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Regional artificial intelligence and the geography of environmental technologies: does local AI knowledge help regional green-tech specialization?

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Regional artificial intelligence and the geography of environmental technologies: does local AI knowledge help regional green-tech specialization?

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ABSTRACT

We investigate the extent to which artificial intelligence (AI) is harnessed by regions for specializing in green technologies. By considering the transformative role that AI is playing in the invention process and connecting it to the regional development of environmental technologies, we examine the relationship between green-revealed technological advantages and local AI for EU-28 (NUTS-3) regions over the period 1982–2017. Results show that AI knowledge favours the green-tech specialization of regions, provided that they were already green-tech specialized in the past. Conversely, AI even reduces this capacity in regions that have not already specialized in green technologies.

KEYWORDS

green technologies; artificial intelligence; regional specialization; twin transition

JEL O31, O33, R11, R58

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1. INTRODUCTION

Recent research in regional studies and economic geography has shown that the local development of environmental technologies is a crucial leverage of regions' capacity to increase their environmental sustainability and become 'green' (Demirel et al., 2019; Gibbs & O'Neill, 2017; Truffer & Coenen, 2012). While green-techs can themselves have negative environmental returns (such as the resource inefficiencies and emissions generated by their production plants and the 'electronic waste' produced at the end of their life cycle) (Hansen et al., 2021), the so-called 'sustainability transition' in fact passes through a suitable recombination of technologies, institutions and behaviours, which can lead to the establishment of more environmentally sensitive 'socio-technical systems' (Geels, 2002).

The regional capacity for developing environmental technologies, and specializing in their invention, has in turn been investigated and appears as unevenly distributed across space. Their 'relatedness', as the synthesis of their cognitive proximity to pre-existing technologies, has emerged as an important driver of both the acquisition of regional green-tech advantages and of their maintenance over time (Castellani et al., 2022; Montresor & Quatraro, 2020), along with other regional factors that interact with or even condition this: in particular, the green-tech life cycle (Barbieri et al., 2020a) and regional environmental policies (Santoalha & Boschma, 2021). Among the other factors, the extent to which regional green-tech specialization can benefit from the opportunities of the digital transformation offered by Industry 4.0 is still relatively unexplored (Benassi et al., 2020; 2022). This lack of research is an unfortunate gap, particularly with respect to artificial intelligence (AI), whose economic transformative role has been shown to have an important territorial dimension (Buarque et al., 2020; Capello & Lenzi, 2021b; Laffi & Boschma, 2022) and whose 'Earth-friendly' applications can extend to several environmental domains (World Economic Forum (WEF), 2018).

Given the high policy priority that, especially in the aftermath of the COVID-19 pandemic, both the green and the digital transition are receiving at the European level,[1] the absence of studies on the possible combination of the local development of environmental and AI technologies represents an unfortunate gap. This gap has two

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dimensions, which the present paper aims to fill. On the one hand, empirical evidence for the creation and integration of AI technologies at the regional scale is almost non-existent, and its incipient analysis is mainly carried out at a fairly aggregate (e.g., NUTS-2) level (Buarque et al., 2020). On the other hand, theoretical analysis of the mechanisms through which the distinguishing features of AI can intersect with those of green technologies at a local level is also scant and remains mainly speculative (WEF, 2018).

When filling this twofold gap, we combine economic geography and patent-based innovation studies and investigate the extent to which AI knowledge can be harnessed for the development of green technologies at the regional level. In doing so, we position our work in and extend a recent stream of research that has started investigating the regions' capacity to diversify their environmental technologies by branching pre-existing related technologies and by drawing on local technologies with general-purpose properties (GPTs), for example, the so-called key enabling technologies (KETs) (Montresor & Quatraro, 2020). We contribute to this research in three original ways. First, rather than looking at the simple 'entry' of a new green technology in the regional knowledge-base, we extend the analysis to the regions' capacity of having, acquiring or eventually keeping a green-tech specialization over time, as in the recent work by Castellani et al. (2022). In other words, we place a greater emphasis on the regional experience in specializing in green-tech; we do so as we focus on a potential GPT technology for which, unlike KETs, such an experience represents a crucial driving variable. This is the second element of originality. As we will argue in section 2, while possibly GPT, like KETs, AI reveals an additional distinguishing feature that enriches the set of mechanisms through which it can affect green-tech regional specialization: it is a potential 'invention in the method of inventing' (IMI), whose actual occurrence requires a fairly large set of data to be originally recombined, also and above all at a local level. This makes the 'history' of green-tech knowledge in the region, acting as a leverage to spur the accumulation of green-tech data over time, a crucial aspect to consider with the local stock of AI knowledge. The third element of novelty is empirical. With respect to previous studies (e.g., Montresor & Quatraro, 2020, is at the NUTS-2 level) we make an original effort towards granularity in terms of environmental domains, AI applications and, above all, NUTS-3 administrative units. Indeed, to the best of our knowledge, this is the first study to rely on a very disaggregated map of the local endowment of AI knowledge across European regions and which inspects its role at a local-, technology- and time-specific level of analysis.

Relying on a three-way fixed effects (FEs) linear probability model (LPM) and checking its robustness in several respects, we find that the stock of AI knowledge actually helped EU-28 regions specialize in green technologies over the period 1982–2017, provided they had already done so in the past. Conversely, the same stock even reduces this capacity in regions that have not already specialized in green technologies. AI does not appear suitable for regional green-tech specialization per se, but AI knowledge at the basis of the digital transformation can help already green(-tech) regions to remain green.

The remainder of the paper is organized as follows. Section 2 presents the relevant literature and research hypotheses. Sections 3 and 4 describe the data used and the empirical methodology, respectively. Section 5 discusses the main results and their robustness. Section 6 concludes and offers possible policy implications and avenues for future research.

2. BACKGROUND LITERATURE AND RESEARCH HYPOTHESES

Despite its already extended history as a technology and research field (Nilsson, 2010), 'the economics of AI' is still at an incipient stage (Agrawal et al., 2019).[2] Of the identified domains – including 'productivity, growth, inequality, market power, innovation, and employment' (Agrawal et al., 2019, front page) – academic research has been hesitant to investigate the potential role of AI in environmental sustainability. This lack of research is unfortunate because this potential has already been recognized in the debate involving businesses and international organizations. Among others, in 2018 the World Economic Forum (WEF) has produced a report in which several cases of 'Earth-friendly AI' have been identified in addressing different environmental problems. For example, new AI knowledge has been decisive in the advancement of climate change technologies, as in the development of new optimized energy system forecasting, of technologies for air cleaning, as with real-time air pollution monitoring and simulations, and of technologies to face weather and natural disasters, as with climate informatics for enhanced climate modelling. Interestingly, these are cases in which inventions in the AI domain, rather than adoptions of AI, can help the introduction of eco-innovations (EI), as previous studies (Lee, 2020; Lee & He, 2021) and some examples of co-occurring AI and EI patent codes of our patent-based analysis reveal (see section 3.2).

While the search for specific cases of environmentally friendly AI advances, the academic literature on their functioning unfortunately still lags behind, especially at the local level. Although regional economics and, in particular, urban planning have addressed the role of AI in different domains since the mid-1980s (Baráth & Futó, 1985; Sashi & Ramakrushna, 2003; Silva, 2004) – especially through its contribution to geographic information systems (GISs), spatial modelling (Openshaw, 1992), urban land dynamics and regional business and energy loads forecasting (Che-Chiang & Chia-Yon, 2003; Ning & Silva, 2010) – the general mechanisms through which AI can affect the development of green technologies at the local level remain unexplored.

An important contribution to fill this research gap can be made by considering recent work in the economics of technological change, with regard to the AI impact on innovation, and extending it to the domain of EI and green-tech specialization/diversification at the regional level. As Cockburn et al. (2019) have recently argued, AI has two potential features that could crucially affect the unfolding of the innovation process. As we argue below, each feature has major implications when we consider AI as part of the regional knowledge base, and are thus capable of affecting the process of Schumpeterian knowledge recombination through which innovations have been claimed to locally emerge and geographically distribute (Balland, 2016).

2.1. AI and the local endowment of GPTs

The first distinguishing feature of AI is its possible application across a wide range of domains, into which it complementarily introduces rapid innovations because of its own ultimate innovation. Because of this, AI is potentially the most important GPT of our times (Trajtenberg, 2019), asking us to extend to it what innovation studies have taught us about previous technologies of this kind, such as computers and the internet (Bresnahan & Trajtenberg, 1995). In making such an extension, some critical positions have emerged, claiming that the 'GPT jacket' would be too strict and even misfitting for a 'system technology' such as AI, which rapidly develops infrastructural properties not included in that categorization (Vannuccini & Prytkova, 2020). Also on the empirical side, recent studies have cast doubt about the extent to which, by referring to publication or patent data across the world, some families of AI (e.g., deep learning) can help to navigate complex knowledge landscapes in the way of a GPT (Bianchini et al., 2020). Doubts have also been raised about the extent to which some other related technologies (such as those included in the Industry 4.0 paradigm) actually show a technological base (e.g., in terms of citations) consistent with GPT properties (Martinelli et al., 2021).

In spite of these caveats about the general GPT features of AI across the world of science, its possibly local GPT role deserves close scrutiny, especially in the development of regional green technologies. Indeed, the GPT endowment of places can help the recombination of existing local knowledge from which the regional specialization in technologies has been argued to descend also in the green domain. On the one hand, being cross-cutting and horizontal in their application to the regional knowledge base, GPT can be expected to move the local technological frontier ahead and widen the set of knowledge items that need to be recombined to allow the region to master the complexity of green technologies. On the other hand, by advancing through the co-occurrence of applications and inventions, GPT also arguably increase the set of interfaces between the several knowledge modules and disciplines that are usually recombined in the development of environmental technologies. These expectations have been confirmed by previous studies with respect to the new generation of GTP represented by the so-called KETs,[3] which have been found to favour regional technological diversification in general (Montresor & Quatraro, 2017) and with respect to green technologies in particular (Montresor & Quatraro, 2020). As AI could possibly share the previous two GPT mechanisms with KETs, we expect the local endowment of the relative knowledge to also favour regional green technologies. Indeed, it can be claimed that the GPT properties of AI enable regions to better combine the complex knowledge items on which the inventive development of green technologies relies and allow them not only to obtain a new specialization, as revealed in the literature, but also to maintain this specialization over time, where the specialization is already present. Given the caveats about the actual GPT nature of AI, a sort of meso-proof can be obtained by testing the following research hypothesis:

> *Hypothesis 1: The local endowment of AI knowledge positively correlates with the regional capacity to specialize in green technologies.*

Another effect of the local endowment of GPT on the development of regional technologies is its influence on the explorative extent to which regions can recombine their extant knowledge base. On the one hand, we might expect GPT to help more in making regions specialize in technologies that are more cognitively distant from others, that is, less related to them (Balland, 2016). This would be consistent with their providing regional interfaces that facilitate wider opportunities for recombining existing knowledge, which could thus involve more cognitively distant knowledge items. This has been observed by Montresor and Quatraro (2020) in looking at the role of the regional specialization in KETs in driving regional green-tech branching: in the presence of KET specialization, such a green-tech branching actually becomes less related. On the other hand, however, a substitution relationship between GPT and relatedness for the occurrence of regional green-tech specialization is not guaranteed and rather depends on the specific nature of the former in relation to the latter. In particular, GPT technologies vary among themselves, also and above all, due to the complexity of their inherent knowledge base and for the effect this complexity can have on their building interfaces for local knowledge recombination to occur. Given the nature of AI as a large technical system, whose advancement involves a larger amount of (possibly big) data and more infrastructural factors than other GPT (Vannuccini & Prytkova, 2020), such as KETs, AI arguably represents a quite complex GPT, which could thus work harder in the more complex role of combining and recombining more distant knowledge items. This is particularly the case of the knowledge recombination that leads to environmental technologies, which have been shown to draw, in turn, on a complex, transdisciplinary and close to the scientific frontier kind of knowledge (Barbieri et al., 2020). In light of this, we could expect AI to help more in making regions specialize in technologies that are less cognitively distant from existing local ones, that is, in more cognitively related technologies.

Once more, as the actual GPT nature of AI is still under scrutiny, we do not feel there are enough aprioristic expectations for a substitution rather than complementary relationship between its local endowment and relatedness in driving green-tech specialization. Still, we expect that AI would significantly moderate the impact of relatedness on the development of regional environmental technologies, and not only on the development of new ones in terms of diversification. Indeed, following Castellani et al. (2022), we expect that the extent of cognitive proximity that relatedness expresses between technologies not only affect regions in their capacity of making a new technology enter in the local knowledge base, but also their capacity to keep the technology within the region over time, where it is already present. In the absence of unambiguous predictions about the way in which AI knowledge could moderate the effect of relatedness at stake, we remit the sign recognition of such a moderation effect to the test of the following hypothesis:

Hypothesis 2: AI knowledge significantly moderates the relationship between relatedness and the regional capacity to specialize in green technologies.

2.2. AI and local inventions of the methods of inventing

The second and possibly more distinguishing feature of AI compared with previous GPT is its potential role of IMI, that is, a research tool itself, capable of changing the procedures ('playbook') for innovation to occur in the many domains in which AI is applied. As Cockburn et al. (2019) put it, this means that AI is 'opening up the set of problems that can be feasibly addressed, and radically altering scientific and technical communities' conceptual approaches and framing of problems' (p. 7).

While an important potential feature, the actual IMI function of AI crucially depends on its application to large sets of granular data on both social and physical phenomena and behaviours. The power of AI actually improves as it is applied to larger and larger datasets.

Extending this argument to our regional research question, we expect that the capacity of AI to act as IMI locally in the development of green technologies will crucially depend on the extent to which regions have experience with green technologies. Such an experience is in fact necessary to generate large sets of data on the functioning and applications of green technologies through which AI can advance the frontier of the relative innovation methods and increase the regional specialization in the relative technologies. In brief, it could be argued that AI would be able to spur local inventions in the methods of green inventing (IMgI), and thus increase the capacity to specialize in green technologies, providing regions have already consolidated experience of these methods. In principle, one might argue that AI knowledge available at the local level could compensate for the lack of pre-existing experience in the green-tech, and that regions could draw on AI to remedy the lower innovative combinatorial opportunities that the lack of specialization in the green domain inevitably entails. Still, we do not expect that such a compensation effect could provide non-green-tech-specialized regions with an advantage over regions that are already specialized in green-tech, and which, consequently, can count on the big data requirement that renders the IMI property of AI effective.

This last set of considerations has an important implication for the way we should search for the relationship between regional environmental technologies and AI knowledge. In addition to their relatedness to the knowledge base of the region, its green-tech specialization 'history' should be explicitly retained, especially in moderating the relationship between AI and the capacity to gain or maintain such a specialization. On this basis, in controlling for the role of path dependence in regional green-tech specialization, we put forward the following hypothesis:

Hypothesis 3: The correlation between local AI knowledge and the regional capacity to specialize in green technologies is higher for regions that have experience of such a capacity.

3. DATA AND METHODOLOGY

Our empirical analysis refers to EU-28 regions at the NUTS-3 level for the period 1982–2017. It is based on a longitudinal dataset obtained by combining different sources, of which the focal ones include the Organisation for Economic Co-operation and Development's (OECD) REGPAT dataset (Maraut et al., 2008) and the European Regional Database (Cambridge Econometrics). To the best of our knowledge, this paper is the first to adopt a NUTS-3 level of geographical analysis in dealing with the role of AI. Previous work has used a larger scale, generally NUTS-2, regions (e.g., Buarque et al., 2020), or had a more general focus, such as Industry 4.0 (e.g., Capello & Lenzi, 2021a). Naturally, the use of smaller regions creates some computational problems, especially for some intense data computing variables such as technological relatedness (see below). Nevertheless, we believe this is the appropriate level of analysis for two main reasons. First, especially in some European countries, NUTS-2 regions are quite large and comprehend smaller administrative locations with heterogeneous socio-economic characteristics. These are arguably reflected in heterogeneous capabilities of specializing in green technologies, which should thus be investigated in a disaggregated manner (Castellani et al., 2022). Second, the recombination of local knowledge that AI is expected to facilitate (see section 2.2) can also be argued to vary across the different NUTS-3 in the NUTS-2 regions, as the former delimit heterogeneous knowledge bases, of which that of the latter is far from being the sum. Of course, in some cases NUTS-3 could miss one or both of the two phenomena we describe, but as usual this will have to be considered in investigating its holding on a systematic basis. In spite of these advantages, we are aware that there could possibly be a modifiable area unit problem (MAUP), and we test the robustness of our results at the NUTS-3 level by re-running our econometric models at the NUTS-2 level as well.

Using our dataset, and a set of variables we define in the following sections, we test Hypothesis 1 by estimating whether region r's 'capacity' to specialize in a certain green technology, c, at time t ($GreenTech_{rct}$) significantly correlates with its stock of inventive capacity in AI at $t-1$ (AI_{rt-1}). The focus on regions' green-tech specialization in accounting for the local development of environmental technologies is driven by the economic geography approach with which we investigate it (Montresor & Quatraro, 2020). Following such an approach, a revealed regional advantage in a certain technology is taken as a standard to denote its entry and/or presence in the local knowledge base, as well as to build up the matrix of cognitive proximities among technologies that are synthesized in the idea of relatedness, which we also use (Balland, 2016).

Drawing on section 2, in the baseline model we run this estimate by retaining among the regressors, region r's specialization in the same technology at $t-1$ (proxied by the lag of the dependent, $GreenTech_{rct-1}$), the relatedness to its knowledge base (measured by $Relatedness_{rct-1}$) and a vector of regional characteristics ($\bar{X}_{rt-1}$):

$$\begin{aligned} GreeTech_{rct} &= \alpha + \beta GreenTech_{rct-1} + \gamma AI_{rt-1} \\ &\quad + \delta Relatedness_{rct-1} + \theta \bar{X}_{rt-1} + \vartheta_t \\ &\quad + \mu_c + \pi_r + \varepsilon_{rct} \end{aligned} \tag{1}$$

where ϑ_t, μ_c, π_r are time, technology and regional FEs, respectively; and ε_{rct} is an error term with standard properties.

To test the other research hypotheses proposed in section 2, we augment the baseline model of equation (1) by progressively including some interaction terms among our focal (lagged) regressors. First, although we have not built a hypothesis based on that, we interact $GreenTech_{rct-1}$ with relatedness to see whether regions with previous green-tech experience are more 'conservative' in renewing their specialization over time by making relatedness more important for such renewal to happen. Second, in order to test Hypothesis 2, we interact (the lag of) AI with *Relatedness* to see whether a substitution relationship actually exists between them, as opposed to a complementary one. We then address the issue of regions' green-tech experience of Hypothesis 3 by interacting (the lag of) AI knowledge stock with the lag of the dependent variable, expecting this interaction to be positive. Finally, we saturate the model with all the previous interactions together.

3.1. Dependent variable

As noted above, our dependent variable refers to region r's capacity to specialize in green technologies at time t, irrespective of the history of the same capacity. Consistent with our theoretical arguments in section 2, we define this variable in a technology-specific way, c. In other words, we examine whether the regional endowment of AI knowledge correlates with the regional capacity to develop green technologies generically, not simply across the broad spectrum of such technologies (see below) but specifically, that is, with respect to each and every field, c, which can be deemed green and in which EIs can thus be introduced. The choice of using region–technology–time data, instead of region–time data, to build up our focal dependent variable is in line with the extant literature (Montresor & Quatraro, 2020; Santoalha & Boschma, 2021) and has two main motivations. First, in doing so, we are better able to test whether AI actually works across the board, like a GPT, by facilitating the development of green technologies of different kinds, which refer to different and specific environmental domains. Second, by focusing on each and every green technology (or, as we will see, patent CPC), we can build up a more precise relatedness variable, which measures the density of the cognitive proximities that the relative green technology reveals with respect to those present in the knowledge base of the region. If we had focused on region–year data instead, we would have been forced to relate the green technologies in which regions specialize to those in its knowledge base in average terms and thus less accurately.

Following the literature on the geography of innovation (Balland, 2016), we define our dependent variable, $GreenTech_{rct}$, as a dichotomous variable that takes the value of 1 if region r is specialized in a green technology c at time t, and 0 otherwise:

$$GreenTech_{rct} = \begin{cases} 1 \ if \ RTA_{rct} > 1 \\ 0 \ if \ RTA_{rct} \leq 1 \end{cases} \tag{2}$$

where RTA_{rct} relates region r's share of total patents in technology c to its total share of global patents:

$$RTA_{rct} = \frac{\dfrac{PAT_{rct}}{\sum_r PAT_{rct}}}{\dfrac{\sum_c PAT_{rct}}{\sum_r \sum_c PAT_{rct}}} \tag{3}$$

If the former share (at the numerator) is larger (smaller) than the latter (at the denominator) and $RTA_{rct}$is higher (lower) than 1, the region can be said to be (not) specialized in a certain green technology, c. Accordingly, the same region is considered to be (not) capable of eco-innovating systematically in the relative field; thus, $EI_{rct} = 1$ (0).

In spite of the loss of information that the dichotomization of RTA entails, such a transformation, which is consistent with the extant literature (Montresor & Quatraro, 2020; Santoalha & Boschma, 2021), does also have a twofold motivation. On the one hand, it allows us to easily map those green technologies that are part of or enter in (depending on its pre-existence) the regional knowledge base, taking the presence of a specialization as a guide-post to this. On the other hand, it enables us to directly map the cognitive proximity between these green technologies and those that are part of the regional knowledge base.

As in previous studies on the topic (e.g., D'Agostino & Moreno, 2019; Montresor & Quatraro, 2020; Santoalha & Boschma, 2021), we define as green any patent with at least one technological class, c, included in the ENV-TECH classification: a classification of environmental technologies developed by the OECD (Haščič & Migotto, 2015), examining the International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes reported for those patents for which the applicants have applied to the European Patent Office (EPO). Table A1 in Appendix A in the supplemental data online provides a description of the environmental technology aggregates and their corresponding CPC classes.[4] The identification of environmental technologies is based on the full-length CPC code of the patent class; however, for computational purposes, we use 69 CPC codes (at the four-digit level) to set up the final database. As is well known, patent data have a discrete nature, and for this reason, their distribution experience peaks over time. To smooth this behaviour, we follow the extant literature and aggregate patent data into nine four-year time periods.[5]

Figure 1 reports the geographical distribution of our dependent variable, showing how the investigated regions distribute in terms of the number of their green-tech specializations over the most recent sub-period (2014–17).

Quite interestingly, unlike for other standard (non-green) technologies, no clear pattern is evident from the map. In fact, although some clusters are evident (e.g., northern Italy, Denmark and most of Finland and Sweden), it is difficult to identify a classic core–periphery mechanism by looking at Figure 1 alone. This result is indicative of a geography of green technologies that does not fully overlap with the general innovation geography and whose 'special' determinants, such as AI possibly, require special attention.

3.2. Regressors and controls

Our focal regressor, AI_{rt}, measures region r's availability of AI technological knowledge, and is still proxied by regional patent applications, PAT_{rct}, in those c domains that can be deemed AI related ($c \in AI$). Unlike with respect to EI, however, this regressor is not green-tech, but simply region specific. This is an important methodological choice that has different motivations. First, as we will see below, AI-related patents are identified by examining patent classes and/or patent keywords that only 'talk' about the nature and typologies of AI technologies, regardless of their specific domain of application, that are green or not green in nature. Mapping regional AI onto each and every green technology c with respect to which we have built our dependent variable, $GreenTech_{rct}$, would therefore require an additional identification criterion for our focal regressor. The most viable solution might appear to be that of considering, for each regional green-tech c, those regional AI patents that are also 'marked' by the respective green-tech patent code, that is, in which AI- and EI-related codes co-occur. However, considering this green-tech-specific regional AI regressor, and examining this correlation with the regional specialization in the same technology, would amount to an aprioristic identification of the relationship that we are instead looking for, and would drastically reduce the scope of the analysis with respect to what we have elaborated in section 2. Indeed, we maintain that AI knowledge is expected to help green technologies by operating as a GPT and an IMI on a wide set of green and non-green technologies rather than by simply being co-invented in a green-tech field. In other words, we expect that it is the regional endowment of AI that will matter for regional *GreenTech* and that the former will have an effect on the latter, which is across the board and invariant with respect to the different domains in which EIs can occur. Notwithstanding the above, we also check the robustness of our results against a more stringent definition of AI patents, defined by all patents that combine at least one AI patent class and one green patent class (see the robustness check section).

As AI and other kinds of regional knowledge develop cumulatively over time, we maintain that the role of AI on regional green technologies should be proxied by the stock of AI knowledge available at a certain period in time, t, rather than by its current or lagged flows. Accordingly, we follow the existing literature (Griliches, 1990; Hall et al., 2000) and build AI_{rt} using the perpetual inventory method formula:

$$AI_{rt} = AI_{rt-1}(1-\delta) + \sum_{c \in AI} PAT_{rct} \tag{4}$$

where AI_{rt-1} is the stock of region r's AI patents at period $t - 1$; δ is the depreciation rate, which is assumed to be constant at 5%; and PAT_{rct}, with $c \in AI$, is the number of new patents whose technologies c refer to AI in period t.[6] In order to have a more accurate measurement, the AI patent stock is computed using information for the whole period for which patent data are available (1977–2017).

To identify AI-related technologies from patent information, we follow the recent contributions by Buarque et al. (2020) and Calvino et al. (2018), who adopt the classification developed by the World Intellectual Property Organization (WIPO) (2019). In turn, the WIPO suggests a mixed search strategy that relies on (1) relevant patent classes and (2) a search of relevant AI-related keywords in patent titles/abstracts/claims. For example, patents pertaining to the following CPC-based classes are identified as AI technologies: data processing, AI (CPC class Y10S706) and computer systems based on biological models (CPC class G06N003). Similarly, patents reporting the stem words (where all suffixes have been removed) 'artificial intelligence' or 'computational intelligence' are identified as AI-related.[7] As we state below, we check the robustness of our results against an alternative definition of AI technologies (see Tables B6 and B7 in Appendix B in the supplemental data online).

As mentioned in section 2, the AI patents identified capture new inventive knowledge that we expect could be helpful in advancing the development of green technologies. While postponing the systematic search of this correlation to the results, we notice here that the contents of some exemplificative patents, in which AI- and EI-related

Figure 1. Number of green-tech specializations (EIs) by region, 2014–17.

patent codes co-occur, actually point to some correlation. The patent document with publication number EP3189726A1, for example, covers an irrigation system controlled and optimized via an AI optimization algorithm, which gathers data through sensors and predicts and distributes the optimal amount of water needed, based on the information collected. By using machine learning algorithms, this invention can thus be expected to improve the technological knowledge about the efficient management of water resources. Similarly, the patent document published with number EP3078611A1 refers to the use of artificial neural networks and sensors to classify solid waste and send it to the appropriate waste disposal department: still a novel piece of knowledge potentially useful for green technologies about waste management.

Figure 2 shows the geographical distribution of the *AI stock* knowledge across the retained regions for the most recent period (2014–17). Compared with the distribution of green technologies, the distribution of AI appears more concentrated in a few 'hotspots'. This result is not surprising, given that AI is more recent and AI patents are still relatively few compared with those associated with other technologies. However, this result calls for a deeper analysis of the reasons for the emergence of these hot spots and how they might or might not be related to green technologies.

In addition to AI, two variables are crucial for testing our arguments in section 2. The first is region *r*'s experience with green technologies to which AI can be applied. As noted above, we proxy this experience by lagging our focal dependent variable by one period, $GreenTech_{crt-1}$. The fact that region r is already specialized in a focal green technology c indicates, by definition, that the same region has previously put in relatively more inventive effort and obtained relatively more patented outcomes than in other domains. In other words, $GreenTech_{crt-1}$ reveals (when equal to or greater than 1) the presence of a comparative advantage of r in the inventive development of c: an advantage that the region has arguably obtained having relatively more focal capabilities and knowledge, and in this sense being more experienced in technology c, than non-specialized regions. Consistently with Hypothesis 3, we argue that this kind of pre-existing experience in c could give regions an advantage in understanding how to

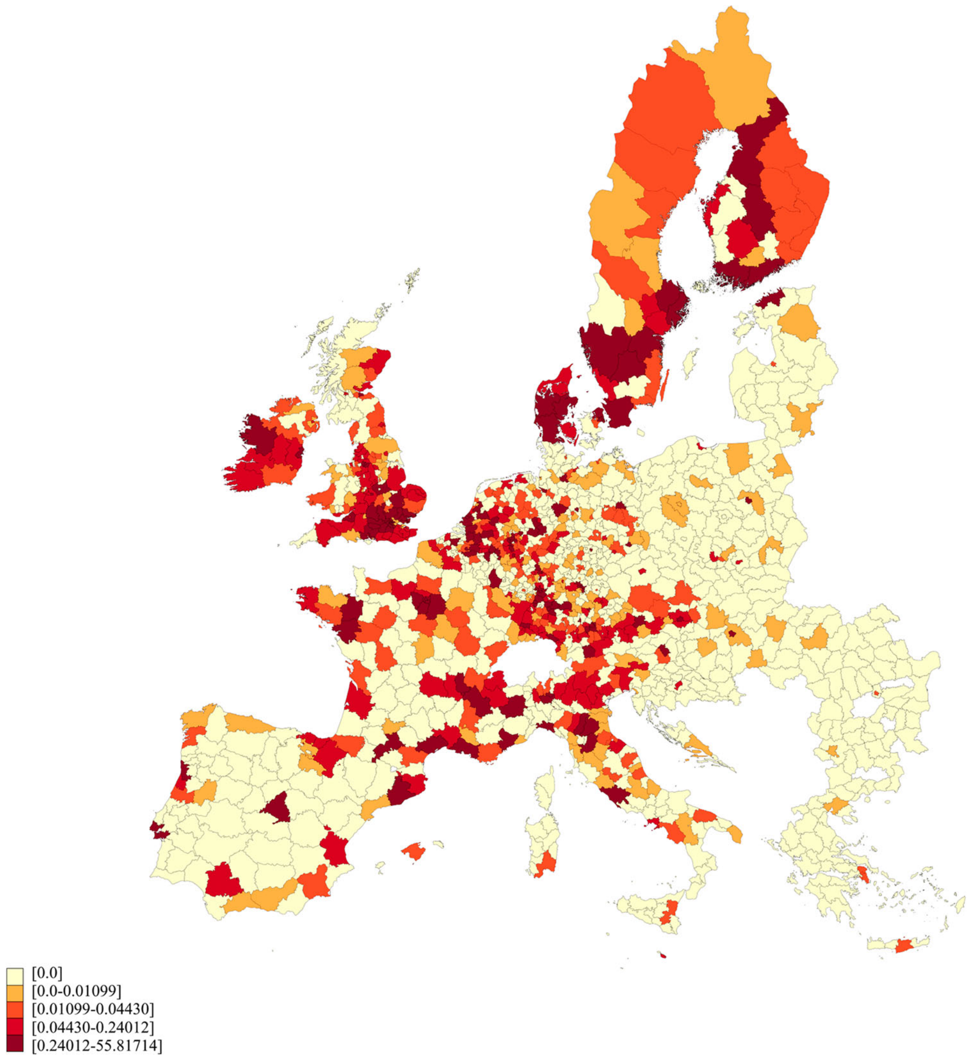

Figure 2. Artificial intelligence (AI) knowledge stock by region, 2014–17.

apply AI and set it to work in its development. The second variable of interest in examining the regional capacity to specialize in a certain technology, c, is its relatedness to the stock of knowledge of the focal region, $Relatedness_{rct-1}$. Drawing on the notion of technological/cognitive proximity in economic geography (Boschma, 2005), substantial research efforts have been applied to finding a relatedness measurement suited to this purpose (e.g., Colombelli et al., 2014; Essletzbichler, 2015; Kogler et al., 2013; Rigby, 2015). Among the different alternatives, we refer to the relatedness specification by Santoalha and Boschma (2021). In particular, we first examined regional patent applications in technological fields using pairwise comparison. This was in order to identify concurrent patenting that can reveal a proximity linkage between each regional green technology c at time t, and each and every one of those technologies (out of the remaining z) in which it was specialized at time $t - k$. All the individual proximity linkages to green technology c were then grouped together through a density indicator for the same technology, and an average density was finally calculated with respect to all the green technologies of region r (for details, see Appendix A3 in the supplemental data online).

In conclusion, we control for several specific factors that may confound our focal relationship. In equation (1), vector $\bar{X}_{rt-1}$ includes the gross value added (GVA) per employee of regions as a proxy for their level of economic development; and the regional stock of patents at time $t - 1$, overall, as a proxy for generic regional innovativeness, which naturally can affect regional innovativeness in the green domain. As for the crucial role of environmental regulations, the lack of regional data on such regulations forced us to resort to a country-specific indicator (the Environmental Policy Stringency) that drastically reduced the number of observations and thus suggested we should implement it in a robustness check (see Table B10 in Appendix B in the supplemental data online). As a further robustness check, in Appendix B online we follow Castellani et al. (2022) and, by taking advantage of the regional information on the polluting emissions of plants contained in the European Pollution Release and Transfer Registry (E-PRTR), we control for what can be

Table 1. Descriptive statistics ($n = 654{,}810$).

Variable	Mean	SD	Minimum	Maximum
GreenTech	0.05	0.21	0	1
AI stock	14.31	169.00	0	8003.57
Relatedness	0.12	0.05	0	0.50
Patent stock	1883.00	12,771.93	0	406,044.70
GVA per employee	45.11	14.71	3.06	316.39

Note: Number of regions: 1267 NUTS-3 regions; number of green technologies: 69; period of coverage: 1982–2017.

considered the regional exposure to environmental policy (see Table B11 in Appendix B online).

Table 1 provides the descriptive statistics of the variables used in the econometric analysis.

3.3. Econometric strategy

Regarding our econometric strategy, we estimate our baseline model (equation 1) by relying on a three-way FEs LPM. We prefer this approach to the estimation of a more standard logit or probit model for three main reasons. First, given the refined level of analysis (NUTS-3 regions), a non-linear estimation strategy (such as logit and probit) would have been more prone to an incidental parameter problem (Greene, 2015). Second, non-linear models are more computationally intensive because of the need to maximize the maximum likelihood via computer power. Finally, the usual drawbacks of the LPM are not crucial in the present paper. While the heteroskedasticity of error terms can be easily accommodated by computing robust standard errors (which we do; see the notes to tables of results and the robustness check section), the fact that the LPM does not bound the predicted probability in the unit interval is unfortunately unavoidable. Nevertheless, our current interest in the estimation of the relationship between AI and *GreenTech*, as opposed to the prediction of *GreenTech*, makes the LPM an ideal estimation strategy.[8]

An important point in estimating our econometric model concerns the possibility that the effect of local AI knowledge on *GreenTech* could span the regional boundaries and come to spill over the green-tech specialization of spatially contiguous regions. In order to ascertain this eventuality, we have built spatial weights for each period in our data and implemented a standard Moran's test for spatial autocorrelation. Results show that we do not reject the null hypothesis of i.i.d. errors for nearly all our time periods (five of them, totalling 20 years). On this basis, we proceed to discuss the results of the model we have presented in equation (1) and, to further control for the issue at stake, we will run a robustness check that computes standard errors robust to spatial correlation (see Table B5 in Appendix B in the supplemental data online).

4. RESULTS

Table 2 presents the results of our empirical analysis starting with the baseline, more conservative model in column (a), followed by three models with the interaction terms included separately in columns (b–d). The final model, with all the interaction terms included simultaneously, is presented in column (e), while an additional specification including the triple interaction between *AI*, *GreenTech* lagged and *Relatedness* is reported among the robustness checks (see Table B8 in Appendix B in the supplemental data online). For the purposes of interpretation of the regression results, all continuous variables have been normalized to a range between 0 and 1.

First, note that nearly all the controls used are significant and have the expected sign. A larger stock of patents in a region, denoting a higher degree of general innovativeness for the region, positively correlates with the region's capacity to eco-innovate and specialize in specific green technologies. The same capacity also appears to be path dependent, as the lag of the dependent variable *GreenTech* is also significant and positive. The development of green technologies as place dependent is also confirmed. The regional propensity to specialize in a certain environmental technology positively correlates with its relatedness to those technologies the regions is already specialized in, suggesting that the recombination of cognitively proximate local knowledge is possibly the channel through which this specialization occurs, supporting previous work on this issue (Montresor & Quatraro, 2020; Santoalha & Boschma, 2021). The only exception to this confirmed picture is the non-significant (although positive) coefficient of regional GVA per employee, which is nevertheless in line with the results of previous works on green-tech specialization (Montresor & Quatraro, 2020; Santoalha & Boschma, 2021). Note that the significance of the results does not change when all the interaction terms are included simultaneously in the final model in column I.

Coming to the core of our analysis, one of the most interesting results in Table 2 is that, in model (a), *AI* and *GreenTech* are significantly but negatively correlated, thus contradicting Hypothesis 1. Given our theoretically grounded expectation that AI 'will possibly' help the inventive development of, and the regional capacity to specialize in, green technologies (see section 2), at first glance this result might seem to be counterintuitive and call for deeper reflection. Certainly, at least part of the explanation of this result could precisely rely on the prospective and potential nature of the regional green-tech impact that AI has been expected to have. Given the still incipient stage of development at which (at least the last generation of) AI stands and the early stages of the

Table 2. *GreenTech* (dependent variable) and AI at the NUTS-3 level: linear probability model (LPM).

	(a)	(b)	(c)	(d)	(e)
GreenTech (t – 1)	0.227***	0.181***	0.227***	0.223***	0.162***
	[0.005]	[0.018]	[0.005]	[0.005]	[0.017]
AI stock (t – 1)	−0.379**	−0.384**	−2.391***	−0.521***	−2.285***
	[0.149]	[0.152]	[0.443]	[0.167]	[0.443]
Relatedness	0.091***	0.088***	0.092***	0.090***	0.088***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
Patent stock (t – 1)	0.404***	0.410***	0.445***	0.382***	0.426***
	[0.117]	[0.119]	[0.106]	[0.113]	[0.109]
GVA per employee (t – 1)	0.016	0.017	0.014	0.015	0.013
	[0.025]	[0.025]	[0.025]	[0.026]	[0.026]
GreenTech(t – 1)*Relat.		0.166***			0.213***
		[0.058]			[0.054]
AI(t – 1)*Relat.			9.837***		8.594***
			[2.054]		[1.934]
GreenTech(t – 1)*AI(t – 1)				0.995***	1.003***
				[0.220]	[0.221]
NUTS-3 FEs	Yes	Yes	Yes	Yes	Yes
CPC FEs	Yes	Yes	Yes	Yes	Yes
Period FEs	Yes	Yes	Yes	Yes	Yes
N	654,810	654,810	654,810	654,810	654,810
R^2	0.171	0.171	0.172	0.172	0.172

Note: The analysis covers 69 green CPC classes in 1267 NUTS-3 regions over nine four-year periods covering 1982–2017. The dependent variable takes the value of 1 if a region specializes in a green technology in a given period, and 0 otherwise. Robust standard errors clustered at the NUTS-3 level are shown in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

lifecycle of (at least some of the) available environmental technologies (Barbieri et al., 2020a), it could be the case that AI is not helping the development of green technologies 'now', that is, in the temporal window that the available data allow us to observe. In turn, this possibility may be explained by the fact that AI spurs regions to specialize in technologies other than the green technologies that we are examining, that is, technologies marked by a higher degree of maturity and by 'new and larger volumes of data', on which the application of AI, as noted above, depends (Hall & Pesenti, 2017, p. 2).

Regarding the interaction terms, first, notice that the interaction between relatedness and the lagged dependent variable, $GreenTech_{rct}$, is significantly positive in model (b). In regions that have already acquired a revealed technological advantage in a certain environmental domain, the role of relatedness in keeping the relative specialization increases in importance, as could be expected. Quite interestingly, having been able to exploit the relatedness-based recombination of existing knowledge to enter the green-tech realm makes regions more dependent on the 'power' of relatedness to remain in this realm and keep the specialization.

The interaction between relatedness and our focal AI regressor in model (c) is also significant, supporting Hypothesis 2. Furthermore, its sign is positive and represents another extremely important result of our analysis: the complexity of environmental technologies seems to call for 'special' enabling technologies to complement relatedness and to make it work better in favouring recombinant EIs. AI appears to be another of these relatedness-reinforcing technologies, differentiating it from the relatedness-substituting role that has been found with respect to the previous generation of KETs (Montresor & Quatraro, 2020).

Coming to Hypothesis 3, the positive and significant coefficient of the interaction term between the lagged values of *GreenTech* and *AI* in model (d), fully confirms this hypothesis. Regions with a pre-existing revealed comparative advantage in the focal green-tech do actually benefit from the presence of AI in keeping that specialization over time. In other words, as expected, pre-existing experience with environmental technologies might compensate for their short-life effect from scratch and possibly allow regions to develop that large set of information/data that make AI function as an IMI. In brief, while an unconditional endowment of AI leads regions to prioritize other technologies, circumventing green technologies, AI helps regions that have already specialized in green technologies keep their green-tech specialization over time.

All in all, apart from Hypothesis 1, Hypotheses 2 and 3 are confirmed in the relative models. Furthermore, note that when we saturate the model and include all the previous three interaction terms (model e), the sign and significance remain unaltered, thus increasing our degree of confidence in the results discussed above.

In order to control for the robustness of previous results, we have conducted a set of checks on several issues that may affect our estimates: (1) the level of analysis

(NUTS-2 instead of NUTS-3); (2) biases due to model stringency; (3) robust standard errors for different cluster definitions; (4) measurement error in the definition of AI; (5) inclusion of the triple interaction of the focal regressors; and (6) controlling for environmental regulation and exposure to environmental policy. Discussion and results on the analysis above is reported in Appendix B in the supplemental data online.

In conclusion, we should underline that the correlations identified are not only highly significant and interesting due to their sign/direction but also quite appreciable in terms of intensity. AI appears particularly relevant in lowering the capacity of regions to specialize in green technologies: all else being equal, an increase of 0.1 in AI_{rt} (with AI_{rt} ranging between 0 and 1) leads to a nearly 3.8 percentage point decrease in the probability of green specialization (specification a). The effect of AI is also effective in reinforcing regions' capacity to keep their green-tech specialization. An increase of 0.1 in AI_{rt} increases the probability of specializing in green technologies by nearly 5 percentage points for regions that have already specialized in green-tech (specification d). Finally, the contribution of AI_{rt} to the probability of specializing in green technologies at provincial (NUTS-3) level increases by 13 percentage points when there is an interquartile increase in the value of relatedness (from 0.17 to 0.3, in specification c), thus confirming the interpretative framework of recombinant innovations under which we have conducted our analysis.

5. CONCLUSIONS

The green transition and the digital transformation are two of the most relevant and investigated patterns of development that regions are currently experiencing and to which policy makers are devoting substantial resources. While continuous research has been dedicated to their respective analysis, to the best of our knowledge, no previous work has attempted to investigate, on a systematic and disaggregated basis, the extent to which the two transitions can cross over at the regional level by possibly reinforcing each other.

Attempting to fill this gap, in this paper, we have investigated the extent to which the regional endowment of AI, as one of the main drivers of the recent digital transformation, reveals a distribution that significantly correlates with geographical regions in terms of green-tech specialization as one of the main drivers of their green transition.

With all the caveats of a patent-based analysis of regional technologies (regarding which, see Acs et al., 2002), our results provide an interesting reading of the extent to which the two transitions can actually meet. At regional level, the relationship between AI and green technologies is not as straightforward as might be thought. In fact, the frequently hypothesized role of AI in green technology and future environmental sustainability is not supported by our empirical analysis. Contrary to expectations, the unconditional availability of AI in a region generally favours non-green-tech sectors. The exception is represented by regions that already display a green-tech revealed technological advantage. Although we can speculate on the reasons for this negative relationship, for example, referring to the large volume of data necessary to effectively use AI, doing so requires further research in the future. In particular, future studies should focus on the maturity of green technologies (Barbieri et al., 2020) since in regions that are already 'green', AI seems to have a positive, not negative, effect on green specialization. For the time being, however, we have arguments to conclude that AI does not appear suitable for the regional green (-tech) transition. Nevertheless, this study sheds light on an important boundary condition on the negative relationship depicted above: the digital (AI) transformation can help regions that are already green(-tech) remain so, thus pointing to a path-dependent process in the geographical agglomeration of technologies (green and digital), which may have important implications for the development of sound territorial policies.

This conclusion is accompanied by an important policy implication that is particularly relevant at a moment in which green and digital 'deals' are at the centre of the policy debate. Policy package (e.g., mix) interventions devised to search for the complementarity between AI and green technologies should be wisely implemented if positive geographical externalities are to be expected, for example, by paying crucial attention to the green-tech competencies and skills that are already present in regions (Consoli et al., 2016; Vona et al., 2019). Indeed, should they be missing, rather than serving as complements, the two patterns of transition could pose a crucial trade-off to policymakers for the solution to which they are required to act.

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regarded as stating an official position of the European Commission. The usual caveats apply.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

NOTES

1. See https://ec.europa.eu/commission/presscorner/detail/en/ip_20_940/.
2. AI broadly refers to technologies that exhibit human-like intelligence (Furman & Seamans, 2019), such as machine learning, autonomous robotics and vehicles, computer vision, language processing, AI-enabled traffic lights, and neural networks. While interest in the economics of AI has been growing in recent years, the history of AI technology dates back at least to the 1960s. The current season of 'AI Spring' should not forget the numerous 'winters' AI technological development has experienced (Floridi, 2020; Klein & Frana, 2021; Russell & Bohannon, 2015). This is an important aspect to consider when defining the temporal window along which to investigate its effects. To this end, section A2 in the supplemental data online explores how different AI technological waves could have influenced green-tech specialization and provides additional robustness checks to our results, which are largely confirmed.
3. These technologies include (European Commission, 2012): industrial biotechnologies, nanotechnologies, micro- and nanoelectronics, photonics, advanced materials, and advanced manufacturing technologies.
4. Following Barbieri et al. (2020a), we have converted IPC classes into CPC classes from ENV-TECH using the concordance table provided by the EPO and the US Patent and Trademark Office (USPTO) (see https://www.cooperativepatentclassification.org/).
5. The time periods are as follows: 1982–85, 1986–89, 1990–93, 1994–97, 1998–2001, 2002–05, 2006–09, 2010–13 and 2014–17.
6. Depreciation rates of 10% and 15% yield identical results.
7. For the list of CPCs and keyword searches, see WIPO (2019, methodological appx).
8. Following Boschma et al. (2013), we also run a dynamic panel data model estimation strategy via generalized method of moments (GMM) implementation à la Blundell and Bond (1998). Our results are fully supported in this robustness check and are available from the authors upon request. We thank one of the reviewers for this suggestion.

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