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Relatedness and regional specialization in green, digital, and twin economic activities: evidence from the UK

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Abstract

This paper examines the geography and relatedness of green, digital, and twin (both green and digital) economic activities across UK local authorities, contributing to debates on whether the two domains are truly synergistic. Using an innovative web-based real-time industry classification dataset covering about 200,000 firms, we identify regional specializations and compute industry-relatedness from firm-level co-occurrence patterns. Spatial mapping and urban scaling analyses reveal interesting patterns: digital industries tend to concentrate in large urban centres, while green and twin industries are more dispersed. Furthermore, regression models show that relatedness in one domain (e.g. green) is positively associated with specialization in the other (e.g. digital), with twin industries exerting the strongest mutual influence on both green and digital domains. These results provide empirical support that capabilities in one domain can facilitate diversification into the other, and that twin activities act as a bridge linking them. By explicitly identifying activities that are simultaneously green and digital, and by quantifying their relatedness to other industries, this paper offers new insights into the structural interdependencies underpinning the twin transition and its geography.

JEL Classification O30 · O32 · Q55 · R11

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1 Introduction

The *twin transition*, embodying the simultaneous shift towards greener, more sustainable practices and the rapid digitalization of economies, is becoming increasingly important in economic geography, regional science, and related fields, as it holds important implications for regional development (Cattani et al. 2025; Cicerone et al. 2023; Diodato et al. 2023; Zhang and Du 2025; Faggian et al. 2025; Brueck et al. 2025; Bürscher et al. 2025). The concept of a twin transition has been promoted primarily by governments and policymakers, most notably by the European Union, generating significant enthusiasm in the policy sphere. In this regard, the twin transition is one of many instances where policy precedes scholarly research, with policymakers advocating for and promoting a concept that has yet to be fully understood from an academic perspective (Faggian et al. 2025; Kovacic et al. 2024). In this vein, many critical voices have also raised concerns about the idea of a twin transition, arguing that synergies between the green and digital domains should not be taken for granted and that potential negative effects of one domain on the other must be considered (Casanas and Kovacic 2025; Horn and Felt 2025). This, in turn, calls into question how coherent a twin transition policy strategy can truly be (Gao 2025; Kovacic et al. 2024). The growing body of research on the twin transition can be seen as a response to this situation.

However, for scholarly research as well as for good policy evaluation, tracking green and digital economic activities in firms and across space poses several challenges. That is, traditional classification systems such as NACE and SIC, and even conventional metrics like patent data, are often inadequate in capturing the dynamic nature of green and digital sectors. This gap in measurement hinders the ability to design and implement effective policy instruments that could support and foster the twin transition (Kriesch et al. 2025). Addressing this empirical research gap, our paper leverages a dataset that provides a real-time industry classification based on machine learning techniques to identify and classify green, digital, and twin domains in the UK. As such, the dataset enables the identification of economic activities linked to green sectors (e.g. renewable energy), digital sectors (e.g. communication technologies), and twin sectors (e.g. smart grids). This innovative dataset transcends the limitations of traditional classification systems, offering a more nuanced and timely understanding of economic activities.

Against this background, the first aim of this paper is to identify which regions in the UK are leading the twin transition. This is essential, as there is a concern that the twin transition might lead to increasing spatial inequalities (Consoli et al. 2023; Grashof and Basilico 2025; Vale et al. 2024; Zhang et al. 2025). To the potential harm of rural or less-developed areas, the concentration of digital and green economic activities in urban regions poses a significant challenge. Our analysis thus aims to shed light on the geographical distribution of these activities across the UK, providing insights into how the twin transition is unfolding in different regions and what it implies for the overall economic landscape.

As a consequence of the uneven geography of the twin transition, which we will uncover in the empirical part of the paper, a second research gap emerges regarding

how the twin transition might be fostered in different regions. As such, the second aim of the paper is to uncover diversification opportunities for regions to engage in green, digital, and twin activities. For this, we analyse the comparative advantages of UK regions in green, digital, and twin economic activities, linking them to relatedness metrics. We use various regression models to interpret these advantages, focussing on the relatedness densities in the alternate domains. In this sense, we also contribute to the ongoing scholarly debate on the extent to which the digital and green domains are actually synergistic, as we provide evidence that they are—at least from an industry-relatedness and regional-specialization perspective.

The structure of this paper is laid out as follows: Sect. 2 explores the existing literature on the twin transition in regional science and economic geography, and it discusses the concepts of relatedness, specializations and regional diversification. Section 3 provides a detailed description of our data and methodology, while Sect. 4 presents our findings on the geographical distribution of green, digital and twin economic activities in the UK localities, along with relatedness patterns and regional specializations. Finally, Sect. 5 wraps up the paper with a discussion on policy implications and avenues for future research.

2 Background literature

2.1 Defining the twin transition and its regional implications

The twin transition is a concept that is gaining importance in economic geography, regional studies, and related fields. It is characterized by the parallel push towards greener modes of production and the widespread adoption of digital technologies. The move towards a more sustainable and digital economy is altering the way economies organize themselves and how regions evolve and develop, making it a critical area of study (Diodato et al. 2023; Damioli et al. 2025; Faggian et al. 2025). In the literature, the twin transition is considered to not be merely about technological advancement or environmental awareness in isolation. Instead, it represents a holistic change about how economies structure and function. On the one hand, the green domain of the twin transition focuses on the shift towards environmental sustainability, including the development of renewable energy solutions, climate change mitigation measures, and the use of sustainable manufacturing practices, among other activities (Losacker et al. 2023). On the other hand, the digital aspect considers the adoption and integration of digital technology across all sectors. These changes will have a significant impact on how firms operate, how work is carried out, and how economic activities are managed (Balland and Boschma 2021; Zhang et al. 2025). Empirical analyses suggest that the twin transition has the potential to completely reshape regional economic landscapes, affecting which industries thrive and which may decline (Fouquet and Hippe 2022; Bachtrögler-Unger et al. 2023; Faggian et al. 2025). The shift towards digitalization, for instance, has the potential to give rise to new industries while transforming existing ones, potentially creating new economic hubs and changing the competitive advantages of different regions (Balland and Boschma 2021; Consoli et al. 2023). Similarly, the green transition can spur the

growth of new industries such as renewable energy or electric vehicle production, which could become the bedrock of many regional economies (Losacker et al. 2023; Grashof and Basilico 2025; García-Riazuelo et al. 2025).

However, according to recent literature, the twin transition may be linked to the potential increase of spatial inequalities and economic divergence (Cattani et al. 2025; Cicerone et al. 2023; Abbasiharofteh and Kriesch 2024; Kriesch et al. 2025). The advantages of this ongoing transformation may not be evenly distributed across space. Urban and more economically advanced regions with better access to technology and higher levels of investment are likely to benefit more from the opportunities presented by the digital and green transitions. On the other hand, rural, geographically isolated, or less-developed regions could face challenges adapting to these changes, which could further widen the economic gap between different regions (Rodríguez-Pose and Bartalucci 2024). An important topic that has been widely discussed in recent literature is the impact of policies on the outcomes of the twin transition. Economic geographers argue that it is essential to have proactive and inclusive policy measures in place to ensure that the benefits of the twin transition are distributed fairly across regions (Bachtrögler-Unger et al. 2023; Barbero et al. 2025). Among others, this includes an evenly distributed deployment of digital infrastructure, higher support for education and training in new technologies, and offering incentives for green practices across a larger set of industries.

In summary, the twin transition (referring to the transformation towards more digital and sustainable conscious economic activities) has significant implications for regional development. The literature in economic geography and regional science shows that this change has the potential to be transformative, but also comes with challenges, particularly in terms of spatial inequalities. It is important for regions to understand and navigate these changes if they want to adapt and thrive in a world that is increasingly focussed on both digital technology and environmental protection (Faggian et al. 2025). Against the background of previous research on the twin transition, we assume that there is an uneven geography of economic activities related to the twin transition also in the empirical context of this paper, the UK—a matter we will explore in the empirical sections.

2.2 Relatedness and regional specialization in the twin transition

The uneven geography of green, digital, and twin economic activities, as described in the previous section, manifests in regional specializations, meaning that some regions engage in a particular economic activity to a disproportionate extent. Regional specializations are, as is widely acknowledged in the economic literature, beneficial for the local economy, as they foster knowledge spillovers, thick labour pools, and other agglomeration effects that generate positive spatial externalities (Arrow 1962; Marshall 1890; Porter 1998; Romer 1986). This effect is further reinforced by the ability of specialized regions to attract capital, skilled labour, and complementary firms, such as suppliers and specialized service providers, which create a self-reinforcing dynamic of growth. In the context of the twin transition, it

is therefore crucial to understand how regions might develop specializations in the green, digital, or twin domain, and how this is rooted in existing local capabilities.

Empirical evidence supports the idea that the development of regional specializations is indeed rooted in territorial capabilities, not a product of random events. In other words, developing new specializations can be understood as a branching process where new activities emerge from existing related ones, leveraging shared resources such as knowledge, skills, technologies, and inputs (Breschi, et al. 2003; Frenken and Boschma 2007; Saviotti and Frenken 2008; Rigby 2015; Boschma 2017; Grillitsch and Asheim 2018; Hidalgo et al. 2018). This process is shown to be facilitated by cognitive proximity among economic activities that have been measured by a variety of metrics such as intersectoral mobility of workers, co-location of technologies, industries, and occupations, among others (Boschma et al. 2013; Neffke et al. 2018; Henning 2020). The emergence of new specializations within regions reflects, indeed, the existing collective capacity of local agents to forge regions with distinctive industrial structures. Consequently, the development of new specializations tends to align with pre-existing activities, highlighting the importance of a region's existing portfolio of local capabilities, which significantly influences the emergence of new activities and shapes path-dependent developmental trajectories. In economic geography, this process is commonly referred to as related diversification, where promising domains for regional specialization are not to be chosen because of their general appeal but because they boost regional potential and productive assets already present in the region. Research shows in fact that regions do tend to develop specializations in new fields closely related to their existing knowledge base (Asheim et al. 2011; Neffke et al. 2011; Rigby 2015). As a matter of fact, this phenomenon, "the principle of relatedness", persists across different variables, relatedness measures, spatial levels, and observation periods, underscoring the universality and strength of related diversification in regional development (Hidalgo et al. 2018). In this regard, the concept of industry-relatedness refers to the idea that industries benefit from being connected or "related" to other industries that share knowledge, skills, technologies, or market demands. This foundation is key for regions to develop specializations in new yet interconnected economic activities (Boschma 2017; Frenken et al. 2023; Neffke et al. 2011).

Understanding relatedness within the context of the twin transition is thus crucial in guiding regions to understand potential strategic pathways for leveraging existing local strengths and capabilities and embrace new specialization opportunities in the green and digital domains.

While some recent studies explore the interplay between green and digital economies, within the twin transition framework (Cicerone et al. 2023; Bachtröglger-Ungeret et al., 2023; Abbasiharofteh and Kriesch 2024; Bürscher et al. 2025), it is still not clear how the green and digital sectors can actually complement each other to achieve synergies. In fact, the mechanisms that support the mutual reinforcement of these sectors remain somewhat ambiguous. For instance, it is not yet well understood how a region that excels in green industries can effectively capitalize on this strength to gain a competitive edge in digital sectors, and vice versa.

Against this background, we argue that relatedness is a core channel through which the twin transition can be analysed and better understood, an aspect that, to

date, has not been studied in depth in the scholarly literature on the twin transition. In the empirical part of the paper, we compute the relatedness between green, digital, and twin economic activities and link these measures to regional-specialization patterns. This approach sheds light on the actual synergies (here understood as relatedness) between the digital and green domains, and on how strongly a twin transition can be fostered at the regional level. We distinguish between economic activities that are green (but not digital), digital (but not green), and twin (both green and digital) (following Kriesch et al. 2025). An example of a twin economic activity is Agri-Tech. Agri-Tech (agricultural technology) refers to the application of technology in farming and agriculture to increase productivity, efficiency, and sustainability. As an innovative industry, Agri-Tech combines the green and digital domains by using digital tools to enhance productivity in a green domain (Salihu et al. 2025).

The existing literature, however, typically operationalizes the twin transition by examining the green and digital domains separately, without explicitly identifying activities that are truly twin in nature, encompassing both domains. While we discuss this issue in greater detail in the empirical sections, the arguments above allow us to formulate propositions that guide our empirical analysis. Specifically, we argue that relatedness to green and to digital activities is associated with stronger specialization in twin activities at the regional level. Likewise, relatedness to twin activities is associated with stronger specialization in both green and digital activities. Finally, we assume that links between local relatedness and specialization in green and digital activities exist but are weaker than those involving twin activities.

3 Empirical strategy

3.1 Data

As discussed above, digital, green, and twin industries are increasingly recognized for their role in driving local economic growth, as many other emerging sectors. However, identifying and measuring these emerging sectors has challenges. By its very nature, digital, green, and twin economic activities are difficult to classify into rigid, top-down categories due to their evolving features (Nathan & Rosso 2015). As a result, the application of Standard Industrial Classification (SIC) codes to emerging sectors has been questionable. For this reason, we make use of a modern real-time industry classification (RTIC) approach in this paper. We employ RTICs from The Data City (www.thedatacity.com) not only to identify companies operating in green, digital, and twin domains but also to flag specific subsectors within these broader categories. This granular industrial activity approach enables a detailed analysis of the composition and characteristics of these domains. The Data City provides real-time insights into the UK's business landscape, with data on over 5 million companies. Of these, 1.6 million have been matched to their websites, and more than 200,000 have been classified using RTICs based on website content analysis. The platform includes detailed information on each company, such as sector classification, growth stage, company category, turnover, employee count, and geographical location.

In this regard, RTICs offer insights into around 51 sectors, including AI, Life Sciences, FinTech, and 385 subsectors. As such, RTICs provide an up-to-date understanding of emerging industries. For the classification, The Data City uses web scraping techniques, gathering real-time data from various sources across the internet. The data are updated bimonthly and sourced from reputable entities like Companies House, CreditSafe, and Dealroom.co, ensuring high accuracy and reliability. In a sophisticated approach, they blend machine learning algorithms with specialized training by experts within business, consulting, policy, and academia to accurately classify and understand current firm activities based on their website content.

This paper is one of the pioneering efforts to investigate this new data source, demonstrating its promising utility for (regional) research. The data used in this paper, sourced from The Data City in 2024, include information on over 200,000 companies and 385 subsectors, of which we linked 166 to digital sectors, 45 to green sectors, and 13 to the twin domain. In light of the literature discussed above, we operationalize the twin transition by identifying economic activities that are green, digital, or both (twin). Our classification methodology began with previous existing approaches to mapping green, digital, and twin activities (Bachtrögler-Unger, 2023) and was tailored to match The Data City's subsector descriptions (see their website). We classify subsectors as "green" if their activities enhance environmental sustainability, such as clean energy and cleaner production methods. Subsectors are categorized as "digital" if they involve innovative digital technologies, including artificial intelligence and the Internet of Things. Furthermore, we classify subsectors as "twin" if they intersect both areas, as exemplified by using digital technologies for environmental applications like environmental monitoring, smart grids, and Agri-Tech. In Tables 7, 8 and 9 in the appendix, we provide a list of all RTICs in green, digital, and twin domains, as well as the number of firms active in the respective industry. We collaboratively refined and validated this classification through a triangulation process.

We argue that the RTIC approach mitigates many of the limitations inherent in using SIC data. For example, firms often self-select their SIC code closest to their primary business activity without considering their diversification strategies. In some cases, the selection is based on financial or tax reasons and hardly there are fines for misclassification or incentives for classification updates as businesses evolve. This issue is intensified in innovative companies, particularly in the digital and green sectors, where cross-industry specializations are common. Consequently, there is growing consensus on the need for additional data sources to provide a deeper understanding of the emerging specializations and competencies in green and digital industries (Losurdo et al. 2019; Nathan and Rosso 2015; Kriesch et al. 2025). In addition, emerging industries are normally constituted by numerous small and young firms in line with business formed around a new product or idea. These companies or industrial activities normally exist when there is a technology replacement or in sectors where there exists a continuous development of commercial strategies, research and development, and business models. The constant transformation of these sectors makes it particularly difficult to categorize accurately across time. SIC codes, last updated in 2007, are indeed outdated and misaligned with today's dynamic industries such as FinTech and AI, just to name a few examples. Unlike

SICs, which often relegate modern activities to broader “not elsewhere classified” categories, RTICs, instead, can reflect real-time company activities and offer the granularity needed to identify new sectors. Another major issue with SIC codes is their assignment process: companies must select one to four SIC codes at their inception, often choosing out of convenience or from limited options. This leads to misclassification and inaccuracies in economic data. RTICs directly address these shortcomings. They are derived from how companies describe themselves on their websites and are continuously updated, ensuring that classifications evolve with the economy. Our database enables direct comparison of the two systems, as each company is associated with both RTIC and SIC codes. Preliminary evidence indicates that a substantial share of firms in sectors such as Net Zero, FinTech, and AI are captured by RTICs but overlooked by SICs, reflecting the latter’s inability to keep pace with technological and market change. For illustration, Tables 10 and 11 in the appendix report the top 20 SIC codes and the top 20 RTIC codes by number of companies classified. What clearly emerges is that many companies are placed under residual SIC categories due to limited options. Moreover, many companies are not elsewhere classified (n.e.c). For these reasons, expanding the use of RTICs offers several advantages for economic analysis, especially in identifying and categorizing emergent and dynamic activities such as the ones taking place in green, digital, and twin domains. With these advantages, it is understandable to see more scholars now developing new industrial classifications using web data (Abbasiharofteh et al. 2023; Kinne and Lenz 2021; Kriesch and Losacker 2024; Abbasiharofteh and Kriesch 2024).

In summary, we argue that the data and our approach provide a useful basis for analysing the geography of green, digital, and twin activities in the UK. In our analysis, the company data are therefore aggregated to the local authority level across the UK, facilitating an exploration of the geographical distribution and regional dynamics of these sectors. By capturing a wide array of innovative activities and precisely identifying subsectors within the green, digital, and twin domains, our methodology offers a comprehensive and contemporary lens through which the economic geography of the UK can be analysed and understood.

3.2 Methods

Our dataset provides a granular, up-to-date representation of firm fields of activity, as a proxy for their competencies. Through network analysis, we draw connections (henceforth *proximities*) between firms’ activities, thereby identifying the co-existence of activities in the digital, green, and twin sectors. These connections illustrate the various forms of market, technological, and cognitive proximities between firms’ activities and represent the basis of relatedness metrics. In the literature, these proximities are also referred to as *pairwise relatedness*, indicating the degree of relatedness (or proximity) between one industry and another. The degree of proximity between pairs of activities is computed using network analysis tools which enables us to build a network of connections based on firms’ involvement. The network is based on a dummy matrix X , where columns represent industrial classifications

(RTICs) and rows represent firms. Each cell takes the unit value if the company is involved in the industry. The pairwise proximities between industries are measured based on a co-occurrence measure, which essentially captures the likelihood that two activities will appear within the same company. The proximity between two industries is high if they frequently co-occur, implying that they share similar resources or technological requirements. For instance, consider industry A and industry B. These industries will exhibit high proximity (relatedness) if the number of companies in which the two tags (representing the industries) coexist is large. The basic idea is that if two industries require similar inputs in terms of resources, infrastructures, knowledge, or capabilities (Hidalgo et al. 2007; Hidalgo and Hausmann 2009; Frenken et al. 2023), they tend to exhibit substantial co-occurrence within the same firm more than randomly, indicating a strong relationship or complementarity between them. Formally, the *proximity* index between each pair of industries i and j is computed by taking the minimum between the conditional probability of a company being specialized in industry i given that it is specialized in industry j and the conditional probability of a company being specialized in industry j given that it is specialized in industry i , as follows:

$$\varphi_{i,j} = \min (P(x_{i,c}|x_{j,c}), P(x_{j,c}|x_{i,c}))$$

where $x_{i,c}$ is an indicator taking value 1 if the revealed comparative advantage (RCA) of company c in sector i is higher than 1 and zero otherwise, where $x_{j,c}$ is an indicator taking value 1 if the RCA of company c in sector j is higher than 1 and zero otherwise, and where the conditional probability is calculated using all companies c . If two RTICs coexist in many companies, it is highly likely that they are related.

We applied these methods to both 51 RTICs and 385 sub-RTICs. In this regard, network representations are useful to show the links between industries. Due to space limitations, we provide the network of RTICs (51 nodes) and not sub-RTICs, linked together by their degree of pairwise relatedness (proximity) (see Fig. 1). However, the subsequent analysis utilizes the proximity network of the 385 sub-RTICs. Table 1 displays the top 10 highest proximity values in the sub-RTIC network.

In the next step, we use the pairwise proximity values to compute relatedness density metrics on the regional level. The application of relatedness density metrics provides the identification of those industries and technological domains in which regions are more likely to reach or maintain a competitive advantage. In other words, relatedness density allows us to determine whether a region possesses the relevant capabilities to diversify into a new industry and design paths of diversification strategies favouring structural change towards those activities that reveal an affinity to the regional economy (Asheim et al. 2011; Boschma 2014; McCann & Ortega-Argilés, 2015; Boschma 2017). As explained in Sect. 2.2, according to the “principle of relatedness”, the likelihood of regions entering an economic activity depends on the cognitive proximity between the new activity and a region’s prior activities (Hidalgo et al. 2018). Relatedness density is an industry-specific and place-specific index that measures the average proximity of each industry to the productive structure of the local economy (Boschma et al., 2012; Boschma 2017; Cortinovis et al.

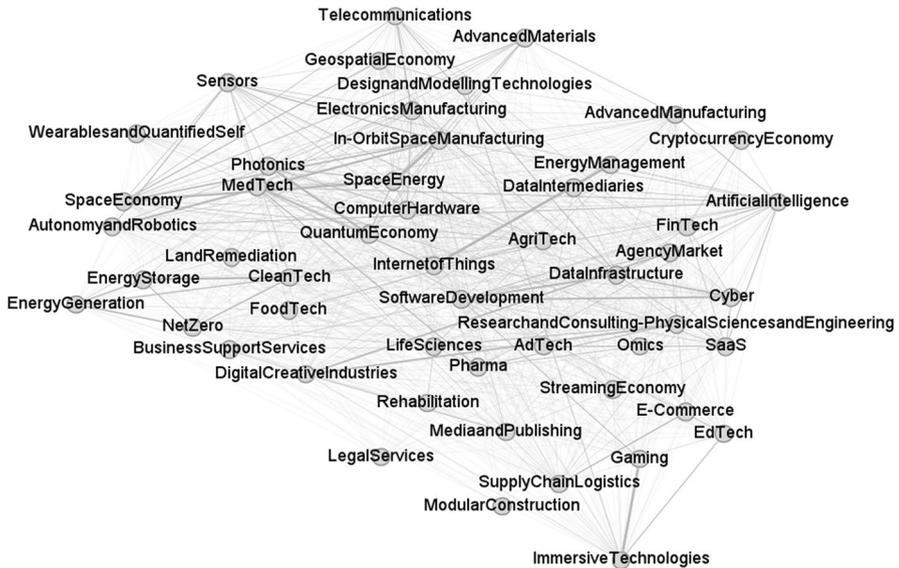


Fig. 1 Network representation of the RTICs (51 nodes). Thicker links represent higher pairwise relatedness, nodes represent RTICs. For visual clarity and ease of explanation, we display the RTIC network, as the sub-RTIC network is too dense and extensive for effective visual assessment

2017)—or, in other words, its *diversification potential*—and can be used to anticipate changes in specialization patterns.

In our empirical analysis, we are interested in analysing the distinct effect of three types of relatedness density (digital, green, and twin) on the regional specialization in the respective others. For example, in order to compute the *digital relatedness density*, we first compute the standard local relatedness density of existing technological capabilities to each industry i . To do that, we construct a two-mode matrix X , where columns represent the industries and rows represent the 374 UK local authorities. Each cell of the matrix indicates how many companies in each local authority are involved in industry j . From this matrix, we compute the specialization matrix through the RCA and the relative dummy matrix, where specialization is only recorded when the locality r has an RCA larger than 1 in that industry. So, each cell of the local authority matrices indicates if the local authority can be considered specialized in industry j . The dummy matrix represents the x in the *DigRel* formula. In a second step, we average the links (or *proximities*¹ $\phi_{i,j}$) connecting the focal industry i to only digital industries j which the local authority r is specialized in. Formally:

¹ We recall here that pairwise proximities are computed based on the co-occurrence in the company level matrix.

Table 1 The 10 highest proximity values in the sub-RTICs network

sub-RTIC A	sub-RTIC B	Proximity
Space economy: engineering	Space economy: In-orbit manufacturing	0.822
Sensors: environmental monitoring	Sensors: Industry4.0	0.604
Quantum economy: photonics	Quantum economy: quantum computing	0.596
Space economy: launch services	Space economy: launch vehicles	0.564
Space economy: launch infrastructure	Space economy: launch services	0.554
AdTech: programmatic platforms	AdTech: publishers	0.537
Computer hardware: semiconductor electronics	Electronics manufacturing: electronic components and boards	0.532
In-orbit space manufacturing: debris	Space energy: space infrastructure	0.528
NetZero: diversion of biodegradable waste	NetZero: waste management and recycling	0.518
Geospatial economy: data capture	Geospatial economy: data processing and visualizations	0.515

$$DigRel_{i,r} = \frac{\sum_j \phi_{i,j} x_{j,r}}{\sum_j \phi_{i,j}}$$

where: $x_{j,r} = \begin{cases} 1 & \text{if } RCA_{j,r} \geq 1 \\ 0 & \text{otherwise} \end{cases}$
 where: $j = \begin{cases} 1 & \text{if } j \text{ is a digital industry} \\ 0 & \text{otherwise} \end{cases}$

We repeat the same computations for the *green relatedness density* and the *twin relatedness density*. Figures 2 and 3 depict the measurement process through network representations.

4 Results

Using the dataset on green, digital, and twin economic activities described above, and applying the relatedness measures, we present our results as follows. Regarding the first aim of this paper, i.e. to identify which regions in the UK are leading the twin transition and to shed light on the geographical distribution of these activities, we provide descriptive statistics on the distribution of green, digital and twin economic activities across UK regions, complemented by scaling analyses. These results are presented in Sect. 4.1. Regarding the second aim of the paper, we seek to identify diversification opportunities for regions to enter green, digital, and twin

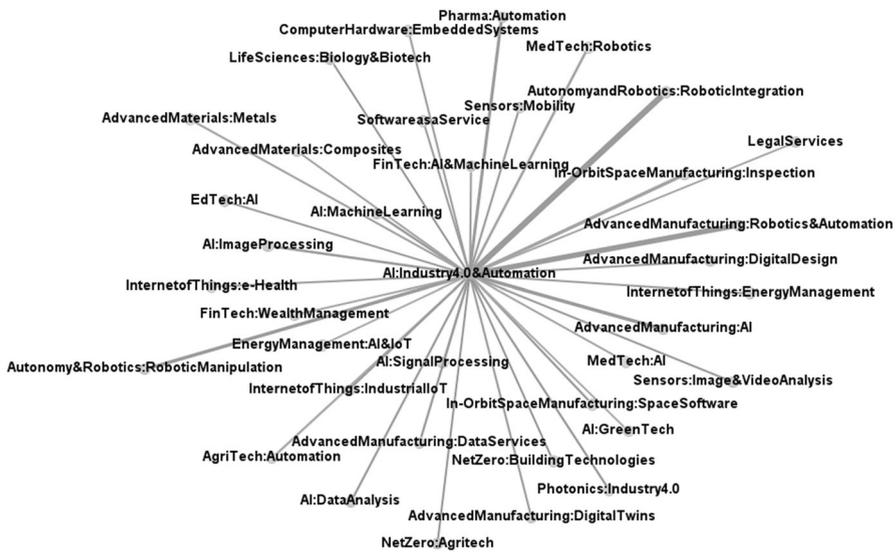


Fig. 2 Network representation of sub-RTICs (nodes) and their proximities (links) with a focal exemplary industry “AI: industry 4.0 and automation” (red node). Thicker links represent stronger connections. Weaker links and the related nodes are not displayed. Because of space limitation, only a random sample of the total 385 sub-RTICs is represented

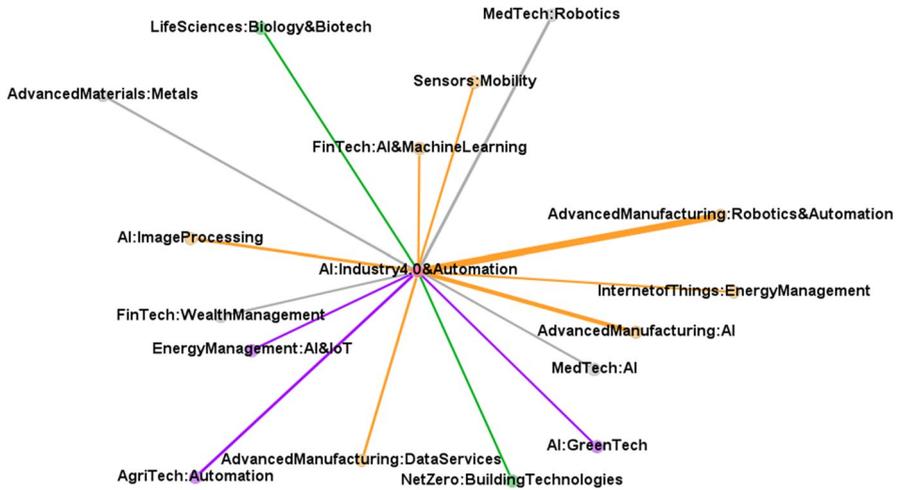


Fig. 3 Network representation of sub-RTICs (nodes) and their proximities (links) with the focal exemplary industry “AI: specialization industries” (nodes) and their proximities (links). Partitions identify the digital (orange), green (green), and twin (violet) industries. Weaker links and the related nodes are not displayed

activities. To this end, we use various regression models to analyse how regional specialization in one domain is associated with relatedness densities in the other domains. The corresponding results are presented in Sect. 4.2.

4.1 Geography of the twin transition in the UK

To begin, we employ maps to gain insights into the geographical distribution of the twin transition across the UK. Firstly, we illustrate the specialization levels in green, digital, and twin industries at the local authority level (see Figs. 4 and 6 in the appendix). We measure regional specialization in different industries using the RCA. For each region r and industry i , the RCA is defined as:

$$RCA_{r,i} = \frac{\frac{C_{r,i}}{C_r}}{\frac{C_i}{C}}$$

where $C_{r,i}$ denotes the number of firms in region r active in industry i , C_r the total number of firms in region r , C_i the total number of firms (nationally) active in industry i , and C the total number of firms in the UK. A value greater than one indicates that a region is specialized in a given industry, as its local share exceeds the national average, whereas values below one indicate a relative under-specialization. Additionally, we present the spatial distribution of the relatedness density within these industries (see Fig. 5), a matter that we will come back in more detail in the next section. Analysing the specializations, several intriguing patterns emerge. First, digital industries appear predominantly concentrated in the South of England, particularly

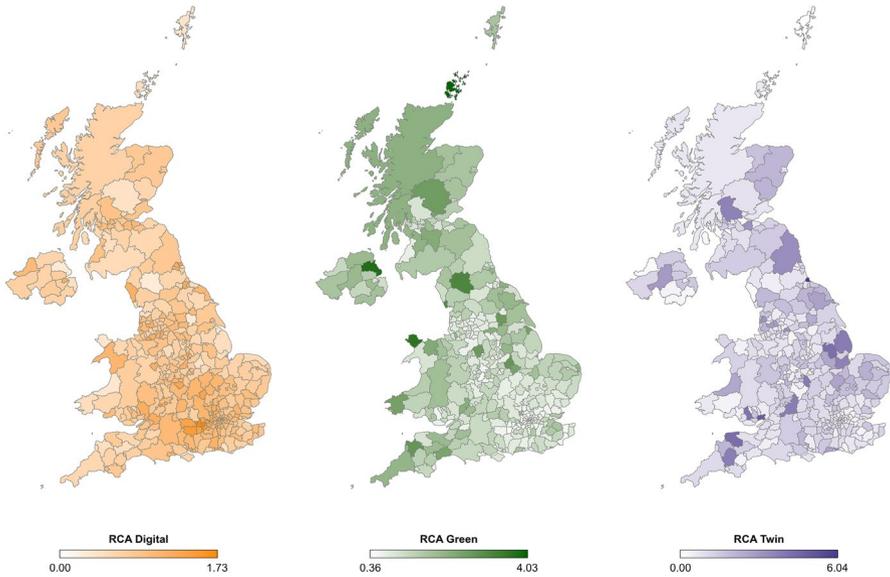


Fig. 4 Specialization of UK local authorities in digital, green, and twin industries. Notes: This figure shows the RCA of UK local authorities in digital (left panel), green (central panel), and twin (right panel) industries. A darker colour denotes a stronger specialization. A binary version of these maps is provided in Fig. 6 in the appendix

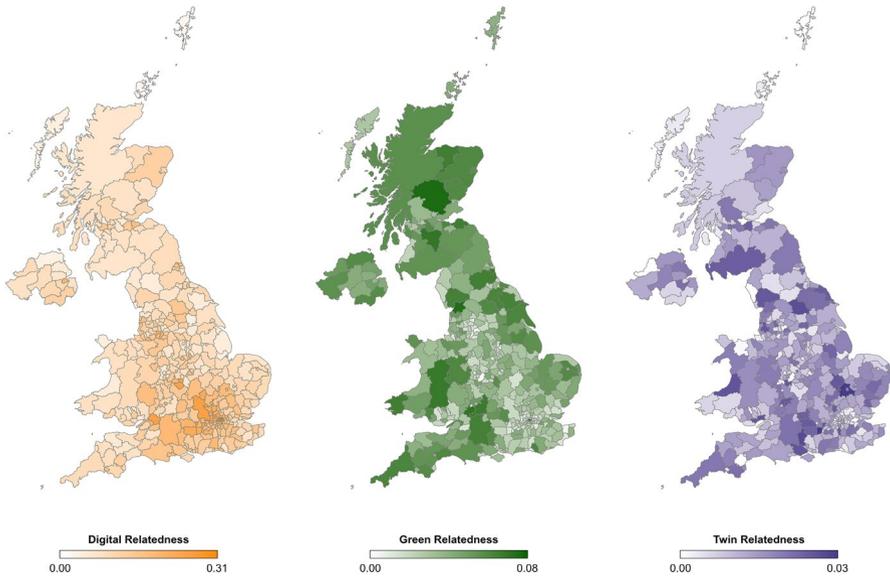


Fig. 5 Unequal potential of UK local authorities to develop digital, green, and twin technologies. Notes: This figure shows the potential of UK local authorities to develop digital (left panel), green (central panel), and twin (right panel) technologies in the future. The values used are relatedness density scores averaged across all digital, green, and twin sub-RTICs. A darker colour denotes a higher potential

in regions like Buckinghamshire, South Gloucestershire, Warwick, and around the London area. In contrast, green industries are more spatially dispersed, with local specializations in more rural areas, such as Perth and Kinross, South Lanarkshire, and Powys. The twin industries, which combine elements of both the green and digital sectors, show a significant presence in areas like South Cambridgeshire, as well as in Newport and Cheltenham. Interestingly, there is a lack of spatial autocorrelation and co-location patterns. For instance, regions strong in twin industries do not necessarily exhibit strength in green and/or digital industries, and vice versa.

To gain a deeper understanding of the geographical aspects of the twin transition, we investigate the urban scaling laws of green, digital, and twin industries. Drawing from existing literature on urban scaling (Bettencourt et al. 2007; Bettencourt 2013), we estimate the relationship between the number of firms active in these industries Y in a given region r and its population N . This relationship is modelled by a power law function:

$$Y_r = \alpha N_r^\beta$$

Here, α is a normalization constant, and β is the scaling exponent that captures the relationship between economic activity and population size. Specifically, a β value greater than 1 indicates that the economic activity in the relevant sector scales superlinearly with population size, showing increasing returns to scale. A β of 1 suggests linear scaling, where activity is proportional to population size. Conversely, if β is less than 1, it implies sublinear scaling, indicating decreasing returns to scale. To quantify the scaling relationship between economic activity in sector Y and population size N , we estimate β using a log-transformation of the original function:

$$\ln Y_r = \alpha + \beta \ln N_r + \epsilon_r$$

In this equation, ϵ represents Gaussian white noise. This method allows us to analyse how industry size (number of firms in a given sector) correlates with population size in different regions.

The findings from our urban scaling analysis are detailed in Table 2. We provide corresponding scaling plots in Fig. 9 in the appendix. The analysis reveals that digital economic activities exhibit superlinear scaling with regional populations. This suggests a higher concentration of digital companies in metropolitan regions; specifically, a 10% increase in regional population corresponds to a 12.8% rise in the number of digital firms. On the other hand, both green industries and those involved in twin activities display scaling coefficients below one, indicating a less urban presence. In these sectors, a 10% population increase results in only a 9.2% increase in green activities and an 8.9% increase in twin activities. Therefore, green and twin industries appear to benefit less from urbanization economies and are more prevalent in less populated areas. These scaling analysis results align with the patterns observed in the descriptive maps, reinforcing our understanding of the spatial distribution of these industries.

Table 2 Urban scaling laws for digital, green, and twin sectors

	Dependent variable					
	Digital companies (1)	Non-digital companies (2)	Green companies (3)	Non-green companies (4)	Twin companies (5)	Non-twin companies (6)
Population	1.276*** (0.060)	1.062*** (0.040)	0.918*** (0.049)	1.176*** (0.048)	0.887*** (0.062)	1.115*** (0.044)
Constant	- 9.633*** (0.718)	- 6.044*** (0.479)	- 5.734*** (0.588)	- 7.319*** (0.576)	- 7.803*** (0.745)	- 6.381*** (0.528)
Observations	373	373	373	373	373	373
R ²	0.548	0.654	0.483	0.616	0.352	0.631
Residual Std. error (df = 371)	0.698	0.466	0.572	0.560	0.725	0.514
F Statistic (df = 1; 371)	450.498***	701.300***	346.841***	594.778***	201.871***	635.384***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

4.2 Relatedness and regional specializations

In the next step, we conducted a series of regression (OLS) analyses to explore the relationship between the relatedness of local-industry observations in green, digital, and twin sectors, and local revealed comparative advantages in these domains. Specifically, we analysed how the relatedness of a region–industry pair in, e.g. green domains, affects the RCA in digital and twin sectors within the same local authority and vice versa. We conducted separate regressions for RCAs in each industry, treating them as dependent variables. $RCA_{r,i} = \frac{c_{r,i}}{\frac{c_r}{c_i}}$ To address the skewness and asymmetry of the traditional RCA, we follow Cicerone et al. (2020) and use its symmetric form (sRCA), based on the transformation originally proposed by Dalum et al. (1998) and Iapadre (2001). The sRCA is defined as:

$$sRCA_{r,i} = \frac{RCA_{r,i} - 1}{RCA_{r,i} + 1}$$

which rescales the index to range from -1 to $+1$. Values greater than zero indicate relative specialization (greater local share than national average), while values below zero indicate relative under-specialization.

The key independent variable in the regression models is the relatedness density of each region–industry observation to the other two sectors (green, digital, and twin). In all models, we controlled for agglomeration effects (using population density), innovation capacity (measured by patents per capita), and local GDP per capita. We also account for unobserved heterogeneity at the regional and industry levels, including fixed effects for both. We ran the regression models with standard errors clustered by regions. The regressions can be denoted as follows:

$$DigitalRCA_{i,r} = \alpha + \delta GreenRel_{i,r} + \delta TwinRel_{i,r} + \theta \bar{X}_r + \nu_i + \mu_r + \varepsilon_{i,r}$$

$$GreenRCA_{i,r} = \alpha + \delta DigitalRel_{i,r} + \delta TwinRel_{i,r} + \theta \bar{X}_r + \nu_i + \mu_r + \varepsilon_{i,r}$$

$$TwinRCA_{i,r} = \alpha + \delta DigitalRel_{i,r} + \delta GreenRel_{i,r} + \theta \bar{X}_r + \nu_i + \mu_r + \varepsilon_{i,r}$$

The dependent variable is the normalized, symmetric RCA of industry i in region r . On the right-hand side of the equations, α denotes the intercept, and δ the coefficient of our main relatedness density variables of interest, which vary by region r and industry i . θ denotes the coefficients for \bar{X} , a vector of all control variables, which vary by region. ν denotes industry fixed effects, μ region fixed effects, and ε is the region–industry-specific error term. The data for the control variables refer to 2022, while the RTIC data used to compute the specialization and relatedness measures were sourced from The Data City in 2024 and collected from firm websites over a preceding period of time. We provide descriptive statistics for all variables in Table 6 in the appendix.

The findings of the OLS regressions, detailed in Table 3, reveal nuanced inter-sectoral dynamics. There is a supportive relationship between the green and digital sectors; relatedness in one positively influences the specialization in the other. The same holds true for twin sectors relatedness. This variable positively affects regional competitive advantages in both the green and digital sectors. However, twin industries have a stronger positive impact on green industries than digital relatedness variables do, and similarly, twin industries have a more positive influence on digital sectors than green industries do, as anticipated in Sect. 2.2. This suggests that while the green and digital sectors mutually support each other, the twin sector—embodying characteristics of both green and digital—plays a more influential role in enhancing the RCA of both sectors. In line with that, our findings also reveal that relatedness to both digital and green industries is positively associated with gaining a competitive edge in twin sectors. This means that advancements in these twin industries could be achieved through diversification strategies from either the green or digital domain. These insights are crucial for several reasons. Firstly, they reveal the inherent synergies between the green and digital industries. While these sectors do

Table 3 Results of OLS regressions. Symmetric relative comparative advantage RCA (dependent variable) and relatedness in digital, green, and twin industries at the UK local authority level. Observations are place- and industry-specific (374 LAs and 385 industries). Standard errors clustered at the regional level (local authority) are reported in parentheses

	Dependent variable		
	Digital RCA (1)	Green RCA (2)	Twin RCA (3)
Green relatedness	0.053*** (0.009)		0.051*** (0.005)
Digital relatedness		0.016*** (0.03)	0.023*** (0.002)
Twin relatedness	0.344*** (0.024)	0.233*** (0.024)	
Patents per capita	yes	yes	yes
Population density	yes	yes	yes
GDP per capita	yes	yes	yes
Industry FEs	yes	yes	yes
Local Authority FEs	yes	yes	yes
Constant	− 0.006 (0.080)	− 0.081* (0.043)	− 0.078*** (0.024)
Observations	126,720	126,720	126,720
R ²	0.241	0.306	0.335
Adjusted R ²	0.236	0.302	0.332
Residual Std. error (df = 126,005)	0.283	0.151	0.083
F Statistic (df = 714; 126,005)	55.943***	77.878***	89.093***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

support each other, their interrelationship is moderated significantly by the presence of twin industries. Secondly, this finding underscores the necessity for researchers to focus on the twin transition *sensu stricto*. Instead of solely examining green and digital economic activities, as is common in many studies, it is crucial to also consider activities that are simultaneously green and digital (truly twin activities). This perspective is essential to fully understanding and leveraging the dynamics of the twin transition.

For a robustness check, we split our dataset into two categories: prosperous areas (constituting one-third of the dataset) and less prosperous areas (comprising the remaining two-thirds), to assess potential differences between different types of localities and the effects of the relatedness densities across green, digital, and twin sectors. We use the mean GDP per capita to split the dataset, which corresponds to 31,352 (London excluded, following Rocchetta et al. 2021). The findings suggest that the influence of industry-relatedness on the RCA in the digital, green, and twin sectors is largely uniform, irrespective of the local economic status. In other words, while there is an uneven geography of regional specializations in the green, digital, and twin domains, as demonstrated above, the diversification potentials do not appear to be bound to the economic strength of regions. The results are detailed in Table 4 in the appendix. As a robustness check, we also ran logit and probit models using binary specifications of the RCA. The results remain robust to these changes. The models do not suffer from multicollinearity, as evidenced by the correlation matrix in Table 5 in the appendix. In all models, the variance inflation factors are well below the commonly accepted threshold of 5.

5 Conclusion and discussion

Achieving green and digital transitions has become an urgent matter. This has spurred a growing body of research exploring the capacities of regions to progress the two individual transitions, and to integrate them effectively (Faggian et al. 2025). However, much research has gone into assessing the diverse impact of the twin transition, particularly through the lens of green and digital innovations as reflected in regional patenting activities. Less research has leveraged real-time industrial data to explore how firms' knowledge bases and activities contribute to the twin transition (Kriesch et al. 2025). With this study, we contribute to the empirical research on the geography of the twin transition and its economic activities. By employing real-time industry classification (RTIC) data, our study surpasses traditional methods in capturing green, digital, and twin industries. Our analysis reveals significant geographical variations in the distribution of these industries across the UK, with implications for local development and policymaking. Key findings include that digital industries tend to cluster in urban, more populated areas, exhibiting superlinear scaling with population size. In contrast, green and twin industries show less urban concentration, indicating a more dispersed development pattern. This highlights the potential for spatial inequalities as a result of the twin transition, underscoring the need for region-specific strategies. Furthermore, our study analyses industry-relatedness, uncovering interconnections among green, digital, and twin sectors. While green

Table 4 Symmetric relative comparative advantage (RCA) as a dependent variable and relatedness in digital, green, and twin industries at the UK local authority level: linear model (LM). Observations are place- and industry-specific (374 local authorities and 385 industries) and have been split into high and low GDPpp local authorities, using the mean GDPpp value (excluding London) as the threshold

	Dependent variable					
	Digital RCA		Green RCA		Twin RCA	
	High GDPpp regions (1)	Low GDPpp regions (2)	High GDPpp regions (3)	Low GDPpp regions (4)	High GDPpp regions (5)	Low GDPpp regions (6)
Green relatedness	0.060*** (0.023)	0.040*** (0.014)			0.062*** (0.006)	0.047*** (0.004)
Digital relatedness			0.015*** (0.006)	0.015*** (0.005)	0.022*** (0.003)	0.025*** (0.003)
Twin relatedness		0.334*** (0.032)	0.264*** (0.025)	0.225*** (0.018)		
Controls and FEs	yes	yes	yes	yes	yes	yes
Constant	0.370*** (0.072)	- 0.028 (0.076)	- 0.051 (0.036)	- 0.081* (0.043)	- 0.032 (0.020)	- 0.077*** (0.023)
Observations	42,624	84,096	42,624	84,096	42,624	84,096
R ²	0.285	0.228	0.292	0.326	0.358	0.336
Adjusted R ²	0.277	0.223	0.284	0.321	0.350	0.332
Residual Std. error	0.306 (df=42,128)	0.267 (df=83,492)	0.151 (df=42,128)	0.150 (df=83,492)	0.085 (df=42,128)	0.082 (df=83,492)
F statistic	33.980*** (df=495; 42,128)	40.955*** (df=603; 83,492)	35.178*** (df=495; 42,128)	66.896*** (df=603; 83,492)	47.369*** (df=495; 42,128)	70.177*** (df=603; 83,492)

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5 Correlation matrix

	green_REL	digital_REL	twin_REL	RCA_green	RCA_digital	RCA_twin	POP_density	GDPpp
digital_REL	- 0.2***							
twin_REL	0.12***	- 0.01***						
RCA_green	0.5***	- 0.12***	0.09***					
RCA_digital	- 0.11***	0.44***	- 0.01*	- 0.07***				
RCA_twin	0.06***	0.01*	0.29***	- 0.02***	- 0.04***			
POP_density	- 0.04***	0.18***	- 0.03***	- 0.02***	0.08***	- 0.01***		
GDPpp	0.01***	0.16***	- 0.01**	0.01**	0.07***	0.01*	0.41***	
PATpp	0.01*	0.02***	0.02***	0.01*	0.01**	0.01**	- 0.2***	0.01***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

and digital industries already display positive synergies, they benefit even more from the relatedness of twin industries, which embody characteristics of both. This insight is crucial for understanding the dynamics of local economic restructuring in the context of the twin transition.

Here, we see one of the main contributions of our work. While many studies have questioned the synergies between digital and green industries, arguing that the two domains are only loosely connected (Casanas and Kovacic 2025; Horn and Felt 2025), we provide evidence that they actually are strongly related. First, by mapping economic activities that are truly twin (both green and digital), such as Agri-Tech or smart grids, we show that there are genuine overlaps where green and digital industries meet. Second, by revealing a positive association between local specializations in green or digital industries and relatedness density in the respective other domain, we demonstrate that capabilities in one domain affect the other. This indicates that there are diversification opportunities in green or digital domains if there are capabilities in the respective other domain. These opportunities are even stronger for diversification into the twin domain, which is possible when starting from either a green or a digital local capability base. The theoretical contribution of our empirical analysis lies in revealing the relatedness between green and digital industries, as well as their relatedness to truly twin activities, i.e. those that are both green and digital. While previous studies and most policymakers have often simply assumed such relatedness, we are among the first to show that there is a form of cognitive proximity among green, digital, and twin economic activities that also appears to manifest at the local level.

In that regard, understanding the synergies between the green and the digital transition is crucial for policymakers and businesses to navigate the challenges and opportunities of the future economy. Our research contributes to this understanding by comprehensively analysing the twin transition in the UK, highlighting the key drivers, barriers, and implications for different sectors. It emphasizes the need for industrial strategies and policies that are region-specific and transition-type specific in order to harness the benefits of this twin process, considering the unique economic and industrial landscapes of UK regions. In this sense, our results speak to recent UK policy strategies, including the UK Science and Technology Framework (published in 2025) and Invest 2035: the UK's modern industrial strategy (published in 2024). While these strategies focus on several sectors related to the twin transition and emphasize place-specificities, they (at least in our understanding) seem to overlook potential diversification pathways into the twin domain from existing green or digital capabilities in the regions. More clearly highlighting these pathways, and the relatedness between green and digital domains, could strengthen the strategic orientation of future policy initiatives in the UK.

However, a few limitations of our study should be borne in mind when interpreting the results presented above. While RTICs provide a granular, topical, and up-to-date representation of the UK economy, the data still have certain limitations. The

approach The Data City uses to build the RTICs is based on information provided by the companies as well as a keyword library constructed with the help of experts in the industrial field (used afterwards in the web scraping exercise). Therefore, the classification is likely to include companies that write about specific industries as their main activity, which may, however, not encompass the entire value chain of a good. As a result, many of the RTICs labelled as green might overlook activities that some would consider environmentally friendly but are not part of the company's main activities. Similarly, companies could be classified as belonging to a green RTIC while only making a minor contribution to a green good within its value chain. It should also be acknowledged that the data does not represent the full UK economy, but rather its digitally active part. This naturally entails biases in terms of geographical and sectoral coverage, headquarter effects, firm size, and other characteristics—an issue also noted in related web data-based studies (see, e.g. Kriesch and Losacker 2024; Abbasiharofteh et al. 2023; Dahlke et al. 2025). Nevertheless, for the purposes of this paper, where we explicitly aim to examine the relatedness of emerging sectors, the data offer rich insights. In addition to the data limitations in identifying green, digital, and twin industries, there are further limitations. First and foremost, our analysis is cross-sectional due to data availability. In the literature, regional diversification is typically modelled as a dependent variable explained by a time-lagged relatedness measure (Balland et al. 2019). With our data, this approach is not feasible, as our core independent variable of interest (relatedness) can only be computed for the same year as our dependent variable (specialization). This also implies that we refrain from labelling our study a diversification study in the strict sense. Instead, we investigate diversification potentials by relating relatedness to specialization. This distinction should be kept in mind when positioning our study within the broader diversification literature. Secondly, due to the cross-sectional nature of our data, we are unable to employ econometric techniques that would permit causal inference. Our findings should therefore be interpreted as indicative of correlations rather than causal relationships.

In terms of research avenues, we advocate for future studies to conduct in-depth analyses of specific regions in case study designs to discern variations in green, digital, and twin development trajectories. We also advocate for more research aimed at accurately distinguishing between economic activities that are genuinely “twin”, both digital and green, instead of merely identifying instances where green and digital activities co-occur. In this context, we contend that innovative data sources, particularly those utilizing text data, will be necessary to identify and understand these emerging economic activities, as traditional data sources may fall short. Therefore, we encourage fellow researchers to delve into these new data sources to advance our understanding of these sectors and their geography.

Appendix

See (Figs. 6, 7, 8, and 9, Tables 4, 5, 6, 7, 8, 9, 10, and 11).

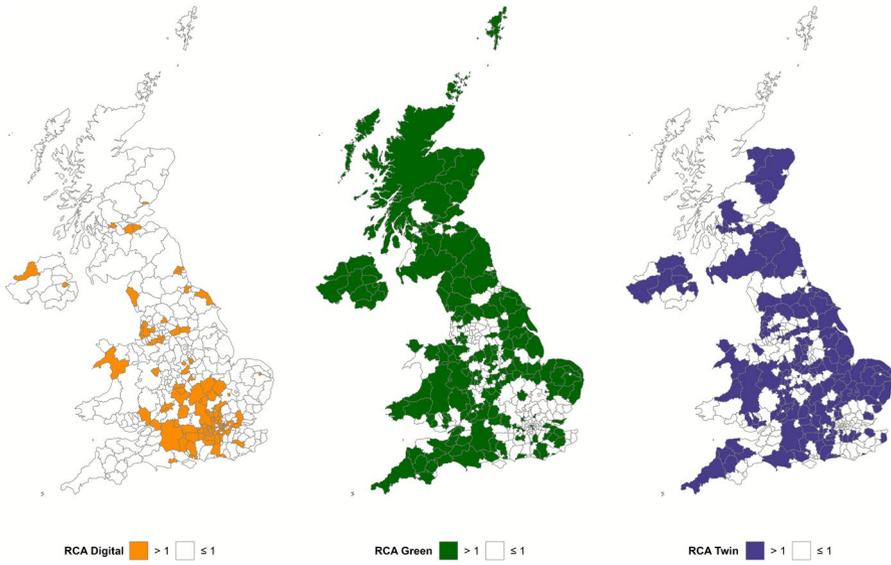


Fig. 6 Specialization of UK local authorities in digital, green, and twin industries. Notes: This figure shows the specialization of UK local authorities in digital (left panel), green (central panel), and twin (right panel) industries. Regions with an RCA higher than 1 are considered specialized. The maps are a binary version of the maps provided in Fig. 4

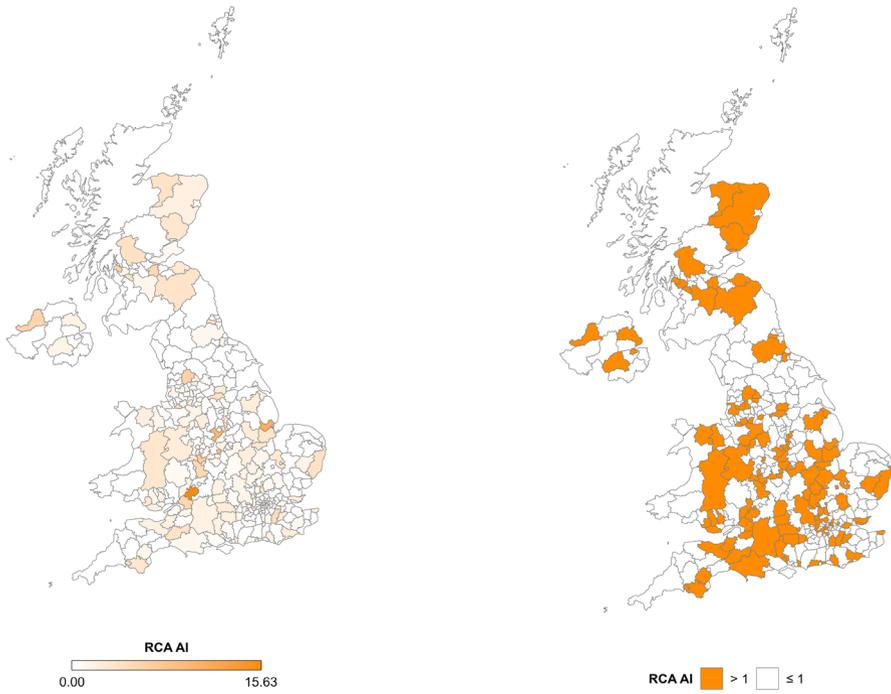


Fig. 7 Specialization of UK local authorities in artificial intelligence, Industry 4.0, and automation. Notes: The left panel shows the RCA (share of companies involved in the focal industry in a region in relation to the average share among all regions) where a darker colour denotes a higher specialization. The right panel shows the binary equivalent, where regions with an RCA higher than 1 are considered specialized in AI industries

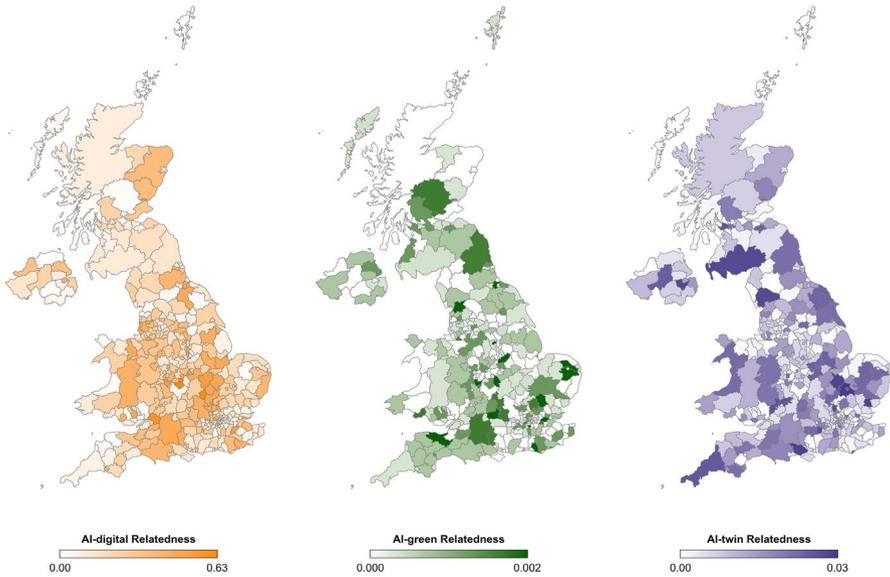


Fig. 8 The relatedness of artificial intelligence, Industry 4.0, and automation with the digital, green and twin UK specializations. Notes: This figure shows the potential of UK local authorities to develop artificial intelligence, Industry 4.0, and automation, given the current digital (left panel), green (central panel), and twin (right panel) specializations. The values used are relatedness density scores between the focal industry and all the other digital, green, and twin sub-RTICs in each UK local authority. A darker colour denotes a higher relatedness

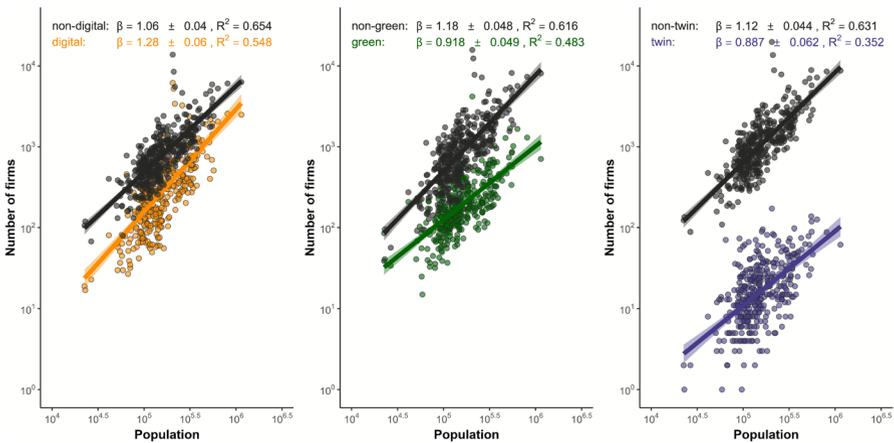


Fig. 9 Urban scaling laws for digital, green, and twin sectors (aggregated). Notes: This figure shows the urban scaling laws for the digital (left panel), green (central panel), and twin (right panel) sectors. Scaling coefficients larger than 1 indicate increasing returns to scale, meaning that firms in the respective sector concentrate in more populated areas

Table 6 Descriptive statistics

Variable	Mean	SD	Min	Max
green_REL	0.035	0.105	0.000	0.969
digital_REL	0.124	0.159	0.000	0.989
twin_REL	0.010	0.041	0.000	0.734
RCA_green	-0.044	0.235	-1.000	0.992
RCA_digital	-0.214	0.457	-1.000	0.984
RCA_twin	-0.015	0.140	-1.000	0.976
POP_density	1,709.97	2,481.13	25.5	15,702.9
GDPpp	31,352.51	22,979.21	14,698	382,206
PATpp	0.00087	0.00099	0.000001	0.00314
N green companies	254	305	2	4180
N digital companies	445	614	0	6164
N twin companies	22	22	0	171
POP	179,672	121,166	2271	1,142,494

Table 7 Digital RTICs

RTIC	Sub-RTIC	N companies
Ad Tech	Ad Exchange	76
Ad Tech	Advertisers	120
Ad Tech	Data Management and Analysis	564
Ad Tech	Programmatic Platforms	175
Ad Tech	Publishers	157
Advanced Manufacturing	Artificial Intelligence	527
Advanced Manufacturing	Augmented and Virtual Reality	186
Advanced Manufacturing	Computer Aided Manufacturing	2271
Advanced Manufacturing	Data Services	420
Advanced Manufacturing	Digital Design	1781
Advanced Manufacturing	Digital Twins	118
Advanced Manufacturing	Industrial IoT	465
Advanced Manufacturing	Robotics and Automation	946
Agency Market	Digital Transformation	216
Agency Market	E-commerce platforms	2243
Artificial Intelligence	Blockchain	221
Artificial Intelligence	Data Analysis	828
Artificial Intelligence	Enabling Platforms	562
Artificial Intelligence	Image Processing	192
Artificial Intelligence	Industry 4.0 and Automation	352
Artificial Intelligence	Life Sciences	332
Artificial Intelligence	Machine Learning	1044
Artificial Intelligence	Natural Language Processing	159
Artificial Intelligence	Signal Processing	476
Artificial Intelligence	Systems Optimization	177

Table 7 (continued)

RTIC	Sub-RTIC	N companies
Autonomy and Robotics	Collaboration and Integration	118
Autonomy and Robotics	Reasoning and Acting	146
Autonomy and Robotics	Robotic Integration	344
Autonomy and Robotics	Robotic Manipulation	177
Autonomy and Robotics	Robotic Mobility	284
Autonomy and Robotics	Sensing and Perception	485
Computer Hardware	Central Processing Units	9
Computer Hardware	Embedded Systems	448
Computer Hardware	Field Programmable Gate Arrays	347
Computer Hardware	Graphics Processing Unit	19
Computer Hardware	Semiconductor electronics	960
Cryptocurrency Economy	Blockchain	312
Cryptocurrency Economy	Mining	154
Cyber	Cryptographic Authentication	387
Cyber	Endpoint Security	1038
Cyber	Identity Management	846
Cyber	Incident Detection and Response	1449
Cyber	IoT Security	686
Cyber	Network Security	2038
Cyber	Risk Management	2589
Cyber	Threat Management	1170
Data Infrastructure	Data Centre Cooling	145
Data Infrastructure	Data Centres	1002
Data Infrastructure	Data Infrastructure Hardware	3687
Data Infrastructure	Data Infrastructure Services	6360

Table 7 (continued)

RTIC	Sub-RTIC	N companies
Data Infrastructure	Data Infrastructure Software	1967
Data Infrastructure	Data Storage	2554
Data Infrastructure	Trusted Execution Environments	453
Data Intermediaries	Data Cooperatives	368
Data Intermediaries	PDS/PIMS	238
Data Intermediaries	Undefined Intermediaries	1027
Design and Modelling Technologies	3D Modelling and Scanning	561
Design and Modelling Technologies	Computer Aided Design	795
Design and Modelling Technologies	Digital Twins	302
Design and Modelling Technologies	XReality	228
Digital Creative Industries	Non-fungible Tokens	53
Digital Creative Industries	Streaming	402
E-Commerce	Inventory	111
E-Commerce	Platform	387
E-Commerce	Tracking	1437
Ed Tech	Artificial Intelligence	122
Ed Tech	Devices	450
Ed Tech	Digital Learning	610
Ed Tech	Immersive Experiences	200
Ed Tech	Learning Management Systems	469
Electronics Manufacturing	Communications	1946
Electronics Manufacturing	Computer manufacture	690
Electronics Manufacturing	Electromedical technologies	494
Electronics Manufacturing	Electronic components and boards	950
Fin Tech	Analytics	846

Table 7 (continued)

RTIC	Sub-RTIC	N companies
Fin Tech	Artificial Intelligence and Machine Learning	223
Fin Tech	Blockchain	111
Fin Tech	Cryptocurrencies technologies	183
Fin Tech	Cyber Security	259
Fin Tech	Digital Banking	243
Fin Tech	Enterprise Software	517
Fin Tech	Insurtech	191
Fin Tech	Lendingtech	310
Fin Tech	Online Banking	601
Fin Tech	Open Banking	187
Fin Tech	PayTech	542
Fin Tech	PropTech	225
Fin Tech	RegTech	137
Fin Tech	Software as a service	169
Fin Tech	Transfer FX	376
Gaming	Enabling Technology	216
Gaming	Game Development Studios	1025
Geospatial Economy	Data Capture	2142
Geospatial Economy	Data Processing and Visualization	1941
Geospatial Economy	Geospatial and GIS Technologies	590
Geospatial Economy	Navigation Technologies	724
Immersive Technologies	Architecture & Construction	174
Immersive Technologies	Augmented Reality	434
Immersive Technologies	Emerging Markets	21
Immersive Technologies	Gaming	155

Table 7 (continued)

RTIC	Sub-RTIC	N companies
Immersive Technologies	Haptics	34
Immersive Technologies	Hardware	31
Immersive Technologies	Manufacturing & Engineering	108
Immersive Technologies	Media	245
Immersive Technologies	Metaverse	121
Immersive Technologies	Mixed Reality	362
Immersive Technologies	Virtual Reality	1059
In-Orbit Space Manufacturing	Space Software	213
Internet of Things	Connectivity Platforms	79
Internet of Things	e-Health	236
Internet of Things	Energy Management	341
Internet of Things	Industrial IoT	113
Internet of Things	Smart Cities and Transport	280
Pharma	Automation	151
Pharma	Research and Data Analytics	452
Photonics	Industry 4.0	246
Quantum Economy	Photonics	136
Quantum Economy	Quantum Computing	126
Sensors	Autonomous Vehicles	851
Sensors	Image and Video Analysis	637
Sensors	Industry 4.0	1210
Sensors	Mobility	555
Software as a Service (SaaS)	Analytics	728
Software as a Service (SaaS)	Communications	271
Software as a Service (SaaS)	Finance and Accounting	396

Table 7 (continued)

RTIC	Sub-RTIC	N companies
Software as a Service (SaaS)	Healthcare	251
Software as a Service (SaaS)	Human Resources	349
Software as a Service (SaaS)	Marketing	607
Software as a Service (SaaS)	Real Estate	158
Software Development	API Development and Integration	583
Software Development	Cloud Computing	1069
Software Development	Desktop	388
Software Development	Dev Ops	581
Software Development	Embedded Software	470
Software Development	Games Development	677
Software Development	Mobile Development	959
Software Development	Security Engineering	2295
Software Development	UI/UX Development	509
Software Development	Web Development	1017
Space Economy	Communications	200
Space Economy	Cyber Security and Encryption	99
Space Economy	Data Infrastructures	193
Space Economy	Exploration	41
Space Economy	Geospatial Analytics	123
Space Economy	Geospatial Platforms	152
Space Economy	Ground Segment	64
Space Economy	Software	150
Streaming Economy	Enabling Tech	173
Streaming Economy	Immersive Tech	97
Streaming Economy	Live Streaming	266

Table 7 (continued)

RTIC	Sub-RTIC	N companies
Streaming Economy	On Demand Streaming	193
Streaming Economy	Real-time Data Stream	103
Supply Chain Logistics	Automation	266
Supply Chain Logistics	Blockchain and Digital Twins	68
Supply Chain Logistics	Freight Tracking Tech	355
Supply Chain Logistics	Management Platforms	510
Supply Chain Logistics	Supply Chain Visibility	217
Telecommunications	5G Radio Access Network	199
Telecommunications	Broadcasting	520
Telecommunications	Fibre Connectivity	513
Telecommunications	Network Providers	423
Telecommunications	Satellite Communications	246
Telecommunications	Site Services	1321
Telecommunications	Wireless Connectivity	512
Wearables and Quantified Self	Apps	104

Table 8 Green RTICs

RTIC	Sub-RTIC	N companies
Advanced Materials	Biomaterials	101
Agri-Tech	Ag Sciences	423
Agri-Tech	Vertical Farming	109
Clean Tech	Adapted Goods	321
Clean Tech	Agriculture Forestry and Biodiversity	339
Clean Tech	Energy Production Management and Storage	2288
Clean Tech	Environmental Protection and Monitoring	1104
Clean Tech	Mining Fuels and Biofuels	377
Clean Tech	Water Processing	763
Energy Generation	Bioenergy	590
Energy Generation	Hydrogen	210
Energy Generation	Hydropower	403
Energy Generation	Nuclear	97
Energy Generation	Nuclear Fusion	76
Energy Generation	Offshore Wind	791
Energy Generation	Onshore Wind	821
Energy Generation	Renewable Thermal	704
Energy Generation	Solar	906
Energy Storage	Batteries	2704
Energy Storage	Hydrogen	423
Energy Storage	Mechanical	519
Energy Storage	Thermal	117
Energy Storage	Uninterruptible Power Supply	208
Food Tech	Food Surplus	212
Land Remediation	Brownfield Regeneration	545

Table 8 (continued)

RTIC	Sub-RTIC	N companies
Life Sciences	Biology and Biotech	1116
Life Sciences	Environmental Sciences Products and Services	2945
Life Sciences	Synthetic Biotechnology	313
Net Zero	Agri-Tech	416
Net Zero	Building Technologies	473
Net Zero	Carbon Capture	204
Net Zero	Diversion of Biodegradable Waste from Landfill	2535
Net Zero	Energy Cooperatives	522
Net Zero	Energy Storage	1222
Net Zero	Green Finance	369
Net Zero	Grid	511
Net Zero	Heating	1143
Net Zero	Low Carbon Consultancy Advisory & Offsetting Services	1292
Net Zero	Low Carbon Energy Generation	2599
Net Zero	Low Emission Vehicles	1236
Net Zero	Pollution Control and Mitigation	580
NetZero	Renewable Energy Planning Database	7381
Net Zero	Renewables	5338
Net Zero	Waste Management and Recycling	4508
Photonics	Photovoltaics	186

Table 9 Twin RTICs

RTIC	Sub-RTIC	N companies
Agri-Tech	Automation	145
Agri-Tech	Drone Technology	83
Agri-Tech	Management Platforms	169
Agri-Tech	Precision Farming	70
Agri-Tech	Remote Sensing	365
Artificial Intelligence	Green Tech	333
Electronics Manufacturing	Energy Generation or Distribution Tech	783
Energy Management	AI and IoT	397
Energy Management	Energy Management Systems	636
Energy Management	Smart Grid	154
Energy Management	Smart Meter	146
Food Tech	Agri-Tech	522
Sensors	Environmental Monitoring	1001

Table 10 Top 20 SIC codes by number of companies classified

SIC Code	SIC Description	# of companies	% of companies
82990	Other business support service activities n.e.c	13,005	0.065
62020	Information technology consultancy activities	12,143	0.061
63990	Other information technology service activities	9623	0.048
70229	Business consultancy activities other than financial management	9392	0.047
62012	Business and domestic software development	6750	0.034
96090	Other service activities n.e.c	6094	0.031
74909	Other professional, scientific and technical activities n.e.c	6020	0.030
86900	Other human health activities	5226	0.026
78109	Other activities of employment placement agencies	4978	0.025
73110	Advertising agencies	3984	0.020
74100	Specialized design activities	3551	0.018
64209	Activities of other holding companies n.e.c	3415	0.017
70100	Activities of head offices	3054	0.015
68209	Other letting and operating of own or leased real estate	2926	0.015
78200	Temporary employment agency activities	2892	0.015
86230	Dental practice activities	2789	0.014
71111	Architectural activities	2756	0.014

Table 10 (continued)

SIC Code	SIC Description	# of companies	% of companies
69102	Solicitors	2720	0.014
81210	General cleaning of buildings	2491	0.013
71129	Other engineering activities	2473	0.012

Table 11 Top 20 RTIC codes by number of companies classified

RTIC Category	sub-RTIC	# of companies	% of companies
Business Support Services	Employment and Recruitment Services	10,767	0.053
Business Support Services	Landscaping and Cleaning Services	10,064	0.049
Life Sciences	Human Health Services	9650	0.047
Net Zero	Renewable Energy Planning Database	7381	0.036
Business Support Services	Office Support Services	6818	0.033
Data Infrastructure	Data Infrastructure Services	6360	0.031
Business Support Services	Security Services	5553	0.027
Net Zero	Renewables	5338	0.026
Life Sciences	Life Sciences Manufacturing	4560	0.022
Net Zero	Waste Management and Recycling	4508	0.022
Data Infrastructure	Data Infrastructure Hardware	3687	0.018
Agency Market	Creative	3585	0.018
Media and Publishing	Printing Services	3487	0.017
Life Sciences	Research	3229	0.016
Agency Market	Performance Marketing	3214	0.016
Agency Market	Branding	3177	0.016
Rehabilitation	Psychiatric Rehabilitation	3170	0.016
Digital Creative Industries	Architecture	3103	0.015
Digital Creative Industries	Advertising	3003	0.015
Life Sciences	Environmental Sciences Products and Services	2945	0.014

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Declarations

Conflict of interests The authors declare no conflict of interests.

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References

- Abbasiharofteh M, Krüger M, Kinne J, Lenz D, Resch B (2023) The digital layer: alternative data for regional and innovation studies. *Spat Econ Anal* 18(4):507–529
- Abbasiharofteh M., Kriesch L (2024) Not all twins are identical: the digital layer of “twin” transition market applications (No. 2024/16). Lund University, CIRCLE-Centre for Innovation Research
- Arrow K (1962) The economic implications of learning by doing. *Rev Econ Stud* 29(3):155–173
- Asheim B, Boschma R, Cooke P (2011) Constructing regional advantage: platform policies based on related variety and differentiated knowledge bases. *Reg Stud* 45(7):893–904
- Bachtrögler-Unger J, Balland PA, Boschma R, Schwab T (2023) Technological capabilities and the twin transition in Europe: opportunities for regional collaboration and economic cohesion. MPRA Paper 117485, University Library of Munich, Germany
- Balland PA, Boschma R (2021) Mapping the potentials of regions in Europe to contribute to new knowledge production in Industry 4.0 technologies. *Reg Stud* 55(10–11):1652–1666
- Balland PA, Boschma R, Crespo J, Rigby DL (2019) Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Reg Stud* 53(9):1252–1268
- Barbero J, Collado LA, Rodríguez-Crespo E, Santos AM (2025) The twin transition in the European Union: assessing regional patterns of EU-funded investments. *Eur Plan Stud* 33(10):1801–1821
- Bettencourt LM (2013) The origins of scaling in cities. *Science* 340(6139):1438–1441
- Bettencourt LM, Lobo J, Helbing D, Kühnert C, West GB (2007) Growth, innovation, scaling, and the pace of life in cities. *Proc Natl Acad Sci U S A* 104(17):7301–7306
- Boschma R (2014) Constructing regional advantage and smart specialization: comparison of two European policy concepts. *Ital J Reg Sci* 13(1):51–68
- Boschma R (2017) Relatedness as a driver of regional diversification: a research agenda. *Reg Stud* 51(3):351–364
- Boschma R, Iammarino S, Steinmueller E (2013) Geography, skills and technological change. *Reg Stud* 47(10):1615–1617
- Boschma R, Frenken K (2012) Technological relatedness and regional branching. In: *Beyond territory* pp 64–68
- Breschi S, Lissoni F, Malerba F (2003) Knowledge-relatedness in firm technological diversification. *Res Policy* 32(1):69–87
- Brucek C, Losacker S, Liefner I (2025) China's digital and green (twin) transition: insights from national and regional innovation policies. *Reg Stud* 59(1):2384411

- Bürscher T, Scherngell T, Neuländtner M (2025) How does digital knowledge shape regional green diversification? European evidence from a twin transition perspective. *Reg Stud* 59(1):2564840
- Casanas CG, Kovacic Z (2025) Implementing the twin transitions: a critical perspective from the Spanish energy sector. *Environ Sci Policy* 164:104012
- Cattani L, Montresor S, Vezzani A (2025) Firms' eco-innovation and Industry 4.0 technologies in urban and rural areas. *Reg Stud* 59(1):2243984
- Cicerone G, McCann P, Venhorst VA (2020) Promoting regional growth and innovation: relatedness, revealed comparative advantage and the product space. *J Econ Geogr* 20(1):293–316
- Cicerone G, Faggian A, Montresor S, Rentocchini F (2023) Regional artificial intelligence and the geography of environmental technologies: does local AI knowledge help regional green-tech specialization? *Reg Stud* 57(2):330–343
- Consoli D, Castellacci F, Santoalha A (2023) E-skills and income inequality within European regions. *Ind Innov* 30(7):919–946
- Cortinovis N, Xiao J, Boschma R, van Oort FG (2017) Quality of government and social capital as drivers of regional diversification in Europe. *J Econ Geogr* 17(6):1179–1208
- Dahle J, Schmidt S, Lenz D, Kinne J, Dehghan R, Abbasiharofteh M, Rammer C (2025) The WebAI paradigm of innovation research: Extracting insight from organizational web data through AI (No. 25–019). ZEW Discussion Papers
- Dalum B, Laursen K, Villumsen G (1998) Structural change in OECD export specialisation patterns: despecialisation and 'stickiness.' *Int Rev Appl Econ* 12(3):423–443
- Damioli G, Bianchini S, Ghisetti C (2025) The emergence of a 'twin transition' scientific knowledge base in the European regions. *Reg Stud* 59(1):2355998
- Diodato D, Huergo E, Moncada-Paternò-Castello P, Rentocchini F, Timmermans B (2023) Introduction to the special issue on "the twin (digital and green) transition: handling the economic and social challenges." *Ind Innov* 30(7):755–765
- Faggian A, Marzucchi A, Montresor S (2025) Regions facing the 'twin transition': combining regional green and digital innovations. *Reg Stud* 59(1):2398555
- Fouquet R, Hippe R (2022) Twin transitions of decarbonisation and digitalization: a historical perspective on energy and information in European economies. *Energy Res Soc Sci* 91:102736
- Frenken K, Boschma RA (2007) A theoretical framework for evolutionary economic geography: industrial dynamics and urban growth as a branching process. *J Econ Geogr* 7(5):635–649
- Frenken K, Neffke F, van Dam A (2023) Capabilities, institutions, and regional economic development: a proposed synthesis. *Camb J Reg Econ Soc* 16(3):405–416
- Gao X (2025) The EU's twin transitions towards sustainability and digital leadership: a coherent or fragmented policy field? *Reg Stud* 59(1):2360053
- García-Riauelo Á, Duarte R, Sarasa C, Ortega-Argilés R (2025) Spatial distribution and drivers of renewable energies in European regions. *Energy Econ* 144:108340
- Grashof N, Basilico S (2025) Divergent paths for green transition: regional disparities in technology diversification. *Reg Stud* 59(1):2363327
- Grillitsch M, Asheim B (2018) Place-based innovation policy for industrial diversification in regions. *Eur Plan Stud* 26(8):1638–1662
- Henning M (2020) Regional labour flows between manufacturing and business services: reciprocal integration and uneven geography. *Eur Urban Reg Stud* 27(3):290–302
- Hidalgo CA, Hausmann R (2009) The building blocks of economic complexity. *Proc Natl Acad Sci U S A* 106(26):10570–10575
- Hidalgo CA, Klinger B, Barabási AL, Hausmann R (2007) The product space conditions the development of nations. *Science* 317(5837):482–487
- Hidalgo C, Balland PA, Boschma R, Delgado M, Feldman M, Frenken K, Glaeser E, He C, Kogler D, Morrison A, Neffke F, Rigby D, Stern S, Zheng S, Zhu S (2018) The principle of relatedness. *Springer Proceedings in Complexity*, 451–457
- Horn C, Felt U (2025) On the environmental fragilities of digital solutionism. Articulating 'digital' and 'green' in the EU's 'twin transition'. *J Environ Policy Plan* 1–19
- Iapadre PL (2001) Measuring international specialization. *Int Adv Econ Res* 7(2):173–183
- Kinne J, Lenz D (2021) Predicting innovative firms using web mining and deep learning. *PLoS ONE* 16(4):e0249071
- Kovacic Z, García Casañas C, Argüelles L, Yáñez Serrano P, Ribera-Fumaz R, Prause L, March H (2024) The twin green and digital transition: high-level policy or science fiction? *Environ Plan e Nat Space* 7(6):2251–2278

- Kriesch L, Losacker S (2024) Bioeconomy firms and where to find them. *Region* 11(1):55–78
- Kriesch L, Abbasiharofteh M, Losacker S (2025) The geography of digital and green (twin) firms in Germany. *Reg Stud Reg Sci* 12(1):513–516
- Losacker S, Hansmeier H, Horbach J, Liefner I (2023) The geography of environmental innovation: a critical review and agenda for future research. *Rev Reg Res* 43(2):291–316
- Losurdo F, Marra A, Cassetta E, Monarca U, Dileo I, Carlei V (2019) Emerging specializations, competences and firms' proximity in digital industries: the case of London. *Pap Reg Sci* 98(2):737–753
- Marshall A (1890) *Principles of Economics*. Mac-Millan
- McCann P, Ortega-Argiles R (2015) Smart specialization, regional growth, and applications to European Union cohesion policy. *Reg Stud* 49(8):1291–1302
- Nathan M, Rosso A (2015) Mapping digital businesses with big data: some early findings from the UK. *Res Policy* 44(9):1714–1733
- Neffke F, Henning M, Boschma R (2011) How do regions diversify over time? Industry-relatedness and the development of new growth paths in regions. *Econ Geogr* 87(3):237–265
- Neffke FM, Otto A, Hidalgo C (2018) The mobility of displaced workers: how the local industry mix affects job search. *J Urban Econ* 108:124–140
- Porter ME (1998) Clusters and the new economics of competition. *Harv Bus Rev* 76(6):77–90
- Rigby DL (2015) Technological relatedness and knowledge space: entry and exit of US cities from patent classes. *Reg Stud* 49(11):1922–1937
- Rocchetta S, Ortega-Argilés R, Kogler DF (2021) The non-linear effect of technological diversification on regional productivity: implications for growth and smart specialisation strategies. *Reg Stud* 56(9):1480–1495
- Rodríguez-Pose A, Bartalucci F (2024) The green transition and its potential territorial discontents. *Camb J Reg Econ Soc* 17(2):339–358
- Romer PM (1986) Increasing returns and long-run growth. *J Polit Econ* 94(5):1002–1037
- Salihu H, Jibril H, Roper S, Ortega-Argiles R, Yuan PY (2025) Mapping the innovation and digitalization infrastructure for agricultural technology in the UK
- Saviotti PP, Frenken K (2008) Export variety and the economic performance of countries. *J Evol Econ* 18:201–218
- Vale M, Peponi A, Carvalho L, Veloso AP, Queirós M, Morgado P (2024) Are peripheral regions in troubled waters for sustainability transitions? A systematic analysis of the literature. *Eur Urban Reg Stud* 31(2):116–131
- Zhang YJ, Du M (2025) Greening through digitalization? Evidence from cities in China. *Reg Stud* 59(1):2215824
- Zhang G, Tranos E, Zhu R (2025) Local demand for AI skills: a multiscale perspective in Great Britain. *Ann Am Assoc Geogr*.

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