Regional transformation; between policy intervention and knowledge dynamics?

by

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1. Introduction

1.1 Background and motivation

Regions have emerged as an important spatial scale through which to understand processes of economic development (Lundvall, and Borrás, 1997; Asheim and Isaksen, 2002; Boschma, 2005, 2015; Boschma et al., 2017; Isaksen and Trippl, 2016; Neffke et al., 2011). This regional turn, however, has sought to provide answers to several important questions about how the process of economic development unfolds differently across regions, and more directly how and why it is that regions transform differently (Pike, Rodríguez-Pose and Tomaney, 2007; Trippl *et al.*, 2020). Debates about how to understand regional transformation and the dimensions which contribute to the differing experience of regions are ongoing, with recent experiments in the realm of policy providing new sources of data and evidence to uncover important aspects of how regional transformation unfolds (Martin, 2010; Boschma *et al.*, 2017).

Of particular concern to this thesis is how processes of regional transformation lead to economic growth. The relationship between the more quantitative focus on growth, versus the more qualitative focus on development, is discussed in greater detail in the work of Feldman *et al.* (2015) and further discussed in the more recent work of Feldman and Storper (2018), who highlight the frequency with which the terms of growth and development are often used interchangeably. Feldman and Storper (2018) further highlight that the terms frequently correlate in practice, such as in the example of per capita income (indicating growth) and the human development index (indicating development), which show strong correlation in the range of 0.95, for example. Furthermore, the authors highlight that the precise direction of causation between growth and development remains unclear (for example, does growth in income drive investment in education or does educational investment produce income growth). Here, then, economic growth tends to be a focus of macroeconomists who rely on the use of quantifiable metrics such as gross national product, as opposed to economic development which instead is typically concerned with infrastructure, public health, and education, for example.

What this current thesis is focused on is understanding how economic growth can be achieved through processes of regional transformation and the ways in which knowledge dynamics in a region can lead to innovation, which, in turn, can lead to productivity improvements, which, in turn, stimulate regional economic growth, and how it is that such changes in a region's economy are stimulated through such processes of regional transformation. A core focus of this current research is on the structural changes which can take place in a regional economy, by, for example, focusing on the changes in sectoral and technological composition in a given region's economy in order to understand this regional economic growth. Regional transformation, in this sense, can be considered a process whereby the economic activities, or portfolios of economic activities in a region, transform or change over time. The transformation process, then, can be seen as leading to regional economic growth, with the exact contributory factors of such an outcome being the subject of considerable scholarly attention (Glaeser *et al.*, 1992; Frenken, Van Oort and Verburg, 2007; Beaudry and Schiffauerova, 2009; Isaksen and Trippl, 2016; Oinas, Trippl and Höyssä, 2018). The transformation then of regional economies varies markedly, with the outcomes of such processes of change remaining a phenomenon which plagues policymakers and scholars alike (Frenken, Van Oort and Verburg, 2007; Bellini, Lazzeri and Rovai, 2020; De Propris and Bailey, 2021). However, recent work has begun to provide greater clarity on the factors which go into the process of regional transformation, with the knowledge bases which exist in regions, alongside the respective role of policy, being an area of considerable promise in explaining the structural changes which produce broader regional transformation processes (Frenken, Van Oort and Verburg, 2007; Asheim, Moodysson and Tödtling, 2011; Borrás, 2011; Asheim, 2019; Trippl *et al.*, 2020).

Regional transformation processes, however, are not random, and far from being a black box in which little is known, considerable scholarship has shed light on the factors which help explain the differences we can see across regions (Davis, 1985; Dosi, 1988; Boschma and Wenting, 2007; Lo Turco and Maggioni, 2016; Grillitsch, Asheim and Trippl, 2018; Hane- Weijman, Eriksson and Rigby, 2021). What has become increasingly clear, particularly given the growth in attention paid to evolutionary approaches to understanding economic geography, is that history evidently matters. Such evolutionary approaches take seriously what has gone before as shaping what may come to exist in the future; in short, new economic activities do not begin from nothing but evolve out of current regional structures and can be seen to branchout from earlier activities (Boschma and Wenting, 2007; Frenken, Van Oort and Verburg, 2007;Eriksson, 2011; Content and Frenken, 2016; Boschma *et al.*, 2017). This focus on the role of history, and the path a region is on, has led to considerable advances in our understanding of regional transformation. For example, it pays greater attention to the use of measures, such as relatedness, in understanding that changes in a regional economy are likely to come from activities that are related to existing economic activities already present in a region. It also helps to shed light on processes of regional branching[1] of activities in a region (Boschma, 2011; Boschma and Frenken, 2011; Tanner, 2014; Essletzbichler, 2015; Kuusk, 2021).

While regional transformation is not static, it is also not typically nor necessarily a process which unfolds with any great rapidity; often taking months, years, and even decades for the patterns of regional transformation to become apparent, with the process throughout being one which is often subject to change (Neffke, Henning and Boschma, 2011). Conversely, while individual regions may not move with any great rapidity, regions, in general, do exist in a competitive, fast-moving environment, one where changes are rapid; where outcomes are often contingent on specific decisions or environments one often has little control over (Smętkowski, 2018; Trippl, Grillitsch and Isaksen, 2018). As such, decisions taken in other regions can often exert considerable influence on the success or failure within a given region and where technological changes are both a consistent opportunity and threat to a given region's economic profile (Runiewicz-Wardyn, 2013; Mewes and Broekel, 2020; Kogler *et al.*, 2022). The competitive position then of a region in this changing environment is oftentimes strongly influenced by the knowledge portfolio a region contains (Gertler, 2003; Eriksson, 2011; Thomas, Faccin and Asheim, 2020; Balland and Boschma, 2022). The immovability, or rather the stickiness of large swathes of knowledge in a region, is, by some, considered to be a particularly powerful conduit of regional transformation and a key source of the competitive advantage of a region (Gertler, 2003; Kuusk, 2021). However, it can also be argued that, in contrast, knowledge dynamics alone are not sufficient, and they should be mobilised and tapped into through well-conceptualized and well-implemented policy interventions, in order to stimulate a successful regional economic transformation (Asheim, Moodysson and Tödtling, 2011; Balland *et al.*, 2019; Esparza-Masana, 2022). This debate is particularly relevant for many scholars, as some of the most prominent policy interventions in recent years have soughtto focus on the contributory role of regional knowledge dynamics in transformations. Indeed, itseeks to move away from one size fits all policy in order to better understand processes of regional transformation, alongside paying attention to the outcomes of policy interventions in processes of regional transformation (Tödtling and Trippl, 2005). However, the practical implementation of such interventions and their links with the existing knowledge portfolio in regions is a relatively understudied aspect of regional transformation, particularly given the relative recency of such conceptualisations of both policy interventions (and the logics which

[1] In its broadest sense regional branching refers to the process by which new activities arises from related activities in a region

underpin them) and the changing nature of knowledge dynamics in a region's competitive position.

The motivation then for this current thesis is to provide a better, clearer insight into how two key aspects of regional transformation – namely the role of existing regional knowledge portfolios and, relatedly, the role of policy interventions – can support regional transformation processes. Such a contribution is then, in turn, motivated by recent efforts at the policy level in a European context, to address regional imbalances by tapping into particular regional knowledge portfolios, rather than targeting more 'fashionable' areas (Ascani, Crescenzi and Iammarino, 2012; Iammarino, Rodriguez-Pose and Storper, 2019), as well as attempts to stimulate growth in regions through a focus on innovation (Dominique Foray, David and Hall, 2011; Kaivo-oja *et al.*, 2017; Grillitsch and Asheim, 2018). What follows then is an insight into the motivation behind this thesis, alongside a clear articulation of what the primary research questions which drive this thesis forward are.

1.2 Aim, Research Questions and Contributions

While, as discussed above, considerable research has begun to unpack regional transformation, its construction as a concept, as well as its constituent parts and its policy relevance, there remains considerable scope to expand this understanding in light of recent theoretical and empirical advances in how its unfolding can differ across regions. In lieu of this, this current thesis aims to better understand how it can be measured, what role knowledge plays in its unfolding, and relatedly what can policy do to influence how regional transformation unfolds. This thesis builds on considerable previous scholarly work, expanding on the crucial role played by a number of critical dimensions, not least the role played by knowledge, proximity, policy, actors, and institutions in, not only influencing the direction of regional economies, but more accurately as a crucial driving force behind the transformation of a given region (Maskell and Malmberg, 1999; Gertler, 2003; Boschma, 2005; Malmberg and Maskell, 2006; Rodríguez-Pose, 2013; Grillitsch *et al.*, 2022). Much work, to date, has focused on whether regions benefit more from specialisation in a few industries or from having a diversity of industries, often pitched as a face-off between Marshall-Arrow-Romer (MAR) and Jacobs externalities (Glaeser *et al.*, 1992; Paci and Usai, 2000; Beaudry and Schiffauerova, 2009; De Groot, Poot and Smit, 2009; Caragliu, de Dominicis and de Groot, 2016). In recent years, another dimension has emerged, which is seen as taking a middle-road approach to this perennial debate. This middle ground is the notion of relatedness, which this current thesis aims to make a clear contribution toward, in understanding how this dimension relates to regional transformation efforts. Related variety assumes that regions benefit neither from being specialised in a few activities nor from hosting a wide variety of activities. Instead, various. related activities provide the optimal conditions for knowledge spillovers across activities (Frenken, Van Oort and Verburg, 2007). Such a concept has found widespread use across muchof the literature (Eriksson, 2011; Neffke, Henning and Boschma, 2011c; Runiewicz-Wardyn, 2013; Fitjar and Timmermans, 2017; Bond-Smith and McCann, 2020; Kuusk, 2021a). Although what we know about how its different constructions in the literature impact its efficacy remains to be seen, it is an issue that this thesis contributes toward, by exploring its use in policy, as well as its construction as a measure used in the regional transformation literature.

This thesis makes a theoretical contribution by providing evidence on how it is that regional transformation processes unfold, the measures used to capture this transformation process, the role of policy interventions in the process. This thesis contributes further to addressing a macro-concern of the literature, and when (and why) interventions are necessary for a regional transformation (Uyarra, Ribeiro and Dale-Clough, 2019; Gianelle, Guzzo and Mieszkowski, 2020; Rodríguez-Pose, 2020). The intention here is to take a better account of approaches to understanding regional transformation. This will be achieved by orienting the thesis around the following research questions.

1. **RQ1:** Do regions diversify into new jobs from related industries or related occupations?
2. **RQ2:** What is the role of actors in entrepreneurial discovery processes in such regional transformation processes?
3. **RQ3:** How do Smart Specialisation strategies support related diversification?

The thesis studies regional transformation from the perspective of relatedness and regional branching and explores the role of skill- and industrial-relatedness therein (RQ1), as well as the application of the smart specialization policy, which is initiated to support related diversification processes (RQ3). While the results clearly show a strong link and relevance of this policy for related-diversification-based regional transformation, paper two (RQ2) highlights the importance of actors in entrepreneurial discovery processes in such transformation, which introduce important variations from the overall relatedness-based transformation pattern.

1.3 Overview of papers

While a comprehensive summary of the papers included in the thesis is contained in chapter 5, what follows here is a brief overview of the papers, which provides a snapshot into the aims and findings of the papers, as well as how they relate to the overarching theme of this thesis.

	Paper I	Paper II	Paper III
Title	How regions diversify into new jobs: From related industries or related occupations?	One coast, two systems: Regional innovation systems and entrepreneurial discovery in Western Norway	Searching through the Haystack: The Relatedness and Complexity of Priorities in Smart Specialization Strategies
Co-authors	Tom Broekel; Silje Haus-Reve and Rune Dahl Fitjar	Marte C.W Solheim; Stig-Erik Jakobsen and Arne Isaksen	Tom Broekel and Rune Dahl Fitjar
Aim	To investigate how regions diversify into new jobs – unique industry-occupation combinations – by analysing whether they do so from related industries or related occupations	To investigate whether differences in entrepreneurial discovery processes are due to the regional innovation system of the region and whether these differences also influence regional stakeholders' perceptions of regional transformation.	To investigate which economic domains regional policy makers choose in Smart Specialisation strategies, focusing on the complexity of the economic domains and their relatedness to other economic domains in the region
Methodology	• Linear probability panel regressions • Linked employer-employee data for all industry-occupation combinations in Norwegian labour-market regions over the time 2009 – 2014	• Sequential explanatory design approach • Quantitative data to analyse the regional industry structure in Stavanger & Bergen • Qualitative analysis of interviews with key stakeholders in both regions	• Logistic regression • Cross-sectional choice model • Use both an unconditional & conditional binary choice model • Data from 128 NUTS regions across Europe
Findings	• New jobs are more likely to emerge in a region when related occupations or industries are present. • Relatedness is substantially more relevant for more complex occupations • Co-presence of occupational and industrial relatedness is most conducive for diversification into more complex jobs.	• Stakeholders in a diversified and regionally network RIS expressed continued support for regional diversification efforts • Stakeholders in a specialized and regionalized national RIS, however, remained committed to the current path and supported regional transformation along this route.	• Relatedness greatly impacts the likelihood of a domain being chosen as a priority. • Complexity is also positive and significant at all levels, although generally at somewhat lower levels of significance • The results do not show any evidence of an interaction between relatedness and complexity • Both models (unconditional & conditional binary choice) yield similar results
Status	To be submitted	Published: Growth & Change	Published: Economic Geography
Relevant Research Question	RQ1	RQ2	RQ3

Table 1 – Summary of papers

1.4 Outline of the PhD thesis

The remainder of the thesis is structured as follows: Chapter 2 provides the theoretical framework of this thesis and looks at the regional transformation in the context of economic geography, diversification and efforts at regional branching (2.1), before turning to the knowledge dynamics involved in regional transformation (2.2) and concluding with a focus on the operationalisation of regional transformation (2.3), looking at the rationale for policy intervention. Chapter 3 presents the data and methods used in this thesis, while chapter 4 is concerned with the empirical context of the thesis. Chapter 5 then turns to a summary of the papers in this thesis, before chapter 6 concludes the thesis.

2. Theoretical Framework

This chapter presents the theoretical framework of this thesis, which rests upon several interlocking streams of literature. The thesis is oriented around an investigation into the mechanisms of, and approaches to, understanding regional transformation and its translation into policy, as expressed by recent attempts at regional innovation policy more broadly. The relevant literature covered in this thesis generally encompasses much of the work on evolutionary economic geography (EEG) (Boschma and Frenken, 2006) and the related concept of regional related diversification and regional branching. It does so in order to better understand how regions transform across different spatial and temporal contexts (Boschma *et al*., 2017; Boschma and Frenken, 2006; De Propris and Bailey, 2021; Martin, 2010; Martin and Sunley, 2006). Here, we orient this discussion on the relevant theory to this thesis around the themes of related diversification, regional branching, and how it is that knowledge dynamics shape regional transformations, before turning to the role of policy interventions, typically understood through efforts at regional innovation policy.

Furthermore, this thesis applies a theoretical lens that focuses on the structure of a regional economy, to contribute to broader processes of regional transformation. Here then, we are concerned with a focus on how it is that regional economic transformation can come to depend on a set of distinct structures which may inhibit or stimulate regional economic growth, and instead build out from a focus on just aggregated growth of regional economies to instead the incorporation of a more holistic view of the structures of a regional economy and how it is that these transform over time and space. We follow the work of Blankenburg, Palma and Tregenna (2008), in viewing structures as the understanding that each system should be studied as an organized set of interrelated elements which are not to be separated into individual elements. This view we apply to the industrial, sectoral and technological composition of a given regions transformation to explore regional transformation more generally. We follow the work of Jackson (2003, pp. 727-728), that such a structuralist understanding of economic development should "never congeal into structural wholes that overshadow their component parts". Instead, the use of such an approach allows us to pay sufficient attention to the composition of such structures in a regional economy and how they change.

The chapter follows with a review of the literature on regional transformation, focused on identifying why regions transform before investigating how this transformation takes place, in particular, looking at processes of related diversification and regional branching. It then turns to an important driving factor in regional transformations, namely knowledge dynamics or, more particularly, the conceptualisation of knowledge in a regional context, with an emphasis on, knowledge generation and diffusion, sources and types of knowledge, and behavioural influences on knowledge search processes. The chapter concludes with an investigation into how regional transformation is operationalised in a policy context, focusing on the role played by policy interventions in order to stimulate innovation-driven regional transformation.

2.1 Evolution, diversification and branching

Evolutionary approaches to economic geography build on much of the 'evolutionary turn' which has taken place in economics more generally. Such an evolutionary turn has focused on the process and mechanism through which an economy transforms itself from within (Witt,2003, 2006). The understanding of this *self-transformation* is expanded upon by Boschma andMartin (2007, p. 539), who contextualise the evolutionary turn in the context of economic geography. They do so by highlighting that such an understanding is concerned with "the processes by which the economic landscape—the spatial organization of economic production,distribution and consumption—is transformed over time". This turn to the spatial organisation of such activities has opened up a vast array of research avenues in recent years, most notably work on related (and unrelated) diversification, specifically so given the importance of path- dependence (and the related roles of path development, path extension, path renewal and path creation) in being rooted in the history of a given region and forming a basis for a sustained competitive advantage over time and the upgrading of a regions economic bases (Boschma and Wenting, 2007; Saviotti and Frenken, 2008; Boschma, 2017a; Fitjar and Timmermans, 2017).

Related diversification then is concerned with regional diversification processes, wherein a positive effect of the relatedness of a given activity influences the likelihood of diversification into that activity (Boschma, 2017); on the other hand, a negative effect of relatedness indicates unrelated diversification (Boschma and Capone, 2015). While the dichotomisation may imply a sharp distinction, the reality of regional diversification is likely to be different in practice, as new activities are likely to be based on both local related and unrelated capabilities. Indeed this can be seen inthe work of Boschma (2017), and furthermore in the work of Desrochers and Leppälä (2011) and Castaldi,Frenken and Los (2015). The sharp distinction between unrelated and related diversification faces a further challenge, specifically when one takes a recombinant approach to understandingregional diversification, wherein the relatedness which typifies both approaches becomes dynamic, or put simply unrelated activities can become related activities once successful combinations are connected in the regional economy. The relevance here then becomes more apparent, with Saviotti and Frenken (2008) highlighting a potential limitation and concern with reliance on related diversification, namely how sustainable is such reliance over the long-termand whether unrelated diversification is necessary to avoid lock-in in the future. This focus then of sustaining competitive advantage over time and the upgrading of a region's economic basisis an area where the literature on related diversification is seen as being particularly relevant (Boschma, 2017).

Furthermore, related diversification is considered a particularly promising approach, given that building on closely related skills and competences is seen to lead to more local knowledge spillovers, which are assumed to enhance regional growth and employment (Fitjar and Timmermans, 2017). A raft of studies provide the bedrock for this understanding of the positive effect related diversification has on both employment growth (Frenken, Van Oort and Verburg, 2007; Boschma and Iammarino, 2009a; Boschma, Minondo and Navarro, 2013) and also on innovation performance of regions (Antonietti and Cainelli, 2011; Tavassoli and Carbonara, 2014; Castaldi, Frenken and Los, 2015). Given then that the effect of related diversification is likely to have a positive effect on employment and regional growth, we can turn to the work of Boschma and Capone (2015), who highlight that it is in 'co-ordinated market economies' where we see more focus on related diversification. This is because the institutions in such regions are focused on sticking closely to what has been done in the past, against more 'liberal market economies', where there is 'more freedom' to diversify in unrelated activities. We can further see in the work of Petralia, Balland and Morrison (2017) that high-income countries have a higher tendency to diversify into unrelated technologies, in contrast to lower-income countries.

Boschma (2017) sums this up in a European context by highlighting that "Broadly speaking, West European countries tend to diversify in more unrelated industries, while East European countries tend to diversify into new industries that are more closely related to their existing industries".

However, while the operationalisation of regional diversification has typically emphasised the important role of related variety on regional diversification (particularly in the context of reducing risk for policymakers (Balland *et al.*, 2019)), an area which has received increased attention in recent years has been the under-explored role of unrelated variety in supporting such transformation activities or 'long jumps' into complex economic activities which may not be particularly related (Asheim, 2019). While unrelated variety offers a promising avenue for identifying and selecting activities on which to base policy interventions in order to avoid lock-ins, related variety is seen as a key aspect in explaining how it is that *self-sustained* spillovers emerge, without the aid of policy interventions (Coenen *et al.*, 2017).

Related variety is often viewed as a key component of another important concept, namely regional branching. Grillitsch, Asheim and Trippl (2018) highlight the importance of related variety and regional branching in understanding how regions change, wherein the authors highlight that "related variety and regional branching underpin an evolutionary theory of regional industrial change". Regional branching, however, according to Montresor and Quatraro (2017), is succinctly summarised: the situation wherein "the preexisting industry structure is a crucial determinant of the development path that a region embraces". As such, those new activities which appear in a region are likely to be those where there already exists a presence of technologically related activities. This builds on earlier work (Boschma and Frenken, 2011) which states that regional branching stems from a spatial evolution of firm-specific routines, and that new routines develop out of technologically related routines, further emphasising the importance of related variety in regional branching (Nelson and Winter, 1982). However, as is often the case, straightforward summarizations often hide considerable nuance. Grillitsch, Asheim and Trippl (2018), for example, highlight a number of criticisms of the link between related variety and regional branching. For example, they bring to the fore earlier work (Trippl, Grillitsch and Isaksen, 2017) which shows that regional branching does not necessarily have to be an endogenous process, but can instead be stimulated by investments from non-local actors active in related industries. Indeed, while regional branching is an important conceptualisation of new path development, there exist others, as highlighted in other studies (Isaksen, Tödtling and Trippl, 2018).

Regional branching is further seen as being based on aspects of related variety, given the ease at which knowledge spills more easily over some sectors and less so between others (Neffke, Henning and Boschma, 2011; Coenen *et al.*, 2017). Such regional branching processes are understood as being based on specialized yet related organisational routines and technological capabilities, which are further transformed into new industrial activities. Here then, the differentiation of regional branching is the limited role in which it is envisaged that policy can play in influencing the build-up of critical mass in new technological or industrial areas. It is here then that this current thesis will turn, to focus on knowledge dynamics in regional transformation. As highlighted in the work of Grillitsch, Asheim and Trippl (2018), the combination of ex-ante unrelated knowledge with the existing competencies in a region can provide a particularly promising source of regional branching potential in a region. This current thesis will then focus on the respective role of policy interventions in supporting related diversification in regions.

2.2. Knowledge dynamics

Knowledge, its production, use, and dissemination are frequently seen by many as a key aspect of competitive advantage to a region (Asheim and Isaksen, 2002; Gertler, 2003; Broekel and Binder, 2007; Boschma and Frenken, 2010; Witt, Broekel and Brenner, 2012). In evolutionary economic thinking, knowledge production is often described as a cumulative, interactive and path-dependent process (Dosi, 1982; Nelson and Winter, 1982; Balland *et al.*, 2019). Furthermore, knowledge is understood as a crucial ingredient in the development of innovation (typically focused on recombinant knowledge-producing innovation) within a region, and the effect of knowledge-producing innovation and, in turn generating economic growth has provided a fertile ground for economic geography research (Sorenson, Rivkin, *et al*., 2006). However, understanding what constitutes knowledge, and through which mechanisms it flows, within and between regions, remains unclear. In recent years, indeed following the work of Nelson and Winter (1982), who revisited much of the earlier work of (Polanyi, 1966), we have seen considerable scholarly attention paid to the differentiation between codified forms of knowledge, namely knowledge which can be codified or transcribed, and accessed by a wider variety of actors, with the more tacit forms of knowledge, which while expanded upon below, are often seen to be captured in Michael Polanyi's famous, and oft-used aphorism that 'We can know more than we can tell'. This distinction has early roots and is generally viewed as originating in the notion that innovation, which is a process largely contingent on knowledge, is inherently a search process, wherein innovators will explore the possible combinations of ingredients, recipes, and ideas for new and better alternatives (Schumpeter, 1939; Usher, 1954; Nelson and Winter, 1982). Codified knowledge has a distinct advantage here, as a wide variety of actors can more easily access it, thus negating its effect on competitiveness. In contrast, tacit knowledge can be more difficult to capture, even for the actor who holds the tacit knowledge may find it difficult to transmit as tacit knowledge is generally seen to resist transmission, and as such, its 'stickiness' constitutes an area of competitive potential both to individual firms, but also more broadly to the regions which play host to such firms (Asheim and Isaksen, 2002; Sorenson, Rivkin and Fleming, 2006). For scholars of the geography of innovation, this tacit knowledge forms a particularly attractive area of inquiry, given that it may help to explain the differences seen between regions, with regard to the innovative and economic performance alongside the transformative potentials of these regions.

It is, however, important to note that the conceptualisation of knowledge as being based on a tacit vs codified dichotomy has been contested for quite some time (Johnson, Lorenz and Lundvall, 2002), most notably in the work of Asheim and Coenen (2005) who highlight the importance of a more trans-sectoral conceptualisation of knowledge flows (Asheim, 2007). Here then, the authors propose to instead focus on *analytical* forms of knowledge, namely knowledge which generally refers to industrial settings, where scientific knowledge is highly important and where knowledge creation is often based on cognitive and rational processes or on formal models. Analytical, then, is generally seen as a form of knowledge which is more generally codified (although not exclusively so). In contrast to analytical knowledge, the authors further draw attention to *synthetic* knowledge, which is "where the innovation takes place mainly through the application of existing knowledge or through new combinations of knowledge. Often this occurs in response to the need to solve specific problems coming up in the interaction with clients and suppliers" (Asheim and Coenen, 2005, p. 1176). Here, this knowledge is seen as more tacit in nature. In later work, as shown in Table 2 below, another knowledge base was included, namely *symbolic* knowledge, or knowledge focused on more creative understandings of knowledge (Asheim, Boschma and Cooke, 2011). Such a conceptualisation adds further depth to understanding the interplay, not just simply of tacit vs codified forms of knowledge, but, moreover, how such forms of knowledge come to be embedded within actors, firms, and indeed typify particular sectors. This is discussed in greater detail in the earlier work of Asheim (2007). Moodysson and Jonsson (2007) further expand on this notion by highlighting that the central contribution of knowledge bases is, instead, to allow a clear focus on the knowledge inputs into an innovative activity and that, here, knowledge bases offer a clearer advantage to understanding the nature of innovation and its concurrent base of knowledge. Asheim, Boschma and Cooke (2011, pp. 899) then posit that, instead of a focus on whether the knowledge is tacit or codified, “it is more useful to speak of how different knowledge bases are combined and intertwined in a dynamic manner between firms and industries of related variety”. Here then, the focus is less on the form of knowledge per se and more on how knowledge bases interact with related variety; for example, in explaining regional development as discussed above.

	Analytical (science based)	**Synthetic (engineering based)**	**Symbolic (arts-based)**
Rationale for knowledge creation	Developing new knowledge about natural systems by applying scientific laws (know why)	Applying or combining existing knowledge in new ways (know-how)	Creating meaning, desire, aesthetic qualities, affect, intangibles, symbols, images, (know who)
Development and use of knowledge	Scientific knowledge, models, deductive	Problem-solving, custom production, inductive	Creative Process
Actors involved	Collaboration within and between research units	Interactive learning with customers and suppliers	Experimentation in studios, project teams
Knowledge types	Strong codified knowledge content, highly abstract, universal	Partially codified knowledge, strong tacit component, more context-specific	The importance of interpretation, creativity, cultural knowledge, sign values; implies strong context specificity
Importance of spatial proximity	Meaning relatively constant between places	The meaning varies substantially between places	Meaning highly variable between place, class and gender
Outcome	Drug development	Mechanical engineering	Cultural production, design, brands

Table 2 - Differentiated knowledge bases: a typology (Gertler, 2003; Asheim and Coenen, 2005; Asheim, Boschma and Cooke, 2011)

However, the generation of new knowledge is a time-intensive, complex, and often costly process, requiring considerable investments over prolonged periods. As Sorenson et al. (2006) point out, it entails little if any incremental cost on its use once the knowledge is produced. Furthermore, knowledge diffusion can aid in the production of scale economies, helping to stimulate economic development in a region by allowing several firms to benefit from the initial investment, in line with earlier work on agglomeration economics (Marshall, 1890; Romer, 1987). Whether an individual firm would be sufficiently incentivised to pay the costly expense of prolonged investments, only to have the benefits diffused widely, however, is a concern that more often plagues scholars of management, as it impedes an individual firm's competitive position, however, for economic geographers, the broader externalities of investment in knowledge production to the region are more often analysed alongside how regional knowledge bases may help (or hinder) regional transformations (Trajtenberg and Jaffe, 1993; Hausmann, Hwang and Rodrik, 2007; Breschi and Lissoni, 2009). Here, we are more concerned with the role of knowledge in forming the competitive and relational basis of regional economic transformation, and, as such, what follows is an insight into the place-based specificities of knowledge, in particular, zooming in on the tacit forms of knowledge as discussed above and on a region's ability to absorb and deploy knowledge before turning to more behavioural perspectives on knowledge transfer and diffusion as it relates to the role of actors and their biases in creating place-based dimensions of knowledge dynamics which may hinder regional economic transformation by for example producing lock-in situations. The intention here is to highlight the importance of knowledge dynamics in shaping regional transformation processes.

2.2.1 Knowledge and Place

The stickiness of certain forms of knowledge, particularly those that provide an enhanced competitive position for a region, implies an important interaction between knowledge and place. The focus on place, however, is particularly important, given, as we will discuss later, how occupations and, more specifically, jobs (industry-occupations) are vital repositories of knowledge which are likely to aid in (or hinder) the regional transformation process. It does so through enabling higher forms of specialisation or particular diversification opportunities, alongside related knowledge bases potentially improving entry probabilities of certain industries into a region (so-called related diversification) and being central to the construction of regional advantage (Asheim, Boschma and Cooke, 2011). We can see, for example, in the earlier work on the 'learning region' concept, as advanced by several scholars (see for example; Florida, 1995; Asheim, 1996; Morgan, 1997; Morgan and Cooke, 1998; Maskell and Malmberg, 1999; Malmberg and Maskell, 2006) that there has long been a belief that such sticky tacit knowledge does not 'travel' easily and may actively resist travel. This is an aspect which highlights the particularities of the intersection between place and knowledge.

So, when we turn to the relationship between knowledge and place, in this, we focus largely on the role of tacit knowledge. We follow the work of Maskell and Malmberg (1999), that when access to codified knowledge is generally quite widespread, tacit knowledge offers a better insight into the geography of innovation. This is because "The fundamental exchange inability of this type of knowledge increases its importance as the internationalisation of markets proceeds" (Maskell and Malmberg, 1999, p. 172). This line of argumentation that the exchange inability or resistance of certain forms of knowledge creates an explicit geographic dimension is further picked up by (Gertler, 2003), wherein the author identifies three aspects which elaborate this line of argumentation, namely; due to the difficulty in articulating tacit forms of knowledge as well its development being generally experimental it remains difficult to exchange over long distances; that there exists an importance of social context in understanding and interpreting tacit knowledge and related to the previous point, that learning has increasingly become a socially organised process where interactions and knowledge are between a diverse pool of economic entities (Gertler, 2003, p. 79). This understanding of the role of tacit forms of knowledge, and its relationship with both space and the differentiated forms of knowledge, as outlined in Table 2 above, is a core aspect of the contribution of this current thesis. Knowledge, as constructed above, sheds light on two important contributions of this thesis, namely the competitive position of regions and how it affects regional development, and the respective role of regional knowledge bases. This can be a useful source in the identification of regional transformation opportunities.

Central to this socially organised process of learning within a region are the related concepts of trust between the actors in a regional economy which facilitates knowledge exchange and transfer and which, through non-reciprocal exchange, can be damaged and reduce overall knowledge diffusion (see Boschma and Frenken, 2010), alongside the ability of economic actors to absorb new knowledge. The early work of Cohen and Levinthal (1990) sheds light on the potential of actors to absorb new knowledge, which the authors refer to as an 'absorptive capacity'; the authors elaborate that absorptive capacity refers to the ability of firms to recognize the value of new, external information, assimilate it, and apply it to commercial ends constitutes a key aspect of their innovation potential. A central aspect of this absorptive capacity is its path-dependent nature which is evidently related to evolutionary approaches to economic geography, and, in turn, the notion of learning regions as discussed above. For example, Boschma et al. (2014, p 108) acknowledge that "agents are more likely to understand, absorb and implement external knowledge when it is close to their knowledge base", highlighting that knowledge is widely dispersed across several heterogenous actors and that knowledge creation requires combining the different capabilities of these actors (Antonelli, 1995; Nooteboom, 2000). In addition to this, the spatial dimension of knowledge creation is also exemplified by several other key mechanisms which transmit knowledge, such as spinoffs, social networking, labour mobility, and behavioural biases, which we discuss further below (Capello, 1999; Boschma and Frenken, 2011; Eriksson, 2011; Boschma, Heimeriks and Balland, 2014).

However, while a number of authors support the notion of geographic proximity in driving the creation and diffusion of tacit knowledge, it is not without its critics who posit instead that the sharing of tacit knowledge "need not be subject to the friction of distance if relational proximity is present" (Gertler, 2003, p. 86; Bunnell and Coe, 2001). Indeed, as opposed to solely viewing the local as a source of tacit knowledge which is useful in creating a competitive advantage, instead "it is within organisational spaces, with their complex geographies blending action at a distance and local practices, that codified and tacit knowledge are mobilised for competitive advantage" (Amin, 2000, p. 14). Here, instead of the local context being the core of tacit knowledge, organisational (and institutional) context forms a basis of knowledge production, identification, appropriation, absorption, and circulation (Gertler, 2003). While much of this work was later picked up by Boschma (2005). Here the author disaggregates the different forms of proximity, however, it becomes clear that, while different forms of proximity may help or hinder knowledge production and diffusion, it is rather the scale of, or rather how much proximity across which dimensions of proximity,[2] is required to effectively enable knowledge transmission. That rather than knowledge simply being inherently spatially bound, the degree of spatiality matters too (see, for example, Eriksson (2011)) alongside the organisational (Allen, 2000) and institutional (Cooke and Morgan, 1998) environments, which can serve to inhibit knowledge production and diffusion. We can see the contrasts and conflicts across these mechanisms playing out concerning tacit knowledge; for example, Gertler (2003) refers to intra-organisation diffusion of tacit knowledge as being 'devilishly difficult' and not simply a process whereby one approach can be taken and relocated to another. Relatedly, the institutional mechanism is seen by Maskell and Malmberg (1999) as embodying the "regions distinct institutional endowment" and that this endowment "embeds knowledge and allows for knowledge creation" (p.181). Here then, we can view the geography of knowledge happening through a number of key dimensions, such as the proximity dimensions as discussed above in Boschma (2005), alongside network effects, which are explored in the work of Boschma and Frenken (2011), behavioural biases (Broekel and Binder, 2007), and labour mobility (Haas,

[2] Here Boschma, 2005 breaks proximity out to include five different forms of proximity, which are; Cognitive, Organisational, Social, Institutional and Geographical proximity

2000; Fornahl, Zellner and Audretsch, 2005; Eriksson, 2011) as an example of both inter and intra-regional diffusion of knowledge.

Here, we turn to the work of Eriksson (2011), who deconstructs knowledge into skills captured at the employee level, as well as routines captured at the firm level (Nelson and Winter, 1982; Boschma and Frenken, 2006). The author takes an evolutionary perspective wherein knowledge is not viewed as a public good but rather is plant specific and, as such, spatially bound, given that knowledge exhibits a place-specific distinctiveness in the sense that the routines of firms tend to share many characteristics within the same institutional system but differ across institutions (Gertler, 2003; Storper and Scott, 2009). Here, we can also lean on the work of Sonn and Storper (2008), which shows that, despite considerable technological improvements, the localised effect of knowledge diffusion remains present. Malmberg and Maskell (2002) refer to this as the low costs of monitoring the behaviour of firms located close by. Eriksson, here, turns the focus to labour mobility, as the author states that "the mobility of personnel is crucial for the transfer of spatially sticky and locally embedded tacit knowledge between firmsand regions, as well as for the sustained competitiveness of clustered activities" (Eriksson, 2011, pp. 132). Eriksson (2011) further goes on to show that, when looking at labour flows, the mix of geographic and cognitive distance produces considerable growth effects on productivity. Furthermore, knowledge flows via geographic proximity are often at quite a local scale and present an important dimension through which knowledge flows in a region. This then provides the space to unpack more behavioural considerations which help or hinder knowledge transmission and diffusion within regions as the role of actors in regional transformation processes are particularly important; the biases to which they are impacted evidently matter in explaining regional transformation variation between regions.

2.2.2. Behavioural aspects of knowledge flows

The notion of tacit knowledge, rooted in Polanyi's famous aphorism of 'We can know more than we can tell', has faced a considerable challenge in recent years due to it perhaps lacking a crucial element, namely how it shapes what we do (Gertler, 2003) and indeed related to the trans-sectoral perspective outlined in table 2, where it is we do it (Asheim and Coenen, 2005; Asheim, Moodysson and Tödtling, 2011). However, while it may well hide more than it says, it does indicate an important, if understudied, aspect related to the flow of knowledge in a spatial context. The role of behaviour and, in particular, the behavioural biases of actors in explaining how knowledge is found and used in a regional context. Alongside opening the debate on actors, such an investigation also provides space to unpack the socially oriented process of tacit knowledge production by exploring actors' network dynamics (Hall, 1993; Lawson and Lorenz, 1999; Sorenson, Rivkin and Fleming, 2006). In this, we will shift towards a more micro foundational perspective on tacit knowledge, before zooming out to unpack how this impacts a region's ability to transform and compete, with a particular focus on how such biases may impinge an actors' ability to identify opportunities outside a relatively narrow, and path-dependent string of options.

Boschma and Frenken (2010) argue that bringing proximate actors together, while being potentially good for efficiency, does not necessarily increase their innovation performance and may, instead, harm innovation performance (Boschma, 2005; Broekel and Meder, 2008); the authors term these phenomena a 'proximity paradox'. The authors call for more awareness of the need for an optimal level of proximity rather than purely the level of proximity being the area of concern. However, unpacking what this optimal level means is a little trickier than it may appear on the surface, given how proximity informs an actor's search process. Thus, it may, in fact, serve to reduce the ability of actors to identify new combinations, as discussed by Malmberg and Maskell (2002) below.

Brökel and Binder (2007), for example, provide an early insight into how boundedly rational actors search for knowledge. Here, the authors contribute towards understanding how, relying on heuristics that provide approximate solutions, it is that boundedly rational actors produce biases that tend towards a regional search and transfer process. This can be seen both through the spatialisation of human action, which leads to a 'search bias', alongside the social embeddedness of actors being regionally oriented; an example of which can be found in the expression of 'regional identities'. It is argued that these factors, alongside what is proposed in Malmberg and Maskell (2002) who highlight the low costs of monitoring the behaviour of those firms which are located close provides scope for a regional bias to emerge in the evaluation of new knowledge. We can see this regional bias most clearly in the context of tacit knowledge which the authors refer to as a 'tight geographic prison'. While the authors (Broekel and Binder, 2007) acknowledge the lack of appropriate empirical research, the model of influences on knowledge transfers as contained in Figure 1 below, provides an important theoretical lens through whichto evaluate potential influences on knowledge transfers, in order to contextualise the regional bias better and to take better account of how individual actors are likely to tend towards a regional focus in their knowledge search process. Such search biases are also likely to inform the search processes of policymakers; for example, in the context of areas to prioritise in regional transformation policy interventions, an aspect explicitly explored in paper two of this thesis

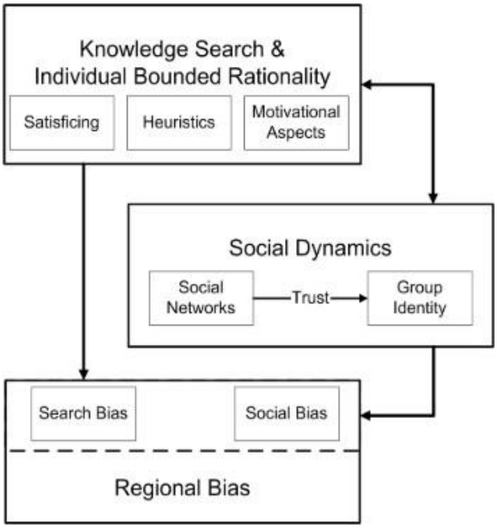

Figure 1 - Influences on knowledge transfer (Broekel and Binder, 2007)

For example, Broekel and Binder (2007) expand on the search bias, rooted in a 'take the best' heuristic as an example of tending towards a regional focus. In this example, actors tend to take the best from what they know, typically through a regional focus. As such, the authors caution that such a focus on making an economic calculus for the best option must be tempered with an understanding that there will exist "a trade-off between frugality and accuracy in such knowledge search problems" (Broekel and Binder, 2007, p. 14). This tending toward the region produces, what Fornahl (2005) refers to, regional embeddedness, which further signals the intricate relationship between knowledge and place, which this current thesis explicitly addresses in paper two.

That actors will tend toward certain biases which inherently work to favour regional dimensions is not altogether surprising, even if it may produce a sub-optimal search (Boschma, Minondo and Navarro, 2013). However, to unpack whether the search process is sub-optimal, we can turn to the work of Sorenson, Rivkin and Fleming (2006), who explore, through the modelling of knowledge according to its complexity, that it is the complexity of the activity which modifies its ability to travel. The authors find that, at both high and low levels of complexity, those recipients who are close to a particular invention see no lasting advantage over those who are more distant but that the benefits are most felt by those who focus on knowledge of moderate complexity. Indeed, the authors summarise their findings as follows "dense social networks, which tend to localize geographically, give firms and individuals close to the source of knowledge an important advantage in reproducing and building upon the knowledge". As such, we can see the interaction of geographic proximity producing some positive effects, and that the search process taking place locally is due in part to behavioural biases which tend towards the regional level. This then raises the important question of the role of networks in driving knowledge diffusion. Here, we follow the argumentation of Broekel and Binder (2007) and Sorenson (2005), wherein the latter acknowledges that "social networks will primarily connect individuals that live close to each other" (p. 81). This is not to say that all social networks must be spatially defined, but that as a tendency it is likely to consist of such actors who are spatially quite close. Here, we can then turn to the work of Boschma and Frenken (2010), who, while acknowledging the relative infancy of network analysis in the geography of innovation at the time (an aspect which in recent years is much less pronounced; see; Plum and Hassink, 2011; Balland, 2016; Shearmu, Carrincazeaux and Doloreux, 2016; Dahesh et al., 2020; Galaso and Kovářík, 2021), also provide a clear evolutionary perspective to the literature on the geography of network formation. The authors, for example, highlight the role of geographic proximity in network formation and acknowledge that effective learning requires face-to-face interaction, as discussed above. However, the authors disentangle several ways the varied proximities impact network formation, rather than exclusively focusing on geographic proximity. For example, by zooming out and looking at the work of Hoekman, Frenken and vanOort (2009) and Maggioni, Nosvelli and Uberti (2007), we can see that collaboration networksoften span a number of regions and provide access to scientific knowledge across regions. However, networks often come with considerable costs to establish and maintain. They may produce lock-ins due to too close cognitive proximity, for example, or involuntary knowledge spillovers at the firm level, leading to a loss of competitive position. Here, one can look towards discussions surrounding proximity as being rather about finding a balance within a network; inthe geographic sense, this implies focusing on ensuring a balance of local and non-local linkages (Fitjar and Huber, 2015; Boschma, 2021).

What, then does the use and application of knowledge imply for regional transformation? We can see, for example, that tacit forms of knowledge offer a key competitive advantage to a region. It likely exerts a considerable influence on successful regional transformation, although how best to capture this transformation and understand the interplay of knowledge with policy will be picked up in the next section. We can also see that actors are typically biased towards local searches, which further expresses the importance of focusing on the regional dimension. Alongside this, the focus on networks allows one to critically evaluate the make-up of networks along their proximity dimensions, an aspect discussed in Hakansson and Lundgren (1997), who highlights that "there is a path dependency in the development of relationships and networks" (p. 122). Here, we can see a case of 'neither too hot nor too cold', as while knowledge spillovers constitute an important dimension of knowledge diffusion, there are reasons why anticipating spillover effects may be complex. Here, we focus on how knowledge and knowledge bases are operationalised in a regional policy context and how attempts to measure it has developed in recent years. Suffice to say, regional knowledge bases can serve as a poisoned chalice, as localised searches may well inhibit the potential to identify breakthrough innovations.

2.3. Operationalising regional transformation

Regional transformation processes have a multitude of constituent parts which shape how they unfold across a region, not least the importance of the history of the region and what has gone before, but more to the point, the knowledge which exists in a region as embedded in the actors in a region. The question of regional transformation, to which we are concerned, then is not only what we know about the factors which influence this process, but also what the role is of policy in stimulating, constraining, or expanding regional transformation processes. The literature on this aspect of regional transformation is dominated by two key components, namely how to measure regional transformation processes, of which there is a wide and varied literature (Qian *et al.*, 2008; Neffke, Otto and Weyh, 2017; Balland *et al.*, 2019; Nedelkoska and Neffke, 2019; Balland and Boschma, 2021, 2021a; Broekel, Fitjar and Haus-Reve, 2021; Buyukyazici, Mazzoni, Riccaboni and Serti, 2022; Iversen and Herstad, 2022), and relatedly how effective policy interventions are in regional transformation processes (Bellini, Lazzeri and Rovai, 2020; Gianelle, Guzzo and Mieszkowski, 2020; Di Cataldo, Monastiriotis and Rodríguez-Pose, 2021; Ferreira et al., 2021; Perianez Forte and Wilson, 2021).

Building on the earlier work on regional innovation systems (Asheim and Isaksen, 2002; Tödtling and Trippl, 2013), Iammarino and McCann (2006) highlight that, given existing industrial structures, technological paths, as well as a region's economic and institutional context, it is now quite clear to policymakers that the appropriate level at which to target one's policy should be at the regional level (Iammarino and McCann, 2006) In a European context, this is generally captured as the 'subsidiarity principle', namely that decision-making should be at the lowest level of governance possible (Wanzenböck, and Frenken, 2018). Furthermore, considerable scholarly attention has been paid to why policy interventions, explicitly tailored to individual regions, are beneficial, such as the essential connections between firms, policymakers, and institutions (such as knowledge-generating institutions) (Morgan, 1997; Tödtling and Trippl, 2013; Grillitsch, 2014), the relatedness of emerging technologies being concentrated in space (Boschma and Iammarino, 2009) and the nature of knowledge diffusion (as discussed in depth above) which are typically generated regionally (Doloreux and Shearmur, 2012) providing just a selection of reasons why such policy interventions targeted at the regional level may be the most appropriate spatial scale in order to stimulate innovation and in turn induce regional transformation and stimulate growth. Of course, as discussed above in the work of Coenen *et al.* (2017), regional branching may, in fact, cast doubt on whether policies (and institutions) can actually influence such transformation processes and, thus, further legitimize a form of 'laissez-faire' policy, it does open up a debate on the necessity for intervention in the first place.

With the insight that regionally targeted policies may be the most appropriate spatial scale for policy interventions, we then discuss why interventions are necessary in the first place. In order to address what motivates a policy intervention, we can turn to the work of McCann and Ortega-Argilés (2013), who acknowledge that, in the case of modern regional innovation policy, there are generally two underpinning logics which motivate policy interventions. The rationales typically fall under addressing either a 'market' failure or, as is more common in recent years, a focus on addressing a 'system' failure. An example of market failure issues is provided in the work of Crafts (2010, 2012), wherein the author highlights such issues as infant industry arguments, agglomeration and spillovers, and rent-switching arguments as clear cases of market failures which merit intervention by policymakers. When looking to identify an example of a system failure intervention logic, we can turn to the work of Hughes (2012), who highlights that conventional system failure arguments include transition and lock-in problems, which limit or inhibit the ability of a system to move towards new technological structures, due to the inertia or sunk costs associated with existing public or private sector investments. Such system failure arguments for interventions are further articulated by McCann and Ortega-Argiles, (2013, p. 195), where the authors state that "even without the market failures which need to be corrected, there is no reason to expect that we would necessarily be in some sort of innovation equilibrium", acknowledging that system failures tend to be more broad-based and comprehensive. Dalum et al. (1992), however, highlight the challenge in evolutionary approaches of organising policy interventions, given that "implicit in evolutionary thinking there are hidden arguments in favour of non-intervention" (p. 298). This is a particularly pertinent concern in the context of a systems approach in understanding regional innovation (or its lack thereof) and it aligns with the insight of branching legitimizing laissez-faire approaches to policy or, namely, that non-intervention becomes the policy. However, such system logic for policy interventions, as highlighted in the work of McCann and Ortega-Argiles (2013), provides the intellectual bedrock for the European Union's Smart Specialisation approach, for example. This is a policy that, in recent years, has been seen as emblematic of regional innovation policy in Europe, and which aims to address system-level failures by targeting interventions at transformative change (Schot and Steinmueller, 2018), in line with a subsidiarity[3] based principle (Grillitsch and Asheim, 2018; Wanzenböck and Frenken, 2018; Rigby *et al.*, 2019). However, the effect of such regional innovation policy – particularly smart Specialisation – on regional economic development and transformations remains to be seen and serves as a core area where this current thesis will contribute (see paper three).

What, then, does this imply for the format of such policy interventions? Boschma (2005) highlights that policymakers, rather than containing all the cards or being all-knowing, must contend with considerable uncertainty and that policy targeted at addressing issues surrounding regional transformation should instead opt for an approach focused on 'trial and error' or namely that experience should guide future interventions and that failure and experimentation is part of the process in dealing with regional transformation (Morgan and Henderson, 2002; Tödtling and Trippl, 2005; Borrás, 2011). This turn towards a greater focus on experimentalism and trial and error has been noted by a number of scholars, most clearly McCann and Ortega-Argiles (2013), as typifying the Smart Specialisation approach, where both experimentalism is encouraged, and other actors distinct from policymakers are included in the search and identification process (referred to as an Entrepreneurial Discovery Process in the literature) and form an important way in which local knowledge is mobilised. This point, however, concerns the notion that the options available to policymakers to fundamentally re-alter the course of regional development may be considerably limited. Instead, policymakers may be better suited to playing the role of "broker", in line with what is proposed in the work of Metcalfe (1994), specifically so in the context of the behavioural biases which may hinder their search and selection process, as discussed above.

[3] Subsidiarity means that decisions should be made at the closest geographical scale which is feasible (Fitjar, Benneworth and Asheim, 2019)

As outlined above, regional innovation policy and innovation is generally an area of policy where a focus on experimentation and trial and error are particularly prominent aspects (Landabaso, 2014; Breznitz, Ornston and Samford, 2018; Veldhuizen, 2020; Di Cataldo, Monastiriotis and Rodríguez-Pose, 2021). Given the uncertain nature of innovation more generally and the limited role with which policymakers can play in stimulating innovation-driven regional transformation, a pertinent question then becomes how we can measure, and indeed understand, regional transformations, against which measures are these experiments being evaluated, and how can such measures better illuminate what we know about regional transformation and how to enable and support them. It is here that we can turn to the work of Rodrik (2004), who highlights the importance of using outcome indicators, consistent monitoring, and ongoing evaluation, all of which are considered to be central elements of any modern policy design and delivery. Indeed, regional innovation policy, given the focus as mentioned above on experimentation, calls for measures which are robust and related to the stated outcomes of policy interventions. However, while progress is being made here, there remains a number of open questions in the literature, an aspect this current thesis seeks to answer, particularly in the context of paper one and paper three on how better to capture the dimensions which typify regional transformation, and what can be learned from experimental approaches, respectively.

A clear example of such regional innovation policy aimed at producing innovation-driven regional transformation in a European context is Smart Specialisation, as introduced above. Smart Specialisation can be understood as place-based approach to economic development policy, characterized by the identification of strategic areas for intervention and based on an analysis of the strengths and potential of a regional economy (Tödtling and Trippl 2005; Foray, David and Hall, 2011; Foray, 2015; Asheim, Grillitsch and Trippl, 2016; Rodríguez-Pose and Wilkie, 2016; Balland *et al.*, 2019). Such identification of strategic areas which warrant an intervention should be based on activities in a region which provide the greatest potential to develop into a competitive advantage for a region. Essentially, smart specialisation interventions are targeted at stimulating regional transformations. Rather confusingly, given the name, this is less focused on promoting further specialisations but is a policy to promote diversification into new economic domains in regions. Much of the literature on Smart Specialisation, to date, has focused on diversification, which is generally constructed as related diversification; this is partly due to the likelihood of success being higher in economic domains closely related to the existing economic structure of the region (Neffke, Henning and Boschma, 2011; Essletzbichler, 2015). However, this differs from the origins of smart specialisation, where the focus is generally on utilizing existing strengths which can be interpreted in a variety of ways.

While identifying such areas on which to base interventions is undeniably a difficult task for many regions (Wu, Ramesh and Howlett, 2015), recent scholarly work in the regional studies literature provides evidence that looking at the dimensions of relatedness and complexity provides a useful basis on which to identify and measure the identification process. Balland et al. (2019), for example, posit that smart specialization requires just such a combination of relatedness (Hidalgo *et al.*, 2007; Neffke, Henning, and Boschma, 2011) and complexity (Hidalgo and Hausmann, 2009), providing a useful visualisation of how such an identification process and intervention strategy can be understood (see Figure 2 below). However, whether such measures have moved from theory to policy practice and what it may tell us about the efficacy of such interventions remains to be seen and will be addressed in papers one and three in this current thesis.

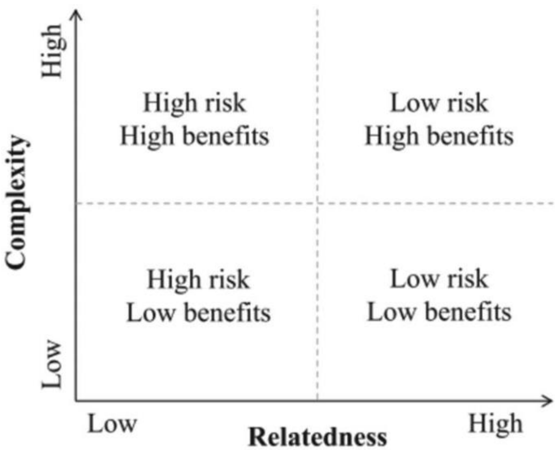

Figure 2 – Framework for smart specialisation (Balland *et al.*, 2019: p. 1259)

While the underlying logic for such a policy intervention and where it should be targeted remains rightly contested (Asheim, 2019), using the above framework does provide a basis on which regions seeking to identify the areas with the greatest potential to develop a competitive advantage can be identified (Boschma, 2014; Boschma and Gianelle, 2014; McCann and Ortega-Argilés, 2015). However, evidence on the effectiveness of such dimensions remains relatively recent, with the dimension of relatedness, for example, containing a number of diffuse conceptualisations in the literature and the effect of relatedness on regional transformation processes being an area of considerable promise for research (Breschi, Lissoni and Malerba, 2003; Saviotti and Frenken, 2008; Neffke, Henning and Boschma, 2011; Neffke and Henning, 2013; Tanner, 2014; Rigby, 2015; Boschma, 2017; Grillitsch and Asheim, 2018; Hidalgo et al., 2018; Bond-Smith and McCann, 2020). The lack of clarity, however, on what relatedness means and the different ways it can be measured are addressed in greater detail in the following chapter, alongside paper one.

Relatedness, in its simplest form, is generally understood as two activities requiring similar knowledge or inputs (Hidalgo *et al.*, 2018). The probability of a region entering or exiting an economic domain can then, in turn, be translated into a risk assessment of diversification-oriented policies. In this context, regions will be more likely to fail if they try to diversify into economic domains unrelated to their current portfolio of economic activities. How best to measure this relatedness, however, is an open debate. However, the effect of different conceptualisations on the regional transformation process is sufficiently clear within the literature on transformation processes (Frenken, Van Oort and Verburg, 2007; Boschma and Iammarino, 2009; Boschma, Minondo and Navarro, 2013; Diodato and Weterings, 2015).

However, rather than purely focusing on the relative relatedness of an activity to a region's portfolio of economic activities, a number of scholars argue that the complexity of the economic domain also matters in regional transformation (Balland and Rigby, 2017; Frenken, 2017). Balland et al. (2019) point to complex knowledge bases functioning like conventional balances of supply and demand: “Technologies that are simple to copy, and which can be moved easily over space, tend to be of little value and thus do not provide a source of long-run rents. Technologies that are more complex and difficult to imitate are more sticky in space” (Balland et al., p. 1254). These sticky and complex technologies/activities tend to offer particular and unique benefits that can form an important basis for a systemically targeted policy intervention to produce innovation-focused regional transformation, as discussed in McCann and Ortega-Argiles (2013). However, whether a complex activity which has a low degree of relatedness to other activities in a region is a promising area for investment (Asheim, 2019) or is instead following a ‘casino approach’ (Balland et al., 2019) serves to highlight the contrasts and important discussions taking place within the literature on using such dimensions.

However, while such interventions may be necessary to stimulate and promote levelling up of regions, and induce or promote positive regional transformation, Boschma (2005, pp. 259) raises an important component of such interventions, namely that “public intervention is focused on a self-defined path of development”. Thus, such interventions towards such paths can be troublesome, as too far from a region’s history may cast doubt on the efficacy of such an intervention, while too close may cast doubt on the necessity for such an intervention. This all raises the need for this current thesis’ contribution to the ongoing debate in studying regional transformation from the perspective of relatedness and regional branching and exploring the respective roles of skill and industrial relatedness therein, before turning to focus on the application of the smart specialization policy across Europe, which is a policy which aims to support related diversification processes. In this, we can see that the results show a strong degree of relevance of this policy for related-diversification-based regional transformation. However, a further connected dimension is addressed in this current thesis, which is concerned with the importance of actors in entrepreneurial discovery processes in regional transformation,which introduces an important additional component away from the overall relatedness-based transformation focus.

3. Data & Methodological Approach

To answer the research questions proposed in this current thesis and to empirically test and contribute to the literature on regional transformations and the respective contributions of knowledge and policy interventions to these processes, the papers included in this thesis rely on both cross-country European-level data sources, as well as detailed linked employer-employee data (LEED) available at the level of Norwegian regions. While largely relying on quantitative methods (the exact methods used are discussed in greater detail below), this thesis also makes use of rich interview data on stakeholders involved in regional transformation processes in order to gain a fuller appreciation of the ‘facts on the ground’ and to unpack how it is that actors in regional transformation processes make sense of the world around them and how this can come to inform decision making.

While the thesis goes into greater depth on the empirical context of the regions under study in chapter 4 below, papers 1 and 2 focus on the case of Norway and its relevance and contribution to the literature on regional transformation. The working definition of a region is based on the work of Hooghe *et al.* (2016), namely that a region is an administrative area at a subnational level, making an intermediate level of government between the nation-state and local government. The first paper uses a linear probability panel regression to estimate how occupational and industrial relatedness impact regional diversification processes. Here, we have sought to model regional transformation as the diversification into new industry-occupation activities (a combination we refer to as jobs in the paper). The second paper uses a sequential exploratory design mixed methods approach, using quantitative data to analyse the regional industry structures in Stavanger & Bergen, before conducting interviews with 22 stakeholders (11 in each region). This is done to understand the role of actors by using a relatively novel approach to exploring regional transformations, in the context of entrepreneurial discovery processes[4] as part of a smart specialisation strategy. The interviews with these stakeholders were conducted in 2018 using a semi-structured interview guide that emphasized regional restructuring. It explored the stakeholders' perception of ideas for future specialization, and identified opportunities and obstacles for future growth areas. The Bergen case comprises six industry actors, two higher education institutions (HEIs) representatives, one intermediate organization, and two policy actors. The Stavanger case consists of eight industry actors, two intermediates, and one policy actor (the breakdown can be found in tables three and four below). In the third paper, we collect regional data on industrial structures and smart specialization strategies at the NUTS-2 level. The data set includes 128 regions across Europe, for which we have data on the selection of economic domains at the regional level; a visual representation of where these regions are is available in figure 6 below. Given that the dependent variable is binary, we employ the use of a logistic regression approach, and given that the decision on areas to prioritise is taken in one year, we use a cross-sectional choice model. Furthermore, given that there is little empirical evidence on whether such decisions for interventions are independent or dependent on each other (given the multiple selections of economic areas to prioritise is taken place in the same regional strategy document), we, therefore, decided to use both an unconditional and conditional binary choice model. However, the results generally align between both models; the observations are grouped by economic domain and region, and we use multiway clustered standard errors at these two levels in all estimations. What follows is a discussion relating to the construction of the primary variables used in this current thesis, followed by a discussion on how this thesis ensures the robustness of the findings. We then expand upon the use of mixed method approaches to unpacking regional transformation processes and how they are operationalised.

[4] An EDP is in line with a Schumpeterian understanding of creative destruction, where entrepreneurial knowledge is seen to exert an influence on the direction and constitution of regional economies and, as such, is considered a dynamic process of change which brings together diffuse sources of regional knowledge to identify new paths and development of current paths (Perianez Forte and Wilson, 2021).

3.1 Constructing Relatedness and Complexity

While the considerations regarding the differing constructions of the variable of relatedness are picked up in and elaborated on in paper one, which explores whether occupational or industrial relatedness matters more for regional diversification processes, relatedness is a widely used dimension when exploring the transformation (or often diversification, looking at related diversification and regional branching as discussed in chapter 2.1 above) of a regional economy. Relatedness across all three papers is considered a dyadic concept. In essence, it captures the relatedness of two entities. In paper one, for example, we look at occupational relatedness in line with the literature, namely as a form of labour flows (Neffke and Henning, 2013; Fitjar and Timmermans, 2017; Neffke, Otto and Weyh, 2017), with the data for the construction of this particular measure of relatedness coming from Statistics Norway, which is then aggregated to the level of 4-digit ISCO-codes[5]. The process of creating the industrial relatedness measure also used in paper one follows an identical path, focusing on the flows of labour between industries, as opposed to purely occupations. For the relatedness measure used in paper three, the construction of the relatedness measure is similar in that it is based on the co-occurrence of economic domains at the regional level. Again, this is in line with much of the established approaches in the literature (Boschma and Gianelle, 2014; Boschma, Balland and Kogler, 2015; Marrocu *et al.*, 2020). The use of relatedness in paper two similarly follows the above approach. The use of relatedness measures in order to unpack the regional transformation process is particularly useful, given that relatedness is often understood as a form of a risk assessment, where a high degree of relatedness in a region can be understood as containing a high likelihood of success in entering new activities. In this sense, it can help to analyse trajectories and directions of regional transformation processes and help understand how likely it is for certain activities to occur and successfully enter regions. However, the use of relatedness in isolation will tell us little without understanding whether there is a particular benefit to a region inentering a new activity here than much of the literature emphasises using another variable considered in this thesis to which we now turn (Asheim, 2019; Balland *et al.*, 2019; Rigby *et al.*, 2019; Hane-Weijman, Eriksson and Rigby, 2021; Davies and Maré, 2021).

The other variable that features prominently across all three papers in this thesis is the complexity of economic activities. However, although complexity is a widely used variable across the literature, no clear common approach to calculate the complexity of economic

[5] The International Standard Classification of Occupations (ISCO) is one of the main international classifications, ISCO is a tool for organizing jobs into a clearly defined set of groups according to the tasks and duties undertaken in the job

domains (for example, in the case of the third paper) exists. Often, much of the literature relies on the Economic complexity index developed by Hidalgo and Hausman (2009). However, the issues of such a measure of complexity in the context of European data (and, in turn, Norwegian data) are relatively well established (Broekel, 2019). Recent attempts, however, have begun to shed further light on these issues and approaches to overcome them (Balland *et al.*, 2022). Building on work in recent years in the labour economics literature, an approach based on the work of Lo Turco and Maggioni (2020) has found widespread use in literature focused on the geography of innovation and, in turn, work focused on regional transformations. The idea of (occupational) skill complexity, then, stems from the work of Caines, Hoffman and Kambourov (2017), which defines a complex occupational task as one that requires specific higher-order skills. These include the "ability to abstract, solve problems, make decisions, or communicate effectively" (Caines, Hoffmann, and Kambourov 2017, p. 1). The approach employed by Caines, Hoffman and Kambourov (2017) then uses the importance of 34 tasks to calculate the complexity of 968 different occupations in the US O*NET survey database by means of the normalized loadings of the first component of a principal component analysis, which we then use a crosswalk of SOC-to-ISCO to be able to connect these 968 different occupations to the 424 four-digit ISCO occupations which allow us to use this data with European (and Norwegian) data. In the context of Norwegian data, we further relate these computations to Statistics Norway's general industry classification (SN2007), which is compatible with the ISCO classification system. The use of relatedness and complexity in this context across the three papers follows a relatively well-established approach in the literature in unpacking processes of regional transformation, particularly processes of regional and related diversification (Balland *et al.*, 2019; Broekel, Fitjar and Haus-reve, 2021; Rigby *et al.*, 2019; Hane-Weijman, Eriksson and Rigby, 2021; Juhász, Broekel and Boschma, 2021; Buyukyazici *et al.*, 2022). The usefulness of these measures was discussed in section 2.3 above, where they relate to capturing the likely success of entry and the relative 'value' of such entries to a region. What follows now is a discussion on the operationalisation of regional transformation, exploring the different constructions in the literature to how one can understand regional transformation.

3.2 Modelling Regional Transformation

Approaches to capture the regional transformation process and, in turn, regional branching can be measured in various ways. In paper one, for example, we take an approach focused on explaining the probability that a new activity emerges in a region based on its relatedness. To disentangle this emergence from broader national-level trends and to dig into the transformation process within a region, we look at regions gaining a specialisation or a regional comparative advantage in an activity. Identifying specialisations is often achieved empirically by looking at an activity's location quotient (LQ) exceeding the value of 1. In order to capture not just existing specialisations in activities but regional transformation and diversification processes, one specification contained in this paper is focused on the 'leap' of an LQ over time. This understanding of leaps in LQ from values significantly below 1 to above 1, as a signal of successful diversification, is relatively widespread in the literature (Hidalgo et al., 2007). In our main model, we test leaps from below 0.5, but try other specifications, finding the effect observed in the paper holds. This approach, however, is not the only way to understand regional transformation and is not the only approach employed in paper one. We also look at regional transformation as the entry of new jobs (industry occupations) into a region. Here, we consider transformation to be an entry event if employment jumps from zero to any positive level in the subsequent year. Such approaches to capturing related diversification in a region can be seen in figure 3 below:

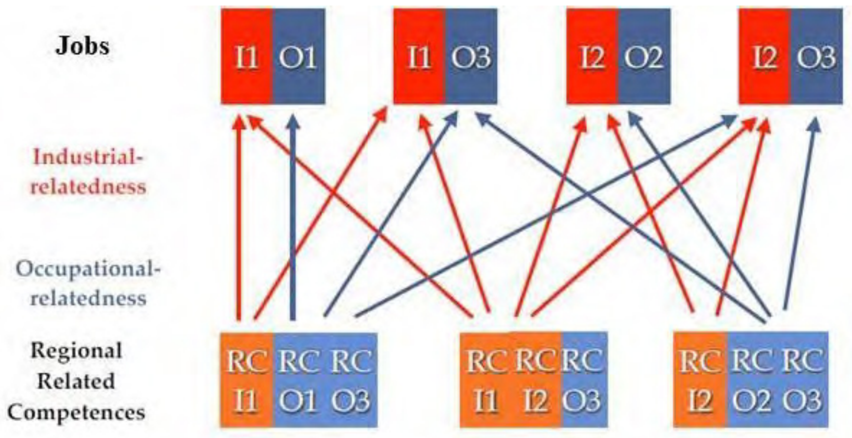

Figure 3 - The influence of relatedness on regional diversification (paper 1)

Here, we adapt the standard approach to modelling related diversification processes (Boschma et al., 2017; Fitjar and Timmermans, 2017). We apply this to the level of jobs and approximate the relatedness of a job to the regional portfolio in two dimensions (industrial and occupational), as illustrated in Figure 3.

In paper three, however, the approach to modelling regional transformation was constructed differently. Rather than exploring the relationship between certain measures of relatedness and observed entry processes, the approach was more focused on how the selection of priority areas across European regions relates to the observed relatedness and complexity of those activities which were chosen by the regions. In order to construct the dependent variable in this paper, data was extracted from selected economic priorities from a region's smart specialization strategy documents, coded by the European Commission's Joint Research Centre. Here, we coded all possible activities in a region (according to the NACE Rev 2 classification system[6]) and dichotomously coded those activities which were selected by each region, exploring the relationship between these activities. These were chosen as the basis for a policy intervention against their respective relatedness and complexity to examine if regions were aligning with the framework for smart specialisation, as shown in figure 2 above.

In both approaches discussed above, regional transformation processes are captured differently. The first approach, as contained in paper one, is concerned with the observed transformation process by the emergence of specialisations and the respective entry of new jobs as a function of industrial and occupational relatedness, whereas in paper three we instead look at economic activities chosen as the basis of policy intervention and examine whether these decisions on economic domains are a function of the relatedness and complexity of those activities. This aligns with our discussion above, regarding observed differences and emergence alongside policy interventions and the role of such interventions in driving regional transformation and the measures used in such interventions. While regional transformation is a dynamic and evolving process, and a number of specifications can be devised to capture the unfolding of this process in a given region, the approach used in papers one and three allows for two important aspects of regional transformation to be explored: the observed experience across regions, alongside understanding what factors shape the likelihood of policymakers selecting for economic activities to be the basis of a policy. We now turn to how the current thesis controls for confounding effects in both studies.

3.3 Controlling for confounding

In both paper one and paper three, we isolate the relationships between our dependent and independent variables. As such, we employ a number of controls to account for confounding

[6] NACE is the statistical classification of economic activities in the European Community and is the subject of legislation at the European Union level, which imposes the use of the classification uniformly within all the member States. (Eurostat, 2008)

alternative influences and improve the robustness of our findings from being otherwise influenced. For example, in paper one, we aim to account for these confounding influences by including controls which look at the degree of specialisation and diversity within the analysis. Specifically, we examine how the region's specialisation shapes the entry of new jobs in the industry and occupation of which the job consists, as well as the diversity of other industries and occupations present in the region. Alongside these diversity and specialisation measures, we also control population density to capture potential differences between urban and peripheral regions, including regional, occupational, industrial, and year-fixed effects in our regressions. Alongside this, we further consider the clustered nature of the observations by means of three-way clustered standard errors at the occupation, industry, and region levels. The purpose here is to allow the analysis to isolate the effect of the different conceptualisations of relatedness on regional transformation processes.

In paper three, given the multi-faceted nature of alternative influences on the selection of economic domains for policy intervention, we include a number of controls to better isolate the relationship between our dependent and independent variables. Firstly, in order to account for the level of development of regions, we included: measures of regional gross domestic product (GDP); the number of patent applications per million capita (to account for the level of innovation already present in the regions); and the share of regional employment of each economic domain to account for the size of activity in a regions portfolio of activities. Alongside these 'developmental' measures of a region, we also account for the external influences on regional priority selection. We do this by measuring whether a neighbouring region or any other region in the same country has selected the same economic domain as a priority, to account for policy mobility (Di Cataldo, Monastiriotis and Rodríguez-Pose, 2021). In addition, we control the number of other priorities the region has selected, as whether an activity was chosen is likely to increase as the number of activities chosen increases. As mentioned above, controlling for confounding influences is an important dynamic of the models used in this analysis. It allows for the papers in the current thesis to more confidently discuss the findings from the analyses and their relationship more broadly with the research questions motivating this thesis generally.

3.4 Mixed method approaches to regional transformation

In paper two, rather than controlling for confounding influences or modelling regional transformation in different ways, a more exploratory approach was taken, both at the scale on which the study into regional transformation was focused (two city regions) alongside the method used to analyse the respective approach to and understanding of regional transformation in these relatively different cases. Here, the paper relies on a sequential exploratory design mixed methods approach. This was chosen because it allows for insights into the quantitative environment to be expressed through the regional industrial profile while also allowing for a deeper understanding of how regional stakeholders understand the transformation processes, both as it has proceeded and as it is likely to proceed in the future. The approach also allows for a clearer analysis of how knowledge exists in different regions and how this knowledge can be used to identify areas for prioritisation and make sense of regional decision-making. As can be seen in figure 4 below, for example, the use of a SED approach allows for an understanding of qualitative data existing within a frame of the quantitative environment. Put simply, the interviewed stakeholders view the current status and future potential of the regional economy through the prism of observable regional economic structures

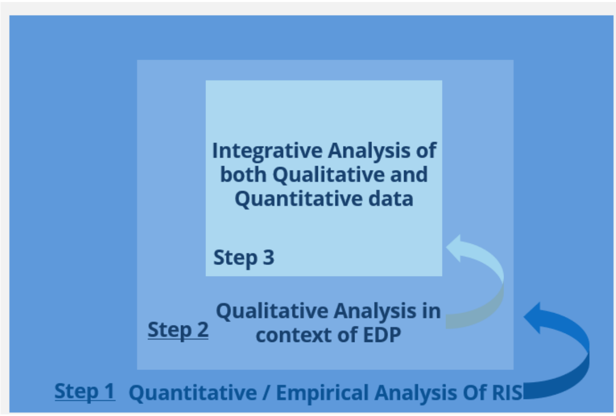

Figure 4 – Sequential Exploratory design approach (paper 2)

The primary variables used in the quantitative exploration in paper two are: relatedness between economic activities; a location quotient of the economic activities in the region (to understand current specialisations); and the level of complexity of those activities. This is in line with the approach discussed above and the share of regional employment of economic activities in both regions.

The qualitative component of this study consists of 22 stakeholder interviews, with 11 interviews conducted in Bergen and Stavanger which lasted between 45 mins and 1 hour and 30 min. Following the transcription of the interviews, an inductive constructivist thematic analysis was undertaken on the transcribed materials, in line with Braun and Clarke (2006). Here, the focus was on extracting and constructing patterns of meaning from the material. This would aid in understanding the stakeholders' perception of future regional industrial development.

Identification number	**Region**	**Type of stakeholder**
BE1	Bergen	Industry actor
BE2	Bergen	Industry actor
BE3	Bergen	Industry actor
BE4	Bergen	Intermediate
BE5	Bergen	Industry Actor
BE6	Bergen	Industry Actor
BE7	Bergen	Industry Actor
BE8	Bergen	Policy actor
BE9	Bergen	Policy actor
BE10	Bergen	Higher Educational Institute
BE11	Bergen	Higher Educational Institute

Identification number	**Region**	**Type of stakeholder**
SV1	Stavanger	Intermediate
SV2	Stavanger	Intermediate
SV3	Stavanger	Industry actor
SV4	Stavanger	Industry actor
SV5	Stavanger	Policy actor
SV6	Stavanger	Industry actor
SV7	Stavanger	Industry actor
SV8	Stavanger	Industry actor
SV9	Stavanger	Industry actor
SV10	Stavanger	Industry actor
SV11	Stavanger	Industry actor

Tables 3 and 4 – Stakeholders interviewed in paper two

The deployed approach serves two key purposes of particular relevance to this current thesis and the broader methods employed in understanding the role of actors in regional transformation processes. Firstly, incorporating detailed information on the current position of a regional economy helps better contextualise actor perceptions. It allows for such interviews to be placed within a broader frame, which can be particularly useful to those who seek to understand issues related to actors and decision-making. Secondly, and related to the first point, it allows for policy interventions and identification processes to make better use of the knowledge that actors in a region possess and speaks more to the move away from top-down approaches to regional innovation policy, by better taking account of the knowledge which, entrepreneurial actors for example hold. However, this method also helped to shed light on the presence of behavioural biases in the search process of actors, an important dimension of policy interventions targeted at regional transformation. This is discussed in greater detail in section 2.2.2 above.

4. Empirical context

The empirical context in which this thesis exists is two-fold (but with considerable contextual overlap). The period under study ranges from 2009-2018, with the studies generally focusing on the regional level. Here, we follow the work of Hooghe et al. (2016), as discussed above, namely that a region is an administrative area at a subnational level making an intermediate level of government between the nation-state and local government. Papers one and two focus on Norway as the empirical locus of study, with paper three zooming out to the European Union level, focusing on NUTS 2 level regions. The purpose of this section is to shed light on the empirical environment in which this current thesis exists, to provide the space in which the data can be interpreted and in which the results can be generalised. This helps provide greater insight into regional transformation more generally than just those cases which this study explores.

The focus on Norway is seen as a particularly pertinent case on which to focus the study, given that it is a generally open economy, with robust institutions enabling the functioning of a high-income market economy. Norway is a small (from a global perspective) to small-medium (in a European context) sized Western European country, with roughly 5.4 million inhabitants. The economy of Norway is generally exemplified by its large maritime industry (Oil and gas and fisheries, primarily), which is understandably located on its coastal regions. The country is generally subdivided along its 11 administrative counties (revised down in recent years from 18) and contains 78 economic regions following the work of Gundersen and Juvkam (2013), which is generally seen as congruent with EU NUTS 4 regions. While the empirical context of paper one is on Norway as a whole and the 78 economic regions mentioned above as the focus, paper two zooms in further on the Bergen and Stavanger regions, as illustrated in figure 5 below.

Figure 5 – Bergen (red) and Stavanger (blue) city regions in Norway (paper 2)

The context of paper three is unique, in that the focus on the European level offers considerable empirical advantages, given the comparative nature of the regions under study. The paper contains data from 128 regions across Europe. The regions taken at the NUTS-2 level include most regions in France, Spain, Portugal, Italy, Denmark, Poland, Greece, and Romania, as well as some regions in the Netherlands and the UK. An illustration of the regions contained in paper three are available below in figure 6.

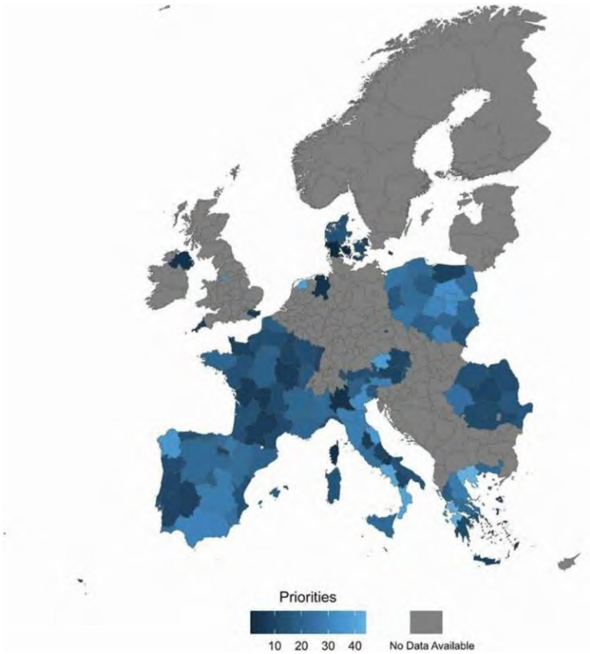

Figure 6 – Regions analysed in paper three

While the broader regional perspective offers a number of advantages, particularly regarding the generalisability of the study, and its ability to allow comparisons of approaches to regional transformation policy interventions, it also provides a number of empirical challenges, such as the role played by regional size. This is an aspect we capture in figure 7 below, which looks at whether the number of priorities chosen by regions was influenced by a region's size and which finds a relatively small effect.

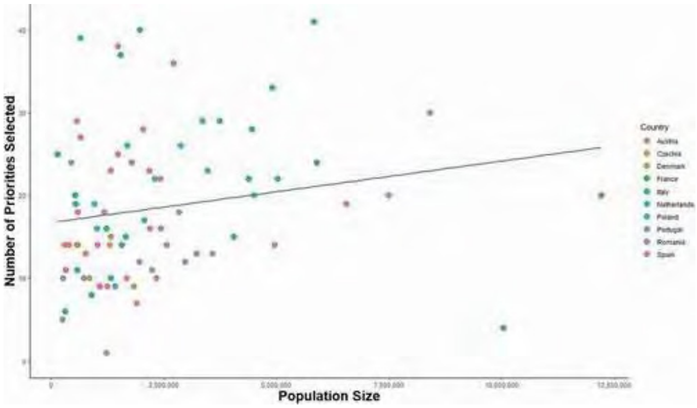

Figure 7 – Population size in the EU and priority selection (paper 3).

While there is considerable heterogeneity between regions in the EU, the states under study operate with considerable variation in the degree of decision-making opportunities available to the regions, operating under varying political systems, which may enable, or inhibit the power of regional actors to make decisions. However, such variation, rather than undermining the empirical context of the study, provides the scope in which effective comparative regional analysis can be undertaken (e.g., Rothstein et al., 2013). As such, the empirical context of the current thesis as a whole provides the scope for a pan-European analysis of approaches to related diversification and regional transformation, as well as allowing for a more focused empirical context, both at the individual nation level (paper one) and at the city-region level within one state (paper two), allows for a case study approach to provide the scope for analysis.

Finally, and related to section 2.3 discussed above, the context in which this current thesis is focused is in the considerable advances we can see in recent years on the evolution of place-based policies more generally and regional innovation policy as a subdomain under this broader place-based move. Such a focus allows both the conditions of regions and their ability to make and implement decisions to be seen as a much more pertinent area of study than broader national-level policies aimed at addressing regional imbalances, stimulating innovation, and promoting growth and economic development. Such a change in the locus of policymaking and its intended effects provides the scope in which comparative analyses of regional development exist and is the space where this current thesis makes both a theoretical and empirical contribution to the development of an emerging field.

5. Summary of papers

This thesis studies how transformation manifests in a region from the perspective of relatedness and regional branching. Here, the focus is on exploring how knowledge and policy interventions contribute to this process of regional transformation. The papers discussed below build on the work of the theoretical framework contained in chapter 2 above and provides greater clarity on the research questions outlined in section 1.2. It then turns to the dimensions which explain these processes of regional transformation across several different regions by deploying the methods discussed in chapter 3, on the data similarly discussed in chapter 3 to uncover how these dimensions impact upon regional transformation processes. What follows is a summary of each of the papers in this thesis, with an insight into their contribution to the overarching frame of this thesis.

5.1 Paper one - How regions diversify into new jobs: From related industries or related occupations?

In paper one, my co-authors and I explore which dimension, occupational or industrial relatedness best explains the emergence of new jobs (industry-occupation combinations) in a region. In this paper, we ask whether this diversification into new jobs benefits from the presence of related industries or rather from related occupations. We then build on the theoretical framework, as discussed above, and look at the relatedness of activities – both industries and occupations, respectively, as an approach to better understanding, and in turn-operationalising, the transformative potential contained within regions by understanding how such activities emerge in a region.

In order to answer this question, we use LEED from official tax registers for all industry-occupation combinations in Norwegian labour-market regions over thetime period, 2009-2014. We identify industries at the four-digit NACE level using the SNI2007 industry classification system. Occupations are defined using the 7-digit level of the Norwegian SSYK98, which is consistent with the international ISCO-88 standard. For all estimations, we rely on the four-digit ISCO level. We find that diversification into new jobs is more likely in a region's related occupations and industries. However, the complementary relationship between occupational and industrial relatedness is particularly important for diversification into more complex activities. This paper provides a key platform on which this current thesis rests, namely that, while several studies have highlighted the importance of relatedness on differing aspects of the regional transformation processes (for example, by showing that occupational relatedness matters more than industrial relatedness for regional growth (Wixe and Andersson, 2017), while the opposite is true for firm growth (Jara-Figueroa *et al.*, 2018), it was less clear which measure of relatedness provided the best insight into the transformation processes via the entry of new jobs in a region. However, while new jobs in a region may signal a regional transformation process, this entry of new jobs into the region can have a positive, negative, or neutral effect on the regional economy, depending on whether the new jobs are more or less valuable than the ones they replace. In line with recent studies on related diversification (e.g. Balland et al., 2019; Hane-Weijman, Eriksson and Rigby, 2021; Davies and Maré, 2021; Juhász, Broekel and Boschma, 2021), and the seminal study of Hidalgo and Hausmann, (2009), we therefore also include the dimension of complexity. Here then, the paper opens up the scope for an analysis of, not just how the dimensions of relatedness matter in regional transformation processes, but also how actors in such processes understand and integrate such dimensions in their thinking and planning for regional transformation (an aspect picked up in paper two). We then look at whether such processes and the actors understanding of them exhibit an influence on the dimensions used in the selection of priority areas for a policy intervention (an aspect further explored in paper three).

5.2 Paper two - One coast, two systems: Regional innovation systems and entrepreneurial discovery in Western Norway

Turning then to the role of actors in understanding and influencing regional transformation processes, paper two looks explicitly at the experience of two city regions on Norway's western coast. This is carried out to explore how these different regions (as expressed by their different regional innovation systems categorisation which is elaborated on within the paper) were likely to differ in the way an entrepreneurial discovery process (EDP) is likely to unfold in the regions.

This paper offers valuable insights into how the larger environment is likely to impact such regional innovation policy interventions by better contextualising the role of the already existing regional innovation systems in modifying both the perceptions of paths open to policymakers and actors in the region but also by showing that the conceptualisation of regional transformations is interpreted through a generally evolutionary perspective on the role and nature of such interventions. The likely impact policymakers can expect to exert over the process of regional transformation by tapping into knowledge held across a number of diverse stakeholders across the regional economy hold is then called into question. Here then, we propose an analytical framework which elaborates on how the different regional innovation systems are likely to impact the decisions needed in policy interventions in the form of a smart specialisation strategy (as operationalised by an entrepreneurial discovery process as discussed above). This analytical framework is seen below in table 5. Here, the focus on the system within a region builds on the earlier work of McCann and Ortega-Argiles (2013), namely by focusing on relying on the system failure logic for intervention, as discussed in chapter 2.3 above.

Type of RIS	Type of strategy from EDP	Changes in the knowledge application subsystem of RIS	Changes in the knowledge creation subsystem	Typical barriers to EDP
Specialized	Develop new, related industries /clusters from one/few existing regional industries	Increase collaboration between related firms regarding the use of new technology and business models, and stimulate 'related spinoffs'	Establish test facilities, provide new education opportunities, etc., in new technology	Strong networks between a fixed set of local actors hampering alternative ideas and competence
Diversified	Strengthen knowledge exchange between and diversification into emerging industries from existing regional industries	Increase collaboration between related and unrelated firms and stimulate 'related/ unrelated' spinoffs	Establish commercialization units and R&D-facilities targeting emerging industries	A fragmented innovation system hinders knowledge exchange between actors of RISs

Table 5 — Expected strategy and regional innovation system (RIS) changes resulting from entrepreneurial discovery processes in two types of RIS

To analytically explore the proposed framework, we deploy a sequential explanatory design approach, using quantitative data to analyse the regional industrial structure of Bergen and Stavanger city regions, followed by a qualitative analysis of interviews with key stakeholders in both regions. We find that the city regions face unique challenges that align with understanding their respective RIS categorization. Furthermore, we find a considerable degree of evolutionary conceptualisations of future regional development and transformation, providing evidence that the framework proposed serves as a useful guide in understanding the development of an EDP. Here, the paper's primary contributions to the current thesis at large involves better codifying how regional transformation processes can be and are operationalised at a regional level. For example, the paper highlights important aspects which typify the different classifications of regions and what this, in turn, implies for policy interventions targeted at stimulating regional transformation. However, while this paper proposes a tangential linkage between the respective relatedness and complexity of activities and how they *may* be used in the selection of activities to prioritise in a region's smart specialisation strategy, a more explicit analysis is required to uncover this key aspect of regional transformation, by more clearly testing for this relationship. We turn to paper three now, which more explicitly looks into this relationship at a macro-regional level.

5.3 Paper three - Searching through the Haystack: The Relatedness and Complexity of Priorities in Smart Specialization Strategies

Given then the important role of relatedness in regional transformation processes and the importance in which policymakers and stakeholders either implicitly or explicitly pay attention to this dimension, what then do we know about the impact of this dimension and, relatedly, the role of complexity in forming the basis for decisions on areas which regions will prioritise in their smart specialisation strategies. This is the focus of the third paper of this thesis which examines which economic domains regional policymakers aim to develop in regional innovation strategies, particularly on the complexity of those economic domains and their relatedness to other economic domains in the region.

Here, the paper, builds on the economic geography literature discussed above in section 2.3, advises policymakers to target related and complex economic domains, and assesses the extent to which regions do this in practice. The paper then draws on data from the smart specialization strategies of 128 NUTS-2 regions. While regions are more likely to select complex economic domains related to their current economic domain portfolio, complexity and relatedness figure independently rather than in combination, in choosing priorities.

We also find that regions in the same country tend to select the same priorities, contrary to the idea of a division of labour across regions that smart specialization implies. Overall, these findings suggest that smart specialization, as an example of a regional innovation policy, may be considerably less place based in practice than it is in theory. There is a need to develop better tools to inform regions' priority choices, given the importance of priority selection in smart specialization strategies and regional innovation policy more broadly. The paper further provides an insight into how transformation processes are operationalised by regions, serving as a culmination of the previous two papers in taking the dimension of relatedness and complexity seriously, as a basis for intervention (in line with paper one). It then analyses how such interventions are implemented, in order to understand whether policymakers are considering such dimensions and whether tapping into diffuse regional knowledge bases as is one of the express aims of such an entrepreneurial discovery process leads to these dimensions coming more to the fore in regional smart specialisation strategies across Europe (in line with the more focused perspective taken in paper two).

6. Conclusion

This current thesis contributes to our understanding of how regions change over time and provides evidence on the roles played in this transformation process by a region's given knowledge dynamics, alongside the role of policy interventions in identifying and stimulating this change process. While in recent years, a considerable evidence base has been accruing on exactly what role knowledge and the actors who often contain such knowledge play in a region's ability to adapt and respond to change, this thesis builds on this by providing richer empirical evidence on exactly which aspects help to explain how it is that regions transform over time and how the respective role of knowledge and policy can support such processes of transformation.

Here then, we can take stock of the main contributions of this thesis to our understanding of such regional transformation processes.

1. We now have clearer empirical evidence that new jobs are more likely to emerge in a region when related occupations or industries are present, and that the complexity of those jobs is likely to be higher when the occupational relatedness in a region is higher (paper one).
2. We also now have clearer evidence that regional transformation is informed by and interpreted through the perspectives of actors and based on current regional paths. That is to say, that the differing narratives between stakeholders within different regions conform to an understanding of, not just how the stakeholders assume change will take place, but more broadly how they will inform the policy options pragmatically available to the policy actors within a region. This is a particularly important finding for understanding the ability of policy to identify and move towards new paths of development and potentially escape situations of lock-in (paper two).
3. Finally, we also provide richer evidence that activities which policymakers will support are likely to be those activities which are related and (although less so) complex activities and that when it comes to making such decisions for interventions, policymakers tend towards considering such alternatives independently of each other as opposed to taking a broader portfolio view (paper three).

This thesis contributes to the literature by contextualising these three insights into the broader literature on regional transformation and sketches out both the theoretical and policy relevance of these findings.

6.1. Theoretical contributions

We turn now to provide a clear insight into what this thesis means in the context of regional transformation and its broader implications for future research, on how it is that regions transform over time. The main theoretical contributions of this thesis are as follows:

1. It unpacks the different ways in which regional economies transform over time, particularly focusing on the evolution of activities through related diversification. This thesis better brings together the literature on relatedness and regional branching and highlights the importance of actors in entrepreneurial discovery processes in such transformation processes.
2. The findings that a region's current economic profile informs not only quantitative analysis of the future potentials of the regional economy but also informs the perceptions held by stakeholders of the paths open to a given region enable a more reflective analytical frame for understanding the choices which policymakers make and how their broader environment informs the knowledge they hold on given activities, and how such knowledge is likely to influence decision-making processes, specifically so given the rise in interest in Entrepreneurial discovery processes due to the central role of such a process in the flagship European regional innovation policy, namely Smart Specialisation.
3. By empirically investigating whether regional policymakers are actually using theoretical advances in understanding regional transformation, such as integrating relatedness and/or complexity in their choices of areas to prioritise, we understand more about what factors inform policymaking and why we may observe deviations away from 'best practice approaches' and how such decision-making processes can be improved through the provision of better tools and information on how such interventions should work.
4. While conceptual advances enable the scholarly community to explore the impact of dimensions such as relatedness on a regional economy, the diffuse understandings of relatedness, for example, provided space to empirically explore the relationship between these different understandings of relatedness and the relationship with diversification efforts. In particular, our findings, on the relative importance of occupational and industrial relatedness allow us to provide a clearer picture of the types of dimensions that can inform future theories about a region's transformation.

6.2. Policy implications

While the policy dimension of regional transformation is a core component of this thesis, there are, however, a number of distinct, broader policy implications which stem from this thesis and the papers contained therein.

Firstly, when focusing on the role of relatedness in stimulating the entry of new jobs into a region, the thesis provides greater nuance to understanding the role played by relatedness in regional diversification efforts. While relatedness is generally considered an important aspect of diversification, future policy should pay attention to the multi-dimensional and context-specific nature of relatedness. We demonstrate in paper one that speaking more precisely on relatedness, for example, by differentiating between industrial and occupational relatedness, may tell us more about the types of capacities and assets a region has, or the knowledge and skills bases available to policymakers, and relatedly the range of motion available in supporting successful entries of new activities. Future policy discussions on relatedness will likely benefit from the work undertaken in this thesis on highlighting how relatedness and its multidimensional construction cannot simply be explained by the inclusion of either dimension of relatedness in isolation. Rather, in combination, relatedness can be understood and operationalised in a policy context.

Similarly, a clear implication for policy stemming from this thesis is a richer understanding of how perceptions of the future potentials of an economy are informed by the current structure of the regional economy, more particularly, as we can see in paper two (and illustrated in table 5 found in chapter 5.2) that a differentiated view on what are the logical policy implications (and more pointedly recommendations) depending on the categorisation of a regions innovation system can be found. Such a view makes it clear that what action a policymaker is likely to take in a region's EDP is influenced by that given region's industrial structure rather than simply a rationalist perspective on what may or may not be the most logical areas in which policymakers should intervene. In this, we highlight the importance of actors in entrepreneurial discovery processes in the regional transformation process, departing from the overall focus on relatedness-based conceptions of regional transformation.

When we then, in turn, zoom out on the experience of policymakers across Europe in identifying the areas in which they intend to prioritise, we can further see the challenge policymakers face in identifying and selecting such activities. For example, policymakers rely on good data, and clear tools, to make effective selections. However, this thesis found that for a number of regions such interventions were either not clear on what the purpose or difference was in this policy intervention. As such, they made decisions largely based on intuition and anecdotal evidence, an insufficient basis on which to base policy. The implication here then becomes clear: policymakers need to be clear on why such an intervention is necessary, what its intended purpose is (and relatedly how to measure such an impact), and how such decisions can and should be taken. This absence of ‘joined-up’ thinking, regarding policy interventions to support regional transformations, becomes clear when we can see a considerable absence of a strategic or portfolio-level prioritisation process.

In sum, policymakers need to think critically about the types of measures they can use to inform their policy interventions, ensuring that such measures and the tools used to operationalise regional transformation are appropriate. Indeed, they must ensure that such interventions are part of a comprehensive strategic whole, rather than simply considered on the merits and demerits individually. This current thesis then, through the three papers, brings together and makes a theoretical and policy contribution by providing fuller evidence on how it is that regional transformation process proceeds across different spatial scales and makes clearer the measure we can use to capture the transformation. The thesis also contributes to understanding the role of policy interventions such as Smart Specialisation in supporting related diversification efforts. Finally, and related to the other two points, the thesis provides empirical evidence on the role of actors in the process of regional transformation, complementing the more common relatedness-based approaches seen in the literature.

6.3. Limitations and further research questions

This thesis has a number of limitations that must be acknowledged and, as such, highlights a need for moderation in the interpretation of the findings. They also shed light on avenues for future research and provide a number of general reflections.

Firstly, the construction of regional transformation is not without its challenges, as this thesis is driven by a desire to understand the role of knowledge dynamics and policy interventions in influencing such processes of regional change; other factors not considered in this thesis may be equally important in explaining the differences we observe in how regions transform over time. Similarly, the construction of transformation is an amalgam of several different but related concepts that explain regional processes of change and shed light on how to understand those processes.

Secondly, while an important dimension used in this thesis is the dimension of relatedness, this dimension comes with a number of limitations which must be acknowledged. Firstly, while this thesis, and explicitly paper one, aims to contribute to the ongoing debate on what the varying measures of relatedness have to offer in terms of explaining processes of regional change, the dimensions strongly overlap. That is to say, that industrial relatedness and occupational relatedness, for example, overlap to a considerable degree with regards to what they capture. Alongside this overlap, a limitation which must be acknowledged, but which also offers a fruitful avenue for future research, is that levels of relatedness do not change drastically over short periods of time. As such, there is a need for more longitudinal analysis of these processes of change. However, and related to the previous point is that what contributes to these changes in relatedness over time and the role policy can play in the process remains contested; that is to say, we know little about the formation of relatedness empirically and how it can be altered, and indeed what such processes of alteration are likely to do elsewhere in a regional economy (that is, of course, assuming that one would aim to influence the relatedness of activity in a region). Another related limitation here also concerns the dimension of complexity. There remains no clear consensus on the approach to use, and considerable debates are ongoing on the merits and demerits of the different approaches and their applicability in different contexts.

Thirdly, concerning the selection of areas for interventions and the search processes which contribute to this selection process, we know very little, given the relatively short time which has elapsed, whether such selection processes will lead to the desired outcome for the policymakers who made the selections and the processes of regional transformation they intended to influence. As discussed in chapter 2.1, regional transformation processes take time. While empirical analysis of such selection processes and their intervention can form an important bedrock of future analyses, they cannot yet shed light on whether those processes and interventions are successful. Related to this limitation, but again an area of potential rich future analyses, is that we still know relatively little about the actual selection process, and 'removing the veil' of not only how the activities for policy intervention are selected, but how resources are allocated, how evaluations are conducted, whether such evaluations produce change on the type and nature of interventions, this particular aspect offers a promising research avenue to investigate regional innovation policy and its use and implementation in practice.

Lastly, as with many such analyses that focus on the regional level and apply it in a particular country, for example, as done in papers 1 and 2, there remain issues of generalisability. While the choice of given regions in this thesis is articulated deeply in the papers below, further studies may benefit from deploying the methods used in this thesis in other parts of the world and at different spatial scales, to test whether the observed effects hold. This limitation also concerns paper three, which looks at a number of countries across the EU and investigates whether the dimensions of relatedness and complexity also influence decision-making for policy interventions worldwide.

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How regions diversify into new jobs: From related industries or related occupations?

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Abstract

Research on the diversification of regional production has examined how regions diversify into related industries or – more recently – into related occupations. However, industries differ significantly depending on which activities regions host within them, and occupations also involve different activities across industries. Hence, studying the combination of occupations and industries – i.e. the specific jobs regions do – provides a more precise reflection of the economic activities going on in a region, and of how these activities change, than studying either in isolation. In this paper, we examine how regions diversify into new jobs – unique industry-occupation combinations – asking whether they do so from related industries or related occupations. We use linked employer-employee data from official tax registers for all industry-occupation combinations in Norwegian labour-market regions over the time period 2009 – 2014. We find that diversification into new jobs is more likely in the presence of related occupations and industries in a region. Furthermore, we find a positive interaction between the two dimensions, suggesting that occupational and industrial relatedness have complementary effects on the likelihood of diversification into new jobs. Their effects also depend on the complexity of the activity. Specifically, occupational relatedness and its interaction with industrial relatedness are particularly important for diversification into more complex activities.

Keywords: *Regional capabilities, jobs, occupations, relatedness, diversification*

Introduction

Regional economies typically evolve by branching from existing activities into related new activities. While this general insight is widely accepted in evolutionary economic geography, the literature has so far only examined evolution within the same type of activity – e.g., between technologies, industries, or occupations. However, economic activities are multidimensional. They involve a person with a specific skill set engaged in an occupation within an industry, typically using different types of technology. This multidimensional perspective has so far been missing from research on related diversification. No research has hitherto examined the relative importance of relatedness across different dimensions for diversification into new types of multidimensional economic activities.

This paper is the first to take such a multidimensional perspective. Specifically, we examine diversification into new jobs. A job can be defined as the unique combination of an industry and an occupation (Goos et al., 2009; Fernández-Macías, 2012; Henning *et al.,* 2019; Henning and Eriksson, 2021). Regions can develop the competence to do a new job drawing on their capabilities in related industries and/or in related occupations. From the literature, we know that regions are more likely to enter new industries if they are already specialised in related industries (Neffke, Henning and Boschma, 2011; Boschma, Minondo and Navarro, 2013; Essletzbichler, 2015). We also know that regions are more likely to enter new occupations if they are specialised in related occupations (Muneepeerakul *et al.*, 2013; Farinha *et al.*, 2019). However, we don't know whether it is industrial or occupational relatedness, or some combination of the two, which matters for entry into new jobs. We also don't know whether there is any interaction between industrial and occupational relatedness in the diversification process. Put differently, we don't know whether occupational relatedness can substitute for industrial relatedness, or whether the two are complements. Finally, we don't know whether the importance of industrial or occupational relatedness depends on the complexity of the activity which the region is diversifying into.

To address these questions, we explore how the entry of new regional specialisations at the level of jobs is shaped by the density of related industries and occupations within the region. We also examine how the interaction between the two dimensions shapes new job entry, and how the importance of each dimension varies depending on occupational complexity. We use linked employer-employee data from Norway for the period 2009–2014. The data includes the firm, industry and occupation of individual employees for each year, which we use to track mobility across industries and occupations. From this, we construct skill-relatedness matrices across industries and occupations, using an approach which is well-established in previous empirical research (e.g. Neffke and Henning, 2013; Timmermans and Boschma, 2014; Fitjar and Timmermans, 2017). Furthermore, we study the specialisation of regions in different jobs by measuring regional employment shares and location quotients at the occupation-industry-region level.

We find that industrial relatedness improves the likelihood of regions developing new specialisations at the level of jobs. Occupational relatedness also has a positive, but somewhat weaker, impact on the entry of new job specialisations. However, occupational relatedness matters in particular for diversification into more complex jobs. The two dimensions of relatedness, occupational and industrial relatedness, are complementary insofar as occupational relatedness has a greater impact on the entry of new specialisations when industrial relatedness is high and vice versa. This complementarity is particularly important for entry into more complex jobs.

The remainder of this paper is structured as follows: In the next section, we discuss the diversification of regions into new economic activities from an evolutionary economic geography perspective. In the third section, we discuss how the occupational and industrial relatedness measures are created. In the fourth section, we describe the data. In the fifth section, we empirically study the diversification of Norwegian regions into new jobs. The final section concludes and discusses policy implications.

Related Diversification in Regional Economies

The process of creative destruction is central to the understanding of evolutionary economic geography. Regional diversification, put simply, is a process in which regions develop new specialisations – and abandon old ones. This process requires specific regional capabilities and assets (Boschma *et al.*, 2017). Over the last decade, a large body of literature in evolutionary economic geography has demonstrated that regional economic development is a path-dependent process. (Boschma *et al.*, 2017). Regions tend to diversify into new activities related to their existing activities, from which they draw and combine local capabilities (Breschi, Lissoni and Malerba, 2003; Saviotti and Frenken, 2008; Neffke, Henning and Boschma, 2011; Neffke and Henning, 2013; Tanner, 2014; Rigby, 2015; Boschma, 2017; Grillitsch and Asheim, 2018; Hidalgo *et al.*, 2018; Bond-Smith and McCann, 2020). Therefore, regional development and diversification processes are not random but shaped by regions' historical legacy (Boschma and Wenting, 2007). Technological and economic trajectories shape the diversification opportunities available to regions (Davis, 1985; Dosi, 1988; Boschma and Wenting, 2007; Lo Turco and Maggioni, 2016; Grillitsch, Asheim and Trippl, 2018). In short, new industries do not begin from nothing but evolve out of current regional structures.

There has been substantial interest in the concept of relatedness and considerable effort devoted to clearly conceptualising the principle of related diversification (Hidalgo *et al.*, 2018). A consistent finding across much of the literature is that economic activities tend to diversify incrementally into related activities. Hence, diversification processes tend to add activities that are complementary to what is already present in a region to the detriment of those activities which are not as closely related (Hane-Weijman, Eriksson and Rigby, 2021). As highlighted by a number of scholars (discussed further in Hidalgo et al. 2018), there are a multitude of ways in which one can approach the concept of relatedness. Hence, previous literature has studied a number of different outcomes, relying on different measures of relatedness.

One part of this literature has examined innovation outcomes, studying the evolution of regions' innovation capacity. It has shown how regions innovate by building on related knowledge from other areas, using data on patenting (Kogler, Rigby and Tucker, 2013; Rigby, 2015), trademarks (Drivas, 2022; Iversen and Herstad, 2022) or other innovation outputs. Another part of the literature has examined how relatedness shapes what economies produce. At the national level, this research has often examined the composition of countries' export baskets (Hidalgo *et al.*, 2007). At the regional level, it has mainly relied on studies of industries, studying how regions branch into new industrial specialisations and their relatedness to their existing industry portfolios (Neffke, Henning and Boschma, 2011; Boschma, Minondo and Navarro, 2013; Essletzbichler, 2015; Xiao, Boschma and Andersson, 2018).

One of the limitations of this literature is that it is mainly preoccupied with the composition and capacity of regions' activity profiles from an industrial perspective (Broekel, Fitjar and Haus-Reve, 2021). Meanwhile, it overlooks that industries often comprise a range of heterogeneous activities and skills, whose precise contents differ across regions. To address this, some recent studies have expanded to also examine the composition of occupations in regional labour markets (Muneepeerakul *et al.*, 2013; Farinha *et al.*, 2019; Hane-Weijman, Eriksson and Rigby, 2021, Buyukyazici et al., 2022).

The use of occupational data is useful for two reasons: First, there is a growing separation of functions and activities within industries across different regions (Markusen *et al.*, 2008), as part of the emergence of global value chains and production networks. Second, multinational enterprises and other large conglomerates produce a wide range of different products and locate different functions in different regions (Dunning, 1997; Iammarino and McCann, 2013; Cortinovis, Crescenzi and van Oort, 2020). Thus, in any given industry or single enterprise, headquarter functions may be located in one region, component manufacturing in another, and assembly in a third. In this context, shifting the focus from the industries in which regional firms are classified to the actual jobs that people working there do will give a better indication of what the region actually produces.

However, the real benefit comes from combining industrial and occupational data, as occupations involve different activities depending on which industry they operate within. For instance, a lawyer working in a law firm does a different job than one who works in an IT company. A job can therefore be defined as a unique combination of an industry and an occupation, borrowing a perspective from the labour economics literature (e.g. Fernández-Macías, 2012). Henning and Eriksson (2021) apply this perspective in a study of regional divergence and labour market polarisation, finding that most municipalities experience job upgrading. However, no previous studies in economic geography have examined how relatedness shapes regions' ability to diversify to do new jobs, understood as unique industry-occupation combinations. Only a handful of papers have looked simultaneously at occupational and industrial relatedness at all, mostly with a view to comparing their effects on the growth of regions (Wixe and Andersson, 2017) or firms (Jara-Figueroa *et al.*, 2018).

The relatedness literature would benefit from studying regional economic activities at a more detailed level than that of industries or of occupations. Analysing activities at the level of jobs, i.e. looking at the combination of industries and occupations, rather than just one or the other, will provide a deeper understanding of the types of activities taking place in regional economies, and the ways in which regions diversify. Diversification may entail regions branching into new occupations within the same industry, or into new industries with the same occupational specialisations. The former would involve e.g. diversifying from component manufacturing by adding assembly jobs, or from back office support services by adding management jobs – changes which are invisible in studies of regions' industry composition. The second would entail e.g. diversifying from back office support services in one industry to also performing similar functions in another industry – a change that may appear radical in studies at the industry level, but which would not show up at all in a study at the occupational level.

Understanding the relative importance of industrial and occupational relatedness in diversification processes is an important endeavour in its own right. However, the real benefit from adopting a multidimensional perspective comes from understanding the relationship between them. Because diversification processes have mainly been studied in a unidimensional way, we don't know how different dimensions of relatedness interact in shaping diversification opportunities. If the region lacks industries which are related to a prospective new activity, can it compensate by having a lot of related occupations? Or does it need relatedness in both dimensions? Examining both industrial and occupational relatedness opens for answering these types of questions.

Industrial and occupational branching

The relatedness literature emerged from classic discussions of whether regional economies benefit more from specialisation in a few industries or from having a diversity of industries, often pitched as a face-off between Marshall-Arrow-Romer and Jacobs externalities (Glaeser *et al.*, 1992; Paci and Usai, 2000; Beaudry and Schiffauerova, 2009; De Groot, Poot and Smit, 2009; Caragliu, de Dominicis and de Groot, 2016). Relatedness represents a third way in this debate. It takes the position that regions benefit neither from being specialised in a few industries nor from hosting a wide variety of industries. Instead, the presence of a variety of related industries provides the optimal conditions for knowledge spillovers across industries (Frenken, Van Oort and Verburg, 2007). The subsequent literature on related variety has shown its benefits for regional growth, whether in terms of employment, productivity or GDP, across different geographical contexts (see Content and Frenken, 2016, for a review).

In parallel with this discussion, research in development economics started exploring how the comparative advantages of national economies evolve over time, introducing the concept of a product space (Hidalgo *et al.*, 2007). This research builds on the idea that economic development is not mainly driven by efficiency improvements in the production of existing products, but by shifting the comparative advantage of the economy from less valuable to more valuable products. However, countries are constrained by their technological capabilities in their ability to develop new comparative advantages. A core idea is that fewer countries will have the capabilities to produce the most complex products, making it more valuable to specialise in their production. Furthermore, countries tend to develop new capabilities by diversifying into products which are closely related to their existing comparative advantages. This implies that relatedness is particularly important for upgrading, i.e., when economies develop capabilities to engage in more complex activities.

These ideas were combined in studies of related diversification at the regional level. Boschma and Frenken (2011) introduced the concept of 'regional branching', picturing the regional economy as a tree which evolves by branching into new activities from the activities that they already do. Empirically, Neffke, Henning and Boschma (2011) showed for Sweden that related industries are more likely to enter the regional economy, while unrelated ones are more likely to exit. The same pattern was shown for Spain (Boschma, Minondo and Navarro, 2013) and the United States (Essletzbichler, 2015). Building on this, later studies have sought to explore how the potential for related and unrelated diversification varies across different regional contexts (Barbour and Markusen, 2007; Tanner, 2014; Boschma and Capone, 2015; Cortinovis *et al.*, 2017; Xiao, Boschma and Andersson, 2018). More recent studies have expanded the focus to also consider other dimensions of regional economies, most notably their occupational structure (Muneepeerakul *et al.*, 2013; Shutters, Muneepeerakul and Lobo, 2016; Farinha *et al.*, 2019). Wixe and Andersson (2017) show that the notion of regions being solely specialised in industries is too narrow, and that instead many regions tend to be more specialised with regards to functions and in turn occupations. Indeed, the current spatial division of labour is increasingly occupation-specific rather than industry-specific (Hane-Weijman, Eriksson and Rigby, 2021). One reason for this is the changing nature of long-term jobs and an increase in the number of workers and employers changing jobs and moving over time (Eriksson and Rodríguez-Pose, 2017), which is itself an important channel for the knowledge flows through which related diversification operates (Kuusk, 2021).

The studies at the occupational level shift the focus from which industries a region has to what it actually does (Neffke, Henning and Boschma, 2008; Boschma and Iammarino, 2009; Rigby, 2012; Essletzbichler, 2015; Grillitsch and Asheim, 2018; Xiao, Boschma and Andersson, 2018). These studies identify the same tendency for regional branching: regions tend to diversify into new occupations which are related to occupations already present in the region. Furthermore, occupational specialisations are interdependent, meaning that current occupational specialisations constrain the future development paths of regions in complex ways (Muneepeerakul *et al.*, 2013; Shutters, Muneepeerakul and Lobo, 2016). These interdependencies may involve complementarities, similarities or synergies (Farinha *et al.*, 2019). Hane-Weijman, Eriksson and Rigby (2021) extend the discussion to also include the complexity dimension, finding that increases in occupational relatedness are more important than occupational complexity in driving employment growth in Swedish regions.

Branching into new jobs

Shifting the focus from industries or occupations to their combination, i.e. jobs, opens up the question of whether regional diversification into new jobs is best captured through the prism of industrial structure (and in turn industrial relatedness) or of occupational structure. In general, we expect job diversification to follow the same pattern as other regional diversification processes, i.e. that new types of jobs are more likely to enter regional economies if they are related to the regions' existing job portfolio. We therefore propose that both occupational and industrial relatedness will impact the likelihood that new jobs enter a regional economy. We formulate hypotheses for each of these relationships, which we will test in the empirical analysis to follow:

H1: The presence of related occupations in the region increases the likelihood of diversification into new jobs.

H2: The presence of related industries in the region increases the likelihood of diversification into new jobs.

However, there is no clear prior evidence to suggest whether relatedness to other industries or to other occupations in the region is more important in driving the entry into new jobs. Studies in other contexts provide conflicting insights, showing that occupational relatedness matters more than industrial relatedness for regional growth (Wixe and Andersson, 2017), while the opposite is true for firm growth (Jara-Figueroa *et al.*, 2018). No previous studies have examined their relative importance for diversification into new jobs.

As discussed above, an important benefit of a multidimensional perspective is that it allows us to examine the relationship between the dimensions. In this case, we have no strong prior expectations, as there is no previous research to suggest whether different dimensions of relatedness function as substitutes or mutually reinforce each other. Hence, we formulate a hypothesis which is open-ended when it comes to direction:

H3: The relationship between occupational relatedness and the likelihood of diversification into new jobs depends on the presence of related industries in the region, and vice versa.

The entry of new jobs into the region can have a positive, negative or neutral effect on the regional economy, depending on whether the new jobs are more or less valuable than the ones they replace. In line with recent studies on related diversification (e.g. Balland *et al.*, 2019; Hane-Weijman, Eriksson and Rigby, 2021; Davies and Maré, 2021; Juhász, Broekel and Boschma, 2021), and the seminal study of Hidalgo and Hausmann, (2009), we therefore also include the dimension of complexity. This allows for an assessment of the importance of industrial and occupational relatedness for entry into simple, intermediate and complex jobs. In line with previous research, we expect relatedness to matter in particular for upgrading, i.e. for entry into more complex jobs, as such jobs require more advanced capabilities which are more difficult to develop (Broekel, Fitjar and Haus-Reve, 2021). Hence, we formulate the following hypotheses:

H4: The relationship between occupational relatedness and the likelihood of diversification into new jobs is stronger for entry into more complex occupations.

H5: The relationship between industrial relatedness and the likelihood of diversification into new jobs is stronger for entry into more complex occupations.

Data and methods

In line with the discussion above, we have constructed a dataset of Norwegian jobs as well as industrial and occupational relatedness, covering the period 2009-2014. The data is sourced from the Linked Employer-Employee data from Statistics Norway. It provides firm- and individual-level data covering all firms and private-sector employees in Norway. More precisely, we rely on individual-level register-data linked to establishments. The data contain detailed longitudinal information on the workplace, industry, occupation and work location of all individuals employed in the private sector in Norway. It covers all inhabitants over the age of 16 who are employed in private establishments and includes a range of information about individual workers and establishments. From this register, we first build a data set of the number of workers in each occupation per industry in each economic region of Norway. We identify industries at the four-digit NACE level using the SNI2007 industry classification system. Occupations are defined using the 7-digit level of the Norwegian SSYK98, which is consistent with the international ISCO-88 standard. For all estimations, we rely on the four-digit ISCO level.

To identify the relevance of occupational and industrial relatedness for job diversification, we use industry-occupation-regions as observations. That is, each observation is a combination of a unique occupation (4-digit ISCO), an industry (4-digit NACE), and a labour market region (functional regions, corresponding roughly to NUTS 4). In our case, that implies potentially differentiating between 78*402*460=14,423,760 (regions*occupations*industries) entities, each observed 6 times (once per year). In practice, we never use the full sample of observations in the empirical models, as we only include observations which are part of the opportunity space for a given region at a given time. For instance, when looking at diversification processes, we exclude jobs in which the region is already specialised, as it cannot (anymore) successfully diversify into this job.

On the basis of industry-occupation-regions, we adapt the (by now) standard approach to modelling related diversification processes (Boschma *et al.*, 2017; Fitjar and Timmermans, 2017). We apply this to the level of jobs and approximate the relatedness of a job to the regional portfolio in two dimensions (industrial and occupational), as illustrated in Figure 1.

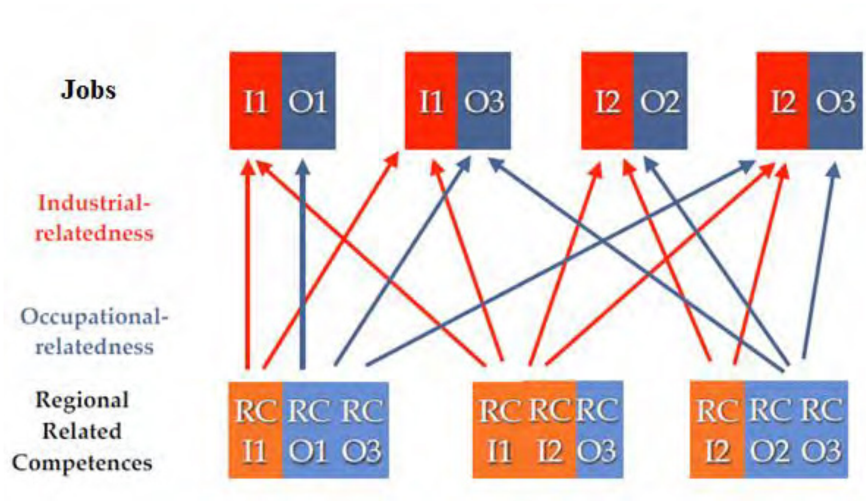

Figure 1 - The influence of relatedness on regional diversification

The occupational relatedness of a job refers to the degree to which related occupations are present in the region, independent of the industry it is classified into. In distinction, industrial relatedness captures the fit of a job with its regional industrial surroundings, regardless of which occupations these include. In the analysis, we also include other dimensions of the regional occupational and industry structure, specifically occupational complexity, industrial and occupational diversity, and industrial and occupational specialisation.

Occupational and industrial relatedness

Relatedness is a dyadic concept. That is, it describes the degree of relatedness between two entities, in this case two occupations or two industries. To quantify the degree of relatedness between two occupations, we follow the literature and use information on labour flows (Neffke and Henning, 2013; Fitjar and Timmermans, 2017; Neffke, Otto and Weyh, 2017). Information on individual worker mobility is obtained from Statistics Norway and aggregated at the level of 4-digit ISCO-codes. In a first step, we construct an occupational relatedness matrix using information on individuals that change their occupation from one year to the next. We count the number of individuals changing from occupation o to occupation k and compare this to the overall number of individuals starting to work in occupation k or leaving work in occupation o. When we observe more mobility between any pair of occupations than what would be statistically expected based on the overall tendency to take up or leave work in these occupations, we consider the occupations to be related. Formally, we measure the skill relatedness between two occupations *o* and *k* in year *t*, as follows:

$$SR_{okt} = \frac{\frac{F_{okt}}{F_t}}{\left(\frac{F_{ot}}{F_t}\right)\left(\frac{F_{kt}}{F_t}\right)} = F_{okt}\frac{F_t}{F_{ot}F_{kt}} \quad \text{(Eq. 2)}$$

In this equation, F_{okt} is the number of workers moving from occupation *o* to *k* in year *t*; F_t is the total number of workers changing their occupation in year *t*, F_{ot} is the total number of individuals that leave occupation *o* in year *t*; and F_{kt} is the number of individuals who enter occupation *k* in year *t*. We furthermore standardise the measure to range between 0 and 2 using this formula:

$$\widehat{SR_{okt}} = \frac{SR_{okt}-1}{SR_{okt}+1} + 1 \quad \text{(Eq. 3)}$$

Using this skill relatedness measure we can gain insight into whether occupations are related. Given the short time frame of the analysis, we can assume that the occupational relatedness of any pair of occupations remains relatively stable across the period of analysis. Consequently, we average all non-missing values of relatedness across all years, implying that we have a time-invariant relatedness value.

The units of observation are industry-occupation-regions, implying that the measure $\widehat{SR_{okt}}$ needs to be projected to this level by means of calculating the relatedness density for each observation (Hidalgo *et al.*, 2007). In contrast to its initial conception, we do not use the location quotient, due to its rather arbitrary cut-off of observations with lower shares than the national average. Rather, we directly rely on occupations' employment shares. For each occupation *o* in region *r*, we weight the regional employment share of any other occupation *k* present in the same region ($EMP.SHARE_{krt}$) with the corresponding relatedness measure in year *t* ($\widehat{SR_{okt}}$). Subsequently, we sum all weighted employment shares, giving the related density of occupation *o* in region *r* and year *t* ($OCC.REL_{ort}$).

$$OCC.REL_{ort} = \sum_{k=1}^{n} EMP.SHARE_{krt} * \widehat{SR}_{okt} \quad \text{(Eq. 4)}$$

For the construction of the second measure of relatedness, industry relatedness, the procedure is identical. We first construct the industry-industry relatedness matrix $\widehat{SR_{ijt}}$ on the basis of the labour mobility between two industries. Again, we average all non-missing relatedness values across all years to obtain a time-invariant industry-relatedness matrix.

In a second step, this matrix is transformed to the industry-region-specific measure of related density for industry *i* based on its relatedness to the *n* other industries *j* in the region, as represented by their employment shares $EMP.SHARE_{jrt}$.

$$IND.REL_{irt} = \sum_{j=1}^{n} EMP.SHARE_{jrt} * \widehat{SR}_{ijt} \qquad \text{(Eq. 5)}$$

Other occupational and industrial characteristics

Besides relatedness, we include various other characteristics of the occupation and industry in the analysis. First, we account for specialisation of the regions with respect to the focal industry and occupation. For this, we calculate the location quotient of industry *i* and occupation *o* in region *r* in year *t* (LQ_{irt}, LQ_{ort}).

Second, we include a measure of both occupational and industrial diversity at the level of the region to account for Jacobs externalities. To quantify both measures of diversity, we use an Alesina fractionalisation index[1] (Alesina *et al.*, 2003).

Finally, H4 and H5 refer to occupational complexity as a moderator of the relationship between relatedness and diversification. In contrast to measuring relatedness, there is not yet an established approach for empirically measuring complexity. Given the similarity with the type of data used in this paper, we follow Lo Turco and Maggioni (2020) and focus on occupation (task) complexity, which is well-established in labour economics. In practice, to examine the complexity of occupations, we rely on the index of Caines, Hoffman and Kambourov (2017). The index measures to what degree occupations involve solving complex problems, finding original solutions, applying critical thinking, analysing data and information, etc. Since this

[1] This index is commonly used in studies of diversity in other contexts, such as ethnic or birthplace diversity. Applied to the study of occupational diversity at the region level, the construction of this index is as follows: $OCC.DIV_{rt} = 1 - \sum_{O=1}^{O} s_{ort}^2$, where s is the proportion of employees in region *r* at time *t* that work in occupation *o*; O is the number of different occupations represented in that region in the same year. The index ranges between 0 and 1. A maximum diversity value nearing 1 reflects a situation where a region consists of an equal number of people in each occupation. A value of 0 reflects a situation where all the employees have the same occupation. We follow the same logic constructing a variable measuring industry diversity at the regional level over time, $IND.DIV_{rt}$.

complexity measure is based on a modification to the 1990 US Census occupational codes, it requires translation to the ISCO-based occupations in the Norwegian data. Therefore, we reconstruct the measure by extracting the same 35 variables from the 2019 O*NET data and running a principal component analysis in the style of Caines et al. (2017). We obtain complexity scores for 967 occupations. These occupations are translated to 4-digit ISCO-occupations using the SOC-ISCO crosswalk from the US Bureau of Labor. As this is a one-to-many matching (967 SOC to 424 ISCO occupations), we aggregate the according SOC-based complexity values by averaging across all SOC codes associated with one ISCO code, resulting in complexity values for 424 ISCO occupations. These are matched to the occupational dimension of the industry-occupation-region-based data. That is, all observations with the same occupational code will have the same complexity value. Notably, the complexity values are also time-invariant as we exclusively use the 2019 O*NET data and as we do not expect significant changes in occupational complexity within the short time period covered.

Empirical approach

We follow the established literature and measure the diversification of a regional economy into new jobs by modelling the probability with which a new activity emerges in a region. Emergence is defined as an activity expanding its presence in a region beyond the national average, i.e., the region gains a specialisation or a revealed comparative advantage in the activity. Empirically, this is captured by the location quotient exceeding a value of 1. To account for the presence of some noise and random changes in employment and patent numbers, we require that the location quotient (LQ) increases from 0.5 to above 1 as signal of a successful diversification (Hidalgo et al., 2007). We use a linear probability model to explain the likelihood that the location quotient of an activity in a region changes from below 1 in one year to above 1 in the next. That is, regions with LQ > 0.5 are excluded from the sample.

Specifically, we first fit the following model to test H1 and H2:

$$Entry_{oirt} = \beta_0 + \beta_1 OCC.REL_{ort} + \beta_2 IND.REL_{irt} + \beta_3 OCC.LQ_{ort} + \beta_4 IND.LQ_{irt} + \beta_5 OCC.DIV_{rt} + \beta_6 IND.DIV_{rt} + \beta_7 POPDEN_{rt} + \gamma_o + \delta_i + \theta_r + \sigma_t + \varepsilon_{oirt} \quad \text{(Eq. 6)}$$

In addition to the specialisation and diversity variables presented above, we control for population density to capture potential differences between urban and peripheral regions ($POPDEN_{rt}$). We also control for a wide range of factors by including regional-, occupational-, industrial-, and year-fixed effects (NACE FE, ISCO FE, REGION FE, YEAR FE). We further consider the clustered nature of the observations by means of three-way clustered standard errors at the occupation, industry, and region levels.

Second, we examine the interaction between industrial and occupational relatedness to test H3.

$$Entry_{oirt} = \beta_0 + \beta_1 OCC.REL_{ort} + \beta_2 IND.REL_{irt} + \beta_3 OCC.REL_{ort} * IND.REL_{irt} + \beta_4 OCC.LQ_{ort} + \beta_5 IND.LQ_{irt} + \beta_6 OCC.DIV_{rt} + \beta_7 IND.DIV_{rt} + \beta_8 POPDEN_{rt} + \gamma_o + \delta_i + \theta_r + \sigma_t + \varepsilon_{oirt} \quad \text{(Eq. 7)}$$

In a final step, we explore whether the importance of occupational and industrial relatedness may depend on occupational complexity, testing H4 and H5, respectively. We do this in two different ways: First, by including interaction terms between occupational relatedness and occupational complexity (Eq. 8), and – in a separate analysis – between industrial relatedness and occupational complexity (Eq. 9).

$$Entry_{oirt} = \beta_0 + \beta_1 OCC.REL_{ort} + \beta_2 IND.REL_{irt} + \beta_3 OCC.COMP_{ot} + \beta_4 OCC.REL_{ort} * OCC.COMP_{ot} + \beta_5 OCC.LQ_{ort} + \beta_6 IND.LQ_{irt} + \beta_7 OCC.DIV_{rt} + \beta_8 IND.DIV_{rt} + \beta_9 POPDEN_{rt} + \gamma_o + \delta_i + \theta_r + \sigma_t + \varepsilon_{oirt} \quad \text{(Eq. 8)}$$

$$Entry_{oirt} = \beta_0 + \beta_1 OCC.REL_{ort} + \beta_2 IND.REL_{irt} + \beta_3 OCC.COMP_{ot} + \beta_4 IND.REL_{irt} * OCC.COMP_{ot} + \beta_5 OCC.LQ_{ort} + \beta_6 IND.LQ_{irt} + \beta_7 OCC.DIV_{rt} + \beta_8 IND.DIV_{rt} + \beta_9 POPDEN_{rt} + \gamma_o + \delta_i + \theta_r + \sigma_t + \varepsilon_{oirt} \quad \text{(Eq. 9)}$$

Second, we explore the relationship using sub-sample analyses. Here, we estimate Eq. 7 on five sub-samples of occupations divided into quintiles by their level of complexity. This also allows for an examination of whether the importance of the interaction between industrial and occupational relatedness varies between less and more complex occupations.

The corresponding descriptives of the variables are shown in Appendix 1 and 2 with the correlation plot between the variables contained below in Figure 2.

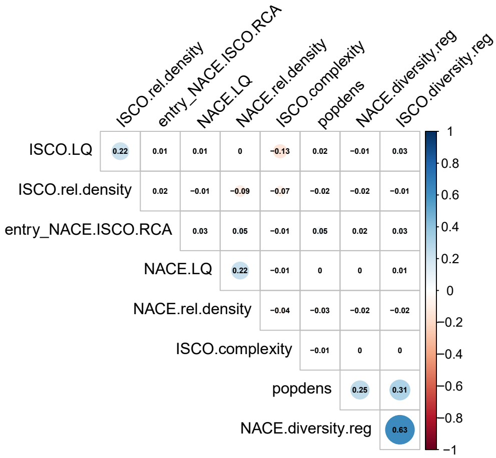

Figure 2: Correlation plot, Entry Model LQ (LQ <0.5)

Findings

Table 1 shows the results of the linear probability panel regressions, which estimate how occupational and industrial relatedness impact regional diversification processes, testing H1 and H2. The primary models explain diversification as approximated by the growth of an activity's LQ from LQ<0.5 to a value above the national average, i.e., LQ>1, indicating that the region has developed a new revealed comparative advantage (RCA) in the activity. In the appendix, we include models with different operationalisations of the dependent variable. We present the models with different specifications with respect to the inclusion of fixed effects. The data at hand allows for four types of fixed effects (Region, Year, Industry, Occupation).

Table 1: Entry models
Dependent variable: LQ <0.5 to LQ>1

	Model 1	**Model 2**	**Model 3**	**Model 4**
IND.REL	0.005 (0.001)***	0.005 (0.001)***	0.005 (0.001)***	0.004 (0.001)***
OCC.REL	0.001 (0.000)+	0.001 (0.000)+	0.003 (0.001)***	0.002 (0.000)***

Table 1: Entry models
Dependent variable: LQ <0.5 to LQ>1

	Model 1	**Model 2**	**Model 3**	**Model 4**
IND.LQ	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***
OCC.LQ	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)	0.000 (0.000)
IND.DIV	0.018 (0.020)	0.018 (0.019)	0.017 (0.019)	0.017 (0.019)
OCC.DIV	−0.013 (0.018)	−0.013 (0.018)	−0.011 (0.018)	−0.011 (0.018)
POPDEN	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
IND.REL × OCC.REL				0.003 (0.001)***
Num. obs.	9194115	9194115	9194115	9194115
RMSE	0.08	0.08	0.08	0.08
Cluster-robust std.err	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
IND FE	YES	NO	YES	YES
OCC FE	YES	YES	NO	NO

Note: *** p<0.001, ** p<0.01, * p<0.05. Robust standard errors in parentheses, clustered by industry, occupation, and region.

Concerning the key variables of interest, industrial and occupational relatedness, we find IND.REL to be significantly positive in all models, supporting H2. OCC.REL also becomes significantly positive when excluding occupational fixed effects (Model 3 in Table 1)[2]. This provides partial support for H1. Consequently, relatedness at the industrial and occupational levels shows the expected signs (Table 1, models 2 and 3, respectively). This serves to confirm the importance of relatedness. That is, new jobs are more likely to emerge in a region when related industries and – to some extent – occupations are present.

For the other dimensions of industrial and occupational composition, industrial specialisation (IND.LQ) is significantly positive in all models and specifications. The estimated coefficients are all close to zero due to the low likelihood of entry. This result indicates that regions are more likely to diversify into new jobs when it is specialised in the corresponding industry, lending further credence to the idea of path-dependence in diversification (Boschma and Wenting, 2007). When we add the occupational perspective, the estimated results show the same pattern, but the effect of occupational specialisation (OCC.LQ) is less consistent across models. The coefficient is significantly positive in the primary model (Table 2). However, it is insignificant or even significantly negative when we define diversification as changes from zero to positive employment (Appendix 3). This implies that jobs with some positive employment in a region are somewhat more likely to grow beyond the national average when the region is already specialised in the corresponding occupation. However, occupational specialisation is not associated with the entry of completely new jobs in the region.

Table 2: Interaction between relatedness and complexity
Dependent variable: LQ <0.5 to LQ>1

	Model 1	**Model 2**	**Model 3**
IND.REL	0.005 (0.001)***	0.005 (0.001)***	0.006 (0.001)***

[2] In appendix 3 we also present results for models in which successful diversification means employment growth in an activity from zero to any positive value. The results for these latter models confirm consistent with the findings obtained using a jump in LQ as an indication of diversification.

Table 2: Interaction between relatedness and complexity Dependent variable: LQ <0.5 to LQ>1			
	Model 1	**Model 2**	**Model 3**
OCC.REL	0.002 (0.001)***	−0.003 (0.001)*	0.002 (0.001)***
OCC.COMPL	0.000 (0.000)	0.000 (0.000)***	0.000 (0.000)
OCC.REL:OCC.COMPL		0.000 (0.000)***	
IND.REL:OCC.COMPL			0.000 (0.000)
Num. obs.	9125410	9125410	9125410
RMSE	0.08	0.08	0.08
Cluster-robust std.err	YES	YES	YES
Year FE	YES	YES	YES
Region FE	YES	YES	YES
IND FE	NO	NO	NO
OCC FE	NO	NO	NO

Note: *** p<0.001, ** p<0.01, * p<0.05. Robust standard errors in parentheses, clustered by industry, occupation, and region.

Next, we move on to test H4 and H5 about the relationship between complexity and relatedness, which we explore in a first set-up by means of an interaction effect (Table 2). of the inclusion of OCC.COMPL prevents the inclusion of occupational fixed effects since it is measured at the occupational level. Therefore, we cannot include this fixed effect in the models testing H4 and H5.

The models do not indicate a significant relationship between complexity and industrial relatedness (model 3), as the corresponding coefficient remains insignificant. The LR-test (Chisq: 192.79, Pr(>Chisq): <2.2e-16) still suggests that including the fixed effects improves the model (Table 2). The interaction between occupational relatedness and complexity is positive and significant, supporting H4. Occupational relatedness has a significantly larger effect for the entry more complex occupations. Conversely, the interaction between industrial relatedness and complexity is negative and significant, contrary to H5. Industrial relatedness is somewhat less important for the entry for more complex occupations.

The interaction plot (Figure 3) gives some further insights on what these interactions mean in practice. For its construction, we divide the distribution of OCC.COMPL into five equal groups of observations: the first represents those activities that are among the 1/5 activities with the lowest complexity score (*Very simple*). The second represents those within the next fifth (*Simple*) and so on until the sample that features the 1/5 of the most complex activities (*Very complex*). We will use this division for the subsequent subsample analysis. For the visualisation of the interaction, we use the median value of each subsample to calculate the corresponding marginal effects. In case of the interaction of industrial relatedness (IND.REL) and occupational complexity (OCC.COMPL), it indicates a weak negative relationship, i.e., the impact of relatedness on the entry probability is higher for groups of occupations with lower levels of complexity.

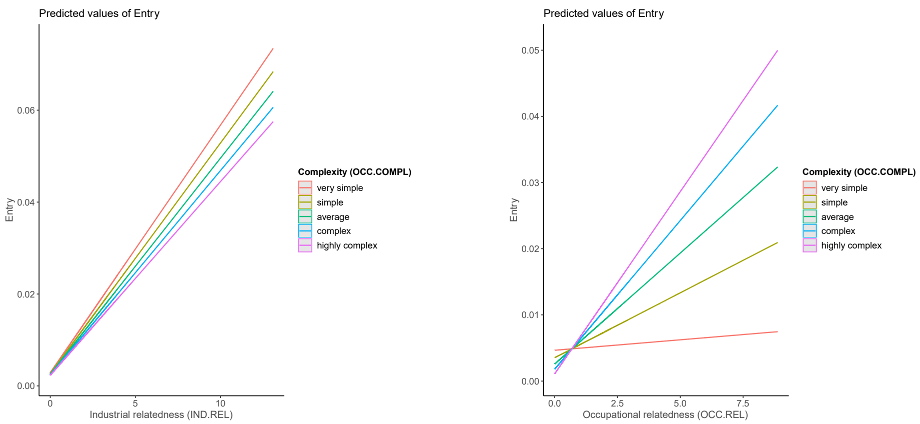

Figure 3: Interaction plots for complexity (OCC.COMPL and occupational/industrial relatedness, Entry Model LQ (LQ <0.5)

In contrast, we find a strong and robust interaction between occupational complexity (OCC.COMPL) and occupational relatedness (OCC.REL). The interaction term is significantly positive in the main model (Table 2, model 2), the LR-test supports the inclusion of this effect (Chisq: 25,556.2, Pr(>Chisq): <2.2e-16), and the interaction plot (Figure 3) clearly suggests systematic variance in the effects of relatedness related to the level of complexity. That is, the entry probability of activities (industry-occupations) in regions is facilitated by occupational relatedness, with the effect of the latter being conditional on occupational complexity. In accordance with theory, relatedness is substantially more relevant for more complex occupations, whereby the biggest jumps in effect strength are visible for average, complex, and highly complex activities. Put differently, occupational relatedness is of much less relevance for very simple and (to a lesser degree) simple activities. While this result is robust across specifications (see Appendix 3), we run an additional test using a subsampling approach. In Table 3, we present the results for five subsamples (very simple, simple, average, complex, and highly complex) that are created based on the quintiles of OCC.COMPL's distribution in the total sample.

Table 3: Entry models, subsampled by levels of complexity

Dependent variable: RCA < 0.5 to RCA >1

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
IND.REL	0.004 (0.001)***	0.004 (0.001)***	0.003 (0.001)***	0.002 (0.001)***	0.002 (0.001)**
OCC.REL	0.000 (0.001)	0.001 (0.000)***	0.003 (0.001)***	0.003 (0.001)***	0.005 (0.001)***
POPDENS	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)*	0.000 (0.000)
IND.LQ	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.001 (0.000)***	0.001 (0.000)***
OCC.LQ	0.000 (0.000)*	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)+
IND.DIV	0.031 (0.029)	0.027 (0.024)	0.021 (0.020)	0.010 (0.016)	−0.019 (0.014)
OCC.DIV	−0.035 (0.037)	0.011 (0.032)	−0.027 (0.025)	0.009 (0.030)	0.009 (0.025)

Table 3: Entry models, subsampled by levels of complexity

Dependent variable: RCA < 0.5 to RCA >1

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
IND.REL: OCC.REL	0.001 (0.001)	0.002 (0.001)*	0.004 (0.001)***	0.008 (0.001)***	0.010 (0.001)***
RMSE	0.08	0.08	0.08	0.07	0.07
Num. obs.	1783988	1823321	1830502	1829175	1858424
IND FE	YES	YES	YES	YES	YES
OCC FE	NO	NO	NO	NO	NO
Region FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Cluster-robust std.err	YES	YES	YES	YES	YES

***p < 0.001; **p < 0.01; *p < 0.05. All models include region- and years FE. Robust standard errors in parenthesis, clustered by industry, occupation, and region.

The results provide even more insights into the relationship of complexity and relatedness than the interaction-based analysis: While for the simplest occupations (model 1), it is industrial relatedness that contributes to diversification, the positive effects shift towards occupational relatedness and its interaction with industrial relatedness as the levels of complexity grow (models 2 – 5)[3]. That is, the main effect for industrial relatedness disappears for occupations that are of average or higher complexity. In a mirroring fashion, the interaction between OCC.REL and IND.REL becomes significant to a higher degree. The main effect of OCC.REL is significant for all but very simple occupations, however, it reaches the highest level of significance only for the most complex activities. In sum, these models are very much in line with the predictions. To enter activities

[3] Note that the significances and sign of coefficients for IND.REL and OCC.REL do not change when excluding their interaction.

of higher complexity, occupational relatedness and its interaction with industrial relatedness is particularly important. In sum, the results suggest that while occupational relatedness is more important for the diversification into complex activities than industrial relatedness, its effect is further strengthened by higher levels of industrial relatedness. That is, co-presence of occupational and industrial relatedness is most conducive for diversification into more complex jobs.

Conclusion

Relatedness is widely seen and empirically confirmed to be a crucial driver of regional diversification. In most studies, relatedness is conceptualised and empirically estimated in a single dimension, most frequently at the level of industries. However, an increasing number of studies have shown that relatedness has multiple dimensions that matter for different aspects of diversification processes. This article combines the two dimensions, examining how regions diversify into new jobs – understood as unique occupation-industry combinations.

We ask whether the diversification into new jobs benefits from the presence of related industries or rather from related occupations. We find that both industrial and occupational relatedness increase the likelihood of entry of new specialisations at the level of jobs. The association with industrial relatedness is most robust, while occupational relatedness is only significant when we leave out occupational fixed effects. Moreover, there is a positive interaction between the two, indicating that there is a complementary relationship between different dimensions of relatedness. Furthermore, occupational relatedness is more important for the diversification into more complex activities. Indeed, the interaction plots show that occupational relatedness does not matter at all for diversification into very simple activities. Meanwhile, there is a slight negative interaction between industrial relatedness and complexity, indicating that industrial relatedness is slightly less important for complex activities. Finally, the interaction between industrial and occupational relatedness is particularly important for diversification into complex activities. That is, diversification into very complex jobs is more likely when locations offer both occupational and industrial relatedness.

These findings broaden the understanding of the role of relatedness in regional diversification processes and provide further evidence of how relatedness must be conceptualised as being multidimensional, with different dimensions providing complementary benefits for diversification. While we disentangle relatedness into two distinct dimensions (industrial and occupational), other dimensions are likely to characterise relatedness, and these may show distinct ways in which they substitute or complement other dimensions. More research is needed to explore this further and deepen our understanding of how relatedness works.

Alongside this, the paper provides important evidence on the conditionality of relatedness processes on the complexity of economic activities. The importance of relatedness for diversification is context-dependent (Neffke and Henning, 2013; Broekel, Fitjar and Haus-Reve, 2021; Hane-Weijman, Eriksson and Rigby, 2021; Mazzoni, Innocenti and Lazzeretti, 2022). This implies that future policy advice building on insights into relatedness structures should pay attention to this multidimensional and context-specific nature of relatedness.

However, there are also limitations in the analysis that need to be acknowledged. Empirically, both dimensions of relatedness overlap, with relatively small changes of time within individual industries and occupations, respectively. Once the heterogeneity of occupations are accounted for by means of fixed effects, occupational relatedness is not significantly related to diversification. Put differently, levels of relatedness do not change drastically over short periods of time, making the empirical identification of their influence challenging. In the analyses where we examine occupational complexity as a moderator, we cannot include occupational fixed effects, and we don’t know how their omission influences the results. We also have to acknowledge that there is still no agreement on how to best capture occupational complexity empirically. While we follow a promising approach by Lo Turco and Maggioni (2020), which is based on the transformation of information on task complexity of occupations in the US to the Norwegian context, future studies are advised to explore alternative data sources and measures of complexity.

These limitations notwithstanding, this paper has implications for both research and policy on diversification and regional development processes. Economic activities have many dimensions and are related to other activities in each of these dimensions. We show that relatedness in different dimensions has both independent and complementary effects on the diversification into new activities. Research and policy advice building on analyses of a single dimension in isolation risks overlooking the importance of activities which may be related in other dimensions. Hence, researchers and policy-makers need to recognise that any given analysis shows only a partial description of the relatedness between activities and can only account for a subset of potential related diversification opportunities. Furthermore, the importance of relatedness is context-dependent, varying for instance between entry into simpler and more complex activities. Research and policy in this area need to recognise this and avoid one-size-fits all solutions.

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Appendix

Appendix 1: Descriptives Entry Model LQ (LQ <0.5)

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Entry	10,763,903	0.006	0.079	0.000	0.000	0.000	1.000
IND.LQ	14,098,445	0.841	3.622	0.000	0.000	0.838	653.440
OCC.LQ	14,098,445	0.853	1.539	0	0.2	1.1	316
IND.DIV	14,098,445	0.970	0.018	0.818	0.967	0.980	0.988
OCC.DIV	14,098,445	0.959	0.012	0.877	0.955	0.965	0.979
IND.REL	14,098,445	0.422	0.790	0.000	0.000	0.500	13.095
OCC.REL	14,098,445	0.584	0.786	0	0.03	0.8	11
OCC.COMPL	13,981,242	47.514	16.062	0.000	36.087	60.302	89.979
popdens	12,089,991	21.778	35.673	1.211	3.649	22.071	225.241

Appendix 2: Descriptives Entry Model employment

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Entry	79,826,360	0.001	0.034	0.000	0.000	0.000	1.000

IND.LQ	94,000,432	1.126	9.826	0.000	0.000	0.560	866.195
OCC.LQ	93,702,940	0.953	5.004	0.000	0.000	0.976	740.204
IND.DIV	95,787,724	0.971	0.018	0.818	0.967	0.981	0.988
OCC.DIV	95,787,724	0.959	0.012	0.877	0.955	0.965	0.979
IND.REL	95,787,724	0.216	0.558	0.000	0.000	0.154	13.095
OCC.REL	95,787,724	0.252	0.501	0	0	0.3	11
OCC.COMPL	92,182,686	45.221	15.892	0.000	33.518	58.396	89.979
popdens	82,256,070	23.555	38.773	1.211	3.676	25.965	225.241

Appendix 3: *Dependent variable:* Emp = 0 to Emp > 0

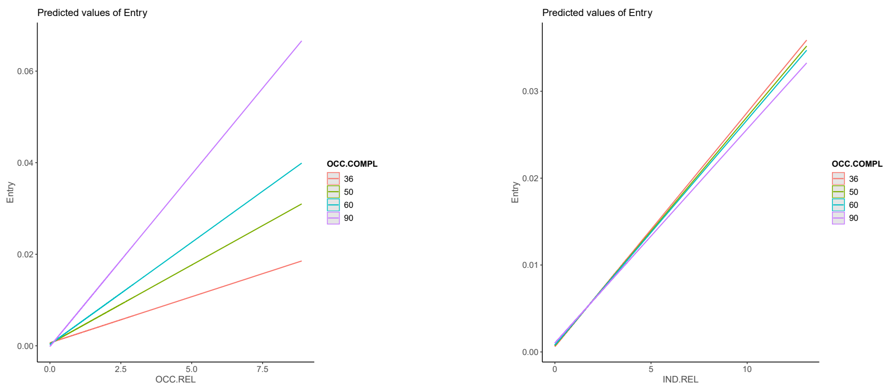
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
popdens	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
IND.LQ	0.000 (0.000) ***	0.000 (0.000) **	0.000 (0.000) ***	0.000 (0.000) ***	0.000 (0.000) ***	0.000 (0.000) ***	0.000 (0.000) **
OCC.LQ	0.000 (0.000)*	0.000 (0.000)*	0.000 (0.000) **	0.000 (0.000) **	0.000 (0.000) **	0.000 (0.000) **	0.000 (0.000) **
IND.DIV	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)	0.002 (0.003)	0.003 (0.003)	0.003 (0.003)
OCC.DIV	−0.001 (0.003)	−0.001 (0.003)	0.000 (0.003)	0.000 (0.003)	0.000 (0.003)	0.000 (0.003)	0.000 (0.003)

Appendix 3: *Dependent variable:* Emp = 0 to Emp > 0

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
IND.REL	0.002 (0.000) ***	0.003 (0.001) ***	0.002 (0.000) ***	0.002 (0.000) ***	0.002 (0.000) ***	0.002 (0.001) *	0.003 (0.001) **
OCC.REL	0.000 (0.000)	0.000 (0.000)	0.002 (0.000) ***	0.002 (0.000) ***	−0.002 (0.001)	0.002 (0.000) ***	0.002 (0.000) ***
OCC.COMPL				0.000 (0.000)	0.000 (0.000)*	0.000 (0.000)+	0.000 (0.000)+
OCC.REL*OCC.COMPL					0.000 (0.000)***		
IND.REL*OCC.REL						0.000 (0.000)	0.000 (0.000)
Num.Obs.	65694843	65694843	65694843	63330585	63330585	63330585	63330585
AIC	−254149589.6	−254039400.3	−254017942.3	−242970752.9	−242992176.1	−242970822.1	−242863856.6
BIC	−254149461.6	−254039272.3	−254017814.3	−242970609.2	−242992016.5	−242970662.5	−242863697.0
RMSE	0.03	0.03	0.04	0.04	0.04	0.04	0.04
Cluster-robust std.err	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Regon FE	YES	YES	YES	YES	YES	YES	YES
Occ FE	YES	YES	NO	NO	NO	NO	NO

Appendix 3: *Dependent variable:* Emp = 0 to Emp > 0

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Ind FE	YES	NO	YES	YES	YES	YES	NO



Appendix 4: Interaction Plots for *Dependent variable:* Emp = 0 to Emp > 0

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One coast, two systems: Regional innovation systems and entrepreneurial discovery in Western Norway

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Abstract

This paper introduces an analytical framework for understanding how specialized and diversified regional innovation system (RIS) differ in the way an entrepreneurial discovery process (EDP) is likely to unfold. To analytically explore the proposed framework, we deploy a sequential explanatory design approach, using quantitative data to analyze the regional industry structure of the city regions of Bergen and Stavanger in Western Norway, followed by a qualitative analysis of interviews with key stakeholders in both regions. We find that the city regions face unique challenges that align with an understanding of their respective RIS categorization, providing evidence that the framework proposed serves as a useful guide in understanding the development of an EDP.

1 | INTRODUCTION

According to Foray (2015, pp. 23–24), regional industry development starts with an entrepreneurial discovery. The notion of entrepreneurial discovery can be considered an "essential phase, the decisive link that allows the system to re-orient and renew itself" (Foray, 2014, p. 495). While regions restructure their economy in different ways, in line with Foray (2015), we regard an entrepreneurial discovery to be *one* first step in the growth or restructuring of a regional economy. However, different preconditions, challenges, and opportunities are present in diverse regions and impact how regions undergo renewal and reorientation processes. Regional industrial restructuring can also be initiated by highly resourceful actors, such as in the case of large industry lead development, state lead development, and development led by external investors. However, this paper aims for a theoretical and empirical contribution of how entrepreneurial discovery process (EDP) will most likely unfold in regions with different regional innovation system (RIS) characteristics.

Recently, there has been an upsurge in policy focusing on Smart Specialization in general and, more pertinent to this paper, the EDP (Lopes et al., 2019). This focus on place-based policies which prioritize a bottom-up approach inclusive of several unique stakeholders can be considered to constitute a renewed focus on the constituent parts of a region's regional economic profile (Mieszkowski & Kardas, 2015; Rodríguez-Pose & Wilkie, 2016; Santini et al., 2016). At the same time, this focus must remain cognizant of multiple stakeholders' diverse interests within a region. This dual-challenge, which many regions face, leads some to question whether there is a need for "differentiated regional entrepreneurial discovery processes" (Isaksen et al., 2018) to be more cognizant of these particularities different regions possess. From this point of departure, this research explores whether one can incorporate an understanding of RIS in how EDP can best be operationalized and contextualized within a given region. To explore whether RIS can be used to inform how EDP will manifest in different regions, we develop an analytical framework which provides an insight into the challenges which different RISs will face through an EDP, and through a sequential explanatory design (SED), bring together quantitative and qualitative insights on two city regions (Bergen and Stavanger) in Western Norway, to explore the proposed analytical framework empirically.

The framework (Table 1) distinguishes between specialized and diversified RISs (Isaksen & Trippl, 2016). In specialized RISs the regions' industry structure is dominated by one or a few industries and the knowledge infrastructure and the policy support system are strongly adapted to the region's specialized industrial base. Diversified RISs, on the other hand, have an industrial structure consisting of many different, and relatively large industries, and these RISs also have several knowledge and supporting organizations that promote innovation activity in a wide range of economic and technological fields.

The analytical framework also considers where RIS actors find their main collaborators and knowledge sources in innovation processes and distinguishes then between regionally networked and regionalized national RISs (Asheim et al., 2019). Important innovation partners for firms in networked RISs are local universities, R&D institutes and technology transfer agencies. In regionalized national RISs, firms cooperate primarily with actors outside the region in innovation processes, and often with science partners.

On this basis, our research question is; *How are regions with specialized and diversified regional innovation systems likely to differ in their engagement with an entrepreneurial discovery process*?

It is through this that we investigate two core assumptions that underpin our research question, namely that;

(i) The development of an EDP is likely to differ between regions, characterized by specialized versus diversified RISs.

TABLE 1 Analytical framework—Expected strategy and regional innovation system (RIS) changes resulting from entrepreneurial discovery processes (EDPs) in two types of RISs

Type of RIS	Type of strategy from EDP	Changes in the knowledge application subsystem of RIS	Changes in the knowledge creation subsystem	Typical barriers for EDP
Specialized	Develop new, related industries/clusters from one/few existing regional industries	Increase collaboration between related firms regarding the use of new technology and business models, and stimulate “related spinoffs”	Establish test facilities, provide new education opportunities, etc. in new technology	Strong networks between a fixed set of local actors, hampering alternative ideas and competence
Diversified	Strengthen knowledge exchange between and diversification into emerging industries from existing regional industries	Increase collaboration between related and unrelated firms and stimulate “related/unrelated” spinoffs	Establish commercialization units and R&D- facilities targeting emerging industries	A fragmented innovation system, hindering knowledge exchange between actors of RISs

(ii) The connectiveness of RIS, regionally networked versus regionalized national, will also influence on the EDP.
(iii) The narratives surrounding entrepreneurial discovery and regional development strategies differ between stakeholders in specialized and diversified RISs.

The paper demonstrates differences between the two city regions under study. We find the Stavanger region to share several similarities with a specialized and regionalized national RIS. In contrast, the Bergen region more closely resembles a diversified and regionally networked RIS. The paper provides further evidence that the analytical framework proposed therein can provide strategies of EDPs that are more cognizant of the differences between RISs present in different regions.

2 | ENTREPRENEURIAL DISCOVERY PROCESS

Entrepreneurial discovery is a key aspect of the Smart Specialization strategy. At its core, entrepreneurial discovery assumes human agency, for example, individuals who initiate and carry out an innovation process. These individuals include entrepreneurs that start new firms and persons that perform innovation activities in existing firms. However, discoveries are also made by other actors such as organizations that provide complementary assets or deliver innovation support (e.g., research institutes and cluster organizations) to many different clients and customers (Garud & Karnøe, 2003). Herein, following Foray (2015, p. 2) EDP's include both those processes which are organized, managed, and institutionalized and those which are more continuous, occur spontaneously and constitute a less formalized EDP. It is here also that we seek to take account of how the formalized structure of the clusters within the Bergen RIS are likely to engage differently in an EDP, than that which we observe in the case of Stavanger where, given the specialized industrial structure, dominant players act outside organized regional policy processes and, in this sense, we rely on both conceptualizations of EDP in our analysis. The case of Stavanger, as discussed further below may also come to rely on the notion of "temporary or pop-up" innovation systems stemming from the work of Frenken (2017) to support the development of unrelated diversification in their EDP given the allure to current stakeholders to instead support further path dependence. This paper relies on both interviews with key stakeholders in the Stavanger and Bergen regions such as with firms, universities, intermediates, financial institutions, alongside conducting a quantitative analysis to provide a clearer picture as to how an EDP process is likely to develop given the latent differences which exists in both city regions.

The discovery itself, for example, an innovation, is the very beginning of the regional development process when seen through the lenses of EDP (Foray, 2015). The next step includes the demonstration by an entrepreneur or a firm that, for example, a new production process, is possible and potentially profitable. Demonstration supports the spillovers of the entrepreneurial knowledge to more economic actors, the entry and agglomeration of similar and complementary firms, and as a result, some form of industrial and innovation system changes that can stimulate regional development can take place, possibly making the EDP process more managed and institutionalized. In sum, an entrepreneurial discovery may result in the creation of new, or reuse of existing, knowledge for a region, which can initiate completely new economic activities, upgrade existing ones, and change parts of the RIS.

2.1 | Two types of RISs

An EDP is likely to occur differently in specific regions, such as regions dominated by different types of RIS. This reflects the fact that "in general, entrepreneurial discoveries relate to existing structures and local knowledge" (Foray, 2014, p. 498). A RIS is typically seen to consist of two subsystems underpinned by an institutional infrastructure (Asheim et al., 2019). The subsystems contain

(i) A region's industry (firms, entrepreneurs, clusters, value chains) and
(ii) The knowledge infrastructure of universities, R&D institutes, incubators, etc.

The institutional infrastructure includes formal regulations, legislation, and informal societal norms that may stimulate or hamper entrepreneurship, knowledge flow, and innovation cooperation between actors in the subsystems.

Regional innovation systems differ in many respects, and the literature contends that different types of RISs have different potentials to support entrepreneurship, innovation, and industrial growth and restructuring (Isaksen & Trippl, 2016; Njøs & Jakobsen, 2018). We distinguish between RISs based on the geography of innovation collaboration and on the state of the two subsystems, which also impacts the institutional framework's working. Regarding innovation collaboration, one type of RIS, the regionally networked ones, finds their important innovation partners mostly within the region (Asheim et al., 2019). Interactive learning among local actors characterizes innovation processes in networked RISs. Another type of RISs, the regionalized national, represents a more science driven innovation model. Parts of the industry are functionally integrated in national and international innovation systems and finds innovation partners outside the region.

We also distinguish two types of RISs based on structural characteristics of the two subsystems. The first type is *specialized* RIS. This type is dominated by one or a few industries and may have some large clusters that include the dominant industries. The knowledge and support organizations in regions characterized by a specialized RIS are, first, tailored to the regions' narrow industrial base. The institutional framework also supports the dominant industries; policies may be tuned to support the development of these industries, and the industrial culture (informal institutions) forms together with the growth of the large regional industries and become adapted to these. It is often stated that specialized RIS may experience lock-in situations (Grabher, 1993). This includes close and stable ties between regional firms, groupthink interpretation stemming from long-standing personal ties, and policy support focused on already strong industries, all of which may hamper the inflow of new ideas and knowledge and hamper industrial restructuring.

The second type is diversified RISs. These have a heterogeneous industrial structure, for example, with clusters in different types of industries. The knowledge and support organizations are also varied, including, among others, education facilities, and R&D institutes that can facilitate innovation in different economic and technological fields. The institutional framework may include a more diverse range of policy tools and a regional industrial culture that stimulates entrepreneurship and regional industrial restructuring to a more considerable extent than is the case in specialized RISs. This reflects the more extensive and more diverse exchange of ideas and knowledge in diversified compared to specialized RISs.

2.2 | Entrepreneurial discoveries in different RISs

We argue that the type of RIS, specialized versus diversified, that characterizes a region will influence various stakeholders' ideas to support future industrial development. More precisely, we contend that the proposal for EDP will differ between stakeholders in the two types of RISs. We propose in the analytical framework in Table 1 that entrepreneurial discovery type of policy in specialized RIS will aim to diversify the industrial structure by developing new but related industries; This resembles the structural transformation logic of "transition" and "diversification" in the words of (Foray, 2015, p. 25). Both logics include the growth of new activities and industries from existing but related activities and competence. These capture "both the present limits of and potential for innovation and transformation of the existing structures" (Foray, 2015, p. 26). The EDP in diversified RISs can strengthen collaboration and knowledge flows between firms in different industries and support emerging industries that employ competence from existing related and unrelated industries. Such strategies are also similar to transition and diversification but also include "radical foundation" in the words of Foray (2015, p. 26). The last logic includes the creation of new activities with no direct link to existing structures, for example, those which are unrelated to the regions industrial profile. We further contextualize this table through a case study of two different RISs in Western Norway, the city region of Bergen and Stavanger.

The analytical framework in Table 1 outlines what changes need to occur in the two subsystems of RISs to lower barriers and contribute to growth and renewal in specialized and diversified RISs. Specialized RISs that are in danger of lock-in, followed by stagnation and decline, need to increase the exchange of ideas, information, and knowledge. The framework proposes more collaboration between existing firms within the regions' few strong industries and clusters, extra-regional collaborations, and new knowledge organizations or new activities in existing knowledge organizations. In addition, some changes in the institutional infrastructure, such as policy tools to support emerging firms and industries. Diversified RISs often have several opportunities due to the flurry of research activity and entrepreneurship, which is present across several industries. A possible hampering factor can be a lack of support for new initiatives by a possibly fragmented RIS. Therefore, the analytical framework proposes stimulating collaboration and knowledge flow between several existing industries and clusters and supports diversification from new related and unrelated industries.

2.3 | Barriers as systemic and transformational failures

Entrepreneurial discovery processes should aim to lower barriers to future industrial development. Barriers to EDP in the two types of RISs proposed above can be discussed using the concepts of innovation system failures and transformational failures. The identification of systemic failures to innovation opened up a new rationale for justifying policy interventions in the economy besides focusing on market failures (Weber & Truffer, 2017). Three distinct types of innovation system failures of relevance are identified (Woolthuis et al., 2005). The first is capability failures, which involve innovation system actors such as firms and knowledge and support organizations lacking appropriate competence to carry out or support innovation activity. Such failures are likely to be found in both specialized and diversified RISs. The second is coordination failures. These include in specialized RISs, the risk of too much information, and knowledge exchange between a fixed set of actors only, which hinder the inflow of complementary and alternative ideas and competence. In diversified RISs, a lack of interactions and knowledge exchange between actors in the RIS can occur due to a fragmented and "chaotic" innovation system. Third, institutional failures occur when formal institutions (laws, regulations, etc.) and informal institutions (norms and implicit "rules of the game") hinder innovation. This may represent an innovation barrier in both types of RIS but can probably be the most severe in specialized RISs that rely much more on one or a few industries only and potential innovation failures in these can be significantly more damaging.

These system failures hinder RISs to efficiently support innovation activity in *existing* regional industries, while they do not necessarily stimulate the development of new regional industries. Therefore, "the rather static concept of system failures' (Weber & Truffer, 2017, p. 113) could be expanded to include transformational system failures understood as the failures of innovation systems to support new industries" emergence. These failures can potentially be more severe in specialized than in diversified RISs. Diversified RISs include more various economic actors and thus more related and unrelated knowledge flow than specialized RISs of similar size, which *could* hamper EDPs more in the specialized RISs. One way in which this can be overcome is proposed by Frenken (2017), wherein the author refers to a notion of a "temporary or pop-up innovation system" being useful to enable niche experimentation, which the author refers to as particularly useful in the context of sustainable transition processes. The use of such a temporary or pop-up innovation systems can help to support the development of unrelated diversification, a particular challenge which specialized RISs can face as the potential for lock-in to emerge is particularly strong in the case of a specialized industrial structure.

3 | DATA AND METHODS

3.1 | SED

This paper uses a SED approach, which allows for insights into the quantitative environment, as expressed through the regional industrial profile, to provide a richer analysis of the qualitative data into how regional stakeholders understand the future development of their region, as expressed through in-depth interviews. This paper builds on an understanding of qualitative data existing within a frame of the quantitative environment or put simply, the interviewed stakeholders (of which a full description of the interviewed stakeholders can be found in Appendix A) view the current status and future potential of the regional economy through the prism of observable regional economic structures. These structures can be expressed by quantitative data in line with an understanding of SED as expressed by Bowen et al. (2017, p. 10) namely that "The reason for collecting sequential quantitative and qualitative data into one study brings together two types of information providing greater understanding and insight into the research topics that may not have been obtained analyzing and evaluating data separately." In this sense, the analysis is focused on the integration of the quantitative environment, with the insights provided using the qualitative stakeholders' interviews to provide a clearer picture of the differences likely to emerge in the case of an EDP in different RISs.

3.2 | Case selection

The two city regions analyzed are Bergen and Stavanger, located on the western coast of Norway, located approximately 200 kilometers from one another (see Map 1).

MAP 1 Locations of Bergen (red) and Stavanger (blue)

3.3 | Bergen case study

The Bergen region includes the municipalities of Bergen and Bjørnafjorden, Samnanger, Austevoll, Sund, Fjell, Askøy, Vaksdal, Modalen, Osterøy, Meland, Øygarden, Radøy, Lindås, Austrheim, Fedje, and Masfjorden and the total number of inhabitants is 401,999 (Statistics Norway, 2020). The region differs from the Stavanger region, most notably in the prominence of its *manufacturing, construction, and wholesale and retail trade* sectors. The region's primary industries are the petroleum sector, the seafood sector, and the maritime sector. The petroleum sector is dominated by a large supplier industry, including several multinational companies. The seafood sector includes both fisheries and processing industry, but more recently, this sector has been dominated by the salmon farming industry. Several of the largest salmon farming companies in the world have their headquarters in the Bergen region. The maritime industry consists of both shipping companies, shipyards, and suppliers. Other important industries in the region are the media, financial, and tourism sectors. A key point of departure in the Bergen region is that given the varied nature of its industrial structure, as compared to Stavanger, there exists several distinct cluster projects in the Bergen region (Njøs et al., 2016).

This diversified RIS does manifest itself in a few important areas, most notably in education, where the region has a well-functioning and comprehensive knowledge-creating subsystem consisting of higher education institutions (HEIs) and various research institutions. This includes the University of Bergen, Western Norway University of Applied Sciences (HVL), Norwegian School of Economics (NHH), The Institute of Marine Research, and Norwegian Research Centre

(NORCE). Much of the activity within this knowledge-creating subsystem is directed toward supporting the region's leading industry sectors.

Moreover, the existence of a well-functioning RIS in the region is manifested through a complex set of linkages between the knowledge-creating subsystem and the regional industry. As discussed above, many of these linkages are managed through formally organized industry cluster projects. There are publicly funded industry cluster organizations for several of the industry sectors in the region, including the three main sectors (petroleum, maritime, and seafood). For a long-time, they have stimulated networking and collaboration both between industry actors and between industry actors and HEIs. Norwegian Centres of Expertise (NCE) Subsea (now GCE Ocean Technology) was set up in 2006 to stimulate innovations within the subsea segment of the oil and gas sector but have now a much wider target group focusing on different types of ocean technology. NCE Maritime Clean Tech was established in 2014 to promote green solutions within the maritime sector, while NCE Seafood was set up in 2015 to encourage sustainable development within the seafood sector. One of the main aims for these cluster organizations is to ensure the development of research-based innovation through close collaboration with HEIs and R&D institutions (Njøs & Jakobsen, 2016, 2018). Several of the HEIs in the region are also members of these industry clusters. In addition, there are also cluster organizations in the region initiated by the largest HEI. The University of Bergen has developed "knowledge clusters" to promote knowledge sharing and collaboration with regional industry actors, public administration, and cultural and societal entities. This includes a healthcare cluster, a marine research cluster, and an energy and technology cluster, but also other constellations (University of Bergen, 2019). There is also the NCE Media Cluster, set up in 2014, in close collaboration between the University of Bergen and the key media firms in the region. The media cluster represents a hybrid between a knowledge cluster promoted by an HEI and a public-funded industry cluster. Given that Bergen has a number of industries and several HEIs in which an EDP could prioritize, it serves as a pertinent example of how a diversified RIS can engage with a bottom-up approach, and this development of formally organized cluster projects in the case of Bergen constitutes an important difference between the two city regions, and could help to explain the differences which have emerged in recent decades between the two city regions as the development of such clusters is not such a feature in the case of Stavanger.

3.4 | Stavanger case study

The Stavanger region includes the municipalities of Stavanger, Sandnes, Sola, Klepp, Hå, Time, Strand, Gjesdal, Randaberg, Rennesøy, Finnøy, Forsand, and Kvitsøy, with a total number of inhabitants of 348,990 (Statistics Norway, 2020). The Stavanger region has traditionally focused on one industry—which was similar in many respects to the case of Bergen. In Stavanger, in a historical sense much of the focus has been on the herring and related canning industry, however in recent decades the focus shifted to becoming the "oil capital" in Norway which refers to the dominance of the oil and gas sector within the regional economy and the presence of national headquarters of several large oil and gas firms. The change to a clearer focus on oil and gas came into existence with the establishment of offshore petroleum activity in the late 1960s and "has since evolved through an interplay between petroleum firms, suppliers, large R&D institutes and universities, and supportive policies" (Andersen & Gulbrandsen, 2020, p. 5). Stavanger has increasingly specialized in its industrial structure on the oil and gas sector, whereas Bergen's diversified industrial structure has provided the impetus for the formation of distinct cluster projects centered around the different industries present in Bergen.

Several institutions were established in the Stavanger region following the discovery of oil and gas deposits in the North Sea, which was made official in 1969. These institutions were created specifically to develop this industry within the regional economy. Andrews and Playfoot (2014) observe that relatively quickly, the region and at the national level in general, there was a drive to establish the skills, demands, and industry requirements necessary to build an internally stable workforce (Andrews & Playfoot, 2014, pp. 1–15). The supportive policies that emphasized "positive discrimination" toward Norwegian companies during the industry's build-up further fueled the development of the region's industrial structure (see Solheim & Tveterås, 2017, pp. 906–907). It led to a situation whereby the region was primarily focused on the extraction of oil and gas from the North Sea, and much of the regional industrial structure coalesced around this industry, and a process of specialization developed (see Figure 4). For this reason, Stavanger provides a useful example of a specialized RIS in operation and given its national character with regard to policy support and knowledge infrastructure and self-propelling growth, a clear rationale for the creation of formally organized regional-oriented clusters did not exist, as we can see in the case of Bergen and as such the creation and management of clusters is less so a feature in Stavanger as in Bergen. The national character produces a situation that leads Stavanger to rely to a greater extent than Bergen on externally produced knowledge and in the sense of knowledge production Stavanger could be considered more a case of a regionalized national innovation system, while Bergen more closely resembles a regional networked innovation system (Asheim & Isaksen, 2002, p. 84). We can see that while the upgrading of the former University College in Stavanger (Høgskolen i Stavanger (HiS)) to University status in 2005 has led to a greater role being played by the University in the local RIS, it is focused largely on oil and gas research has however led to continued reliance on the more national and international level HEI's to play a large role in industry-HEI interactions within Stavanger. As such the conceptualization of Stavanger as regionalized national RIS is understood as one with a regional concentration at the industry level but still relies to a large extent on interactions with HEIs at the national and international level. Stavanger as such, has, as said, traits that resemble a regionalized national RIS (Asheim & Isaksen, 2002). This entails "regional clusters where the knowledge providers stimulating firms' innovation activity mainly are found outside the region" (Asheim & Isaksen, 2002, p. 84). Given that there exists an advanced and specialized HEI focus in Stavanger with the oil and gas industry (see Figure 3), we see that there is a strong degree of engagement from HEI in Stavanger with the wider regional industrial actors as discussed further within Ahoba-Sam (2019). Ahoba-Sam (2019) highlights that the linkages between researchers and local actors proliferate due in part to conditions in the region, namely that "The region seems to provide relevance for their research areas and provided a platform to engage in problem-solving efforts with regional industries" (Ahoba-Sam, 2019, p. 261). However, in the case of knowledge linkages, specifically so in the oil and gas industry within the Stavanger region one must conceptualize the early and ongoing linkages as those which have been to a large degree extra-regional, namely to other parts of Norway such as with both Norwegian University of Science and Technology and its applied research arm, SINTEF.

3.5 | Quantitative approach

Two data sets were constructed for both Stavanger and Bergen, respectively, to allow exploratory analyses to be undertaken. The Stavanger region data set was constructed based on 461 industry-level unique observations, and the data set for the Bergen region contains 313 industry-level unique observations for the year 2016, with the difference stemming from differing representation across industry subgroups, a full list of industry subgroups can be found at Statistics Norway (2008). Occupations are categorized by Statistics Norway's general industry classification (SN2007), which allows for comparability between the two regions.

The primary variables used in this exploratory analysis of the differing regional economic structures are the concepts of ***relatedness*, *location quotient*,** and ***complexity*** and using these variables it becomes possible to more manifestly outline how the EDP in the differing RISs is likely to unfold.

Our measure of ***relatedness*** is computed in line with Hidalgo et al. (2007) approach to understanding relatedness. In this paper, relatedness is understood as two activities, such as products, industries, or research areas that require similar knowledge or inputs (Hidalgo et al., 2018, p. 452). Relatedness can be understood as a form of a risk assessment, where a high degree of relatedness in a region can be understood as containing a high likelihood of success in entering new activities, be that technology, products or industries, and vice versa, a low degree of relatedness indicating a higher likelihood of failure in entering new activities.

The Computation of ***location quotients*** (***LQ***) for both regions is constructed to capture the specialization within a given region in relation to the national context. LQ is used to compare the share of a sector in the local economy in relation to the average employment observed in the broader national economy. A value above one indicates a revealed comparative advantage within the region. The use of relatedness and LQ allows for a broad analysis of the potential for prioritized activities within an EDP to take root and be successful, given the industry's linkages to the regional industrial profile.

We also compute ***complexity*** values (as per Balland et al., 2018; Balland & Rigby, 2017; Deegan et al., 2021) within each industry as organized according to Statistics Norway's general industry classification (SN2007). In order to better understand the potential of industries within both city regions, we constructed a variable called *indregmeancomplexity*, which calculated the mean complexity within each given region based on occupational skill complexity in line with Caines et al. (2017) and Neffke et al. (2017). A complex occupation can be considered to be those which are based on ones "ability to abstract, solve problems, make decisions, or communicate effectively" (Caines et al., 2017, p. 1), and is considered an important dimension to use in tandem with the concept of relatedness (Balland et al., 2018).

Alongside relatedness and complexity, and with the aim being to capture those activities which are both large and potentially influential in a region, we also compute a value which we call ***shareregemp***. We use *shareregemp* to capture the share of regional employment, which a given industry consists of within both city regions. At the same time, this value can be used to better contextualize the given size of employment in both regions and point us toward the dominant employers within the regions.

3.6 | The qualitative approach

Based on previous studies by the authors, key stakeholders in Bergen and Stavanger have been identified with the intention to select stakeholders from the private and public sectors and in positions to be well-informed on regional industry development challenges. In total, 22 stakeholders were selected (11 in each region). The interviews with these stakeholders were conducted in 2018, using a semi-structured interview guide that emphasized regional restructuring, explored the stakeholders' perception of ideas for future specialization, and identified opportunities and obstacles for future growth areas.

The Bergen case comprises six industry actors, two representatives for higher education institutions (HEIs), one intermediate organization, and two policy actors. The Stavanger case consists of eight industry actors, two intermediates, and one policy actor (see Appendix A).

The interviews lasted between 45 min—one and a half hours and were recorded and transcribed. Inductive constructivist thematic analysis (as per Braun & Clarke, 2006) was conducted on the transcribed interview material. This enabled us to extract and construct patterns of meaning from the data material (as per Solheim & Moss, 2021; see Staller, 2015). Herein the data were categorized based on extracting meaning concerned with the key stakeholders' perception of future regional industrial development.

3.7 | The usefulness of the analytical framework

In line with the discussion above on the development of an analytical framework, which culminates in Table 1, what follows below is a discussion rooted within the SED methodological approach into how Table 1 provides an insight into how these concepts interact through a case study of two city regions. With descriptive statistics, based on the computations of the variables discussed above, we first explore the empirical situation in which both regions exist and provide further evidence into the respective classifications of Bergen and Stavanger. Following the contextualization, we then explore how stakeholders across the differing dimensions, as contained within Table 1, are likely to engage with a bottom-up approach and how this engagement could be understood and operationalized in different RISs. It is here which we provide a richer insight into how EDPs are likely to interact differently with different RISs as expressed through the cases selected.

4 | RESULTS

4.1 | The empirical situation

The Stavanger and Bergen city regions differ markedly across several of the key variables we outlined above, and here we provide an insight into how these differences manifest. Across all the plots, different industrial subgroups are contained within the broader industry classifications, leading to different variables within the same broad industry classification. As we can see in Figure 1 below, Bergen has a number of industries wherein it has an ***LQ*** which is above one (and in many cases significantly above 1) and, as such, could be considered a region which is uniquely concentrated in a number of industries when compared to the national average, thus indicating a potential revealed comparative advantage across several industries. In contrast, for Stavanger, the specialized nature of its RIS can be observed by the high degree of employment contained within the uniquely concentrated industry of mining and quarrying (constituting the oil and gas sectors) and much smaller industries (as measured by their share of employment) which appear to have a revealed comparative advantage. Through the analysis of the LQ in both regions we are more clearly able to identify and express the differences which exist in both regions, and are better positioned to identify the different industrial structures, not least in how the different structures influence the motivation for cluster formation. We can also use the LQ to more clearly support

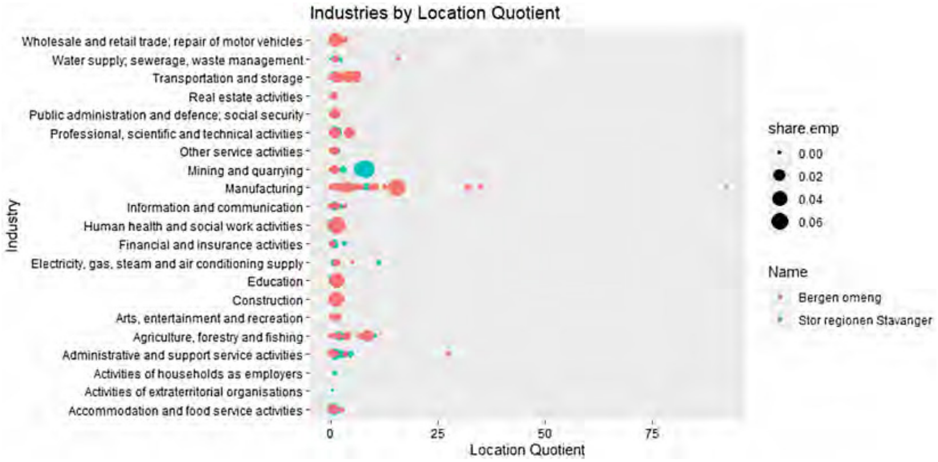

FIGURE 1 Industries by location quotient

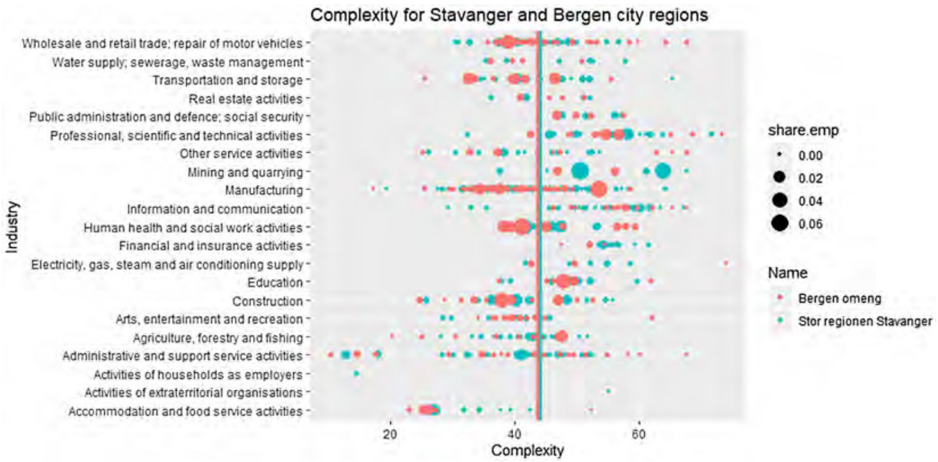

FIGURE 2 Industry regional mean complexity by industry

the argument that the difference in the respective regions is likely to produce divergent outcomes with regards to the EDP of both regions. An important point here is that the use of the LQ helps to identify the starting position of the regions in engaging with the EDP more generally, but given both the ongoing nature of the EDP and it is the recency of the process in both regions, it is not yet possible to identify the outcome of the EDP on the region's economic and industrial structures.

We can similarly see a trend emerge regarding the ***complexity*** of the industries within both city regions (expressed in Figure 2), where industries are represented by their level of complexity, with the vertical axis outlining the average complexity within both city regions. We observe that complex industries largely dominate in the Stavanger city region, with a high share of employment industries of *mining and quarrying*, with support industries such as *Professional,* *scientific and technical activities*, and *information and communication* being sizable with regards to their share of employment and being quite complex industries. This pattern is apparent across all the variables we used to explore the differing regional economic systems. However, looking at Bergen, we can observe a different dispersion of complex industries from the case of Stavanger. We see that while the level of complexity differs across relatively large industries, such as; within *construction, human health, and social work activities, and manufacturing*, the picture is much less clear with regards to being overly dominated by a single large and complex industry such as is apparent in Stavanger with regards to mining and quarrying. The complex industries' dispersion is quite close on average, with Stavanger's average complexity value standing at 44.00 versus the average complexity of Bergen's industry standing at 43.68 out of a possible 100, with 100 representing the maximum level of complexity and 0 the minimum.

We observe the differing structures of both city regions regarding the share of employment within different industries (Figure 3). The presence of differing dominant sectors points toward a need for further analysis within the qualitative stage of this paper into how the different industrial structures impact a region's EDP. Of particular note is the *mining and quarrying* sector within Stavanger, and the *manufacturing* (including several different branches), respectively within Bergen, which further expresses the difference which one can observe across the different RISs of Stavanger and Bergen.

A similar story also emerges when looking at the differences between the two city regions with regards to the ***relatedness*** of the regions' industries. Stavanger is dominated by industrial subgroups, which are contained within the *mining and quarrying* industry, alongside those subgroups which are contained in ancillary industries such as *professional, scientific, and technical activities* alongside *construction* (Figure 4). The relatedness of industries within Stavanger is on average higher than observed in the Bergen region (27.16 vs. 25.05 in Bergen), which supports Bergen's classification as a more diversified region. However, notable exceptions exist within *transportation and storage, manufacturing*, in addition to *agriculture, forestry, and fishing*, and within *construction*, as we likewise can see within Stavanger. This finding with regards to the relatedness with other domains in Stavanger conforms to what we see discussed within Herstad and Sandven (2017), that the challenge for the region stemming from this "is to ensure that ideas, information, and knowledge generated within

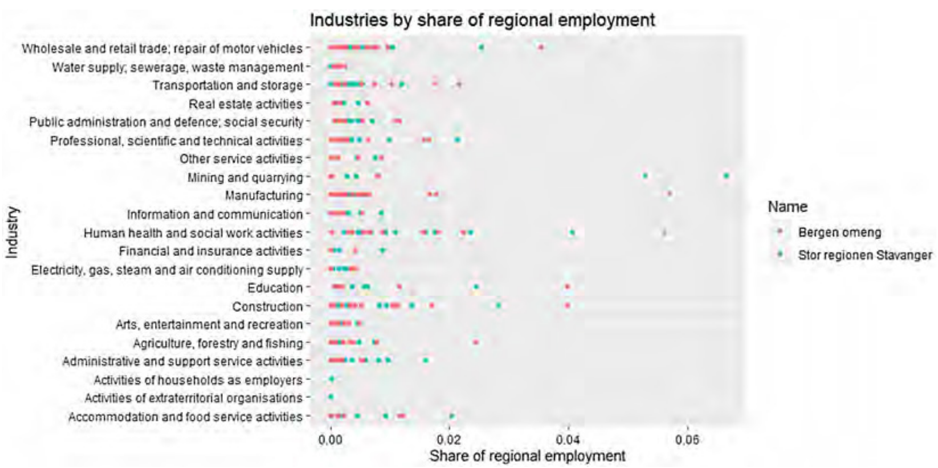

FIGURE 3 Industries by share of employment

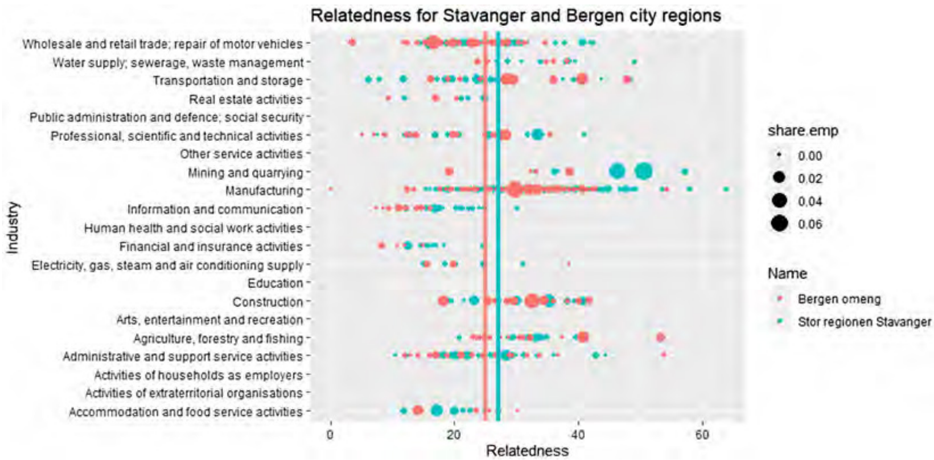

FIGURE 4 Industry relatedness by city region

the oil & gas sector spill over into the broader economy and benefits activities beyond those directly associated with oil & gas extraction. This points to the importance of active intervention through RIS construction" (Herstad & Sandven, 2017, p. 123) and furthermore conforms to a notion of Frenken's "temporary or pop-up innovation systems" which we argue could be particularly useful in the case of Stavanger to support niche experimentation (Frenken, 2017).

4.2 | Two different narratives

While in the empirical situation as discussed above, we have sought to add further context in which the qualitative data can be understood, what follows here is an analysis of the usefulness of the analytical framework based upon the qualitative data. We interpret the interviews' results in line with the analytical framework, as outlined in Table 1 above. Furthermore, we compare the results between the different regions to better answer the research question.

4.3 | Changes in the knowledge application subsystem

4.3.1 | Bergen

The stakeholders we interviewed in Bergen expressed considerable consistency regarding the vision for the regions' future. Most of the stakeholders argue that diversification is the right way forward. In other words, in Bergen, firms should look for new markets that are not very different from their existing market, which is in alignment with Table 1.

As an example, a representative for the petroleum sector provides this insight into the thinking around the use of enabling technologies which serve as a conduit between different sectors: "*We introduce our companies to new markets. Particularly related industries, according to the theories. And then there is aquaculture, renewable energy, and deep-sea mining. We use subsea technology as an enabling technology to get it done.*" (BE5).

A representative from the maritime sector further echoes this: "*I think the broader value chain is something we will live from in the future, and there are many firms that are entering new markets gradually, for instance, aquaculture and fisheries. Our firms are very adaptable*" (BE6). Moreover, a representative from the regional authorities states the following: "*So it is in a sense in our 'smart specialization thinking' that we are going to adapt and develop the interfaces of fisheries, salmon farming, the energy sector, the oil and gas sector, shipping, but also agriculture and tourism. We are so lucky in our region that we have several legs to stand on. When one industry has a tough market situation, others can have a rise. Working on interfaces between industries has become such an important part of our regional policy*" (BE9). Building on this, we echo that diversified regions have many legs to stand on and as such can move relatively more fluidly between industries to identify areas for prioritization in the region; however, of particular concern to regional authorities is precisely this increased collaboration between several stakeholders, in line with Table 1 above.

Among the stakeholders, less focus is placed on developing industries that are new to the region. The argument for more radical diversification mainly exists among representatives for higher education institutions. One of which states: "*I think it is crucial that the region also develops other legs to stand on when it comes to business. Not least, smart technologies, disruptive technologies, and ICT are central. It is important that we take as a starting point the fantastic industry structure we have in our region, but existing industry structure should not restrict our ambitions and how we need to develop*" (BE11).

4.3.2 | Stavanger

Differing considerably from the structure in Bergen is the understanding of the dominance of the oil and gas industry in Stavanger and its considerable importance to the regional economy. This understanding conforms considerably with that which one would expect to exist in a region with a specialized industrial structure. One of the stakeholder's states that, "*I think that the oil and gas industry will be the most important industry in a long, long, long time. I think so. That is going to be our main thing. But what I believe is that new technology will come. We have always been able to readjust our technology. We have a supplier sector that no one else has that is incredibly creative. I think that we will work like crazy to make the oil and gas industry greener, less emissions, make products that make it more viable*" (SV5).

As emphasized in the quote above, several of Stavanger's stakeholders emphasize a belief that the oil and gas industry will remain the largest component of the regional economy into the future. The use of technology developed specifically within the oil and gas industry being applied to other industries has also been highlighted, as well as the "greening" of the industry, which is similarly a concern echoed within Bergen. However, in the context of the specialized RIS which exists within Stavanger, stakeholders have also argued in favor of "green restructuring" within the already existing oil and gas industry, such as when the same stakeholder as above emphasizes that; "*We have a social responsibility to continue to deliver green oil. We can say it like that, green oil and gas*" (SV5). Along similar lines, the downturn of the oil price, as well as increased emphasis on a "green shift" (Njøs et al., 2020) has led to a subsequent "rebranding" attempt of Stavanger from the "Oil capital" to the "Energy capital" of Norway which can be considered an attempt to emphasize this shift.

A number of stakeholders interviewed express concern for the future of Stavanger; given the broader change which we can see within the oil and gas sector, one such stakeholder expresses doubts over the viability of the aforementioned "rebranding" attempt and the broader issues facing Stavanger: "*I don't know what it will look like, but I hope we have found our new identity. Because we are in mind, heart, and soul, an oil and gas region, and that is what we are known for. But we now talk about the energy region. We don't own that as wholeheartedly as we did with oil and gas*" (SV1). This concern over the potential decline of the dominant industry within a specialized RIS and the region's prospects following the transition away from this industry sheds some light on the unique issues that specialized regions will likely face in an EDP and shows that some stakeholders in Stavanger are skeptical of whether increased collaboration, in line with Table 1, can be achieved to re-orient the regional industrial profile.

An issue that is made apparent in the interviews, concerning diversification is that "*the systems are weighted incorrectly to the advantage of established structures*" (SV3) and that "*In the past, we have seen that it is hard to keep up the restructuring-agenda if it is going too well in a region*" (SV6), this is a particularity which is likely to afflict those RIS which are more specialized, as there may exist less room for maneuver among stakeholders. The high wages that exist in the oil and gas sector within the specialized RIS of Stavanger could serve as a poisoned chalice to the region and have long-lasting consequences on recruitment and the labor market more generally (Fitjar & Timmermans, 2017). We can similarly see this challenge expressed by a stakeholder who states that "*the worst that can happen now is an upturn in the oil price. Then people are vacuumed back, and restructuring processes in Statoil, Aker, Aibel, and others will be reversed*" (SV5), within this quote we can see the crux of the issue for a specialized RIS in the knowledge application subsystem, namely that the dominant actors within the system may siphon off much of the potential for a gradual transition within the region, due in part to their ability to "vacuum" off much of the impetus for such a change to occur.

4.4 | Changes in the knowledge creation subsystem

4.4.1 | Bergen

We can observe that a number of the stakeholders argue for a "regional fit" between the knowledge creation and knowledge application subsystem: "*There is the need to link business restructuring and changes in businesses, closer to changes in the education system. So, transition in business is also transition in universities*" (BE9); this observation aligns closely with the analytical framework in Table 1, to focus more on commercialization. Similarly, other stakeholders build on this need for change within the knowledge creation subsystem, wherein they state that "*We need to make changes in our education programs to adapt them to the changes ongoing in our region. So as a higher education institution, we are keen to be close to the region that we serve.*" (BE10).

Still, one of the main challenges seems to be to establish a better link between the two subsystems, which could be considered one of the main requirements for a well-functioning RIS. One of the stakeholders, representing an intermediate organization, says: "*It is clear that we have a strong academic environment on one side and a strong business environment on the other side. But there should be a bridge between them, between the production of knowledge and the use of knowledge. We are strong on both sides and must work on how we can achieve the best possible exchange*" (BE4). One of the industry representatives has a more specific focus on making the ongoing research activities in HEIs more relevant for the industry: "*What we work for here is, after all, is to promote industry-driven research. We try to work towards academia and to get research projects in academia that the industry really needs*" (BE5). This observation of greater collaboration between the knowledge-creating subsystem and industry closely aligns with that which we propose in the analytical framework in Table 1.

Different initiatives and strategies have been launched in the region to strengthen the collaboration between academic institutions and the industry. As put forward by one of the HEIs in the region: "*When it comes to education, research and innovation, the knowledge clusters that we work with are perhaps the most important in terms of interaction. Media City is a brilliant example of how we try to interact with local, regional, and international industry actors. Some of the success criteria are that we see much more collaboration between our students, researchers, and industry actors manifested through joint projects, joint applications, increased revenues, and so on and so forth*." (BE11).

A characteristic of Bergen is a strong presence of cluster organizations. As illustrated in the presentation of our cases, there are public-funded cluster organizations mobilizing for R&D and innovation within all the region's main sectors (petroleum, seafood, maritime, and media,). Most of them have been initiated by the industry, while HEI's has been pivotal in the development of others (such as the NCE Media Cluster). Thus, the ideas of cluster formation are actively used to promote sound and sustainable economic development of the region (Njøs et al., 2020). The advantage of this is that these formally organized units give a potential for developing a coherence strategy and common vision for each of the clusters. However, a potential drawback is that you get several organizations promoting regional industry development, and it can be difficult to coordinate their effort and avoid duplication and inefficiency, as outlined in table 1. There is also the need for coordinating regional and national initiatives (Njøs et al., 2020). A representative from the subsea industry argues: "*It is clear that the system here and the system nationally suffers from being, I almost called it, the chaos of many small benefactors. Very often, each of them is too small to really make the big difference and take on the big responsibilities. I have made myself a strong advocate for these superclusters to optimize the system and get better profit*" (BE5).

There is a need for enhanced coordination within the region to overcome a potential challenge faced by diversified regions, namely poor coordination of actors. To overcome this coordination problem that diversified RISs face, one representative for the regional authorities' states: "*We want to have broad ownership around the strategic direction. We cannot sit here and decide, and then nobody cares. That is why we must work very closely in partnership with universities and the industry, and we also need to mobilize the inhabitants*" (BE9). Within this understanding of the regional authorities' role, we can see the integration of an EDP logic, in which diversified RISs are likely to focus on knowledge exchange among different types of stakeholders.

4.4.2 | Stavanger

As the HEI and research institutes in Stavanger were developed to provide teaching and training primarily for the oil and gas industry, the tension of future development and establishment of new courses is mentioned and captured by one of the stakeholders: "*It quickly turns into a chicken and egg discussion concerning if one should offer an education on jobs that do not exist today. Or is so that when one educates people within new areas, then something new is created because one has new knowledge that is being distributed that makes that one creates new dynamics. Bergen, for example, has not experienced the oil crisis the same way as us because they are more diversified, they have broader industry and industry basis. That is why they were not hit as hard by the crisis as we were*" (SV6): It is, in fact, the case that the knowledge creation subsystem within Bergen is much more developed and offers more education opportunities when compared to Stavanger, whether this is because of the diversified nature of the RIS present there, or instead, whether the presence of this knowledge creation subsystem instead spurred the development of a diversified RIS is outside the remit of this paper, however it does pose some pertinent questions pertaining to the potential shortfalls of the knowledge creation subsystem within the more specialized RIS of Stavanger, and open up a discussion on what this may in fact signal to the potential areas for which the region can prioritize in a likely EDP.

The importance of local knowledge-creating institutions, however, is expressed by one stakeholder, who signals toward the importance of the university and technology transfer office (TTO) "*If the idea does not come from University of Stavanger, or Validé (TTO), they struggle a lot. Not invented here syndrome*" (SV8). This importance of particular nodes within the knowledge creation subsystem (in this case, the primary university within the region and a TTO) may signal the broader issue of resistance to external pressures and influences on the knowledge creation subsystem within the RIS of Stavanger and point toward a real need to establish test facilities, provide new education opportunities, etc. in new technology in line with that which is proposed in Table 1, to overcome these shortfalls. Similarly, and as mentioned above, this focus on internal sources of innovation being privileged does provide a particular paradox, given that much of the knowledge linkages within the dominant sectors of oil and gas, are indeed extra-regional, largely toward SINTEF and NTNU which are in Trondheim.

4.5 | Barriers to change

4.5.1 | Bergen

Several barriers to future change and upgrading of the RIS were reported throughout the stakeholder interviews. For instance, it has been argued that there is a specific resistance toward change; the focus on traditions is referred to as a potential blind spot: "*Our well-established companies in the region, they are struggling a little to somehow see that here are major changes going on. I must say, I might be a little worried because their emphasis on traditions and can blind them.*" (BE2). A HEI argues that the region needs to focus more on upgrading its industrial competence: "*It is a concern that the business sector in Norway to a much lesser extent than Germany, France, and Italy hire people with PhDs. It worries me that we may not have what it takes to drive a knowledge-based change in the industry. We need to succeed in a transition from a resource-based to a knowledge-based economy*" (BE11).

In addition, several stakeholders point toward the lack of venture capital as one of the main barriers to future change; "*Our biggest challenge to succeed in restructuring is a lack of capital. The oil will come to an end, and that the level of investment in other and newer sector has a challenge in matching the oil companies' large investment budgets. So, the gap there is important to be aware of.*" (BE3). A specific focus on the need to promote further growth among newly established firms with international potential was also highlighted, and a lack of capital constituting a primary challenge for these firms: "*We need to develop the ecosystem to become a growth-based ecosystem that can truly develop and scale up new international export-oriented companies. So how do we develop the ecosystem to be that scalable? I feel we here have a missing component.*" (BE7). These challenges contribute to a particular barrier to change which can exist within diversified RISs, namely that of a disjointed or fragmented innovation system hindering knowledge exchange and leading to persistent and debilitating coordination problems in the RIS (Mueller-Using et al., 2020).

4.5.2 | Stavanger

The case study highlights several barriers to change that are concerning what could be considered "conformity-seeking"-behavior (Isaksen et al., 2018). This conformity-seeking behavior was exemplified by what one stakeholder refers to regarding risky investments and access to capital for start-ups, that the institutions are "*not doing it at all. The structures are security-seeking*" (SV3). This risk-aversion strategy flows logically from a specialized RIS, wherein a dominant player constitutes a safe investment; this is expressed by one stakeholder who states that "*We are not good at taking risk on new technologies in new areas besides oil and gas. It costs a lot, a lot more than the old, safe." (SV5).*

The issue of risk-aversion and conformity-seeking behavior is not necessarily a novel insight. However, the focus within a specialized RIS on those safe issues constitutes a considerable risk for the region, is in becoming overly dependent, and hampering alternative ideas and competence. The issue in the region, as stated by one stakeholder, is "*capital. Capital to dare to take risks on things that one does not know. One is good at taking risk on oil and gas companies because one knows that, one understands that market, one has earned money in that market in the past. But to dare to take risks in foreign areas…*" (SV5). The importance of personal networks also becomes apparent in the identification of opportunities for investment, given the dearth of other options for investors and for new firms "*It is hard to find an optimal match between investors and start-ups. There is no suitable arena where you meet investors, you go to neighbours and friends*" (SV3). This point further underscores the role of informal networks, and speaks to a typical trait of specialized RIS wherein there is increased importance attributed to close and stable ties (Grabher, 1993). This focus on close ties, which in certain situations may be beneficial, the threat in a specialized RIS is that they could lead to an emphasis being placed on path-dependent industrial development and focus too much on already existing knowledge and industries, this focus on those activities which are already existing and seek to further develop rather than build on from is expressed by one stakeholder who states that "*The closer to the dock you are, the lower our risk. We are terrified of Forus,*[1] *they are far from the dock, and are primarily concerned with administration, that might as well be located in Houston*." (SV10). Building on from this focus on prioritizing what one knows to the detriment of what one does not, a representative from a financial institution state that "*If it is a family we have known for several years (…), they fix it, and we are in. But if it is an Olsen that we do not know, we say no. That is probably the case for other banks as well*" (SV10). This focus on prioritizing what one knows, while on the surface may appear logical and consistent, poses a risk to the specialized RIS of Stavanger moving out from over-reliance on a dominant sector, which, although dominant now, very much has limitations (in both a physical sense, but also in line with trends toward a green transition). We can also see an over-concentration being referred to by one of the stakeholders, and hints toward a "pile-in" effect occurring, where those sectors which are dominant are receiving the lion's share of the investment within an area, thus leading to further and further concentration to the detriment of those areas where capital and investment is much scarcer "*We cannot be with everyone. That is why we choose our known ones. The ones that have much, receive even more*" (SV10).

5 | CONCLUSION

This paper utilizes a SED approach deployed on two city regions located on the western coast of Norway. The design allowed us to carefully examine how differing RISs are likely to engage with an EDP to address future regional industrial development. The research was motivated by the twin aims of answering whether: (i) the development of an EDP is likely to differ between regions, characterized by a specialized and regionalized national RIS versus a diversified and regionally networked RIS and (ii) the narratives surrounding entrepreneurial discovery and regional development strategies differ between stakeholders in these specialized and diversified RISs.

The paper analyses data gathered on the quantitative regional economic profiles along the dimensions of industrial relatedness, the share of regional employment, skill complexity, and location quotient. We then combine this quantitative data with interviews with key stakeholders based on an analytical framework (as outlined in Table 1) for incorporating how differing RISs interact with EDP targeted at regional industrial development.

By applying the analytical framework with empirical data as outlined using the SED methodological approach, we found that in the case of specialized and regionalized national RISs, stakeholders remain cognizant of the dominant role of the dominant sector within the regional economy. However, there are notable differences among stakeholders' narratives about this dominance's merits or demerits. While some identify development stemming from this dominant sector as the direction the regional economy should seek to develop, others see a greater need to focus on new industry development to mitigate the potential risk of overreliance. Juxtaposed against this in what can be considered a more diversified and regionally networked RIS, such as that which we observe in Bergen, we can see a greater focus being placed on improving the linkages among the differing stakeholders and a focus on how best to build relationships within the RIS, alongside an understanding of the merits as expressed by policy actors that a diversified RIS has “a number of legs to stand on.” The differing narratives between stakeholders within different RISs conform to an understanding of not just how the stakeholders assume change will take place but more broadly inform the policy options pragmatically available to the policy actors within the RIS, given these narratives are rooted in an understanding which we have explored with quantitative data on the regional economic profile of the different RISs.

With regards to the policy changes that one would assume are likely to take place within the different RISs, the clarity on the differing narratives aids in understanding which policy options are both likely to be pursued in an EDP. Within the specialized RIS of Stavanger, we are likely to see a push for change in the institutional infrastructure, which is focused on building clusters in related, emerging regional industries, as this provides the impetus for the RIS to mitigate the overreliance on a dominant sector, while at the same time, mitigate another serious risk, of moving too far from established industries and potentially stretching too far from its current activities. While in the more diversified RIS, we are likely to see this diversity in the regional economic profile be further embraced and centralized by the relevant policy actors, wherein the logical extension would be to focus policy on strengthening the diversification of a regions industry mix through seizing upon opportunities of developing new industries and markets at the intersection between existing industries.

With regards to the limitations of this study, one notable limitation is the use of Norwegian data, which, while rich in it is depth, may face limitations with regards to the generalizability of the study. However, by contextualizing Norwegian data in the broader context of the RIS literature, we have sought to mitigate this limitation, as while the scale of the differences in RISs may be apparent between more disparate regions, the degree to which this difference is likely to exist between two regions within the categorizations of specialized and diversified RISs is unlikely to impede further studies. While the limitation does serve to restrain this study, it also provides ample space for further research to test the analytical framework in different contexts and to empirically explore the framework in the context of different methodological approaches and across different regions. Another limitation and opportunity for future research which this paper provides is for a fuller analysis as to the outcomes of the EDP in the respective regions. While the authors note that this is an emerging practice, which is hampered by the recency of many regional EDPs, it does provide scope for further research on how the different RISs produce different outcomes from their EDP.

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CONFLICT OF INTEREST

No conflict of interest has been declared by the authors.

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ENDNOTE

[1] Forus is an industrial park located approximately 10 km south of Stavanger and is one of the main locations of administration and hosts the headquarters of several multinational firms.

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APPENDIX A

OVERVIEW OF STAKEHOLDERS

Identification number	Region	Type of stakeholder
BE1	Bergen	Industry actor
BE2	Bergen	Industry actor
BE3	Bergen	Industry actor
BE4	Bergen	Intermediate
BE5	Bergen	Industry Actor
BE6	Bergen	Industry Actor
BE7	Bergen	Industry Actor
BE8	Bergen	Policy actor
BE9	Bergen	Policy actor
BE10	Bergen	Higher Educational Institute
BE11	Bergen	Higher Educational Institute
SV1	Stavanger	Intermediate
SV2	Stavanger	Intermediate
SV3	Stavanger	Industry actor

Identification number	Region	Type of stakeholder
SV4	Stavanger	Industry actor
SV5	Stavanger	Policy actor
SV6	Stavanger	Industry actor
SV7	Stavanger	Industry actor
SV8	Stavanger	Industry actor
SV9	Stavanger	Industry actor
SV10	Stavanger	Industry actor
SV11	Stavanger	Industry actor

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Searching through the Haystack: The Relatedness and Complexity of Priorities in Smart Specialization Strategies

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abstract

This article examines which economic domains regional policy makers aim to develop in regional innovation strategies, focusing in particular on the complexity of those economic domains and their relatedness to other economic domains in the region. We build on the economic geography literature that advises policy makers to target related and complex economic domains, and assess the extent to which regions actually do this. The article draws on data from the smart specialization strategies of 128 NUTS-2 regions across Europe. While regions are more likely to select complex economic domains related to their current economic domain portfolio, complexity and relatedness figure independently, rather than in combination, in choosing priorities. We also find that regions in the same country tend to select the same priorities, contrary to the idea of a division of labor across regions that smart specialization implies. Overall, these findings suggest that smart specialization may be considerably less place based in practice than it is in theory. There is a need to develop better tools to inform regions' priority choices, given the importance of priority selection in smart specialization strategies and regional innovation policy more broadly.

Key words:
smart specialization
regional policy
complexity
relatedness
innovation policy
European cohesion policy

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In recent years, smart specialization has become the dominant approach to regional innovation policy in Europe. Smart specialization is a place-based approach to economic development policy, characterized by the identification of strategic areas for intervention and based on an analysis of the strengths and potential of a regional economy (Tödtling and Trippl 2005; Foray, David, and Hall 2011; Foray 2015; Asheim, Grillitsch, and Trippl 2016; Rodríguez-Pose and Wilkie 2016; Balland et al. 2018a). This identification of priorities should target economic domains where regions have the greatest potential to develop competitive advantage. Thus, smart specialization seeks to ensure the focus on those sectors or economic domains embedded in the region and related to its existing strengths.

For higher-level authorities, this helps to avoid unnecessary duplication across regions within their territories (Foray, David, and Hall 2011; Hassink and Gong 2019). Indeed, early evaluations show much heterogeneity across regions in their priorities, potentially reflecting the achievement of this aim (McCann and Ortega-Argilés 2016). Furthermore, contrary to what its name might suggest, smart specialization is not about promoting further specialization in existing clusters, but rather a policy to promote diversification into new economic domains.

Of course, assessing the potential of a region to succeed in developing a new economic domain is a difficult task. However, the regional studies literature widely acknowledges that relatedness and complexity may provide a useful basis for the design of smart specialization policies (Boschma 2014; Boschma and Gianelle 2014; McCann and Ortega-Argilés 2015; Balland et al. 2018a). Following the related diversification literature, the likelihood of success is higher in economic domains closely related to the existing economic structure of the region (Neffke, Henning, and Boschma 2011; Essletzbichler 2015). Meanwhile, competition from other regions is lower in more complex economic domains where succeeding is comparatively more difficult (Hausmann, Hwang, and Rodrik 2007). While an abundance of papers advises policy makers to target related and/or complex economic domains (Frenken, Van Oort, and Verburg 2007; Boschma and Iammarino 2009; Boschma, Minondo, and Navarro 2013; Diodato and Weterings 2015; Balland and Rigby 2017; Frenken 2017), we know little about whether policy makers are actually doing this—

specifically, to what extent complexity and relatedness are already factors in regions' selection of priority areas.

However, a recent article concludes that regional strategies are detached from the economic conditions of the region and tend to mimic neighboring regions' strategies (Di Cataldo, Monastiriotis, and Rodríguez-Pose 2021). Although the benefits of relatedness and complexity in regional diversification processes were already fairly well established at the start of the first programming period for smart specialization (2014–20), much of the theoretical and empirical literature had not yet been developed. However, regions were meant to identify areas where they had unique potential to develop competitive advantage. Hence, examining whether they targeted economic domains consistent with the overall policy aim of diversification is of interest. This requires comparing the regions' actual priorities to the priorities that state-of-the-art research on diversification processes would recommend.

Assessing relatedness and complexity is a demanding task, likely to exceed many regions' policy capacity (Wu, Ramesh, and Howlett 2015). When smart specialization was first implemented, few tools were available to assist regions. Therefore, very few used formal tools such as product space modeling or value-chain analysis. Instead, most regions relied on informal methods, such as regional profiling, strengths, weaknesses, opportunities, and threats (SWOT) analysis, and focus groups, to analyze the regional context (Griniece et al. 2017a). Hence, the extent to which regions can identify the areas in which they have the most potential is unclear. The inability to do so would limit smart specialization's potential to work in practical policy making.

To analyze the extent to which regions tend to select areas where they have the potential to develop competitive advantage, we examine which economic domains they prioritize in their smart specialization strategies. A limited body of research has examined why regions select the priorities they do. We find that regions are more likely to select as priorities economic domains that closely relate to the region's economic structure or represent highly complex economic domains. However, regions tend to select economic domains that are either related or complex; they do not combine the two dimensions. Hence, they do not incorporate the advice to select complex economic domains that are also related to their economic structure. Furthermore, even when controlling for regional characteristics, we find that regions in the same country tend to select the same priorities. Contrary to the place-based ideals of smart specialization, fashionable national policy may strongly influence what strategies actually emerge.

The remainder of the article is structured as follows. The next section provides an overview of the debate on smart specialization and insights into the existing empirical evidence for how regions should and actually do prioritize. This is followed by a section that explains the empirical data and methods. The penultimate section presents and discusses the results, while the last section concludes the article.

Smart Specialization as a Policy Approach

Since 2014, smart specialization has been the central concept in the EU's approach to both regional innovation policy and cohesion policy. Under the 2014–20 program for the European Structural and Investment Funds, access to EU funding became conditional on the region having a smart specialization strategy (so-called ex-ante conditionality). As a result, "[o]ver the past five years, more than 120 Smart Specialization Strategies have been developed across Europe," and more than €67 billion ($80 billion) have been made available to support them (Gómez Prieto, Demblans, and Palazuelos

Martínez 2019, 5). The EU's aim was for the application of smart specialization to lead to the launch of 15,000 new products to market, 140,000 new start-ups, and 350,000 new jobs by 2020 (Gómez Prieto, Demblans, and Palazuelos Martínez 2019, 5).

However, several scholars have raised doubts concerning the operationalization of smart specialization, accusing it of being undertheorized (Foray, David, and Hall 2011; Boschma 2014), lacking an empirical base (Morgan 2015; Iacobucci and Guzzini 2016; Santoalha 2019), poorly implemented, and ineffective in peripheral regions (McCann and Ortega-Argilés 2015). While building on laudable ideas, the rush to implement smart specialization meant that many regions simply did not have time to go through the extensive process that developing a proper strategy would require (Fitjar, Benneworth, and Asheim 2019). Rather than developing place-based policies tailored to their economic conditions, many regions—especially those with low-quality government—simply copied neighboring regions' strategies (Di Cataldo, Monastiriotis, and Rodríguez-Pose 2021).

Some scholars also highlight the term *smart specialization* itself as challenging. Many local actors had difficulties understanding the concept (McCann and Ortega-Argilés 2015; Capello and Kroll 2016; Griniece et al. 2017b; Foray 2019; Gianelle, Guzzo, and Mieszkowski 2019). In this context, specialization does not imply a cluster policy in the Porterian tradition (Asheim, Grillitsch, and Trippl 2017) but, rather, indicates 'diversified' specialization (Hassink and Gong 2019). Hence, regions should identify economic domains in which they can potentially develop a competitive advantage and aim to diversify into those domains (Marrocu et al. 2020). However, the word s*pecialization* led some policy makers to believe that they should mainly prioritize existing specializations in line with traditional cluster policy. This discrepancy in understandings can lead to wholly divergent implementations and ultimately divergent results (Hassink and Gong 2019).

While smart specialization does provide an important counterweight to previous top-down approaches, the lack of a robust and well-founded evidence base on which to build the concept created difficulties for the regions (Morgan 2015). Its operationalization made this most evident, prompting criticism that it was a "perfect example of policy running ahead of theory" (Foray, David, and Hall 2011, 1). Given the ambitious goals of the concept and its centrality in the EU's innovation and cohesion policy framework, this lack of a clear evidence base is worrying. Smart specialization must be based on diagnoses of the regional economy that identify potential sources of competitive advantage (Crescenzi, de Blasio, and Giua 2020). The significant challenge of how best to operationalize the concept has led to a flurry of research aiming to inform regions on how they should select priorities (Foray, David, and Hall 2011; Balland et al. 2018a; Gianelle, Guzzo, and Mieszkowski 2019; Whittle 2020). However, most of this evidence did not exist when EU regions first developed smart specialization strategies in 2014. Hence, very few regions used tools to analyze the regional context, which would have allowed them to identify priority areas in accordance with the policy recommendations of this research (Griniece et al. 2017a).

Smart Specialization, Relatedness and Complexity

The successful development of smart specialization relies on evidence on how regions can sustain competitive advantage over time and upgrade their economic basis. The literature on related diversification addresses precisely these issues (Boschma 2017). Hence, this literature has considerable potential for informing smart specialization policies. Balland et al. (2018a) argue that smart specialization requires a combination of relatedness (Hidalgo et al. 2007; Neffke, Henning, and Boschma 2011) and complexity (Hidalgo and Hausmann 2009), and therefore, these factors should influence the choice of economic domains for regional policy to prioritize.

The literature on related diversification emphasizes the role of relatedness in shaping path-dependent regional development (Boschma and Iammarino 2009; Frenken 2017). A primary determinant of regions' ability to enter new activities (e.g., products, technologies, industries) is the presence of related activities in the region (Neffke, Henning, and Boschma 2011; Essletzbichler 2015). Relatedness is defined by two activities requiring similar knowledge or inputs (Hidalgo et al. 2018). The probability of a region entering or exiting an economic domain can be translated into a risk assessment of diversification-oriented policies. In this context, regions will be more likely to fail if they try to diversify into economic domains unrelated to their current portfolio. A pertinent question for policy is whether relatedness involves a market failure that requires intervention (Mewes and Broekel 2020). Notably, in addition to opening comparatively easy paths of diversification, relatedness also constrains quick transformations into economic domains in which regions lack competence.

However, the complexity of the economic domain also matters in diversification. While diversifying into simple economic domains is relatively easy, diversifying into complex ones is much harder. However, this also implies greater potential value in complex economic domains, with less competitive pressure. Much of the recent research on complexity builds on the seminal works of Fleming and Sorenson (2001), Sorenson, Rivkin, and Fleming (2006), and Hidalgo and Hausmann (2009). Notably, Hidalgo and Hausmann (2009) propose that the ability to create and utilize complex knowledge forms the basis of competitive advantage. Balland et al. (2018a) point to complex knowledge bases functioning like conventional balances of supply and demand: "Technologies that are simple to copy, and which can be moved easily over space, tend to be of little value and thus do not provide a source of long-run rents. Technologies that are more complex and difficult to imitate are more sticky in space" (Balland et al. 2018a, 1254). These sticky and complex technologies tend to offer particular and, indeed, unique benefits, corresponding to the idea of smart specialization to support the emergence of unique (regional) competitive advantages.

Hence, we must combine the two dimensions to assess a region's potential for diversifying into a new economic domain (Hidalgo et al. 2007; Asheim, Moodysson, and Tödtling 2011; Neffke, Henning, and Boschma 2011; Balland et al. 2018a, 2018b; Asheim 2019). The smart specialization framework by Balland et al. (2018a) in Figure 1 can help in designing or evaluating smart specialization policies in general and guiding the choice of priority areas in particular. This framework advises regions to aim at activities (e.g., technologies and sectors) that closely relate to their existing competencies and are complex, as these have low risk (high relatedness) and high potential benefits (high complexity). If regions seek to minimize risks and maximize benefits, most priority areas that they choose should fall into this category.

Using both relatedness and complexity in this assessment is fundamental, as the two dimensions also interact. The development of complex economic domains is inherently more difficult. Hence, relatedness is more important for diversification into complex economic domains than for diversification into simple ones. Whilst complex economic domains do offer advantages, selecting them as priorities requires that they be rooted in activities related to the current regional economic profile. Otherwise, regions are unlikely to succeed with no existing competence on which to build. Conversely, developing the capabilities for relatively simple economic domains will be easier.

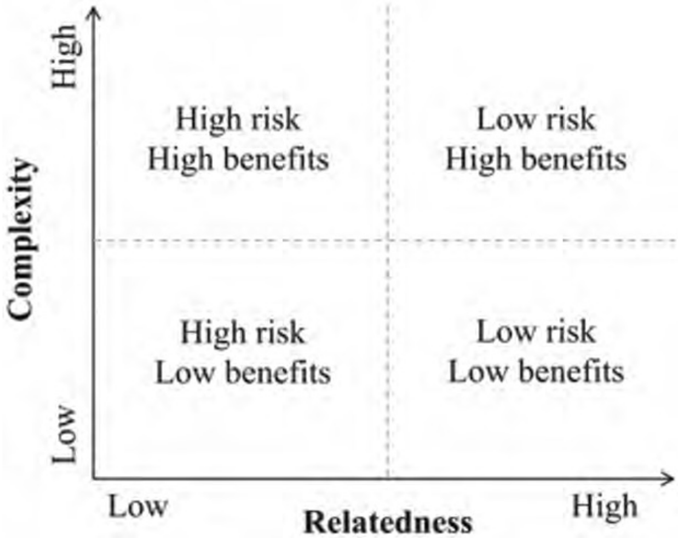

Figure 1. Framework for smart specialization.

Hence, the presence in the region of related economic domains may not matter very much for such processes.

On this basis, we formulate three hypotheses. We do not intend them as predictions for how regions will actually develop smart specialization strategies. Indeed, most of the evidence suggests that regions do not systematically assess economic domain relatedness or complexity (Griniece et al. 2017b; Di Cataldo, Monastiriotis, and Rodríguez-Pose 2021). Rather, we present these hypotheses as policy recommendations from the diversification literature, against which we can evaluate the priorities that regions have actually chosen. This allows an examination of the extent to which the implementation of smart specialization in regional strategies corresponds to the overall policy aims of promoting diversification.

H_1: The relatedness of an economic domain to the region's existing economic domains increases the probability of it being chosen as a priority in regions' smart specialization policies.

H_2: The complexity of an economic domain increases the probability of it being chosen as a priority in regions' smart specialization policies.

H_3: The impact of relatedness on the probability of a domain being chosen as a priority in regions' smart specialization policies is higher for more complex economic domains.

Other Influences on Policy

Identifying and prioritizing economic domains that are both complex and related to regions' economic profiles is not a straightforward process. Even scientists lack a common definition or measure of complexity. This becomes even more challenging when also identifying what are often rarities in regional economic structures. That is, domains that are place specific, difficult to replicate, and that may be difficult to develop organically. Naturally, this involves comparing the focal region to others, requiring substantial capacities for data access, analysis, and evaluation. Although peer review between regions has formed a central component of the monitoring process of smart specialization since the early stages of its implementation (Midtkandal and Rakhmatullin 2014), it does not necessarily help regions to identify related and complex economic domains. This challenging task requires particular skills that many regions are unlikely to possess.

Hence, various factors other than relatedness and complexity are likely to shape regions' choices of priorities. The development of smart specialization policy has perhaps not adequately considered policies as the result of a political process rather than a technocratic exercise that always selects the optimal policies. To understand how regions implement smart specialization, we also must consider how political factors influence the selection of economic domains to prioritize. We highlight the influence of two such factors: large incumbent economic domains and neighboring regions.

As argued above, the idea behind smart specialization is to promote diversification. However, the name—specifically referring to specialization—can confuse policy makers, leading them to interpret it as a policy to promote further specialization in existing strengths (Capello and Kroll 2016; Gianelle, Guzzo, and Mieszkowski 2019; Hassink and Gong 2019). Therefore, we could expect many regions to target large incumbent economic domains as priority areas. Such economic domains are also more visible in the region and, thus, may serve as focal points in discussing potential priorities. Large incumbent economic domains also have resources for lobbying policy makers to prioritize their economic domain, and they employ a large number of voters. Hence, the current size of an economic domain may influence the likelihood of its selection as a priority.

Furthermore, in addition to intraregional factors, external influences shape policy. The literature on policy mobility and policy diffusion emphasizes that policies tend to move across regions, as governments try to learn from best practices in neighboring jurisdictions (Shipan and Volden 2008; Cochrane and Ward 2012). This is also common when selecting economic domain priorities and is part of the reason for the emergence of *Silicon Somewheres* (Hospers 2006) and other one-size-fits-all approaches to regional development (Tödtling and Trippl 2005), precisely what smart specialization tries to avoid. Nonetheless, evidence of spillovers from neighboring regions also applies to smart specialization strategies. Regions tend to replicate neighboring regions' strategies, to secure funds or save time when meeting the deadlines that rapid implementation of the policy may impose (Di Cataldo, Monastiriotis, and Rodríguez-Pose 2021). To examine the importance of policy mobility in the selection of economic domain priority choices, we must consider how regional priorities correspond to those of neighboring regions or other regions in the same country. The similarity in priorities across neighboring regions may reflect either similar economic structures across several regions or learning or copying from nearby practices. The national political context also likely inspires and restricts regional choices.

Data and Methods

Relatedness, Complexity, and Economic Domain Priorities in EU Regions

To study how the relatedness and complexity of economic domains shape the likelihood of their selection as priority economic domains within regions' smart specialization strategies, we collected regional data on industrial structures and smart specialization strategies at the NUTS-2 level. The data set includes 128 regions across Europe for which we have data on the selection of economic domains at the regional level. These NUTS-2 regions have developed smart specialization strategies,[1] and they include most regions in France, Spain, Portugal, Italy, Denmark, Poland, Greece, and Romania, as well as some regions in the Netherlands and the UK. Figure 2 provides a full overview of the spatial distribution of these regions. Economic domains are differentiated at the two-digit NACE industry level, implying the division of regional economies into sixty-six industries. The data covers 2012–18.

The central variable is whether a region has selected a particular economic domain as a priority in its smart specialization strategy. We extract information on the selected economic priorities from regions' smart specialization strategy documents, coded by the European Commission's Joint Research Centre (European Commission 2021). Accordingly, the dependent variable, ECONOMIC DOMAIN PRIORITY CHOICE, is based on data the European Commission makes available through its Smart Specialization Platform. This is coded dichotomously, with the value of 1 indicating an economic domain's selection as a priority and 0 otherwise.

The central explanatory variables are RELATEDNESS and COMPLEXITY. We compute relatedness between economic domains based on co-occurrence at the regional level, following established practice in the literature (Boschma and Gianelle 2014; Boschma, Balland, and Kogler 2015; Marrocu et al. 2020). Accordingly, we compute location quotients (LQ) based on employment data from the Structural Business Statistics (SBS) data set (Eurostat 2020). LQ exceeding 1 (i.e., the region is more specialized in this economic domain than the average European NUTS-2 region) implies that the region has a revealed comparative advantage (RCA) in this economic domain. Subsequently, we count the frequency of economic domains' RCA coinciding in regions and normalize this number, as Van Eck and Waltman (2009) suggest. On this basis, we calculate the normalized relatedness density for each economic domain and region (for details, see Boschma, Balland, and Kogler 2015).[2] High values of this variable indicate that a region has a comparative advantage in many other economic domains related to the focal economic domain.

As of today, there is no common approach to calculate the complexity of economic domains. Frequently, the so-called Economic Complexity Index is used (Hidalgo and Hausmann 2009), but it is a rather indirect measure of complexity, and applying it to European data has many problems (for a discussion, see Broekel 2019). Fortunately, the labor economics literature offers an interesting alternative that the geography of innovation literature has also picked up recently (Lo Turco and Maggioni 2020). More precisely, we rely on the idea of (occupational) skill complexity from Caines, Hoffmann, and Kambourov (2017), which defines a complex occupational task as one that requires certain higher-order skills. These include the "ability to abstract, solve problems, make decisions, or communicate effectively" (Caines, Hoffmann, and Kambourov 2017, 1). In total, Caines, Hoffmann, and Kambourov (2017) use the importance of 34 tasks to calculate the complexity of 968 different occupations in the US O*NET survey database, by means of the normalized loadings of the first component of a principal component analysis. Large values imply that the occupation requires a higher ability to abstract, solve problems, communicate, and make decisions. The highest value is observed for

[1] In other countries, NUTS-1 or NUTS-3 regions developed the smart specialization strategies. These are not included in the analysis.

[2] We use the EconGeo package in R (Balland 2017) to do this.

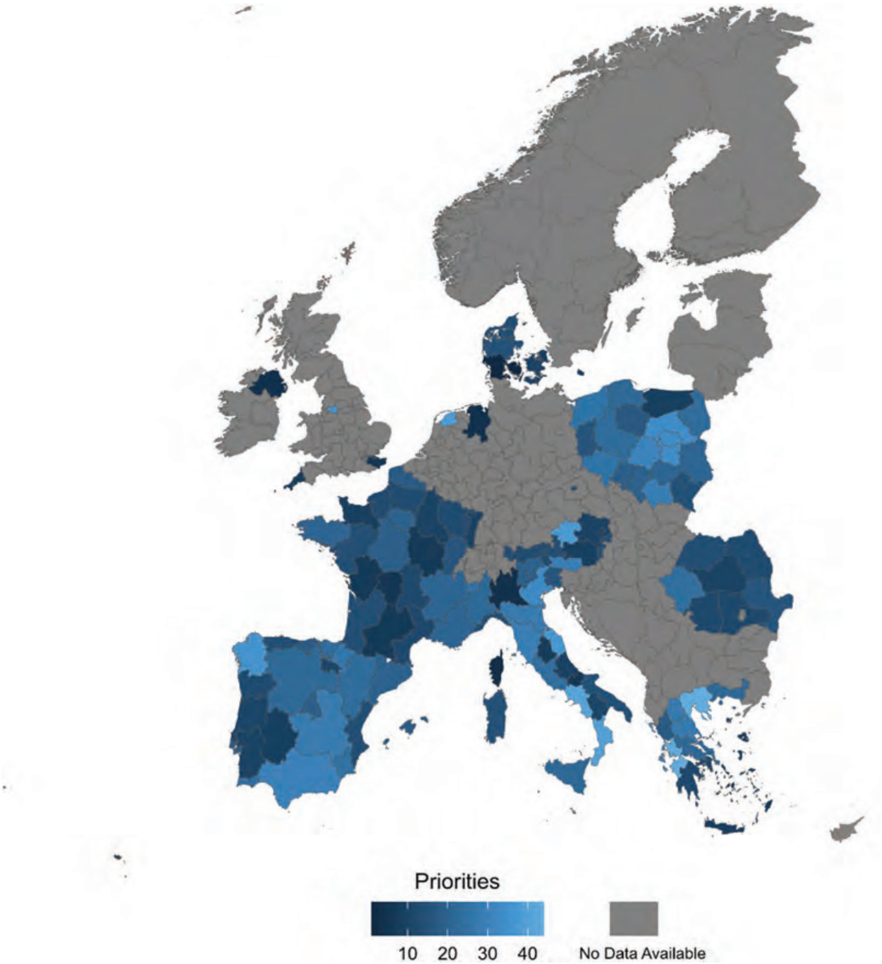

Figure 2. Number of priorities selected by NUTS 2 regions.

physicists and astronomers and the lowest for vehicle cleaners. As Caines, Hoffmann, and Kambourov (2017) show, this variable positively correlates with wage levels and growth, underlining the economic benefits of more complex occupations. We use the 2019 Standard Occupational Classification to International Standard Classification of Occupations (SOC-to-ISCO) crosswalk to connect the 968 SOC occupations to 424 four-digit ISCO occupations and make the measure compatible with European data. In a further step, we use the shares of the 424 occupations in each two-digit NACE industry in Europe to aggregate the information into the final variable COMPLEXITY. That is, we estimate the weighted mean complexity of each two-digit NACE industry based on its composition of 424 ISCO occupations.

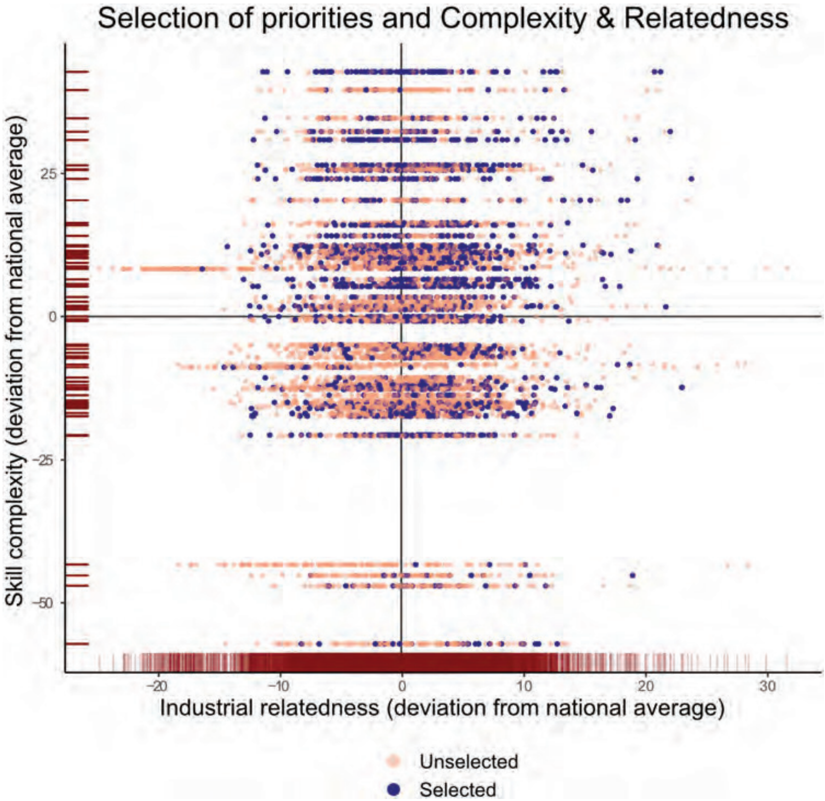

Figure 3. Relatedness and complexity of economic domains in EU regions and the selection of priority economic domains.

To highlight the dispersion of economic priorities, Figure 3 presents an overview of the distribution of economic domains (either selected or not selected as priorities) across all regions. The lighter, yellow-colored dots show economic domains that were not chosen as priorities, while darker blue dots are those chosen as priorities. The Y-axis represents complexity as expressed by deviation from the respective national average and the X-axis represents relatedness similarly by its deviation from the corresponding national average. We use the national instead of the European average as benchmarks, to account for the substantial variation in countries' relatedness and complexity values.

The figure indicates no clear pattern in the selection of domains, in terms of their RELATEDNESS and COMPLEXITY.[3] Regions do select some domains that are both complex and related, but they also frequently select complex domains that are not related to their existing economic strengths. Many regions also select rather simple

[3] For a more extensive discussion of these domains in the context of the framework for smart specialization in Figure 1, see Asheim (2019).

Table 1

Number of Prioritized Economic Domains, by Relatedness and Complexity

	Below Average Complexity	Above Average Complexity
Above average relatedness	505 (2169)	734 (2250)
Below average relatedness	318 (1927)	564 (1974)

Note: Figures in brackets refer to the total number of domains in each quadrant.

domains. Notably, we observe a large number of priorities that are below average in both complexity and relatedness. The previously presented framework shows few reasons to prioritize these as domains for future development.

Table 1 summarizes the distribution of selected priorities by their level of relatedness and complexity, again using national averages as benchmarks. The combination of above (national) average relatedness and above (national) average complexity is the most frequent configuration of selected priorities, which supports the idea that the design of smart specialization strategies at the regional level was relatively successful in targeting economic domains in which the regions had the potential to develop competitive advantage.

Empirical Approach

The dependent variable is binary, calling for the application of a logistic regression approach. As the decision on priorities occurs only once for each region during the observation period, we opt for a cross-sectional choice model, despite the availability of all other variables for multiple years. Moreover, to approximate the socioeconomic situation at the time the decision was made, that is, when regions wrote their smart specialization strategy documents, we exclusively consider the variables' mean values for the five years prior to the year in which the region adopted its smart specialization strategy.

Unfortunately, we have very little information about the decision-making process for selecting priorities in regional smart specialization strategies. From an empirical point of view, it particularly matters if the decision about an individual economic domain i is made independently of considerations regarding other economic domains. Put differently: Is each choice made independently of other alternatives, or does it depend on whether the region prioritizes other economic domains? If the choice is independent, an unconditional binary choice model can apply. If it depends on other choices, we should instead use a conditional binary choice model. Besides the assumption of independent choices, the two approaches have other important differences. Notably, in the conditional choice model, the design of the model fully accounts for region-level factors that do not vary across choice alternatives, substantially reducing the potential for omitted variable bias. However, it also precludes the inclusion of variables at this level, a major drawback. As both approaches have good arguments in their favor, we estimate both models and compare their results.

An initial look at the data reveals that the number of priorities selected varies greatly across regions (Figure 4), from a minimum of three to a maximum of forty unique economic domains.[4] The number of priorities only weakly correlates to the population

[4] These numbers differ from those reported by Marrocu et al. (2020), who find a variation from two to fifteen priority areas in smart specialization strategies. The difference stems from the fact that Marrocu et al. (2020) use the priority descriptions as the basis for the analysis, while we use the distinct economic domains mentioned within those descriptions.

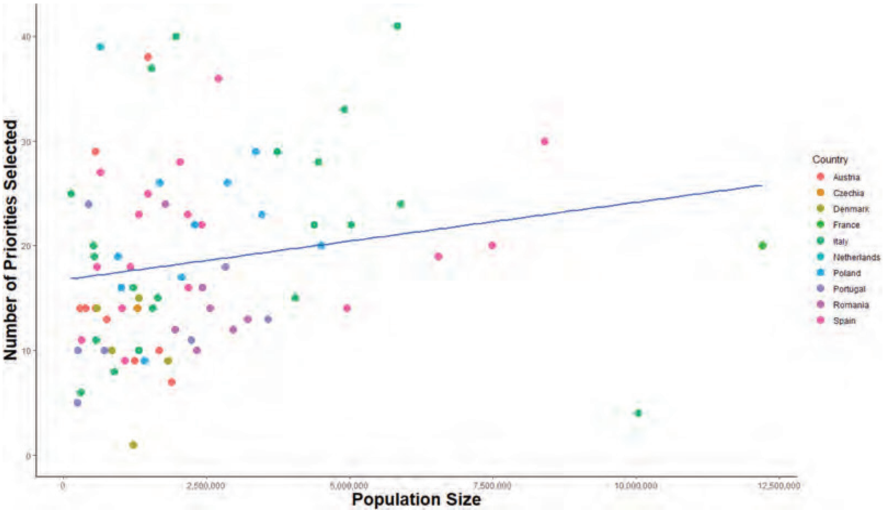

Figure 4. Number of economic domain priorities selected by region.

size of the region. For instance, the second largest region has selected four priorities, while the smallest has selected almost thirty. It is also not related to the number of economic domains in which the region currently has a comparative advantage (LQ > 1). Hence, we find no clear pattern that can account for variation in the number of priorities that regions select (Figure 5). Put differently, the number of chosen priorities does not seem to correspond to a particular strategy or follow obvious systematic patterns that reflect certain regional characteristics, contrary to what would have been expected with nonindependent decisions.

In both modeling approaches (conditional and unconditional), the dependent variables represent the likelihood that a region has selected an economic domain as a priority.

The unconditional logit model takes the following form:

$$
\begin{aligned}
logit(Priority_{i,j}) = & \beta_0 + \beta_1 Relatedness_{i,j} + \beta_2 Complexity_i \\
& + \beta_3 Relatedness_{i,j} * Complexity_i + \beta_4 \boldsymbol{Development}_j + \beta_5 Size_{i,j} \\
& + \beta_6 \boldsymbol{External}_{i,j} + \beta_7 No.\,of\,priorities_j + \varepsilon_{i,j}
\end{aligned}
$$

The conditional logit model follows broadly the same structure, except that the regions simultaneously evaluate all economic domains as potential priorities. However, the conditional logit framework does not allow for the inclusion of variables that do not vary within the region. Hence, the conditional model does not include the controls for development and the number of priorities.[5]

In both models, we examine whether the probability of selecting an economic domain as a priority economic domain is a function of its relatedness to other economic

[5] We use the region as a grouping variable and apply the conditional logit model in a common panel regression set-up.

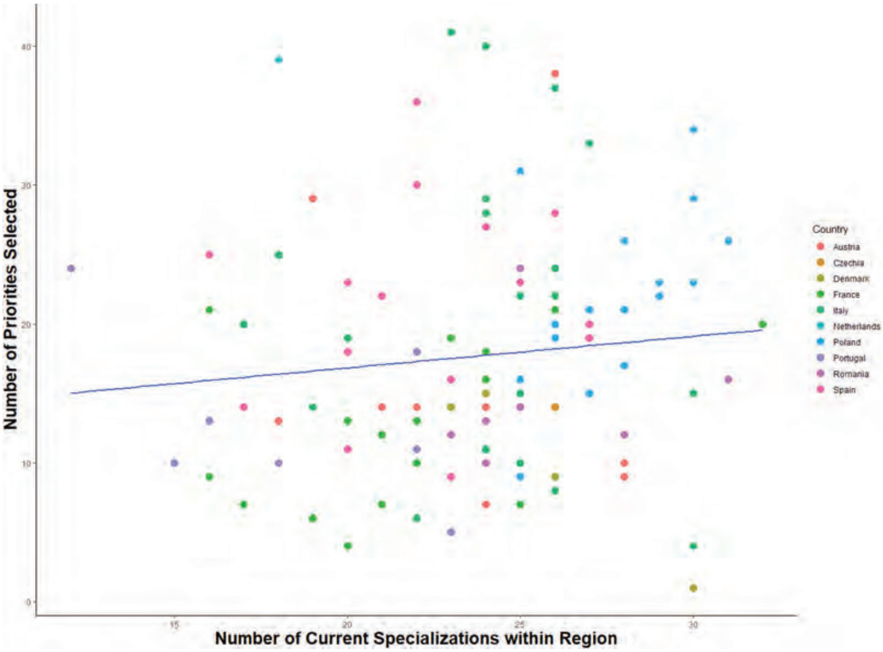

Figure 5. Number of selected priorities and current specializations.

domains in the region and its complexity. We also test whether regions will more likely select complex economic domains related to their existing economic structure—following the smart specialization framework recommendations—by including an interaction term between RELATEDNESS and COMPLEXITY in the regression models.

To isolate the relationships between these variables and the priority selection, we control for three main confounding influences: first, the region's general development level, measured by regional gross domestic product (GDP) per capita and the number of patent applications per million capita; second, the size of the economic domain in the region, measured as the relevant NACE two-digit industry's share of regional employment; and finally, external influences from other regions, measured by whether a neighboring region or any other region in the same country has selected the same economic domain as a priority, to account for policy mobility. In addition, we control for the number of other priorities that the region has selected. Appendix Table A1 shows descriptive statistics for all variables included in the model.

Given that the observations are grouped by economic domain and region, we use multiway clustered standard errors at these two levels in all estimations. Using fixed effects in the unconditional model leads to overspecification issues. Therefore, we use fixed effects at the country level as a second-best option and support this choice by comparing the results with those of the conditional model. Both models yield very similar results, with only minor differences in the coefficients and levels of statistical significance. Consequently, we consider the results of both models jointly to discuss the findings.

The Dispersion of Economic Priorities

Table 2 shows the results of the unconditional logistic regression analysis and Table 3 those of the conditional model, using odds ratios. Appendix Tables A2 and Tables A3 additionally show the same results, displaying regression coefficients.

The coefficient for RELATEDNESS is positive and highly significant in all models. RELATEDNESS has a considerable impact on the likelihood of a domain being chosen as a priority. The coefficient varies between 1.02 and 1.05 in the unconditional model, and between 1.06 and 1.08 in the conditional model. This implies that an increase of one unit in the relatedness of an economic domain to other economic domains in the region increases the odds of it being chosen as a priority by between 2 percent and 8 percent, depending on the model. Hence, regions are more likely to select priority areas when they have related capacities in other economic domains. This confirms $\mathbf{H_1}$. Notably, the observed relations between RELATEDNESS and priority selection are stronger than those reported by Marrocu et al. (2020).

The coefficient for COMPLEXITY is also positive and significant at all levels, although generally at somewhat lower levels of significance. In particular, the significance level of the coefficient drops when we control for whether another region in the same country has chosen an economic domain as a priority (NAT.PRIO). The effect size is also notably lower than that of RELATEDNESS. In both models, a one-unit increase in the complexity of an economic domain is associated with an increase of between 1 percent and 2 percent in the odds of it being selected as a priority.[6] These findings support $\mathbf{H_2}$. Accordingly, both dimensions of the smart specialization framework (Balland et al. 2018a), RELATEDNESS and COMPLEXITY, whether by accident or design,[7] influence the decision of whether an economic domain is chosen as a priority in regions' smart specialization strategies.

However, the smart specialization framework also proposes an interaction between these two variables, that is, that regions should mainly select complex economic domains related to their current portfolio. To address this, we include an interaction between the two variables in the regression. The results do not show any evidence of an interaction between RELATEDNESS and COMPLEXITY. The interaction term is not significant, and if anything, it tends to be negative. Hence, regions are not more likely to prioritize complex economic domains that are related to their other economic domains than those that are not. While RELATEDNESS and COMPLEXITY individually are useful in predicting the likelihood of a domain being chosen as a priority, there is no positive interaction between the two. Regions tend to prioritize economic domains that are complex regardless of their relatedness, which reflects a tendency to pick winners regardless of the regional economic landscape—quite opposite to the aims of smart specialization (Fedeli et al. 2020). This aligns with the findings of Crescenzi, de Blasio, and Giua (2020) that some regions may select priority areas that are too advanced and, therefore, unrelated to their production system. They also tend to prioritize related economic domains regardless of their levels of complexity.

[6] The generally lower levels of significance and impact of COMPLEXITY may partly be due to it being a variable that does not vary across regions, just across economic domains, in contrast to the industry-region-specific nature of RELATEDNESS.

[7] As discussed above, regions did not have formal tools at their disposal to allow them to analyze the relatedness or complexity of different priority areas directly (Griniece et al. 2017). Nonetheless, more informal methods, such as focus groups or SWOT analyses, could also lead to the identification of priorities related to the region's existing strengths, and/or which would represent an upgrade to more complex economic domains.

Table 2

Unconditional Choice Model

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	0.0390***	0.0228***	0.0026***	0.0011***	0.0031**	0.0016**
	(1.7829)	(2.5474)	(4.0447)	(5.5885)	(7.3579)	(9.0251)
Relatedness	1.0352**	1.0515*	1.0316***	1.0547*	1.0261***	1.0440*
	(1.0111)	(1.0221)	(1.0094)	(1.0221)	(1.0074)	(1.0196)
Complexity	1.0172**	1.0265	1.0196**	1.0331*	1.0073*	1.0179
	(1.0064)	(1.0143)	(1.0067)	(1.0148)	(1.0032)	(1.0117)
Relatedness:Complexity		0.9997		0.9996		0.9997
		(1.0003)		(1.0003)		(1.0003)
Share.emp			1.0492	1.0494	1.0413	1.0418
			(1.0667)	(1.0671)	(1.0430)	(1.0432)
log(GDP)			0.9603	0.9679	0.8756	0.8819
			(1.1377)	(1.1383)	(1.2205)	(1.2223)
log(Patents)			0.9992	1.0000	1.0184	1.0197
			(1.0204)	(1.0207)	(1.0287)	(1.0286)
log(Priority + 1)			3.0212***	3.0254***	4.2687***	4.2691***
			(1.1122)	(1.1122)	(1.1299)	(1.1298)
Neigh.Prio					1.0127	1.0125
					(1.0073)	(1.0074)
Nat.Prio					1.0418***	1.0418***
					(1.0033)	(1.0033)
R^2	0.1088	0.1091	0.2346	0.2351	0.4009	0.4012
Clustered SE	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	9080.7605	9080.9057	8306.2178	8304.9696	7110.9961	7111.2307
BIC	9165.0775	9172.2492	8417.7406	8423.4626	7236.4593	7243.6640
Log Likelihood	−4528.3802	−4527.4529	−4137.1089	−4135.4848	−3537.4981	−3536.6153
Deviance	9056.7605	9054.9057	8274.2178	8270.9696	7074.9961	7073.2307
Num. obs.	8320	8320	7865	7865	7865	7865

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table 3

Conditional Choice Model

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Relatedness	1.0826***	1.0899***	1.0800***	1.0883***	1.0665***	1.0748***
	(1.0162)	(1.0223)	(1.0165)	(1.0229)	(1.0172)	(1.0221)
Complexity	1.0187**	1.0232	1.0202**	1.0253	1.0074*	1.0127
	(1.0069)	(1.0143)	(1.0068)	(1.0138)	(1.0031)	(1.0106)
Relatedness:Complexity		0.9999		0.9999		0.9998
		(1.0003)		(1.0003)		(1.0003)
Share.emp			1.0484	1.0486	1.0363	1.0366
			(1.0674)	(1.0675)	(1.0428)	(1.0429)
Neigh.Prio					1.0216	1.0216
					(1.0112)	(1.0112)
Nat.Prio					1.0421***	1.0421***
					(1.0036)	(1.0036)
Clustered SE	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind
Deviance	8409.5354	8409.1372	8394.0455	8393.5351	7077.6389	7077.1804
Num. obs.	8320	8320	8320	8320	8320	8320
Num. groups: Region	128	128	128	128	128	128

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Accordingly, in many instances, the chosen priority is unlikely to contribute to upgrading their economic basis—again, contrary to the aims of smart specialization. Accordingly, $\mathbf{H_3}$ is rejected.

Notably, the unconditional and the conditional models yield very similar results, both for the main and the control variables. No formal test determines whether the conditional model is more appropriate. Nonetheless, this suggests that the unconditional model fits the data well, with the conditional model providing little additional value. Substantially, this supports the idea that regions indeed evaluate each domain as a potential priority, independently of other domains, rather than taking a portfolio approach to the selection of priorities.

Most of the control variables—in particular, GDP and PATENTS—remain nonsignificant. The nonsignificant coefficients also imply that we do not find evidence that more developed regions with a presumably larger capacity—as more innovation output or larger economies reflect—select a larger number of priorities. This is consistent with the findings of Di Cataldo, Monastiriotis, and Rodríguez-Pose (2021).

We also do not find the employment share of the focal economic domain to have a significant coefficient in any models, although the direction tends to be positive. Hence, we cannot establish whether regions mainly employ smart specialization strategies to promote diversification or to further strengthen existing specializations.

The controls for the priorities of neighboring regions (NEIGH.PRIO) and other regions in the same country (NAT.PRIO) capture the influence of policy mobility. Only NAT.PRIO has a significant coefficient. The significance is robust in all model specifications and holds in both the unconditional and conditional models. Hence, regions in the same country tend to select the same priority areas. When at least one other region in the country has also selected an economic domain, the odds that an economic domain is selected increase by 4 percent.

Finally, in the unconditional model (Table 2), we also control for the general propensity to select priorities, as approximated by the total number of other priorities a region has chosen (PRIORITY). Obviously, the coefficient is significantly positive. In regions that tend to choose a larger number of priorities, each economic domain has a greater likelihood of selection.

Conclusion

This article examines whether the selection of economic domain priorities in regional smart specialization strategies corresponds to the recommendations of the related diversification literature. We find that regions tend to prioritize domains related to their current specializations or that are complex. However, we do not find an interaction between the two dimensions, that is, relatedness does not matter more for the selection of complex economic domains as priorities than for the selection of simple ones.

These findings open broader discussions surrounding the role of policy actors and institutions, and how they select priorities. The process for identifying smart specialization priorities often lacks solid data and tools to guide the selection of domains, and the identification of priorities is based on intuition and anecdotal evidence (Iacobucci and Guzzini 2016). A key question for smart specialization is why relatedness does not matter more when regions select complex economic domains. Regions seem to aim for related diversification without considering the attractiveness of the economic domains into which they are diversifying. This may support activities that are likely to take place anyway and may fail to stimulate new, otherwise unrealized domains. Alternatively, they tend to chase after fashionable domains, regardless of whether they have the requisite competencies to succeed in these areas. Neither approach is consistent with the types of selections that smart specialization seeks to encourage.

Of course, relatedness and complexity are not the be-all and end-all of smart specialization. It is entirely possible that in some cases, the entrepreneurial discovery process may identify entirely new combinations of economic domains that nobody thought would be related and, therefore, that the relatedness framework cannot capture. It may also develop ideas that could make hitherto simple economic domains more complex. However, this is unlikely to account for a general tendency across regions to consider relatedness and complexity independently of each other.

This raises the question of whether smart specialization can deliver on its objectives to promote diversification and upgrading of regional economies in Europe. Thus, we provide further support for the contention of Di Cataldo, Monastiriotis, and Rodríguez-Pose (2021, 16) that "S3 strategies may be individually 'smart,' but collectively sub-optimal." These findings are consistent with earlier literature highlighting the difficulties of translating the complex smart specialization policy concept into practical implementation (Marques and Morgan 2018; Gianelle, Guzzo, and Mieszkowski 2019; Hassink and Gong 2019). Developing tools that can support the selection of regional priorities and ensure that they are consistent with the aims of smart specialization requires more work.

Related to this point is another insight from the empirical analysis. The similarity in the results of the conditional and unconditional regression models adds some empirical support for the view that policy makers are likely to assess potential priorities one by one, rather than jointly. Put differently, regions seem to evaluate each economic domain independently, rather than relative to other domains. In addition to its relevance for the empirical modeling of such choices, this finding also suggests that no strategic or portfolio approach applies to the selection of priorities. With this approach, regions are unlikely to exploit potential complementarities between targets and adopt a coherent intersectoral regional strategy. However, testing this more explicitly requires more empirical research.

The analysis has limitations that must be duly acknowledged. We do not know whether the strategies were successful or unsuccessful in promoting diversification, only whether the priorities were consistent with the recommendations of the diversification literature. We also do not have insights into the processes by which regions developed their strategies, nor do we know whether the tendency for regions in the same country to select similar priorities reflects policy mobility or similar underlying conditions. This calls for further research on additional factors that shape regions' priorities. Alongside this, there are various alternative measures of complexity besides the one used in this article, and the use of another indicator might have yielded different results. However, Broekel (2019) discusses in detail the frequently used approach by Hidalgo and Hausmann (2009) that produces generally unhelpful results for European regions. In contrast, the complexity indicator in this article is based on insights into occupational tasks and remains widely accepted in labor economics. Nonetheless, future studies could employ alternative measures of complexity.

This article contributes to what is already a spawning literature that seeks to evaluate the effectiveness of smart specialization, indeed, to better understand "how 'smart' smart specialization truly is" (Di Cataldo, Monastiriotis, and Rodríguez-Pose 2021, 3). As the first phase of smart specialization (2014–20) comes to an end, this article can help further an understanding of the challenges remaining for operationalizing smart specialization. It points to the need for a clearer policy logic and more easily accessible tools to inform regions' priority choices. The improved identification and selection of economic domains that a region should prioritize could achieve this, with the selection of priorities an important component of the effectiveness of smart specialization strategies in the future. Future research can also benefit from the large swaths of data that will become available with the release of the outcomes of the 2014–20 period.

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Table A1

Descriptive Statistics

Variable	*N*	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Choice	8,704	0.246	0.430	0	0	0	1
Relatedness	8,704	33.079	7.652	5.417	28.142	38.186	73.863
Complexity	8,320	57.195	19.808	0.000	44.603	68.444	100.000
Share.emp	8,704	1.247	2.291	0	0.1	1.3	22
Neigh.Prio	8,704	5.452	7.821	0	0	12	60
Nat.Prio	8,704	23.524	26.387	0	0	36	126
GDP	8,432	22,197.960	10,337.350	4,050.000	14,862.500	28,452.500	56,020.000
Patents	8,296	136.258	300.954	0.600	7.980	146.444	2,568.383
Priority	8,704	17.426	9.240	0	10	22	44

Table A2

Unconditional Choice Models with Coefficients

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	−3.2443***	−3.7808***	−5.9707***	−6.8357***	−5.7837**	−6.4684**
	(0.5782)	(0.9351)	(1.3974)	(1.7207)	(1.9958)	(2.2000)
Relatedness	0.0346**	0.0502*	0.0311***	0.0533*	0.0258***	0.0431*
	(0.0111)	(0.0219)	(0.0093)	(0.0219)	(0.0074)	(0.0194)
Complexity	0.0171**	0.0261	0.0194**	0.0326*	0.0073*	0.0177
	(0.0064)	(0.0142)	(0.0067)	(0.0147)	(0.0032)	(0.0117)
Relatedness:Complexity		−0.0003		−0.0004		−0.0003
		(0.0003)		(0.0003)		(0.0003)
Share.emp			0.0480	0.0482	0.0405	0.0410
			(0.0645)	(0.0649)	(0.0421)	(0.0423)
log(GDP)			−0.0405	−0.0326	−0.1328	−0.1256
			(0.1290)	(0.1295)	(0.1992)	(0.2007)
log(Patents)			−0.0008	−0.0000	0.0183	0.0195
			(0.0202)	(0.0205)	(0.0283)	(0.0282)
log(Priority + 1)			1.1057***	1.1071***	1.4513***	1.4514***
			(0.1063)	(0.1064)	(0.1221)	(0.1220)
Neigh.Prio					0.0126	0.0125
					(0.0073)	(0.0073)
Nat.Prio					0.0409***	0.0409***
					(0.0033)	(0.0033)
R^2	0.1088	0.1091	0.2346	0.2351	0.4009	0.4012
Clustered SE	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
AIC	9080.7605	9080.9057	8306.2178	8304.9696	7110.9961	7111.2307
BIC	9165.0775	9172.2492	8417.7406	8423.4626	7236.4593	7243.6640
Log Likelihood	−4528.3802	−4527.4529	−4137.1089	−4135.4848	−3537.4981	−3536.6153
Deviance	9056.7605	9054.9057	8274.2178	8270.9696	7074.9961	7073.2307
Num. obs.	8320	8320	7865	7865	7865	7865

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table A3

Conditional Choice Models with Coefficients

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Relatedness	0.0794***	0.0861***	0.0769***	0.0846***	0.0644***	0.0721***
	(0.0161)	(0.0220)	(0.0164)	(0.0226)	(0.0171)	(0.0219)
Complexity	0.0186**	0.0229	0.0200**	0.0250	0.0074*	0.0126
	(0.0068)	(0.0142)	(0.0068)	(0.0137)	(0.0031)	(0.0106)
Relatedness:Complexity		−0.0001		−0.0001		−0.0002
		(0.0003)		(0.0003)		(0.0003)
Share.emp			0.0472	0.0474	0.0357	0.0360
			(0.0652)	(0.0653)	(0.0419)	(0.0420)
Neigh.Prio					0.0214	0.0213
					(0.0112)	(0.0112)
Nat.Prio					0.0413***	0.0413***
					(0.0036)	(0.0036)
Clustered Std.Err.	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind	Reg & Ind
Deviance	8409.5354	8409.1372	8394.0455	8393.5351	7077.6389	7077.1804
Num. obs.	8320	8320	8320	8320	8320	8320
Num. groups: Region	128	128	128	128	128	128

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$