ECONOMIC STATISTICS CENTRE OF EXCELLENCE

A COLLABORATION WITH

Office for National Statistics

Regional diversification into green and digital economic activities – The case of UK Local Authorities

Gloria Cicerone, Sebastian Losacker and Raquel Ortega-Argilés

ESCoE Discussion Paper 2024-07

July 2024

ISSN 2515-4664

DISCUSSION PAPER

Regional diversification into green and digital economic activities – The case of UK Local Authorities
Gloria Cicerone, Sebastian Losacker and Raquel Ortega-Argilés
ESCoE Discussion Paper No. 2024-07
July 2024

Abstract

Regions are currently facing a twin transition, involving a shift towards more environmentally friendly economies as well as the digitalization of economic activities. Against this backdrop, this paper examines the geography of green, digital, and twin economic activities in the UK, utilizing a novel dataset that captures these emerging sectors through a real-time industrial classification of firms. Additionally, the paper employs a relatedness approach to analyse local capabilities in the twin domain. The results underscore the crucial role of twin activities, encompassing both green and digital elements, in facilitating regional diversification into these respective sectors.

Keywords: Twin Transition; Urban Scaling; Relatedness; Regional Diversification; Industry Classification

JEL classification: O30; O32; Q55; R11

Gloria Cicerone, Gran Sasso Science Institute (GSSI), Italy and The Productivity Institute, Alliance Manchester Business School, The University of Manchester, UK
gloria.cicerone@gssi.it

Published by:
Economic Statistics Centre of Excellence
King's College London
Strand
London
WC2R 2LS
United Kingdom
www.escoe.ac.uk

Regional diversification into green and digital economic activities – The case of UK Local Authorities

Gloria Cicerone [1], Sebastian Losacker [2, 3] and Raquel Ortega-Argilés [4]

[1] Gran Sasso Science Institute (GSSI), Italy and The Productivity Institute, Alliance Manchester Business School, The University of Manchester, UK

[2] Department of Geography, Justus Liebig University Giessen, Germany

[3] CIRCLE - Center for Innovation Research, Lund University, Sweden

[4] The Productivity Institute and MIOIR, Alliance Manchester Business School, The University of Manchester, UK

Abstract

Regions are currently facing a twin transition, involving a shift towards more environmentally friendly economies as well as the digitalization of economic activities. Against this backdrop, this paper examines the geography of green, digital, and twin economic activities in the UK, utilizing a novel dataset that captures these emerging sectors through a real-time industrial classification of firms. Additionally, the paper employs a relatedness approach to analyse local capabilities in the twin domain. The results underscore the crucial role of twin activities, encompassing both green and digital elements, in facilitating regional diversification into these respective sectors.

Keywords: *Twin Transition; Urban Scaling; Relatedness; Regional Diversification; Industry Classification.*
JEL CODES: O30; O32; Q55; R11.

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 and urban studies, and related fields, as it holds significant implications for regional development (Cattani et al., 2023; Cicerone et al., 2023; Diodato et al., 2023; Zhang & Du, 2023). However, tracking green and digital economic activities in firms and across space is one of the main challenges in research on the twin transition. Traditional classification systems such as NACE and SIC, and even conventional metrics like patent data, are often inadequate in capturing the dynamic nature of these evolving sectors. This gap in measurement hinders the ability to design and implement effective policy instruments that can support and foster the twin transition. Addressing this research gap, our paper leverages a data set that provides a real-time industry classification based on machine learning techniques to identify and classify emerging sectors in the UK, specifically focusing on green, digital, and twin domains. 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 data 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. 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 geographic 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. 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, focusing on the relatedness densities in the alternate domains.

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

2. Background Literature

2.1 Defining 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 dual thrust towards greener, sustainable practices 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). Twin transition literature shows evidence that twin transition is not 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. 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 businesses operate, how work is carried out and how economic activities are managed. Empirical analyses have predicted that the twin transition has the potential to completely reshape regional economic landscapes, affecting which industries thrive and which may decline (Fouquet & Hippe, 2022; Bachtrögler-Unger et al., 2023). 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. Similarly, the green transition or move towards sustainability can spur the growth of industries such as renewable energy or sustainable agriculture, which could become the bedrock of regional economic development (Losacker et al., 2023).

However, according to recent literature, the twin transition may be linked to the potential increase of spatial inequalities and economic divergence (Cattani et al., 2023; Cicerone et al., 2023). 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 & Bartalucci, 2023). 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). Among others, this includes an evenly distributed deployment of digital infrastructure, higher support for education and training in new technologies and offering incentives for sustainable practices across a larger set of industries.

In summary, the twin transition (referring to the transformation towards a more digital and sustainable conscious practices) has significant implications for local development. The literature in economic geography shows that this change has the potential to be transformative, but also comes with associated 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 focused on both digital technology and the environment.

2.2 What kind of related diversification is needed for the twin transition?

Empirical evidence supports the idea that regional development is rooted in territorial capabilities, not a product of random events. Regional development and diversification 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 & Boschma, 2007; Saviotti and Frenken, 2008; Rigby, 2015; Boschma, 2017; Grillitsch and Asheim, 2018; Hidalgo et al., 2018). The main idea is that workers' intersectoral mobility is more likely to take place between activities that rely on similar or related capabilities (Boschma et al., 2013; Neffke et al., 2018). The emergence of new technologies and new sectors within regions reflects, indeed, the existing collective capacity of local agents to forge regions with distinctive technological and industrial structures. Consequently, diversification 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. At the same time, regions with a narrow range of activities or inadequate capabilities face considerable challenges in forging new specializations. Lagging regions can become locked into historical low-development trajectories. In these cases, finding ways to break these rather deterministic patterns to transition to higher productivity growth paths could be critical. Based on these arguments, evolutionary scholars have stressed the relevance of unrelated diversification for long-term development strategies (Saviotti, 1996; Saviotti and Frenken, 2008).

The relatedness concept is a key principle in the European Smart Specialization strategy, which supports policy prioritization and resource allocation through a bottom-up approach (Foray et al. 2009, 2012; Iacobucci, 2014; McCann and Ortega-Argilés 2015; Iacobucci and Guzzini 2016), where promising domains are not to be chosen because of their general technological appeal but because they boost regional potential and technological and productive assets already present in the region. 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). Research shows in fact that regions do tend to diversify into new fields closely related to their existing knowledge base, no matter whether it concerns diversification in new industries (Asheim et al., 2011; Neffke et al. 2011), jobs (Muneepeerakul et al. 2013) or technologies (Rigby, 2015).

When exploring local industrial diversification and development, it is important to consider the twin transition and the role of industry-relatedness. 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 diversify into new yet interconnected economic activities (Boschma, 2017; Frenken et al., 2023; Neffke et al., 2011). Understanding the dynamics of relatedness within the context of the twin transition is crucial in guiding local areas to understand potential strategic pathways for leveraging existing local strengths and capabilities and embrace new opportunities in the green and digital domains.

Recent studies explore the interplay between green and digital economies, within the twin transition framework (Cicerone et al., 2023; Bachtrögler-Ungeret et al., 2023). However, it is still not clear how the green and digital sectors can complement each other to achieve mutual benefits. 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.

In regions where there is an important presence of green industries, like renewable energy or sustainable manufacturing, a dense network of individuals and resources can facilitate diversification into digital or twin domains. The incorporation of digital technologies in these green industries, such as the use of smart grids in renewable energy, demonstrates how regions can leverage their green relatedness to branch into digital fields. It is important to consider that regions with a high degree of relatedness in digital domains may have an advantage in diversifying into green and twin fields. The skills and infrastructure developed in the digital arena, such as advanced data analytics and artificial intelligence, can be a valuable asset for many green industries. On the other hand, the converse is also true – regions with a strong presence in green or twin sectors may have the potential to develop their digital capabilities and gain competitiveness in the digital domain. In conclusion, the interplay of green and digital is central to navigate the twin transition effectively at firm, industry, local and regional levels.

3. Empirical strategy

3.1 Data

Digital and green industries are increasingly recognized for their pivotal role in driving local economic growth, as many other emerging sectors. Identifying and measuring with accuracy emerging sectors has associated important challenges. By its very nature, digital and green sectors are challenging to classify in rigid, top-down categories due to their evolving features (Nathan & Rosso, 2015). For this reason, the application of Standard Industrial Classification (SIC) codes to emerging sectors such as digital green industries has been questionable. 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 & Rosso, 2015).

Emerging industries are normally constituted by numerous small and young firms in line of 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. In the literature, there have been various attempts to capture and measure specializations in both high-tech/digital and green sectors. They involved traditional methods like the use of SIC codes, as well as innovative and 'unstructured' data sources, such as company websites and databases with advanced tagging systems and alternative industry category codes (Nathan & Rosso, 2015). Despite these methods, the constant transformation of these sectors makes them particularly difficult to categorize accurately across time. Standard Industrial Classification (SIC) codes, last updated in 2007, are indeed outdated and misaligned with today's dynamic industries such as FinTech and AI. This rigid, one-size-fits-all system leads to misclassification, vague insights, and missed opportunities. For this reason, expanding on the use of Real-Time Industrial Classifications (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 & Lenz, 2021; Kriesch & Losacker 2024).

Developing industry-relatedness metrics with RTICs facilitates accurate computation of current proximities between different sectors in regional economies. In this paper, RTICs from The Data City (www.thedatacity.com) are employed 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 firm-level analysis of the composition and characteristics of these sectoral domains. The Data City provides real-time data on the UK's business landscape, offering comprehensive information on over 5 million companies. Their platform includes detailed information on each company such as company category, growth stage, employee data, turnover rate, sector classifications, and location.

Real-Time Industrial Classifications (RTICs) offer insights into around 51 sectors, including AI, Life Sciences, FinTech, and 385 sub-sectors. RTICs provide an up-to-date understanding of emerging industries. The Data City uses web scraping techniques to gather real-time data from various sources across the internet. The data is updated bi-monthly and sourced from reputable entities like Companies House, CreditSafe, and Dealroom.co, ensuring high accuracy and reliability for various uses, including government policy, economic consulting, and corporate finance. A sophisticated approach blends machine learning algorithms with specialized training by experts within business, consulting, policy, and academia to accurately classify and understand the current firm activities and specializations.

This study is one of the pioneering efforts to investigate this new data source, demonstrating its promising utility for future research endeavors. The dataset includes information on over 200,000[1] companies and 385

[1] The total number of companies listed as individual legal entities and flagged as active is approximately 5 million. However, only 2 million of these companies have an online presence, and among them, more than 200,000 are classified in an RTIC.

subsectors, of which we linked 166 to digital sectors, 45 to green sectors, and 13 to the twin domain. 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. We collaboratively refined and validated this classification through a triangulation process. Still, there are some limitations to the data. 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 scrapping 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. However, we argue that despite these limitations, the data and our approach provide a useful basis for analysing the geography of green, digital, and twin activities in UK firms. In a last step, the company data is 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, this methodology offers a comprehensive and contemporary lens through which the economic geography of the UK can be analysed and understood.

3.2 Methods

Our data set provides a granular, up-to-date representation of firm activities, as a proxy for their capabilities and competencies. Through network analysis, we draw connections (henceforth *proximities*) between firms' activities, thereby identifying key emerging activities in the digital, green, and twin sectors and highlighting their most significant interconnections. These connections illustrate the various forms of market, technological, and cognitive proximities between industries and represent the basis of relatedness metrics.

The degree of proximity between pairs of industries is computed using network analysis tools to create a network of fields of activity in which firms are involved. The network is based on a dummy matrix X, where columns represent industries (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 industries will appear together within the same economic context, such as within a company in this case. The proximity between two industries is high if they frequently co-occur, implying that they share similar capabilities, resources, or technological requirements.

For instance, consider industry A and industry B. These industries will exhibit high proximity 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 & 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. The larger the intersection of the needed capabilities, the greater the number of firms where the two industries exhibit such co-occurrence, and the closer their proximity. Formally, the *proximity* index between each pair of industries i and z 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 z and the conditional probability of a company being specialized in industry z 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 RCA of company c in sector i is higher than 1 and zero otherwise and where the conditional probability is calculated using all companies c. The higher the value of the proximity values, the more interconnected the network.

If two specializations (and the embedded competences) coexist internally within many firms (many firms are involved in both simultaneously), it is highly likely that they (the two specializations) are well connected, and therefore, if a company is specialized in only one of them, the other industry represents a good diversification option and driver by which the firm could grow.

We applied these methods to both 51 RTICs and 385 sub-RTICs. Network representations are useful to show the links between industries, which include relationships that have not yet been recognized but which are based on common competences. Due to space limitations, we only show the network of RTICs (51 nodes) linked together by their degree of connectedness (proximity) (see Figure 1). 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.

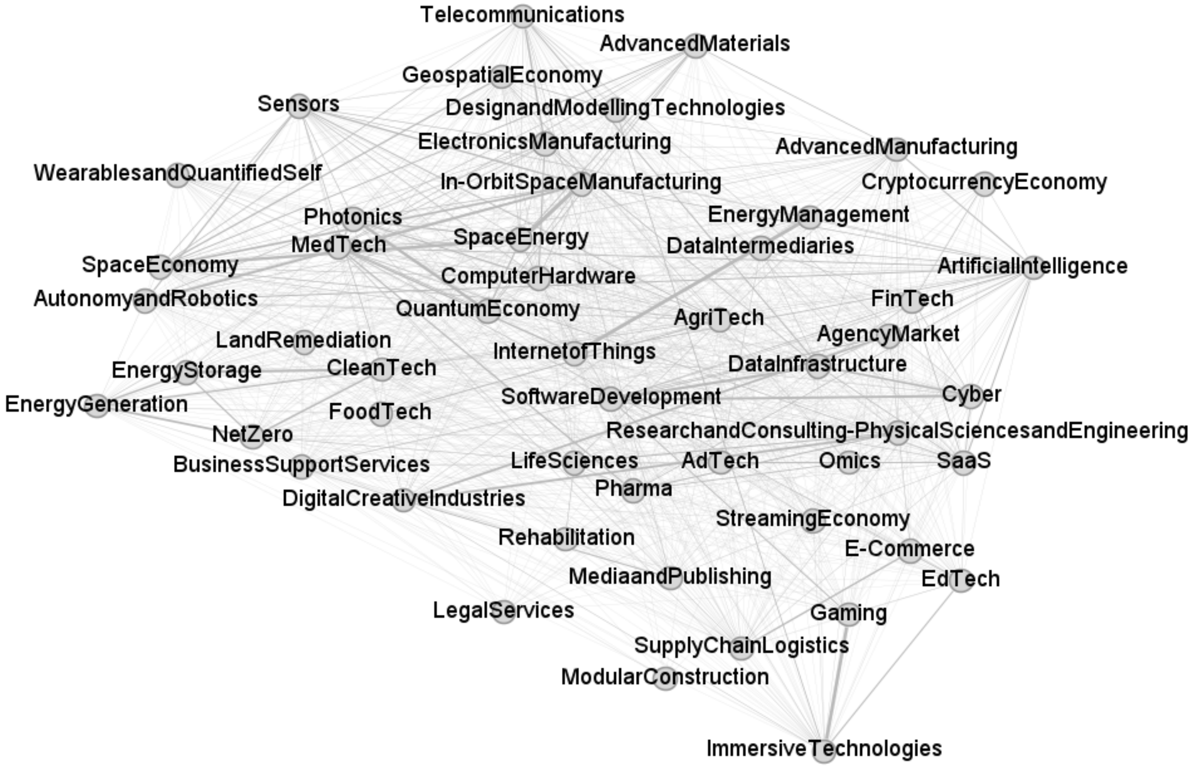

Figure 1: Network representation of the RTICs (51 nodes). Thicker links represent stronger connections, nodes represent RTICs. For visual clarity and ease of explanation, we display the RTIC network, as the sub-RTIC network is too dense and extensive for effective visual assessment.

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

Industry A	*Industry B*	*Proximity*
Space Economy: Engineering	Space Economy: In-orbit manufacturing	822
Sensors: Environmental Monitoring	Sensors: Industry4.0	604
Quantum Economy: Photonics	Quantum Economy: Quantum Computing	596
Space Economy: Launch Services	Space Economy: Launch Vehicles	564
Space Economy: Launch Infrastructure	Space Economy: Launch Services	554
AdTech: Programmatic Platforms	AdTech: Publishers	537
Computer Hardware: Semiconductor electronics	Electronics Manufacturing: Electronic components and boards	532
In-Orbit Space Manufacturing: Debris	Space Energy: Space Infrastructure	528
NetZero: Diversion of Biodegradable Waste	NetZero: Waste Management and Recycling	518
Geospatial Economy: Data Capture	Geospatial Economy: Data Processing and Visualizations	515

In the next step, we use the proximity index to compute relatedness metrics. The application of relatedness 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 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 toward those activities that reveal an affinity to the regional economy (Asheim et al., 2011; Foray et al., 2012; Boschma, 2014; Valdaliso et al., 2014; Foray, 2015; McCann & Ortega-Argilés, 2015; Iacobucci & Guzzini, 2016; Boschma, 2017; D'Adda et al., 2019b; Whittle, 2020; Boschma, 2021). 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 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., 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 the three types of relatedness (digital, green and twin) on the regional development of new fields. In order to compute the *digital relatedness*, we first compute the standard local relatedness 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 (relative comparative advantage) 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 (1). In a second step, we average the links (or *proximities*[2] $\phi_{i,j}$) connecting the focal industry *i* to only digital industries *j* which the local authority *r* is specialized in. Formally:

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

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

where: $$j_{\square} = \begin{cases} 1 & if\ j\ is\ a\ digital\ industry \\ 0 & otherwise \end{cases}$$

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

[2] We recall here that proximities are computed based on the co-occurrence in the company level matrix.

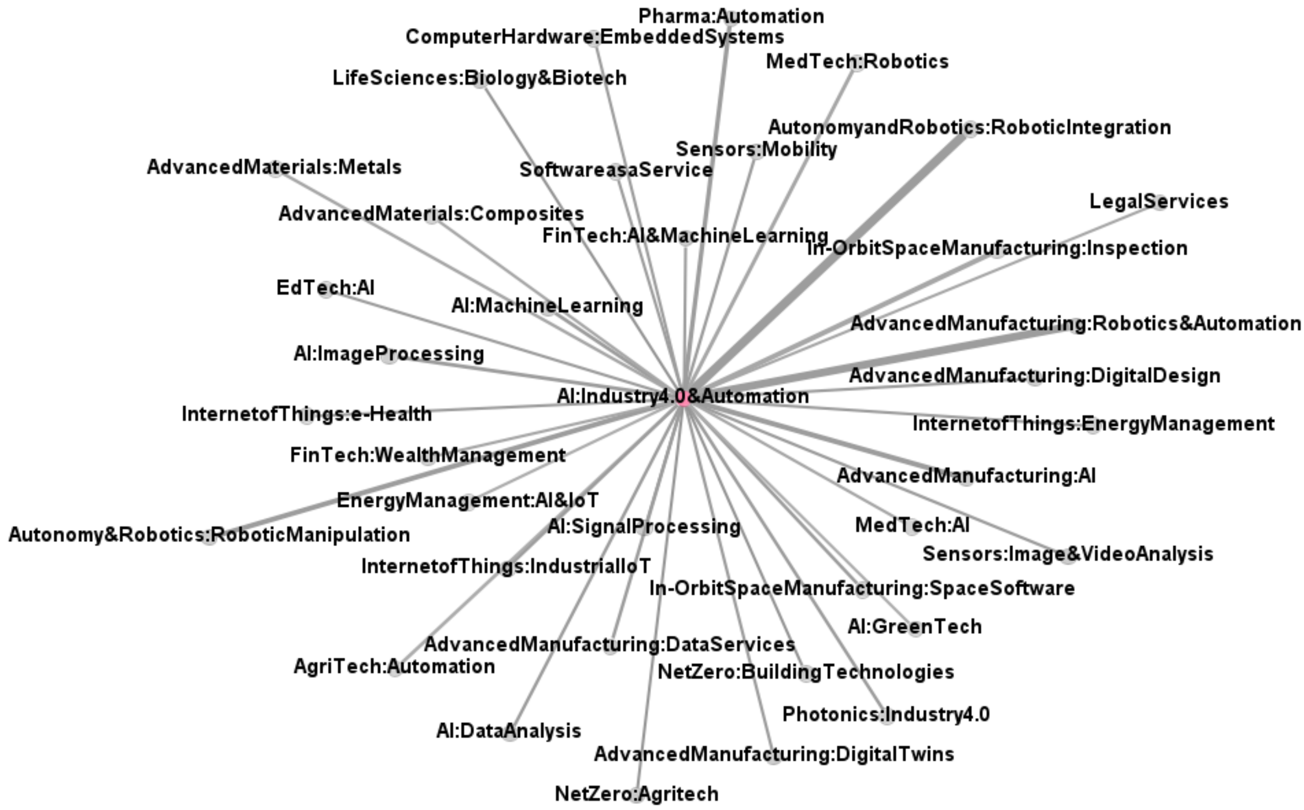

Figure 2: Network representation of subRTICs (nodes) and their proximities (links) with a focal exemplary industry "AI: industry 4.0 and automation" (red node). Thicker links represent stronger connections. Weaker links and the related nodes are not displayed. Because of space limitation, only a random sample of the total 385 subRTICS have been represented.

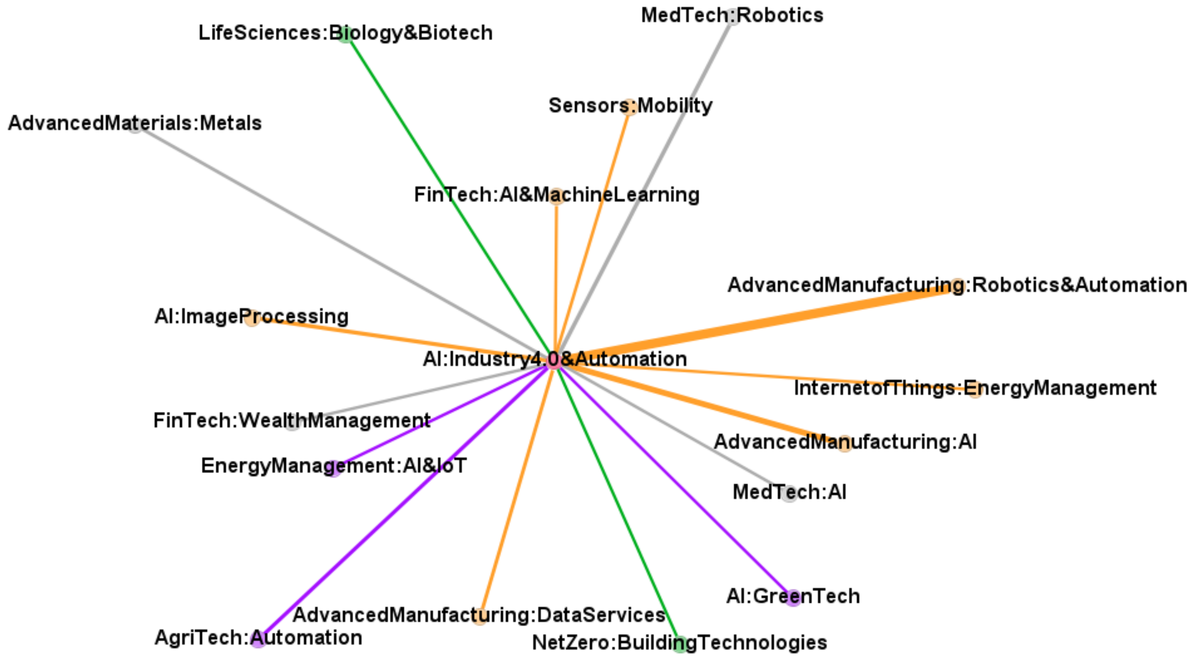

Figure 3. Network representation of subRTICs (nodes) and their proximities (links) with the focal exemplary industry "AI: specialization industries" (nodes) and their proximities (links). Partitions identify the digital (orange), green (green) and twin (violet) industries. Weaker links and the related nodes are not displayed.

4. Results

4.1 Geography of the twin transition in the UK

To begin, we employ maps to gain insights into the geographic distribution of the twin transition across the UK (see maps in Figure 4). We illustrate the specialization levels (RCA), in green, digital, and twin industries at the local authority level. Additionally, we present the spatial distribution of the relatedness density within these industries. Analysing the specializations, several intriguing patterns emerge. First, digital industries appear predominantly concentrated in the South of England, particularly 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 & 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 i at time t and its population N. This relationship is modelled by a power law function:

$$Y_{i,t} = \alpha N_{i,t}^{\beta}$$

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 super-linearly 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 sub-linear 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:

$$\ln Y_{i,t} = \alpha + \beta \ln N_{i,t} + \epsilon_{i,t}$$

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 Figure A.4 in Appendix A. 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.

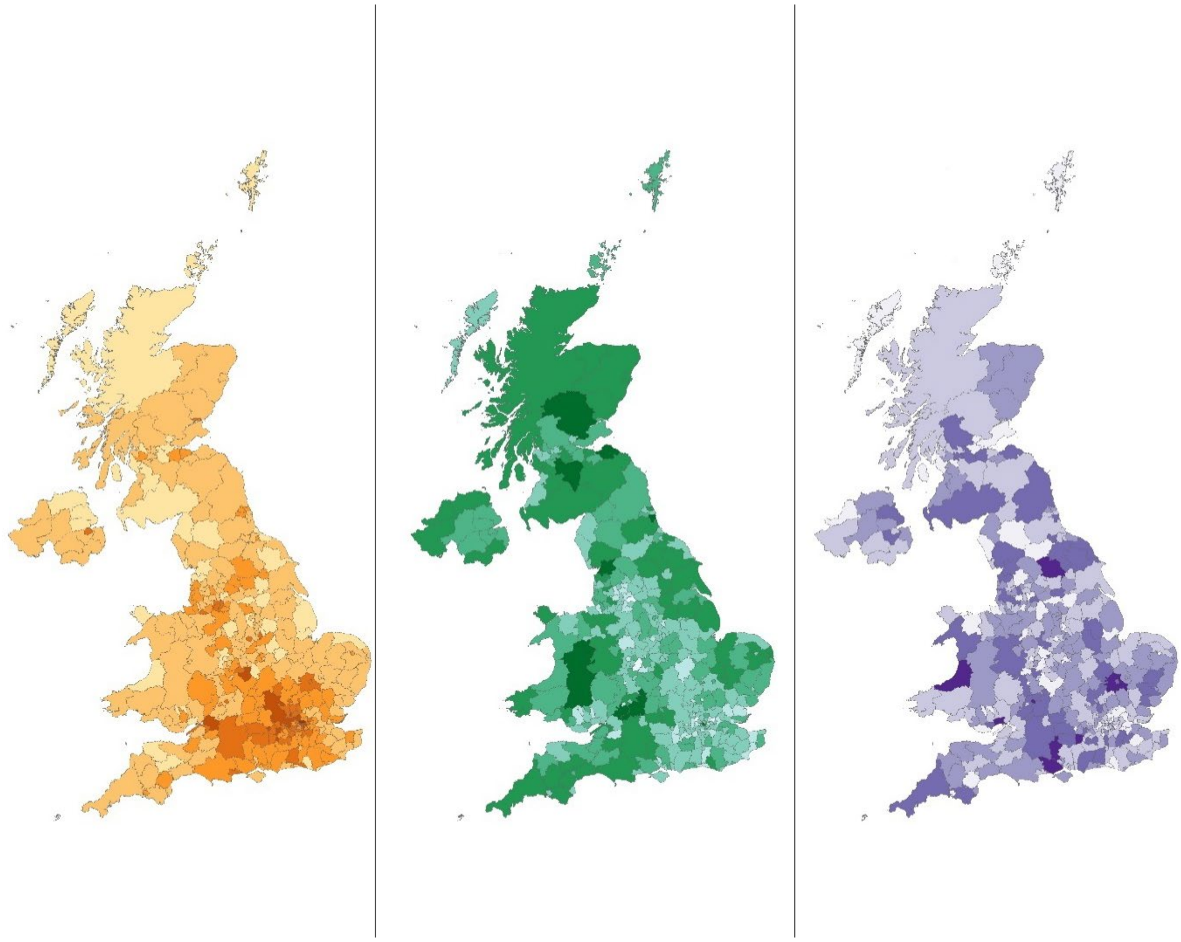

Figure 4: Unequal potential of UK local authorities to develop digital, green and twin technologies. Notes: This figure shows the potential of UK local authorities to develop digital (left panel), green (central panel) and twin (right panel) technologies in the future. The values used are relatedness density scores averaged across all digital, green, and twin sub-RTICs. A darker color denotes a higher potential.

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

	Dependent variable:					
	Digital Companies	Non-digital Companies	Green Companies	Non-green Companies	Twin Companies	Non-twin Companies
	(1)	(2)	(3)	(4)	(5)	(6)
Population	1.276***	1.062***	0.918***	1.176***	0.887***	1.115***
	(0.060)	(0.040)	(0.049)	(0.048)	(0.062)	(0.044)
Constant	-9.633***	-6.044***	-5.734***	-7.319***	-7.803***	-6.381***
	(0.718)	(0.479)	(0.588)	(0.576)	(0.745)	(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***

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

4.2 Relatedness and regional diversification

We conducted a series of regression analyses to explore the relationship between the relatedness of local-industry observations in green, digital, and twin sectors and local competitive advantages (RCA) 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 competitive advantages in each sector (digital, green, and twin), treating them as dependent variables. The key independent variable in these models is the relatedness 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 (see Figures A.1, A.2, A.3 in Appendix A for additional maps). We also account for unobserved heterogeneity at the regional and industry levels, including fixed effects for both. In addition, we ran the same models with standard errors clustered by regions, pointing to very similar results.

$$\boldsymbol{DigitalRCA}_{i,r} = \alpha + \delta \boldsymbol{GreenRel}_{\boldsymbol{i,r}} + \delta \boldsymbol{TwinRel}_{\boldsymbol{i,r}} + \theta \bar{X}_{r,t-1} + \vartheta_t + \mu_c + \varepsilon_{c,r,t}$$
$$\boldsymbol{GreenRCA}_{i,r} = \alpha + \delta \boldsymbol{DigitalRel}_{\boldsymbol{i,r}} + \delta \boldsymbol{TwinRel}_{\boldsymbol{i,r}} + \theta \bar{X}_{r,t-1} + \vartheta_t + \mu_c + \varepsilon_{c,r,t}$$
$$\boldsymbol{TwinRCA}_{i,r} = \alpha + \delta \boldsymbol{DigitalRel}_{\boldsymbol{i,r}} + \delta \boldsymbol{GreenRel}_{\boldsymbol{i,r}} + \theta \bar{X}_{r,t-1} + \vartheta_t + \mu_c + \varepsilon_{c,r,t}$$

Our findings, detailed in Table 3, reveal nuanced intersectoral 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. 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 sectors. These insights are crucial for several reasons. Firstly, they challenge the inherent synergies between the green and digital industries. While these sectors do support each other, their interrelationship is complex and moderated significantly by the presence of twin industries. Secondly, this finding underscores the necessity for researchers to focus on the twin transition to broaden their scope. 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 broader perspective is essential to fully understanding and leveraging the dynamics of the twin transition.

As a robustness check, we also compute the symmetric RCA, whose values vary between -1 and 1, and replace it with the standard RCA on the left side of the regressions. This allows us to select only the specializations (y=RCA >0) in each macro-sector (digital, green, twin). Results are consistent with those from previous baseline models.

In the next step, we split our dataset into two categories: most 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 across green, digital, and twin sectors. This analysis uncovers consistent industry dynamics across local authorities. This suggests 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. The results are detailed in Appendix B.

Table 3: Relative comparative advantage RCA (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 LAs and 385 industries).

	Dependent variable:		
	Digital RCA	Green RCA	Twin RCA
	(1)	(2)	(3)
Green Relatedness	0.053^{***}		0.051^{***}
	(0.012)		(0.004)
Digital Relatedness		0.016^{***}	0.023^{***}
		(0.004)	(0.002)
Twin Relatedness	0.344^{***}	0.233^{***}	
	(0.027)	(0.015)	
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	-0.081^{*}	-0.078^{***}
	(0.080)	(0.043)	(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 = 126005)	0.283	0.151	0.083
F Statistic (df = 714; 126005)	55.943^{***}	77.878^{***}	89.093^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

5. Conclusion and Discussion

In conclusion, our research sheds new light on the "twin transition" in the UK, a phenomenon characterized by the concurrent shift towards sustainable, greener practices and rapid digitalization in economic activities.

By employing innovative Real-Time Industry Classification (RTIC) data, this study surpasses traditional methods in capturing the evolving landscape of green, digital, and twin sectors. Our analysis reveals significant geographical variations in the distribution of these sectors across the UK, with implications for local development and policy-making. 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 delves into the concept of industry-relatedness, uncovering interconnections among green, digital, and twin sectors. While green and digital sectors already display positive synergies, they benefit even more from the relatedness of twin sectors, which embody characteristics of both. This insight is crucial for understanding the dynamics of local economic restructuring in the context of the twin transition.

In that regard, understanding the synergies between these two transitions 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 necessity of tailored approaches to harness the benefits of this transition, considering the unique economic and industrial landscapes of UK local areas.

We advocate for future studies to conduct in-depth analyses of specific local 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.

References

Abbasiharofteh, M., Krüger, M., Kinne, J., Lenz, D., & Resch, B. (2023). The digital layer: alternative data for regional and innovation studies. *Spatial Economic Analysis*, 1-23.

Asheim, B., Boschma, R., and Cooke, P. (2011) Constructing regional advantage: platform policies based on related variety and differentiated knowledge bases. *Regional Studies* 45(7), 893–904.

Bachtrögler-Unger, J., Balland, P. A., 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.

Bettencourt, L. M. (2013). The origins of scaling in cities. *Science*, 340(6139), 1438-1441.

Bettencourt, L. M., Lobo, J., Helbing, D., Kühnert, C., & West, G. B. (2007). Growth, innovation, scaling, and the pace of life in cities. *Proceedings of the National Academy of Sciences*, 104(17), 7301-7306.

Boschma, R. (2014). Constructing regional advantage and smart specialization: Comparison of two European policy concepts. *Italian Journal of regional Science:* 13(1), 51-68.

Boschma, R. (2017). Relatedness as a driver of regional diversification: A research agenda. *Regional Studies*, 51(3), 351-364.

Boschma, R. (2021). Designing Smart Specialization Policy: relatedness, unrelatedness, or what? *Papers in Evolutionary Economic Geography (PEEG)* 2128, Utrecht University, Department of Human Geography and Spatial Planning, Group Economic Geography, revised Sep 2021.

Boschma, R., & Frenken, K. (2012). *Technological relatedness and regional branching*. In: Beyond territory (64-68).

Boschma, R., Iammarino, S., & Steinmueller, E. (2013). Geography, skills and technological change. *Regional Studies*, 47(10), 1615-1617.

Breschi, S., Lissoni, F., & Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. *Research Policy*, 32(1), 69-87.

Cattani, L., Montresor, S., & Vezzani, A. (2023). Firms' eco-innovation and Industry 4.0 technologies in urban and rural areas. *Regional Studies*, 1-13.

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?. *Regional Studies*, 57(2), 330-343.

Cortinovis, N., Xiao, J., Boschma, R., & van Oort, F. G. (2017). Quality of government and social capital as drivers of regional diversification in Europe. *Journal of Economic Geography*, *17*(6), 1179-1208.

D'Adda, D., Iacobucci, D. and Palloni, R. (2019) Relatedness in the implementation of Smart Specialization Strategy: a first empirical assessment, *Papers in Regional Science*, doi: 10.1002/pirs.12492

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". *Industry and Innovation*, 30(7), 755-765.

Foray, D. (2015) *Smart Specialization: Opportunities and Challenges for Regional Innovation Policy*. London: Routledge.

Foray, D., David, P. A., & Hall, B. (2009). Smart specialisation–the concept. *Knowledge economists policy brief,* 9(85), 100.

Foray, D., Goddard, J., Beldarrain, X. G., Landabaso, M., McCann, P., Morgan, K., Nauwelaers, C., Ortega-Argiles, R. & Mulatero, F. (2012). *Guide to Research and Innovation Strategies for Smart Specialisations (RIS 3)*, Brussels.

Fouquet, R., & Hippe, R. (2022). Twin transitions of decarbonisation and digitalization: A historical perspective on energy and information in European economies. *Energy Research & Social Science*, 91, 102736.

Frenken, K., & Boschma, R. A. (2007). A theoretical framework for evolutionary economic geography: industrial dynamics and urban growth as a branching process. *Journal of economic geography*, 7(5), 635-649.

Frenken, K., Neffke, F., & van Dam, A. (2023). Capabilities, institutions, and regional economic development: a proposed synthesis. *Cambridge Journal of Regions, Economy, and Society*, 16(3), 405-416.

Grillitsch, M., & Asheim, B. (2018). Place-based innovation policy for industrial diversification in regions. *European Planning Studies*, 26(8), 1638-1662.

Hidalgo, C., Balland, P.A., 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.

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26), 10570-10575.

Hidalgo, C. A., Klinger, B., Barabási, A. L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science* 317(5837): 482–487

Iacobucci, D. (2014). Designing and implementing a smart specialisation strategy at regional level: Some open questions. *Italian Journal of regional Science:* 13(1), 107-126.

Iacobucci, D., & Guzzini, E. (2016). Relatedness and connectivity in technological domains: Missing links in S3 design and implementation. *European Planning Studies*, *24*(8), 1511-1526.

Kinne, J., & Lenz, D. (2021). Predicting innovative firms using web mining and deep learning. *PloS one*, *16*(4), e0249071.

Kriesch, L., & Losacker, S. (2024). Bioeconomy firms and where to find them. *REGION*, 11(1), 55-78.

Losacker, S., Hansmeier, H., Horbach, J., & Liefner, I. (2023). The geography of environmental innovation: A critical review and agenda for future research. *Review of Regional Research*, 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. *Papers in Regional Science*, *98*(2), 737-753.

McCann, P., & Ortega-Argiles, R. (2015) Smart specialization, regional growth, and applications to European Union Cohesion Policy. *Regional Studies* 49(8), 1291–1302.

Nathan, M., & Rosso, A. (2015). Mapping digital businesses with big data: some early findings from the UK. *Research 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. *Economic geography*, *87*(3), 237-265.

Neffke, F. M., Otto, A., & Hidalgo, C. (2018). The mobility of displaced workers: How the local industry mix affects job search. *Journal of Urban Economics*, 108, 124-140.

Rigby, D. L. (2015). Technological relatedness and knowledge space: entry and exit of US cities from patent classes. *Regional Studies*, 49(11), 1922-1937.

Rodríguez-Pose, A., & Bartalucci, F. (2023). The green transition and its potential territorial discontents. *Cambridge Journal of Regions, Economy, and Society*.

Saviotti, P. P. (1996). Technological evolution, variety and the economy. Books.

Saviotti, P. P., & Frenken, K. (2008). Export variety and the economic performance of countries. *Journal of Evolutionary Economics*, 18, 201-218.

Valdaliso, J. M., Magro, E., Navarro, M., Aranguren, M. J., & Wilson, J. R. (2014) Path dependence in policies supporting smart specialisation strategies: Insights from the Basque case. *European Journal of Innovation Management,* 17 (4), 390–408.

Whittle, A. (2020) Operationalizing the Knowledge Space: Theory, Methods, and Insights for Smart Specialization. *Regional Studies, Regional Science* 7 (1), 27–34.

Zhang, Y. J., & Du, M. (2023). Greening through digitalization? Evidence from cities in China. *Regional Studies*, 1-15.

Appendix A

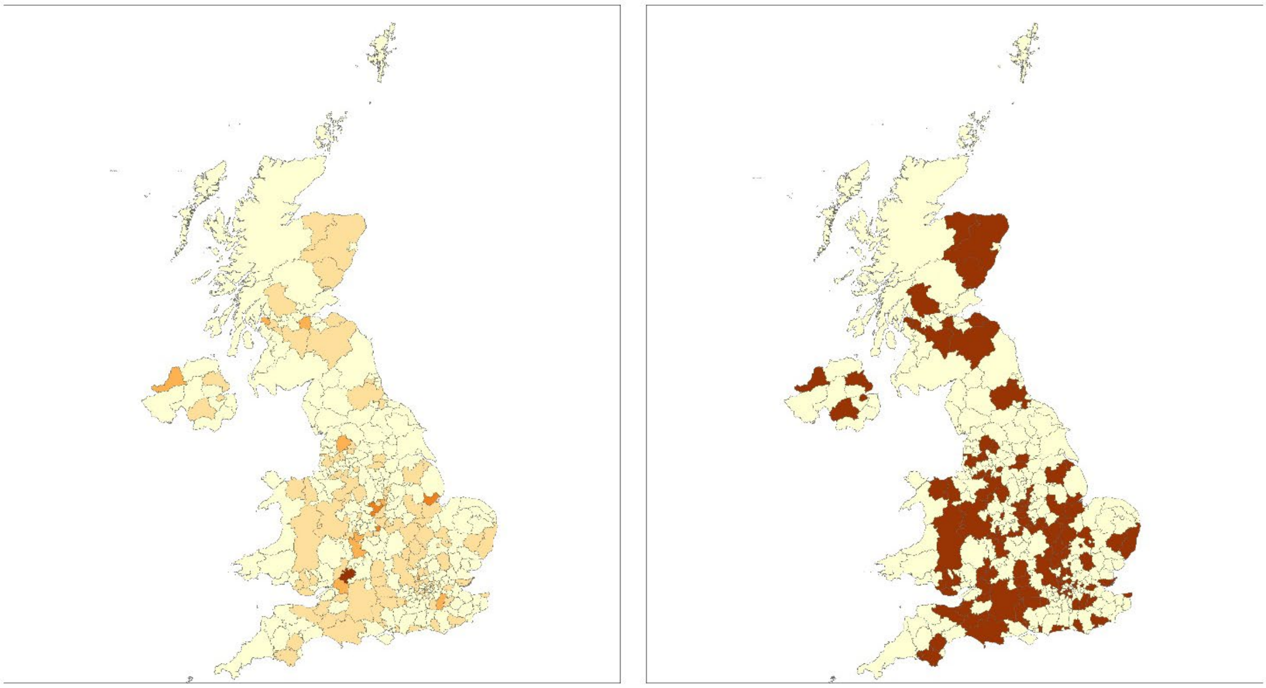

Figure A.1: Specialization of UK local authorities in Artificial Intelligence Industry 4.0 and Automation. Notes: The left panel shows the RCA (share of companies involved in the focal industry in a region in relation to the average share among all regions) where a darker color denotes a higher specialization. The right panel shows the binary equivalent of the RCA values.

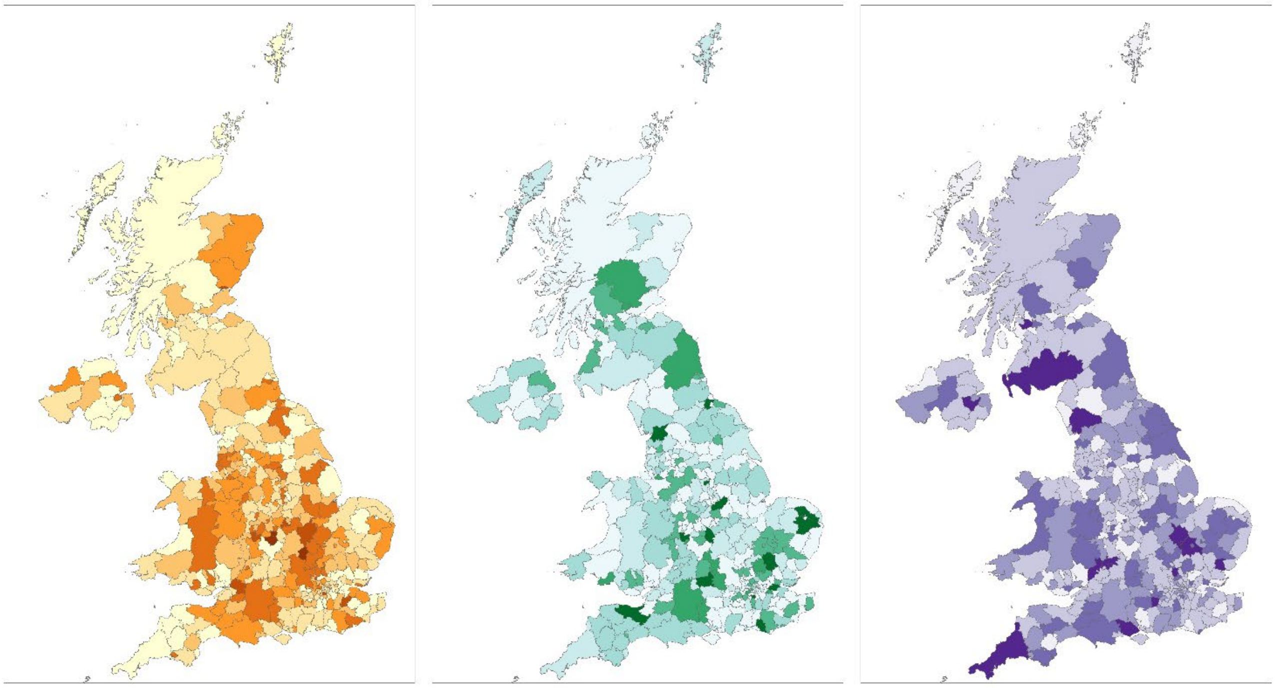

Figure A.2: The Relatedness of Artificial Intelligence Industry 4.0 and Automation with the digital, green and twin UK specializations. Notes: This figure shows the potential of UK local authorities to develop Artificial Intelligence Industry 4.0 and Automation, given the current digital (left panel), 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 color denotes a higher connection.*

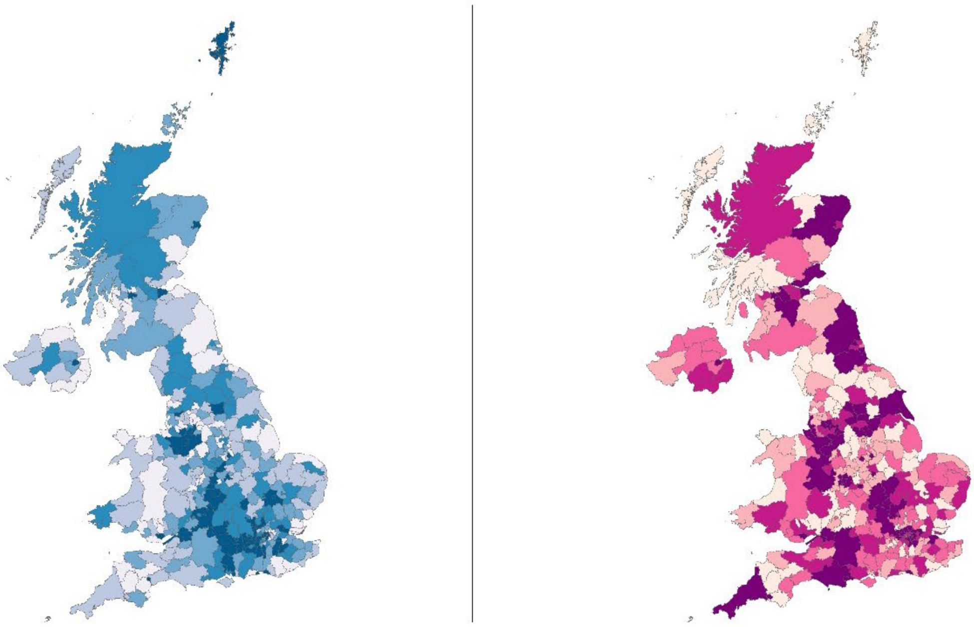

Figure A.3: GDP per person and population of UK local authorities. Notes: This figure shows GDP per person (left panel) and population in absolute values (right panel) of UK local authorities. A darker color denotes a higher connection. Maps are in quantiles.

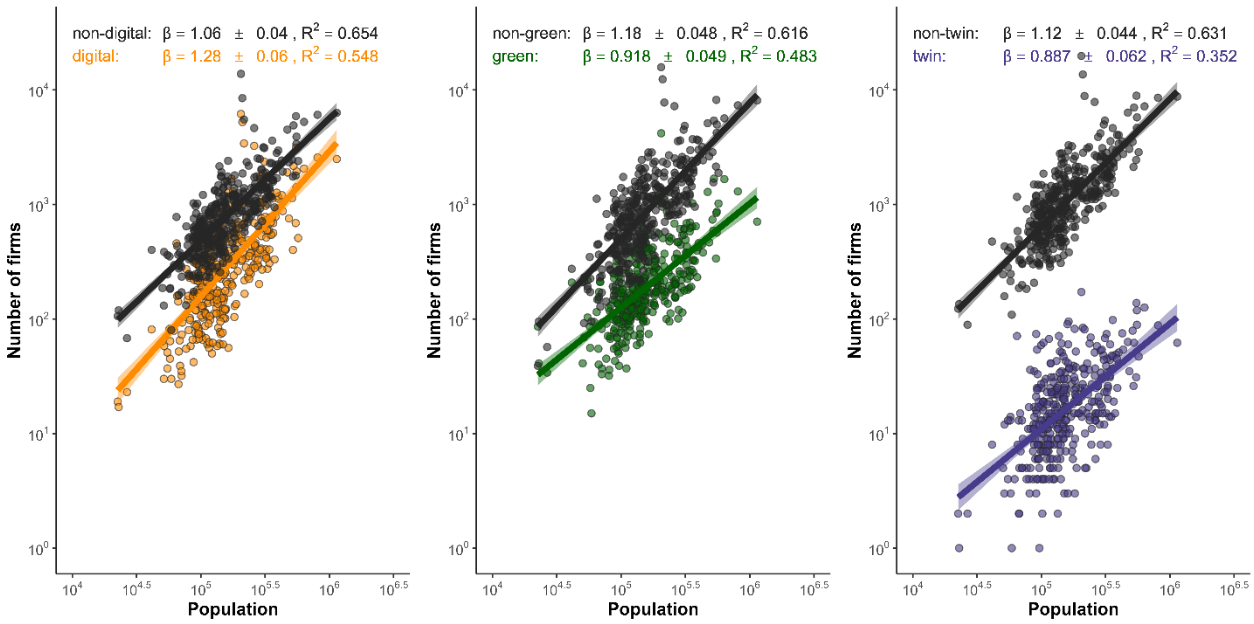

Figure A.4: Urban Scaling laws for digital, green and twin sectors. Notes: This figure shows the urban scaling laws for the digital (left panel), green (central panel) and twin (right panel) sectors. Scaling coefficients larger than 1 indicate increasing returns to scale, meaning that firms in the respective sector concentrate in more populated areas.

Appendix B

Table B.1: 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.

	Dependent variable:					
	Digital RCA		Green RCA		Twin RCA	
	High GDPpp regions	Low GDPpp regions	High GDPpp regions	Low GDPpp regions	High GDPpp regions	Low GDPpp regions
	(1)	(2)	(3)	(4)	(5)	(6)
Green Relatedness	0.060^{***}	0.040^{***}			0.062^{***}	0.047^{***}
	(0.023)	(0.014)			(0.006)	(0.004)
Digital Relatedness			0.015^{***}	0.015^{***}	0.022^{***}	0.025^{***}
			(0.006)	(0.005)	(0.003)	(0.003)
Twin Relatedness	0.369^{***}	0.334^{***}	0.264^{***}	0.225^{***}		
	(0.050)	(0.032)	(0.025)	(0.018)		
PATpp	yes	yes	yes	yes	yes	yes
POP density	yes	yes	yes	yes	yes	yes
GDPpp	yes	yes	yes	yes	yes	yes
Industry FEs	yes	yes	yes	yes	yes	yes
Local authority FEs	yes	yes	yes	yes	yes	yes
Constant	0.370^{***}	-0.028	-0.051	-0.081^{*}	-0.032	-0.077^{***}
	(0.072)	(0.076)	(0.036)	(0.043)	(0.020)	(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 = 42128)	0.267 (df = 83492)	0.151 (df = 42128)	0.150 (df = 83492)	0.085 (df = 42128)	0.082 (df = 83492)
F Statistic	33.980^{***} (df = 495; 42128)	40.955^{***} (df = 603; 83492)	35.178^{***} (df = 495; 42128)	66.896^{***} (df = 603; 83492)	47.369^{***} (df = 495; 42128)	70.177^{***} (df = 603; 83492)
Note:						*p<0.1; **p<0.05; ***p<0.01