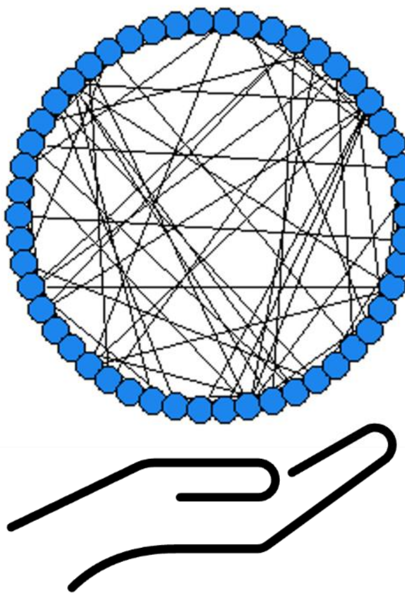
Unlocking Regional Potential: The Impact of Interregional Linkages on Smart Specialisation

Master's thesis in Economic Geography



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Abstract

Limited regional capacities can hinder effective specialisation into new innovative activities that drive regional transformations. In this regard, interregional linkages can help to promote innovative activities despite these deficits, though exploiting these opportunities requires sufficient absorptive capacity. This study on 198 NUTS-2 regions in Europe examines how interregional linkages may influence the emergence of new specialisations, and how these effects differ by regional type. Particular emphasis is placed on specialised diversification under the S3 framework and the prioritised technological domains, offering a novel approach to contribute to the still limited understanding of how different types of interregional linkages across regions can support smart specialisation processes. Using linear probability models, the results suggest that in less innovative regions, linkages to advanced regions can compensate for a lack of regional capabilities. Conversely, in advanced regions, interregional linkages that provide access to complementary capabilities may enhance the impact of regional capabilities on specialisation in S3 priorities.

Keywords: Smart Specialisation Strategies, Regional Diversification, Interregional Collaborations, Innovation, Regional Capabilities

Contents

Table of Figures

Table of Tables

1. Introduction

Regional economic divergence and structural challenges has emerged as a significant threat to economic progress, social cohesion and political stability in Europe (Capello & Cerisola, 2023; Diemer et al., 2022; Iammarino et al., 2019). According to Grillitsch and Sotarauta (2020) a key driver of these growing disparities is the increasing reliance on knowledge-intensive activities for economic development, which are predominantly concentrated in urban centres due to agglomeration effects, skills matching and knowledge spillover (cf. Pike et al., 2016). Concurrently, the European Union (EU) is facing rising discontent and Euroscepticism (Koeppen et al., 2021; Rodríguez-Pose & Dijkstra, 2021), which is, beyond individual factors (Koeppen et al., 2021) intrinsically linked to geographical characteristics, such as long-term economic and industrial decline (Dijkstra et al., 2020; Rodríguez-Pose, 2018).

In order to address these regional inequalities, the European Regional Development Fund (ERDF) aims to strengthen economic, social, and territorial cohesion by investing in growth and employment in Member States and regions, as well as fostering European territorial cooperation (European Commission, 2010; Liargovas & Papageorgiou, 2024). In this regard, in many regions of Europe, the EU has become the most important investor in economic development by actively reinforcing research and innovation capacities (Rodríguez-Pose & Dijkstra, 2021). As such, innovation, knowledge and learning constitute a key driver of long-term regional economic growth and endogenous growth (European Commission, 2010; Pike et al., 2016). During the 2014 – 2020 period, the ex-ante conditionality to the financial support of by the ERDF was the application of the so-called Smart Specialisation Strategies, in short S3 (D'Adda et al., 2020; Foray, 2018).

Regarding the three key elements of the smart specialisation schema – embeddedness, relatedness, but also the connectivity to other regions – it appears that lagging regions typically, tend to face weaknesses in at least two of the three key elements (McCann & Ortega-Argilés, 2015) and seem to encounter significant challenges in applying this strategy (Benner, 2020a). Indeed, S3 runs the risk of favouring advanced regions, while peripheral regions have little chance of catching up in the race for technological development (Kogler et al., 2023b; McCann & Ortega-Argilés, 2015). This can be attributed to the lack of sufficient local capacity and knowledge spillovers (Iacobucci & Guzzini, 2016), weak institutions and a smaller pool of innovative actors (Grillitsch & Nilsson, 2015; Papamichail et al., 2023) making it difficult to develop a critical mass in key industrial sectors and build the comparative advantages necessary to initiate a regional transformation based on local characteristics (Barzotto et al., 2019b;

Capello & Kroll, 2016). Moreover, limited access to external knowledge and a weaker absorptive capacity further exacerbate this situation (Belussi et al., 2018; Farole et al., 2011). Yet the connectivity to other regions could serve as a mechanism to compensate for these deficits and support diversification into new technology domains (De Noni et al., 2018; Grillitsch & Nilsson, 2015; Kogler et al., 2023b).

Although the importance of exogenous knowledge sources for regional knowledge production and regional development is already well recognised in the literature (e.g. Bathelt, 2007; Bathelt et al., 2004; Breschi & Lenzi, 2016; Camagni & Capello, 2013; Tavassoli & Carbonara, 2014; Trippl et al., 2009), smart specialisation and its underlying concepts of regional diversification remain predominantly conceptualised on local factors and tend to overemphasise the endogenous determinants of a region's innovative capacity (Giustolisi et al., 2023; Hassink & Gong, 2019). Consequently, it often lacks practical implementation, empirical research, and a nuanced perspective on the opportunities of interregional linkages for knowledge creation (Kogler et al., 2023b; Kruse, 2024) and innovation-based structural change (Giustolisi et al., 2023) for new path development in Smart Specialisation (Balland & Boschma, 2021b; Radosevic & Ciampi Stancova, 2018; Rigby et al., 2022). To address this gap this study provides new insights into the value added by interregional linkages to the implementation of Smart Specialisation Strategies (S3) using an analysis of co-patenting activities within a fixed effects linear probability model.

In conceptualizing technological development as a branching process, where regions tend to develop new specialisations closely linked to existing activities (cf. Uhlbach et al., 2022), the study differentiates between the effects of interregional linkages to knowledge-intensive regions and those enabling access to complementary capabilities. Additionally, it explores how these effects vary depending on regional type. Consequently, this should enable more targeted policy measures to promote regional diversification through interregional collaboration, while avoiding ineffective or even detrimental outcomes (cf. De Noni & Ganzaroli, 2024). Unlike previous studies, this research does not assume that technological diversification per se is beneficial. Instead, this study emphasises the alignment of emerging technological specialisations within the prioritised domains and explicitly taking the respective regional S3 into account.

This study is structured as follows: The first section introduces the concept of smart specialisation and its relation to related diversification and path-dependent capacities. Subsequently, interregional linkages and their opportunities are presented while possible region-specific constraints on their exploitation are elaborated. The methodological section outlines key variables, data sources and the estimation strategy. The study concludes with an evaluation of the findings' robustness, drawing out key policy implications, directions for future research and limitations.

2. Smart Specialisation Strategies and Related Diversification

S3 has been pivotal in shaping the European Union's 2020 flagship 'Innovation Union' programme, commonly referred to as RIS3 (Barzotto et al., 2019a; McCann & Ortega-Argilés, 2015) promoting smart, sustainable and inclusive growth (Foray et al., 2011; Foray et al., 2012). Smart specialisation aims to transform a region's economic structure by developing comparative advantages in new transformative activities (Foray, 2018; Foray et al., 2021; McCann & Ortega-Argiles, 2013; Uyarra et al., 2018). Thereby, regions are encouraged to develop their innovation strategies by leveraging existing structures and local potential to explore diversification opportunities (Capello & Kroll, 2016; Foray et al., 2021; McCann & Ortega-Argiles, 2013). The notion 'specialisation' characterises the process in which regional authorities are required to identify technological domains where they should concentrate investments in R&D and innovation, rather than spreading them in too many different fields (D'Adda et al., 2020; Foray & Goenaga, 2013; Mariussen et al., 2016).

The identification of such domains is known as the entrepreneurial discovery process (Foray, 2014) and should be broadly conceptualised in an interactive process to encompass all relevant actors, organisations, and agencies capable of discovering domains for assuring existing and future competitiveness (Asheim et al., 2017; Foray & Goenaga, 2013; Gianelle et al., 2020). The translation of the discovered domains into reality is stimulated by enhanced local connections and the triggered spillover effects, which lead to the entry and agglomeration of firms around the new activity (Foray, 2014; Foray et al., 2011; McCann & Ortega-Argiles, 2013). In this context, the argument of "smart" emphasises the need of achieving a critical mass within highly connected domains where new technological adaptations are most likely to be applied, offering the greatest potential for innovation and diversification from knowledge spillovers (D'Adda et al., 2020; Foray, 2018; McCann & Ortega-Argilés, 2015). This is considered a crucial condition for leveraging the resulting synergies, complementarities, and agglomeration effects, which are essential for driving innovation, creativity, and R&D

productivity (Foray, 2014). Thus, structural changes as the main outcome of a smart specialisation process and as the accumulative process of linking current and future regional strength invariably involve some kind of related diversification in a particular domain of activity and knowledge (Foray & Goenaga, 2013). In this context, relatedness serves as a key principle guiding regions in their smart specialisation efforts (Boschma & Gianelle, 2014; Santoalha, 2019b).

Hidalgo et al. (2018) intuitively illustrate the principle of relatedness by comparing two activities—such as the production of shirts and blouses—that use similar inputs materials and technologies (cf. Boschma, 2017). This overlap in knowledge bases and the cognitive proximity within a region creates opportunities for mutual learning and the effective exchange of ideas, capabilities, and knowledge (Boschma, 2005; Boschma & Frenken, 2012; Nooteboom, 2000; Nooteboom et al., 2007). Accordingly, a related variety of knowledge and industries is especially conducive to innovation and regional development, as it triggers technological dynamism through the (re-) combination of knowledge (Bathelt & Storper, 2023; Boschma & Gianelle, 2014; Frenken et al., 2007). This concept aligns with Schumpeter's conception of technological innovation as a cumulative process of new combinations of ideas (Castaldi et al., 2015; Neffke et al., 2011)[1]. The specialised diversification into related technologies would also amplify the problem of overspecialisation and a regional lock-in (Boschma & Gianelle, 2014; Hassink & Gong, 2019; Martin, 2006). Furthermore, this can also prevent diversification per se, as this could risk developing new economic activities that are not embedded in the region or, even worse, building 'cathedrals in the desert' (Balland & Boschma, 2022; Boschma & Gianelle, 2014; Uhlbach et al., 2022). Empirical studies support the positive relationship between related variety and the stimulation of regional innovations can be found in Aarstad et al. (2016), Castaldi et al. (2015), Miguelez and Moreno (2018) and Tavassoli and Carbonara (2014).

1 The importance of relatedness of activities and the concept of related variety is deeply associated with the work of Marshall (1920) and Jacobs (1969). Whereas the Marshallian externalities emphasise intra-industry spillovers, known as localisation (specialisation) externalities, the Jacobian externalities emphasise that the variety of industries within a geographic region promotes knowledge externalities and finally innovative activity and economic growth. A more detailed debate on agglomeration benefits around specialisation and diversification can be found in the work of De Groot et al. (2016), Beaudry and Schiffauerova (2009) and in the context of regional diversification by Whittle and Kogler (2020).

3. Path dependent capabilities

3.1. Regional Knowledge Space

For the implementation of S3, the emergence of new technologies or industries in a region is not random but reflects the existing capacities of regional actors, shaping specific technological and industrial profiles (Balland et al., 2019). In this sense, regional development can be seen as an evolutionary process by the recombination of capabilities, where the regional economy functions as a portfolio of products requiring specific, non-rivalrous, and partially non-excludable capabilities. Through this lens, diversification becomes a process of acquiring these regional capabilities (Frenken et al., 2023). This evolutionary logic of capabilities and relatedness implies that regional diversification is a path-dependent process, influenced by past and present conditions, with some development paths more likely than others (Boschma & Capone, 2016; Kogler & Whittle, 2018; Martin, 2006). Consequently, the region-specific capabilities as the key source of regional diversification, encompass information about both the opportunities but also limits for likely future diversification (Boschma, 2017; Boschma & Capone, 2016; Kogler & Whittle, 2018) and determine what can be achieved by regional smart specialisation policies (Boschma & Gianelle, 2014; Kogler et al., 2023a). When a region lacks the skills required for a new activity, it becomes more difficult and risky to develop them (Balland & Boschma, 2019; Boschma, 2017). Therefore, regions are expected to diversify into activities related to existing local industries and structures, building on their existing capabilities (Boschma, 2017; Boschma et al., 2012; Neffke et al., 2011; Zhu et al., 2017) — a concept known as 'regional branching' (Frenken & Boschma, 2007).

This logic follows the concept of the knowledge space as a network of related technologies that outlines the technological repertoire of recombinant possibilities within a region, capturing both the current state of knowledge accumulation as well as the dynamic interconnections and evolution over time (Balland et al., 2019; Kogler et al., 2023a; Rigby, 2015). By understanding how the effect of new entry depends on the existing knowledge base and potential connections, the region's ability to adopt and implement new technological capabilities can be predicted, which makes the regional knowledge spaces as a useful instrument for the implementation of smart specialisation strategies (Kogler, 2017; Kogler et al., 2023a).

3.2. Regional differences and challenges in diversification

Nonetheless, the constraints of path-dependence driving the diversification into new industries are not equally restrictive for all regions, as capabilities can vary widely across domains and offers different degrees of freedom (Boschma & Capone, 2016). Consequently, the opportunities and barriers to S3 development vary across European regions, necessitating consideration of geographical specificities (Foray et al., 2012; Trippl et al., 2020). In fact, the impact of relatedness on the probability of new industrial specialisations depends on the innovation capacity of a region, whereby the dependency is more prominent in regions with lower resources and capabilities (Boschma & Capone, 2016; Xiao et al., 2018).

In this respect, the study of Xiao et al. (2018) revealed that relatedness is a greater driver of diversification in regions with weaker innovation capacity. In light of the path-dependency outlined, it is therefore not surprising that S3 has been widely criticised as a policy that was not effective for peripheral and lagging regions (e.g. Barzotto et al., 2020; Capello & Kroll, 2016; Hassink & Gong, 2019; McCann & Ortega-Argilés, 2015), although they represent the main target of the Cohesion of the European Union (Gianelle et al., 2020). Given the nature of spatial uneven concentrated innovations, knowledge spillovers and technological capabilities across regions (Belussi et al., 2018; Feldman & Kogler, 2010), lagging regions struggle to catch up with those with established knowledge bases (Kogler et al., 2023a). These regions typically have fewer innovative capabilities and stakeholders, limiting their opportunities for related diversification and smart specialisation (Barzotto et al., 2019a; Benner, 2020a; Grillitsch & Trippl, 2016; Marrocu et al., 2023; McCann & Ortega-Argilés, 2019). Moreover, the scope for benefiting from local knowledge spillovers is limited (Grillitsch & Nilsson, 2015). However, lagging regions are not only characterised by the lack of a critical mass of strong dynamic stakeholders in related industries, but also by the absence of universities, research and high-tech clusters institutions (Tödtling et al., 2013) essential for regional diversification (Quatraro & Scandura, 2024) and smart specialisation (Capello & Kroll, 2016; Grillitsch & Trippl, 2016; Vallance et al., 2018). This would imply that identifying smart specialisation in R&D-based industries in lagging regions has limited impact and if an innovation project is beneficial for an industry involved, no spillover effects for other local actors and wider local society may be generated (Capello & Kroll, 2016).

Finally, missing the relevant organisational and institutional conditions for innovations that enable a sustainable economic development requires to overcome too many barriers (Capello & Kroll, 2016; McCann & Ortega-Argilés, 2015; Whittle & Kogler, 2020) and hinders the ability of lagging regions to successfully participate in RIS3 initiatives (Barzotto et al., 2019b;

Hassink & Gong, 2019; McCann & Ortega-Argilés, 2015; Sörvik et al., 2019) to foster innovation and development (Grillitsch & Trippl, 2016) and catch up on divergence (Zhu et al., 2017). In contrast, core regions exhibit a dense industrial landscape by a specialisation in a large number of interrelated industries involved in the S3 process, offering more opportunities for knowledge-related advantages, such as improved such as mutual learning and exchange (Duranton & Puga, 2004; McCann & Ortega-Argilés, 2015; Mieszkowski & Barbero, 2021) as well for the diversification into related industries (Hidalgo et al., 2007; Marrocu et al., 2023; Xiao et al., 2018; Zhu et al., 2017). This combination of size and diversity (McCann & Ortega-Argilés, 2015) imply, that core regions will experience higher growth rates compared to peripheral regions by redeploying their current capacities more efficiently (Boschma & Capone, 2016; Hidalgo et al., 2007). Thus, the greater potential advantages make S3 a strategy that is more conducive to advanced regions and consequently those regional types that are not prioritised by EU cohesion policy (Capello & Kroll, 2016; McCann & Ortega-Argilés, 2015). Obviously, lagging regions require more funding but have a lower capacity to absorb and effectively utilise these funds, contributing to the persistence of the so-called "regional innovation paradox" (Gianelle et al., 2020; Hassink & Marques, 2015; Oughton et al., 2002; Uyarra et al., 2018).

4. The Role of External Knowledge and Interregional Linkages

4.1. Interregional Linkages as a Compensation Mechanism

Regional capabilities and specialisation in core technological competencies alone do not guarantee regional production or improved productivity. To sustain long-term growth, regions must invest in existing competences and incorporate new technological elements to expand their knowledge base (Bathelt et al., 2004; Frenken et al., 2023; Rocchetta et al., 2022). While related diversification relies on local knowledge, expanding into new areas often requires external knowledge. In fact, evidence indicates that the creation of scientific and technological knowledge is increasingly becoming a collective effort and a critical competence to strengthen the capability of regions to innovate (Varga et al., 2020). Therefore, developing inter-organisational collaborations to identify new technological opportunities is almost inevitable (Belussi et al., 2018; De Noni et al., 2017; Fitjar & Rodríguez-Pose, 2013; Grillitsch & Nilsson, 2015).

In this sense, the path-dependent process of diversification is also influenced by relationships with other regions, which can provide learning opportunities (Boschma & Capone, 2016; Marrocu et al., 2023). Thus, in selecting their specialisation priorities, regions should adopt an outward orientation for interregional policy engagement and consider potential connections with other European regions based on complementarities or similarities (Iacobucci & Guzzini, 2016; Uyarra et al., 2014). These interregional links, often referred to as "connectivity" in most S3 documents (Iacobucci & Guzzini, 2016), constitute the other key element of the smart specialisation scheme alongside the already described elements of "embeddedness" and "relatedness" (McCann & Ortega-Argilés, 2015). By addressing fragmentation and lack of critical mass, interregional linkages provide regions the access to external and specific knowledge components to diversify new activities (Balland & Boschma, 2021b; De Noni et al., 2018; Uyarra et al., 2018). At the same time, they may substitute advantages typically associated with regional agglomeration (Barzotto et al., 2019a; Johansson & Quigley, 2004), ensuring sufficient resources for innovation (Uyarra et al., 2018). In this way, the interregional linkages may act as a mechanism to compensates for weak industrial specialisations and the lack of local knowledge spillovers, while providing opportunities for learning and knowledge transfer and overcome structural deficits (e.g. Barzotto et al., 2019a; De Noni et al., 2018; Eriksson & Lengyel, 2019; Fitjar & Rodríguez-Pose, 2014; Grillitsch & Nilsson, 2015).

Kogler et al. (2023b) connected the concept of regional branching to knowledge diversification through the lens of interregional collaboration networks, particularly via inventors and firms. Their study highlights the critical role of these collaborations in fostering new specialisations in the region. Further, they demonstrate that external collaborations, especially within multilocation firms, can compensate for the absence of related local knowledge and facilitate diversification into both related and unrelated technologies. The compensation mechanism is also illustrated by the Møre og Romsdal region in Norway, as shown in a case study on S3 by Asheim et al. (2017), where access to extra-regional resources overcame its narrow knowledge base and peripheral location, leading to opportunities for related diversification and new path development

However, there are two positions in the discussion on the role of interregional collaborations and spillovers for regional capabilities. While some argue that collaborations often play a compensatory role, others suggest they reinforce and complement the internal knowledge portfolio. While the abovementioned literature suggest that collaborations often play a compensatory role, some evidence suggests that they can also have a reinforcing function and aim to complement the internal knowledge portfolio (Balland & Boschma, 2021b; Bathelt et al., 2004; Whittle et al., 2020). In this regard, Balland and Boschma (2021b) explore the role of interregional collaborations within the context of Smart Specialisation Strategies (S3) in European regions. Their study highlights interregional linkages, which provide access to complementary and new knowledge, positively influence the probability of regions diversifying into new technologies. However, they also find that these linkages cannot compensate for weak or absent regional capabilities but rather reinforce existing capabilities, enhancing the region's ability to enter new technological domains.

4.2. Effects of Absorption Capacity on Knowledge Spillovers

While interregional linkages offer opportunities for diversification and regional growth, they are not a panacea for overcoming development deficits or compensating for a lack of capacity. Not all interregional knowledge spillovers operate the same way or provide similar benefits across different regions, particularly lagging ones (Rodríguez-Pose & Wilkie, 2019). The extent to which a region can benefit from these external knowledge spillovers depends on the local knowledge base and the degree to which the spillovers are complement existing knowledge (Boschma & Iammarino, 2009; Boschma et al., 2023; Breschi & Lenzi, 2015; Content & Frenken, 2016). Drawing on Cohen and Levinthal (1990), this concept refers to a region's absorptive capacity—its ability to recognize, assimilate, and apply new information for productivity gains and competitive advantages (Grillitsch & Nilsson, 2015; Miguélez & Moreno, 2015).

Miguelez and Moreno (2018) found that the greater the similarity between extra-regional knowledge flows and the existing local knowledge base, the more conducive it is to regional innovation. At the same time, the cognitive proximity between the regional knowledge base and extra-regional knowledge should not be too small to ensure the learning process is not repetitive and breakthrough innovation and an economic renewal occur, but also not too large to enable the absorption of extra-regional knowledge (Boschma & Frenken, 2012; Boschma & Iammarino, 2009)[2]. In this context, the study of Whittle et al. (2020) shows that externally oriented inventor networks increase the likelihood of new technology entering a region, with external knowledge being easier to absorb if the region has related technologies. Focusing on less developed regions, the study of Santoalha (2019b) indicates, that external collaborations only contribute to diversification if strong internal interactions exist to integrate external knowledge. Balland and Boschma (2021b) reveals that peripheral regions tend to diversify less into new technologies, however, once they have complementary linkage, they will experience an increased capacity to develop new technologies. This is consistent with the study by Ascani et al. (2020) which highlights the importance for internal specialisation and the synergistic

[2] Further discussions on the optimal cognitive proximity between knowledge for the generation of innovations can be found in Nooteboom (2000), Nooteboom et al. (2007), Boschma (2005) and Boschma and Frenken (2012)

nature between internal and external sources of complementary knowledge in highly specialised industries to support local innovation.

However, Eriksson and Lengyel (2019) found opposing results. According to them, industries only moderately represented in a region and thus where the degree of industry specialisation tends to be lower, benefit more from external linkages than those that are already regionally strong embedded. Barzotto et al. (2019a) suggest that, although extra-regional collaboration generally promotes the technological development of lagging regions, collaborations based on technological similarity may be less favourable for these regions than for leading regions. In the context of green technological diversification and the role of international linkages, Corrocher et al. (2024) found that relatedness mediates diversification patterns differently across country types. For catching-up countries, complementary linkages enhance related diversification, while for leading countries, these linkages enable unrelated diversification.

4.3. Region-specific Qualities of External Linkages

The literature also shows that not all connections carry the same value and that the benefits and incentives in participating in extra-regional collaboration might differ (Barzotto et al., 2019b; Kogler et al., 2023b). Besides the relatedness of knowledge flows and the existing knowledge base of the regions (Balland & Boschma, 2021b; Boschma & Frenken, 2011), increasing EU cohesion at regional level may also depend on whom a region is connected with (De Noni et al., 2018). Building extra regional collaboration with companies and institutions in more technologically advanced regions might be a particularly effective strategy (Barzotto et al., 2019b; McCann & Ortega-Argilés, 2015; Woolford et al., 2020). In a similar vein, De Noni et al. (2018) argue that linkages to inventors from knowledge-intensive regions improve the innovation performance of lagging regions. The authors further refer to Sebestyén and Varga (2013) and Sun and Cao (2015), which suggest that the quality of interregional knowledge networks in Europe is related to the level of knowledge of the partners in the networks.

Consequently, the participation of inventors from knowledge-intensive regions is likely to provide access to a more diversified knowledge base and compensate for the lack of local institutional support. Similar to this, Montresor and Quatraro (2017) found that evidence about the prevalence of interregional spillovers with respects to key enabling technologies in regional branching. Nonetheless, even in highly developed countries, sparsely populated and peripheral regions often struggle to benefit from knowledge spillovers generated in core region, as these regions typically lack the necessary connections, absorptive capacity, and scale to effectively leverage such spillovers (Farole et al., 2011; Trippl et al., 2018). Moreover, innovation networks appear to be highly selective, and technologically advanced companies are more likely to partner with those having similar technical competences and knowledge specialisation (Barzotto et al., 2019b). Evidence for this is provided by the study by Amoroso et al. (2020), according to which most interregional cooperation among European regions in the Framework Programmes 2007-2013 took place between more developed regions, although there was also a considerable proportion (22% of the total of research cooperation between more and less developed regions. Likewise, the findings of Broekel and Hartog (2013) suggest that urban regions characterised by high population density and regions with high research intensity are more likely to be linked to other regions in R&D cooperation networks. This discrepancies in external connection between regional types may be reinforced by the path-dependency of repeated interregional cooperation between co-inventors (Abbasiharofteh et al., 2023a; Glückler, 2007; Sun & Liu, 2016; Tóth et al., 2021).

The lack of conducive conditions in lagging regions hinders the development of innovative capacities, making it difficult to leverage comparative advantages(Rodríguez-Pose & Wilkie, 2019). These challenges are rooted in insufficient entrepreneurial and innovative activities (McCann & Ortega-Argilés, 2015; Mieszkowski & Barbero, 2021) which result in a lack of industrial sectors with the necessary critical mass on a global scale (Capello & Kroll, 2016). Additionally those lagging regions are lacking absorption capacity and rather weak local institutions (Barzotto et al., 2020; Boschma, 2021).

Interregional linkages through co-inventor networks are expected to positively impact regional diversification and facilitate S3 implementation (Balland & Boschma, 2021b; Kogler et al., 2023b). Linkages that provide complementary linkages are expected to help regions acquire missing capabilities by providing (related) knowledge inflows. Together with collaborative linkages to knowledge-intensive regions, which are expected to be particularly favourable (De Noni & Ganzaroli, 2024; De Noni et al., 2018), these interregional linkages might compensate for missing capabilities for a related diversification (Barzotto et al., 2019a; Grillitsch & Nilsson, 2015). What has also been shown is that the benefits of interregional linkages can vary between different types of regions (Corrocher et al., 2024; Rodríguez-Pose & Wilkie, 2019).

There is still uncertainty about whether less peripheral regions derive more (Balland & Boschma, 2021b; Eriksson & Lengyel, 2019) or less benefits (De Noni et al., 2018; Farole et al., 2011; Trippl et al., 2018) from interregional linkages. On the other hand, more developed regions obtain a higher absorptive capacity, stronger institutional frameworks and more extensive collaboration networks to leverage external knowledge (Barzotto et al., 2020; De Noni et al., 2018). Although the policy of smart specialisation acknowledges the role of interregional collaboration, practical implementation and research related to this has so far remained limited (Kruse, 2024; Radosevic & Stancova, 2015). Although studies in the context of Smart Specialisation those by Balland and Boschma (2021b), have successfully contributed to the understanding of how interregional linkages can provide relevant capabilities and promote regional diversification, they neglect one important implications: Smart specialisation is about a specialised diversification, and not a diversification per se. This study, however, specifically focuses on technology classes associated to the priorities selected by the regions. Consequently, regional diversification and the entry of new activities does not encompass all possible technology classes, but only those that are incorporated in the respective S3 priority of the region.

Furthermore, while some studies have addressed the regional differences in the context of S3 and interregional linkages, a more comprehensive and nuanced exploration remains underrepresented. Emerging evidence suggests that interregional linkages to knowledge-intensive regions might compensate for missing local capabilities, enabling regions to specialise in new technologies. Conversely, complementary interregional linkages are likely to reinforce and enhance the effects of existing regional capabilities supporting targeted diversification aligned with S3 priorities. Given these dynamics, it is crucial to further investigate how interregional interdependencies influence the successful implementation of S3 across different regional contexts (cf. Marrocu et al., 2023).

The arguments presented in the previous chapter serve as a starting point for formulating hypotheses for a further empirical study aimed at answering the following research question: *How do interregional linkages contribute to the implementation of Smart Specialisation Strategies (S3) across different regional types?* To address this question and explore the role of interregional linkages in promoting related diversification aligned with respective S3 priorities, two hypotheses are proposed, each subdivided to account for two types of interregional linkages.

Hypothesis 1 is designed to test the direct effect of interregional linkages on technological diversification into new S3 priorities:

- **H1a**: Interregional linkages to knowledge-intensive regions promote technological diversification into new technologies aligned with targeted S3 priorities.
- **H1b**: Complementary interregional linkages promote technological diversification into new technologies aligned with targeted S3 priorities.

Hypothesis 2 examines the interplay between local capabilities and interregional linkages:

- **H2a**: Interregional linkages to knowledge-intensive regions can compensate for missing regional capabilities, enabling specialisation into new technologies aligned with targeted S3 priorities.
- **H2b**: Complementary interregional linkages reinforce the effects of existing regional capabilities, enabling specialisation into new technologies aligned with targeted S3 priorities.

5. Empirical Framework

The following section of the study describes the methodological approach to examines the impact of interregional cooperation on regional technological diversification in line with the respective S3 priorities by analysing co-patenting activities and resulting linkages. First, the data basis, i.e. patents derived from the OECD REGPAT dataset is described. Subsequently, the approach to estimate the impact of these interregional collaborations on regional technological diversification is described using a linear fixed-effects probability model to estimate the probability of regions to developing new technological specialisation.

5.1. Data

Inter-regional collaboration for research can take various forms, involving different objectives but also durations, participating actors and instruments of partnership (Uyarra et al., 2014, p. 30). In this study, however, interregional linkages are measured by using co-patent activities and the resulting links between inventors who collaborate in at least one the patents granted by the European Patent Office (EPO). This approach allows to approximate the role of collaborations in regional innovation (Fleming et al., 2007; Lobo & Strumsky, 2008 cited in Abbasiharofteh et al., 2023a; De Noni et al., 2018). The primary data source is the OECD REGPAT dataset (version of January 2024) covering the patent applications registered by the European Patent Office (EPO) between 1977-2024. Despite their limitations, patents are frequently used as a reliable indicator for technology and innovation analyses (Lybbert & Zolas, 2014), knowledge production (Tanner, 2016) and of a regions ability to introduce commercially viable, tangible, and applied innovations (Rodríguez-Pose & Wilkie, 2019).

The patent data is further divided into two non-overlapping five-year periods (2011-2015, 2016-2020), as five-year periods in empirical analyses using patent data is common practice (Moreno & Ocampo-Corrales, 2022). The database contains addresses of inventors and assignees as well as International Patent Classification codes (IPC), that reflect their technological class and subsets of knowledge (Kogler et al., 2017). Following Santoalha (2019b), this classification system is the most widely used in the use of EPO patent applications.

Patents are assigned to regions at the second level of the Nomenclature of Territorial Units for Statistics (NUTS-2-Level) classification version of 2013 based on the inventor's region of residence as similarly proposed by Jaffe et al. (1993). The selection of the NUTS-2-Level based on the fact, that this spatial scale is the common level at which RIS3 are adopted (Sörvik & Kleibrink, 2015). Further the Structural Funds within the EU Cohesion Policy is solely based on the classification of NUTS 2 region and used as framework by Member States to apply their regional policies (Eurostat, 2022; Santoalha, 2019a). Patents, however, often have multiple IPC codes and are linked to several inventors across different regions. In measuring knowledge spaces, it is argued that knowledge is an indivisible asset and therefore non-fractional counts are applied (Boschma et al., 2023; Moreno & Ocampo-Corrales, 2022; Tanner, 2016). When a breakthrough technology is present in a location, the idea fully entirely there (Boschma et al., 2023). Thus, a patent involving inventors from different regions is assigned to each of these regions (Tanner, 2016). This further prevents biases of the regional networks from the modifiable area unit problem (Abbasiharofteh et al., 2023a).

In order to indicate the regional industrial structure and thus the regional types, similar to Asheim (2019), the EU Regional Innovation Scoreboard 2014 is used, which classifies region according to their relative innovation performance into Innovation Leaders, Innovation Follower, Moderate Innovators and Modest Innovator. Regions with inconclusive classification due to changes in the NUTS classifications, i.e. within Croatia, were removed due to the preservation of a consistent data set. Overseas territories of the EU were not included. Besides, the countries Cyprus (CY00), Lithuania (LT00), Luxembourg (LU00), Latvia (LV00) and Malta (MT00) were included in the analysis on their NUTS 2 Level. Due to the problem of insufficient variation in the observations of the Modest Innovators, the regional types are further subdivided into core and periphery regions, analogous to De Noni et al. (2018) or Balland and

Boschma (2021b). Here, Innovation Leaders and Innovation Follower are aggregated into *core regions* and Moderate and Modest Innovators into *peripheral regions*. This results into a count of 104 core and 95 peripheral regions. The NUTS 2 level was chosen as it is generally used by Member States in the implementation of their regional policy and is therefore the appropriate level for analysing regional/national policy issues (EUROSTAT, 2022). Appendix 1 cartographically shows the division into core and peripheral regions according to the innovative performance and a strong concentration of core regions in central Europe.

Similar to the studies of Sörvik and Kleibrink (2015) and McCann and Ortega-Argilés (2016), the S3 priorities were obtained from the Smart Specialisation Platform of the European Commission and the tool Eye@RIS3[3]: Innovation Priorities in Europe. Eye@RIS3 is an interactive open data tool that gathers an overview of the envisaged RIS3 priorities of regions and countries in Europe (Sörvik & Kleibrink, 2015) for the period 2014-2020 and was last fully updated in September 2018. The key investment targets of the S3 in a region are defined by their economic domain (Di Cataldo et al., 2022), which is based on the Statistical Classification of Economic Activities in the European Community at the 2-digit level (NACE rev. 2). However, regions often indicate their specialisation domains using natural language such as "biotech", "health and wellness", "mechatronics", etc, which reduces comparability and limits the possibility to perform quantitative analysis (D'Adda et al., 2020).

To address this issue, a solution similar to that of D'Adda et al. (2020) is applied, where the specialisation domains selected by regions are defined using the IPC. This allows the identification of technological domains rather than industry, aligning with the S3 logic. The standard approach to assigning patent data to economic industries is to apply probabilistic concordances (Neuhäusler et al., 2019). Comparable to the study of Kim et al. (2024), Belussi et al. (2018) or Panori et al. (2022) using the IPC v.4—NACE rev.2 concordance table by Lybbert & Zolas (2014) enables patent-specific matching at the IPC level of the regionalised PATSTAT database to the prioritised economic domain. The concordance table is based on an algorithmic links with probabilities (ALP) approach, that mines patent data using keywords from the description of the industry classification and processes the resulting matches according to probability weights (Lybbert & Zolas, 2014). To illustrate, the technology class B62M ("Rider propulsion of wheeled vehicles or sledges; Powered propulsion of sledges or cycles; Transmissions specially adapted for such vehicles") is assigned to ISIC Rev. 4 Division 30 ("Manufacture of other transport equipment") with a probability of 90%.

[3] https://s3platform.jrc.ec.europa.eu/map

Important to note is that S3 measures have been implemented at different spatial levels in European countries, including national and NUTS 1 to NUTS 3 territorial levels. Selected priorities at NUTS 1 level will be allocated to NUTS 2 level as they are expected to be aligned with the higher level S3 measures, which will also allow for a more coherent and specific regional strategy. Unlike the approach of Kim et al. (2024), the S3 measures designed at the NUTS 3 level in Finland or Sweden, for example, are not aggregated to the NUTS 2 level. The reason for this is that aggregation at NUTS 2 level would lead to an exaggerated range of prioritised domains, which could no longer be consistent with the specific strengths and priorities of the individual regions. Patent applications for a region and a corresponding technology class can appear multiple times as they can be assigned to several economic domains. Yet only the technologies that were available in all periods are retained (cf. Qiao & Wu, 2024). Further, only technology classes are considered in which a corresponding region does not already have an RTA in period t1 (2011-2015) and therefore a specialisation would still have been possible in the subsequent period t2 (2016-2020). The final dataset comprises 628 technology classes within 199 regions on Nuts-2-level, resulting in a total of 46,425 observations. Similar to the study of Mewes and Broekel (2020) and Uhlbach et al. (2022) on regional technological diversification, the observations are limited to only cases in which an entry is possible and specialisation does not already exist in the respective region.

5.2. Methodological Approach

Based on various studies on regional technological diversification (Balland & Boschma, 2021b; Rigby, 2015), the emergence of a new technological specialisation is captured by entry of a new revealed technological advantage (RTA). The RTA is a measure that quantifies the degree of specialisation of a region in each technological domain within a period (Kogler et al., 2023b) and hence reflects the technological base of a region (Boschma et al., 2023). The RTA is expressed as a binary variable assigned a value of 1 if the share of patents in technology class *i* within the regional technological base exceeds that in the technological base of the reference group, which in this case consists of 198 regions in the EU. Otherwise, the RTA is 0

Formally, according to Balland and Boschma (2021b), a region r therefore has an RTA in the production of technological knowledge *i* (*r* = 1, … , *n*; *i* = 1, …, *k*) so that $RTA_{r,i}^{t}$ = 1 if:

$$\frac{patents_{r,i}^{t} \ / \ \sum_i patents_{r,i}^{t}}{\sum_r patents_{r,i}^{t} \ / \ \sum_r \sum_i patents_{r,i}^{t}} > 1,$$

where $patents_{r,i}^{t}$ denotes the total number of patents in technology *i* in region *r* and in period *t*.

The independent variables encompass the relatedness density of technological classes, the inter-regional collaboration between inventors, differentiated according to the regional type as well the access to complementarity interregional linkages. The knowledge proximity (relatedness φ) between technological class *i* and industry *j* in period *t* between technology classes is calculated by using co-occurrence analysis and measuring frequency with which two IPC classes appear in the same patent document (Balland & Boschma, 2021b; Balland et al., 2019; Moreno & Ocampo-Corrales, 2022). Similar to the approach of Balland (2019), he co-occurrences are standardized to control for randomisation using the association probability measure developed by van Eck and Waltman (2009), as it is implemented in the *relatedness* function of the EconGeo R package (Balland, 2017). This results in a matrix of 628 x 628 IPC classes based on the co-occurrence analysis of the 198 regions for each period, whereby the diagonal is set to zero. For simplicity, relatedness φ is expressed as a binary variable, where φ > 1, denotes a relatedness between technological classes (cf. Rigby, 2015; Uhlbach et al., 2022). The described approach also implies that the relatedness is influenced by technological changes and appearances. Thus, the relatedness between the technology pair might differ over the considered time periods (cf. Boschma et al., 2015).

The resulting proximity (degree of relatedness) between the individual technology classes makes it possible to model the knowledge space of a regional economy and to analyse influence of relatedness on technological change (Balland et al., 2019; Heimeriks & Balland, 2016). For this purpose, *relatedness density* (RD) shows how embedded a technology is within the local knowledge space (Balland & Boschma, 2019; Kim et al., 2024; Kogler & Whittle, 2018). Based on the studies by Hidalgo et al. (2007) and Boschma et al. (2015) the RD around a given technology i in a region r at time t is calculated by dividing the technological relatedness (φ) between technology i and all other technologies j in which the region r has a relative technological advantage (RTA) by the sum of the technological relatedness of technology i to all other technologies j within the EU (reference region) at the same time t (Balland et al., 2019). This can be expressed with the following equation:

$$RD_{i,r,t} = \frac{\sum_{j \in r, j \neq i} \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}} * 100$$

RD ranges from 0 to 100 and has a minimum value of 0 if region r is not specialized in any technologies j related to technology i at time t, while it has a maximum value of 100 if all technologies j related to i are present in region r as RTA at time t (Cortinovis et al., 2017; Kogler & Whittle, 2018). Consequently, the higher the RD for a new technology, the closer is the technology to the region's knowledge base on average and thus the higher the probability that a region will diversify into a new technology (Balland et al., 2019; Kim et al., 2024; Xiao et al., 2018).

The average relatedness density between existing technologies and all potential alternative technologies in a region reflects the overall regional potential for developing new technologies (Balland et al., 2019). Figure 1 shows significant differences in branching potential both between countries and within regions in Europe. Central Europe generally shows high potential for developing new technologies, in contrast to many regions in southern and eastern Europe, where branching opportunities are much lower. High values are found in well-developed regions, such as Lombardia and Veneto in Italy, Tübingen in Germany or Upper Austria, while only few of them are developing regions such as Mazowieckie in Poland. In contrast, the lowest levels of relatedness density are detected in the small and less developed areas of Greece, Romania and Bulgaria, which might be because of the weak and sparse production space of these regions, where co-specialisations are rare. It is also noteworthy that regions in France (Auvergne and Corse), Belgium (Luxembourg), Algarve (Portugal), but also southern Italy (e.g.

Molise) have a low relatedness density, which suggests a strong territorial specialisation of the production area of these countries (cf. Balland et al., 2019; Marrocu et al., 2023).

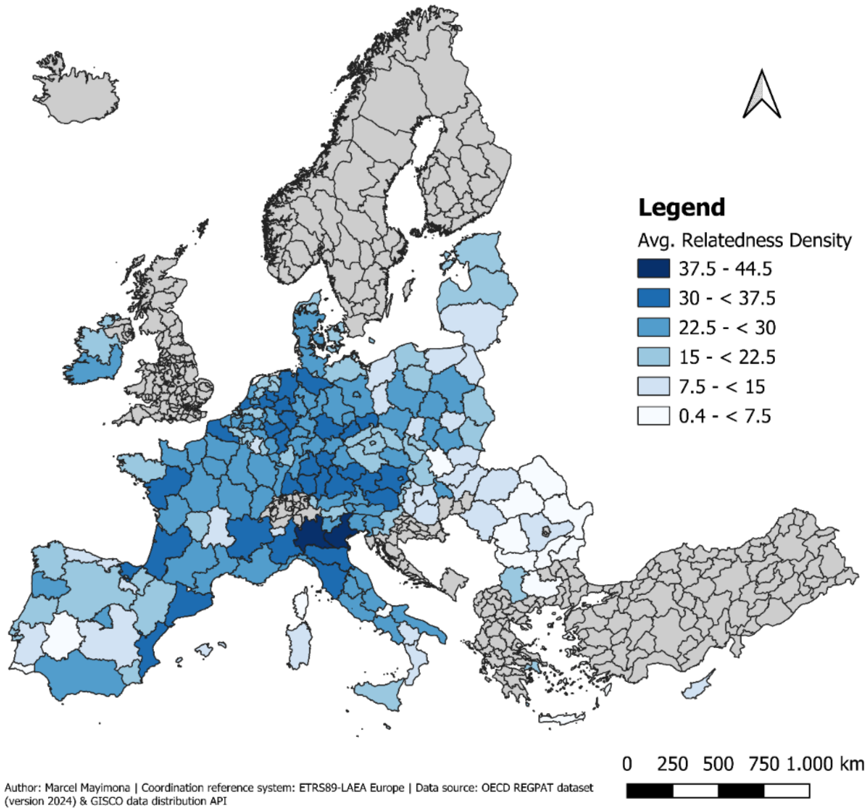

Figure 1: Branching opportunities across European regions.

While this approach effectively illustrates the regional technology map by acknowledging technological relationships using co-occurrences within the same patent document may omit other important factors (Moreno & Ocampo-Corrales, 2022). An alternative approach to measure relatedness is to use the minimum of the pair-wise conditional probability that a region is specialised (RTA > 1) in both technologies (Hidalgo et al., 2007; Kogler et al., 2023b). Using RTA co-occurrences to approximate relatedness suggests that two technologies may not be close in a cognitive sense, but rather in terms of the regional capabilities that support their development. (Moreno & Ocampo-Corrales, 2022; Xiao et al., 2018). This includes aspects such as infrastructure, institutions, human capital, and other capabilities along with knowledge (Boschma & Capone, 2016; Hidalgo et al., 2007). However, due to concerns about multicollinearity between the variables of complementary linkages (covered later), the first approach is chosen.[4]

[4] An overall methodological overview for detecting and measuring the intensity of relatedness between industries can be retrieved by Whittle and Kogler (2020) or Iacobucci and Guzzini (2016).

Next, based on the principle of co-occurrence of information on patent applicants in the same patent, the variables for analysing the role of interregional linkages in technological diversification are derived. The first indicator, *Knowledge-intensive Linkages* (*KL*), counts for every NUTS-2-region r in every technological class i, the number of linkages to other knowledge-intensive regions in a period t, whereby two patent applicants appearing together in the same patent document constitute an interregional link (Xu & Tao, 2024). Hereby, interregional linkages that connect a region with a core region are considered as knowledge-intensive linkages, inspired from De Noni et al. (2018). Similar to the regional type, knowledge-intensive regions are classified as "Innovation Leader" or "Innovation Follower" according to the Regional Innovation Scoreboard. Further, self-loops are excluded (cf. Corrocher et al., 2024).

The second variable *Complementary Linkages* (*CL*) is based on the work of Balland & Boschma (2021b). It measures, for each potential new technology, the extent to which a region r is connected to other regions s that exhibit a Revealed Technological Advantage (RTA) in technologies j related to potential new technology i, in which region r lacks an RTA. These interregional linkages provide access to external capabilities that are lacking locally but could increase the ability to diversify into new technology areas. The objective of *CL* is therefore to capture the possible impact of external and related capacities on regional diversification into new technologies through inter-regional linkages based on co-inventor networks.

To construct the variable *CL*, as outlined by Balland & Boschma (2021b), several steps are necessary. Initially, it is determined which technologies i are missing in region r (RTA < 1), as only technologies for which entry into the region is possible are considered. Subsequently, for these missing technologies, related technologies j are determined that are relevant to each technology i. The next step involves identifying other regions s that have a co-inventor linkage with region r, whereby for region s one now investigates how many related technologies j they have a specialisation in which region r itself does not already possess a specialisation. This number of related technologies missing in region r, but in which region s is specialised, is set in relation to the total existing number of related technologies. This gives the amount of RD that can potentially be added by region s to the RD of region r in technology i. Finally, the added RD of technology i is multiplied by the number of links between the co-inventors that region r maintains with each region s. Summing this up for each technology i in region r across all connected regions s gives the variable *CL*.

Hence, the more linkages between two regions exist, the more relevant the complementary capabilities of the other region could for region *r*. The value of CL increases as the RD in region *r* decreases and will be 0 if region *r* has already reached the maximum RD value in technology *i*, indicating full specialisation in all related technologies making further links unnecessary. The value also equals 0 and if there are no interregional connections to regions that could potentially be added to the *RD* of region *r*.

As a concrete example, the region of Schleswig-Holstein (DEF0) has the priority of "Maritime economy: Maritime technologies, specialized ship construction, offshore energy (wind, oil, gas), maritime biotechnology, production facilities, wind parks, facilities to refuel ships with LNG or other alternative fuels, and innovative harbour infrastructures". For this priority, the region lacks specialisation in technology class F02C "Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants" within the domain "D.35 – Electricity, gas, steam, and air conditioning supply." Based on the co-occurrence of technology classes in the same patent document, there are a total of 87 related technologies, of which Schleswig-Holstein itself is specialised in 34. This results in a degree of proximity (relatedness) between the technology F02C and the technological portfolio by Schleswig-Holstein of 34%. However, Schleswig-Holstein gains access to relevant capabilities that enhance its ability to diversify into technology F02C through three existing co-inventor collaborations with the regions of South Holland (NL33) and Madrid (ES30), respectively. An example of such a related technology is the technology class F01K "Steam engine plants; steam accumulators; engine plants not otherwise provided for; engines using special working fluids or cycles". The impact of these two interregional linkages is determined by the number of related technologies for F02C that are missing in Schleswig-Holstein but in which South Holland (22/87) and Madrid (8/87) are specialised. Consequently, the CL for Schleswig-Holstein around technology F02C is given the interregional linkages to the two regions is then 103.4463[5].

[5] CL = 3*9.195 + 3*25.287 = 103.4463.

5.3. Estimation Strategy

The role of interregional linkages through co-inventor collaborations in technological diversification in the respective priorities of the regions of their Smart Specialisation Strategies can be examined, similar to Kogler et al. (2023b), by estimating the entry of a specialisation in a technology using a fixed-effect linear probability model (LPM) . Formally, this is represented by:

$$ENTRY_{i,r,t} = \beta_1 X_{i,r,t-1} + \beta_2 Z_{i,r,t-1} + \psi_i + \delta_r$$

The binary variable $ENTRY_{i,r,t}$ measures whether the region enters a new RTA in the respective technology. The main independent variables are the technological relatedness density (*RD*) variable on the level of IPC class *i* and region *r* ($X_{i,r,t-1}$) and the interregional linkages variables ($Z_{i,r,t-1}$) consisting of the value of complementary linkages (*CL*) and the count of linkages to knowledge-intensive regions (*KL*). Additionally, the models include technology (ψ_i) and region (δ_r) fixed effects to capture all other unobserved factors that might influence regional diversification (cf. Mewes & Broekel, 2020; Uhlbach et al., 2022). Since a time delay with which the dependent variable reacts to the change in the explanatory variable can be assumed and to avoid potential endogeneity issues, all the independent variables are lagged by one time period t, corresponding to 5 years (Balland et al., 2019; Mewes & Broekel, 2020). As the interregional linkages variables are highly skewed, they were log-transformed in the regression models[6]. Regarding the coefficients for the complementary linkages and knowledge-intensive linkages, positive effects are expected in the entry model (H1). The interaction terms between interregional linkages and relatedness density are expected to have negative effects for *KL* and positive effects for *CL* (H2).

There is an ongoing debate about the appropriateness of Linear Probability Models (OLS) or non-linear specification (e.g. logit) models (Boschma et al., 2015; Corrocher et al., 2024). The main advantage of using the LPM over logistic regression when estimating binary outcomes is the simplicity of the estimation and interpretation of the coefficients and interaction terms (Kogler et al., 2023b). Moreover, Boschma et al. (2015) refer to King and Zeng (2001), who argue in favour of LPM that too many zeros in the dependent variable can lead to inconsistent parameter estimates, as often occur in empirical research on technological diversification (Corrocher et al., 2024). By taking reference to Greene (2012) , Cortinovis et al. (2017) emphasise that the large number of dummy variables could lead to inconsistent results for probit

[6] As those variables contains many 0s, log(X+1) is used.

or logit models. Additional complications in non-linear models arise when calculating marginal effects, as the computation relies on assumptions about the distribution of unobserved heterogeneity captured by fixed effects, and results are highly sensitive to specification errors (Boschma & Capone, 2015). Another important point to note is that according to Boschma et al. (2015), standard errors need to be adjusted for clustering when errors are correlated within regions and technologies. This allows controlling for omitted variables specific to regions (δ_r) and technologies (ψ_i) (cf. Uhlbach et al., 2022). Consequently, similar to the studies of regional diversification by Boschma et al. (2023), Kogler et al. (2023b) or Heimeriks & Balland (2016) the method of estimation will be the fixed effects linear model with heteroskedasticity robust standard errors.

The probability distribution of the assignments of IPC technology classes to economic domains is shown in Figure 2 and exhibits a pronounced left skewness. It is important to note that an IPC 4-digit code can be assigned to multiple domains with different probabilities. While this approach allows consideration of the heterogeneity of sectors in terms of technologies (Neuhäusler et al., 2019), it may lead to overestimation (cf. Wurlod & Noailly, 2018) and duplication of other variables, potentially distorting the results. Since the assignment does not follow a normal distribution and one cannot straightforwardly adopt only assignments above 95%, an intuitive procedure would be to take the median (=0.113), the 75th percentile (=0.366), and the 90th percentile (=0.792). These values are used as thresholds for allocation and are not weighted further. This approach also allows identification of the intensity of the assignments required for the analysed relationships to exist. Importantly, the seemingly low value of the median threshold should not be overestimated. The allocation based on the median threshold allows, for example, the correct assignment of the IPC 'B64G - Cosmonautics; Vehicles or equipment therefor' to the economic class H.51 'Air transport' with a probability of around 31%, which is anchored in the priority for 'Innovative materials and technologies for space, sensors and navigation systems, electro-mechanical systems, and avionics' by Sardinia (ITG2), among others.

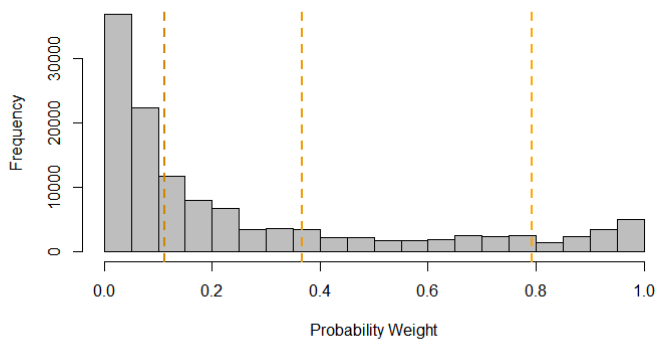

Figure 2: Histogram of the Probabilities of IPC to NACE Assignment

Additionally, two control variables at the regional level are included when the regression is not controlled for region fixed effects. First, the regional GDP per capita, which reflects economic wealth and performance and is found to be an important driver of technological diversification. In this regard, well-developed regions tend to have more opportunities to diversify into new and more advanced activities than less developed regions (Mewes & Broekel, 2020; Moreno & Ocampo-Corrales, 2022; Petralia et al., 2017). Second, the population density as an indicator of agglomeration and urbanisation effects that can better support regional innovation performance (Boschma et al., 2023; De Noni et al., 2018). Both variables are logarithmized and originate from Eurostat[7]. The descriptive statistics and correlation matrix[8] are provided in Tables 1 and 2, respectively. The mean probability of a region developing a new specialisation in technology within their S3 priorities is around 14%.

Table 1: The descriptive statistics of main variables.

	Obs.	Mean	Std. Dev	Min	Pctl(25)	Pctl(75)	Max
Entry	46,425	0.14	0.35	0.00	0.00	0.00	1.00
Relatedness Density – *RD*	46,425	21.19	12.30	0.00	12.50	28.57	100.00
Knowledge-intensive Linkages (log) – *KL*	46,425	0.24	0.73	0.00	0.00	0.00	6.45
Knowledge-intensive Linkages$_{t0+t1}$ (log) - KL_{t0+t1}	46,425	0.24	0.73	0.00	0.00	0.00	6.45
Complementary Linkages (log) – *CL*	46,425	8.76	1.68	0.00	7.71	10.00	12.77
Complementary Linkages$_{t0+t1}$ (log) – CL_{t0+t1}	46,425	8.76	1.68	0.00	7.71	10.00	12.77
GDP per Capita (log) – GDPpc	46,425	10.38	0.92	8.01	9.69	11.02	13.37
Population Density (log) – Pop.Dens.	46,425	5.00	0.92	3.16	4.41	5.45	8.89

All of the correlation coefficients between the explanatory variables used in the regressions were below the recommended threshold of 0.8 (Mason & Perreault Jr, 1991; Oh et al., 2015). The values refer to the entire distribution of the variable levels, where observations for a region and corresponding technology class may appear multiple times, as they can be assigned to several economic domains. In this context, according to De Noni and Ganzaroli (2024), the

[7] A very small number of regional data were converted by the 'NUTS Converter' of the European Union due to changes and thus different versions of the NUTS classification to the version of the S3 priorities, which originate from the 2013 version. Nuts Converter: https://urban.jrc.ec.europa.eu/tools/nuts-converter?lng=en

[8] The correlation coefficients were computed using the Pearson method.

correlation level is thus more informative, and high values do not necessarily indicate collinearity problems within the models, especially as they do not include fixed effects by region and technology class. To further ensure robustness, each independent variable was similar to the study of Ascani et al. (2020) also controlled in a pooled OLS regression using a Variance Inflation Factor (VIF). The multicollinearity test of the model, when all independent variables[9], – namely Relatedness Density, Knowledge-intensive Linkages, Complementary Linkages, GDP per Capita, Population Density – are included, shows values (1.447, 1.180, 2.206, 2.229, 1.447) below the critical threshold of 5 (Miguélez & Moreno, 2015). Thus, multicollinearity does not appear to be a major concern.

Table 2: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Entry	1.000	0.082	0.074	0.047	0.083	0.042
(2) Relatedness Density	0.082	1.000	0.488	0.179	0.524	0.278
(3) Complementary Linkages	0.074	0.488	1.000	0.386	0.680	0.499
(4) Knowledge-intensive Linkages	0.047	0.179	0.386	1.000	0.301	0.204
(5) GDP per Capita	0.083	0.524	0.680	0.301	1.000	0.517
(6) Population Density	0.042	0.278	0.499	0.204	0.517	1.000

[9] The control variables for Knowledge-intensive Linkages$_{t0+t1}$ and Complementary Linkages $_{t0+t1}$ were for obvious reasons excluded from the VIF analysis due to their inherent collinearity with the respective independent variables.

6. Results

The econometric analysis results are now presented. For this purpose, different model versions were estimated, with variables added stepwise to check robustness and highlight changes when additional variables were included, or the sample was subdivided according to regional type. This approach is validated by improvements in Goodness-of-Fit metrics such as the Akaike Information Criterion (AIC) and Log-Likelihood, which consistently show better model performance with each step. These metrics confirm that including interregional linkages and control variables enhances the robustness and explanatory power of the models, justifying the stepwise approach and ultimately the use of regional fixed effects. All independent variables refer to the entry of a technological specialisation within a region's S3 priority. the models presented in the results section are based on the specification of an assignment probability for IPC to NACE classification, calculated at the median level (approximately 11.3%). Additionally, technology fixed effects are introduced in every model to control for characteristics inherent to specific technology classes, such as technological trends. Table 3 illustrates the findings of the regional entry model of new specialisation in technologies associated with respective S3 priorities for a region. Model 1 serves as a basic model without the explanatory variables of interregional interdependencies, but only the Relatedness Density (*RD*), which a positive and significant effect ($p < 0.01$).

Models 2-4 extend the basic model in a stepwise manner by including the interregional linkages and control variables. Model 2 indicates a significant ($p < 0.01$) positive effect of knowledge-intensive linkages (*KL*) on technological diversification in selected priorities. To account for the path dependencies of network connection, *KL* is controlled by including additionally the count from the previous period, meaning 2006 – 2015 ($_{t0+t1}$). The controlled effects of KL_{t0+t1} appear to be significant ($p < 0.01$) negative.

In Model 3, the variable of complementarity linkages (*CL*) is introduced, showing a significant ($p < 0.01$) and positive relationship of *CL* on the entry of new technological specialisation in selected S3-priorities. Likewise, a path dependency of the complementary linkages is controlled by considering the number of preceding periods additionally (CL_{t0+t1}). The results indicate a significant ($p < 0.01$) negative effect. *Pop. Dens.* exhibit a negative coefficient, although their direct influence on the likelihood of new technology entries is not statistically significant. The regional *GDPpc* appears to have a positive and significant ($p < 0.01$) impact on technological entry in the model without regional fixed effects.

A notable finding in Model 4 is the shift in both the sign and significance of the *KL*. Once the *CL* variables are included, *KL* now turns positive but insignificant. In the Full Model FE (Model 5), regional fixed effects are introduced, leading to changes in both the magnitude and significance of the effects of interest. With these fixed effects, *RD* and *CL* are now significant only at the 5% level. The effects of *KL*, however, remain negative and insignificant. The control variables, including economic and demographic factors have been consequently removed due to collinearity, as region fixed effects absorb all the variation that is consistent within a region.

Table 3: Fixed effect regression (LMP) on the impact of interregional linkages on regional technological diversification in S3-priorities.

	Baseline (1)	KL Model (2)	CL Model (3)	Full Model without FE (4)	Full Model FE (5)	Interaction Model KL (6)	Interaction Model CL (7)
RD	0.0018*** (0.0003)	0.0028*** (0.0003)	0.0021*** (0.0002)	0.0016*** (0.0002)	0.0004** (0.0002)	0.0004** (0.0002)	-0.0010** (0.0004)
KL (log)		0.0349*** (0.0114)		-0.0024 (0.0117)	-0.0050 (0.0114)	-0.0169 (0.0142)	-0.0050 (0.0114)
KL_{t0+t1} (log)		-0.0214*** (0.0065)		-0.0100 (0.0117)	-0.0067 (0.0066)	-0.0068 (0.0066)	-0.0067 (0.0066)
CL (log)			0.0336*** (0.0024)	0.0312*** (0.0028)	0.0084** (0.0040)	0.0084** (0.0040)	0.0029 (0.0047)
CL_{t0+t1} (log)			-0.0154*** (0.0008)	-0.0158*** (0.0009)	-0.0163*** (0.0008)	-0.0163*** (0.0008)	-0.0163*** (0.0008)
GDPpc (log)	0.0195 (0.0050)			0.0212*** (0.0054)			
Pop. Dens. (log)	-0.0006 (0.0040)			0.0015 (0.0037)			
RD x KL (log)						0.0004 (0.0003)	
RD x CL (log)							0.0002*** (4.78e-5)
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	Yes	Yes	Yes
Observations	46,425	46,425	46,425	46,425	46,425	46,425	46,425
R^2	0.05822	0.05693	0.07576	0.07834	0.09271	0.09276	0.09283
Adj. R^2	0.04549	0.04418	0.06327	0.06580	0.07642	0.07645	0.07651
AIC	31,597.3	31,661.2	30,724.8	30,603.1	30,265.3	30,264.6	30,261.4
Log-Likelihood	-15,178.7	-15,210.6	-14,742.4	-14,677.5	-14,312.6	-14,311.3	-14,309.7

Note: The dependent variable Entry equals 1 if a region gains a new revealed technological advantage (RTA) in a given technology during the corresponding five-year window 2016-2020; and 0 otherwise. All independent variables refer to the period 2011-2015. Heteroscedasticity-robust standard errors in parenthesis, Clustered by Region & IPC.
*, **, *** denote significance at the 0.1, 0.05, 0.01 level.

To further investigate whether interregional linkages compensate for a lack of local capabilities to specialise in new technologies within targeted S3 priorities, interaction terms were introduced. Model 6 includes the interaction term of *RD* and *KL* (*RD x KL*) with regional fixed effects and indicates significant changes as well. In contrast to the Full Model FE, *RD* turns now negative and less significant ($p < 0.05$). The direct effect of *KL* does not change much with the introduction of the interaction term, remaining negative and insignificant. However, the coefficient for *CL* is becoming insignificant. Finally, the interaction term, *RD x KL*, appears positive but not significant.

To account for the need of more regionally differentiated perspective and a more outward-looking approach within the framework of Smart Specialisation Strategies (S3), separate regressions were conducted according to the regional type and to analyse the prevalence of compensating/reinforcing effects through interregional linkages. Model 8 includes only data for *core regions* and focuses on the interaction of regional capabilities and interregional linkages to knowledge-intensive regions. The coefficient for *RD* is positive and only weakly significant ($p < 0.1$) compared to Model 6. Further, in contrast to Model 6, where the coefficient was also negative but not significant, *KL* turns now highly significant in Model 8 ($p < 0.01$). There are also differences for KL_{t0+t1} compared to Model 6: In Model 8, the coefficient is positive and significant ($p < 0.05$), while it was negative in Model 6. The coefficient of *CL* is positive in Model 8, but not significant compared to Model 6. However, the coefficient for CL_{t0+t1} remains negative and highly significant ($p < 0.01$). For the interaction term *RD x KL*, there are still positive effects compared to Model 6, but these are now weakly significant ($p < 0.1$).

In Model 9, which includes only data for *peripheral regions* and focuses on the interaction of regional capabilities and interregional linkages to knowledge-intensive regions, the coefficient for *RD* is positive but not unlike in Model 6 not significant. The *KL* coefficient in Model 9 is positive and highly significant ($p < 0.01$), indicating a strong positive effect of knowledge-intensive linkages on emerging specialisations in periphery regions. This is a notable change from Model 6, where the *KL* coefficient was negative and not significant. The coefficient of KL_{t0+t1} remains negative but turn now highly significant ($p < 0.01$). The *CL* coefficient in Model 9 is positive like in Model 6 but became now weakly significant ($p < 0.1$). A further change can be observed for the interaction term *RD x CL*: The interaction term is now negative and significant ($p < 0.05$) in Model 8, whereas it was positive and insignificant in Model 6.

Table 4: Fixed effect regression (LMP) on the impact of interregional linkages on regional technological diversification in S3-priorities according to regional types (core /periphery)

	Core – Interaction KL (8)	Periphery – Interaction KL (9)	Core – Interaction CL (10)	Periphery – Interaction CL (11)
RD	0.0004* (0.0002)	0.0004 (0.0002)	-0.0010* (0.0006)	-0.0008 (0.0007)
KL (log)	-0.0367*** (0.0136)	0.1836*** (0.0584)	-0.0217* (0.0113)	0.0717* (0.0371)
KL_{t0+t1} (log)	0.0168** (0.0070)	-0.0646*** (0.0195)	0.0171** (0.0070)	-0.0651*** (0.0192)
CL (log)	0.0060 (0.0047)	0.0094* (0.0054)	0.0002 (0.0054)	0.0051 (0.0070)
CL_{t0+t1} (log)	-0.0153*** (0.0009)	-0.0155*** (0.0016)	-0.0153*** (0.0009)	-0.0156*** (0.0016)
RD x KL	0.0005* (0.0003)	-0.0040** (0.0016)		
RD x CL			0.0002** (6.57e-5)	0.0001* (8.13e-5)
IPC FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	23,276	23,149	23,276	23,149
R2	0.10252	12,702.3	0.10251	0.12154
Adj. R2	0.07371	0.09394	0.07369	0.09350
AIC	17,525.4	12,691.6	17,525.8	12,702.8
Log-Likelihood	-8,307.7	-5,628.8	-8,037.9	-5,634.4

Note: The dependent variable Entry equals 1 if a region r gains a new relative technological advantage (RTA) in a given technology i during the corresponding five-year window t+1 (2016-2020); and 0 otherwise. All independent variables refer to the period t (2011-2015). Heteroscedasticity-robust standard errors in parenthesis, Clustered by Region & IPC. *, **, *** denote significance at the 0.1, 0.05, 0.01 level.

Model 10 considers now the interaction between regional capabilities and interregional linkages providing access to related but missing capabilities and explicitly focuses on *core regions.* The results are likewise described by their changes compared to Model 7. For *KL* an increase of the significance can be observed, becoming now weakly significant negative in Model 10 ($p < 0.1$). Further KL_{t0+t1} turns positive and highly significant ($p < 0,01$) in contrast to the non-significant result in Model 7. The interaction term *RD x CL* remains positive and significant in both Model 7 and 10; its significance level decreases to $p < 0.05$ in Model 10.

Moving now to Model 11, which focuses instead on *peripheral regions.* The negative effects of *RD* decreases in significance in Model 11 and turns now insignificant. On the other hand, the coefficient for *KL* becomes positive and turns now weakly significant ($p < 0.1$), contrasting with the negative and non-significant result in Model 7. The coefficient of KL_{t0+t1} remains negative but changes from being insignificant to highly significant ($p < 0.01$). A further change can be observed for the interaction term *RD x CL*, which remains positive, but its significance decreases to a weak level ($p < 0.1$).

7. Robustness check

To test the robustness of the results, two checks were conducted. First, following the approach of Corrocher et al. (2024) the analysis was repeated by redefining regional entry as a new specialisation based on a Revealed Technological Advantage (RTA) threshold > 1.5. . This threshold was also applied to the construction of the key variables, Relatedness Density (RD) and Complementary Linkages (CL) (cf. Balland & Boschma, 2021b). However, Appendix 3 reveals that only the effect of complementary linkages for RTA > 1.5 remained consistent with the original findings. In the differentiated analysis by regional types in Appendix 4, only the reinforcing effects of complementary knowledge on regional capabilities in core regions were confirmed.

Second, similar to Simensen and Abbasiharofteh (2022), to ensure that false-positive results are excluded in the models with interaction terms, a set of models were constructed in which the variables capturing the effects of Complementary Linkages (*CL*) and Knowledge-Intensive Linkages (*KL*) were transformed into dummy variables. For each variable, the dummy variable took the value of one if the original *CL* or *KL* value was greater than a selected percentile, otherwise it took the value of zero. For the 65th percentile as threshold, the outcomes in Appendix 5 show robust results for the interaction of *RD* x *CL*, as well as the same interaction in the regional differentiated analysis for core regions (Appendix 6). Similarly, the results for the interaction term *RD x KL* for peripheral regions in Appendix 8 remained consistent with the original finding, indicating compensating effects. Higher thresholds cannot support the initial results completely.

Although the initial analysis demonstrated significant relationships between the variables of interest, the robustness checks revealed inconsistencies. Specifically, when applying the alternative specification of the RTA, the main results did not hold up as expected. In contrast, the robustness test designed to exclude false-positive result suggests robust results for the discussed interaction terms. Therefore, the findings should be interpreted with caution, recognizing that the detected reinforcing or substituting effects of interregional linkages may be sensitive to the model specification.

8. Discussion

8.1. Discussion of the Results

Before interpreting and discussing the results, it is important to note that this analysis, like the studies by Boschma et al. (2023) or Kogler et al. (2023b), does not discuss the magnitude of the coefficients. One major reason is that the coefficients can take on negative values and, theoretically even exceed 1 (Kogler et al., 2023b), which would be problematic when predicting probabilities of occurrence. Another reason lies in epistemology and the different scaling or units of measurement of the independent variables, which complicates the comparability of the coefficients and their interacted impact on the dependent variable.

To begin with, the *Relatedness Density (RD)* variable, which is central to the literature on regional diversification, shows strong significance in the fixed-effect regression models (Models 1-4). Thus, in line with previous studies on regional diversification (e.g. Balland & Boschma, 2021b; Boschma et al., 2023; Rigby, 2015; Xiao et al., 2018), the local presence of related technologies promotes the emergence of new technological advantages in European regions. The results further confirm the previous finding, that regions are expected to diversify into new activities that are closely related to existing local activities and the existing knowledge space, thereby leveraging their established local capabilities (Boschma, 2017; Boschma et al., 2012; Neffke et al., 2011; Zhu et al., 2017). This is further supports the evidence that regions maintain a cohesive industrial portfolio over time (Boschma & Frenken, 2011; Neffke et al., 2011), pointing to the prevalence of a path-dependent process (Boschma & Capone, 2016; Henning et al., 2013; Kogler & Whittle, 2018).

However, when regional fixed effects are introduced in the Model 5 to account for unobserved heterogeneity across regions, the significance of *RD* decreases. This suggests that while *RD* remains an important factor, its impact may be partially influenced by other region-specific characteristics. Further, when considering the interactions between *RD* and interregional linkages, the direct impact of *RD* on technological diversification becomes also less pronounced, suggesting a complex interplay, where the direct effect of relatedness might be moderated by the interregional collaboration.

For the interregional linkages to knowledge-intensive regions (*KL*), no statistically significant direct effect on technological diversification within targeted S3 priorities can be found. In fact, these are even negative. Hence, in contrast to the preceding assumption by De Noni et al. (2018) or (Barzotto et al., 2019b), the involvement of inventors from European knowledge-intensive regions and access to capabilities from advanced regions alone may not sufficiently foster the implementation technological diversification into new technologies aligned with targeted S3 priorities.

Similarly, when considering the interaction effects of *KL* with regional capabilities, this coefficient is positive but not significant, indicating that interregional linkages may not strongly promote technological diversification when considered alongside local capabilities. The lack of significance, along with the negative coefficient, might also indicate that other factors, such as the absorptive capacity of the region or the nature of the knowledge exchanged, play a critical role. This is particularly relevant as knowledge from more advanced regions can be expected to be more complex and therefore not necessarily useful for weaker regions to convert into comparative advantages (cf. Balland & Rigby, 2017; Juhász et al., 2021; Qiao & Wu, 2024).

On the other hand, the results for complementary linkages (*CL*) in Model 7 indicate that they do indeed promote technological diversification into new technologies aligned with targeted S3 priorities. This suggests that regions with linkages to other regions providing related but missing technological capabilities are more likely to develop new technological specialisations aligned with targeted S3 priorities. These findings are consistent with those of Balland and Boschma (2021b) and Xu and Tao (2024),who also identified a significant effect of complementary linkages on the emergence of new technological specialisations. To further elaborate on the argument of Balland and Boschma (2021b), what matters is the connection in terms of access to the capabilities required for new activities, and not being connected per se to knowledge-intensive regions that offer the similar capabilities of the local knowledge base. The emphasised importance of diverse and complementary knowledge (cf. Trippl et al., 2018) fits in with discussions about the optimal cognitive proximity of knowledge exchange, whereby a partial overlap enables mutual learning effects and the exchange of capabilities (cf. Boschma, 2005; Nooteboom, 2000; Nooteboom et al., 2007). The results seems to be in line with Bathelt and Storper (2023), Boschma and Frenken (2011) and Feldman and Kogler (2010) according to whom these knowledge combinations should be broad enough to tap into different areas of economic change and to protect against downturns in very high cognitive proximity in knowledge exchange that weaken the respective competitive advantages.

Nonetheless, one thing to keep caution is the change of sign of RD, when it is interacted with CL. This is interpreted as the circumstance that the combined effect of RD and complementary linkages becomes more pronounced when these variables are considered together, potentially revealing an interdependent effect that was not as apparent when the variables were analysed separately. While one might consider this as a potential sign of multicollinearity, this is deemed less likely due to the results of two previous reviews which showed no significant multicollinearity issues. Moreover, the assumption of no prevalence of multicollinearity is supported by the study by Balland and Boschma (2021b), which applied the same variables and dataset, thereby reinforcing the validity of the observed relationship.

The controlled effects of CL_{t0+t1} appear to be significant negative, which might seem counterintuitive initially, as one might expect interregional linkages to generally have a positive impact on technological diversification. However, this interpretation needs to be considered in the context of the dependent variable, which measures a region's entry into only new, previously non-existent technological specialisations and the path dependency of knowledge flows (cf. Kogler et al., 2023a; Sun & Liu, 2016). Accordingly, the controlled linkages may have contributed to the acquisition of specialisations, whose entry is now no longer possible.

Interpreting the results in relation to hypothesis 1a and 1b - which state that interregional linkages promote technological diversification into new technologies with targeted S3 priorities – no significant effects are found for knowledge-intensive linkages. This suggests that these linkages do not significantly contribute to diversification in S3 priorities, leading to the conclusion that hypothesis 1a cannot be confirmed. Conversely, significantly positive effects were observed for complementary linkages, highlighting their importance in promoting regional innovation and smart specialisation strategies. Therefore, hypothesis 1b can be supported.

Appendix 2 provides additional insights into how different specifications of the probability of assigning technology classes (IPC) to economic classes (NACE) may influence the analysis of interregional linkages in technological diversification. Changes in results are observed with different thresholds: median (~11.3%), 75th percentile (~36.6%), and 90th percentile (~79.2%). Additionally, Model 4 in Appendix 2 includes all technology classes, regardless of their assignment to priority S3. The coefficient for *RD* remains only significant and positive for the consideration of all IPCs. The coefficient for RD remains significant and positive only when all IPCs are considered. Compared to Model 5, the coefficients for CL show a highly significant effect when all technology classes are included. However, for the 90th percentile threshold, the effect becomes only weakly significant. KL remains insignificant across all models. In the sample considering all IPCs, regardless of S3 priorities, this variable even turns negative. Roughly speaking, it can be observed that the broader the allocation of the IPC, the more visible the effects of interest become in terms of significance and magnitude. Thus, the intensity of the allocations must not be too strict in order to the positive and significant effects of *CL* but also *RD* happen.

To determine whether relatedness and interregional linkages function as substitutes or complements for regional capabilities, it is essential to interpret their respective interaction terms. According to Balland and Boschma (2021b) and Kogler et al. (2023b), a negative interaction effect might indicate that local capabilities in a region can be compensated by interregional linkages, enabling diversification into technologies that are not related to the local knowledge base. In this sense, local relatedness and complementary linkages would be substitutes. On the other hand, a positive interaction effect suggests that interregional linkages and local capabilities are not mutually exclusive but complements, jointly promoting new technological and related diversification in S3-priorities (cf. Corrocher et al., 2024; Xu & Tao, 2024). Given that the coefficient for *KL* is statistically insignificant in the Full Model – FE (5) and in Interaction Model KL (Model 6), the focus shifts to complementary linkages and their potential in mediating the effects of relatedness.

The change of *RD* coefficient to a significantly negative coefficient in Model 7 compared to Model 5 indicates that when the interaction with *CL* is considered, the direct impact of *RD* on technological diversification decreases. This might suggest that the presence of strong complementary linkages might reduce the need for the exclusive reliance on a local related knowledge base to promote a regional diversification in S3-priorities. Furthermore, the positive interaction effect observed in Model 7 indicates that the combined impact of *RD* and *CL* becomes more pronounced, potentially revealing an interdependent relationship between the two variables that was not as evident when considered separately. The nuanced relationship between both variables indicates that, while *RD* and *CL* individually might not necessarily enhance the likelihood of new technological specialisations in S3 priorities—and could even reduce it—their combination appears to significantly increases the likelihood of technological entry. This finding s consistent with earlier studies (Balland & Boschma, 2021a; Corrocher et al., 2024; Xu & Tao, 2024) according to which interregional technological linkages tend to induce a related diversification.

In the differentiated analysis by regional type, there is initially no clear evidence for *core regions* that the combination of local capabilities with external, knowledge-intensive links significantly promotes technological diversification in S3-priorities. The expected compensating effect between *RD* and *KL* is therefore not strongly supported by the results in this context. This outcome may stem less from the absorptive capacity of the core regions, which tends to be present. Rather, it is due to the minimal value added by similar knowledge for core regions, which tend to have already strong regional capacities (cf. Feldman & Kogler, 2010; Trippl et al., 2018).

In contrast, the further differentiation by regional type reveals a more complex interplay between local capabilities and linkages from knowledge-intensive regions for *peripheral regions* the results indicate that in peripheral regions, interregional linkages to knowledge-intensive regions play a crucial role in enabling new technological specialisation within their S3 priorities. Regional capabilities, however, appear to have no significant effect on the entry of new technologies within selected S3 priorities in peripheral regions. Nonetheless, the significant negative effect of the interaction term suggests compensatory effects between *KL* and *RD*, where the lack of regional capabilities can be mitigated through connections to knowledge-intensive regions. This finding aligns with the conclusions of Kogler et al. (2023b) and Eriksson and Lengyel (2019), who suggest that in the absence of usually essential local relatedness, it is still possible to develop an emerging knowledge specialisation through external collaborations.

Regarding the relationship of *CL* and *RD* in the case of core regions, the results suggests that although each factor on its own is insignificant or only weakly significant, their interaction can amplify the effects of related local capabilities and induce a corresponding diversification within the S3 priorities in the European. Thus, in line with the results of Balland and Boschma (2021b), *CL* tend to reinforce the impact of regional capabilities on the development of new technological specialisations in S3 priorities. However, this also implies that, weak regional capabilities cannot be effectively compensated for by establishing linkages with other regions, even when those interregional linkages provide access to relevant complementary capabilities. For peripheral regions, on the other hand, such complementary effects are not evident. This may be partly because peripheral regions typically have fewer interregional linkages, which could limit the potential for these linkages to significantly impact technological diversification within S3 priorities (Barzotto et al., 2019b; Farole et al., 2011; Trippl et al., 2018).

Similar to previous and recently studies (Balland & Boschma, 2021b; Corrocher et al., 2024; Xu & Tao, 2024), the results emphasise the ambiguity of interregional linkages in promoting technological diversification across different types of regions: Initially, the regression without regional differentiation in Table 3 suggests that for S3 priorities, only complementary linkages tend to enhance the impact of regional related capabilities on the development of new technological specialisations. However, a more detailed analysis by regional types reveals a nuanced picture. First, the initial results can be confirmed in the case of core regions, which may benefit from the synergy between complementary linkages and relatedness density by leveraging the effects of their related capabilities to specialise in new technologies within the respective S3. Second, linkages to knowledge-intensive regions are now found to be particularly beneficial for peripheral regions, which was not significant without a regionally differentiated examination. These linkages provide access to capabilities from knowledge-intensive regions, which are quite similar to the local knowledge base, and may effectively compensate for a lack of regional capacity. Consequently, this enables peripheral regions to engage in smart specialisation, enhancing their potential for technological diversification.

With regard to the anticipated hindering effects of similar knowledge flows on their competitive advantages (e.g. Boschma & Frenken, 2011), explicit consideration of the exit of specialisations in their diversification process, such as by Qiao and Wu (2024), is required although the negative effects for *KL* might be an indicator. Finally, the results seem to align with the analysis of the EU's 7th Framework Programme for research and technological development by Amoroso et al. (2020), who conclude that technological complementarity is sought when two developed regions are involved, whereas similarity tends to be prioritized in other cases.

To conclude, the detailed analysis emphasises a more complex interaction and provides only partial evidence for the assumption that knowledge-intensive linkages can compensate for a lack of regional capacities. This effect is observed primarily in peripheral regions, leading to the conclusion that H2a is not fully supported. Regarding the assumption of a reinforcing effect by complementary linkages, evidence was found only for core regions, where these linkages may act as substitutes for regional capabilities. Therefore, H2b cannot be fully confirmed either.

8.2. Policy Implications and Future Research Directions

The discussion on future research and policy implications is twofold, including both a thematic orientation and a methodological orientation In term of political implications, the evidence emphasises that different groups of regions may require differentiated policies (cf. Santoalha, 2019b). As noted in this paper, there are significant regional differences in initial preconditions and endogenous growth potential to diversify into related technologies and to utilise local but also external capacities for the implementation of the respective S3 strategies. In line with Rodríguez-Pose and Wilkie (2019), policy makers should therefore be aware that only certain policy 'levers' are inevitably available in regional contexts.

This is particular relevant for the new programming period 2021-2027, in which the smart specialisation strategy will continue to play an important role for regional development and cohesion, driven by a sustainability dimension based on an innovation paradigm and a green transition of existing economic structures (Kruse, 2023; Provenzano & Seminara, 2022). The proposed shift from S3 to Smart Specialisation Strategies for Sustainable and Inclusive Growth (S4+), which reinforces the S3 mission-oriented policy approach for sustainable development, plays a pivotal role in this context (McCann & Soete, 2020). Hereby, the regional differences in green technology development capabilities pose a potential threat to regional cohesion and threats to widening further disparities across Europe (Bachtrögler-Unger et al., 2023). In the tension between sustainability, regional cohesion and social inclusivity, it is therefore particularly important to ensure that the green transition not only benefits the more prosperous regions, but also to involve the less developed regions. Leveraging the transformative and collaborative nature of smart specialisation and embrace that weaker the regions are also sufficiently incentivised and supported to engage in the development of innovations might constitute the basis for successful deployment of the European Green Deal at regional level. Consequently, S3 elements focused on enhancing knowledge connectivity will now become even more critical (Kruse, 2023, 2024; McCann & Soete, 2020).

The methods used in this study on interregional linkages, relatedness density and the entry of new specialisations could be used in the context of the twin transition to uncover untapped potential for interregional collaboration and to compensate for unequal potential in a target manner through their benefits. However, as this study reveal, not all interregional knowledge spillover work in the same way or offer the same benefits to lagging regions. Policy makers need to identify the types of extra-regional knowledge spillovers that offer the greatest benefit to local innovators and to target resources accordingly to untapped potentials in green transition. The synergies of regional capabilities and interregional linkages providing complementary knowledge seems to be particularly effective in facilitating new technological entries in advanced regions. Therefore, if a technology is strongly embedded in the region but lacks a specialisation of green technologies, they are advised to strive for technological complementarity in their collaborations. Peripheral regions, on the other hand, are advised based on the findings to initiate targeted collaborations with core regions in technologies with the same knowledge base to overcome weak capabilities within in their S3-priorities. However, in enhancing the competitiveness of lagging regions through collaboration with technologically advanced regions, it is important to keep in mind that the knowledge transfer requires a certain absorptive capacity to benefit from such collaborations. This requires at the same time strengthening the absorptive capacity of lagging regions by promoting specialisation and strengthening the localisation of human capital and organisational capacities within these regions (De Noni & Ganzaroli, 2024; De Noni et al., 2018). Initial studies (e.g. Castellani et al., 2022; Corrocher et al., 2024; Moreno & Ocampo-Corrales, 2022), have already examined regional diversification in context of the green transition and sustainable development, providing a foundation for further research needed.

From a methodological perspective, the use of patent data as a primary measure of innovation and regional capacity reflects a linear model of innovation that presumes a direct and uniform relationship between knowledge input and innovation output (Marques & Moreno). However, invention, innovation, and diffusion are not necessarily intertwined processes, whereby not all industries or firms depend on patents for the generation and application of new knowledge (Camagni & Capello, 2013; Iacobucci & Guzzini, 2016). This is particularly relevant for lagging regions where small firms in low-tech industries and as patents are disproportionately concentrated among a few large firms, leading to a distorted representation of innovation activities (Iacobucci & Guzzini, 2016). This linear perspective contributes to the perception of the outlined regional innovation paradox (Marques & Morgan, 2018). Further it neglects other forms of innovation, especially beyond the scope of science, technology and innovation (STI), such as social, organisational, market and service innovations (D'Adda et al., 2020). The discourse on smart specialisation has often overemphasized analytical and synthetic knowledge bases while ignoring the importance of symbolic knowledge bases and their role in regional industrial path development of smart specialisation (Asheim et al., 2017; Benner, 2020a; Camagni & Capello, 2013). These synthetic and symbolic knowledge bases rely more on the "doing-using-interacting", which describes informal innovative activities and serve a counterpart to the STI Mode (Alhusen et al., 2021; Trippl et al., 2016).

Given the challenges of the linear scope for STI, future research should investigate more in alternative measures and indicators that better capture the systemic and diverse nature of innovation and to explore the effect of interregional collaboration on different quality dimensions (De Noni, Montresor; Hassink & Gong, 2019). "n this regard, the extent of innovation cooperation with firms from other regions, whether they are suppliers or competitors, offers promising potential for further linking interregional collaborations with the DUI-Mode of innovative activities and in terms knowledge flows (Alhusen et al., 2021; Jensen et al., 2007). An application of such a variable as a proxy for DUI innovations modes was already applied, for example, in the study by Parrilli and Radicic (2021). Through such learning-by-interacting situations, firms can leverage the expertise and innovations of other firms which may lead to the development or improvement of new products, finally increasing the firm's innovative activities. These learning-by-interaction indicators can be further differentiated based on whether they are intra-sectoral, offering access to similar knowledge (equivalent to the same IPC), or extra-sectoral, providing access to related or unrelated knowledge (as indicated by assignment to a related industry or IPC). The groundbreaking new possibilities for representing tacit knowledge flows through the digital layer approach could serve as a valuable data basis. inter-firm hyperlinks, combined with novel machine-learning methods, to construct a network of inter-firm relations (Abbasiharofteh et al., 2024; Abbasiharofteh et al., 2023b). The supplementation of the combination of web-based hyperlink and text data analysis with patent information in order to model the influence of the dimensions of proximity on the innovative capacity of companies was recently performed by Liu et al. (2024).

8.3. Limitations of the Study

In this study, several limitations must be acknowledged, in addition to the previously discussed issues regarding the reliance on patent data and the partly inconsistent results from robustness checks. First, in contrast to other studies, no bundled time periods are provided. This, however, is common in the regional diversification literature to ensure that a new specialisation in a region is not merely an artefact of short-term fluctuations (Drivas, 2022; Neffke et al., 2011). Unfortunately, this could not have been implemented as the S3 strategies were only introduced during the 2014-2020 programming period. Further, patent data, which serve as the basis for this study, do not sufficiently cover an additional period due to typical delays in patent approvals.

Second, in addition to related variety, unrelated variety emerges as a crucial factor in regional development, enabling further regional path creation facilitated by with interregional linkages (e.g. Boschma & Capone, 2015; Castaldi et al., 2015; Trippl et al., 2018). While this study does not explicitly address and appears to ignore diversification into unrelated variety, new specialisations through extra-regional inputs to learning and innovation and the observed compensation mechanism for missing relatedness essentially represent a form of unrelated diversification (cf. Corrocher et al., 2024; Grillitsch et al., 2018; Kogler et al., 2023b).

Third, innovation policy should not only support the development of related domains with potential specialisation, but also in those that are more complex than the ones they already produce (Balland & Rigby, 2017). Introducing complexity and its implication for the absorptive capacity would very likely have an impact on the entry of specialisations and consequently on the results (cf. Pinheiro et al., 2022). Further, it is then questionable whether collaborations with peripheral regions, which are characterised by less complex knowledge, are conducive to core regions and their orientation towards more complex technologies (Balland & Rigby, 2017; Barzotto et al., 2019a).

Fourth, economic activities are embedded in specific socio-economic contexts (Hassink & Gong, 2019). Consequently, institutions have a crucial role in economic interaction, as they create the basic conditions for the exchange of information and knowledge (Bathelt & Glückler, 2014; Cortinovis et al., 2017). Further they influence the directions of regional path development (Benner, 2019, 2020b) and have an impact on whether comparative advantages can be obtained in new industries that are cognitively related or distant from existing structures (Boschma & Capone, 2015). Although, they might be captures by the regional fixed effects, they are a key factor in innovation and in the implementation of economic development strategies (see also: Capello & Kroll, 2016; Di Cataldo et al., 2022; Papamichail et al., 2023; Rodríguez-Pose, 2013; Trippl et al., 2020).

Fifth, the dynamics of knowledge flows in the analysis are limited to interregional collaboration within the EU and the regions participating in the Smart Specialisation programme. Collaborations with regions outside the EU are therefore not taken into account. At the same time, intra-regional collaborations, which promote the recombination and exchange of knowledge within a regional innovation system and create innovations through the cross-fertilisation of knowledge between different sectors (cf. Boschma & Frenken, 2011; De Noni et al., 2017), receive insufficient attention. These aspects are only implicitly included in the relatedness density. However, interregional collaborations seems to be not independent from intra-regional collaborations (Amoroso et al., 2020; Sun & Cao, 2015).

Sixth, as Camagni and Capello (2013) and Foray (2018), points out, the geography of innovation is far more complex than a simple core-periphery model and is not limited to high-tech sectors or cutting-edge research, but is widely distributed across different sectors and invention processes, even beyond formal R&D. In many regions, the focus is not on inventing at the frontier but on creating complementarities within existing sectors. At the same time, there is rising consensus to not focus only on the less-developed region, but also regions stagnating in regional development (Diemer et al., 2022; Rodríguez-Pose et al., 2024).

Lastly, as shown in the discussion, the assignment of IPC classes to economic domains is sensitive to the threshold specification. Valuable insights might be lost due to these thresholds, whereas incorporating assignment probabilities as weights in the regression could have been an alternative. However, this would have resulted in the duplication of IPC classes and consequently of the other independent variables, leading to significant distortions. The novel approach of linking S3 priorities with technology classes and selecting appropriate thresholds requires further research. This criticism also includes the rather rigid assumption that the S3 priorities are optimally selected. In fact, however, only a few regions implement their S3 strategies "by the book" (Marrocu et al., 2023). Evidence indicates that many regions have difficulties in implementing S3 strategies, which also involves imitations or the picking-the-winner principles (see also Capello & Kroll, 2016; Di Cataldo et al., 2022; Foray, 2019; Gianelle et al., 2020; Sotarauta, 2018; Trippl et al., 2020). Logically, this implies an impact on the results, as interregional linkages may still be appropriate to the regional characteristics, but do not correspond to the chosen priorities.

9. Conclusion

Lagging regions, in particular, often face difficulties in implementing Smart Specialisation Strategies (S3) and initiating the necessary innovative activities and transformations, which bears the risk of further exacerbating existing disparities. The strong focus on endogenous growth determinants, however, tends to overlook the (untapped) potential of exogenous knowledge and interregional linkages to develop comparative advantages despite limited capabilities. In this regard, there are still differing perspectives on whether interregional cooperations can effectively compensate for regional deficits or whether, in combination with local capabilities, they rather promote the emergence of new technological specialisations. Hence, the objective of this study was to contribute to a more nuanced understanding of the potential of interregional collaboration in promoting innovation and economic growth in different regional contexts. Starting point is the research question of how interregional linkages contribute to the implementation of S3 in different types of regions. For this purpose, 198 European NUTS2 regions and the emergence of new technological specialisations within their respective S3 priorities in the period 2015-2020 were investigated.

The results suggest that, in contrast to linkages to knowledge-intensive regions, complementary linkages that provide access to related and missing capabilities promote technological diversification into new technologies with targeted S3 priorities. By distinguishing between core and peripheral regions, the study further provides empirical evidence for an ambiguity of interregional linkages in promoting technological diversification in synergy with regional capacities. For core regions, the results indicate that complementary linkages enhance the impact of existing regional capabilities, thereby supporting the development of new technological specialisations in S3 priorities. In contrast, for peripheral regions, the findings suggest compensating effects, where weak local capacities can be substituted by linkages to core regions, thereby supporting these regions in overcoming their structural deficits through the access to relevant knowledge and enabling diversification into new technological domains. Regarding to the regional disparities within the EU and the difficulties in implementing successful S3, this study further emphasised the potential of interregional collaboration in promoting cohesion, but also in the successful implementation of S3 through the associated supporting benefits.

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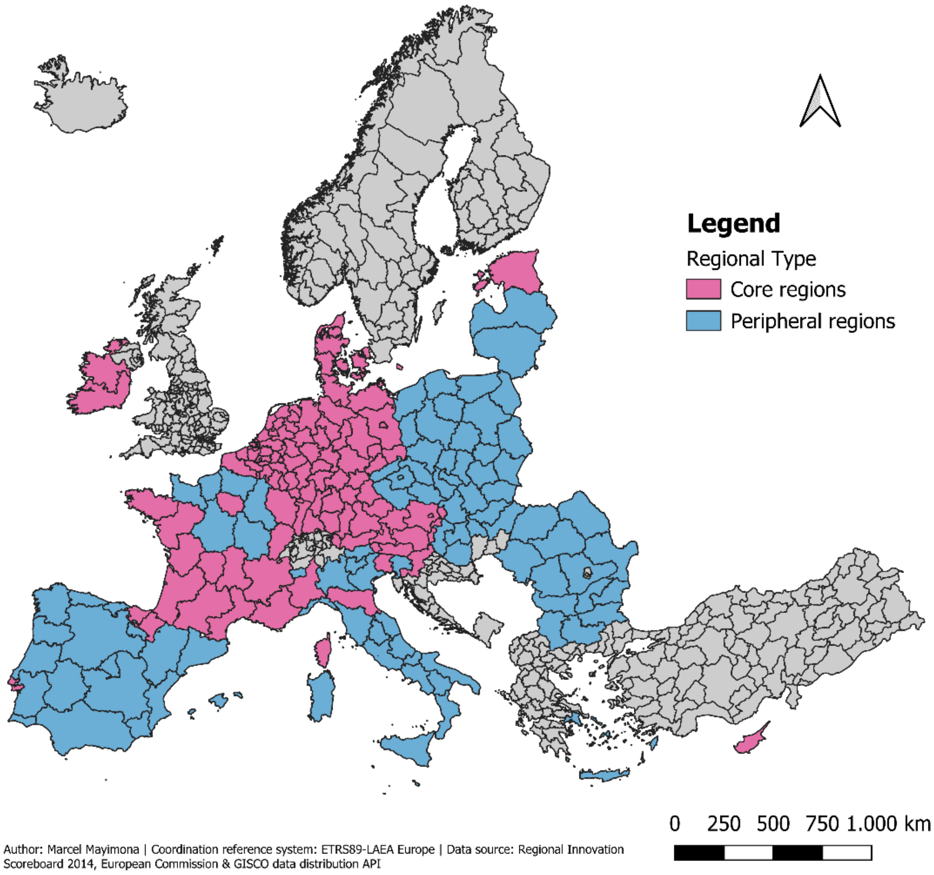
Appendix

Appendix 1: Regional Classification of Europe according to the innovative performance: Core vs. Periphery



Appendix 2: Fixed effect regression (LMP) on the impact of interregional linkages on regional technological diversification in S3-priorities depending on the IPC to NACE assignments.

	Full Model FE	IPC – 75	IPC – 90	All – IPC
	(1)	(2)	(3)	(4)
RD	0.0004**	0.0004	0.0001	0.0004**
	(0.0002)	(0.0002)	(0.0003)	(0.0001)
KL (log)	-0.0050	-0.0112	-0.0225	-0.0012
	(0.0114)	(0.0147)	(0.0236)	(0.0081)
KL_{t0+t1} (log)	-0.0067	-0.0041	0.0003	-0.0097**
	(0.0066)	(0.0079)	(0.0130)	(0.0048)
CL (log)	0.0084**	0.0082	0.0111*	0.0113***
	(0.0040)	(0.0056)	(0.0058)	(0.0028)
CL_{t0+t1} (log)	-0.0163***	-0.0168***	-0.0146***	-0.0157***
	(0.0008)	(0.0010)	(0.0014)	(0.0006)
IPC FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	46,425	30,567	12,615	98,262
R^2	0.09271	0.10085	0.10044	0.08153
Adj. R^2	0.07642	0.07786	0.06808	0.07370
AIC	30,265.3	20,022.1	7,218.7	56,971.9

Note: The dependent variable Entry equals 1 if a region gains a new revealed technological advantage (RTA) in a given technology during the corresponding five-year window 2016-2020; and 0 otherwise. All independent variables refer to the period 2011-2015. Heteroscedasticity-robust standard errors in parenthesis, Clustered by Region & IPC.
*, **, *** denote significance at the 0.1, 0.05, 0.01 level.

Appendix 3: Fixed effect regression (LMP) on the impact of interregional linkages on regional technological diversification in S3-priorities based RTA > 1.5.

	Baseline	KL Model	CL Model	Full Model without FE	Full Model FE	Interaction Model KL	Interaction Model CL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RD	0.0013***	0.0017***	0.0014***	0.0012***	0.0003*	0.0003	-0.0005
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0005)
KL (log)		0.0281***		0.0037	0.0018	-0.0040	0.0018
		(0.0076)		(0.0072)	(0.0070)	(0.0087)	(0.0070)
KLt0+ t1 (log)		-0.0148***		-0.0062	-0.0031	-0.0032	-0.0031
		(0.0041)		(0.0041)	(0.0043)	(0.0043)	(0.0043)
CL (log)			0.0318***	0.0298***	0.0171***	0.0171***	0.0152***
			(0.0021)	(0.0072)	(0.0031)	(0.0031)	(0.0031)
CLt0+ t1 (log)			-0.0149***	-0.0150***	-0.0156***	-0.0156***	-0.0156***
			(0.0008)	(0.0041)	(0.0030)	(0.0030)	(0.0008)
GDPpc (log)	0.0070**			0.0091**			
	(0.0035)			(0.0043)			
Pop. Dens. (log)	0.0013			0.0027			
	(0.0030)			(0.0029)			
RD x KL (log)						0.0003	
						(0.0003)	
RD x CL (log)							9.5e-5
							(5.92e-5)
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	Yes	Yes	Yes
Observations	50,544	50,544	50,544	50,544	50,544	50,544	50,544
R2	0.03423	0.03409	0.05034	0.05107	0.06180	0.06183	0.06180
Adj. R2	0.02226	0.02211	0.03856	0.03923	0.04634	0.04635	0.04632
AIC	23,208.0	23,215.5	22,358.0	22,326.8	22,144.5	22,144.8	22,146.5
Log-Likelihood	-10,984.0	-10,987.7	-10,559.0	-10,539.4	-10,252.2	-10,251.4	-10,252.2

Note: The dependent variable Entry equals 1 if a region gains a new revealed technological advantage (RTA) in a given technology during the corresponding five-year window 2016-2020; and 0 otherwise. All independent variables refer to the period 2011-2015. Heteroscedasticity-robust standard errors in parenthesis, Clustered by Region & IPC.
*, **, *** denote significance at the 0.1, 0.05, 0.01 level.

Appendix 4: Fixed effect regression (LMP) on the impact of interregional linkages on regional technological diversification in S3-priorities according to regional types (core /periphery) based on RTA > 1.5.

	Core – Interaction KL (8)	Periphery – Interaction KL (9)	Core – Interaction CL (10)	Periphery – Interaction CL (11)
RD	0.0002	0.0004	-0.0014**	0.0007
	(0.0003)	(0.0003)	(0.0006)	(0.0008)
KL (log)	-0.0154*	0.0006	-0.0062	-0.0051
	(0.0093)	(0.0364)	(0.0072)	(0.0263)
KL_{t0+t1} (log)	0.0120**	-0.0109	0.0121**	-0.0110
	(0.0047)	(0.0146)	(0.0047)	(0.0146)
CL (log)	0.0176***	0.0127***	0.0132***	0.0134***
	(0.0042)	(0.0047)	(0.0040)	(0.0048)
CL_{t0+t1} (log)	-0.0149***	-0.0142***	-0.0149***	-0.0142***
	(0.0010)	(0.0013)	(0.0010)	(0.0013)
RD x KL	0.0005*	-0.0003		
	(0.0003)	(0.0015)		
RD x CL			0.0002***	-3.88e-5
			(6.4e-5)	(0.0001)
IPC FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	26,201	24,343	26,201	24,343
R^2	0.07880	0.08144	0.07878	0.08144
Adj. R^2	0.05262	0.05360	0.05260	0.05360
AIC	12,607.6	9,731.2	12,608.3	9,731.2
Log-Likelihood	-5,578.8	-4,148.6	-5,579.1	-4,148.6

Note: The dependent variable Entry equals 1 if a region gains a new revealed technological advantage (RTA) in a given technology during the corresponding five-year window 2016-2020; and 0 otherwise. All independent variables refer to the period 2011-2015. Heteroscedasticity-robust standard errors in parenthesis, Clustered by Region & IPC.
*, **, *** denote significance at the 0.1, 0.05, 0.01 level.

Appendix 5: Fixed effect regression (LMP) on the impact of interregional linkages on regional technological diversification in S3-priorities capturing CL variables as dummies.

	Baseline (1)	KL Model (2)	CL Model (3)	Full Model without FE (4)	Full Model FE (5)	Interaction Model KL (6)	Interaction Model CL (7)
RD	0.0018*** (0.0003)	0.0028*** (0.0003)	0.0026*** (0.0003)	0.0020*** (0.0003)	0.0005** (0.0002)	0.0004** (0.0002)	0.0002 (0.0002)
KL (log)		0.0349*** (0.0114)		0.0688*** (0.0113)	0.0093*** (0.0116)	-0.0024 (0.0144)	0.0093 (0.0116)
KL_{t0+t1} (log)		-0.0214*** (0.0065)		-0.0925*** (0.0110)	-0.0140*** (0.0067)	-0.0142*** (0.0067)	-0.0139 (0.0067)
CL (log)			0.0739*** (0.0106)	0.0043 (0.0043)	-0.0038* (0.0110)	-0.0038* (0.0110)	-0.0223*** (0.0129)
CL_{t0+t1} (log)			-0.0845*** (0.0105)	-0.0197*** (0.0066)	-0.1326*** (0.0107)	-0.1325*** (0.0107)	-0.1324*** (0.0107)
GDPpc (log)	0.0195 (0.0050)			0.0249*** (0.0057)			
Pop. Dens. (log)	-0.0006 (0.0040)			0.0043 (0.0043)			
RD x KL (log)						0.0006 (0.0003)	
RD x CL (log)							0.0007*** (0.0003)
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	Yes	Yes	Yes
Observations	46,425	46,425	46,425	46,425	46,425	46,425	46,425
R^2	0.05822	0.05693	0.06303	0.06650	0.08398	0.08403	0.08405
Adj. R^2	0.04549	0.04418	0.05037	0.05380	0.06753	0.06756	0.06759
AIC	31,597.3	31,661.2	31,359.7	31,195.3	30,709.9	30,709.4	30,708.1
Log-Likelihood	-15,178.7	-15,210.6	-15,059.9	-14,973.7	-14,535.0	-14,533.7	-14,533.0

Note: The dependent variable Entry equals 1 if a region gains a new revealed technological advantage (RTA) in a given technology during the corresponding five-year window 2016-2020; and 0 otherwise. All independent variables refer to the period 2011-2015. Heteroscedasticity-robust standard errors in parenthesis, Clustered by Region & IPC.
*, **, *** denote significance at the 0.1, 0.05, 0.01 level.

Appendix 6: Fixed effect regression (LMP) on the impact of interregional linkages on regional technological diversification in S3-priorities according to regional types (core /periphery) capturing CL variables as dummies.

	Core – Interaction KL (8)	Periphery – Interaction KL (9)	Core – Interaction CL (10)	Periphery – Interaction CL (11)
RD	0.0004*	0.0004	2.4e-5	0.0003
	(0.0002)	(0.0003)	(0.0003)	(0.0003)
KL (log)	-0.0253*	0.2102***	-0.0102	0.0877**
	(0.0137)	(0.0586)	(0.0115)	(0.0378)
KL_{t0+t1} (log)	0.0113	-0.0716***	0.0117	-0.0722***
	(0.0071)	(0.0198)	(0.0071)	(0.0194)
CL (log)	0.0003	-0.0307	-0.0222	-0.0372
	(0.0123)	(0.0265)	(0.0151)	(0.0411)
CL_{t0+t1} (log)	-0.1314***	-0.1000***	-0.1315***	-0.1005***
	(0.0108)	(0.0267)	(0.0109)	(0.0268)
RD x KL	0.0006*	-0.0043***		
	(0.0003)	(0.0016)		
RD x CL			0.0009**	0.0002
			(0.0004)	(0.0009)
IPC FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	23,276	23,149	23,276	23,149
R^2	0.09612	0.11337	0.09611	0.11279
Adj. R^2	0.06710	0.08507	0.06709	0.08447
AIC	17,690.9	12,917.1	17,691.1	12,932.1
Log-Likelihood	-8,120.5	-5,741.6	-8,120.5	-5,749.0

Note: The dependent variable Entry equals 1 if a region gains a new revealed technological advantage (RTA) in a given technology during the corresponding five-year window 2016-2020; and 0 otherwise. All independent variables refer to the period 2011-2015. Heteroscedasticity-robust standard errors in parenthesis, Clustered by Region & IPC.
*, **, *** denote significance at the 0.1, 0.05, 0.01 level.

Appendix 7: Fixed effect regression (LMP) on the impact of interregional linkages on regional technological diversification in S3-priorities capturing KL variables as dummies.

	Baseline (1)	KL Model (2)	CL Model (3)	Full Model without FE (4)	Full Model FE (5)	Interaction Model KL (6)	Interaction Model CL (7)
RD	0.0018*** (0.0003)	0.0027*** (0.0003)	0.0021*** (0.0002)	0.0016*** (0.0002)	0.0004** (0.0002)	0.0004** (0.0002)	-0.0010** (0.0004)
KL (log)		-0.0003 (0.0048)		-0.0167*** (0.0047)	-0.0129** (0.0050)	-0.0246** (0.0101)	-0.0129** (0.0050)
KL_{t0+t1} (log)		-0.0122 (0.0088)		-0.0119 (0.0085)	-0.0131 (0.0083)	-0.0128 (0.0083)	-0.0131 (0.0083)
CL (log)			0.0336*** (0.0024)	0.0313*** (0.0028)	0.0085** (0.0040)	0.0085** (0.0039)	0.0030 (0.0047)
CL_{t0+t1} (log)			-0.0154*** (0.0008)	-0.0158*** (0.0008)	-0.0163*** (0.0008)	-0.0163*** (0.0008)	-0.0163*** (0.0008)
GDPpc (log)	0.0195*** (0.0050)			0.0211*** (0.0054)			
Pop. Dens. (log)	-0.0006 (0.0040)			0.0016 (0.0038)			
RD x KL (log)						0.0004 (0.0003)	
RD x CL (log)							0.0002*** (4.78e-5)
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	No	No	No	No	Yes	Yes	Yes
Observations	46,425	46,425	46,425	46,425	46,425	46,425	46,425
R^2	0.05822	0.05657	0.07576	0.07831	0.09275	0.09279	0.09286
Adj. R^2	0.04549	0.04382	0.06327	0.06578	0.07645	0.07648	0.07655
AIC	31,597.3	31,678.7	30,724.8	30,604.2	30,263.4	30,263.0	30,259.5
Log-Likelihood	-15,178.7	-15,219.4	-14,742.4	-14,678.1	-14,311.7	-14,310.5	-14,308.7

Appendix 8: Fixed effect regression (LMP) on the impact of interregional linkages on regional technological diversification in S3-priorities according to regional types (core /periphery) capturing KL variables as dummies.

	Core – Interaction KL (8)	Periphery – Interaction KL (9)	Core – Interaction CL (10)	Periphery – Interaction CL (11)
RD	0.0004*	0.0004	-0.0010	-0.0008
	(0.0002)	(0.0002)	(0.0006)	(0.0007)
KL (log)	-0.0124	0.1109**	0.0044	-0.0143
	(0.0097)	(0.0500)	(0.0054)	(0.0264)
KL_{t0+t1} (log)	0.010	-0.0611***	0.0102	-0.0568***
	(0.0087)	(0.0220)	(0.0087)	(0.0214)
CL (log)	0.0057	0.0096*	-9.67e-5	0.0053
	(0.0047)	(0.0054)	(0.0054)	(0.0070)
CL_{t0+t1} (log)	-0.0151***	-0.0156***	-0.0151***	-0.0157***
	(0.0009)	(0.0016)	(0.0009)	(0.0016)
RD x KL	0.0006**	-0.0043***		
	(0.0003)	(0.0016)		
RD x CL			0.0002**	0.0001*
			(6.61e-5)	(8.11e-5)
IPC FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	23,276	23,149	23,276	23,149
R^2	0.10223	0.12186	0.10220	0.12134
Adj. R^2	0.07341	0.09383	0.07337	0.09330
AIC	17,532.9	12,694.3	17,533.8	12,707.9
Log-Likelihood	-8,041.4	-5,630.2	-8,041.9	-5,636.9

Template Research Data Management Plan

Instructions: this is the template for a data management plan. Please fill this in and discuss it with your supervisor during the design phase of the thesis. If your thesis is nearly complete, please add this as an appendix to the thesis. The purpose of making a dmp to think ahead. How will you manage the data gathered for your project? It is not about providing the 'right' answers, but making your research transparent. Some items just require ticking, some require further explanation.

1. General	
1.1 Name & title of thesis	Marcel Mayimona Unlocking Regional Potential: The Impact of Interregional Linkages on Smart Specialisation and Innovation in Europe
1.2 *(if applicable)* Organisation. Provide details on the organisation where the research takes place if this applies (in case of an internship).	University of Groningen (Rijksuniversiteit Groningen)

2 Data collection – the creation of data	
2.1. Which data formats or which sources are used in the project? For example: - theoretical research, using literature and publicly available resources - Survey Data - Field Data - Interviews	Provide a short description of the sources/data that you are going to use. Patent data from the OECD REGPAT Database from PATSTAT (EPO database) Regional data as control variables derived from the Eurostat (Population) Beside that literature and publicly available resources (policy papers) for the theoretical foundation
2.2 Methods of data collection What method(s) do you use for the collection of data. (Tick all boxes that apply)	☐ Structured individual interviews ☐ Semi-structured individual interviews ☐ Structured group interviews ☐ Semi-structured group interviews ☐ Observations ☐ Survey(s) ☐ Experiment(s) in real life (interventions) ☒ Secondary analyses on existing data sets (if so: please also fill in 2.3) ☒ Public sources (e.g. University Library) ☐ Other (explain):
2.3. (If applicable): if you have selected 'Secondary analyses on existing datasets': who provides the data set?	☐ Data is supplied by the University of Groningen. ☒ Data have been supplied by an external party: OECD STI Microdata lab – OECD REGPAT database, January 2024

3 Storage, Sharing and Archiving	
3.1 Where will the (raw) data be stored *during* research? If you want to store research data, it is good practice to ask yourself some questions: • How big is my dataset at the end of my research?	☒ X-drive of UG network ☐ Y-drive of UG network ☐ (Shared) UG Google Drive ☐ Unishare ☒ Personal laptop or computer

• Do I want to collaborate on the data? • How confidential is my data? • How do I make sure I do not lose my data? Need more information? Take a look at the site of the Digital Competence Centre (DCC)) Feel free to contact the DCC for questions: dcc@rug.nl	☐ External devices (USB, harddisk, NAS) ☐ Other (explain):
3.2 Where are you planning to store / archive the data after you have finished your research? Please explain where and for how long. Also explain who has access to these data NB do not use a personal UG network or google drive for archiving data!	☒ X-drive of UG network ☐ Y-drive of UG network ☐ (Shared) UG Google Drive ☐ Unishare ☐ In a repository (i.e. DataverseNL) ☐ Other (explain): The retention period will be 0 years. Besides the course teacher no one has access to the data
3.3 Sharing of data With whom will you be sharing data during your research?	☒ University of Groningen ☐ Universities or other parties in Europe ☐ Universities or other parties outside Europe ☐ I will not be sharing data

4. Personal data	
4.1 Collecting personal data Will you be collecting personal data? If you are conducting research with personal data you have to comply to the General Data Privacy Regulation (GDPR). Please fill in the questions found in the appendix 3 on personal data.	No
If the answer to 4.1 is ‘no’, please skip the section below and proceed to section 5	
4.2 What kinds of categories of people are involved? Have you determined whether these people are vulnerable in any way (see FAQ)? If so, your supervisor will need to agree.	My research project involves: ☐ Adults (not vulnerable) ≥ 18 years ☐ Minors < 16 years ☐ Minors < 18 years ☐ Patients ☐ (other) vulnerable persons, namely (please provide an explanation what makes these persons vulnerable) (Please give a short description of the categories of research participants that you are going to involve in your research.)
4.3 Will participants be enlisted in the project without their knowledge and/or consent? (E.g., via covert observation of people in public places, or by using social media data.)	Yes/no If yes, please explain if, when and how you will inform the participants about the study.
4.4 Categories of personal data that are processed. Mention all types of data that you systematically collect and store. If you use particular kinds of software, then check what the software is doing as well. Of course, always ask yourself if you need all categories of data for your project.	☐ Name and address details ☐ Telephone number ☐ Email address ☐ Nationality ☐ IP-addresses and/or device type ☐ Job information ☐ Location data

	☐ Race or ethnicity ☐ Political opinions ☐ Physical or mental health ☐ Information about a person's sex life or sexual orientation ☐ Religious or philosophical beliefs ☐ Membership of a trade union ☐ Biometric information ☐ Genetic information ☐ Other (please explain below):
4.5 Technical/organisational measures Select which of the following security measures are used to protect personal data.	☐ Pseudonymisation ☐ Anonymisation ☐ File encryption ☐ Encryption of storage ☐ Encryption of transport device ☒ Restricted access rights ☐ VPN ☐ Regularly scheduled backups ☐ Physical locks (rooms, drawers/file cabinets) ☐ None of the above ☐ Other (describe below):
4.6 Will any personal data be transferred to organisations within countries outside the European Economic Area (EU, Norway, Iceland and Liechtenstein)? If the research takes places in a country outside the EU/EEA, then please also indicate this.	no

5 – Final comments	
Do you have any other information about the research data that was not addressed in this template that you think is useful to mention?	