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Combining digital and green technologies in regions: how to close the gap with respect to the frontier?

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Abstract

This paper focuses on the combination of green and digital technologies at the regional level. Using patent data, we put forward an original measurement of the regional speed of green-digital (i.e. twin) combination: the temporal distance between the time at which a combination is realised for the first time in the frontier region and the time at which this same combination is accomplished in the focal region. We proceed by investigating the drivers and the technological impact related to this speed. We find that the speed of combination is enhanced by dealing with broad and diverse twin technologies. The speed at which the gap is closed, also crucially depends on the interdependencies between green and digital domains, captured by the overlap in their knowledge bases. Counterintuitively, the longer the combination paths, the faster the region combines green and digital technologies. This finding is then rationalised further looking at the policy and network characteristics. Finally, we find that the earlier the combination happens, the greater is likely to be the impact on subsequent inventions, but only for granted patents. Overall, these results are discussed in terms of policy recommendations, given the high attention placed by policymakers on the twin transition.

Keywords: Twin transition; Digital technologies; Green technologies; Regional knowledge base

JEL Classification: O31, O33, R11, R12, Q55

1 Introduction

Climate change and environmental degradation are making increasingly urgent the transition towards an economy where human-produced greenhouse gas emissions are reduced to (net) zero, and natural resources are used more efficiently. Globally, and particularly in Europe, policymakers have taken significant steps to support the green transition, increasingly linking these efforts to the digital transformation. Starting from the new EU Industrial Strategy (European Commission, 2020), and moving towards the new Green-Deal Industrial plan (European Commission, 2023), the green and the digital challenges are jointly considered for shaping the support given to the so-called twin transition (i.e. the green and the digital transition), in which digitalisation increases or enables environmental sustainability (JRC, 2022). On the one hand, new digital technologies, such as AI and big data, are expected to be applied in enabling new green innovations, spanning from smart grids and precision agriculture to predictive maintenance and real-time environmental monitoring. On the other hand, digital technologies are expected to become more environmentally sustainable, for example, by reducing energy consumption in data centres, and minimising the use of critical raw materials in digital device production.

The twin transition is a policy priority in Europe, where the EU Commission and member states have implemented various initiatives aimed at accelerating its progress over time. For instance, European funds allocated through the Recovery Plan include resources dedicated to the twin transition, with spending deadlines set for 2026 as part of the programme's conclusion. Within this policy framework, countries such as Italy are urgently developing support schemes, in order to encourage firms to align, as soon as possible, with the Industry 5.0 paradigm. This paradigm builds on Industry 4.0's focus on digital transformation, incorporating energy efficiency requirements for new digital technologies.

While policymakers are pushing for a faster twin transition, its implementation remains uneven, with significant regional disparities in the capacity to respond to this urgency. On the one hand, regions have different greening capacities (e.g. Barbieri et al., 2020b) and face different direct (e.g. phasing out of brown energy) and indirect (e.g. reallocating labour from brown to green occupations) costs in moving along the green transition (Rodríguez-Pose & Bartalucci, 2023). On the other hand, digitalisation spreads irregularly across places. Regions may develop, adopt, and exploit digital technologies with a gap with respect to other regions (e.g. Corradini & De Propris, 2017). In light of that, the twin transition may also unfold with different timing across regions (Maucorps et al., 2022), with some regions acting faster than other regions in combining new green and digital technologies.

The timing of the transition is the issue which we tackle in the present paper. We contribute to the limited research on the twin transition geography by examining regional disparities in the pace of integrating green and digital knowledge to develop new twin technologies. In innovation geography and regional studies, the research on the twin transition has so far mainly investigated the extent to which the green and the digital transition navigate in parallel, and eventually intersect across places. Furthermore, attention has been placed on the relative weight of green vs. digital technological, and scientific knowledge in driving their combination (see Faggian et al., 2024). Relying on the relatedness approach in evolutionary economic geography, it has been argued that the development of new digital and/or green technologies is facilitated by their cognitive proximity to pre-existing regional technologies, as well as by inter-regional linkages in their invention (e.g. Bachtrögler-Unger et al., 2023). This approach builds on the innovation recombination theory, according to which new technologies are typically developed by recombining existing knowledge in novel ways (Weitzman, 1998; Fleming, 2001). In brief, conceiving knowledge as a combinatorial space, innovations are obtained by firms, as well as by regions aggregating them, through a proper balance between the exploration of novel combinations and exploitation of pre-established combinations. The outcome of this process gets affected by the search of proper knowledge modules and by the configuration of a proper architecture that is able to pull them together. Following this logic, new green and digital technologies are more easily developed in regions by branching pre-existing technologies, as they draw on similar capabilities.

In this paper we rely on the same theoretical background, and we position ourselves in the literature on knowledge recombination (Xiao et al., 2022) to account for the speed at which regions integrate green and digital technologies. More precisely, we analyse how fast regions are capable of locally implementing combinations of green and digital knowledge, compared to their very first combination at the frontier of the knowledge space. To our knowledge, this aspect of the twin transition has not yet been addressed in literature. However, we consider it highly relevant, at the least, for two reasons. Firstly, given the increasing pressure from policymakers on regions to swiftly advance in their twin transition (JRC, 2022; European Commission, 2023), a higher speed could attenuate the costs with which regions can comply with the relative policies. Secondly, the same speed can affect the extent to which regions turn out to be fore-runners in the development of twin technologies, and benefit from the followers' reliance on their prior-art twin knowledge.

In our empirical application, we explore this new dimension within the geography of the twin transition, in relation to two key aspects. Firstly, we analyse how the speed of combining green and digital technologies is influenced by the characteristics of the relative regional knowledge, as well as by the nature of the combinatory patterns of the two technologies. This is useful to identify potential factors affecting the speed of twin transition which policy makers could support. Secondly, we investigate how the pace of combination between green and digital technologies affects the impact of twin inventions on the development of subsequent inventions at the regional level. This aspect is important to understand if the regions' twin speed affects the development of new technological paradigms.

Using the 2022 European Patent Office (EPO) PATSTAT dataset (spring version), we identify green and digital technologies based on previous research in the field (Barbieri, 2016; Martinelli et al., 2021). Then, we define twin (green and digital) inventions based on the co-occurrence of digital and green (5-digit CPC) classes in patents (Kogler et al., 2013). These twin inventions are mapped within the co-occurrence networks of regional and global knowledge spaces across NUTS3 regions in 28 European countries, covering the period from 1996 to 2019.[1] By analysing the periods in which these technologies co-occur, we propose a novel measure to assess the time difference between a given regional combination of green and digital technologies, with respect to when the combination originally took place on the frontier (i.e. the first region achieving this combination).

[1] The countries included are: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Germany, Greece, Finland, France, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Malta, Poland, Portugal, Romania, Slovenia, Slovakia, Spain, Sweden, the Netherlands, and the United Kingdom.

We find that the regional speed of combining green and digital technologies increases with the regional experience of dealing with broad and diverse knowledge associated with the twin transition. The interdependencies between green and digital domains, captured by the overlap in their knowledge bases, drives the speed at which the gap with respect to the frontier is closed. A similar effect is found for the technological specialisation of the inventive teams. We also observe that a higher speed of combination translates into more impactful (i.e. cited) twin patents, but only when granted patents are considered.

The remainder of the paper is structured as follows. Section 2 presents the idea of regional speed in combining green and digital technologies. Moreover, it discusses both the determinants and the technological impact. Section 3 firstly, describes the data; secondly, provides some statistics about green and digit technological combinations; thirdly, presents our new measure of the combination speed of green and digital technologies, and the other variables of our empirical analysis. The results are discussed in Section 4, and Section 5 concludes.

2 The combination of digital and green technologies and its regional speed

Both the green and the digital transition rely largely on the development of new technologies. On the green side, the target of reduction of green-house gas emissions highly depends on not-yet developed environmental technologies (IEA, 2020). On the digital side, the digital transformation occurs by exploiting the General Purpose Technology role of a new wave of technologies: AI, big data, Internet of Things, Additive Manufacturing, among others (Martinelli et al., 2021). Thus, the twin transition is a technological phenomenon, relying on specific functions that are able to combine digital and green technologies. Artificial Intelligence innovations applied to new technologies for environmental monitoring and energy optimization are just one example of a digital technology able to create a combination with green technologies (Cicerone et al., 2023).

Recently, research efforts to identify and map green and digital technologies have been increasing, with analyses typically relying on patent data using text analysis and/or classification codes to identify them (Jindra & Leusin, 2022; Biggi et al., 2024). Building on these measurements, the geographical analysis of twin technologies has been growing. These studies are mainly focused on comparing the role of local scientific/technological knowledge in the green sector and the digital sector (e.g. Fazio et al., 2024; Damioli et al., 2024; Bianchini et al., 2023).

However, to our knowledge, no attention has been paid to the timing and the speed at which regions are able to develop green and digital technologies. As mentioned above, the lack of attention on this aspect is unfortunate, especially given the urgency which policymakers are placing on integrating green and digital technologies across all economic sectors. The relevance of the combination speed and its geographical heterogeneity is clear when we consider that regions have different abilities to develop and implement knowledge combinations. On the one hand, new technological knowledge is generally obtained through the collective inventing activities of actors across the world. The characteristics of technologies are in fact intrinsic and, therefore, global. On the other hand, the landscapes in which technologies operate are largely local. As pointed out in the literature, knowledge bits are difficult to transmit over long distances (Fritsch & Franke, 2004; Acs et al., 2002), and different geographical entities have different propensities with which to accumulate knowledge, due to their intrinsic characteristics (e.g. infrastructures, resources, institutions, and policies). Hence, regions are expected to create combinations, of green and digital technologies, with a temporal gap with respect to the world frontier.

Drawing on the literature about innovation geography, the world frontier can be identified by the state of *world knowledge space* at a certain point in time. This space is composed by the learning processes through which new technological combinations are obtained in the world, through collective efforts that are determining the intrinsic evolution of technologies. More precisely, this space can be thought as a network of relationships among knowledge domains, established through collective inventive activities occurring across the world (Balland, 2016). Regions are contributors to these processes, and they are exposed to them. A new knowledge combination realised through an inventive effort on the frontier increases the size of the world knowledge space. This new combination represents a new bit of knowledge, which could be exploited by other subsequent inventive efforts in different places and to different extents. The local implementation of a new knowledge combination can occur with different lags among regions with respect to the frontier. Those combinations contribute to the local knowledge, or *regional knowledge space/base*, which is the network of relationships among the knowledge domains that are present in the region, and in which the region could possibly be a leader in them (e.g. being specialised in the knowledge domains). Mimicking what is happening at the firm level with the process of innovation adoption (Rogers, 2003), some regions are faster (forerunners) and some others are slower (laggards). The reasons for that and its consequences are addressed in the following sub-sections.

2.1 Determinants of the speed of combining green and digital technologies

Based on the conceptual framework of recombinant innovation theory (e.g. Kogut & Zander, 1993; Schoenmakers & Duysters, 2010), in the following we show how the region's ability to accelerate the development of green-digital knowledge combinations depends on three sets of factors. These are: the characteristics of the regional knowledge base when combining green and digital technologies; the patterns through which green and digital technologies are combined in regions, or their regional relationships; and the type of actors through which new green-digital technologies are regionally developed. We are going to discuss each of them.

The characteristics of the regional knowledge base. To develop or acquire new technologies, regions draw on their regional knowledge base (Asheim & Coenen, 2005). This relates to the interconnected knowledge domains, to which their inventions refer (e.g. Kogler et al., 2013; Basilico & Graf, 2023). Typically, despite the known limitations, patents are used as reliable proxies of regional innovations (Acs et al., 2002). The knowledge domains and linkages (e.g. based on the co-occurrences or citations of patent codes) through which patents are classified define the knowledge that the regions are able to develop (Balland, 2016).

We argue that three features of the regional knowledge base are salient when accounting for the speed of combination between green and digital technologies. The first feature is represented by the local endowment of green and digital knowledge, which regions obtained already when combining them in the past. This twin (green and digital) part of the knowledge base represents the experience accumulated by regions in combining green and digital technologies. This feature can be exploited for more efficient and faster realisation of the same typology of new combinations. Referring to the knowledge space, the experience in creating twin combinations can be captured by looking at the *stock of twin patents* (green and digital) (Aghion et al., 2015). This indicator accounts for the cumulativeness of twin knowledge in two aspects. Firstly, a region has more experience of developing new green and digital technologies if it has already developed them. Secondly, the most recent twin inventions have a higher intrinsic value than past twin inventions, since they are less affected by the asset erosion phenomenon (Dierickx & Cool, 1989; Ramani et al., 2008; Roper & Hewitt-Dundas, 2015). On this basis, we expect that both the experience and more recent instances of the green-digital technology combination already developed in the region increases the speed to implement novel regional combinations.

A second relevant aspect of the regional knowledge base is represented by the breadth of technologies to which regional twin inventions refer. Regional twin patents covering different technological fields encompass multiple sectoral applications. This reveals a basket of opportunities to implement new green-digital combinations developed at the frontier, possibly also making it faster. This is an aspect that the regional *scope of twin patents* captures. The literature shows that having higher patent scope results with higher technological and economic value (Lerner, 1994; Novelli, 2015; Marco et al., 2019). This result is possible due to the wider array of applications that are available in the case of a larger patent breadth. Moreover, inventions with a higher patent scope are usually more radical (Schoenmakers & Duysters, 2010), and this suggests another possible channel of influence. Twin patents with a wider technological breadth, could influence the capacity of regions to react faster to new twin knowledge that is produced at the frontier.

The third and last aspect of the regional knowledge base that we consider refers to the diversity of the knowledge sources on which local twin (green and digital) inventions draw. The literature finds that prior-art knowledge, drawing on different technological domains, leads to more original results (Trajtenberg, 1990). In our specific setting, a local base of more original twin inventions suggests that the focal region has a higher capacity to master a wider set of knowledge inputs. Regions can benefit from this capacity in response to new combined (green-digit) knowledge available at the frontier, making them faster in developing their own combination. The originality of twin patents of a region, defined using the originality measure first proposed by (Trajtenberg et al., 1997) on single patents, can operationalise this idea by looking at the distribution of their backward citations. Originality of patents has been the focus of a variety of analyses at the micro-level, like those dealing with creation of new VC-based start-ups (Gompers et al., 2002), the patents' value after mergers, and acquisitions among firms (Stahl, 2010; Valentini, 2012) and those focusing on technological trajectories (Guerzoni et al., 2014; Plantec et al., 2021). These studies point to the beneficial effect associated to the capacity to draw on diverse knowledge fields. As noted, this is a mechanism that could be scaled up to the regional level, to account for a faster speed of new green-digital combinations.

The relationships between green and digital technologies. The speed at which regions create combinations of green and digital knowledge in local inventions also depends on the patterns with which they generally combine those technologies (Kogut & Zander, 1993). This refers to the complementary set of technologies, with which green and digital technologies are combined in the region. In this respect, extant studies show how technological advancements are propelled by developments in related domains (Acemoglu et al., 2016). On a similar vein the recent work by Barbieri et al. (2023) shows that new green technologies are greatly influenced by advances in other related domains, including non-green domains. Drawing from this point, we argue that stronger relations between green and digital domains could make future combination more efficient, and in turn faster. In other words, the more local digital and green inventions related in terms of technological domains to which they belong (i.e. other than green and digital), the more digital and green technologies are cognitively proximate (Boschma, 2005; Cantner & Meder, 2007). Indeed, this sharing of common knowledge roots denotes the possibility of an overlap between the applications in which new green and new digital regional technologies are developed and, it suggests that they are complementary. Thus, this makes the general integration of green and digital technologies easier. Furthermore, it speeds up the time at which a new green-digital combination, that is available at the frontier, can be implemented locally. This can be operationalised by referring to the idea of knowledge space itself (Basilico & Grashof, 2024). The knowledge space is usually built up by looking at the extent to which different knowledge domains co-occur in the patents of a certain region (Kogler et al., 2013). If this co-occurrence expresses the similarity between the capabilities to develop those technologies (Balland, 2016), a first relationship between green and digital technologies appears salient: the *co-occurrence overlap between green and digital technologies.*

A second relevant feature of the regional relationships between green and digital technologies is represented by their combination length. This is reflected by the possible paths which which green and digital knowledge are combined locally. As the literature on technological trajectories shows (Alessandri, 2023; Fontana et al., 2009; Nomaler & Verspagen, 2021), technologies develop along paths marked by a complex set of direct and indirect relationships with other technologies. The trajectory of the formation of new twin (green and digital) combinations arguably follows this pattern too. Green and digital bits of knowledge can be combined either directly (e.g. by co-occurring in an invention) or indirectly. For example, it might happen that an invention realises a new combination between a digital and a non-green component; this latter is combined in another invention with a green component. Jointly considered, these two inventions create an indirect connection between the digital component and the green component. In the knowledge space there would be a path that connects (albeit indirectly) the digital and green knowledge components. Intuitively, the number of technological steps bridging green and digital knowledge bits increases with the number of intermediate inventions that separate the knowledge constituting the twin technology. Given the possibility that intermediate inventions (steps) bridging green (digital) and digital (green) knowledge could be more than one and vary in number, these steps delineate the combination length of developing a new twin technology at a local level (Basilico & Graf, 2023; Corradini & De Propris, 2017).

This factor has implications on the speed of combining green and digital technologies. A higher average number of steps between green and digital technologies entails a longer combinatory effort and time by regional inventors which, in principle, reduce the regional speed. Indeed, while a longer path of this kind could also enrich the opportunities of combining green and digital technologies (for example, affecting the density of the regional knowledge network), the average number of steps a region takes to locally implement a new green-digital combination at the frontier should negatively correlate with the regional twin speed that we are investigating.

Inventive teams. The third set of factors refers to the actors involved in the combination between green and digital technologies. In particular, we consider how their features might affect the combination speed. The composition of the inventor teams is the first factor to be considered, when looking to the green-digital knowledge produced by inventing (Larivière et al., 2015). A series of characteristics of the inventive team are particularly relevant for twin inventions. The first aspect is represented by the inventor team size. In innovation studies, larger teams are typically found to increase creativity, and to lead to more novel and impactful inventive outcomes (Breitzman & Thomas, 2015). In brief, when the size of the team increases, the set of available information and knowledge resources for inventing grows (Arts & Veugelers, 2015). Therefore, the team is more likely to obtain insights for new and useful ideas, especially in the case of complex inventive tasks, and in uncertain environments (Lee et al., 2015).[2] As twin inventions combine green and digital technologies, which are regarded as complex pieces of knowledge (Barbieri et al., 2020a; Corradini et al., 2021), the advantages of larger teams appears particularly important. Accordingly, we can expect that regions with a higher average dimension of twin-patents inventor teams also have higher capabilities to find the way to swiftly achieve new green-digital combinations.[3]

The second aspect of twin inventions related to actors we consider, is the technological specialisation of the twin inventor teams. The variety of the knowledge background of inventors is an important facilitator of their fruitful interaction. Possible synergies and spillovers increase the productivity of the inventive team. Empirical studies about the impact of team technological variety on firm's performance (Damioli et al., 2023) have provided partial support to this mechanism. The same holds true for the impact that the diversity of affiliations of inventor teams has on patents' scope (Choudhury & Haas, 2018). Drawing on this research, we expect that a higher (average) knowledge diversity of the inventor teams developing regional twin patents makes regional inventorship more powerful. Thus, it would speed up the process of implementing new green-digital combinations that are available in the world knowledge space.

2.2 The impact of the regional speed in combining green and digital technologies

As explained in Section 1, the regions that are able to develop twin technologies faster answer to the urgency put forward by policy makers to push this transition. However, the speed could affect the quality and the impact of twin technologies developed by regions responding to this push.

Drawing on a well-established tradition in the literature, forward citations, in our case of twin patents, can be considered a reliable indicator of this impact (Caballero & Jaffe, 1993; Jaffe & Trajtenberg, 1999). They reflect the significance of the underlying technology for the advancement of subsequent innovations. A higher number of forward citations for a patent indicates its larger spillovers on subsequent inventions, and it highlights the importance of the

[2] The literature has also recognised that the diversity of teams could entail conflicts between mental models and interpersonal tensions (e.g. Damioli et al., 2023), which could also be present in the development of new twin patents.

[3] Recent research shows that the size of teams when implementing innovation activities can be a double-edged sword (Hu et al., 2021), as larger teams require more coordination and mechanisms against possible free-riding, which dampen creativity (Cummings et al., 2013). However, given the complexity and uncertainty characterising the combination of early-stage technologies like green and digital technologies, we expect that the positive effect of team size would more than compensate for the negative effect.

embedded knowledge for driving future waves of technological development (Trajtenberg et al., 1997).

In our case, it is of interest to ascertain if a regional speed in combining green and digital technologies (with respect to the frontier) translates into more impactful twin inventions.

In the body of innovation literature, firms innovating faster are recognised to benefit from competitive advantages from first-mover and fast-follower strategies (Cooper & Kleinschmidt, 1994; Eisenhardt & Tabrizi, 1995; Kessler & Chakrabarti, 1996). However, the same literature shows that innovation speed could be offset by development costs: an innovation produced faster could require more resources (Crawford, 1992). The clash is also observed in the case of product quality, since an innovation produced faster could entail lower performance specifications (Smith & Reinertsen, 1992).

The industrial organisation literature also finds first-mover advantages in the case of the innovation diffusion across firms (Hoppe, 2002). In brief, early technology adoption by firms guarantees higher profits, since they become temporary monopolists. [4] However, this creates trade-offs with the opportunity of cost reduction from accessing a more established technology in a later stage of the technological development. Quite interestingly, conflicting implications are observed when considering differences in the time in which firms are developing, rather than adopting a new technology (Ruiz-Aliseda & Zemsky, 2006). This is an aspect that is closer to our case.

Being faster in the implementation of a new green-digital combination that has been realised at the frontier could have similar implications. On the one hand, faster regions are expected to invent new twin technologies, that slower regions may find beneficial to adopt as they progress toward their own twin transition. In other words, the impact of twin technologies that are developed by early inventors increases as they create more prior-art knowledge, that otherwise would have not available for the inventions of the followers (Capello & Varga, 2013). On the other hand, green-digital combinations that are realised faster may overlook potential additional specifications, checks, and further combinations. Whether early combinations have a citation advantage over later combinations is something that we will leave to an empirical test.

Empirical analysis can also elicit whether the speed of combination per se would exert an effect on the technological impact; that is, after controlling for the likely relation that its driver may have on forward citations.

3 Data and methods

In the following subsections, firstly we describe the data for constructing the different variables (Section 3.1). Secondly, we show the descriptive statistics on the combination of green and digital technologies (Section 3.2). Thirdly, we illustrate the indicator of regional speed in combining green and digital technologies. As we previously argued, the focus on this concept and the original approach to capture it from an empirical point of view represents a main element of originality of this paper. Fourthly, we provide some descriptive statistics for this indicator (Section 3.3). Finally, we present the variables that were used in the analysis of the determinants

[4]The company holding a patent is regarded as a temporary monopolist in the production of that specific product, since other firms cannot, in theory, imitate that product until a reasonable period of time has passed (usually 20 years).

and impact of the indicator, and the relative econometric models (Section 3.4).

3.1 Data

Following the bulk of the literature on innovation at the regional level, our analysis is based on patent data.[5] Our main data source is EPO Patstat 2022 spring version, from which we retrieved patents at the European Patent Office between 1996 and 2019.

Technologies are identified using the Cooperative Patent Classification (CPC) at the 5-digit level. As for green technologies, following the extant literature (Barbieri, 2016), these are captured by all patents with at least one class falling in the three-digit CPC classification Y02, and thus regarded as "green". As for digital technologies, these are captured by identifying "digital" patents using the CPC classes identified for the analysis of Industry 4.0 by Martinelli et al. (2021) and UK IP Office (2013, 2014a,c,b). Following this procedure, the digital patents of our analysis refer to 5 main technologies: robotics[6], 3D printing, Internet of Things, Cloud Computing, Big Data, and Artificial Intelligence (see Table 7 in Appendix A for the illustration of the 5-digit CPC digital classes). Moreover, we count for all the regions, the number of twin patents they have, and we select the regions which are above the 15% level of the distribution. This is done in line with other studies in the field of economic geography (e.g. Pinheiro et al., 2022), in order to consider only active regions which have at least some recombination potential.

The regional analysis of the identified patents is conducted at the most granular level of administrative regions in Europe: the NUTS-3 level. Following the literature, we use inventors' location to assign the patents to specific regions (Cantner & Graf, 2006). We do that as large companies usually tend to patent in their headquarters, which is the place the invention does not necessarily originate from (Graf, 2017). This effect must be considered, otherwise the geographical allocation would be biased, and the majority of patents would be concentrated around large cities.

As illustrated in the theoretical part, we rely on the concept of "knowledge space", which describes the available base of knowledge across locations and worldwide. We construct it for all NUTS 3 regions, and for Europe as a whole following Kogler et al. (2013). The nodes of both networks are represented by CPC classes at 5-digit and the edges are based on the frequency with which couples of 5-digit CPC classes co-occur in each patent.

In addition to patent data, we rely on data provided by Eurostat (for the EU countries) and the Office of National Statistics (for the United Kingdom) [7] to build up a variable for regional Gross Domestic Product (GDP), which we will use as control in our analysis.

[5] For the pros and cons of patent data for measuring regional inventive activities, see Acs et al. (2002).

[6] In the case of robotics, the selection of the sub-classes is performed manually by checking the titles and descriptions of the single CPC 5-digit classes. Only the classes with a digital component have been selected, while the others have been discarded. For example, the class Y10S9 named as "Robots" and containing sub-classes like Y10S901/01 named as "Mobile Robots" and Y10S901/02 named as "Arm Motion Controller" have been excluded from the sample. Whereas, class B25J11/0005 identified as "Manipulators not otherwise provided for: Manipulators having means for high-level communication with users, e.g. speech generator, face recognition means" has been included.

[7] We perform an estimation in the case of missing values for GDP using the function *na kalman* contained in the R package "imputeTS". The estimation of missing values for GDP is limited in number. We performed an estimation on 121 observations out of 17,904.

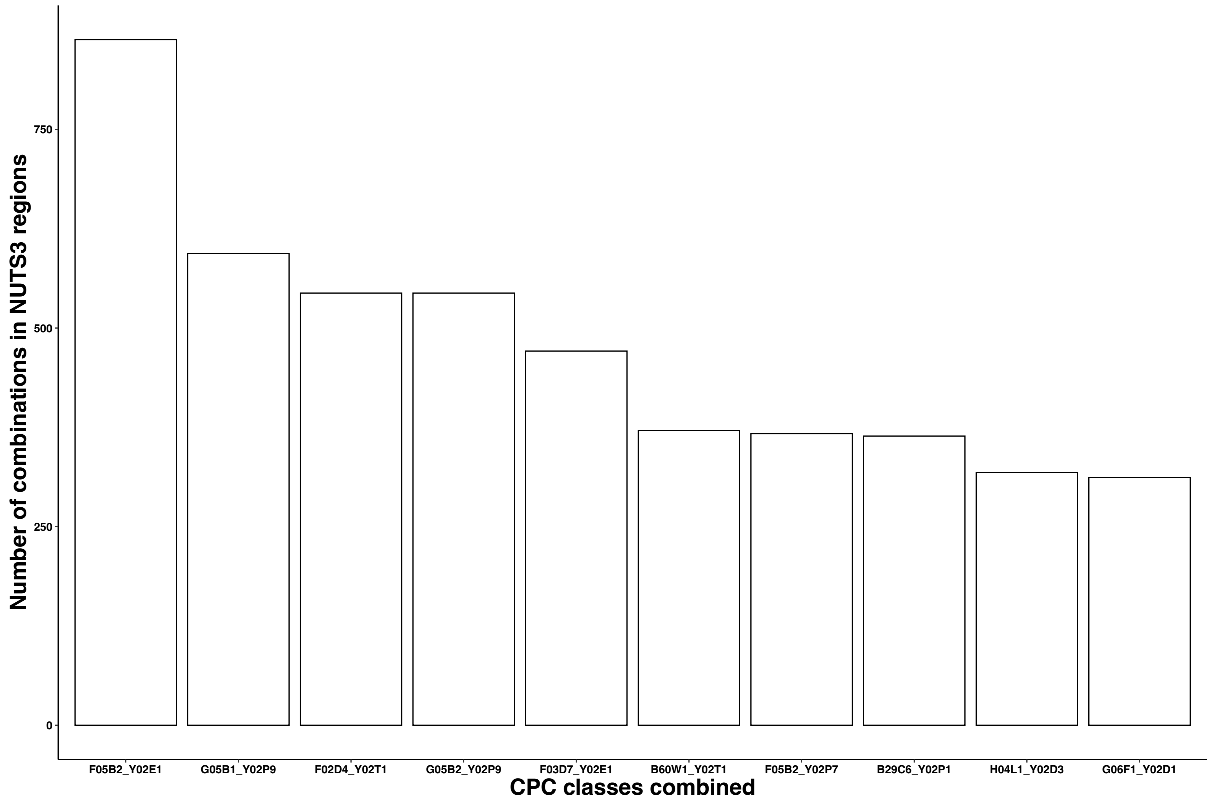

Figure 1: Top 10 frequent combinations of (5-digit CPC) green and digital classes across regions.

3.2 Twin patents: descriptive statistics on the combination of green and digital technologies

Our analysis detects twin patents through the combination of green and digital technologies; that is, based on the joint presence in a single invention of (at least) a green and (at least) a digital technological class.[8]

Figure 1 shows the 10 most common combinations of digital and green technologies in the European regions. The most popular combination is between class F05B2 ("Indexing scheme relating to wind, spring, weight, inertia or like motors, to machine or engines for liquids covered by subclasses F03B, F03D, and F03G") which, in general, comprehends inventions on the development of mechanical components for liquid, wind and spring motors, and Y02E1 ("Energy generation through renewable energy sources"). This combination occurs in technologies that are related to transmission parts, which are supervised by drivers and controlling systems in order to increase energy performance. These transmission parts are components of engines that are used for producing renewable energy (wind turbines, mainly). The second most common combination is between class G05B1 ("Comparing elements, i.e. elements for effecting comparison directly or indirectly between a desired value and existing or anticipated values") and class Y02P9 ("Enabling technologies with a potential contribution to greenhouse gas [GHG] emissions mitigation"). These inventions have elements related to the optimisation of the movement of robots, in terms of reducing programming times, and algorithms to permit an increase in performance of such machines, thus reducing the waste of resources. The third most com-

[8]For alternative ways to identify patents belonging to specific technologies see Björn & Matheus (2022) and Biggi et al. (2024).

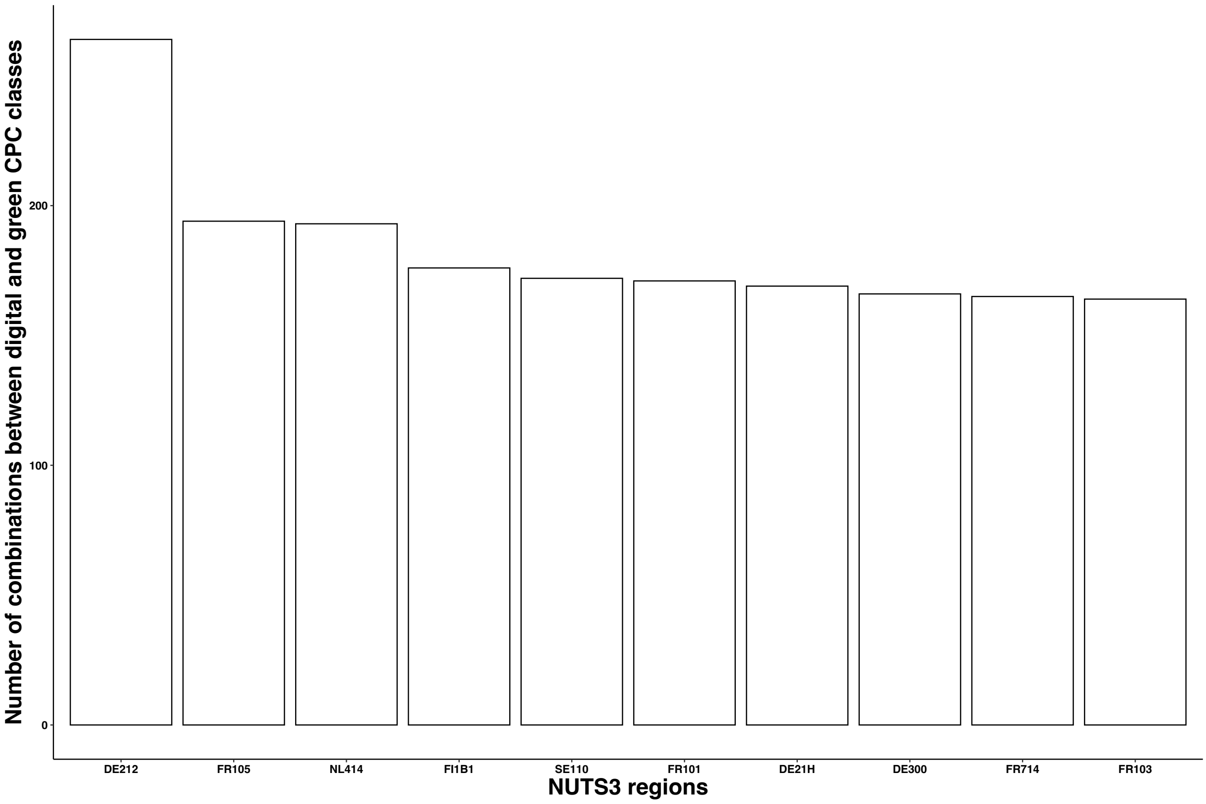

Figure 2: Top 10 regions in combining (5-digit CPC) green and digital classes.

mon combination is between class F02D4 ("Electrical control of combustion engines") and class Y02T1 ("Road transport of goods or passengers"). This patent group is associated with inventions dealing with electrical systems to control combustion or hybrid engines performance, thus avoiding waste of resources. In general, the most common combinations are performed by patents dealing with the reduction and mitigation of the impact of polluting activities, through better control systems for a better deployment of resources.

Figure 2 shows the top 10 NUTS3 regions in Europe with the highest number of combinations between digital and green technologies.

The region with the highest number of twin patents is Munich (DE212), one of the most industrialised cities, both in Germany and in Europe. By looking at the applicants that filed these patents, it is clear that those are mainly multinational corporations related to the automotive industry, the chemical industry, and network communications. These include Bayerische Motoren Werke (BMW), Man Truck & Bus, Linde, and Siemens. The second region by number of twin combinations is Hauts-de-Seine (FR105), which covers the western inner suburbs of Paris, France. Companies like Renault, Peugeot Citroen Automobiles, and Sagemcom Energy & Telecom have their headquarters located there. These companies are worldwide leaders in the automotive industry and in the energy sector. The third region by number of twin combinations is located in The Netherlands: South-East North Brabant (NL414). This region covers some economically important Dutch cities like Eindhoven, Tilburg, and Breda. Companies like Philips (worldwide electronics producer leader) and ASML (producer of machines important for chip manufacturing) have their headquarters there. In general, as expected, the regions with the highest capacity to invent in the twin-transition technological domains are the economically advanced regions, with relevant economic players.

3.3 Average Speed of the regional combination of green and digital technologies

The patent data we have described above, and the identification of twin patents, enable us to put forward a measurement of the regional speed of green-digital technologies combination. To measure it, we build up for a focal region r at time t, an indicator called $AverageSpeed_{r,t}$. This indicator captures the average speed at which, in time t[9], a region r realises the combination between green and digital technologies, relative to when the same combination was first introduced in Europe. In doing so, the indicator accounts for the speed with which a region closes the gap, with respect to the frontier, in combining green and digital technologies.

Figure 3 visually represents the intuition behind this variable. Suppose that a certain combination, between the green technology "Road transport of goods or passengers", identified by the green 5-digit CPC class Y02T1, and the digital technology " Network arrangements, protocols, or services for addressing or naming", identified by the 5-digit CPC class H04L6, is realised for the first time in a region in Europe in year 2000. This would represent the frontier of the knowledge space for this combination. Figure 3a shows the distance between the same two technologies in another European region (i.e. the focal region) in the same year 2000[10].

As Fig. 3b shows, a successful match between the two technologies is observed in the focal region in year 2010, that is, 10 years after the combination was reached at the frontier. Accordingly, to measure this delay, we assign a score of 10 to this specific combination in this focal region. Based on this intuitive depiction of the time distance between the achievement of a combination on the frontier and in the focal region, we create our variable as follows.

Firstly, we define with $DT_{c,r,t}$, the difference in the number of periods between the time in which a twin combination (c) is first realised in a region in Europe (e) $P_{c,e,t}$, and the period in which the same combination is realised in the focal region (r) $P_{c,r,t}$:

$$DT_{c,r,t} = P_{c,r,t} - P_{c,e,t} \tag{1}$$

where this difference is calculated for every combination between green and digital technologies at least once realised in an European region (c), for every region (r), and every time period (t).

Secondly, a standardisation between 0 and 1 of the difference $DT_{c,r,t}$ is performed for each combination c. The resulting value is subtracted from 1, as follows:

$$SDT_{c,r,t} = 1 - \frac{DT_{c,r,t} - \min\limits_{\forall DT \in D_c} DT_{c,r,t}}{\max\limits_{\forall DT \in D_c} DT_{c,r,t} - \min\limits_{\forall DT \in D_c} DT_{c,r,t}} \tag{2}$$

where $\min\limits_{\forall DT \in D_c} DT_{c,r,t}$ is the minimum difference in the number of periods for one combination

[9]Time t for this and the other subsequent variables represents patents across a 5-year moving window. These moving temporal windows are introduced to account for the variability in number of patents filed every year. By using moving windows, we compensate for possible year-to-year variation in the number of patented inventions.

[10]Once the minimum distance for a single technological combination is reached in the knowledge space of the focal region, this is maintained until a new minimum is reached. The calculation is performed in this way to account for the fact that knowledge is cumulative over time (Dosi, 1982).

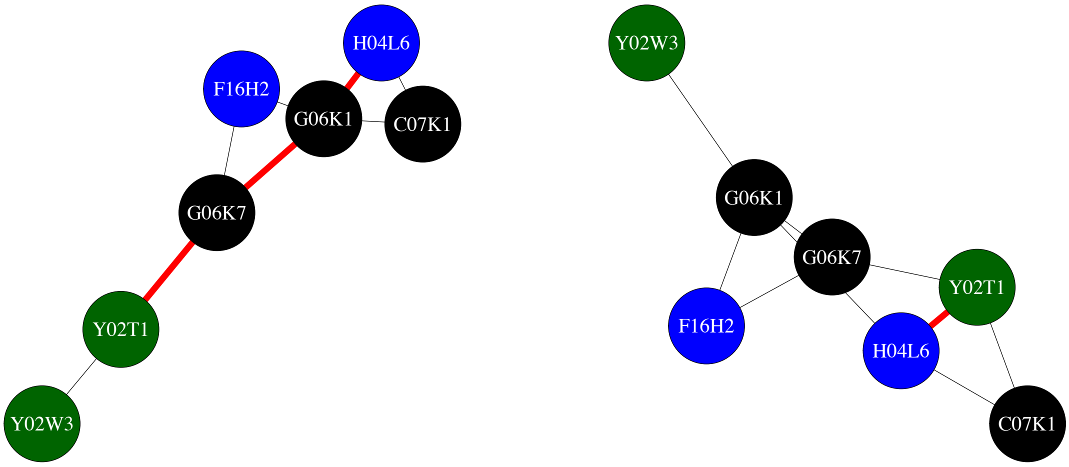

Figure 3: Regional delay in the combination of a digital (Y02T1) and a green (H04L6) technology, realised for the first time (at the frontier) in 2000.

c in each region r for a specific time period t and $\max_{\forall DT \in D_c} DT_{c,r,t}$ is the maximum difference in the number of periods for one combination c in each region r for a specific time period t. As a result, a higher value is given to the combinations that are realised earlier (i.e. with less delay with respect to the frontier region), and a value of 0 is given in the case of no combination. Finally, we take the average of $SDT_{c,r,t}$ for all combinations for each region to construct the *Average Speed* as follows:

$$Avg\_Speed_{r,t} = \frac{\sum_{c \in r \cap t} SDT_{c,r,t}}{TP_{c,r,t}} \tag{3}$$

where $TP_{c,r,t}$ is the total number of twin patents that are present in the region. In this way, $AverageSpeed_{r,t}$ represents the average time that a region r takes to close the gap in each time period t.

Figure 4 shows the relation between the *Average Speed* by period and the average number of twin combinations by period for each region, a baseline indicator of the quantity of successful combinations. Certainly, the correlation between our measure and the benchmark is not negligible (0.6). Nevertheless, not always a region with high number of combinations is able to swiftly combine green and digital technologies, and the other way around. As an example, we take region DE947, which is the district of Aurich (located in North-West Germany). This region does not create a very high number of twin patents, but is able to close the gap between green and digital technologies faster than most other regions. On the other side, region DK042 identifies the district of East Jutland located in Denmark, which achieves a high number of twin combinations, with an average speed which is not among the highest.

In Table 1 we rank the top 10 regions in terms of *Average Speed* by period, and we compare it with the rank in the average number of twin combinations by period. These results confirm that there is a difference between these two variables. The table shows that the region which is faster

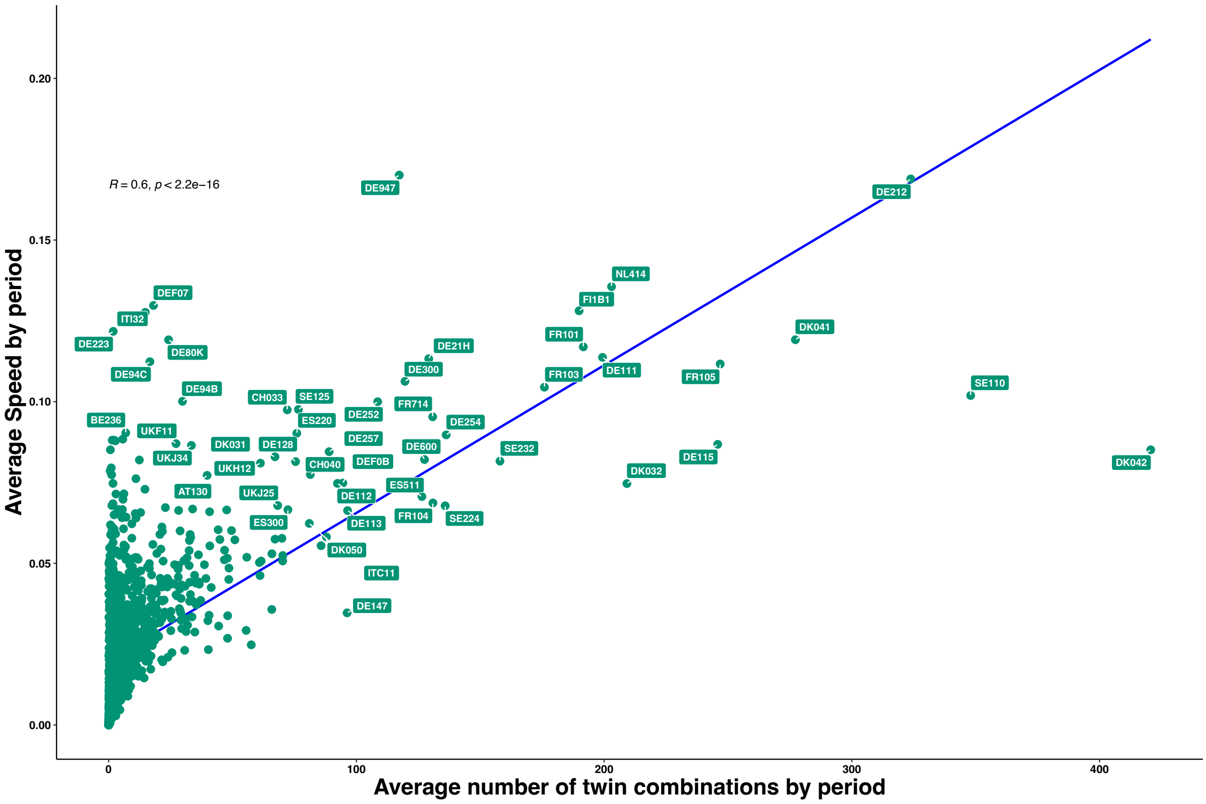

Figure 4: Correlation between average number of twin combinations and Average Speed by period.

in closing gaps is not always the region with the highest number of combinations performed; it ranks in position 22 in this variable.

3.4 Variables and models

Following the conceptual framework exposed in Section 2, in the analysis of *Average Speed* we employ three sets of variables.

Starting with the factors that pertain to *the characteristics of the knowledge base* discussed in Section 2 we create three variables. Firstly, we proxy the regional endowment and experience in combining green and digital technologies by calculating the variable *Stock Patents*. This amounts to the stock of twin patents of region r at time t, calculated by using the Perpetual Inventory Method on yearly patent flows from the patents identified in the period 1996-2000, and a depreciation rate of 15% (Aghion et al., 2015). Secondly, we capture the scope of regional twin inventions, by calculating the variable *Patent Scope*, which counts the average number of CPC classes included in patents identified as twin for each period t and region r. Thirdly, to measure the originality of regional twin patents, with respect to all the patents identified as twin in a region r in a time period t, we calculate the *Originality Backward Cit* index similarly to the index proposed by Trajtenberg et al. (1997). The only difference is the unit of measure, which in the case of those authors it is the single patent, while in our case we consider all the patents belonging to one region r in one time period t. By doing so, we measure the degree of heterogeneity of prior-art knowledge on which regional twin patents are based (as reflected by their backward citations).

As for what we called the *relationships among green and digital technologies* in regions

Table 1: Top 10 regions in terms of Average Speed by period.

NUTS 3 region	Rank Average Speed	Rank Average number
DE947	1	22
DE212	2	3
NL414	3	8
DEF07	4	158
FI1B1	5	11
ITI32	6	190
DE223	7	392
DK041	8	4
DE80K	9	123
FR101	10	10

(point ii) in Section 2, we calculate two variables. Firstly, to capture which are the technologies in common between patents belonging to at least one green class, and patents belonging to at least one digital class, we calculate the variable $Co\_Occ\_Overlap_{r,t}$:

$$Co\_Occ\_Overlap_{r,t} = \frac{N\_class_{g,d,r,t}}{N\_class_{g,r,t} + N\_class_{d,r,t}} \tag{4}$$

where $N\_class_{g,d,r,t}$ is the number of classes which co-occur in both green (g) and digital (d) patents in a region (r) and time period (t); and $N\_class_{g,r,t}$ ($N\_class_{d,r,t}$) is the total number of classes that co-occur in the green (g) (digital (d)) patents of region (r) and in a time period (t). Secondly, to capture the "combination length" of pairing green and digital technologies, we propose a new indicator called *Average Steps*. This indicator shares the logic of our indicator of speed of twin combination, but focuses on the technological steps needed to combine green and digital components. The method for its construction is similar to the one for the *Average Speed*. Therefore, to avoid repetitions, the detailed explanation of which is in Appendix C. This indicator reflects the average number of steps (in terms of distance) that the region must travel in order to close the gap between green and digital technologies. Thus, taking a different perspective with respect to *Average Speed* on the combinatorial power of the region.

The third and last group of independent variables refer to the *inventive teams* developing new twin technologies (point iii) in Section 2), and consists of three variables. Firstly, we calculate the variable *Avg Team Size*, which is the average number of inventors collaborating in regional twin patents. Secondly, we check the technological variety of the same inventor teams and define the variable *Avg Tech Dispersion*. This variable measures the regional average of the ratio between the number of technologies in which a twin inventor has some experience, and the total number of technologies that are present in the region.

As controls we use the *share of public applicants* and the *GDP*. Public actors, like universities and research organisations, are often at the forefront of basic research (Lissoni, 2012). Thus, their research efforts facilitate combinations across different technologies, or are able to a higher extent to contribute to societal goals, such as sustainability or digital accessibility.

Finally, as in other studies in the field (e.g. Pinheiro et al., 2022; Grashof & Basilico, 2024), we control for the economic activity of regions through their GDP. More prosperous regions have higher possibilities of recombination, especially in the case of complex technologies like green and digital.

In the second step of the analysis, we operationalise the argument of Section 2.2 about the impact of *Average Speed*. To do that, drawing on the literature (e.g. Sorenson & Fleming, 2004; Petruzzelli et al., 2015; Lee et al., 2012), in this part of the analysis we use as dependent variable the average number of forward citations for patents identified as twin in each time period t and region r. Therefore, we aggregate at the regional level all the patents identified as "twin" and define the variable *Average Fw Citations* as follows:

$$AverageFwCitations_{r,t} = \frac{Tot\_Fw\_Cit_{r,t}}{TP_{r,t}} \tag{5}$$

where $Tot\_Fw\_Cit_{r,t}$ is the total number of forward citations generated by twin patents in a region r and in a time period t, and $TP_{r,t}$ is the total number of patents identified as twin in a region r and in a time period t. For the regressions regarding the impact, the focal regressor is the *Average Speed* indicator, which this time is considered as an independent variable.

The general econometric model for the regression on the drivers of twin transition is the following:

$$AverageSpeed_{r,t} = \beta_0 + \beta_1 RegionalBase_{r,t} + \beta\_2 RelationshipGreenDigital_{r,t} + \\ \beta_3 InventiveTeams_{r,t} + \beta_4 SharePublicPatents_{r,t} + \beta_5 GDP_{r,t} + \omega_r + \alpha_t + \mu_{r,t} \tag{6}$$

where $AverageSpeed_{r,t}$ is the main dependent variable calculated for each region r and time period t. The $RegionalBase_{r,t}$, $RelationshipGreenDigital_{r,t}$ and the $InventiveTeams_{r,t}$ represent the groups of independent variables calculated for each region r and time period t. $SharePublicPatents_{r,t}$ and $GDP_{r,t}$ are the control variables representing, respectively, the share of public twin patents and the *GDP* calculated for each region r and time period t. Moreover, ω_r and α_t refer to regional and time fixed effects. Finally, $\mu_{r,t}$ represents the residuals.

The general econometric model for the regression on the impact of twin transition is the following:

$$AverageFwCitations_{r,t} = \beta_0 + \beta_1 AverageSpeed_{r,t} + \beta_2 RegionalBase_{r,t} + \\ \beta_3 RelationshipGreenDigital_{r,t} + \beta_4 InventiveTeams_{r,t} + \beta_5 SharePublicPatents_{r,t} + \beta_6 GDP_{r,t} \\ + \omega_r + \alpha_t + \mu_{r,t} \tag{7}$$

where $AverageFwCitations_{r,t}$ is the average number of forward citations for each region r and period t, representing the dependent variable for this model.

The list of variables for our analysis, together with a short description of them, is presented in Table 2. Table 3 reports a summary of their main descriptive statistics. The correlations among the considered variables is presented in Table 8 in Appendix B. In this sense, we capture the fraction of patents filed by a public applicant for every considered region.

Table 2: Variables used in the models

Variable Name	Description
Dependent Variables	
Average Speed	Average standardised difference in time periods for each period and region
Average Fw Citations	Average number of forward citations in twin patents for each period and region
The characteristics of the regional knowledge base	
Stock Patents	Patent stock for the patents identified as twin for each period and region
Patents Scope	Average number of CPC classes included in patents identified as twin for each period and region
Originality Backward Cit	Originality of the patents identified as twin for each period and region
The relationships between green and digital technologies	
Co Occ Overlap	Overlap (co-occurrence) between the tecnologies that are connected to one green or digital technology in each period and region
Average Steps	Average standardised difference in number of steps for each period and region
Inventive teams	
Avg Team Size	Average team size of the patents identified as twin for each period and region
Avg Tech Dispersion	Average number of technologies for each inventor identified as participating in twin patents for each period and region
Control Variables	
Share Public Patents	Share of twin patents which have as an applicant a public institute for each period and region
GDP	Gross Domestic Product for each period and region

4 Results

In this section, we present the results related to the drivers of the speed of the regional twin combination, as well as those related to its impact on the subsequent inventions. Our analysis is based on NUTS 3 - fixed effects panel regressions, which also include time-fixed effects.[11]

4.1 The drivers of the speed of twin combination

4.1.1 Baseline results

Table 4 presents the results of our baseline model in two specifications. In Column 1, we focus on patent applications, as they are usually close to the generation of the invention. In Column 2, we retain only granted patents[12], which explains the drop in the number of observations.

[11]Our baseline estimates employ Driscoll-Kraay standard errors, which are robust to heteroscedasticity, as well as autocorrelation and cross-sectional dependence. In Appendix D (Tables 11, 12, and 13) we show the same results using clustered standard errors. The results of the regression based on clustered standard errors are similar to the ones presented here.

[12]Regarding the sources of inventive activities we considered also granted patents, since both are available in EPO Patstat. While applications are the standard indicator of knowledge development in the regional innovation literature, capturing the extent to which this knowledge generation introduces novelty is important for the analysis of the regional speed at stake.

Table 3: Descriptive statistics

Variable Name	N	Mean	SD	Min	Max
Average Speed	17904	0.033	0.084	0.000	1.000
Average Fw Citations	17904	1.974	5.643	0.000	195.000
Stock Patents	17904	280.188	666.153	2.000	12327.350
Patents Scope	17904	1.083	1.054	0.000	16.000
Originality Backward Cit	17904	0.280	0.387	0.000	0.979
Co Occ Overlap	17904	0.069	0.069	0.000	0.667
Average Steps	17904	0.012	0.046	0.000	1.000
Avg Team Size	17904	2.188	1.688	0.000	17.000
Avg Tech Dispersion	17904	6.627	9.692	0.000	120.250
Share Public Patents	17904	0.042	0.159	0.000	2.000
GDP	17904	12553.021	18432.486	551.190	246936.500

The results reported in Table 4 show how the three sets of drivers considered affect the speed of recombination. Regarding regional knowledge characteristics, prior experience with twin inventions does not accelerate the development of new green-digital technologies in regions. The regional stock of twin patents is not significant, suggesting that the challenges of developing new twin combinations locally are likely too distinct, novel, and complex to be mitigated by the knowledge gained from previous inventions. The complex and early stage nature of the two technologies (Martinelli et al., 2021; Barbieri et al., 2020b) could be a possible explanation of this. Indeed, in this respect, we note that it is the capacity of dealing with broad and diverse twin technological knowledge that affects the speed at which the gap with the technological frontier is closed. The coefficient of the scope and originality indicators of regional twin patents are indeed positive and significant.

The nature of the combinatory patterns that regional green and digital technologies follow also matters. As expected, the more regional green and digital technologies share the set of other technologies they combine with, the faster new twin combinations at the frontier are developed locally. This result, which is reflected in the positive effect of the co-occurrence overlap indicator, supports the recombinant innovation perspective underlying our study, confirming the recognised role of cognitive proximity in obtaining new inventions (Balland et al., 2015). Notwithstanding, concerning the green-digital combinatory patterns, our results also show that the technological distance captured by *Average Steps* is significant and positive. Interestingly, the longer the combination paths that regions must navigate to bridge the (cognitive) gaps between green and digital technologies locally, the faster these combinations occur. We shall get back to this rather counter-intuitive evidence, in what follows, where we aim to assess two alternative mechanisms of it. On the one hand, a policy-related urgency imposed on the need to combine green and digital technologies may result in a virtuous *out-of-necessity* effect. On the other hand, learning advantages may be at the place, which are associated with a longer and more intense process of intermediate knowledge combinations.

Finally, the results about the micro agents of knowledge recombination, namely the twin patents' inventors, confirm our expectations in Section 2 only partially. Larger teams of twin inventions do not contribute to make the combination of green and digital technologies more efficient, and thus faster: the coefficient of *Avg Team Size*, albeit positive, is in fact not significant. *Avg Tech Dispersion*, which accounts for the (technological) variety of the inventor teams,

Table 4: Drivers of the regional speed of twin combinations: combinations of green and digital technologies

	Average Speed	
	Applications	Granted
	(1)	(2)
Stock Patents	0.0000	0.0000
	(0.0000)	(0.0000)
Patents Scope	0.0083***	0.0094***
	(0.0017)	(0.0018)
Originality Backward Cit	0.0712***	0.1047***
	(0.0152)	(0.0211)
Co Occ Overlap	0.2382***	0.2504***
	(0.0618)	(0.0530)
Average Steps	0.6283***	0.5895***
	(0.0704)	(0.0639)
Avg Team Size	0.0002	0.0008
	(0.0006)	(0.0010)
Avg Tech Dispersion	-0.0117**	-0.0112**
	(0.0052)	(0.0045)
Share Public Patents	-0.0017	0.0080
	(0.0058)	(0.0055)
GDP	0.0000***	0.0000***
	(0.0000)	(0.0000)
Constant	-0.0437***	0.0155**
	(0.0114)	(0.0074)
Fixed-effects		
Regions	YES	YES
Years	YES	YES
N	17904	14402
N of groups	1155	1081
F Statistic	147418.33*** (df = 30; 1154)	27527.04*** (df = 28; 1080)
Note:		*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Mechanisms of the speed-distance relation: policy and knowledge network.

	Average Speed				
	Policy			Network	
	Low	Medium	High	Base	Interaction
	(1)	(2)	(3)	(4)	(5)
Average Steps	0.8543***	0.5401***	0.6093***	0.6298***	0.1390
	(0.0866)	(0.0575)	(0.0651)	(0.0708)	(0.1594)
Transitivity				0.0575***	0.0492***
				(0.0207)	(0.0183)
Transitivity#Average Steps					0.8291**
					(0.3219)
Fixed-effects					
Regions	YES	YES	YES	YES	YES
Years	YES	YES	YES	YES	YES
N	6097	8793	2664	17904	17904
N of groups	916	1065	528	1155	1155
F Statistic	77350.62*** (df = 28; 915)	5756.16*** (df = 28; 1064)	10650.98*** (df = 28; 527)	97958.65*** (df = 32; 1154)	63428.36*** (df = 33; 1154)
Note:					*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

instead shows a negative sign. Hence, rather than size, it is the technological specialisation of the inventor teams that increases the speed of recombination.[13]

We should now consider a relevant aspect. Our dependent variable aims at capturing the regions' respective capacities to rapidly catch up in the process of twin technology development. Indeed, technically speaking, if we focus on applications, we are closer to the knowledge generation phase. However, we also risk to capture inventions that do not "tick the novelty box" as per the patent system requirements. In other terms, our variable might end up capturing some attempts to imitate available inventions. To overcome this issue, we rerun our analysis and re-define our variables by considering only granted applications. Column 2 of Table 4 shows the relative results, which are aligned with those of Column 1 and support their robustness.

4.1.2 The relation between the speed and the distance of twin combinations

As already mentioned, the analysis of the determinants of the speed of recombination reveals that this is positively associated with the technological distance in the period the combination was first introduced in the technological space. We want to investigate why this is the case. A first candidate explanation is that inventors are forced to make a virtue out of necessity, for example, by policy requirements: that is, despite the fact that a combination is technologically daring, inventors may be prompted to pursue it due to policy pressures. Such pressures are carried out either in the forms of command and control or market-based incentives (Jaffe et al., 2003; Rosendahl, 2004). Columns 1 to 3 of Table 5 show the results of our baseline model with respect to three sub-samples of regions, belonging to countries in the top, mid, and bottom tertile of the distribution of the Environmental Policy Stringency indicator.[14] If the above argumentation was supported by the data, we should observe the positive relation between speed and technological distance that are to be in place, particularly in the countries where the policy pressure is highest. Instead, the initial positive association between the speed and the distance of the recombination is present, regardless of the policy stringency band we consider.

[13] As far as the two additional control variables are concerned, we note that only the size of the regional economy actually affects - as expected, in a positive manner - the speed of combination.

[14] As is well known, this is a synthetic indicator that captures the extent to which different kinds of environmental policies, such as market-based (e.g. carbon taxes), non-market based (e.g., emissions limits), and technology-support based (e.g., R&D subsidies to clean technologies), are implemented across countries (Botta & Koźluk, 2014; Van der Zwaan et al., 2002; Calel, 2020; Calel & Dechezleprêtre, 2016). While a regional indicator of stringency could better suit our analysis, to our knowledge, existing data are not available at this subnational level.

As emerged above, the length of the green-digital combination exerts a positive effect on its speed: such a relation may depend on the network structure of the focal regional knowledge base. When exploring a second candidate explanation for this rather counter-intuitive evidence, we consider that a large distance between green and digital components may also entail greater opportunities for short-cuts that speed up the combination. In other words, this means that a combination of green and digital components may happen faster, taking the shortest path available to connect the two technologies. We make use of the so-called *Clustering Coefficient*, otherwise called *Transitivity* indicator, which detects high density substructures inside a network. In brief, this measure of transitivity captures the presence of high-density substructures inside the network, by calculating the ratio between the number of closed triplets and the total number of its triplets (both closed and open) (Wasserman & Faust, 1994; Graf, 2017).[15] Intuitively, this gives us an indication about the capacity of the network of closing triangles of nodes. Having a high clustering coefficient gives to the network the property of "small world networks" (Wasserman & Faust, 1994): networks with low distances in which most of the nodes are not neighbours to one another, but they can be reached from every other node via a small number of steps (Watts & Strogatz, 1998). [16]

Applied to our setting, regions with a knowledge space marked by higher *Transitivity*, and resembling more the property of small world networks, can be claimed to find short paths between two technologies – including green and digital technologies – to a larger extent than regions with lower *Transitivity*. Following this logic, we expect that the transitivity of the regional knowledge may have an effect on the speed of the combination, and that it could also be complemented by the presence of many points from which short-cuts can be taken, that is, by the combination length (i.e. captured by *Average Steps*).

Our results are reported in Columns 4 and 5 of Table 5. In Column 4 we note that the presence of a high density structure increases the speed of combination, despite the fact that the initial positive association between distance and speed remains positive and significant. The variable capturing the average number of technological steps, ceases to be significant when we introduce the above mentioned interaction in Column 5. Rather than the distance *per se*, what speeds up the combination is the possibility to find short-cuts applied to a network that allows several departures from the explored (and shortest) path.[17]

4.2 The technological impact of the regional twin speed

We also account for the impact that fast-combined twin technologies can have on subsequent technological developments. Our aim is to ascertain whether the speed at which twin technological solutions are achieved determine their capacity to act as seeds for following technological developments.

Table 6 reports the results of these estimates which, once again, distinguish between patent applications (Column 1) and granted patents (Column 2). Before looking at the impact of

[15] A triplet is a set of three nodes, present in the network, which are connected by either two (open triplet) or three (closed triplet) ties.

[16] Evidence for the role of transitivity in innovation studies can be found in Verspagen & Duysters (2004); Schilling & Phelps (2007).

[17] In Table 10 we perform the same analysis aimed at investigating the role of policy and network characteristics, while focusing on granted patents only. Results are consistent.

Table 6: Technological impact of the regional speed of twin combinations: combinations of green and digital technologies.

	Average Fw Citations	
	Applications	Granted
	(1)	(2)
Average Speed	-0.1685	1.1695**
	(0.8513)	(0.5821)
Stock Patents	0.0009***	0.0008**
	(0.0001)	(0.0004)
Patents Scope	0.2631***	0.4855***
	(0.0922)	(0.0824)
Originality Backward Cit	-0.0996	-0.1056
	(0.1430)	(0.2095)
Co Occ Overlap	4.2215***	5.4334***
	(1.2668)	(1.0642)
Average Steps	-0.5363	-2.1140*
	(0.8736)	(1.1425)
Avg Team Size	0.3179***	0.2350*
	(0.1213)	(0.1300)
Avg Tech Dispersion	-0.3577**	-0.3811**
	(0.1802)	(0.1697)
Share Public Patents	-1.8063**	0.2887
	(0.7819)	(0.6668)
GDP	-0.0000***	0.0000*
	(0.0000)	(0.0000)
Constant	5.0470***	0.0000
	(0.2604)	(0.0000)
Fixed-effects		
Regions	YES	YES
Years	YES	YES
N	13988	10821
N of groups	1063	950
F Statistic	962169.38*** (df = 31; 1062)	15631.53*** (df = 29; 949)
Note:		*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Average Speed, let us note that the technological impact of regional twin inventions is significantly correlated with some of the regional twin speed determinants. As far as the characteristics of the regional knowledge base are concerned, we note that a larger stock of twin patents entails a higher average impact on subsequent inventions. A positive correlation also emerges with the patent scope of regional twin patents: the capacity to deal with broad combinations ensures an impact premium. Regions' capacities for developing more impactful twin technologies are also increased by the combination of more cognitively overlapping constitutive technologies. As we have seen in the previous section, such an overlapping could accelerate the technological development process, and faster innovation cycles could, in turn, lead to more impactful outcomes. The findings regarding the characteristics of inventor teams confirm the role of their technological specialisation. Nevertheless, there is also evidence of a team-scale effect, differently from what emerged when analysing the determinants of the speed of combination.

Focusing on the effect of the speed of green and digital combinations (*Average Speed*), we observe that this positively influences the impact that regional twin patents could have on subsequent technological developments, but this is only true when focusing on granted twin patents. As we have argued in Section 2, regions that are faster in developing new green-digital combinations develop new twin technologies on which other regions, and possibly slower regions, could draw upon along their own route towards the twin transition. More rapid developments of new twin technologies might lead to increased visibility and recognition of the patents involved, and thus render them more likely to be cited and referenced in future technological research and development.

Returning to our arguments, it seems that this positive effect would more than compensate the potentially negative effects we have also envisaged; for example, those effects descending from the fact that green-digital combinations realised faster, may overlook potential additional specifications, checks, and further combinations, thus leading to a decrease in their impact. In interpreting this result, we should consider that faster twin applications do not have such an effect. In fact, the coefficient of Average Speed is non-significant, albeit negative, in the regression based on all patent applications (Column (1)). This is quite an interesting result, which suggests that it is only when the examiners' quality checks (on novelty, utility, subject matter, and non-obviousness) are passed (i.e. when they are granted), that speeding up combination increases the impact of twin inventions on subsequent developments.

5 Conclusions

In pursuit of more environmentally sustainable patterns of growth, the digital transformation of economic systems is increasingly expected to converge with their green transition. European policymakers have framed this transition pattern as the "twin transition" (European Commission, 2020; JRC, 2022). Particularly, though not exclusively, in Europe, the twin transition has been established as an urgent and pivotal policy target. This has spurred a growing body of research exploring the drivers and consequences of twin transition (Diodato et al., 2023; Gerli et al., 2023), including the varying capacities of regions to advance the two individual transitions, and to integrate them effectively (Faggian et al., 2024)

The ascertained uneven geography of the twin transition poses a significant challenge, given the urgency with which policymakers, particularly in Europe, are advocating for and implementing its rollout, often through support funds (such as, for example, those linked to the Recovery Plan), that are intended for its rapid deployment.

Given the time pressure on the twin transition, understanding the speed at which regions can implement it emerges as a crucial area of investigation. In particular, considering the reliance of the twin transition on the development of new green and digital technologies, it is essential to explore the temporal gap between the global availability of new green-digital knowledge combinations and their local implementation. Bridging this gap more quickly enables regions to lower the costs of complying with environmental policies addressing the green functionalities and impacts of digitalisation. Moreover, accelerating this process positions regions as frontrunners in the twin transition, serving as benchmarks for those regions that are striving to catch up.

Despite its importance, the analysis of regional speed in the twin transition has been overlooked in the existing body of literature, which has primarily focused on regions' capacities to develop green and digital technologies, either independently or in combination (Fazio et al., 2024; Damioli et al., 2024; Bachtrögler-Unger et al., 2023). These studies have predominantly drawn on recombinant innovation theory, emphasising that, also in the context of the twin transition, innovation requires firms and regional actors to construct novel knowledge architectures, by originally re-combining existing and new knowledge modules in the green and digital domains (Weitzman, 1998; Fleming, 2001).

Building on this theoretical foundation, our paper contributes to the literature on the geography of the twin transition by addressing the gap in the analysis of its regional speed. Specifically, we propose a novel conceptualisation of this notion, grounded in the idea of the regional knowledge space and its temporal alignment with the unfolding of the global knowledge space. Moreover, we propose a novel patent-based indicator to measure the average speed at which regions locally implement new green-digital combinations that are developed at the global frontier (i.e. in the global knowledge space), as an original methodological contribution to the empirical literature on recombinant innovation. Leveraging patent data from EPO PATSTAT for the period 1996–2019, we provide cross-regional evidence of this indicator, and investigate two key aspects of it. Firstly, we provide an analysis of the knowledge-based drivers that affect the speed of technological combination in the twin transition domain. Secondly, we assess the technological impact of faster technological combinations between digital and green knowledge, in terms of forward citations of new twin patents.

Regarding the determinants of regional speed in implementing new green-digital combinations at the frontier, our findings highlight several key correlations that have important policy implications. Firstly, prior local experience in twin technologies does not appear to significantly influence regional speed, indicating that path dependency neither facilitates nor hinders the ability to adapt quickly to the evolving global knowledge space. This suggests that regions cannot rely solely on historical expertise in twin technologies to accelerate their progress. Policy support to increase the volume of innovative efforts in combining green and digital technologies does not seem to reduce the gap with the frontier.

Secondly, the speed at stake rather appears to benefit from the quality of inventive efforts, particularly when twin patents draw from a broader and more diverse regional knowledge base. This finding calls for a selective kind of policy support, targeting regional projects with the potential to enrich the diversity and depth of green-digital knowledge combinations.

Thirdly, regions are apparently faster at integrating new green and digital bodies of knowledge when they are co-developed with related technologies, suggesting the importance of the (indirect) cognitive proximity between them. Regional science and technology policies should, therefore, encourage collaborations which enhance the interplay between green and digital technological domains that share other similar application domains.

Fourthly, regions navigating longer paths to bridge green and digital technologies tend to exhibit higher regional twin speed, providing that these paths are located in denser regional knowledge networks. This indicates that policies which are aiming at accelerating the twin transition should focus on expanding the density of the technological spectrum, across which green and digital knowledge can be integrated.

Finally, prompt local implementation of green-digital combinations correlates positively with technologically specialised inventor teams. This underscores the need for policies which foster collaborative inventive efforts, bringing together focused expertise and skills, in order to achieve targeted advancements in the twin transition.

Regarding the technological impact of regional twin speed, our findings show that faster regions tend to develop green-digital patents with higher forward citations. This suggests that faster regions hold an advantage in generating prior-art knowledge serving as a benchmark for lagging regions, supporting their twin transition. Apparently, this effect seems to outweigh the potential decline in patent quality, that might arise from excessively rapid combinations in the twin realm.

However, as we noted earlier in this paper, this positive impact is observed only when the local combinations meet the quality standards that are necessary for patent grants. This is a notable result, indicating that, providing the same quality requirements are satisfied, accelerating regional combination speed in the twin domain can yield significant technological benefits for regions, and by extension, economic benefits for them. This finding reinforces the rationale for policies that are aimed at enhancing regional speed, particularly through the levers which are identified in the first part of our analysis.

Our results do not come without limitations. Firstly, there is a bias towards more advanced regions, since patent data are scarcely available for less developed regions. To deal with this issue, we have already excluded extreme cases (Pinheiro et al., 2022). Secondly, the applicants which emerge as prominent for the twin transitions, from the descriptive analysis, are multinationals or big companies. This effect is due to a size effect because, usually, those big companies are patenting, while small and medium-sized companies use other forms of protection. Finally, the choice of taking the 5-digit CPC level can be regarded as arbitrary, and it does not permit to identify green and digital technologies more precisely.

However, the limitations described above can be the starting point for future research in the field of recombination theory. Firstly, an aspect which should be considered is the typology of organisations (i.e. public or private) which are able to speed up the combination activities between green and digital technologies. Secondly, the integration with other datasets could provide insights on the effective adoption of twin technologies in regions, an aspect which is still under-researched in the literature.

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A 5-digit CPC classes identified as digital

Table 7: 5-digit CPC classes identified as digital technologies.

CPC5	Source	Macro category
H04W4	Martinelli et al. (2021)	IoT
G05B2	Martinelli et al. (2021)	Cloud Computing
G06F1	Martinelli et al. (2021)	Big Data
G16Z9	Martinelli et al. (2021)	Big Data
G16B4	Martinelli et al. (2021)	Big Data
G16B5	Martinelli et al. (2021)	Big Data
G16H5	Martinelli et al. (2021)	Big Data
G16C2	Martinelli et al. (2021)	Big Data
G06Q1	Martinelli et al. (2021)	Big Data
G06Q3	Martinelli et al. (2021)	Big Data
G06F3	Martinelli et al. (2021)	Big Data
G06N	Martinelli et al. (2021)	Big Data
G06F2	Martinelli et al. (2021)	Big Data
B25J9	Martinelli et al. (2021)	Robotics
B25J1	Martinelli et al. (2021)	Robotics
B60W3	Martinelli et al. (2021)	Robotics
G05D1	Martinelli et al. (2021)	Robotics
Y10S7	Martinelli et al. (2021)	AI
G06N2	Martinelli et al. (2021)	AI
G06N7	Martinelli et al. (2021)	AI
G06N3	Martinelli et al. (2021)	AI
G06T2	Martinelli et al. (2021)	AI
G06T3	Martinelli et al. (2021)	AI
G06T9	Martinelli et al. (2021)	AI
G05B1	Martinelli et al. (2021)	AI
G10L1	Martinelli et al. (2021)	AI
Y10S1	Martinelli et al. (2021)	AI
F02D4	Martinelli et al. (2021)	AI
B29C6	Martinelli et al. (2021)	AI
F03D7	Martinelli et al. (2021)	AI
F05B2	Martinelli et al. (2021)	AI
F16H2	Martinelli et al. (2021)	AI
G10K2	Martinelli et al. (2021)	AI
G10L2	Martinelli et al. (2021)	AI
H04N2	Martinelli et al. (2021)	AI
G06F1	UK IP Office (2014a)	Big Data
G06F7	UK IP Office (2014a)	Big Data
G06Q1	UK IP Office (2014a)	Big Data
G06F	UK IP Office (2013)	3D Printing
H04L	UK IP Office (2013)	3D Printing
G08G1	UK IP Office (2014b)	Robotics
B60W1	UK IP Office (2014b)	Robotics
G06F1	UK IP Office (2014c)	IoT
G05B1	UK IP Office (2014c)	IoT
H04W8	UK IP Office (2014c)	IoT
H04W4	UK IP Office (2014c)	IoT
G08C1	UK IP Office (2014c)	IoT
H04W7	UK IP Office (2014c)	IoT
H04B7	UK IP Office (2014c)	IoT

B Correlation table

Table 8: Correlation table.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Average Speed	-	0.11***	0.44***	0.28***	0.10***	0.14***	0.44***	0.13***	0.14***	0.00	0.05***	0.00
(2) Average Fw Citations		-	0.00	0.06***	-0.04***	0.17***	0.06***	0.17***	-0.03***	0.00	0.00	-0.05***
(3) Average Steps			-	0.17***	0.08***	0.01	0.31***	0.10***	0.11***	0.01	0.04***	-0.09***
(4) Co Occ Overlap				-	0.38***	0.03***	0.38***	0.34***	0.49***	0.01***	0.19***	-0.26***
(5) Stock Patents					-	-0.20***	0.30***	0.15***	0.81***	0.02***	0.57***	-0.45***
(6) Patents Scope						-	0.06***	0.38***	-0.20***	0.13***	-0.11***	0.13***
(7) Originality Backward Cit							-	0.29***	0.30***	0.03***	0.23***	-0.33***
(8) Avg Team Size								-	0.16***	0.19***	0.10***	-0.33***
(9) Avg Tech Dispersion									-	-0.01	0.40***	-0.34***
(10) Share N Public Patents										-	0.07***	-0.03***
(11) GDP											-	-0.37***
(12) Transitivity												-

Note: *p ¡ 0.1; **p ¡ 0.05; ***p ¡ 0.01

C Average Steps

The variable *Average Steps* captures the average distance from which the region started to close the gap between green and digital technologies at the time when, in another European region, the gap was equal to zero (i.e. successful combination). Using the same example applied in the case of the variable *Average Speed* (Figure 3), we observe that in period 2000, when the combination was realised in a European region, the distance between the green technology Y02T1 and the digital technology H04L6 is three steps (red path). The successful combination is then realised in 2010 (Figure 3b). However, differently from the variable *Average Speed*, we only need to know that, at some point in time, the focal region was able to close the gap. It does not matter exactly when in time the focal region was able to close this gap. Thus, we assign a value of 3 for this specific combination (Y02T1-H04L6) in year 2000, as follows:

$$DS_{c,r,t} = S_{c,r,t} - S_{c,e,t} \tag{8}$$

where $DS_{c,r,t}$ is the difference in the number of steps between the first period in which two possible combinations appeared in an European region. $S_{c,r,t}$ is the number of steps that the region r still needs to close the combination c gap and $S_{c,e,t}$ is the number of steps of the realised combination in a European region (by default, equal to 1). Subsequently, a standardisation between 0 and 1 of the difference $DS_{c,r,t}$ is performed as follows:

$$SDS_{c,r,t} = \frac{DS_{c,r,t} - \min\limits_{\forall DS \in DS_c} DS_{c,r,t}}{\max\limits_{\forall DS \in DS_c} DS_{c,r,t} - \min\limits_{\forall DS \in DS_c} DS_{c,r,t}} \tag{9}$$

where $\min\limits_{\forall DS \in DS_c} DS_{c,r,t}$ is the minimum difference in the number of steps for one combination c in each region r for a specific time period t and $\max\limits_{\forall DS \in DS_c} DS_{c,r,t}$ is the maximum difference in the number of steps for one combination c in each region r for a specific time period t. A higher value is given to the combinations which start to combine from further away, and a value of 0 is given in the case of no combination. Finally, $SDS_{c,r,t}$ is used as a weight to construct the *Average Steps* variable as follows:

$$AverageSteps_{r,t} = \frac{\sum_{c \in r \cap t} SDS_{c,r,t}}{TP_{c,r,t}} \tag{10}$$

where $SDS_{c,r,t}$ is used as the weight for the total number of successful combinations, and

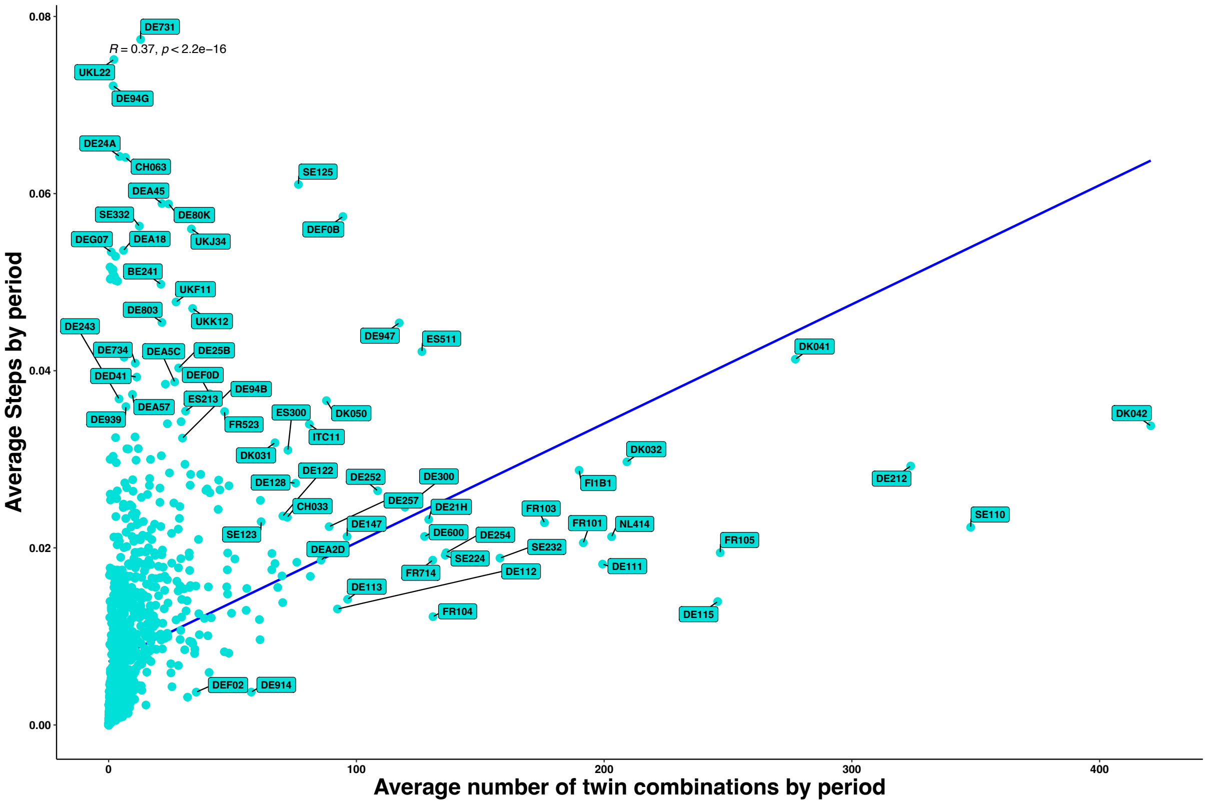

Figure 5: Comparison between the average number of twin combinations by period and the Average Steps by period

$TP_{c,r,t}$ is the total number of twin patents present in the focal region.

Figure 5 shows the comparison between the *Average Steps* by period, and the average number of twin combinations by period. Similarly to Figure 4 (in which *Average Speed* was considered instead of *Average Steps*), there is a difference between the two measures, meaning that the region which is able to close the highest number of combinations, and the region which is able to close the gaps from further away are not always the same. Also, vice versa, this is observable, because it is not always the regions having a very high *Average Steps* per period that are also the regions which are able to close many twin combinations. For example, the region DE731 identified as the city of Kassel does not generate many twin combinations, but it has the ability to close gaps which are further away with respect the other regions. In Table 9, we show the 10 regions with the highest rank in *Average Steps* by period, similarly to table 1. This table shows in more detail what is already observable from the previous Figure 5. Thus, these descriptive results support the fact that our variables are capturing different effects, rather than the mere number of twin combinations performed by each region.

Table 9: Top 10 regions in terms of Average Steps by period.

NUTS 3 region	Rank Average Steps	Rank Average number
DE731	1	211
UKL22	2	387
DE94G	3	393
DE24A	4	342
CH063	5	297
SE125	6	33
DEA45	7	136
DE80K	8	123
DEF0B	9	26
SE332	10	214

D Robustness checks tables

Table 10: Mechanisms of the speed-distance relation: policy and knowledge network. Granted patents.

	Average Speed				
	Policy			Network	
	Low	Medium	High	Base	Interaction
	(1)	(2)	(3)	(4)	(5)
Average Steps	0.7807***	0.4921***	0.6720***	0.5904***	0.1378
	(0.0943)	(0.0436)	(0.0360)	(0.0641)	(0.1457)
Transitivity				0.0472***	0.0383**
				(0.0177)	(0.0164)
Transitivity#Average Steps					0.7178***
					(0.2401)
Fixed-effects					
Regions	YES	YES	YES	YES	YES
Years	YES	YES	YES	YES	YES
N	4717	7557	1969	14402	14402
N of groups	839	981	448	1081	1081
F Statistic	28120.99*** (df = 29; 838)	2252.07*** (df = 29; 980)	5997.80*** (df = 29; 447)	148382.94*** (df = 31; 1080)	13890.61*** (df = 32; 1080)
Note:					*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Drivers of the twin-combination. Clustered standard errors.

	Average Speed	
	Applications	Granted
	(1)	(2)
Stock Patents	0.0000	0.0000*
	(0.0000)	(0.0000)
Patents Scope	0.0083***	0.0094***
	(0.0007)	(0.0010)
Originality Backward Cit	0.0712***	0.1047***
	(0.0023)	(0.0032)
Co Occ Overlap	0.2382***	0.2504***
	(0.0325)	(0.0319)
Average Steps	0.6283***	0.5895***
	(0.0314)	(0.0321)
Avg Team Size	0.0002	0.0008
	(0.0006)	(0.0008)
Avg Tech Dispersion	-0.0117***	-0.0112**
	(0.0037)	(0.0050)
Share Public Patents	-0.0017	0.0080
	(0.0038)	(0.0058)
GDP	0.0000**	0.0000
	(0.0000)	(0.0000)
Constant	0.0262***	0.0155***
	(0.0045)	(0.0051)
Fixed-effects		
Regions	YES	YES
Years	YES	YES
N	17904	14402
Overall R^2	0.3807	0.4021
N of groups	1155	1081
F Statistic	99.44*** (df = 29; 1154)	90.62*** (df = 28; 1080)
Note:		*Clustered (Regions & Year)*
		*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12: Mechanisms of the speed-distance relation: policy and knowledge network. Clustered standard errors.

	Average Speed				
	Policy			Network	
	Low	Medium	High	Base	Interaction
	(1)	(2)	(3)	(4)	(5)
Average Steps	0.8543***	0.5401***	0.6093***	0.6298***	0.1390
	(0.0601)	(0.0352)	(0.0881)	(0.0312)	(0.1496)
Transitivity				0.0575***	0.0492***
				(0.0125)	(0.0120)
Transitivity#Average Steps					0.8291***
					(0.2766)
Fixed-effects					
Regions	YES	YES	YES	YES	YES
Years	YES	YES	YES	YES	YES
N	6097	8793	2664	17904	17904
Overall R^2	0.4109	0.3820	0.3753	0.4039	0.4080
N of groups	916	1065	528	1155	1155
F Statistic	38.28*** (df = 28; 915)	53.07*** (df = 28; 1064)	21.29*** (df = 29; 527)	96.64*** (df = 30; 1154)	105.78*** (df = 31; 1154)
Note:					*Clustered (Regions & Year)* *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 13: Impact on subsequent technological developments. Clustered standard errors.

	Average Fw Citations	
	Applications	Granted
	(1)	(2)
Average Speed	-0.1685	1.1695
	(0.8657)	(0.9985)
Stock Patents	0.0009**	0.0008
	(0.0004)	(0.0006)
Patents Scope	0.2631*	0.4855***
	(0.1481)	(0.1571)
Originality Backward Cit	-0.0996	-0.1056
	(0.1176)	(0.1622)
Co Occ Overlap	4.2215**	5.4334***
	(1.8567)	(2.0338)
Average Steps	-0.5363	-2.1140*
	(0.7546)	(1.2099)
Avg Team Size	0.3179**	0.2350
	(0.1475)	(0.1613)
Avg Tech Dispersion	-0.3577	-0.3811
	(0.3737)	(0.4231)
Share Public Patents	-1.8063	0.2887
	(1.1583)	(1.0716)
GDP	-0.0000*	0.0000
	(0.0000)	(0.0000)
Constant	5.0470***	-2.1389***
	(0.6051)	(0.7987)
Fixed-effects		
Regions	YES	YES
Years	YES	YES
N	13988	10821
Overall R^2	0.0745	0.0705
N of groups	1063	950
F Statistic	18.12*** (df = 30; 1062)	13.47*** (df = 29; 949)
Note:		*Clustered (Regions & Year)*
		*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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