analysis of European regions' green-tech diversification

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Abstract

In this paper we investigate the extent to which Artificial Intelligence (AI) is harnessed by regions for the sake of their sustainable development. By considering the manifold impact that AI is having on innovation, we expect that the local endowment of AI knowledge can help regions diversify in new green technologies, and that its effect is affected by their previous experience in mastering such technologies and by the complexity of their knowledge-base. Using patents by regional applicants as a proxy of the local knowledge-base, we integrate their OECD-based green classification with the identification of AI patents based on different approaches and look at the relationship between new green technological advantages and local AI for EU15 (NUTS3) regions over the period 1982-2013. Econometric results show that AI actually favors the green-tech diversification of regions, but only by conditioning the effect of other green drivers. In particular, AI helps regions specialize in new green-techs providing they have already done it in the past, while it even reduces this capacity in non-already green specialized ones.

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1. Introduction

Along the unfolding of its life-cycle, marked by a sequence of repeated development waves (Agrawal et al., 2018), artificial intelligence (AI) has been envisaged to assist regional development and urban planning in different domains, like in Geographic Information Systems (GIS) and spatial modelling (Openshaw, 1992), in managing urban land dynamics, and in forecasting regional business and energy loads (Ning and Silva, 2010; Che-Chiang and Chia-Yon, 2003).

Within the so-called "Fourth Industrial Revolution" (Schwab, 2016), the convergence between AI and other enabling technologies – like in robotics, internet of things and quantum computing – has imparted a new boost to its application, which has recently come to embrace its harnessing for environmental sustainability. In the "Fourth Industrial Revolution for the Earth Series", dedicated to the potential of its innovations in addressing the environmental and human challenges of the century, the World Economic Forum (2018) has identified the opportunity of extending AI to incorporate "Earth-friendly AI" (p. 4). Putting AI at the service of distributed (e.g. circular) water and energy distribution grids, more accurate climate change models, and improved systems of resilience planning (e.g. in front of natural disasters), represents an only partial gallery of these environmental-friendly AI applications.

The potential of AI in introducing technological breakthroughs for the sake of the environment is allegedly important also and above all at the regional level. As recent research across regional and innovation studies has shown, the development of environmental technologies – for mitigating, eliminating or reversing the environmental impact of economic activities – actually has multiple territorial implications, in terms of spatial agglomeration, regional spillovers, regional systems of innovation, and local-global interactions, to mention a few (e.g. Turner, 2006; Munday and Roberts, 2006; Cainelli et al., 2012; Ghisetti and Quatraro, 2013; Horbach, 2014; Antonioli et al., 2016; Leoncini et al., 2016). In particular, an emerging line of investigation on the geography of eco-innovations (Montresor and Quatraro, 2019; Corradini, 2017; Tanner, 2014; van den Berge and Weterings, 2014) is suggesting that the embeddedness, relatedness and connectivity of the knowledge-base of the regions is capable to favor region-specific patterns of innovation also in the environmental domain. In brief, regions appear privileged, though heterogeneous loci for a technology-led transition towards environmental sustainability (Gibbs and O'Neill, 2017; Truffer and Coenen, 2012).

Drawing on and extending this last stream of research, in this paper we aim at investigating the extent to which AI is actually harnessed for environmental sustainability at the regional level. Drawing on recent analysis of the technological features of AI, and crossing it with the literature on eco-innovations, we argue that its twofold property of "general purpose invention of making inventions" (Cockburn et al., 2019) makes of it a significant driver of the regional capacity to specialize in new green technologies. However, we also maintain that such an impact is not straightforward and rather crucially depends on the nature and complexity of the regional knowledge-base and relatedness to existing technological specialisations.

2. Background literature and research arguments

In spite of its already extended history as a technology and research field,[1] the economic analysis of AI is still at an incipient stage. The newly released book by Agrawal et al. (2019) presents it as a research stream that has just managed to set an "agenda", inspired by the promising results obtained so far about its potential impact on "productivity, growth, inequality, market power, innovation, and employment" (ibid., frontpage). Out of the several identified effects, one that still hesitates to be recognized is the role that AI could have in favoring environmental sustainability, that is, in allowing for a transformative kind of change in the extant models of development, which leads to a greater sensitivity to its environmental impact. In fact, that an environmental impact of AI could exist has been already envisaged in the debate fed by international organizations. The World Economic Forum (2018), for example, has recently produced a report in which, although mainly in terms of potential and opportunities, such an impact has been identified at two levels. At a first level, within the current "rules of the game", AI can work in enhancing the actions that have already been taken to address environmental issues, so that "Earth-Friendly AI" can be identified in addressing: climate change (e.g. optimised energy system forecasting); biodiversity and conservation (e.g. precision monitoring of ecosystems), healthy oceans (e.g. overfishing prevention and control); water security (e.g. water quality simulation and data alerts); clean air (e.g. real-time air pollution monitoring and simulations); and weather and disaster resilience (e.g. climate informatics for enhanced climate modelling). At a higher level, a more systemic and transformational impact on the environment could be brought by "Game-Changers AI", both under current – autonomous and connected electric vehicles; distributed energy grids; smart agriculture; weather forecasting and climate modelling; community disaster-response data and analytics platform; decentralized water; intelligent, connected and liveable cities; oceans data platform; and earth bank of codes – and prospected development ("Further-off AI game changers") – a real-time digital dashboard of the Earth; autonomous farming and end-to-end optimized food system; reinforcement learning for natural sciences breakthroughs; quantum and distributed computing to dramatically scale computational power for AI for the Earth; the home supercomputer and AI research assistants for democratized scientific progress.

While the search for specific environmental-friendly AI is progressing, the general mechanisms through which AI could affect the green transition remain still unexplored. What is more, given the little attention that the economics of AI has dedicated to the meso-level of analysis so far, still uncharted is also the identification of these AI mechanisms for the green transition at the regional level. As we will say, given the high degree of context specificities and regional heterogeneity that environmental sustainability has been proved to reveal (Cooke, 2011; 2012; Truffer and Coenen, 2012; Gibbs and O'Neill, 2017), this is quite unfortunate. Once more, applications of AI to sustainable regional development and urban planning have been already identified since long, at least since the mid-80s (Baráth and Futó, 1985; Sashi and Ramakrushna, 2003; Silva, 2004), especially through its contribution to Geographic Information Systems (GIS) and spatial modelling (Openshaw, 1992). Subsequent applications have extended also to other domains, like in managing urban land dynamics and in forecasting regional business and energy loads (Ning and Silva, 2010; Che-Chiang and Chia-Yon, 2003). Still, the characteristics of AI that could make of it a leverage for regional green development have not received attention yet.

An important contribution to fill this research gap can be obtained by considering some recent work on the AI impact of innovation, and extending it to the domain of eco-innovation and green

[1] In defining AI as "that activity devoted to making machines intelligent, [being] intelligence [… the] quality that enables an entity to function appropriately and with foresight in its environment", Nilsson (2010) suggests that the early years of AI research, initially concentrated on the study of symbolic systems, dates back at least to the 1960s.

diversification at the regional level. As Cockburn et al. (2019) have recently argued, although mainly in its latest technological trajectory - amounting to the development of deep learning and neural networks - AI has two (potential) features that affect the unfolding of the innovation process in a crucial way. First of all, AI is susceptible to be applied across a wide range of domains, into which it complementarily introduces rapid innovations because of its own eventual innovation: in other words, AI has the distinguishing features to emerge as the "most important general-purpose technology (GPT) of our era" (Brynjolfsson and McAfee; Trajtenberg, 2019), asking us to extend to it what innovation studies have taught us about these GPTs (Bresnahan and Trajtenberg, 1995). Second, and possibly most important in comparison to previous GPTs (e.g. microprocessors during the IT revolution), AI is emerging as an "invention of a method of inventing" (IMI), that is, as a research tool itself, capable to change the procedures ("playbook") for innovation to occur in the several domains in which AI is applied.[2] In Cockburn et al. (2019)'s words: "One the one hand, AI based learning may be able to substantially "automate discovery" across many domains where classification and prediction tasks play an important role. On the other, they may also "expand the playbook" is the sense of opening up the set of problems that can be feasibly addressed, and radically altering scientific and technical communities' conceptual approaches and framing of problems."

Although at the price of some delicate incentive and coordination problems in favoring and managing its development (for which, see Bresnahan and Trajtenberg, 1995), this twofold nature of (based-learning) AI makes of it an important leverage for innovations that could be "transformative" in their introducing products, processes, and organizational methods that combine novelty with environmental sustainability (e.g. reduction of environmental risk, pollution and other negative impacts of resources use (including energy use), that is, eco-innovations (EIs) (Kemp and Pearson 2007). On the one hand, in its role of GPT, AI can help satisfy the typically system nature of EIs, requiring their implementation all along the value chains (e.g. green suppliers and green customers) of the focal eco-innovators. Indeed, the development of a new green-friendly AI procedure could reinforce a cycle of complementary eco-innovations between the domain in which it is developed and the sectors in which it is applied, which can enlarge the scope of eco-innovations and make them more systemic. On the other hand, in its role of IMI, AI can also improve the complicate "playbook" for eco-innovating, by enabling a more effective dealing of the higher complexity that has been shown to characterize their development (Consoli et al., 2016; Barbieri et al., 2018). In particular, representing a superior research tool in problems of classification and prediction, AI could help in better grasping and mapping the multiple sources of knowledge on which EIs draw and in more effectively forecasting the wide set of scenarios on which their successful application depends.

The mechanisms through which AI can affect EIs deserve particular attention when the analysis is carried out at the regional level, as we do in the present paper. At this level of analysis, the research on EIs, initially developed in a-spatial framework (Horbach et al., 2012), has recently shown that regions are not equally well-equipped in front of them, and that their EI heterogeneity can be attributed to a variety of factors, among which: the availability of skilled human capital, science and research organizations, and suitable financial mechanisms (Horbach, 2014; Arranz et al., 2019); the awareness of environmental issues and the public support to them (Santoalha and Boschma, 2019; Giudici et al., 2019); as well as more general agglomeration vs. variety/relatedness economies

[2] In this sense, AI would represent the modern equivalent of double-cross hybridization in the classic study by Griliches (1957), in which "Rather than being a means of creating a single a new corn variety, hybrid corn represented a widely applicable method for breeding many different new varieties" (Cockburn et al., 2019).

(Antonioli et al., 2016; Horbach, 2014). Further insights have been gained from the literature on regional diversification, from which it has emerged that also green technologies develop in a path- and place-dependent way, being favored by their relatedness to the exiting regional knowledge-base, but with several nuances (Van den Berge and Weterings, 2014; Tanner, 2016; Barbieri et al., 2018a; Colombelli and Quatraro, 2019; Corradini, 2019; Barbieri et al., 2018a; Barbieri and Consoli, 2019; Montresor and Quatraro, 2019). In particular, in a recent work on the regional capacity to specialize into new green technologies, Montresor and Quatraro (2019) have shown that the set of technologies identified by the European Commission as Key Enabling Technologies (KETs) – i.e. industrial biotechnology, nanotechnology, micro- and nanoelectronics, photonics, advanced materials, and advanced manufacturing technologies – significantly affect such a capacity, by even making it less reliant on relatedness, precisely because of their (heterogeneous) nature of GPT. In brief, the main argument is that, because of their typical horizontal application across the (regional) economic systems and of the co-invention/application that mark their development, GPT like KETs would enable regions more explorative re-combinations of their knowledge-base (Montresor and Quatraro, 2017), also and above all of their extant green-knowledge with respect to their non-green one (Montresor and Quatraro, 2019).

Thinking of the GPT nature that AI has been also recognized to have, we expect that its local availability could also have a role in favoring the explorative recombination of the existing local knowledge in the green domain. To be sure, we expect that AI could also make such a re-combination more effective, given the recognized role of AI breakthroughs in dramatically improving the prediction of which combinations have the highest potential to work (Agrawal et al., 2019a). On the other hand, we also expect that such an impact is highly conditional on the nature and structure of the extant knowledge-base to which AI applies. Indeed, this is the implication of the IMI feature of AI, which KETs do not share, or at least do to an inferior extent (see Cockburn et al., 2019). As Cockburn et al. (2019) have recognized, the IMI function of AI crucially depends on its application to large sets of granular data on both social and physical behavior. The predictive power of AI, which could expectedly change the way of eco-innovating in general, actually improves as it is applied to larger and larger datasets. In our focal regional question, this has two implications. On the one hand, in favoring the green diversification of regions, AI expectedly benefits from the local availability of green knowledge and from the repertoire of environmental experiences that their previous track in mastering green technologies has possibly guaranteed to them. On the other hand, the green-tech impact of AI is arguably greater, the more complex is the knowledge-base of the region, in terms of number and (low) ubiquity of the connections between knowledge fields of which it is constituted. Because of their relevance, these are aspects that will need to be controlled in the empirical application we present in the next Section.

3. Empirical application

Data

We investigate these arguments through an econometric analysis of a longitudinal dataset comprising information on 634 unique technological classes (following the cooperative patent classification) in 933 EU15 (NUTS3) regions observed over the period 1982-2013 (aggregated in eight four-year long time periods), which combines data from two main sources. Our starting point is the OECD RegPASTAT dataset (Maraut et al., 2008). In particular, we adopt a number of different approaches to identify patents pertaining to the AI realm (Cockburn et al., 2019; EPO, 2017;

Seamans and Raj, 2018) and combine it with the green patent classification elaborated by the OECD "Environmental Technologies Indicators, ENV-TECH" (Haščič and Migotto, 2015), to see whether the regional inventive capacity in AI and technological relatedness drive the region capacity to specialize in new green technologies. In order to control for a number of confounding effects in the relationship between the variables of interest, we also draw on the European Regional Database (Cambridge Econometrics) (Montresor and Quatraro, 2019). Our final sample comprises 209,266 NUTS3-CPC-Period observations.

Econometric strategy

From an empirical point of view, we analyse the probability that a region specializes in a green technology. Building upon Santoalha and Boschma (2019) and Montresor and Quatraro (2019), our main dependent variable measures whether a region has a Revealed Technological Advantage in a green technology in a given time period (*RTA Green*). Following the arguments developed in section 2, the main variables of interest are the regional stock of AI patents (*AI stock*) and relatedness density (*Relatedness*) between a given technology and the overall technological portfolio of a region (i.e., proximity to existing technologies).[3] We also include a number of control variables in our specification: 1) the knowledge space position (*KSP*) which measures the positioning and connectedness of a region's technological patterns within the overall knowledge space[4]; 2) the regional stock of patents as measure of the technological stock at the regional level (*Patent portfolio stock*); 3) regional employment rate (*Employment rate*); 4) GDP per capita in constant 2005 euros (*GDP per capita*) and 5) Gross fixed capital formation in constant 2005 euros as measure of capital investment at the regional level (*Gross Fixed Cap Form*). In an attempt to address problems of reverse causality explanatory and control variables are all lagged of one period (*t-4* years). All specifications are estimated at the province-technological-time level (NUTS3-CPC-Period). We adopt a linear probability model to assess the probability that a province specializes in a green technological field adopting the following specification:

$$GreenRTA_{rct} = \alpha + \beta_1 GreenRTA_{rct-1} + \beta_2 AIStock_{rct-1} + \beta_3 Relatedness_{rct-1} + \rho' Controls_{rt-1} + \gamma_r + \vartheta_c + \mu_t + \varepsilon_{rct} \tag{1}$$

Our baseline specification is a three-way fixed-effects model where γ_r is a region fixed effect, ϑ_c is a technology fixed effect and μ_t is a time fixed effect. Since errors are correlated within regions and technologies, we cluster standard errors at the region and technology level.

Apart from the baseline specification (model 1 above), we also estimate additional specifications which investigate: i) the differential role of AI and relatedness in the transition of regions to green technological specialisations (models 2 and 3); ii) the complementarity between relatedness and AI for green tech specialisation (specification 4) and iii) the role of AI, relatedness and their interaction for green tech specialization (specification 5).

$$GreenRTA_{rct} = \alpha + \beta_1 GreenRTA_{rct-1} + \beta_2 AIStock_{rct-1} + \beta_3 Relatedness_{rct-1} + \beta_4 GreenRTA_{rct-1} * AIStock_{rct-1} + \rho' Controls_{rt-1} + \gamma_r + \vartheta_c + \mu_t + \varepsilon_{rct} \tag{2}$$

$$GreenRTA_{rct} = \alpha + \beta_1 GreenRTA_{rct-1} + \beta_2 AIStock_{rct-1} + \beta_3 Relatedness_{rct-1} + \beta_4 GreenRTA_{rct-1} * Relatedness_{rct-1} + \rho' Controls_{rt-1} + \gamma_r + \vartheta_c + \mu_t + \varepsilon_{rct} \tag{3}$$

[3] For a formal definition of relatedness please refer to the appendix A1

[4] For further details on the construction of the KSP measure please refer to appendix A2

$$GreenRTA_{rct} = \alpha + \beta_1 GreenRTA_{rct-1} + \beta_2 AIStock_{rct-1} + \beta_3 Relatedness_{rct-1} + \beta_4 AIStock_{rct-1} * Relatedness_{rct-1} + \rho' Controls_{rt-1} + \gamma_r + \vartheta_c + \mu_t + \varepsilon_{rct} \quad (4)$$

$$GreenRTA_{rct} = \alpha + \beta_1 GreenRTA_{rct-1} + \beta_2 AIStock_{rct-1} + \beta_3 Relatedness_{rct-1} + \beta_4 GreenRTA_{rct-1} * AIStock_{rct-1} + \beta_5 GreenRTA_{rct-1} * Relatedness_{rct-1} + \beta_6 AIStock_{rct-1} * Relatedness_{rct-1} + \beta_7 GreenRTA_{rct-1} * AIStock_{rct-1} * Relatedness_{rct-1} * \rho' Controls_{rt-1} + \gamma_r + \vartheta_c + \mu_t + \varepsilon_{rct} \quad (5)$$

Finally, we investigate whether the effects we obtain differ across different levels of the knowledge space position by splitting the five specifications above according to high KSP (including only the top 10% province–technology observations in terms of KSP) and low KSP (including only the bottom 10% province–technology observations in terms of KSP).

4. Results

As expected from results obtained in the previous literature, past specialisation in environmental technologies is positively and significantly associated with current specialisation, thus corroborating the expectation about a persistence in green technological investment. In all models in Table 2, we also find that relatedness has a positive and significant effect on the probability that a region specialises in a green technological field, which is consistent with previous findings from the literature (Balland, 2016; Boschma et al., 2015; Rigby, 2015). Even more interestingly, we show that relatedness helps transition to green specialisation (non green regions specialise in green technologies) but not persistence (green regions remain specialised in green technologies): this comes from the positive and significant coefficient of relatedness and the negative coefficient of the interaction between Green RTA and relatedness in model 3. Conversely, Table 2 shows that the stock of AI patents at the province level helps persistence in green technological specialisation while it does not facilitate transition to a green specialisation. It seems that AI needs to build upon an existing green knowledge base to exert its effect. Finally, the investing in AI in regions with high relatedness seems to be associated with a less likelihood in persistence in green technological specialization (coefficient of the triple interaction negative and significant in model 6 of Table 2).

Previous literature has shown the importance that position in the knowledge/technological space plays for technological specialization of regions (Balland et al., 2018). For this reason, in Table 3 (specifications 1 to 3) and 4 (specifications 4 to 6) we split the sample between observations with a high level of KSP and observations with a low level of KSP to see whether our results depend upon the positioning and connectedness of a region's technological patterns within the overall knowledge space. Interestingly, we find that the positive (negative) role of AI (relatedness) for persistence (transition) in green technological specialization holds for regions with a low level of KSP only (columns 3 and 5 in Table 3). Finally, we find a certain degree of complementarity between AI and technological relatedness in regions with a low level of KSP (Column 5 in Table 4).

5. Conclusions

TBD

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Table 1: Descriptive statistics

Variable	Mean	Std Dev	Min	Max
Green RTA	0.05	0.22	0.00	1.00
AI Pat	0.58	16.42	0.00	2783.33
Pat	62.39	300.10	0.01	28411.96
KSP	14.41	6.77	0.14	35.89
Relatedness	0.37	0.07	0.00	1.00
Emp rate	0.50	0.13	0.17	1.00
Gross Fixed Cap Form	0.22	0.22	0.01	1.19
GDP per capita	0.03	0.01	0.01	0.11

Table 2: AI and relatedness for environmental technology specialisation

	(1)	(2)	(3)	(4)	(5)	(6)
Green RTA -1	0.330***	0.331***	0.332***	0.330***	0.333***	0.334***
	[0.024]	[0.024]	[0.024]	[0.024]	[0.024]	[0.024]
AI Pat -1	-0.000**	-0.001**	-0.001**	-0.000**	-0.001**	-0.001**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Relatedness	0.003***	0.003***	0.004***	0.003***	0.004***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Green RTA -1 X AI Pat -1		0.025***			0.028***	0.066***
		[0.008]			[0.008]	[0.013]
Green RTA -1 X Relatedness -1			-0.025***		-0.025***	-0.026***
			[0.009]		[0.009]	[0.010]
Relatedness -1 X AI Pat -1				-0.000	-0.000**	-0.000
				[0.000]	[0.000]	[0.000]
Green RTA -1 X Relatedness -1 X AI Pat -1						-0.058***
						[0.015]
KSP -1	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Employment rate -1	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Gross Fixed Cap Form -1	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
GDP per capita -1	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Pat -1	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
NUTS3 FEs	Yes	Yes	Yes	Yes	Yes	Yes
CPC FEs	Yes	Yes	Yes	Yes	Yes	Yes
Period FEs	Yes	Yes	Yes	Yes	Yes	Yes
R sq	0.517	0.517	0.518	0.517	0.518	0.518
NUTS3-CPC-year obs	209266.000	209266.000	209266.000	209266.000	209266.000	209266.000

Linear regressions with robust standard errors clustered by NUTS 3-digits and CPC in parentheses. Dependent variable is the probability to have a Revealed Technological Advantage (RCA) in environmental innovation. Base sample in all columns is a pooled dataset, 1982-2013, with data at 4-year intervals in levels where the start date refers to the dependent variable (i.e., if t=2010-2013, so t-1=2006-2009). All independent variables are standardised and lagged by one period. * p<0.10, ** p<0.05, *** p<0.01

Table 3: AI and relatedness for environmental technology specialisation by level of Knowledge Space Position (KSP) – models 1 to 3

	(1) Low KSP	(2) High KSP	(3) Low KSP	(4) High KSP	(5) Low KSP	(6) High KSP
Green RTA -1	0.302***	0.323***	0.335***	0.323***	0.292***	0.303***
	[0.052]	[0.038]	[0.051]	[0.038]	[0.053]	[0.048]
AI Pat -1	-0.001	-0.000**	-0.003	-0.000**	-0.002	-0.000**
	[0.005]	[0.000]	[0.005]	[0.000]	[0.005]	[0.000]
Relatedness	0.000	0.009***	0.000	0.009***	0.001	0.008***
	[0.001]	[0.002]	[0.001]	[0.002]	[0.002]	[0.002]
Green RTA -1 X AI Pat -1			1.189***	0.005		
			[0.087]	[0.008]		
Green RTA -1 X Relatedness -1					-0.018***	0.044
					[0.007]	[0.044]
KSP -1	-0.013*	0.002	-0.013*	0.002	-0.013*	0.002
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Employment rate -1	0.012**	-0.015**	0.012**	-0.015**	0.012**	-0.015**
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Gross Fixed Cap Form -1	0.006	0.006	0.006	0.006	0.004	0.006
	[0.011]	[0.007]	[0.011]	[0.007]	[0.011]	[0.008]
GDP per capita -1	-0.003	0.010	-0.003	0.010	-0.003	0.010
	[0.008]	[0.009]	[0.008]	[0.009]	[0.008]	[0.010]
Pat -1	0.010*	0.001**	0.010*	0.001**	0.010*	0.001**
	[0.005]	[0.001]	[0.005]	[0.001]	[0.005]	[0.001]
NUTS3 FEs	Yes	Yes	Yes	Yes	Yes	Yes
CPC FEs	Yes	Yes	Yes	Yes	Yes	Yes
Period FEs	Yes	Yes	Yes	Yes	Yes	Yes
R sq	0.756	0.401	0.757	0.401	0.757	0.402
NUTS3-CPC-period obs	20870.000	20773.000	20870.000	20773.000	20870.000	20773.000

High KSP models only include the top 10% NUTS3-CPC observations in terms of KSP. Low KSP models only include the bottom 10% NUTS3–CPC observations in terms of KSP. Linear regressions with robust standard errors clustered by NUTS 3-digits and CPC in parentheses. Dependent variable is the probability to have a Revealed Technological Advantage (RCA) in environmental innovation. Base sample in all columns is a pooled dataset, 1982-2013, with data at 4-year intervals in levels where the start date refers to the dependent variable (i.e., if t=2010-2013, so t-1=2006-2009). All independent variables are standardised and lagged by one period. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: AI and relatedness for environmental technology specialisation by level of Knowledge Space Position (KSP) – models 4 to 6

	(1)	(2)	(3)	(4)	(5)	(6)
	Low KSP	High KSP	Low KSP	High KSP	Low KSP	High KSP
Green RTA -1	0.302***	0.323***	0.323***	0.303***	0.335***	0.303***
	[0.052]	[0.038]	[0.052]	[0.048]	[0.050]	[0.048]
AI Pat -1	-0.002	-0.000**	-0.004	-0.000**	-0.005	-0.000**
	[0.008]	[0.000]	[0.008]	[0.000]	[0.007]	[0.000]
Relatedness	0.000	0.009***	0.001	0.008***	0.001	0.008***
	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Green RTA -1 X AI Pat -1			1.101***	0.003	1.542***	0.014
			[0.095]	[0.007]	[0.149]	[0.013]
Green RTA -1 X Relatedness -1			-0.018***	0.044	-0.010*	0.044
			[0.007]	[0.044]	[0.005]	[0.044]
Relatedness -1 X AI Pat -1	-0.002	-0.000	-0.000	-0.000	-0.003	-0.000
	[0.009]	[0.000]	[0.009]	[0.000]	[0.009]	[0.000]
Green RTA -1 X Relatedness -1 X AI Pat -1					0.316***	-0.015
					[0.076]	[0.017]
KSP -1	-0.013*	0.002	-0.013*	0.002	-0.013*	0.002
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]
Employment rate -1	0.012**	-0.015**	0.012**	-0.015**	0.012**	-0.015**
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Gross Fixed Cap Form -1	0.006	0.006	0.004	0.006	0.004	0.006
	[0.011]	[0.007]	[0.011]	[0.008]	[0.011]	[0.008]
GDP per capita -1	-0.003	0.010	-0.003	0.010	-0.003	0.010
	[0.008]	[0.009]	[0.008]	[0.010]	[0.008]	[0.010]
Pat -1	0.010*	0.001**	0.010*	0.001**	0.010*	0.001**
	[0.005]	[0.001]	[0.005]	[0.001]	[0.005]	[0.001]
NUTS3 FEs	Yes	Yes	Yes	Yes	Yes	Yes
CPC FEs	Yes	Yes	Yes	Yes	Yes	Yes
Period FEs	Yes	Yes	Yes	Yes	Yes	Yes
R sq	0.756	0.401	0.757	0.402	0.757	0.402
NUTS3-CPC-period obs	20870.000	20773.000	20870.000	20773.000	20870.000	20773.000

High KSP models only include the top 10% NUTS3-CPC observations in terms of KSP. Low KSP models only include the bottom 10% NUTS3–CPC observations in terms of KSP. Linear regressions with robust standard errors clustered by NUTS 3-digits and CPC in parentheses. Dependent variable is the probability to have a Revealed Technological Advantage (RCA) in environmental innovation. Base sample in all columns is a pooled dataset, 1982-2013, with data at 4-year intervals in levels where the start date refers to the dependent variable (i.e., if t=2010-2013, so t-1=2006-2009). All independent variables are standardised and lagged by one period. * p<0.10, ** p<0.05, *** p<0.01.

Appendix A: Definition of relatedness and KSP variables

Relatedness

In order to measure technological relatedness between patent classes, following Boschma et al. (2015) and Rigby (2015), we use the distribution of knowledge claims by CPC class on each patent across the EU as a whole. Using data from the OECD RegPASTAT dataset, for each NUTS-3 province *p*, we calculated the density of technology production in the vicinity of individual technologies s. The density relatedness - henceforth relatedness - measures the average proximity of a new potential technology z to a province's current technological structure. A high relatedness value means that the p^{th} province has many developed/potential(?) technologies surrounding the j^{th} technology.

$$Relatedness_{pst} = \frac{\sum_{s \neq z} \varphi_{szt} x_{pzt-5}}{\sum_{s \neq z} \varphi_{szt}} \qquad (1a)$$

where $x_{pst-5} = 1$ if RTA_{pst} [5]>1 (and 0 otherwise) and where:

$$\varphi_{szt} = min\{P(RTA_{pst} | RTA_{pzt}, P(RTA_{pzt} | RTA_{pst})\} \qquad (1b)$$

with $P\left(RTA_{pst} \middle| RTA_{pzt}\right) = \frac{P(RTA_{pst} \cap RTA_{pzt})}{P(RTA_{pzt})}$.

Equation (1a) provides an operational definition of the relatedness of a given technology *s* to all other *z* technologies for which region *p* shows a technological specialization at time *t-4*. The relatedness is calculated on the proximity index, $\varphi_{s,z}$ (Hausmann and Klinger, 2006; Hidalgo et al 2007). The matrix of revealed proximities between every pair of technologies is given by the equation 1a. The intuition behind this measure is that two technologies s and z are highly related to one another, the higher is the frequency by which they are jointly observed as technological specialization in a same region. If two technologies appear very frequently together as domains of

[5] RTA is a binary variable that assumes the value 1 when a region possesses a greater share of patents in technology class s than the reference region *p* (the EU as a whole); and 0 otherwise.

regional specialization, it reasonable to expect that they leverage highly related local innovation capabilities (Boschma et al., 2013). The network representation of the matrix of proximities is the knowledge space, that is an n*n network where the individual nodes s (s¼1,…, n) represent technological categories (CPC classes), and the links between them indicate their degree of proximity $\varphi_{s,z}$.

Knowledge Space Position (KSP)

Knowledge Space Position (KSP) measures the positioning and connectedness of a region's technological patterns within the overall knowledge space.

Following the methodological approach of Cicerone et al (2019), first we calculate a technology *s*'s centrality in the knowledge space. A technology that is more central in the knowledge space will be connected to a greater proportion of the other technology *z*, and therefore will have a higher value for centrality *C*.

$$C_s = \frac{\sum_z \phi_{s,z}}{Z} \qquad (2)$$

This measure shows which CPC classes are located in the dense part of the knowledge space and which are located in the periphery. Secondly, using equation (3), we weight the centrality values using a revealed technological advantages (*RTA)* definition which overcomes the limitation of the standard indicator. Formally, we define the Knowledge Space Position (*KSP*) of a local economy *p* as the sum of technology *s*'s centralities in the knowledge space weighted with the Revealed Symmetric Technological Advantage *RSTA* values of province *p* for technology *j*:

$$KSP_p = \sum_s \left(C_s * RSTA_{s,p}\right) \qquad (6)$$

where *RSTA* values are constructed according to the approach of Iapadre (2001). The *RSCA* formula proposed by Iapadre (Iapadre, 2001) is a variant of the one proposed by Dalum et al. (1998) for the standard Balassa indicator and solves all statistical problems. The modified index used is the following:

$$RSTA_{\,s,p} = \frac{(RTA_{s,p} - RTA_{w,p})}{(RTA_{s,p} + RTA_{w,p})} \tag{7}$$

$$\text{with } RCA_{s,p} = \frac{\left(\frac{X_{s,p}}{X_p}\right)}{\left(\frac{X_{s,r}}{X_r}\right)} \tag{8}$$

$$\text{and } RCA_{w,p} = \frac{\left(\frac{X_{w,p}}{X_p}\right)}{\left(\frac{X_{w,r}}{X_r}\right)} \tag{9}$$

where p = province, s = technology, r = total of other provinces and w = total of the other technologies (net of s). This specialization of the value of technological specialization varies between -1 and 1. Positive (negative) indicate advantages (disadvantages) compared to other European provinces. Strictly speaking we use 1 + the Iapadre index to facilitate visualization within the network diagrams, and to simplify estimation.

Founding their theoretical approach on Hausmann and Rodrik (2003), Hidalgo et al. (2007) empirically show that the production of goods that are located at the core of the so-called product space embodies more sophisticated or complex manufacturing products. The heterogeneous structure of the knowledge space has similar implications: a province centrally positioned within the knowledge network – having high KSP value – embodies more complex knowledge, characterized by an higher level of connection.