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D1.2 The geography of the green, digital and twin technological and scientific specialisation in Europe

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List of Abbreviations

CPC	Cooperative Patent Classifications
DAT	Digital Automation Technologies
EU	European Union
EPO	European Patent Office
OECD	The Organisation for Economic Co-operation and Development
PCT	The International Patent Office
WIPO	World Intellectual Property Organisation
USPTO	The United States Patent and Trademark Office

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1. Introduction

The convergence of digital and green transitions has the potential to address interconnected social, economic and environmental challenges. This convergence, referred to as the twin transition agenda, aims to foster economic growth, enhance competitiveness, and accelerate progress toward sustainability goals (European Commission et al., 2022). While this convergence offers opportunities for transformative change (Bachtrögler-Unger et al., 2023; Piscicelli, 2023), it also poses risks of deepening existing inequalities (Bohnsack et al., 2022; Ha et al., 2022; Mäkitie et al., 2023). Recognising these challenges, the European Commission emphasises the need to ensure that all European regions benefit from the development of digital and green technologies (European Commission, 2024). However, disparities across regional innovation portfolios may constrain their capacity to implement this strategy effectively (Bachtrögler-Unger et al., 2023)

The twin transition is a policy-oriented agenda designed to bridge digital and green transitions (Aloisi, 2025; European Commission et al., 2022). A key question is whether this convergence is occurring and, if so, how it unfolds. Assessing the distribution of regional innovation portfolios is essential in understanding the capabilities of European regions in digital and green technologies and identifying those with the potential to integrate both. While some regions may have developed expertise exclusively in one of these domains, others may have developed in both, strengthening their ability to advance twin technologies. In contrast, regions with weak innovation portfolios in both domains risk lagging behind in industrial development and, consequently, in their competitiveness.

In this context, Bachtrögler-Unger et al. (2023) identified regions optimally positioned to advance digital and green technologies, revealing significant differences in innovation portfolios among high-, middle-, and low-income regions. For instance, high-income regions such as Oberbayern in Germany and Île-de-France in France exhibit strong technological capabilities in both green and digital technologies, whereas regions in Eastern Europe with weaker technological infrastructures face substantial barriers in producing digital and green technologies. This uneven landscape highlights the complexities of integrating digital and green technologies across regions with uneven innovation portfolios, underscoring the need for a deeper understanding of how twin technologies emerge and evolve.

To gain a better understanding of the emergence of twin technologies and the inequalities arising from uneven regional technological capabilities (innovation portfolios), this report examines the cognitive, social, and geographical convergence of digital and green technologies. Specifically, **Deliverable 1.2** addresses two complementary aims: *Landscaping the Green, Digital and Twin Technologies and Mapping Technological Capabilities of European Regions and Cities* (**T1.2**) and *Mapping Green, Digital and Twin Scientific Specialisation in Europe* (**T1.3**). Our proxy of regional technological capabilities is assessed using patent and scientific publications (innovation portfolios), while specialisation is assessed using complex system indicators. The analysis provides a comprehensive perspective on regional disparities in the production of digital and green technologies and their potential to generate twin technologies.

Our framework builds on the idea that synergistic interactions between unrelated knowledge domains can drive the emergence and development of new technologies (Boschma, 2017; Boschma et al., 2017; Castaldi et al., 2015; Frenken et al., 2007). In this context, cognitive convergence between distinct domains (Arroyave et al., 2021; Petersen et al., 2021), such as digital and green technologies, creates

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a shared knowledge space, which facilitates the further development of twin technologies. Moreover, cross-regional collaboration plays a crucial role in diversifying the emerging knowledge space through cross-fertilisation between regions (Balland and and Boschma, 2021), fostering diverse technological advancements in digital and green domains. However, this shared knowledge space is often co-located within regions (Heimeriks and Balland, 2016), as both tacit and codified knowledge are inherently place-dependent and digital and green might share knowledge infrastructures within regions. Therefore, evaluating **cognitive and social convergence within regions** is essential for understanding the uneven distribution of shared knowledge space and its implications for regional inequalities.

This report focusses on the digital aspects of the Fourth Industrial Revolution, particularly automation technologies, which are most likely to generate inequalities in the labour market (Prytkova et al., 2022). Specifically, the PILLARS project (Horizon 2020 GA: 101004703) dataset is used to identify Digital Automation Technologies (DAT), encompassing robotics, computing processing, artificial intelligence, and additive manufacturing (Prytkova et al., 2022). For green technologies, the ENV-TECH and Y02/Y04S tagging schemes capture innovations related to climate change mitigation and adaptation (Favot et al., 2023). These green technologies are further categorised into eight key policy-relevant supply systems and sectors: *clean energy, transport, buildings, food, materials, waste management, nature-based solutions, and phase-out technologies*. This categorisation provides a more detailed understanding of how different systems and sectors are regionally distributed and how they converge with DAT. From a methodological perspective, there is no consensus on what constitutes twin technologies (Bachtrögler-Unger et al., 2023). Therefore, co-citation coupling (Grauwin and Jensen, 2011; Romero-Goyeneche et al., 2022; Yan and Ding, 2012) is employed to map cognitive linkages between DAT and green technologies, enabling the identification of a shared knowledge landscape between them and serving as a proxy for emerging twin patents and scientific publications. Lastly, patents and scientific publications in DAT, green, and twin technologies are geo-localised across 271 NUTS-2 regions (including more than 700 NUTS-3 functional urban-areas), covering 27 European Union (EU) countries and the UK, Norway, Liechtenstein, Iceland, and Switzerland.

This study employs **three families of indicators** to assess the uneven regional distribution of technological capabilities across regions: knowledge unevenness distribution, inter-regional complementarities, and regional diversification potential. Knowledge unevenness distribution is measured using the Gini index (Sitthiyot and Holasut, 2020), which evaluates the **distribution of complex knowledge associated** with DAT, green, and twin patents and scientific publications across European regions. Inter-regional complementarities are evaluated by using Network Analysis to assess **cross-regional collaboration patterns** (Balland and and Boschma, 2021), categorising regions into four types: those with strong national and European collaboration, those collaborating only nationally, those engaged primarily in European collaboration, and those with low collaboration levels. Regions with low collaboration may struggle to diversify their innovation portfolios, while those engaged at both national and European levels are better positioned for technological advancement. Lastly, regional **diversification potential** is assessed by using the relatedness approach (Boschma, 2017) to **identify regions with high or low potential for diversification in DAT and green technologies**. Four regional types emerge: regions with no diversification potential, locked in low technological diversification; green-specialized regions, with strong diversification potential in green but weak in DAT; digital-specialized regions, with the reverse pattern – high DAT and low green diversification

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capabilities; and regions with high diversification potential in both, which are best positioned for the emergence of twin technologies.

Our findings align closely with the **EU Cohesion Policy 2021–2027** (European Commisssion, 2022)**,** particularly the goals of fostering a Smarter and Greener Europe. The results highlight significant fragmentation in DAT, Green, and Twin technologies across European regions, which may hinder the effective implementation of the twin transition agenda (European Commission et al., 2022). Notably, peripheral regions remain disconnected from broader innovation networks, while more developed regions are better positioned to lead in DAT, green and twin technologies. Although some peripheral regions have developed a strong scientific knowledge base, the lack of inter-regional connectivity and collaboration in the invention of new technologies may limit their ability to diversify innovation portfolios, benefit from knowledge spillovers, and integrate into wider European innovation ecosystems. In this context, the twin transition agenda may risk reinforcing rather than reducing structural inequalities unless these disparities are addressed by supporting collaborative governance and improving regional absorptive capacity—not only to produce scientific knowledge but to translate it into invention, market deployment, and regional economic transformation.

The following sections are structured as follows: a more detailed explanation of the green and digital transitions is provided in Section 2, which introduces our conceptual and analytical framework, which is grounded in the relatedness approach and explores the convergence of cognitive, social, and geographical domains. Data and methods are presented in Section 3. Key findings are presented in Section 4, followed by a discussion in Section 5.

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2. Background and rationality

Techno-economical change is characterised by a pattern of convergence and divergence cycle (Roco et al., 2013). Divergence is characterised by competing or conflicting techno-economic forces that can induce fragmentation. In contrast, synergic convergence across unrelated knowledge domains (Petersen et al., 2021) can lead to the emergence and development of new techno-economic paradigms (Perez, 2002). The convergence framework has been essential in analysing technological revolutions such as the Manhattan Project (Hughes, 2003), the Human Genome Project (Helbing, 2012; Petersen et al., 2018) and the Brain Project (Grillner et al., 2016; Petersen et al., 2021). These studies illustrate patterns of public and private collaboration and knowledge integration across various fields to develop radical innovation.

The recombination and convergence of technologies is not a linear process due to institutional barriers (Frickel and Gross, 2005) , complex interactions among social actors (Balland and and Boschma, 2021), fuzzy cognitive translations (Arroyave et al., 2021; Heimeriks and Balland, 2016), market constraints (Stephan, 2012) and possible external shocks (Steijn et al., 2023). The differences in dynamics between DAT and green technologies manifest in several ways, making it difficult to anticipate the directions of their convergence[1]. In this context, the successful convergence of DAT and green technologies relies on integrating knowledge and fostering collaboration, creating trajectories that can address social, economic, and environmental challenges. **Cognitive interactions** establish a shared knowledge base that drives innovation and technological integration (Arroyave et al., 2021; Petersen et al., 2023, 2021), while **social convergence** involve partnerships among firms, institutions, and policymakers, as well as spillovers that promote regional knowledge diffusion (Arroyave et al., 2021; Balland and and Boschma, 2021; Petersen et al., 2023). Together, cognitive and social integration can foster the convergence necessary for the critical emergence of complex knowledge (Arroyave et al., 2021; Bettencourt and Kaur, 2011; Heimeriks and Leydesdorff, 2012), enabling the integration of green and digital domains into new technological trajectories. In addition, understanding regional dynamics is crucial, as complex knowledge is typically rooted in the specific locations where it is produced, relying on tacit and codified knowledge that is place-dependent (Balland et al., 2019; Boschma, 2017; Boschma et al., 2014). This spatial dependency underscores the importance of analysing regional capabilities for diversification and their distribution across different places (Iammarino et al., 2019).

To analyse the regional dynamics of cognitive and social convergence, the framework of regional diversification and relatedness is therefore applied (Balland et al., 2019; Boschma, 2017). This

[1] Green technologies are typically characterised by decentralised production and consumption (Brisbois, 2020; Meeks et al., 2025) and institutional support from diverse actors (Bogers et al., 2022; Lesch et al., 2023). The diversity of actors and the decentralised nature of green technologies represent significant coordination challenges to optimise system processes and production (Brodnik et al., 2025; Kivimaa et al., 2019; Papachristos et al., 2013). For instance, in the circular economy, processes such as collection, processing, and material reuse require the coordination of multiple stakeholders and the support of information and communication systems (Chauhan et al., 2022; Piscicelli, 2023). In this context, DAT offer a valuable solution by enhancing coordination among stakeholders while optimising and standardising processes. Yet, while DAT holds great potential to advance sustainability goals, such as those related to the circular economy, it also introduces significant uncertainties. Not all DAT contribute positively to sustainability (Mäkitie et al., 2023). For example, DAT are extensively adopted across various industrial sectors, including those with a significant dependence on fossil fuels (Bohnsack et al., 2022; Ha et al., 2022). A second example highlights the accumulation and processing of data linked to digital technologies, which can result in considerable greenhouse gas emissions and adversely affect water and soil resources (Al Kez et al., 2022). Another example is the power imbalances between firms in the digital and green technology sectors that may favour the former (Johnstone et al., 2024), potentially diverting focus away from sustainability efforts.

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approach is employed to enhance the understanding of convergence and to gain deeper insights into how existing capabilities within regional invention portfolios shape the convergence of DAT and green technologies, fostering the emergence and development of twin technologies. Regions with well-established innovation portfolios and access to resources are better positioned to integrate green and digital technologies and develop new pathways for twin transitions (Bachtrögler-Unger et al., 2023). Conversely, regions dependent on less complex economic activities face greater barriers to adopting and integrating these technologies (Balland et al., 2019; Balland and and Rigby, 2017; Rigby et al., 2022), potentially exacerbating regional disparities. Additionally, some regions risk becoming locked into less innovative paths (Dolfsma and Leydesdorff, 2009) or trapped in low-complexity economic activities (Balland and Boschma, 2024), increasing their dependence on polluting and inefficient technologies.

Additionally, the relatedness framework provides an evolutionary approach to study the emergence and development of DAT and green technologies. While DAT and green technologies have emerged and developed over the last two decades, their convergence is arguably in the early stages. The early emergence of new technological trajectories is often characterised by high levels of uncertainty and limited resilience, as this knowledge remains weakly embedded in existing regional networks (Heimeriks and Balland, 2016; Whitley, 2000). At this stage, the formation of formal and informal social networks is crucial, as these networks create the conditions necessary for technological incubation (Arroyave et al., 2021; Heimeriks and Leydesdorff, 2012; Petersen et al., 2023, 2021). The integration of knowledge and the collaboration of diverse social actors shape the production of new technological inventions within regions (Balland and and Boschma, 2021). However, not all innovations progress equally; certain technologies may be prioritised over others, a process known as pre-selection (Dosi, 1997; Dosi and Nelson, 2010), which is critical in defining the potential directions of regional technological trajectories. This prioritisation often reflects the structural and regional institutional contexts in which these trajectories emerge.

As trajectories advance beyond the emergence phase, they enter a stage of development marked by growth and acceleration, as evident in the case of DAT and green technologies. This phase involves the diffusion, replication, recombination and improvement of technologies, transitioning from experimental beginnings to broader adoption and diversification (Bettencourt et al., 2009; Bettencourt and Kaur, 2011; Dolfsma and Leydesdorff, 2009; Perez, 2009). Early successes in technological invention often attract investment (Schot and Kanger, 2018), scaling innovations and embedding them within established networks in regions. Over time, these technological trajectories evolve through specialisation, recombination, or coexistence in regions, aligning with broader techno-economic paradigms.

In this direction, the uneven distribution of innovation capabilities across different regions significantly influences the direction of both DAT and green technologies. This distribution can also impact their convergence, leading to distinct regional pathways. Building on these complex evolving dynamics, the emergence and development of technological trajectories can follow at least three pathways (Table 1), each contributing uniquely to the evolution of twin technologies

The first trajectory involves specialisation within a single domain—DAT or green—without significant integration between the two. Despite substantial advancements, DAT and green technologies often exhibit high levels of regional specialisation, as shown by Bachtrögler-Unger et al., (2023). The second trajectory involves the diffusion or amplification of knowledge from one domain to another (Chen and

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Hicks, 2004). For example, the application of Artificial Intelligence (AI) to improve the efficiency of clean energy technologies (Yao et al., 2023) highlights how digital innovations can enhance green trajectories. This diffusion generates expectations about cross-domain applications (Papachristos et al., 2013) but does not necessarily lead to profound diversification within the invention and scientific production domains. In other words, DAT and green technologies may coexist within regions, being produced and applied in complementary ways without exhibiting significant convergence at the knowledge production and invention stage. The third is the convergence of digital and green technologies, resulting in the creation of entirely new technological trajectories. By combining foundational elements from both domains, this trajectory fosters the critical emergence (Arthur, 2009, 2007; Kauffman, 2019) of twin technologies, which hold the potential to drive a new phase of technological development.

To further explore the three pathways of development between DAT and green technologies within regions, the following sub-section outlines a systematic approach to categorising regions based on their potential for twin technologies, providing an analytical framework for understanding their unique opportunities and challenges. The analytical framework allows us to determine the extent to which regions with existing specialisation in either green or digital technologies have the potential to develop twin technologies

Table 2.1: *Trajectories of diversification.*

Pathway	Explanation	Digital, Green, and Twin Transitions	Examples
Digital OR green specialization	Growth and incremental optimization occurs within a single technological domain—either green or digital—without significant integration or interaction between the two.	Reflects the independent advancement of green or digital technologies. Digital domains may focus on AI or IoT, while green domains emphasize renewable energy or energy storage. Although these advancements are significant, they remain siloed across regions, limiting cross-domain synergies required for twin transitions.	Example: Development of energy storage (green) or autonomous driving technologies (digital), with no integration between the two.
Coexistence Diffusion without integration	Innovations or knowledge from one domain influence and enhance technological progress in the other domain through indirect interaction or application.	Supports the complementary evolution of green and digital technologies by enabling digital innovations (e.g., AI, IoT) to enhance green technologies through optimization of energy usage or emissions monitoring. While integration occurs during the diffusion and application phases, it does not extend to the invention stage. This pathway fosters co-existence and partial integration, with limited convergence in the creation of new technologies	Example: Blockchain (digital) tracks renewable energy supply chains (green), enhancing transparency. Integration occurs in application, not in the invention of either technology
Digital AND green Convergence	Represents the integration of digital and green technologies into entirely new technological paradigms, creating new twin technological trajectories	Enables the emergence of entirely new technological trajectories combining digital and green elements. This pathway marks the realisation of twin transitions, fostering novel radical innovations.	Example: Smart grids combining renewable energy with IoT technologies; autonomous vehicles powered by renewable energy

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3. Analytical framework

The analytical framework focuses on identifying the cognitive and social convergence of DAT and green technologies across different European regions. In addition to this, geographical colocation is examined to assess whether DAT and green regions coexist, even in the absence of convergence in their invention or knowledge production. Furthermore, the framework analyses the temporal dynamics of technological trajectories within regions to uncover convergence, divergence, and coexistence patterns between these two technological domains. The next subsection presents the data set, followed by an overview of the methodological framework.

3.1. Data

Digital technologies: Using the dataset generated by the PILLARS project (Horizon 2020 GA: 101004703), DAT were identified as a key focus of analysis (Prytkova et al., 2022). These technologies are particularly relevant to our study, as they have the potential to streamline coordination processes within green technologies, such as those underpinning the circular economy (Chauhan et al., 2022). At the same time, DAT may exacerbate inequalities by displacing human labour (Antonietti et al., 2025; Lee and Clarke, 2019). The dataset captures a range of technologies, including robotics, data acquisition and management, computing, artificial intelligence, intelligent information systems, additive manufacturing, networking, and user interfaces (see Supplementary Material 1, Table S1.1).

The query used for identifying the patents is based on a robust literature review of automation technologies and the fourth industrial revolution (Prytkova et al., 2022). The query contains both IPC codes and keywords in order to ensure the precision of the identification of the patent (Prytkova, Ciarli, and Önder 2022, p. 29-30). Semantic analysis of patent was performed to cluster technologies and applications into coherent groups. Using GloVe word embeddings (Pennington et al., 2014) and the Louvain clustering algorithm (Blondel et al., 2008), 148 subclusters representing distinct technological topics were identified. The novelty and emergence of these clusters were analysed based on co-occurrence patterns. Trends across multiple time periods were examined to highlight both established and emerging technologies in digital automation, providing a comprehensive view of current advancements and potential future trajectories of innovation (see Supplementary Material 1, Table S1.1)

For ***Green technologies,*** *a* systematic collection of green patents was undertaken following the methodology proposed by Favot et al. (2023). This approach integrates multiple classification systems, including the ENV-TECH dataset (developed by OECD), the IPC Green Inventory (WIPO), and the Y02/Y04S tagging scheme (EPO). Following a detailed examination of these methodologies, the ENV-TECH and Y02/Y04S tagging schemes were selected for their precision and ability to capture the highest percentage of green patents. The IPC Green Inventory, however, was excluded due to its broader and less specific definitions of green technologies, such as the inclusion of patents for "corpse disposal technologies," which do not consistently reflect the essence of green inventions.

The ENV-TECH dataset systematically catalogues patents associated with environmental technologies, encompassing areas such as renewable energy generation, waste management, and pollution control. Similarly, the Y02/Y04S tagging scheme identifies patents related to climate change mitigation and sustainable technologies. The Y02 category specifically addresses technologies designed to reduce greenhouse gas emissions, such as carbon capture and storage, energy-efficient transportation, and smart grid systems, while the Y04S category focuses on information and communication technologies that enhance sustainability, including smart metering and energy management systems.

The CPC codes (Cooperative Patent Classifications) from both methodologies were carefully and manually reorganised following the initial ENV-TECH classification into eight technological domains and 27 sectors. This classification provides a comprehensive framework to align green technologies

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with European policy priorities, particularly the European Green Deal, the Circular Economy Action Plan, and the Fit for 55 packages. These categories aim to encapsulate key technological domains that address climate change mitigation and adaptation, fostering a sustainable transition across sectors (see Supplementary Material 1, Table S.1.2).

Gathering patent data in European regions

Using application identifiers from the PILLARS project and CPC codes from the ENV-TECH and Y02/Y04S tagging schemes, patents were retrieved from the PATSTAT global dataset. This comprehensive dataset provides detailed information, including citations, regional localisation, patent families, and CPC codes, enabling an in-depth analysis of technological innovation. Between 2000 and 2021, 1,114,022 patent families were identified for DAT, while 3,618,375 patent families were identified for green technologies.

In order to conduct a comprehensive analysis of the regional distribution of patents, the REGPAT and USPTO datasets were utilised. This dataset allows for the geo-localization of patents across 271 NUTS-2 regions (including more than 700 Nuts functional Urban-areas), which span 27 EU countries, in addition to the UK, Norway, Liechtenstein, Iceland, and Switzerland. This regional approach enables a nuanced understanding of patent activity and innovation trends within these specific geographical areas. Patents are registered in the European Patent Office (EPO), the International Patent Office (PCT) and The United States Patent and Trademark Office (USPTO). This process resulted in the identification of 63,524 DAT patent families and 208,757 green technology patent families.

Lastly, twin patents were identified through a two-step approach. First, 6,075 patent families were found to overlap between the DAT and green technologies datasets, representing twin technologies in the 27 European countries analysed. Second, a co-citation analysis of digital and green patent families was conducted to identify additional patents that exhibit shared knowledge bases. This analysis captures the cognitive integration of DAT and green technologies, highlighting the common building blocks of knowledge that underpin twin technologies. These methodological steps provide a robust framework for examining the convergence of green and digital technologies. Further details on the co-citation analysis and the cognitive convergence of these technologies are presented in the following section.

Gathering scientific data in European regions

Scientific publications are retrieved from OpenAlex by leveraging the descriptions of green and digital technologies identified in the patent analysis. The descriptions of patent CPC codes at the 4-digit level, gathered in the previous step, are employed alongside classifications from the PILLARS project, as well as the ENV-TECH and Y02/Y04S tagging schemes. The identification process involves matching these definitions with the structured metadata available in OpenAlex, which includes a comprehensive comparison with the summary, subfields, fields, and key concepts across the 4,516 distinct topics categorised within the OpenAlex database.

The relevance of the identified topics is assessed through text similarity analysis using the Jaccard similarity index. The similarity distribution is analysed to determine an appropriate cut-off point by identifying the tail of the distribution. The cut-off threshold is further refined by random sampling of 200 topics, with Type I and Type II errors being reduced to 5% and 7%, respectively. As a result, 445 topics from Open Alex were selected, including 169 digital topics, 211 green topics, and 65 shared or twin topics. These 445 topics encompass over 12 million relevant publications, reflecting a global spectrum of research contributions related to green and digital technologies. In this case, co-citation analysis is not performed because the Open Alex topics are generated using this approach. Thus,

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identifying common DAT and green topics offers a strong method for recognizing publications related to twin technologies.

In the subsequent phase, a systematic filtering process is undertaken to refine the dataset by identifying scientific publications associated with European researchers. This is accomplished by analysing author affiliations provided in OpenAlex and cross-referencing them with the 2021 NUTS-2 regional classification system. Consequently, a total of 422,921 unique DAT publications, 442,781 unique green publications and 131,933 to both technological domains, representing twin technologies. Each publication is geolocated to its corresponding NUTS-2 and NUTS-3 regions, enabling a structured regional analysis of research outputs related to DAT and green technologies.

3.2. Methodological Framework

The methods are divided into two complementary analyses. The first set of analyses focuses on answering and understanding how DAT, green and twin technological innovations are evolving across European regions. This analysis uncovers the cognitive and social convergence of green, digital and twin patents within regions. The second analysis focuses on the co-existence of digital and green technologies within regions. This analysis permits us to analyse to what extent regions with existing specialisation in DAT or green technologies possess the potential to develop twin technologies. The rationality is that even if a region does not have capabilities in twin technologies, the co-location of DAT and green technologies represents potentialities for developing twin technologies either in the invention or diffusion side.

Cognitive convergence

The cognitive integration of knowledge can be analysed using various methodological frameworks, particularly in patent data studies. While OpenAlex topic codes provide a straightforward approach to identifying twin topics, classifying patents is more complex. Common methods include identifying shared patent codes (Basilico et al., 2024; Kogler et al., 2013), applying Natural Language Processing (NLP) for text similarity analysis (Bekamiri et al., 2024; Hain et al., 2022; Prytkova et al., 2022), and constructing co-citation networks (Grauwin and Jensen, 2011; Romero-Goyeneche et al., 2025, 2022). Each method has distinct strengths and limitations, which are important to consider when examining the convergence of DAT and green technologies.

Analysing shared patent codes provides a straightforward and practical approach, offering insights into the institutionalisation and application of patents (Basilico et al., 2024; Kogler et al., 2013). However, this method often lacks the granularity needed to uncover overlapping technological landscapes, potentially underestimating the number of twin patents that integrate DAT and green technologies. NLP models, in contrast, provide the most detailed analysis by examining titles, keywords, claims, and abstracts (Bekamiri et al., 2024; Hain et al., 2022; Prytkova et al., 2022). While this approach can reveal nuanced conceptual overlaps, it requires significant computational resources and may introduce challenges in identifying commonalities between different technological domains with very different technological definitions, such as green (e.g., circularity) and digital (e.g., efficiency). Moreover, shared language does not always imply shared technological trajectories, leading to a potential overestimation of twin patents and a miscalculation of the directions of regional trajectories. Co-citation networks offer a balanced alternative by analysing the interface between patents or scientific publications through shared citations (Grauwin and Jensen, 2011; Romero-Goyeneche et al., 2025, 2022). This approach provides a robust conceptual and empirical

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understanding of the common knowledge underpinning DAT and green technologies. Citations serve as a uniform and concrete representation of the knowledge utilised by patents, making this method particularly suited for exploring their technological trajectories.

Given these considerations, a combined methodological approach is adopted to ensure both depth and accuracy in identifying twin patents (Figure 3.1). The first step involves identifying DAT and green patent families using common CPC codes. This step allows us to locate **institutionalised twin patent families** where green and digital technologies intersect. Subsequently, the **undirected contribution** of DAT and green technologies to twin technologies is undertaken using co-citation coupling—a common knowledge landscape between DAT-twin and green-twin patent families. In addition, **emerging twin technologies** are mapped by analysing the co-citation network between DAT and green technologies. In the co-citation networks, nodes represent green, digital or twin patent families, and shared citations define links between them. Four matrices are generated to calculate the correspondence probability of interactions between green, digital and twin patent families (for more detail, see Supplementary Material 2)

I. **Digital-Twin Interaction Matrix (undirected contribution):** This matrix represents the interactions between digital patent families and twin patent families. It provides insights into how DAT patents connect to twin patent families.

II. **Green-Twin Interaction Matrix (undirected contribution):** This matrix captures the interactions between green patent families and twin patent families, illustrating the connections that green technologies have with twin patents.

III. **Digital-Green Interaction Matrix (emerging twin technologies):** This matrix represents the directed interactions from digital to green patent families, revealing the extent to which this DAT shared common knowledge with green families.

IV. **Green-Digital Interaction Matrix (emerging twin technologies):** This matrix captures interactions from green patent families to digital patent families, focusing on the flow of knowledge or technological overlap from green to DAT domains.

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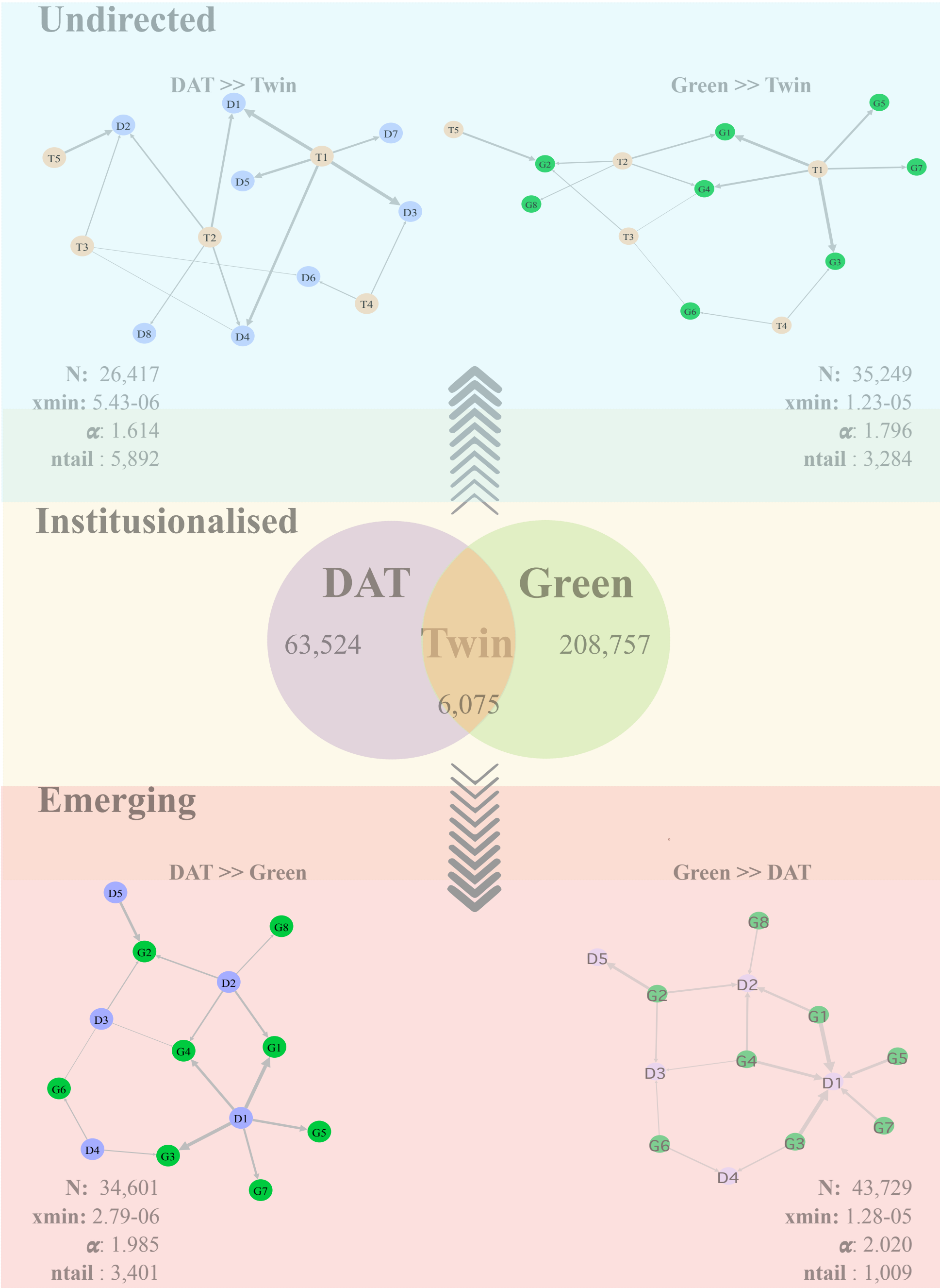

Figure 3.1. Twin patent families' data collection.

The data collection process involves three complementary steps. First, common patent families in both the DAT and green technological domains are identified, representing institutionalised twin technologies. These patents act as a seed pool, reflecting early instances of convergence between the two domains, and are thus considered twin patent families. Second, additional twin patent families are captured by analysing shared citations between DAT or green patents and the institutionalised twin technologies, reflecting an indirect contribution to convergence. Third, the analysis explores emerging links between DAT and green patents, excluding the identified twin patent families to avoid bias. This approach assumes that shared citations between green and digital patent families reveal a foundational knowledge base that, while not formalised in patent classifications, is critical for the emergence of twin technologies. In the resulting networks, N indicates the number of nodes (patent families) analysed, xmin is the cut-off point in the power-law model, α (alfa) is the exponent of the power-law distribution, and nmin refers to the final number of patent families included in each network. Patent families are merged, and duplicates removed to ensure data accuracy.

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The identification of twin patents based on their cognitive similarity enables us to analyse which regions are fostering the twin transition. By analysing the probability of twin patents emerging within specific regions, it is possible to understand the cognitive convergence between green and digital technologies. By estimating the probability of a region accumulating knowledge in twin technologies, twin regions can be identified, providing valuable insights into the spatial dynamics of technological advancement.

Subsequently, knowledge unevenness distribution is analysed using the Gini Index (Sitthiyot and Holasut, 2020), which measures the concentration or dispersion of patents across regions. A Gini Index between 0.00 and 0.30 indicates evenness and a balanced distribution, while values from 0.30 to 0.50 suggest moderate unevenness, where some regions take a leading role while others remain engaged. Scores between 0.50 and 0.70 reflect high unevenness, with a few regions dominating, whereas values from 0.70 to 1.00 indicate extreme concentration in regional hubs.

Social Convergence (inter-regional complementarities)

Our proxy for social convergence is based on the existence of complementary inter-regional linkages—reflected in spillovers and measured through collaboration between regions engaged in producing twin patents and scientific publications (Balland and and Boschma, 2021). Using the twin patent dataset previously presented and twin scientific publications, network analysis is conducted to explore the interconnections and knowledge flows between regions. Network analysis is an effective tool for analysing the dynamics of knowledge exchange, offering valuable insights into how interactions occur and how external knowledge is integrated within innovation capabilities (Balland and and Boschma, 2021; Balland and and Rigby, 2017; Breschi and Lenzi, 2015; Fleming et al., 2007; Guan and Liu, 2016)

In this context, the degree of shared spillovers across regions is computed to measure the extent to which knowledge from other regions is utilised and incorporated. By quantifying these spillovers, patterns of knowledge exchange and regional interconnectedness are revealed, providing deeper insights into the role of these flows in fostering innovation and regional development. As highlighted by Breschi and Lenzi, (2015), regions often rely heavily on local and national networks for knowledge exchange. Due to the absence of a cohesive policy for regional integration in the digital and green transitions, regions may encounter higher costs associated with transferring and integrating knowledge from distant regions. To address these dynamics, the calculation of shared spillovers is conducted based on network measures and similarity indices.

The collaboration network is constructed as follows: regions at the NUTS-2 and NUTS-3 level serve as the nodes of the network ($\boldsymbol{v_{ij}}$), with their interactions $\boldsymbol{c_{ij}}$ represented by shared patents or scientific publications. If a patent or publication is associated with multiple regions, it indicates that inventors or scientists from these regions contributed to its development. For the purpose of this explanation, patents will be used as the primary example; however, the same methodology applies to scientific publications. The resulting network is a one-mode, undirected network $\boldsymbol{N}$, where edges represent co-occurrences $\boldsymbol{c_{ij}}$ of regions $\boldsymbol{v_{ij}}$within the same patent.

In order to establish the similarity between a pair of regions, the Jaccard similarity is used. In our case, the similarity of region $\boldsymbol{v_1}$ and region $\boldsymbol{v_2}$ is calculated as follows:

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$$J(v_1 v_2) = \frac{|v_1 \cap v_2|}{|v_1| + |v_2| - |v_1 \cap v_2|}$$

Where $|v_1 \cap v_2|$ is the share number of patents between region v_1 and region v_2

Finally, the analysis distinguishes between collaboration within the same country and collaboration across different countries. In this step, the Jaccard index values for each pair of regions are aggregated separately for both cases.

The analysis distinguishes between collaboration within the same country and collaboration across different countries. In this step, regions are classified into four distinct categories (Figure 3.2): (1) regions with a high degree of collaboration both domestically and internationally, (2) regions with strong domestic collaboration but limited international connections, (3) regions that exhibit high international collaboration but low domestic engagement, and (4) regions with minimal collaboration overall.

A more granular analysis of regional collaboration is conducted at the functional urban-area[2] using the NUTS-3 regions classification. While regional trends are captured at the NUTS-2 level, the functional urban-area level is crucial for understanding collaboration dynamics in sectors, as cities function as innovation hubs where firms, universities, and institutions form dense knowledge networks. Network analysis is applied to uncover collaboration patterns and identify leading functional urban areas in converging DAT and green technologies.

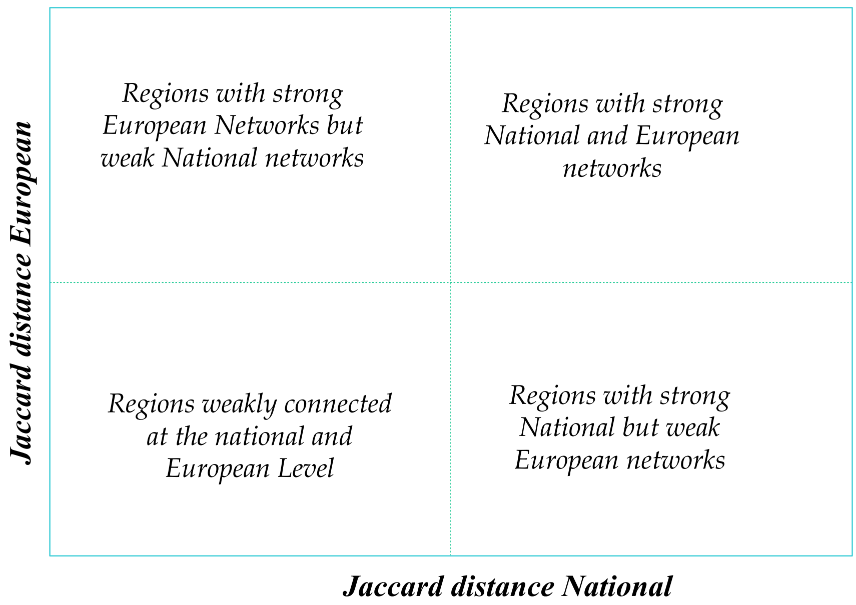

Figure 3.2. National and international collaboration of regions.

To analyse the structural properties of the network, network metrics are computed using the package igraph[3]. Table 3.3. shows the description and interpretation of each metrics following Newman, (2018). The **network's diameter** measures the shortest path between any two NUTS-3 regions, offering insights into the overall connectivity of the system. **Density** quantifies how interconnected

[2] https://ec.europa.eu/eurostat/web/metropolitan-regions/methodology#:~:text=Metropolitan%20regions%20based%20on%20the,least%201%20NUTS%203%20region.
[3] https://igraph.org

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the network is by calculating the proportion of observed connections relative to the total possible connections between cities. The **average degree** represents the mean number of connections per city, indicating the general level of collaboration across urban areas. **Degree centralisation** assesses the extent to which the network is dominated by a few highly connected cities, known as hubs, which reflects potential hierarchical structures in the collaboration network. **Country assortativity** measures the tendency of cities to collaborate more frequently with those within the same country rather than across borders, highlighting the degree of national versus international integration. The **clustering coefficient** captures the local cohesiveness of the network by indicating the likelihood that two cities, connected to the same third city, are also directly connected to each other. This is relevant for understanding the formation of regional knowledge clusters. To identify distinct regional collaboration structures, the **Louvain modularity** method is used to detect communities of cities that are more densely connected internally than with the rest of the network**. The number of modules** derived from this method provides an indication of how fragmented or cohesive the urban collaboration landscape is in Europe. Additionally, **betweenness centrality** highlights spillover regions—cities that act as key intermediaries in the network, facilitating knowledge exchange between different urban clusters. These regions play a crucial role in bridging knowledge gaps and promoting technology diffusion across European urban areas.

Table 3.3 *Network collaboration metrics.*

Metric	Description	Range	Interpretation
Diameter	The longest shortest path between any two cities in the network.	≥ 1 (depends on network size)	High values indicate There are cities that are far apart in terms of collaboration (higher than 3-4)
Density	The proportion of observed connections relative to the total possible connections.	0 - 1	High values indicate the network is highly interconnected.
Average Degree	The mean number of connections per city.	≥ 0 (depends of networks connectivity)	High values indicate Cities have more collaborations on average.
Degree Centralization	The extent to which the network is dominated by a few highly connected cities.	0 - 1	Values close to 1 indicates that few cities dominate the collaboration network.
Country Assortativity	The tendency of cities to collaborate more frequently within the same country.	-1 to 1	Values close to -1 indicates cities collaborate more across borders rather than within countries, while values close to 1 indicates that Cities tend to collaborate more within their own country.
Clustering Coefficient	The likelihood that two cities connected to the same third city are also directly connected.	0 - 1	Low values indicates that collaboration is spread out.

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Metric	Description	Range	Interpretation
Modularity	The extent to which the network is divided into distinct, densely connected communities.	0 - 1	High values indicate strongly defined communities with limited external collaboration, indicating the formation regional clusters.
Number of Modules	The total number of communities detected using the Louvain modularity method.	≥ 1 (depends on network structure)	High values indicate many distinct collaboration communities exist.

Regional Convergence (Regional Diversification Potential)

Our proxy for regional convergence is based on analysing the diversification potential of DAT and green technologies in each region. While some regions develop capabilities in both areas, others tend to specialise in either digital or green technologies (Balland et al., 2019). The Relatedness Density Average (RDA) is calculated for each region as a proxy for DAT and green capacities aimed at diversification using the *EconGeo* in R project (Balland, 2017). This approach is designed to evaluate spatial and technological proximity while identifying opportunities for diversification (Balland et al., 2019; Hidalgo et al., 2007), serving as an indicator of technological potential to develop DAT or green technologies. The method involves creating co-occurrence matrices, normalising these to assess technological relationships through the relatedness index, and integrating them with regional specialisation data (for further details, see Supplementary Material 3).

The regional analysis is performed in three analytical steps, each building upon the previous one to provide a nuanced perspective on regional development. Our analytical framework aims to operationalise the regional convergence of DAT and green technologies within regions. Using the analysis of relatedness (Balland et al., 2019; Hidalgo et al., 2007), regions are systematically categorised into four regional trajectories to uncover their potential for developing twin technologies (Figure 3.3). The rationale behind this analysis is that even regions lacking current twin technology capabilities can leverage the co-location of DAT and green technologies as a foundation for fostering twin technologies, whether in invention or diffusion processes. Notice that for this analysis, twin patents and scientific publications were excluded in order to avoid an overestimation of the co-occurrence of DAT and green diversification capabilities.

First, co-evolving regions with high digital and green capabilities demonstrate the strongest potential for developing twin technologies. Within this category, DAT and green technologies may either co-exist or converge (Table 1). Second, regions specialising in either DAT or green technologies demonstrate partial capabilities, offering opportunities for strategic diversification. Third, trapped regions with low diversification in DAT and green technologies face significant challenges, often lacking the foundational knowledge base for transitions. Notice that the distinction between high or low levels of diversification is determined by using the median of the European region's RDA value (see supplementary Material 2)

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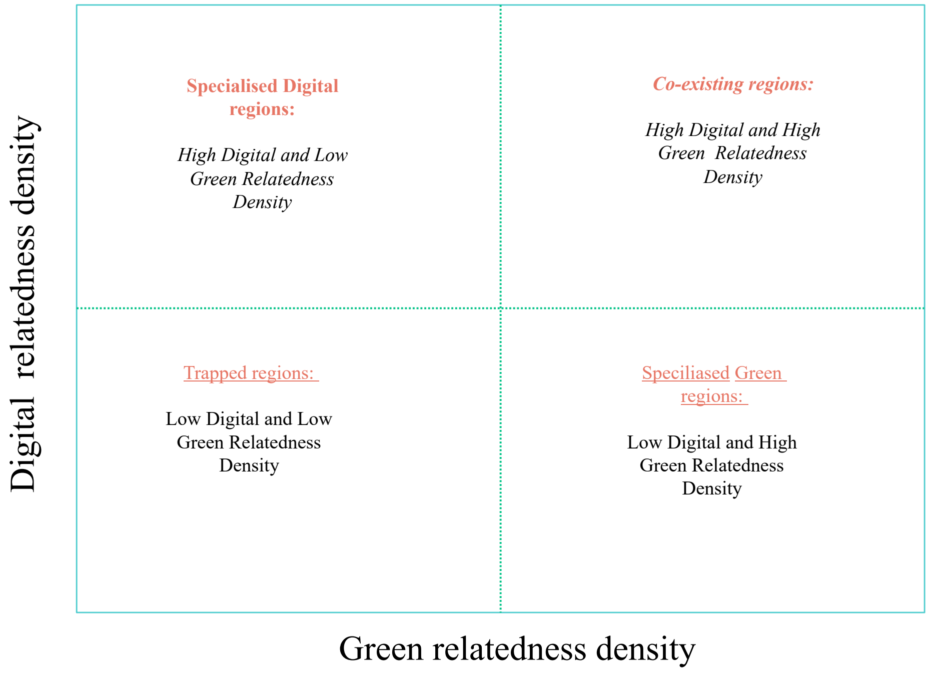

Figure 3.3. Regional trajectories in digital, green and twin technologies.
This analysis assesses the extent to which regions with existing specialisations in either green or digital technologies possess the potential to develop twin technologies. Even in regions without current capabilities in twin technologies, the co-location of green and digital technologies suggests opportunities for twin transitions, either through invention or diffusion. This approach emphasises the latent potential of regions with overlapping technological domains.

The next step incorporates temporal dynamics to capture the evolution of regional invention trajectories using the Relatedness Density Average (RDA) for DAT and green technologies. The analysis spans four distinct periods. The emergence phase includes two-time windows: 2000–2006 (Period 1) and 2007–2011 (Period 2). The development phase includes 2012–2016 (Period 3) and 2017–2021 (Period 4). The classification is based on the fact that the production of DAT and green technologies has experienced exponential growth since 2011. Transitions between categories across these periods are analysed using Principal Component Analysis (PCA), providing robust statistical insights into regional trajectories, for more detail see Supplementary Material 4. For instance, this analysis can identify regions that transition from low diversification in digital and green technologies in Period 1 to developing strong green capabilities in Period 2 and subsequently regressing to low diversification in Period 3. By tracing these trajectories, this step highlights regions that are progressing, stagnating, or regressing, offering insights into the dynamic nature of regional development.

This multi-step approach enables us to trace regional trajectories and identify patterns of diversification. It reveals regions that are stuck in cycles of low diversification, specialized areas with limited integration, and those that have the potential to embrace twin transitions. By integrating spatial, temporal, and statistical analyses, the methodology offers a comprehensive understanding of regional capabilities and their potential for DAT, green and twin technologies.

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4. Empirical Findings

This section presents the mapping of regional capabilities in DAT, green, and twin technologies across Europe by analysing patents and scientific publications. The analysis begins by characterising technological domains and regional trends in DAT and green technologies. It then explores the cognitive, social, and geographical dimensions of these technologies to assess their convergence. By examining these dimensions, the study uncovers regional disparities in knowledge capabilities, providing systematic insights into the uneven distribution of technological resources across European regions.

4.1. Data Characterisation

Table 4.1 provides an overview of the data used in the analysis, collected following the methodology outlined in Section 3. The dataset spans from 2000 to 2021. Green technologies have a higher number of patents and publications, as they cover a broader range of innovations, whereas the analysis of digital technologies is limited to DAT. However, DAT has nearly the same number of publications as green technologies due to the use of OpenAlex topics, which do not strictly confine digital technologies to automation but also include broader applications. For example, the OpenAlex topic on 'Natural Language Processing' covers various fields, such as topic modelling and text recognition, which, while not strictly related to automation, are still considered under DAT technologies in the scientific publications dataset.

Table 4.1. *Data characterisation.*

Domain	Patents	Publications
DAT	63,524	494,824
Green	208,757	515,512
Twin	17,049	160,940

A detailed characterisation of the data is presented in Figure 4.1, which shows eight technological domains in green technologies and their interaction with DAT. The analysis distinguishes between patent activity and scientific publications to capture invention and knowledge production variations. Panel (a) illustrates the frequency of patents across different green technology domains. Clean Energy, Phase-out technologies, Waste Management, and Sustainable Transport emerge as the most patented areas, indicating their significance in green innovation. Panel (b) explores the integration of DAT within green technology patents. Sustainable Materials show the highest level of convergence with DAT, followed by Clean Energy and Buildings. Moreover, although Waste Management and Phase-out technologies are highly patented, they exhibit limited integration with DAT, highlighting a gap between DAT and green technological synergy in these technological domains. Panel (c) shows the frequency of scientific publications where Clean Energy, Sustainable Materials, and Sustainable Food dominate. Notably, Sustainable Food and Nature-Based Solutions (NbS) have a stronger presence in scientific research compared to patent activity, suggesting different research and development priorities in scientific knowledge. Panel (d) examines the convergence of DAT within scientific publications on green technologies. Clean Energy, Sustainable Transport, and Sustainable Materials are leading in the integration of DAT. Interestingly, while Sustainable Food features prominently in

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scientific output, it shows minimal integration of DAT, indicating limited digital incorporation in food-related publications.

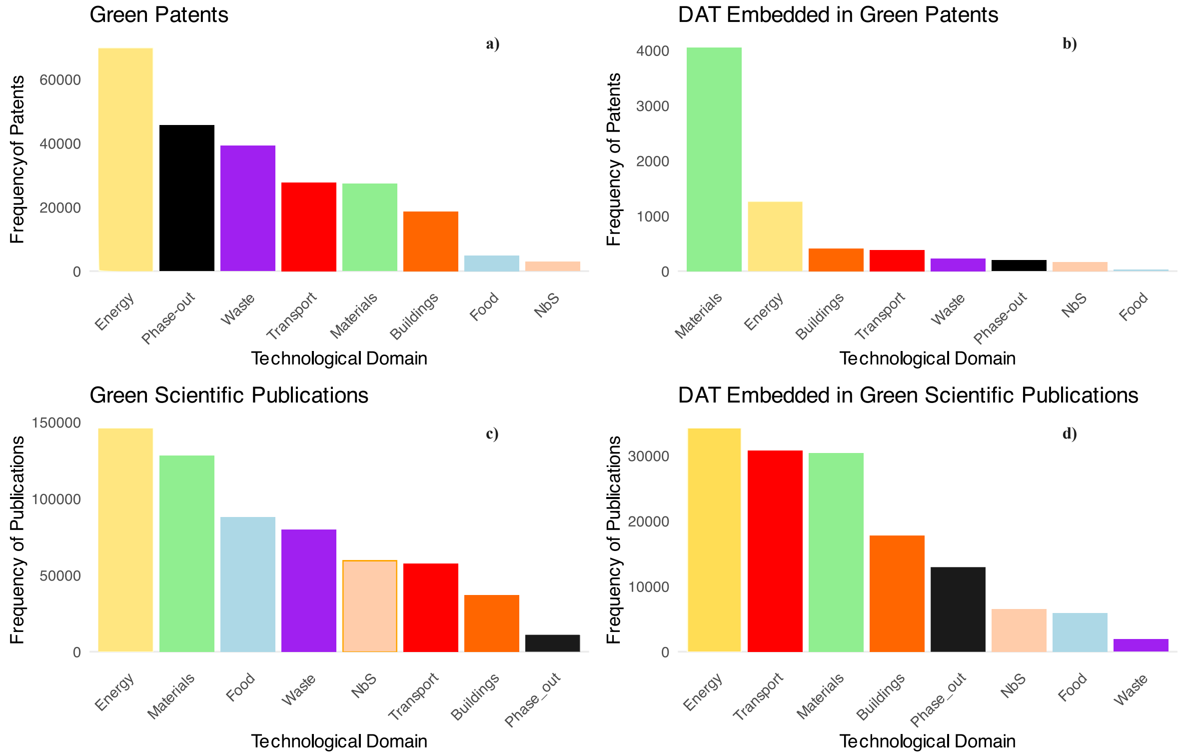

Figure 4.1. Frequency of patents and scientific publications associated with eight green technological domains.

Panel (a) displays the frequency of patents related to each technological domain. Panel (b) illustrates the frequency of patents where Green Technological Domains intersect with DAT. Panel (c) presents the frequency of publications associated with green technologies. Panel (d) shows the convergence of DAT and green technologies in scientific publications.

Despite differences in focus, both patent activity and scientific publications consistently highlight Clean Energy, Sustainable Materials, Sustainable buildings and Sustainable Transport as key domains where green and digital technologies intersect. However, areas such as Waste Management and Phase-out show strong patenting activity but less scientific attention, while Sustainable Food and NbS receive more focus on academic research than on technological development. These patterns reflect both overlap and divergence between inventions and research in the development of green technologies.

A more detailed analysis is presented in Figure 4.2, showing the most frequent Cooperative Patent Classification Codes (CPC) associated with DAT and green technologies. The most frequent CPC codes in the DAT dataset are related to Machine Learning, Neural Networks, and ICT-based healthcare. In contrast, scientific publications focus on broader topics such as Artificial Intelligence (AI), Optical Fiber Communication, and 5G networks. Regarding green technologies, the top ten Green Patent CPC codes emphasise areas such as energy storage, wind turbines, and vehicles. Similarly, the main OpenAlex topics reflect research efforts in renewable energy and eco-friendly materials. While Open Alex topics provide broader descriptions of the technologies, the patent data highlights specific applications across various sectors, including marketing, healthcare, project management, biomedical devices, automobiles, aviation, and manufacturing.

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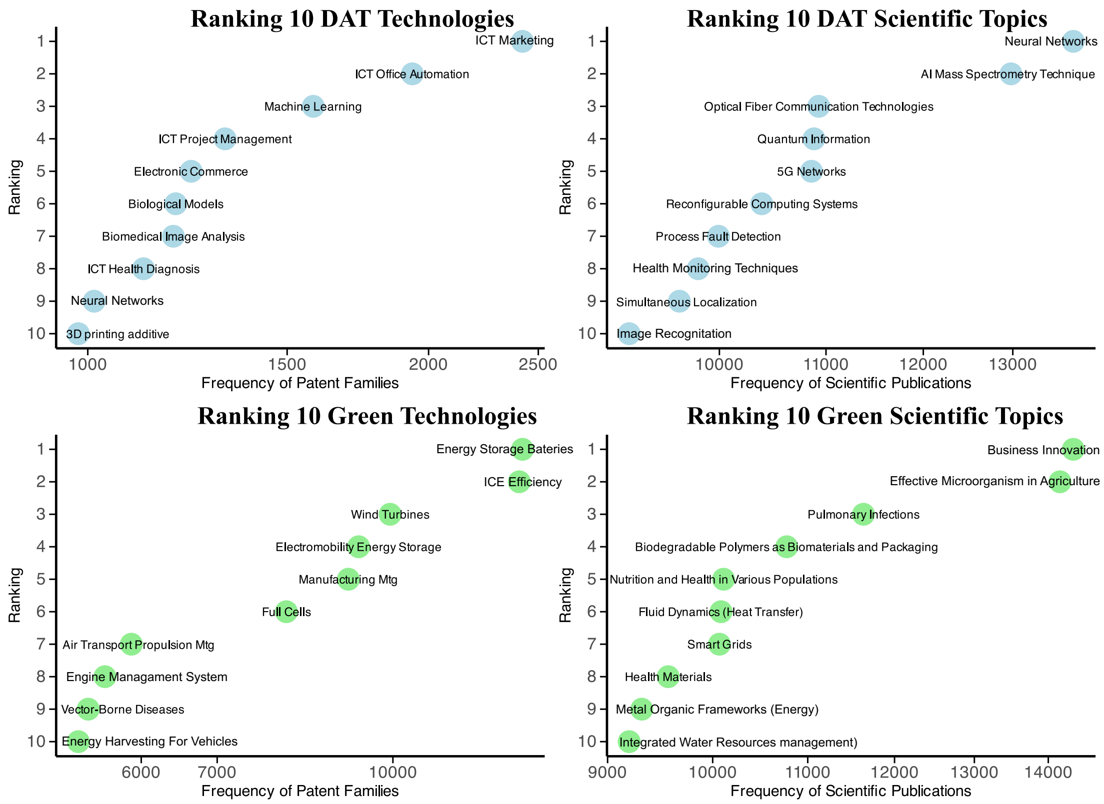

Figure 4.2. The top 10 technologies are categorised using CPC codes.
Open Alex topic descriptions were utilised to identify the most frequent scientific topics. Digital technologies are represented in blue, while green technologies are indicated in green.

4.2. Green and Digital Regional Characterisation

This subsection presents the characterisation of the regional distribution of patents and scientific publications of DAT and green technologies in Europe. The analysis provides an initial understanding of regional inequalities in the production of these technologies. The results reveal a pronounced concentration of knowledge accumulation in DAT and green technologies, with significant disparities among European regions, as illustrated in Figure 4.3. The Gini Index, which quantifies regional inequality in the distribution of patent families and scientific publications, indicates similar levels of disparity across the four categories analysed: DAT patents exhibit the highest level of inequality with a Gini Index of 0.689, followed by green patents at 0.669, DAT publications at 0.624 and green publications at 0.608.

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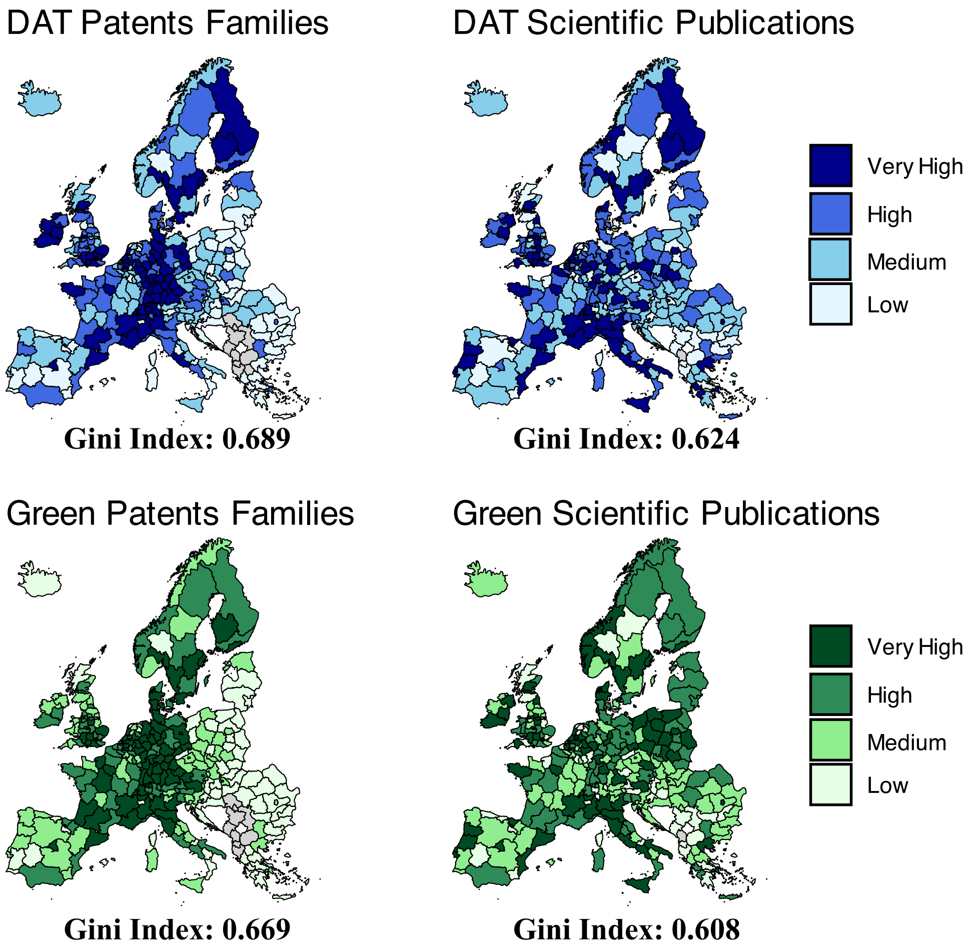

Figure 4.3. European distribution of patents and scientific publications in DAT and Green technologies. *The intensity of the colours indicates the probability of finding either a patent or a scientific publication in each region. The distributions of the probabilities are fitted using quantiles with probability (0, 0.25, 0.5, 0.75, 1).*

The comparison between patents and publications reveals that scientific knowledge accumulation does not always lead to invention activity. A key distinction between patenting and publishing is the broader geographical distribution of scientific publications. While some regions actively engage in both patenting and publishing, others demonstrate significant disparities between scientific knowledge production and invention.

For DAT, 49.85% of regions show a similar degree (high or low) probability of developing DAT in patenting and publishing, whereas for green technologies, this overlap is lower at 43.81%. Regions with a strong presence of patents and publications are mainly industrial hubs, including Germany, France, the UK, and Scandinavia. In contrast, regions in Southern and Eastern Europe show lower levels of technological production. However, green patents are less concentrated than DAT patents, indicating a broader regional engagement in green technological development. Notably, several regions in Spain, and Italy play a significant role in green technology innovation, contrasting with the more centralised nature of DAT patents.

Overall, while patenting activity is highly concentrated in a few industrial hubs, publications are more evenly spread, with greater participation from regions in Southern and Eastern Europe. These areas contribute to scientific knowledge production but are less engaged in the invention process. For example, several regions in Italy play a significant role in publishing research on DAT and green technologies, yet only a limited number of these regions also demonstrate substantial patenting

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activity. This suggests that while knowledge creation occurs in a wider range of regions, the transition from research to innovation remains concentrated in specific technological hubs.

4.3. Knowledge unevenness distribution.

This subsection presents the results of the analysis conducted on the convergence of DAT and green technologies (twin technologies). These technologies were identified by examining the **cognitive convergence of DAT and green technologies** through co-citation networks. A total of 17,049 twin patent families and 160,940 scientific publications are utilised for the regional analysis. The analysis of inequalities is again accessed through analysing the regional distribution of patents and scientific publications.

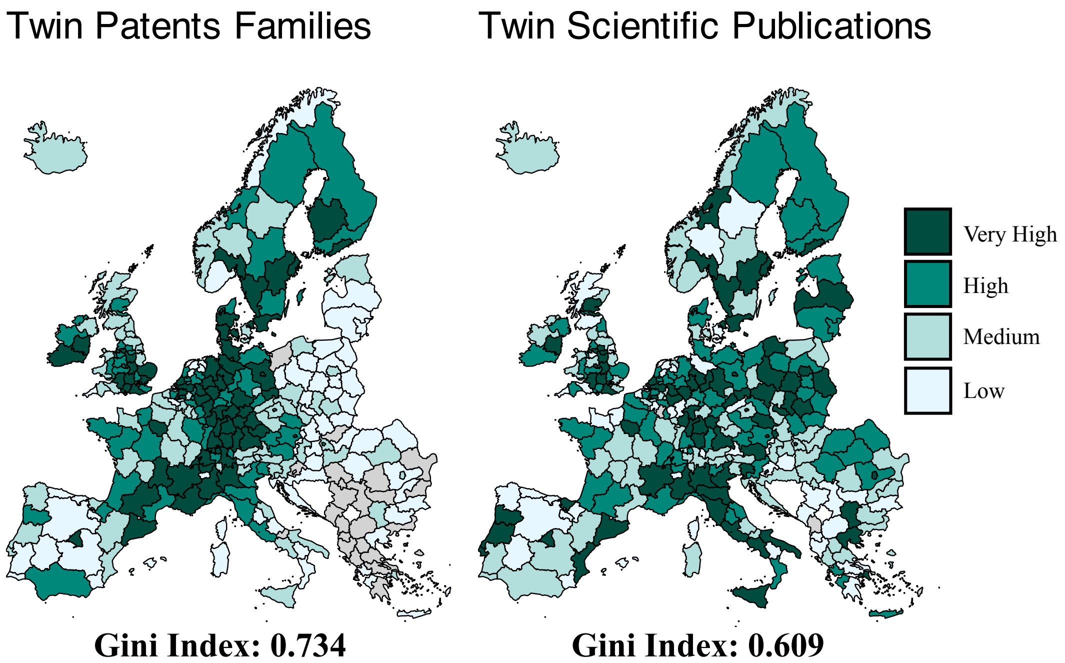

Figure 4.4. European distribution of patents and scientific publications in DAT and Green technologies. *The intensity of the colours indicates the probability of finding either a patent or a scientific publication in each region. The distributions of the probabilities are fitted using quantiles with probability (0, 0.25, 0.5, 0.75, 1).*

The results indicate that patents are more unevenly distributed than scientific publications, consistent with previous findings (Figure 4.5). The results indicate that DAT and green converging patents are significantly more concentrated than scientific publications (Figure 4.4). The Gini Index for twin patents is 0.734, reflecting high regional inequality, while for scientific publications, it is 0.609, indicating a more even knowledge distribution. Additionally, only 47.09% of regions exhibit similar patenting and publishing activity, suggesting that scientific knowledge accumulation and technological innovation are unevenly distributed across regions. These findings align with trends in DAT and green technologies, highlighting that their cognitive convergence is following similar patterns of regional disparities as DAT and green technologies. Notice that for the analysis of DAT and green technologies, convergence patents and scientific publications were excluded to identify unique patterns in each subset of the analysis.

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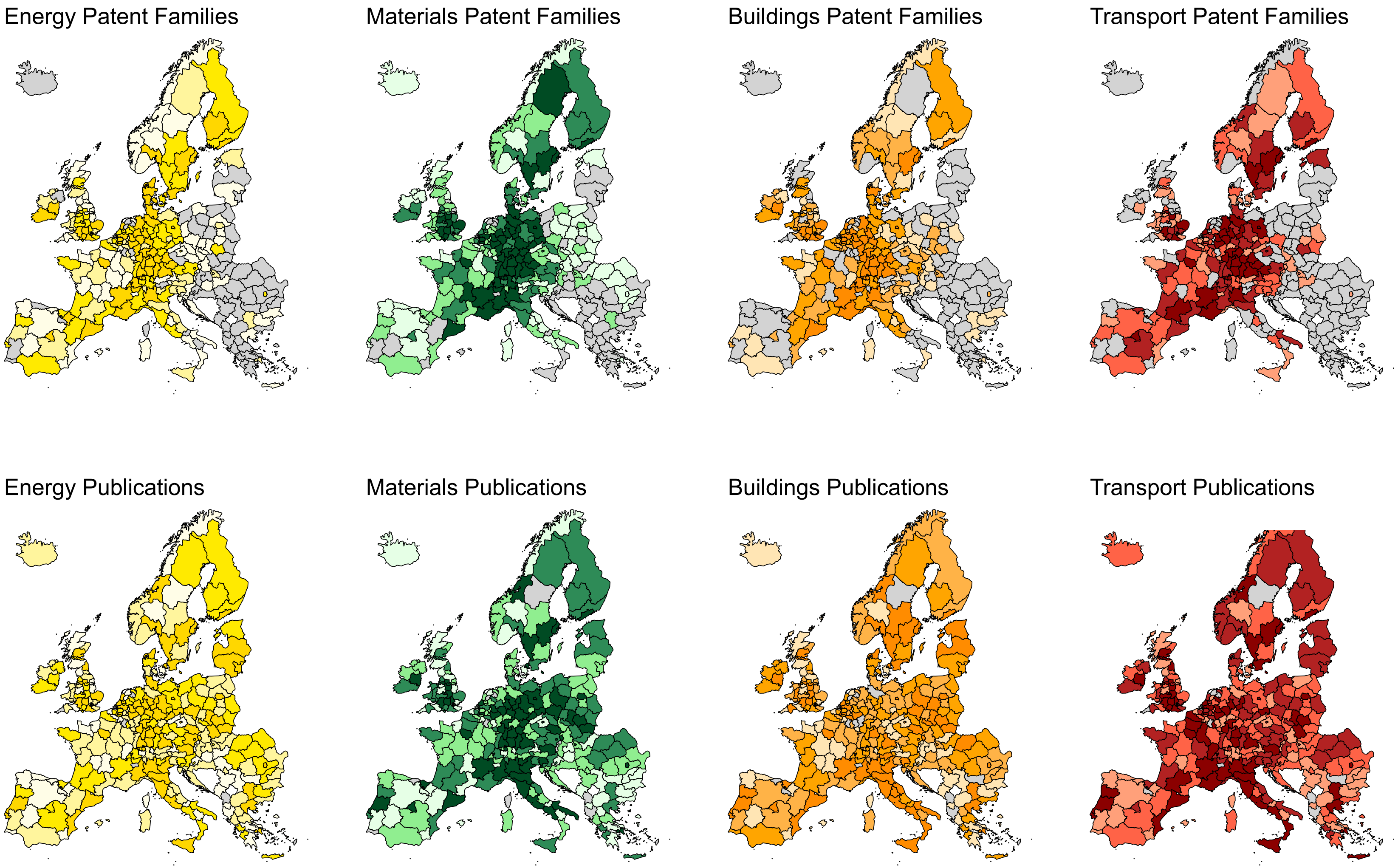

Figure 4.5. Distribution of DAT and green technologies convergence in European regions.
The intensity of the colours represents the probability of finding a patent in a given region. Darker colours indicated a higher probability of finding a patent in a giving region.

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In order to provide a detailed analysis of the convergence between DAT and green, the most frequent sectors are evaluated, including Clean Energy, Sustainable Materials, Sustainable Buildings, and Sustainable Transport (Figure 4.5). The Gini index results are summarised in Table 4.2. The Gini Index underscores the varying degrees of patenting concentration across sectors, emphasising the need to consider regional and sectoral dynamics when analysing the emergence of twin technologies. Sustainable transport exhibits the highest unevenness (Gini Index = 0.817), whereas clean energy publications show the lowest (Gini Index = 0.631). Despite these sectoral differences, all four evaluated sectors display higher uneven distribution in patenting activity, whereas scientific knowledge is more evenly distributed. This analysis confirms that while scientific knowledge production is widespread across European regions, patenting activity remains highly concentrated. Southern and Eastern Europe play a significant role in the scientific production of clean energy, sustainable transport, sustainable materials, and sustainable buildings. However, in many regions, scientific knowledge does not consistently translate into invention, highlighting a disparity between knowledge creation and technological development, where science is widespread, but innovation remains concentrated in a few regions.

Table 4.2. *GINI index indicator for the fourth twin sectors.*

	GINI Index Patents	GINI Index Publications
Clean Energy	0.755	0.631
Sustainable Materials	0.784	0.653
Sustainable transport	0.818	0.647
Sustainable Building	0.762	0.637

In the following section, the results of twin technologies will be further examined by analysing collaboration networks in patenting and publishing. The analysis contributes to analysing if these regions falling behind in the development of twin technologies are building networks to increase their capabilities to develop these technologies

4.4. Inter-regional complementarities (Social Convergence)

This section presents an analysis of inter-regional collaboration. The results show the extent of cooperation within the same country, referred to as national collaboration, and cooperation between regions from different countries, referred to as European collaboration. The analysis allows us to identify potential inequalities in the collaboration networks created by each region. Network analysis is applied to map these relationships, and the strength of connections is measured using the Jaccard Similarity Index.

Figure 4.6 categorises regions into four distinct groups based on their collaboration patterns. Regions characterized by strong collaboration both at the European and national levels are indicated in orange. Regions that primarily engage in national collaboration are depicted in green. Those that predominantly collaborate with areas outside their country are marked in red, while regions displaying weak or no collaboration at either level are shown in blue. This classification provides insights into the spatial structure of knowledge flows and the extent to which regions engage in collaborative networks that facilitate technological invention.

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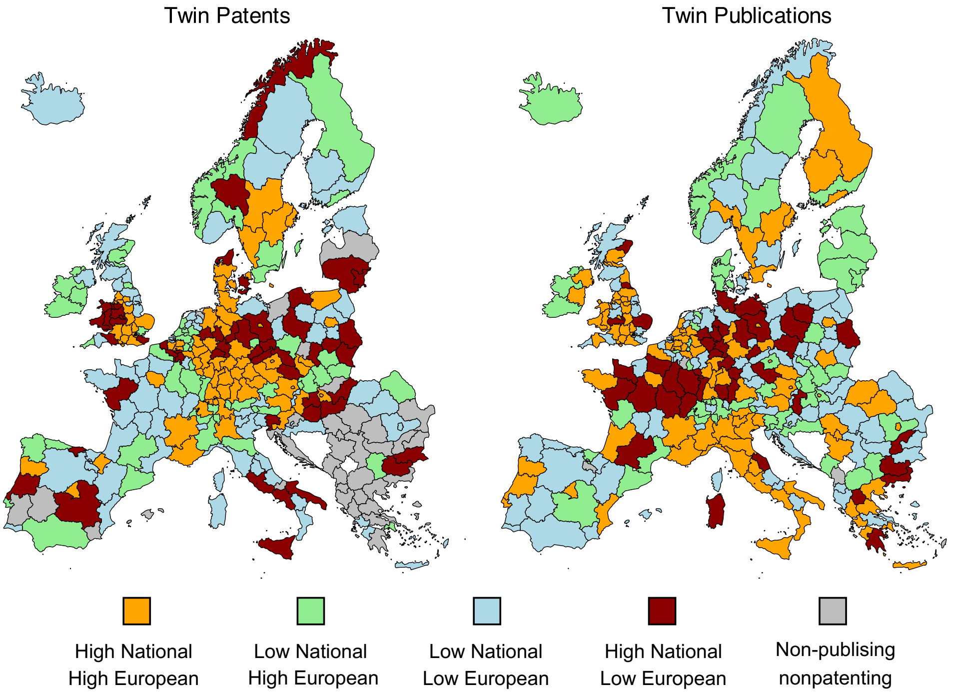

Figure 4.6. National and European Collaboration in twin technologies.

The results uncover significant patterns of the emergence of twin technologies and the disparities in knowledge accumulation. Central European regions, in line with previous findings, exhibit strong collaboration networks at both the national and European levels, reinforcing their role in both invention and scientific knowledge production. In contrast, Eastern European regions tend to display lower levels of collaboration, with some engaging in limited national cooperation. This lack of interconnections in scientific publications and patents may constrain their ability to translate scientific knowledge into technological invention, reinforcing existing inequalities in innovation capacity. A different pattern is observed in Southern European regions, where strong collaboration in scientific knowledge production is evident at national and European levels. Yet, these regions lack robust collaboration networks in twin patents. This is particularly evident in Italy, where regions engage in European scientific collaboration, while most lack strong linkages both nationally and internationally in the field of invention.

These findings underscore the role of social collaboration in shaping the development of twin technologies and how disparities in knowledge networks influence regional innovation capabilities. The convergence of knowledge across regions is critical for translating scientific research into technological applications, which in turn enhances the social, economic, and environmental benefits of converging DAT and green technologies. The limited scientific collaboration observed in Eastern European regions may restrict their opportunities for transforming knowledge into technological advancements, further entrenching disparities in the capacity to participate in innovation-led economic growth. However, the case of Southern European regions indicates that even when regional and national scientific collaboration is strong, the absence of a well-developed collaboration network in the invention may still limit their ability to develop twin technologies and capture the economic and technological benefits of scientific knowledge production.

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Functional Urban-areas Collaboration Networks

A more granular analysis of regional collaboration is conducted at the functional urban-area level using the NUTS-3 regions classification, focusing on the convergence of DAT and Green technologies across Clean Energy, Material and Processing, Sustainable Buildings, and Sustainable Transport. Figure 4.7 illustrates that collaboration is largely structured within national boundaries, with urban areas in France, the United Kingdom, Switzerland and Germany emerging as key regional hubs. The colour of the nodes indicates the country, while the size of the betweenness centrality indicates their role as a connection in the urban collaboration network. Each sector is composed of a different number of urban areas, with the lowest having 284 urban areas (transport) and the largest having 769 urban areas (sustainable materials).

In the fourth sector analysed, Germany has more than 40% of the nodes (urban areas), showing a highly uneven concentration of knowledge in twin technologies across systems and sectors. Furthermore, cross-border collaboration remains limited, suggesting weak spillovers between European urban areas. This pattern is further supported by network metrics (Table 4.3), where high modularity (0.758–0.867) and country assortativity (0.666–0.769) indicate the concentration of knowledge within national clusters. These findings suggest that regions specialise in particular technological niches but may lack integration with other regions working on complementary innovations, as indicated by the high diameter of the networks (8-11) and low cluster coefficients (0.26-0.52). Consequently, knowledge exchange across clusters is likely limited, restricting diversification and reinforcing regional disparities in technological capabilities.

Furthermore, the centralisation degree is relatively low across all networks (0.09–0.123), indicating that no single urban area is a collaboration hub at the European level. Instead, the network structure is characterised by smaller cities primarily connected to large cities within their own countries rather than forming cross-border collaborations. While this structure distributes innovation participation more widely, it also prevents smaller regions from directly benefiting from interactions with regions in other countries. This structure has significant advantages in the long-term stability of innovation and resilience, as technological redundancy in national networks might support the decline of innovation in some cities. Yet, these structures are highly vulnerable to the loss of the main city hubs, and their decline in innovation might produce cascade effects deeply affecting smaller cities depending on them. Moreover, central innovation hubs remain disconnected from each other (high network diameter), limiting the diffusion of cutting-edge knowledge and slowing down radical innovation in converging DAT and twin technologies. Therefore, these regions might struggle to integrate global knowledge, leading to slow diversification.

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Table 4.3. Network metrics for the collaboration network in twin technologies.

Metric	Energy	Materials	Buildings	Transport
Nodes	601	769	319	284
Edges	2155	4291	816	712
Diameter	12	8	11	11
Density	0.0121	0.0147	0.0161	0.0179
Average Degree	7.2512	11.2874	5.1348	5.0563
Degree Centralization	0.1212	0.1741	0.0908	0.1235
Country assortativity	0.6668	0.6661	0.7059	0.7686
Clustering Coefficient	0.2648	0.525	0.3625	0.3695
Modularity	0.8181	0.7582	0.8485	0.8673
Number of Modules	27	29	20	23

In summary, European and national collaboration networks play a fundamental role in overcoming barriers to translate scientific knowledge into invention, particularly in the invention of converging DAT and green technologies. The diversification of knowledge and skills through inter-regional collaboration is essential for fostering the emergence and diffusion of these technologies across European regions. However, the uneven distribution of collaborative networks illustrates broader inequalities in technological development, where some regions remain peripheral in innovation dynamics despite contributing to scientific knowledge production. Without addressing these disparities, regions with weaker invention linkages may struggle to fully capitalise on their scientific capabilities, further consolidating the concentration of innovation capacity in a limited number of regions.

In addition, the urban-urban collaboration network shows that while twin invention collaboration networks are not overly centralised, they remain highly localised, with national boundaries shaping collaboration patterns. The weak connectivity between leading innovation hubs and the strong modularity suggests that regions prioritise collaboration with their closest neighbours to reduce knowledge transfer costs. This fragile structure of collaboration signals that the convergence of DAT and green technologies is in an early stage of emergence, with traditional knowledge hubs leading patent production but facing structural restrictions on diversification and cross-fertilisation—both of which are critical for radical innovation. The capabilities for technological development remain anchored in traditional knowledge hubs, where each country's specialised knowledge production limits broader integration. Therefore, understanding how regions specialise in DAT and green technologies is essential to assessing their potential to innovate in twin technologies, as explored in the following subsection.

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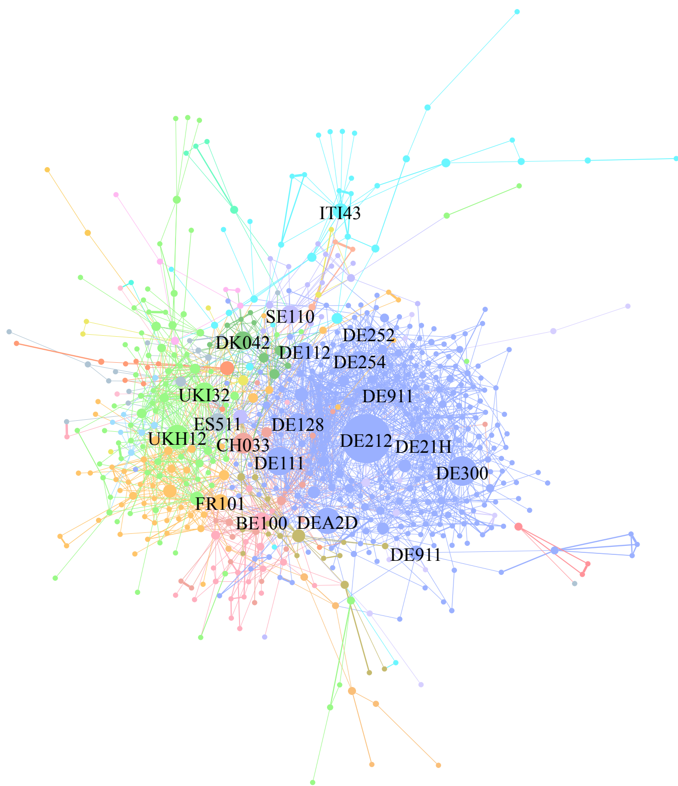
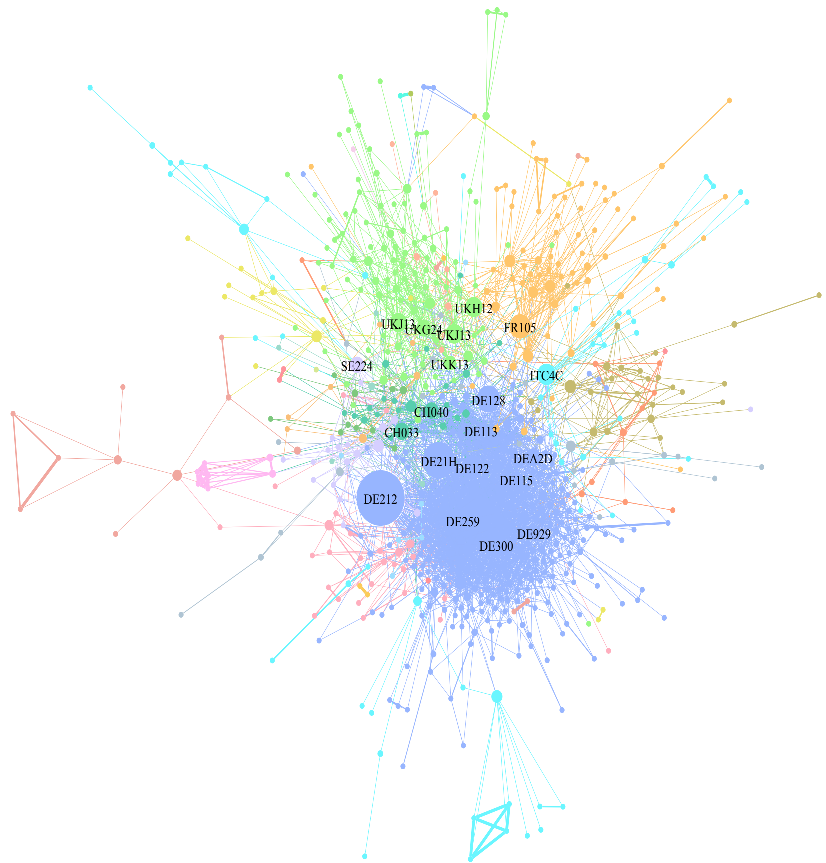
Collaboration Networks in Twin technologies

Clean Energy Patenting
Collaboration in Twin Technologies



Sustainable Materials Patenting
Collaboration in Twin Technologies



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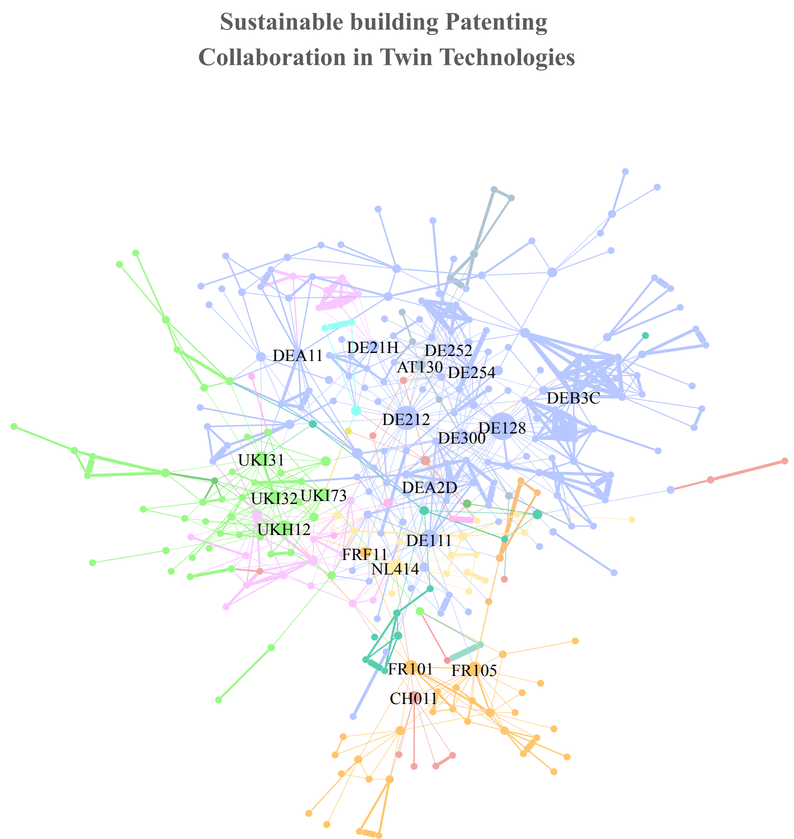

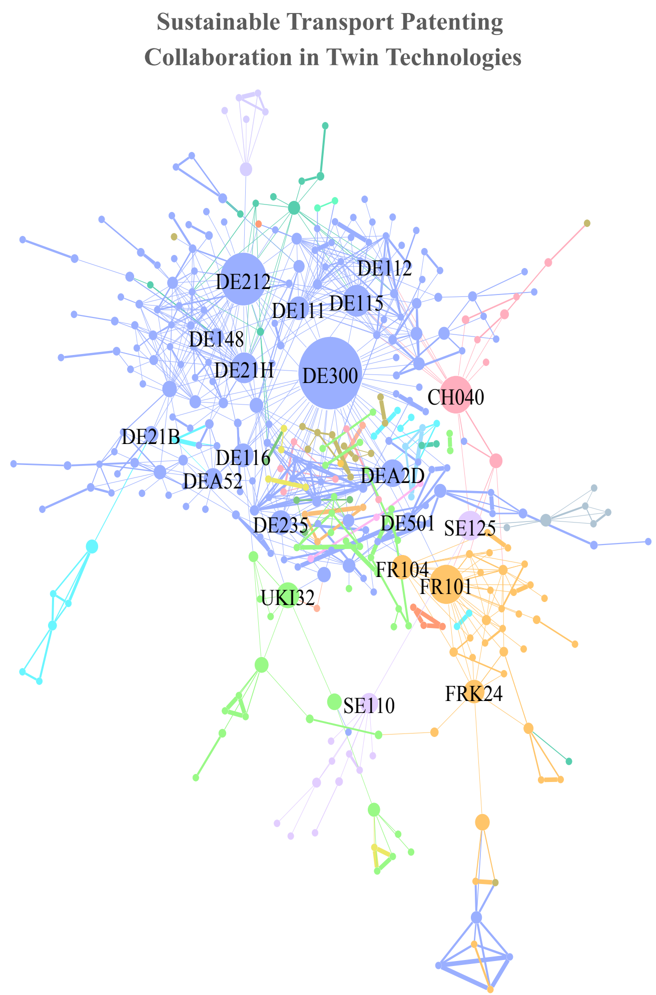

Figure 4.7. Network of Collaboration in converging DAT and green technologies NUTS-3.

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4.5. Regional Diversification Potential (regional convergence)

In previous sections, the cognitive and social convergence between DAT and green technologies was analysed to identify regional capabilities related to scientific knowledge production and patenting activity in twin technologies. This section shifts the focus to the geographical dimension by examining the colocation of DAT and green patents and scientific publications across European regions. To accurately capture the separate dynamics of DAT and green technologies, patents and publications previously identified as highly converged between these domains (twin patents and publications) were excluded. This approach allows us to isolate the regional convergence patterns in DAT and green technologies without the influence of their strongest cognitive overlaps.

This shows the analyses of the patent dataset, while the analysis of scientific publications is in Supplementary Material 5**.** The focus is on patent data as it has been shown to elucidate more regional inequalities. The goal here is not to directly compare patents with publications but rather to assess their distinct temporal variations.

Geographical patenting

Figure 4.8 presents the results of the patent analysis across the four-time windows. Five key patterns emerge from the analysis. First, many regions accumulating diversification capabilities in DAT also accumulate capabilities in green technologies, suggesting possible complementarities between industries, infrastructure, and knowledge production. For instance, regions in Germany and northern Italy appear well-positioned to develop both DAT and green technologies. The second pattern distinguishes between early and late movers in DAT and green technologies. Regions that adopted DAT or green technologies early in the emergence phase are more likely to continue developing them in later periods, while late adopters often struggle to catch up. Spain provides a clear example: lacking strong capabilities in DAT and green technologies during the emergence phase, the country significantly increased its capabilities in green technologies in the third period. However, by the final time window, Spain once again falls into a cycle of low diversification. This finding underscores the importance of building absorptive capacity early in the technological trajectory, as early investments in technological development enhance the likelihood of successful technological diversification later.

Third, a persistent divergence remains in Eastern Europe. While some regions show slight improvements over time, the overall trend is one of low diversification capabilities. Unlike regions in Western and Northern Europe, which have gradually expanded their technological portfolios, Eastern European regions face structural barriers that limit their engagement in DAT and green technologies, even during the development phase. Similarly, the fourth pattern highlights a growing inequality between core and peripheral regions. Core regions—primarily in Central and Northern Europe—continue to strengthen their position in both DAT and green technologies, reinforcing their role as innovation hubs. In contrast, peripheral regions either remain trapped in low diversification cycles or specialise in only one of the two technologies. This divergence suggests that existing regional innovation policies may not enable broader technological diffusion, potentially exacerbating technological inequalities across Europe.

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The temporal analysis is summarised in Figure 4.9, where the initial four trajectories identified in each time window are expanded into nine categories, providing detailed insight into the different paths that regions have followed from 2000 to 2021. In Figure 5.10-a, regional trajectories of European regions are displayed, while Figure 5.10-b presents the results of the Principal Component Analysis (PCA). Figure 5.10-c shows the variance explained, revealing that over 95% of the variance is accounted for by the three first axes, which confirms the robustness of the classification. By utilising the three dimensions of the PCA, the cluster analysis is detailed, providing a clearer representation of the temporal trajectories. For instance, ten clusters are identified by the PCA, which are consolidated into nine regional trajectories through the merging of two groups that predominantly followed a converging path, along with regions where no patents were identified.

The first category, represented by a light greenish-blue colour, includes regions where DAT and green technologies show high diversification potential, particularly in Central Europe, the southern UK, Norway, and Switzerland. These regions have the highest potential for developing DAT and green technologies. These regions were previously identified as hubs for developing twin technologies (Figure 4.4) and have strong European collaboration networks (Figure 4.6), indicating a convergence pathway where co-existence and hybridisation occur (Table 2.1). The second group, indicated by a purple colour, comprises regions that fluctuated between DAT and green technologies across the four-time windows evaluated, such as Sicily. The next two categories are associated with specialisation in green technologies. The dark green regions specialise in green technologies, while the lighter green areas represent regions that were initially trapped in a low diversification cycle but developed capabilities in green technologies in the last periods. Examples of these regions include Latvia and central Portugal. Similarly, the next two categories relate to DAT. The darker blue regions consistently specialise in DAT, such as Midi-Pyrénées in France, while the lighter blue areas represent regions that were initially trapped in a low cycle of diversification but in the last periods have shown potential for developing DAT diversification, as seen in Vest in Romania. The final three categories relate to regions that are trapped in a cycle of low diversification. The dark pink colour indicates areas that consistently demonstrated low diversification capabilities in both DAT and green technologies. The lighter pink categories represent regions that sought to develop capabilities in DAT (lighter pink) and green technologies (the lightest pink) but ultimately remained trapped in a cycle of low diversification. A clear example is found in regions of Spain, which developed diversification capabilities in green technologies during the third period but ended up in the trapped category by the last period, as mentioned previously.

Overall, the results demonstrate that regional technological pathways are dynamic rather than fixed. Some regions maintain their technological strengths, while others shift their specialisation over time, either catching up or falling behind. The PCA visualisation offers a structured view of these shifts, revealing both persistent inequalities and opportunities for technological recovery in certain regions. These findings provide valuable insights for targeted interventions to support regions facing diversification constraints and enhance the potential for DAT, and green technologies across Europe.

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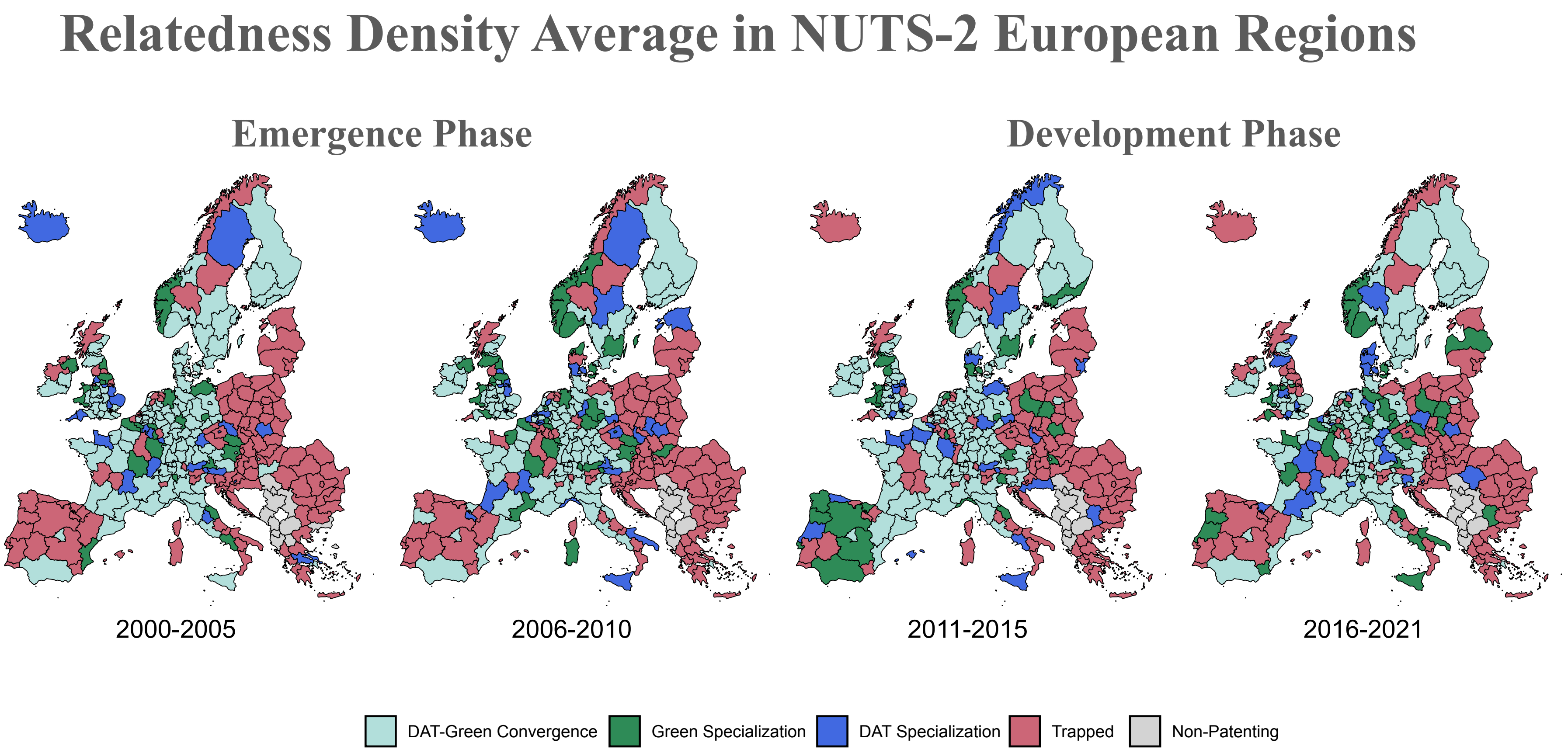

Figure 4.8. Relatedness Density Average in DAT and Green technologies from 2000 to 2021 using patent data.

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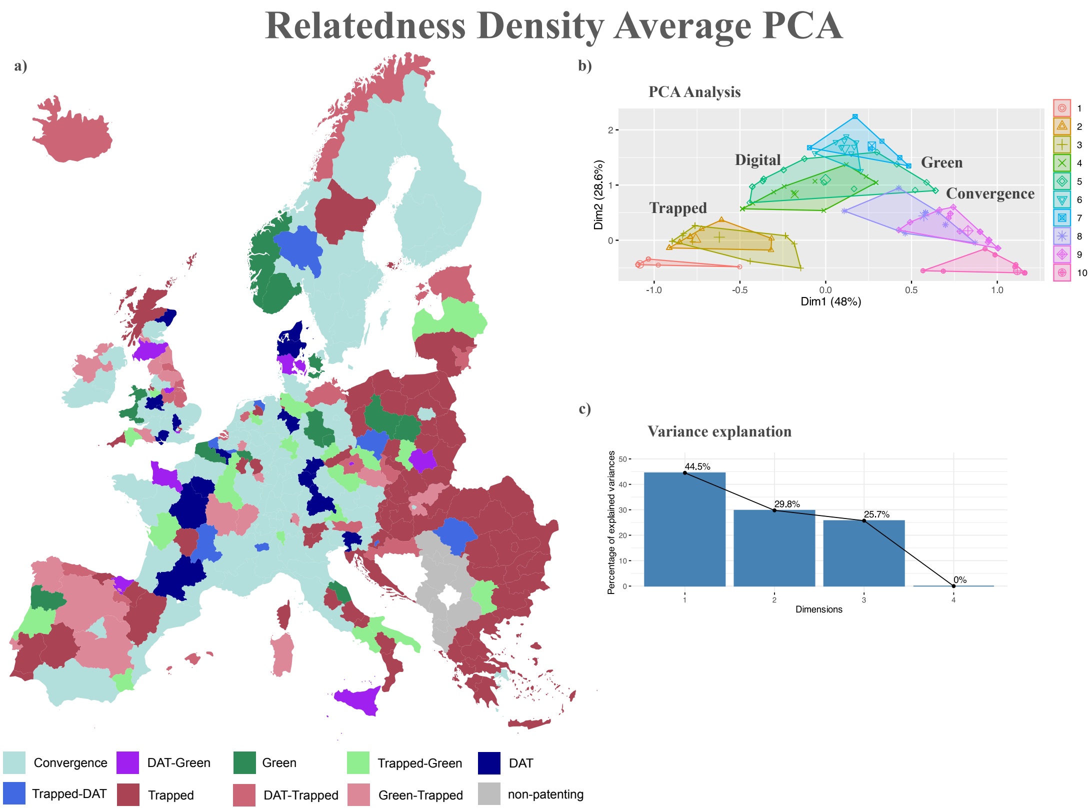

Figure 4.9. Regional Trajectories for Diversification in DAT and Green Technologies using patent data.
Panel (a) displays the regional classification based on diversification trajectories in DAT and green technologies. Panel (b) presents the results of the Principal Component Analysis (PCA), which identifies key patterns in regional technological development. Panel (c) illustrates the variance explained by the first three PCA axes, which together account for more than 95% of the total variance, confirming the robustness of the classification.

In summary, the analysis of regional technological capabilities in DAT and green technologies reveals distinct patterns across Europe. Our examination of patenting activity identifies key regional trajectories and their evolution over time. While some regions consistently develop robust capabilities in DAT and green technologies, others follow specialised pathways or remain trapped in low diversification cycles. Patent analysis indicates that regions enhancing their capabilities in DAT often do the same in green technologies, particularly in Central Europe, northern Italy, and parts of the UK. Early pioneers tend to maintain their advantage, while latecomers struggle to catch up. Notable regional disparities exist, with Eastern and Southern Europe showing lower diversification potential.

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5. Discussion

The significance of our study lies in its systematic exploration of the cognitive, social, and geographical convergence of DAT and green technologies. Unlike previous studies, which have primarily focused on mapping DAT and green technologies separately (Bachtrögler-Unger et al., 2023), our approach systematically examines their convergence and evaluates the uneven regional innovation portfolios shaping the emergence of twin technologies in Europe. ***Task 1.2****, Landscaping the Green, Digital and Twin technologies and mapping technological capabilities of European regions and cities*, and ***Task 1.3****, Mapping Green, Digital and Twin Scientific Specialisation in Europ*e, have been undertaken by analysing regional trajectories using patent data and scientific publications from 2000 to 2021. Our findings demonstrate that early adopters of DAT and green technologies are more likely to develop these technologies further, while later adopters struggle to establish consistent trajectories, increasing the uneven distribution of innovation portfolios across regions over time.

Specifically, our findings show the persistence of low diversification regions in DAT and green technologies, particularly in parts of Southern and Eastern Europe, suggesting lock-in effects (Dolfsma and Leydesdorff, 2009; Simoens et al., 2022), where structural barriers limit certain regions' ability to diversify into new technological developments. The results indicate that these regions, Southern and Eastern Europe, are engaged in the production of scientific knowledge in DAT and green technologies, but they are not effectively translating this knowledge into inventions, highlighting an innovation bottleneck (Dosi, 1997, 1988) that may lock these regions into a low diversification cycle. Scientific knowledge is produced across regions, but structural and institutional barriers limit the ability of certain regions to appropriate and transform scientific advancements into technological development. Rather than merely reinforcing pre-existing inequalities, this bottleneck might actively shape the trajectory of twin technologies within an asymmetrical innovation landscape, where many regions contribute to knowledge production, but only a few regions fully capture its technological and economic benefits.

Moreover, the functional urban-areas collaboration network in Europe exhibits a fragmented structure that reinforces regional inequalities in innovation. Smaller cities primarily connect to larger cities within their own countries rather than forming cross-border collaborations, while large cities remain spatially distant from one another, restricting knowledge flows and diversification across European urban centres. This pattern facilitates incremental innovation within regions but limits interregional diversification, making radical breakthroughs less likely (Balland and and Boschma, 2021; Castaldi et al., 2015). The high modularity and diameter of the evaluated networks underline this fragmentation, as innovation remains concentrated in specialised clusters, hindering the integration of complementary knowledge bases essential for transformative technological advancements (Bachtrögler-Unger et al., 2023). Since breakthrough innovations often require the combination of diverse knowledge domains (Castaldi et al., 2015; Dolfsma and Leydesdorff, 2009; Frenken et al., 2007), the structural separation between these clusters poses a significant barrier. As a result, technological path dependencies within European regions are reinforced, slowing the diversification of capabilities, particularly in twin technologies, where the convergence of digital and green innovation is fundamental. Moreover, this fragmented structure maintains regional inequalities by restricting knowledge diffusion beyond national invention clusters, limiting the ability of less innovative regions to integrate into broader technological ecosystems.

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The temporal analysis of regional diversification capabilities shows that early-adopter regions are more likely to develop strong trajectories of diversification in DAT and green technologies, while peripheral regions consistently fall behind in building similar capacities. These findings reinforce the concerns of the EU Cohesion Policy 2021–2027 (European Commisssion, 2022), as they highlight that many peripheral regions lack the institutional and innovation capacity to specialise in either DAT or green technologies. Despite the strategic emphasis on fostering a Smarter and Greener Europe, the results suggest that peripheral regions often face limitations in institutional capacity, inter-regional connectivity, and innovation ecosystems, which constrain their ability to effectively engage with the twin transitions agenda. In particular, the absence of regional invention capabilities may limit the potential of Eastern and Southeastern regions to capture the benefits of the twin transition agenda. Therefore, rather than narrowing regional disparities, the twin transitions agenda may risk reinforcing existing structural inequalities unless these capability gaps are addressed.

In addition, the temporal analysis shows that although policies for DAT and green technologies have largely evolved separately (Kovacic et al., 2024), their regional development appears to have co-evolved in Central Europe, the south of the UK and the Scandinavian region. One possible mechanism is that DAT has benefited from the favourable policy environment created for green technology development. While EU policy has predominantly prioritised green technologies over DAT (Diodato et al., 2023; Faggian et al., 2025; Mäkitie et al., 2023), expanding green technologies may have indirectly supported DAT growth through shared infrastructure, funding instruments, and overlapping strategic priorities such as competitiveness and efficiency. A complementary mechanism is that green policy has reshaped regional industrial landscapes, weakening some industrial sectors while creating new opportunities not only for green technologies but also for DAT. In this sense, the expansion of green technologies may have indirectly paved the way for the emergence and development of DAT across European regions. Examples of the combined effect of these two mechanisms include AI-driven climate modelling and industrial decarbonisation, which attract sustainability funding while simultaneously strengthening regional AI and automation capacities (Lewis et al., 2024). Similarly, robotics and automation solutions for circular economy initiatives—such as waste sorting or predictive maintenance in renewable energy infrastructure—benefit from green innovation funding despite being fundamentally connected to the digital industry (Chauhan et al., 2022; Piscicelli, 2023).

While this study provides a systematic analysis of the convergence of DAT and green technologies, some limitations should be acknowledged. Although analysing innovation portfolio capabilities through patents and scientific publications reveals regional patterns of knowledge accumulation, it does not account for industrial and governmental investment priorities (Penna et al., 2023), which can shape technological trajectories and influence regional diversification. Additionally, our analysis does not consider the diffusion of DAT and green technologies, where multiple couplings between them may occur (Mäkitie et al., 2023). In addition, a more granular typology of specific technological domains within DAT and green technologies is needed to determine whether their recombination leads to incremental or radical innovation. In this context, Mäkitie et al. (2023) argue that the way in which digital and green transitions converge impacts their transformative potential. While digital technologies can drive incremental improvements—such as optimising energy generation and distribution through sensors and data analysis —they may also cause lock-in of existing systems, limiting the transformative potential of green transitions.

To conclude, our study provides novel insights into the regional emergence and development of DAT, green, and twin technologies. Our findings highlight uneven regional convergence in the cognitive,

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social, and geographical dimensions of DAT and green technologies, revealing varying regional capacities to support the emergence of twin technologies. The interplay between DAT and green technologies is likely to produce diverse techno-economic trajectories, where coexistence, competition, or recombination may shape regional innovation pathways. Ultimately, the way in which policy steers DAT and green transitions will significantly influence the unfolding of twin transition agenda and their social, economic, and environmental impacts. However, institutional barriers remain a key challenge, particularly in Southern and Eastern Europe. Overcoming these barriers requires a deeper focus on regional dynamics, which can reduce uncertainties, lower knowledge transfer costs, foster cohesion, and mitigate trade-offs in the transition process.

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6. Supplementary Material

Supplementary Material 1: Digital Automation Technological and green technologies description

Table S1.1. *Digital Automation Technologies classification.*

Category	Description	Policy Relevance in EU	Examples of Technologies
Robots	Technologies involving machine vision, automation, and robotics for industrial and service applications.	Supports automation and efficiency in industries, aligning with EU priorities for industrial competitiveness and automation.	Machine vision and real-time monitoring, Co-bots, Swarm robotics, Service robotics, Semi-autonomous, Automated platforms/vehicles, Tunnel boring and mining robots, Drones, Robotic vehicles, Exoskeletons, and Robotic Process Automation (RPA)
Data Acquisition and Management	Technologies for data management, including databases, cloud storage, and blockchain systems, facilitate efficient data handling, while data collection technologies, such as healthcare instruments and engineering sensors, generate real-time insights to enhance decision-making across sectors	Aligns with the EU's Data Governance Act by enhancing secure and efficient data storage and management systems.	Scanners, sensors, remote sensing, GPS, CCTV, Scientific and engineering instruments, Healthcare instruments and Data scraping Data base ssytems, Relational databases, cryptography, security, blockchain, and big data analytics.
Computing	Technologies for computational architecture, automated storage, and high-performance computing.	Contributes to advancements in EU high-performance computing initiatives and supports cloud and edge computing strategies.	Computer architectures (e.g. quantum, edge, cloud, HPC, grid computing), automated storage systems.
AI & Intelligent Information Systems	Technologies utilizing artificial intelligence and machine learning for prediction, simulation, and intelligent systems.	Supports the EU's AI Act by advancing responsible AI and enabling predictive analytics in various sectors.	Simulation, Machine Learning, NLP, machine vision, Expert system, predictive systems, speech recognition and text recognition and produciton
Additive Manufacturing	Technologies enabling rapid prototyping and production using digital tools and processes, such as CAD and 3D printing.	Supports the EU Digital Strategy by fostering innovation in digital design, prototyping, and production, promoting advanced	CAD/CAM systems, prototyping, and 3D printing technologies.

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Category	Description	Policy Relevance in EU	Examples of Technologies
		manufacturing processes.	
Networking	Technologies focused on connectivity and communication, including IoT and wireless communication systems.	Promotes connectivity and smart infrastructure development, in line with EU digital and IoT frameworks.	IoT devices, wireless communication systems.
User Interface	Technologies for human-computer interaction, including augmented reality, haptics, and input/output devices.	Supports the EU Digital Strategy by enhancing user interaction in digital environments and enabling seamless integration.	Conventional input devices, Display devices, Augmented reality, Haptics and Tele-haptics, Virtual Reality Touchscreens/kiosks for customer interface, Sound technologies, Neuroscanning and Gamification

Note: Based on Rytkova, Ciarli, and Önder 2022 Appendix B & C. Data Management and Data acquisition technologies were merged in one category due to their similarity

Table S1.2: Green technologies classification.

Category	description	Policy Relevance	Examples
Energy	Technologies for clean energy generation, storage, transmission, and efficient use, critical for sustainable energy transitions.	Aligns with the EU's Renewable Energy Directive and Repower EU; fundamental to achieving the net-zero targets of the European Green Deal and SDGs.	Photovoltaic systems, wind turbines, energy storage systems, smart grid technologies.
Transport	Technologies transforming air, maritime, rail, and road transport to reduce emissions and enhance sustainability.	Integral to the EU Sustainable and Smart Mobility Strategy, focusing on reducing emissions across air, maritime, rail, and road transport.	Electric vehicle batteries, hydrogen-powered ships, rail electrification systems, sustainable aviation fuels.
Building	Technologies aimed at reducing energy consumption and improving efficiency in building construction and usage.	Supports the EU's Energy Performance of Buildings Directive; essential to achieving climate neutrality in urban environments by 2050.	Thermally efficient materials, solar heating systems, energy-efficient lighting.

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Category	description	Policy Relevance	Examples
Food	Technologies focused on sustainable food production, distribution, and consumption to address mitigation and adaptation challenges.	Aligns with the EU Farm to Fork Strategy, addressing both mitigation and adaptation strategies for sustainable food systems.	Precision agriculture, vertical farming systems, bio-based packaging.
Material Producing and Processing	Technologies that minimize environmental impact in material production and processing, supporting industrial and supply chain transformations.	Aligns with the EU Circular Economy Action Plan, focusing on reducing the environmental impact of materials and supporting industrial transformation.	Carbon capture in steel production, alternative cement formulations, sustainable chemical synthesis.
Waste Management	Technologies for recycling, reuse, and waste reduction, essential for mitigating pollution and transitioning to a circular economy.	Addresses the EU Waste Framework Directive, focusing on recycling, reuse, and waste reduction to mitigate historical and ongoing pollution.	Advanced plastic recycling processes, bio-waste processing, circular economy innovations.
Nature-Based Solutions (N)	Technologies leveraging natural processes for ecosystem conservation, restoration, and biodiversity enhancement.	Supports the EU Biodiversity Strategy for 2030, focusing on ecosystem conservation, restoration, and monitoring.	Technologies for afforestation, habitat restoration, biodiversity tracking.
Phase-Out or Transitioning Technologies	Technologies tied to fossil fuel optimization, combustion engines, and nuclear energy, addressing phase-out and transition strategies.	Evaluates technologies linked to the petrochemical industry, combustion engines, and nuclear energy, reflecting diverse regional policy priorities.	Combustion engines, fossil fuel optimization, fusion energy, nuclear energy.

Supplementary Material 2: Cognitive convergence of DAT and green patents

In order to identify additional twin patent families, co-citation coupling is used. This method is widely used in bibliometric methods for identifying meaningful interactions between publications and establishing thresholds of interaction between scientific articles (Grauwin and Jensen, 2011; Romero-Goyeneche et al., 2025, 2022). Similarly, in our analysis, a meaningful coupling between green and digital patent families is determined. For this analysis, the links of every bipartite network are characterised. All patent families and scientific publications that shared at least one linkage with green and digital are identified.

The relevance of each citation is determined based on its probability of appearance in the dataset and the number of citations that every patent has. It is important to note that the probabilities of interaction differ across these matrices due to variations in the sizes of the patent and scientific

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publications datasets. Patent families or scientific publication with higher number of citation have a higher baseline probability of interaction, which is taken into account when calculating these correspondence probabilities.

The **Cognitive Coupling (CC)** is calculated for each dataset using a step-by-step method. The **Digital-Twin Interaction Matrix** is used here as an example to illustrate the process:

I. **Calculate Relative Relevance (RR):** For each cited twin patent family, the **Relative Relevance (RR)** is calculated as:

$$\boldsymbol{RR_{tpf} = \frac{c_{tp}}{\sum_{j=1}^{N} C_j}}$$

Where $\boldsymbol{c_{tp}}$ is the count of occurrences of the cited twin patent family $(\boldsymbol{tp})$, and $\boldsymbol{\sum_{j=1}^{N} C_j}$ is the total count of occurrences of all cited twin patents families $(\boldsymbol{tp})$ in the dataset. This step quantifies the significance of each cited twin patent family $(\boldsymbol{tp})$ relative to the entire set of twin-cited patent families.

II. Determine Weight of Interaction (WI): for each digital patent family $(\boldsymbol{dp})$, the commonly cited patent families shared with twins' patent families $(\boldsymbol{tp})$ are identified $(\boldsymbol{dp\varepsilon\delta tp})$. The weight of interaction (WI) is then calculated as:

$$\boldsymbol{WI_{dp} = \sum\nolimits_{dp\varepsilon\delta tp} RR_{tp}}$$

Where $\boldsymbol{RR_{tp}}$ is the Relative Relevance of each shared twin cited patent family $(\boldsymbol{tp})$ as calculated in Step 1. This calculation aggregates the relative significance of all twin patent families $(\boldsymbol{tp})$ that are linked to a given digital patent family $(\boldsymbol{dp})$,

III. Account for Citation Size with Ratio of Interaction (RI): To adjust for the size of each digital patent family $(\boldsymbol{dp})$, the Ratio of Interaction (RI) is computed as:

$$\boldsymbol{RI_{dp} = \frac{C_{s,dp}}{C_{dp}}}$$

Where $\boldsymbol{C_{s,dp}}$ is the number of citations from the given digital patent family $(\boldsymbol{dp})$ that twin patent families also cite $(\boldsymbol{tp})$ and $\boldsymbol{C_{dp}}$ is the total number of citations made by a given digital patent family $(\boldsymbol{dp})$. This ratio quantifies the proportion of citations from a given digital patent family that overlap with twin patent families, providing a normalised measure of their interaction while accounting for the total citation activity of each digital patent family. This ensures fairness by normalising citation frequencies across patent families of varying sizes.

IV. Calculate Cognitive Coupling (CC): for each digital patent family, $(\boldsymbol{dp})$ the cognitive coupling with twin patent families $(\boldsymbol{tp})$ is calculated by multipling the Weight of Interaction (WI) and the Ratio of Interaction (RI) as:

$$\boldsymbol{CC_{dp} = WI_{dp}.RI_{dp}}$$

This calculation ensures that the CC metric accounts for both the size of each digital patent family and the frequency of shared citations between digital and twin patent families.

After calculating the cognitive coupling of each digital patent family, it is important to assess which linkages or couplings are significant. To identify digital patent families that have meaningful interactions with twin patent families, the distribution of Cognitive Coupling (CC) values across all digital patent families is modelled as follows:

V. Log Transformation of Cognitive Coupling: for each patent digital family, their $\boldsymbol{CC_{dp}}$ values are log-transformed in order to stabilise variance and handle skewness:

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$$Log\ (CC_{dp}) = Log_{10}(CC_{dp} + 1)$$

Where CC_{dp} is the original Cognitve couple valued assaulted in step iv, and +1 avoids issues with undefined logarithms for zero values.

VI. Fit the power-law model: A power model-law distribution is fitted to the log-transformed CC_{dp} values. The probability density function $P(x)$ of the power-low distribution is:

$$P(x) = \frac{\propto -1}{x_{min}}(\frac{x}{x_{min}})^{-\propto}, \qquad x \geq x_{min}$$

Where α is the scaling parameter, x_{min} is the threshold above which the distribution follows a power law and x is the value of $Log\ (CC_{dp})$. The model estimates x_{min} the minimum value at which the power-law behaviour begins, using maximum likelihood estimation (MLE). This threshold separates the 'tail region' of the distribution, representing the most significant cognitive couplings. In this regard, digital patent families (dp) with $Log\ (CC_{dp}) \geq x_{min}$ are selected as meaningful, representing the tail region data of the distribution where significant interactions with twin patent families occur (tp)

Supplementary Material 3: Relatedness Density Average calculation

The Relatedness Density Average (RDA) values range from 0 to 100, with higher values indicating a greater potential for diversification into digital, green, or twin technologies. The calculation of Relatedness Density Average (RDA) provides a comprehensive overview of each region's ability to transition into new technological domains, supporting digital, green twin transitions.

This method is based on the concept of technological similarity between regions. The more similar one region is to all the other, the greater the opportunity for developing comparable diversification patterns. This methodology integrates co-occurrence matrices, relatedness indices, RCA, and relatedness density to systematically evaluate regional diversification potential. By combining these steps, the analysis highlights opportunities for regional technological convergence and specialization. The calculation is performed as follows:

i. Analysing the co-occurrence of technologies across European regions requires the construction of co-occurrence matrices. In this analysis, CPC patent codes are used as a proxy for technologies, with regions examined at the NUTS-2 level. The co-occurrence matrix M represents the distribution of technologies across regions:

$$M = \begin{pmatrix} x_{r_1tc_1} & \cdots & x_{r_1tc_m} \\ \vdots & \ddots & \vdots \\ x_{r_ntc_m} & \cdots & x_{r_ntc_m} \end{pmatrix}$$

Where, $r_{1,}r_2 \dots , r_n$: Regions, $t_{c1,}tc_2 \dots , tc_n$: technological classes, and $x_{r_ntc_m}$ takes binary values 1 if a region $r_{1,}$ has a patent in technology $tc_{1,}$ and otherwise 0

ii. This matrix forms the basis for all subsequent calculations. Each row represents the technological portfolio of a specific region, while each column shows the distribution of a specific technology across regions.

To measure the relationships between technologies, a **technology co-occurrence matrix** C **is derived from** M.

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$$C = \begin{pmatrix} c_{t_1tc_1} & \cdots & c_{tc_1tc_m} \\ \vdots & \ddots & \vdots \\ c_{r_mtc_{1m}} & \cdots & c_{tc_mtc_m} \end{pmatrix}$$

Each element $c_{t_it_{j1}}$ is calculated as:

$$c_{r_1r_2} = \sum_{r=1}^{n} x_{r_itc_j} . x_{r_itc_j}$$

Where, $c_{tc_{ij}}$ represents the number of regions where both technologies tc_i and tc_j converge and n is the total number of technologies.

iii. The Relatedness Index (RI) normalizes the co-occurrence matrix C to assess whether two technologies are more related than expected by chance. It is calculated as

$$R_{t_1t_2} = \frac{c_{t_1t_2}}{\sqrt{c_{tc_1tc_1} . c_{tc_2tc_2}}}$$

Where $c_{t_1t_2}$: observed co-occurrence of technology tc_1 and tc_2, and $c_{tc_1tc_1} . c_{tc_2tc_2}$ is the diagonal representing the total number of tc_1 and tc_2 respectively

The Relatedness Index (RI) indicates regional technological proximity. To identify only significant interactions, it is converted into a binary matrix.

$$R_{tc_1tc_2} = \begin{cases} 1 \; if \; R_{tc_1tc_2} \geq 1 \\ 0 \; if \; R_{tc_1tc_2} < 1 \end{cases}$$

iv. The new step consists of analysing the Relative Technological advantage (RTA) to identify regional specialization, RCA is calculated for each region r and technology tc:

$$RTA^t_{r,tc} = \frac{x^t_{r,tc} / \Sigma_{tn} \, x^t_{r,tc}}{\Sigma_r \, x^t_{r,tc} / \Sigma_{r,t} \, x^t_{r,tc}}$$

$x^t_{r,tn}$ is the total number of patents of a region r in technology tc in a given time window t, $\Sigma_{tn} x^t_{r,tn}$ is the total patents in a region r across all technologies, and $\Sigma_{r,t} \, x^t_{r,tn}$ is the total number of patents in technology tn across all regions.

$$RTA^t_{r,tc} = \begin{cases} 1 \; if \; RTA^t_{r,tc} \geq 1 \\ 0 \; if \; RTA^t_{r,tc} < 1 \end{cases}$$

RTA is a binary variable that takes value 1 when a region r exhibits a higher share of patents in a specific technology class tc, compared to other regions. If the criterion is not met, the Relative Technological advantage (RTA) takes a value of 0.

v. Using the Relative Technological advantage (RTA) $RTA^t_{r,tc}$ and the Relatedness Index $R_{tc_1tc_2}$, the Relatedness Density is calculated to evaluate the likelihood of a region r adopting a new technology tn in a given portfolio, in our case, digital, green or twin.

$$RD_{r,td} = \frac{\sum_{t^i \in N_{tc}} R_{tc_1tc_2} . RTA^t_{r,tc}}{\sum_{t^i \in N_{tc}} R_{tc_1tc_2}}$$

Where N_{tc} is the number the set of technologies related to tc.

$RD_{r,td}$ takes value from 0 to 10; the highest the value, the highest the probability of a region to adopt a new technology tc.

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vi. The Relatedness Density Average (RDA) provides a summary measure of diversification potential for each region, aggregating relatedness density across all technologies:

$$\boldsymbol{RDA_r} = \frac{\sum_t \boldsymbol{RD_{r,td}}}{|\boldsymbol{T}|}$$

Where $|\boldsymbol{T}|$ is the total number of technological classes and $\boldsymbol{RD_{r,td}}$ is the Relatedness Density of each region $\boldsymbol{r}$. The higher the RDA value, the highest the potential to diversify in new technologies.

Supplementary Material 4: Trajectories Analysis

To map regional trajectories across four categories over time, a heuristic approach based on distinct sums was employed. A numerical encoding scheme was utilized to identify the category—'Trapped,' 'Digital,' 'Green,' or 'Co-existing'—assigned to each region during fourth periods. A key requirement of this encoding was that the sum of the values assigned to any three categories should not equal the value assigned to any one category or any of their possible sums. This condition is essential to avoid ambiguity and to ensure clear distinctions between regional trajectories. If the sum of three category values equal another category's value, it would become impossible to distinguish between a region that genuinely belonged to that single category and a region whose scores in three other categories summed to the same value.

The set {1, 3, 5, 10} was used for this encoding. For example:

- **Region 1:** If a region was 'Trapped' in period 1 (value 1), 'DAT' in period 2 (value 3), 'Green' in period 3 (value 5), and 'Trapped' in period 4 (value 10), its cumulative scores would be:
    - Trapped: 1 + 10 = 11
    - DAT: 3
    - Green: 5
    - Coexisting: 0
- **Region 2:** Another region could be 'Digital' in period 1 (value 1), 'Trapped' in period 2 (value 3), 'Trapped' in period 3 (value 5), and 'Green' in period 4 (value 10). Its cumulative scores would be:
    - Trapped: 3 + 5 = 8
    - DAT: 1
    - Green: 10
    - Twin: 0

These examples illustrate that even when regions fall into the same categories across the four periods—albeit in different sequences—their cumulative values remain distinct, allowing for the mapping of varied trajectories. Following the application of this encoding method, each region's pathway is represented through these cumulative scores. Principal Component Analysis (PCA) is then employed to cluster similar pathways based on the relative proportions of time invested in each category. This clustering is independent of the specific numerical values assigned, as long as they preserve the distinct sum property. It is important to note that distinct sums create unique "fingerprints": the distinct sum property ensures that different sequences of category assignments yield different sets of cumulative scores. Subsequently, PCA analyses the patterns of these fingerprints, considering the proportion or relative contribution of each category to the overall trajectory.

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Supplementary Material 5: Geographical Scientific Knowledge Convergence

The analysis of scientific publications reveals distinct trends in the diversification of DAT and green technologies over time (Figure SM4-1). During the emergence phase, knowledge production is highly concentrated in a few regions, whereas the development phase is marked by its diffusion and broader distribution across Europe. These findings highlight the growing scientific potential of DAT and green technologies, underscoring the need to translate this progress into tangible social, economic, and environmental benefits for European regions.

The spatial distribution of scientific publications in DAT and green technologies reveals distinct regional dynamics over time. During the emergence phase (2000–2010), knowledge production remains highly concentrated in a few regions, primarily in Western and Northern Europe, indicating the presence of strong research hubs in the early phases of the development of DAT and green technologies. As the development phase (2011–2021) progresses, scientific activity diffuses across a broader set of European regions. However, this diffusion is uneven—while some regions successfully expand their research capacity in DAT and green technologies, others remain largely excluded from knowledge production, especially in Eastern Europe. Notably, Germany, the Netherlands, and northern Italy strongly converge between DAT and green research.

Additionally, some regions specialise in specific domains, potentially reflecting favourable conditions for sectoral development. France and Spain, for instance, show strong advancements in green research (during the development phase). Eastern European regions show a slower uptake, gradually increasing their presence in scientific publications. However, many peripheral regions, particularly in southeast Europe, such as Greece, remain at the margins of scientific production, indicating structural barriers limiting their ability to develop strong research capabilities in DAT or green technologies.

Similar to the patent analysis, the temporal evolution of scientific publications in DAT and green technologies is categorized into distinct regional trajectories, as summarized in Figure SM4-2. This classification highlights how different regions have developed their research capabilities over time, distinguishing between those that have diversified into both DAT and green technologies, those that specialize in one field, and those that remain trapped in low knowledge production cycles. Regions with strong diversification potential in both DAT and green technologies are primarily concentrated in Central Europe, the UK, and parts of Scandinavia (greenish-blue colour). In contrast, regions trapped in a low diversification cycle are represented in shades of pink. While trapped regions are more spread across Europe in the case of scientific publications, Southern and Eastern Europe still contain the highest concentration of regions with persistently low diversification. Regions specializing in DAT are shown in shades of blue, with darker shades indicating those that have mainly specialised in DAT throughout the four-time windows, such as the Eastern Finland Province. Lighter blue shades represent regions that initially belonged to other categories but eventually specialised in DAT, such as West Wales and the South-West of Finland. A similar classification applies to regions specialising in green technologies, shown in shades of green. Examples of regions specialising in scientific publications on green technologies include Andalusia in Spain and Centre-Val de Loire in France.

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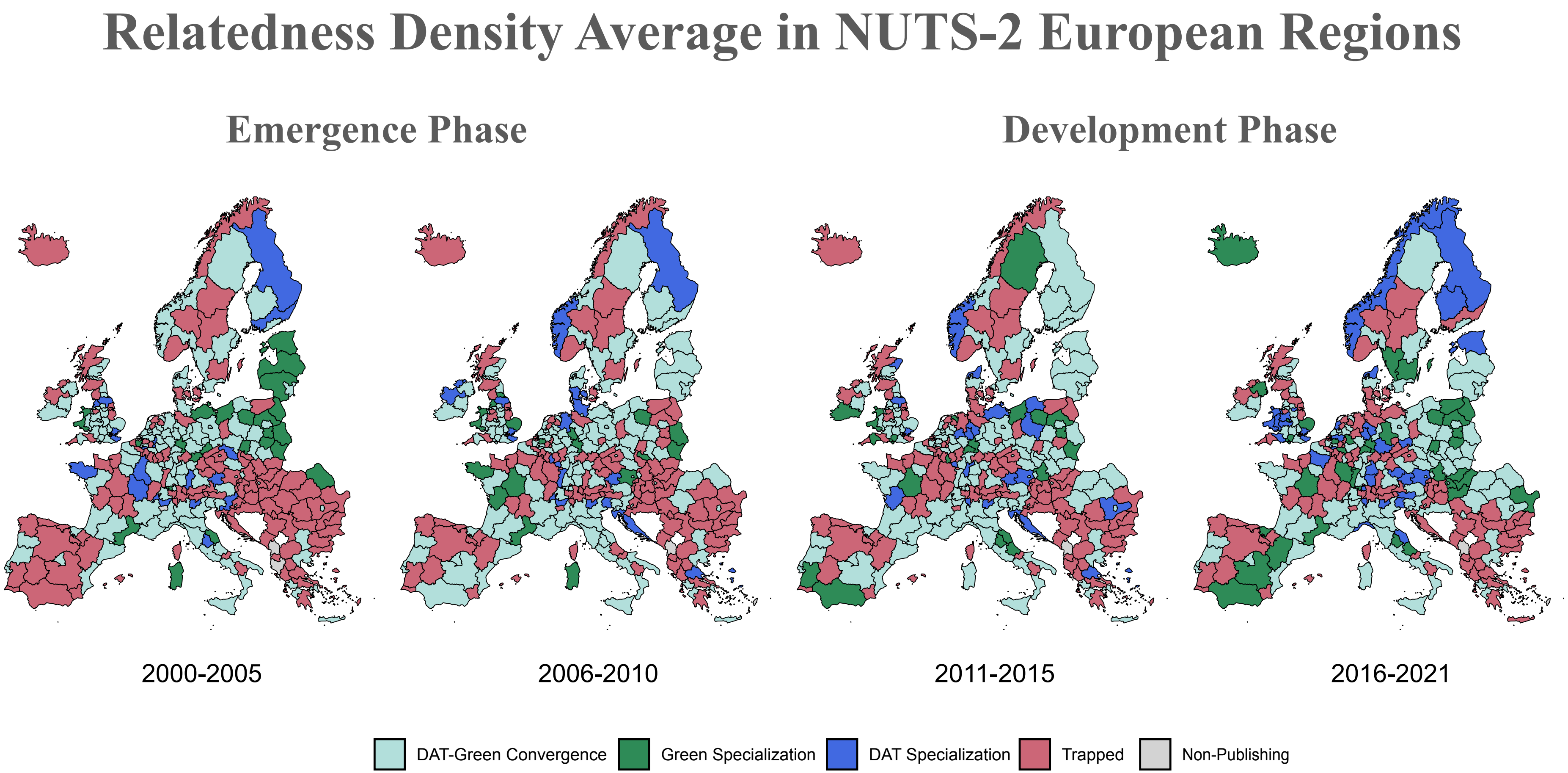

Figure S5.1. Relatedness Density Average in DAT and Green technologies from 2000 to 2021 using scientific publications data.

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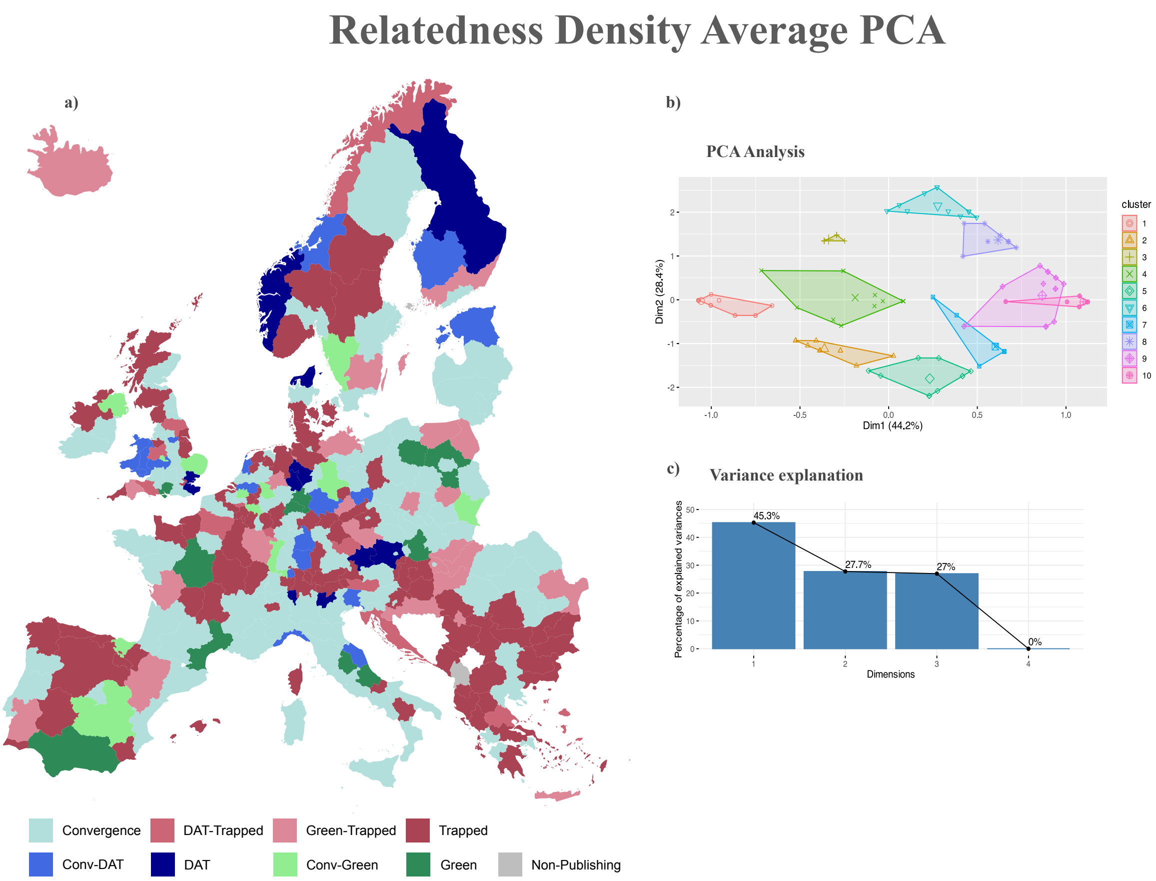

Figure S5.2. Regional Trajectories for Diversification in DAT and Green Technologies using publication data. Panel (a) displays the regional classification based on diversification trajectories in DAT and green technologies. Panel (b) presents the results of the Principal Component Analysis (PCA), which identifies key patterns in regional technological development. Panel (c) illustrates the variance explained by the first three PCA axes, which together account for more than 95% of the total variance, confirming the robustness of the classification

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