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Jason Deegan*, Tom Broekel*, Silje Haus-Reve#* and Rune Dahl Fitjar*
* Department of Innovation, Management and Marketing, Centre for Innovation Research, UiS School of Business and Law, University of Stavanger, N–4036 Stavanger, Norway

#Corresponding author: email: silje.haus-reve@uis.no

Jason Deegan: ORCID-ID 0000-0001-9190-8142

Tom Broekel ORCID-ID 0000-0003-4516-4626

Silje Haus-Reve: ORCID-ID 0000-0002-1801-4596

Rune Dahl Fitjar ORCID-ID 0000-0001-5333-2701

Abstract

This paper adds a multidimensional perspective to the study of related diversification. We examine how regions diversify into new jobs – defined as unique industry-occupation combinations – asking whether they do so from related industries or related occupations. We use linked employer-employee data for all labour market regions in Norway, covering the time period 2009 –2014. Diversification into new jobs is more likely in the presence of related occupations and industries in a region. Furthermore, occupational and industrial relatedness have complementary effects on diversification. Occupational relatedness and its interaction with industrial relatedness are particularly important for diversification into more complex activities.

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

JEL codes: O18, R11, J62, R12

1. 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 and Eriksson, 2021). For example, the occupation of an engineer is significantly shaped by the industry in which it is applied. Consider, for example, the contrast between a biomedical engineer, who designs medical devices, and an aerospace engineer, who develops aircraft and spacecraft systems. Regions specialise in specific jobs, just as they specialise in industries and in occupations. For instance, a region might specialise in aerospace engineering, or in aerospace mechanics, or in car engineering, or in any combination of these.

Furthermore, regions can develop the competence to do new jobs by 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 job 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 industries and occupations shape 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[1]. This is a period of recovery and growth following the financial crisis of 2008 and until the oil price drop in 2014, which affected the Norwegian economy severely due to its reliance on oil exports. 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 an increase in 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 introduce the Norwegian case and explain how we measure occupational and industrial relatedness. In the fourth section, we describe the empirical approach to studying the impact of occupational and industrial relatedness on diversification into new jobs. In the fifth section, we empirically study the diversification of Norwegian regions into new jobs. The final section concludes and discusses policy implications.

2. Related Diversification in Regional Economies

2.1. Related diversification

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. 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 that are 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 (David, 1985; Dosi, 1988; Boschma and Wenting, 2007; Lo Turco and Maggioni, 2016; Grillitsch, Asheim and Trippl, 2018; Fusillo et al, 2023). 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 economies tend to diversify incrementally from existing activities into related new ones. 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, 2022). 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 investigated the composition of countries' export baskets (Hidalgo et al., 2007). At the regional level, it has mainly relied on studies of industries, analysing 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. Consider, for instance, two regions which both specialise in computer manufacturing. However, one hosts mainly headquarter and back-office activities, while the other is engaged in production and repairs. These two regions would have employees with different skill sets and thus different diversification opportunities. To address this, some recent studies have examined the composition of occupations in regional labour markets (Muneepeerakul et al., 2013; Farinha et al., 2019; Buyukyazici et al., 2023; Hane-Weijman, Eriksson and Rigby, 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 specialised 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 occupations of people working there 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 the unique combination of an industry and an occupation, borrowing a perspective from the labour economics literature (e.g., Goos and Manning, 2007; 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 into 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; Davies and Mare, 2021) 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 while maintaining their 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 studies at the occupational level.

Understanding the relative importance of industrial and occupational relatedness in diversification processes is an important endeavour. However, a multidimensional perspective also makes it possible to study the relationship between the two dimensions. Because diversification processes have mainly been studied in a unidimensional way, we do not 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 related occupations? Or does it need to have both related industries and occupations? By including multiple dimensions in the same study, we can answer these types of questions.

2.2. 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). Subsequent research has shown the benefits of related variety 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 producing them. 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', drawing a metaphor of 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 that related industries in Sweden are more likely to enter the regional economy, while unrelated ones are more likely to exit. The same pattern has been identified in 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. Many regions tend to specialise more in functions and in turn occupations than in industries. Indeed, the current spatial division of labour is increasingly occupation-specific rather than industry-specific (Hane-Weijman, Eriksson and Rigby, 2022). One reason for this is the changing nature of long-term jobs and an increase in the number of workers changing jobs and moving across regions 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 (2022) 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.

2.3. Branching into new jobs

We build on these insights from studies of industries or occupations to develop hypotheses about how related diversification processes affect their combination, i.e. jobs. As discussed in section 2.2, regions are more likely to enter industries and occupations that are related to their existing industry and occupation portfolio. We expect job diversification to follow the same pattern. Since jobs are multidimensional, they can be related to both industries and occupations. We therefore expect both occupational and industrial relatedness to impact the likelihood that new jobs enter a regional economy. We develop two corresponding hypotheses, predicting that the relatedness of occupations and industries, respectively, will influence the likelihood of diversification into new jobs:

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.

This also invites 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. The dichotomisation implied in this formulation of the hypotheses allows for an analysis on the respective impacts of industrial and occupational relatedness on diversification into new jobs. 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.

As discussed in section 2.1, an important benefit of a multidimensional perspective is that it also allows us to examine the relationship between the dimensions. Specifically, we here address the question of whether regions can compensate for a lack of related industries by having a higher density of related occupations, or whether both dimensions of relatedness need to be present. We expect the entry of a new job to require both competence in the occupation and in the industry to which it is applied. In short, having skills from related occupations does not help the region to do a job if it lacks the conditions for growing the industry involved. Similarly, regions cannot develop new jobs in an industry if it lacks skills from related occupations. Hence, we expect there to be a complementary relationship between the two dimensions. On this basis, we formulate the following hypothesis:

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 the relationship between industrial relatedness and the likelihood of diversification into new jobs depends on the presence of related occupations in the region.

As discussed in section 2.2, economic development mainly happens through upgrading, i.e., when new jobs are more valuable than the ones they replace. In line with recent studies on related diversification (e.g., Balland et al., 2019; Davies and Maré, 2021; Juhász, Broekel and Boschma, 2021; Hane-Weijman, Eriksson and Rigby, 2022) 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 less complex and more complex jobs. We argued in 2.2 that relatedness is particularly important 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). Given this understanding of the higher importance of relatedness for entry into more complex jobs, we formulate two hypotheses, corresponding to the interaction between complexity and each dimension of relatedness:

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.

3. 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. This period was chosen as changes in both the industry and occupational classification system in 2008 (the introduction of NACE rev. 2.0 and ISCO-08, respectively) hindered the analysis of job-level branching across this shift. While this period was one of considerable tumult in a number of European economies, given the fallout of the financial crisis and the resulting Eurozone debt crisis, Norway was relatively insulated from the more severe impacts of these crises (Steigum and Thøgersen, 2015). GDP per capita contracted by 1.9 percent in 2009, and the following years saw relatively steady growth. Hence, the effects of the broader global trends during this period on industrial and occupational developments were comparatively smaller in Norway than in many other European countries. Appendices 5 and 6 show the composition of the Norwegian industry at the start and end of this period in terms of relatedness and complexity. Although there are observable changes, such as a gradual increase in the complexity of occupations and a modest change in industrial relatedness, these shifts were relatively minor during this period. The oil price reached historic highs in 2011-2013, creating strong barriers for diversification away from Norway's primary export sector, namely the oil and gas industry (Fitjar and Timmermans, 2019). However, the 2014-2016 oil price crisis led to widespread layoffs as investments in that sector generally contracted (Hvinden and Nordbø, 2016; van der Loos et al, 2021), resulting in significant redistribution of labour to other industries. As the oil and gas industry is by nature cyclical, diversification of the economy is a long-standing policy aim for successive Norwegian governments. For instance, the Ministry for Industry and Trade titled its 2013 White Paper on Industrial Policy "Diversity of Winners", noting the need to develop new industrial specialisations, improve diversification capabilities, and promote development in all regions. As a high-cost economy, the white paper also highlights upgrading as essential for competitiveness (Norwegian Ministry of Industry and Trade, 2013).

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 the private sector 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-98 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).[2]

On the basis of industry-occupation-regions, we adopt 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 estimate the relatedness of a job to the regional portfolio in two dimensions (industrial and occupational), as illustrated in Figure 1.

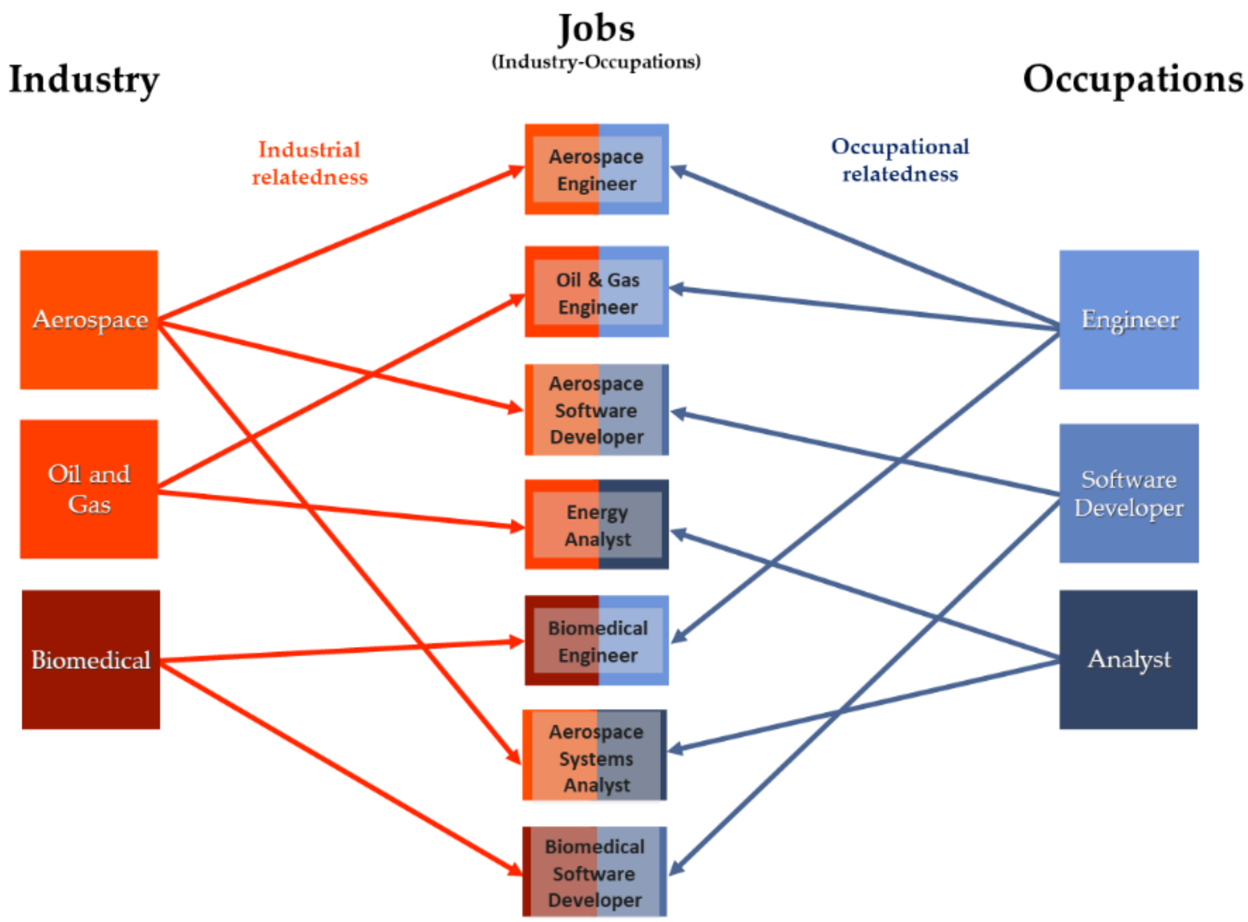

Figure 1. The influence of relatedness on regional diversification.

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. Similarly, industrial relatedness captures the fit of a job with its regional industrial surroundings, regardless of which occupations these include. Here, we highlight that jobs (industry-occupation mixes) are a function of these relatedness dimensions. For instance, to develop a new specialisation in aerospace engineering, regions can draw on related competences in the aerospace industry, in engineering occupations, or in some combination of the two. 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.

3.1 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 individual-level register data 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:

$$SR_{okt} = \frac{\frac{F_{okt}}{F_t}}{\left(\frac{F_{ot}}{F_t}\right)\left(\frac{F_{kt}}{F_t}\right)} = F_{okt}\,\frac{F_t}{F_{ot}F_{kt}} \qquad \text{(Eq. 1)}$$

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:

$$\widehat{SR_{okt}} = \frac{SR_{okt}-1}{SR_{okt}+1} + 1 \qquad \text{(Eq. 2)}$$

We use this skill relatedness measure to assess relatedness between pairs of occupations. Given the short time frame of the analysis, we 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 the relatedness value is time-invariant.

The units of observation are industry-occupation-region-years, so the measure $\widehat{SR_{okt}}$ needs to be projected to this level by 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 rely on occupations' employment shares directly. 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* ($OCC.REL_{ort}$):

$$OCC.REL_{ort} = \sum_{k=1}^{n} EMP.SHARE_{krt} * \widehat{SR}_{okt} \quad \text{(Eq. 3)}$$

In plain English, the occupational relatedness density of a job refers to the degree to which occupations that are related to this job are present in the region. Meanwhile, the industrial relatedness density of a job refers to the degree to which industries that are related to the job are present in the region. For the construction of this measure, the procedure is the same. We first construct the industry-industry relatedness matrix $\widehat{SR_{ijt}}$ using 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 $EMP.SHARE_{jrt}$. Subsequently, we sum all weighted employment shares, giving the related density of industry *i* in region *r* and year *t* ($IND.REL_{irt}$):

$$IND.REL_{irt} = \sum_{j=1}^{n} EMP.SHARE_{jrt} * \widehat{SR}_{ijt} \quad \text{(Eq. 4)}$$

3.2 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}). These measure the extent to which the region is specialised in the industry and in the occupation of which the job is composed, respectively.

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[3], as follows:

$$IND.DIV_{rt} = 1 - \sum_{j=1}^{n} EMP.SHARE_{jrt}^{2} \qquad \text{(Eq. 5)}$$

Industrial diversity (IND.DIV_{rt}) is estimated by subtracting from 1 the sum of the squared employment shares of industries (EMP.SHARE_{jrt}), resulting in an annual region-specific measure of industrial diversity. An equivalent version, for occupational diversity (OCC.DIV_{rt}), is calculated based on regional occupation shares. These are measured at the region-year level and measure the extent to which the region houses a diversity of different industries and occupations, respectively.

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 (2022) 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 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. Looking at the occupational labels, some matches between the classifications appear somewhat surprising. However, lacking an alternative, we use the SOC-ISCO crosswalk at face value.

These are matched to the occupational dimension of the industry-occupation-region-year-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. We do not expect significant changes in occupational complexity within the short time period covered.

4. Empirical approach

We follow the established literature and test for related diversification by estimating the relationship between relatedness and the probability of a new job emerging in a region. Emergence is defined as a job expanding its presence in a region beyond the national average, i.e., the region gains a revealed comparative advantage in the job. Empirically, this is captured by the location quotient exceeding a value of 1. To allow for some noise and random changes in employment, we require that the location quotient (LQ) increases from below 0.5 to above 1 (Hidalgo et al., 2007). We use a linear probability model to explain the likelihood that the location quotient of a job in a region changes from below 0.5 in one year to above 1 in the next. We only include observations where entry is possible, i.e., observations with LQ > 0.5 are excluded from the sample.

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

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

In addition to the specialisation and diversity variables presented above, we control for population density at the region-year level 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 (REGION FE, ISCO FE, NACE FE, YEAR FE). We apply 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.

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

The final part of the empirical analysis addresses hypotheses H4 and H5. Here, we examine whether the importance of occupational and industrial relatedness depends on occupational complexity. We do this in two different ways: First, by including an interaction term between occupational relatedness and occupational complexity (Eq. 8), and – in a separate analysis – between industrial relatedness and occupational complexity (Eq. 9). As occupational complexity does not vary within occupations, we cannot include occupational fixed effects in this analysis.

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

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

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. For its construction, we divide the distribution of the complexity of the occupations, OCC.COMP, into five equal groups of observations: the first represents those activities that are among the 1/5 activities with the lowest complexity score (Q1 - Least complex). The second represents those within the next fifth (Q2 – Less complex) and so on until the sample that features the 1/5 most complex activities (Q5 - *Most complex*). The corresponding descriptive statistics of the variables used in the empirical analysis are shown in Appendix 1 and 2, and Figure 2 shows the correlation plot, which does not indicate severe multicollinearity issues.

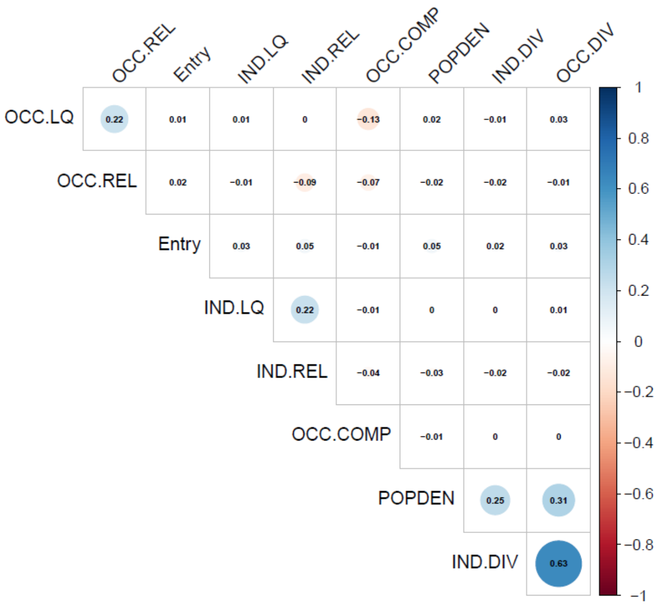

Figure 2. Correlation plot, entry models, LQ <0.5 to LQ>1.

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 hypotheses H1, H2 and H3. These models explain diversification as approximated by the growth of a job'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 job.[4] In Table 1, we present the empirical results with different specifications with respect to the inclusion of fixed effects, as the data 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**
Industrial relatedness	0.516 (0.073)***	0.538 (0.078)***	0.507 (0.072)***	0.386 (0.070)***
Occupational relatedness	0.075 (0.039)+	0.074 (0.038)+	0.251 (0.066)***	0.167 (0.046)***

Industrial specialisation	0.049 (0.007)***	0.049 (0.008)***	0.048 (0.007)***	0.047 (0.007)***
Occupational specialisation	0.024 (0.006)***	0.023 (0.006)***	0.018 (0.011)	0.014 (0.011)
Industrial diversity	1.761 (1.957)	1.750 (1.946)	1.686 (1.918)	1.697 (1.919)
Occupational diversity	–1.252 (1.815)	–1.279 (1.816)	–1.064 (1.808)	–1.060 (1.800)
Population density	–0.004 (0.005)	–0.004 (0.005)	–0.004 (0.005)	–0.004 (0.005)
Occupational relatedness x Occupational complexity				27.885 (7.404)***
Num. obs.	9,194,115	9,194,115	9,194,115	9,125,410
R^2	0.012	0.010	0.010	0.010
R^2 adj.	0.011	0.010	0.010	0.010
R^2 within	0.002	0.004	0.002	0.003
R^2 within adj.	0.002	0.004	0.002	0.003
AIC	–21,097,359.1	–21,080,417.2	–21,083,695.6	–21,086,953.0
BIC	–21,083,577.7	–21,073,751.0	–21,075,485.7	–21,078,729.0
RMSE	0.08	0.08	0.08	0.08
Std. errors	by: Occupation, Industry and Region	by: Occupation, Industry and Region	by: Occupation, Industry and Region	by: Occupation, Industry and Region
FE: Year	X	X	X	X
FE: Region	X	X	X	X
FE: Industry	X		X	X
FE: Occupation	X	X		

First, we examine how industrial and occupational relatedness affect the likelihood of diversification. We find a positive and significant coefficient for industrial relatedness in all models, supporting H2. The coefficient for occupational relatedness is also positive, but only significant when excluding occupational fixed effects from the model (Model 3 in Table 1).[5] Hence, we only find partial support for H1. Overall, this confirms the importance of relatedness, as new jobs are more likely to emerge in a region when related industries and – to some extent – related occupations are present. Using the specialisation of many Norwegian regions in engineering occupations within the oil and gas industry as an example, this would imply that these regions are more likely to diversify into new jobs related to oil and gas, and possibly also into new engineering-related jobs.

Moving on to examine the interaction between the two dimensions, we find a significant interaction term in Model 4, supporting H3. The interaction term is positive, indicating a complementary relationship: when industrial relatedness is complemented by occupational relatedness (or vice versa), the probability of emergence is larger than when only one of the two is present. Hence, if – in the above example – the new diversification opportunities are related to both the oil and gas industry and the engineering occupations, the likelihood of entry is higher.

For the other dimensions of industrial and occupational composition, industrial specialisation is significantly positive in all models and specifications. This result indicates that regions are more likely to diversify into new jobs when they are specialised in the corresponding industry, lending further credence to the idea of path-dependence in diversification (Boschma and Wenting, 2007). For occupational specialisation, the estimated results follow the same pattern but are less consistent across the different models in Table 1 and in the robustness test (Appendix 3).

Table 2. Interaction between relatedness and complexity

Dependent variable: LQ < 0.5 to LQ > 1			
	Model 1	**Model 2**	**Model 3**
Industrial relatedness	0.511 (0.073)***	0.516 (0.074)***	0.648 (0.115)***
Occupational relatedness	0.221 (0.058)***	–0.276 (0.130)*	0.222 (0.057)***
Industrial specialisation	0.051 (0.008)***	0.050 (0.008)***	0.051 (0.008)***
Occupational specialisation	0.019 (0.010)+	0.015 (0.008)+	0.019 (0.010)+
Industrial diversity	1.579 (1.887)	1.467 (1.791)	1.582 (1.889)
Occupational diversity	–0.922 (1.802)	–0.851 (1.789)	–0.921 (1.802)

Population density	–0.005 (0.005)	–0.005 (0.005)	–0.005 (0.005)
Occupational complexity	–0.002 (0.002)	–0.008 (0.002)***	–0.001 (0.002)
Occupational relatedness × occupational complexity		1.233 (0.279)***	
Industrial relatedness x occupational complexity			–0.296 (0.179)
Num. obs.	9,125,410	9,125,410	9,125,410
R^2	0.008	0.009	0.008
R^2 adj.	0.008	0.009	0.008
R^2 within	0.004	0.004	0.004
R^2 within adj.	0.004	0.004	0.004
AIC	–20,886,179.6	–20,888,604.7	–20,886,381.9
BIC	–20,885,071.5	–20,887,482.6	–20,885,259.8
RMSE	0.08	0.08	0.08
Std. errors	by: Occupation, Industry and Region	by: Occupation, Industry and Region	by: Occupation, Industry and Region
FE: Year	X	X	X
FE: Region	X	X	X
FE: Industry			
FE: Occupation			

Table 2 shows the empirical results using Eq. 8 and Eq. 9 to investigate hypotheses H4 and H5. For comparison, we first include a model without the interaction terms (Model 1). This is similar to Model 3 in Table 1, but additionally controls for occupational complexity.[6] The interaction between occupational relatedness and complexity is positive and significant, supporting H4 (Model 2). Conversely, there is no significant relationship between industrial relatedness and complexity (Model 3). Hence, we do not find support for H5. To examine what these interactions mean in practice, we plot the estimated effects of relatedness on the likelihood of entry at different levels of complexity in Figure 3.

For the interaction of industrial relatedness and occupational complexity, the plot indicates a weak negative relationship (Panel 1), i.e., the impact of relatedness on the entry probability is higher for groups of occupations with lower levels of complexity. However, the differences are small, and the relationship is largely the same at all levels of complexity, reflecting the non-significant interaction term.

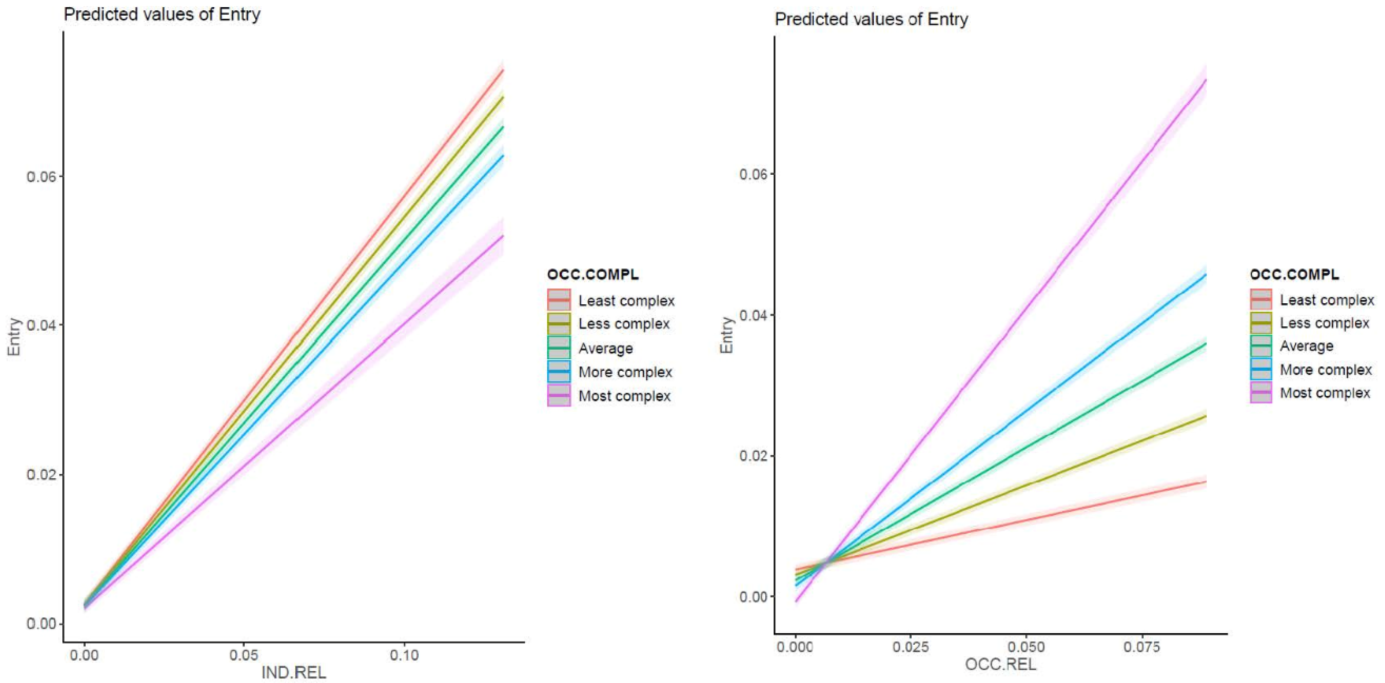

Figure 3. Interaction plots for occupational complexity and industrial/occupational relatedness, entry model LQ(LQ<0.5 to LQ>1). Note: The distribution of the complexity of occupations is divided into different quintiles, where the first quintile, Q1, represents the lowest complexity score (least complex), while Q2 represents the next quintile of complexity (less complex), Q3 represents the mean complexity (average), Q4 represents the first quintile above average (more complex), while Q5 represents the highest complex activity (most complex).

In contrast, the effect of occupational relatedness differs strongly depending on the complexity of the occupation (Panel 2). In accordance with theory, relatedness is much more important for the most complex occupations. The biggest jumps in effect strength are visible for the average, more complex, and most complex activities. For the least complex and (to a lesser degree) less complex activities, there is hardly any effect of occupational relatedness. This result is robust across specifications (see Appendix 3).

Table 3: Entry models, subsampled by levels of complexity, Q1-Q5.

Dependent variable: RCA < 0.5 to RCA >1

	Model 1: Least complex	**Model 2: Less complex**	**Model 3: Average**	**Model 4: More complex**	**Model 5: Most complex**
Population Density	−0.001	−0.003	0.003(0.011)	−0.023	−0.003
	(0.016)	(0.013)	(0.011)	(0.011)*	(0.016)
	0.041	0.045	0.040	0.058	0.055

Industrial Specialisation	(0.007)***	(0.007)***	(0.009)***	(0.010)***	(0.010)***
Occupational Specialisation	0.028	0.005(0.018)	−0.003	−0.014	−0.033+
	(0.012)*	(0.018)	(0.012)	(0.012)	(0.017)
Industrial Diversity	3.094	2.719	2.128	1.012	−1.900
	(2.850)	(2.399)	(1.954)	(1.625)	(1.400)
Occupational	−3.501	1.120	−2.667	0.860	0.893
Diversity	(3.680)	(3.221)	(2.492)	(2.997)	(2.517)
Industrial	0.444***	0.443	0.325	0.225	0.215
Relatedness	(0.090)	(0.093)***	(0.093)***	(0.060)***	(0.072)**
Occupational	0.016	0.137	0.309	0.286***	0.534***
Relatedness	(0.052)	(0.039)***	(0.054)***	(0.069)	(0.053)
Industrial Relatedness	12.320	17.263	37.446	77.874	103.529
× Occupational Relatedness	(8.786)	(7.549)*	(7.713)***	(14.311)***	(14.988)***
Numbers of observations	1,783,988	1,823,321	1,830,502	1,829,175	1,858,424
R2	0.010	0.011	0.011	0.013	0.015
R2 Adj.	0.010	0.011	0.011	0.013	0.014
R2 Within	0.001	0.003	0.003	0.004	0.007
R2 Within Adj.	0.001	0.003	0.003	0.004	0.007
IC	−3858046.4	−3957664.8	−4250977.3	−4554053.3	−4360217.3
BIC	−3851080.8	−3950612.4	−4243922.7	−4547272.3	−4353091.9
RMSE	0.08	0.08	0.08	0.07	0.07
Std.Errors	by: OCC & IND & Region	by: OCC & IND & Region	by: OCC & IND & Region	by: OCC & IND & Region	by: OCC & IND & Region
FE: IND	X	X	X	X	X
FE: Year	X	X	X	X	X
FE: Region	X	X	X	X	X

In Table 3, we run an additional test using a subsampling approach. Here, we estimate Eq. 7 for five subsamples (least complex, less complex, average, more complex, and most complex) that are created based on the quintiles of occupational complexity in the total sample. This also enables us to include the interaction between occupational and industrial relatedness. The results confirm the findings in Table 2 and provide additional insights into the relationship of complexity and relatedness: While for the least complex 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)[7]. That is, the main effect for industrial relatedness disappears for occupations that are of average or higher complexity. In a similar fashion, the interaction between occupational relatedness and industrial relatedness becomes significant to a higher degree. The main effect of occupational relatedness is significant for all but the least complex occupations, however, it reaches the highest level of significance only for the most complex activities. To enter activities of higher complexity, occupational relatedness and its interaction with industrial relatedness is particularly important. For Norway, it is imperative to enter these types of industries to sustain its high labour costs.

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 important in particular for diversification into more complex jobs.

6. 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 as a unidimensional construct, typically applied to industries. However, economic activities have multiple dimensions and relatedness in several of these dimensions may matter for diversification processes. This article combines two such dimensions – industrial and occupational relatedness – to explain how regions diversify into new jobs, understood as unique occupation-industry combinations.

We examine the relative importance of the presence of related industries and of related occupations for the diversification into new jobs. We find that both industrial and occupational relatedness increase the likelihood of entry into 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 a complementary relationship between different dimensions of relatedness. Furthermore, occupational relatedness is more important for diversification into more complex activities. Indeed, the interaction plots show that occupational relatedness does not matter at all for diversification into the least complex activities. Meanwhile, there is no significant interaction between industrial relatedness and complexity. Finally, the interaction between industrial and occupational relatedness is particularly important for diversification into complex activities. Diversification into the most 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 evidence that relatedness must be conceptualised as multidimensional, with different dimensions providing complementary benefits for diversification. While we disentangle relatedness into two distinct dimensions (industrial and occupational), economic activities can also be related in other dimensions. These may substitute or complement each other in various ways. 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, 2022; Mazzoni, Innocenti and Lazzeretti, 2022).

Future policy advice building on insights into relatedness structures should pay attention to this multidimensional and context-specific nature of relatedness. For instance, Norway's approach to industrial policy in this period was oriented towards diversification into new industries to reduce the dependence on oil and gas. Considering that Norway was in particular targeting highly complex new specialisations due to its high labour costs, it might have been a good strategy to pay more attention to occupational relatedness. Anecdotally, the oil price fall immediately following our period of analysis – in 2014 to 2016 – saw the entry of oil workers – engineers, geologists, IT workers – into jobs in industries such as construction, manufacturing, and health (Næsheim, 2016), potentially leading to the development of new specialisations through the use of competence from related occupations.

As all studies, this one also comes with limitations. Empirically, both dimensions of relatedness overlap, with relatively minor changes over time within individual industries and occupations, respectively. Once the heterogeneity of occupations is accounted for by means of fixed effects, occupational relatedness is not significantly related to diversification. Put differently, levels of relatedness stay mostly the same over short periods, 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 do not know how their omission influences the results. We must also acknowledge that there is still no agreement on how to measure occupational complexity. While we follow a promising approach by Lo Turco and Maggioni (2022), 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 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. Furthermore, it can be argued that these dimensions need a longer time to evolve than the time period which we use in the analysis. On the other hand, the granularity of our measures makes it possible to observe the nascent stages of new activities – e.g., the time at which a new job enters a region for the first time – which would easily be lost in longer time-span analyses. This is relevant in order to understand how diversification processes work. 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 provides only a partial picture 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 the least complex and most complex activities. Research and policy in this area need to recognise this and avoid one-size-fits all solutions.

Notes

[1] We start the analysis from the year 2009 because of the revisions of the occupation and industry classifications in 2008, making comparison before and after this year difficult.

[2] In practice, we never use the full sample of observations in the empirical estimations, 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.

[3] This index is commonly used in studies of diversity in other contexts, such as ethnic or birthplace diversity (Alesina et al., 2003). Applied to the study of occupational diversity at the region level, the construction of this index is as follows: $OCC.DIV_{rt} = 1 - \sum_{O=1}^{0} s_{ort}^2$, where s is the proportion of employees in region r at time t that work in occupation o; and 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.

[4] As a robustness test, we include the same analysis for a different operationalisation of the dependent variable in Appendix 3. There, we define diversification as a change of employment in a job from zero to any positive value.

[5] The robustness test in Appendix 3 is consistent with the findings shown here.

[6] Occupational complexity is measured at the occupational level, preventing the inclusion of occupational fixed effects in this model. Model (3) in Table 1 therefore provides the most appropriate baseline.

[7] The significance levels and signs of coefficients for IND.REL and OCC.REL do not change when excluding their interaction.

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Appendix

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

Statistic	N	Mean	St. Dev.	Min	Max
Entry	10,723,244	0.006	0.077	0	1
Industrial Specialisation	14,049,244	0.008	0.036	0.000	6.534
Occupational Specialisation	14,049,244	0.009	0.015	0.000	3.163
Industrial Diversity	14,049,244	0.010	0.0002	0.008	0.010
Occupational Diversity	14,049,244	0.010	0.0001	0.009	0.010
Industrial Relatedness	14,049,244	0.004	0.008	0.000	0.131
Occupational Relatedness	14,049,244	0.006	0.008	0.000	0.112
Occupational Complexity	13,932,124	0.475	0.161	0.000	0.900
Population Density	12,046,926	0.216	0.354	0.012	2.252

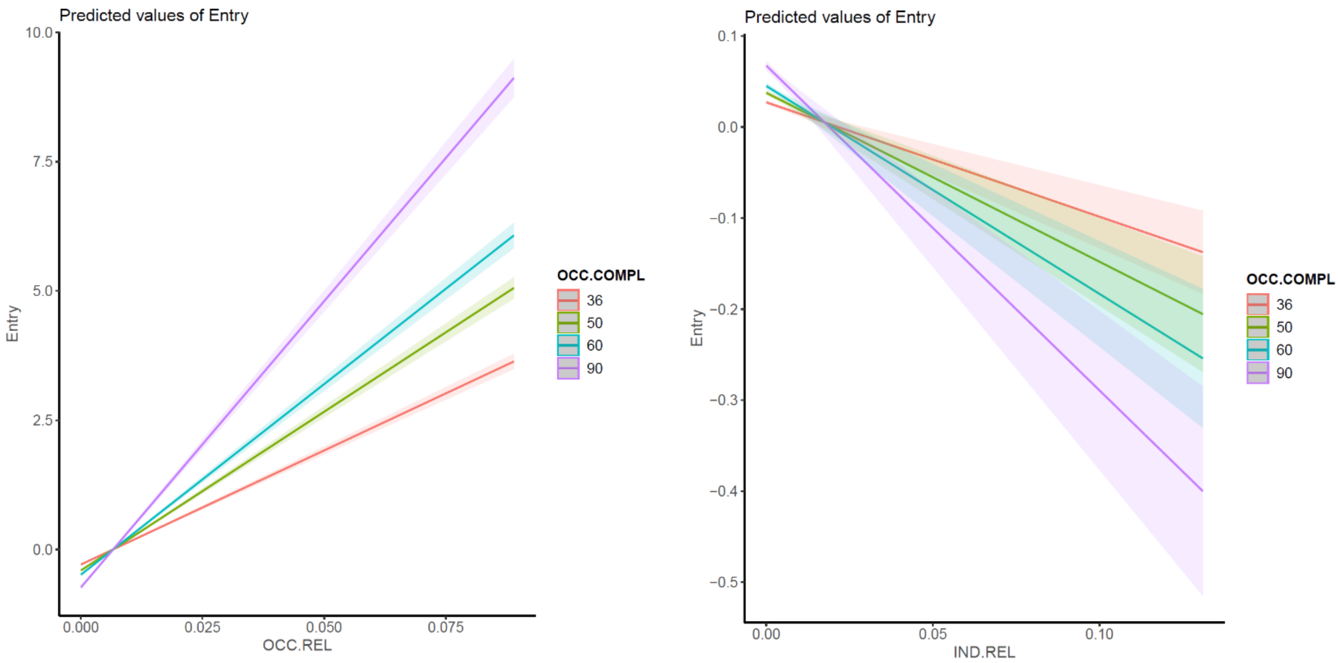
Appendix 2: Descriptive Entry Model employment

Statistic	N	Mean	St. Dev.	Min	Max
Entry	79,826,360	0.001	0.034	0	1
Industrial Specialisation	94,000,432	0.011	0.098	0.000	8.662
Occupational Specialisation	93,702,940	0.010	0.050	0.000	7.402
Industrial Diversity	95,787,724	0.010	0.0002	0.008	0.010
Occupational Diversity	95,787,724	0.010	0.0001	0.009	0.010
Industrial Relatedness	95,787,724	0.002	0.006	0.000	0.131
Occupational Relatedness	95,787,724	0.003	0.005	0.000	0.112
Occupational Complexity	92,182,686	0.452	0.159	0.000	0.900
Population Density	82,256,070	0.236	0.388	0.012	2.252

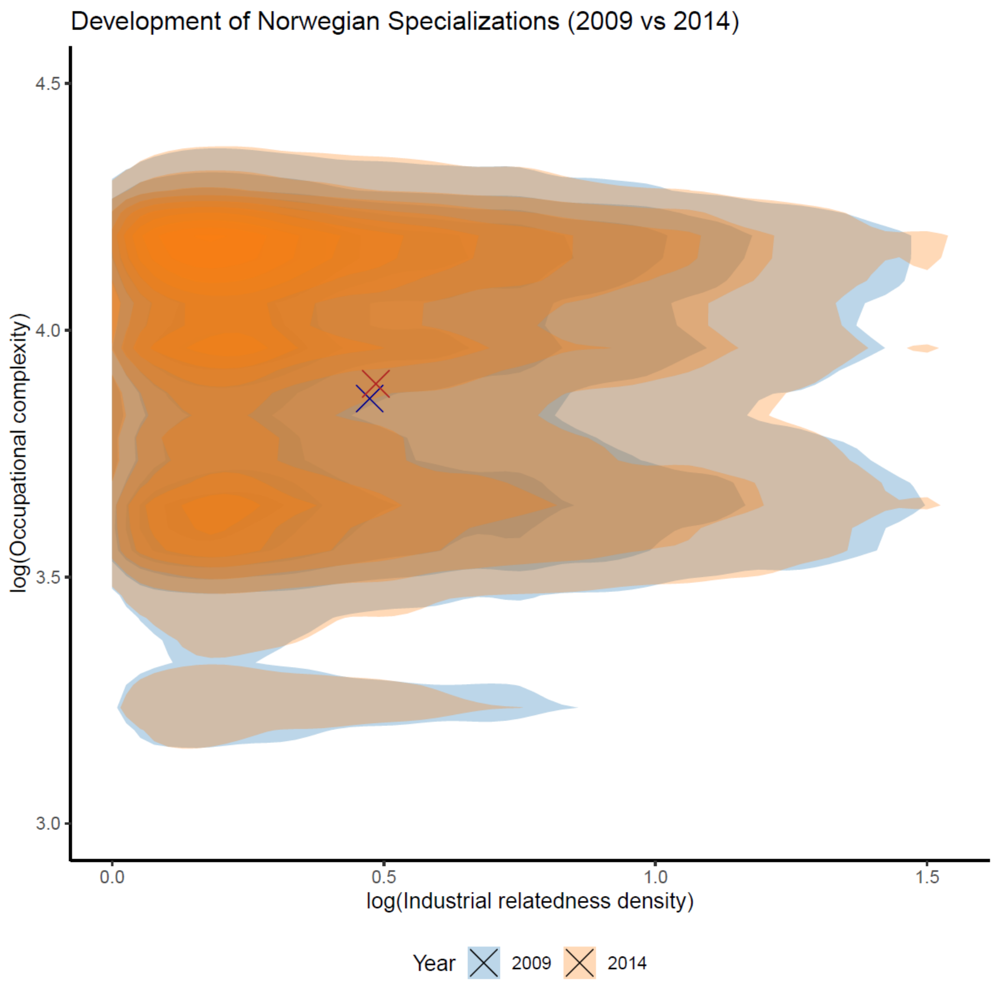
Appendix 3: Dependent variable: Emp = 0 to Emp > 0

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Population Density	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)

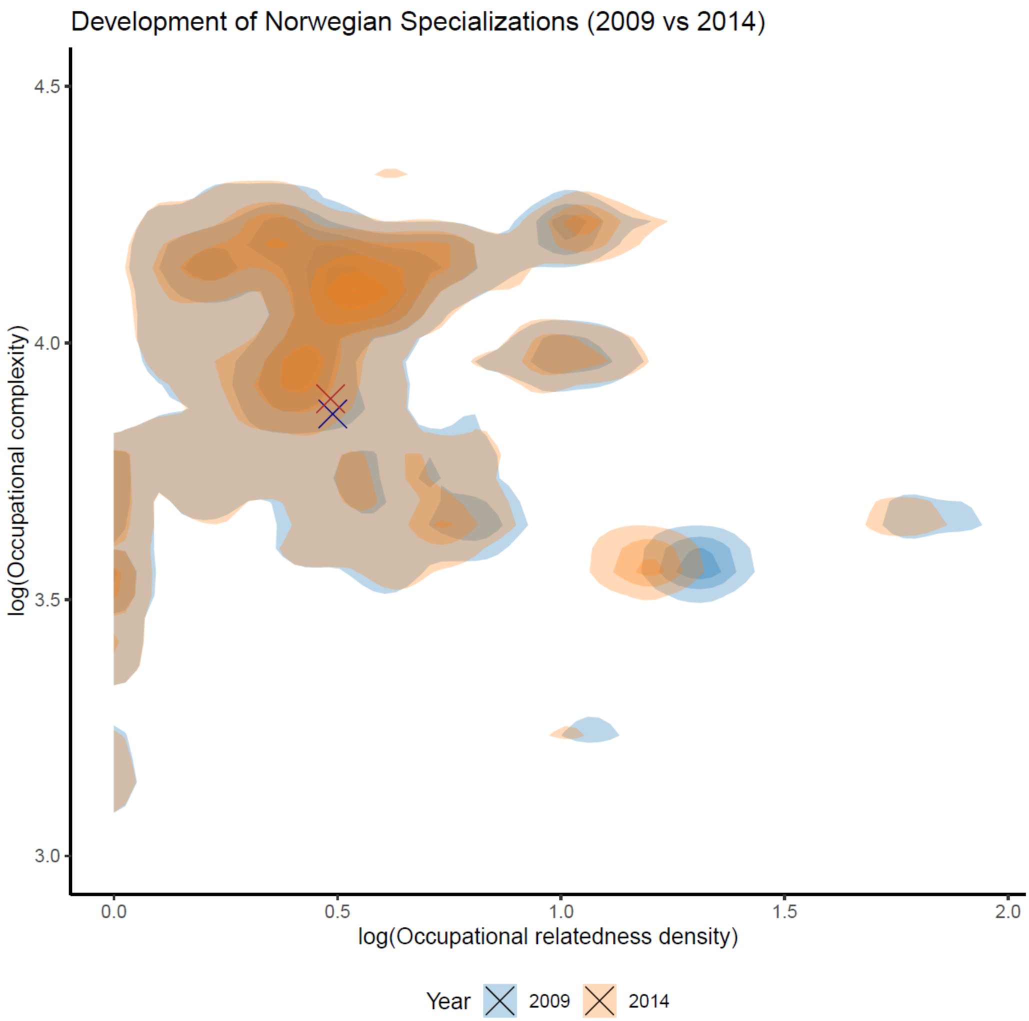
Industrial Specialisation	0.002 (0.000)***	0.001 (0.000)**	0.002 (0.000)***	0.002 (0.000)***	0.002 (0.000)***	0.002 (0.000)***	0.001 (0.000)**
Occupational Specialisation	0.001 (0.000)*	0.001 (0.000)*	−0.002 (0.001)**	−0.002 (0.001)**	−0.003 (0.001)**	−0.002 (0.001)**	−0.002 (0.001)**
Industrial Diversity	0.299 (0.317)	0.308 (0.324)	0.282 (0.295)	0.283 (0.296)	0.248 (0.262)	0.283 (0.296)	0.293 (0.303)
Occupational Diversity	−0.085 (0.274)	−0.085 (0.279)	−0.017 (0.272)	−0.007 (0.278)	0.000 (0.273)	−0.007 (0.278)	−0.008 (0.283)
Industrial Relatedness	0.189 (0.043)***	0.275 (0.057)***	0.185 (0.042)***	0.191 (0.044)***	0.192 (0.044)***	0.210 (0.087)*	0.297 (0.093)**
Occupational Relatedness	0.000 (0.025)	0.000 (0.024)	0.244 (0.050)***	0.244 (0.050)***	−0.162 (0.114)	0.244 (0.050)***	0.243 (0.049)***
Occupational Complexity				0.001 (0.001)	−0.001 (0.001)*	0.00 1(0.000)+	0.001 (0.000)+
Occupational Relatedness × Occupational Complexity					1.015 (0.273)***		
Industrial Relatedness × Occupational Complexity						−0.043 (0.147)	−0.042 (0.144)
Num.Obs.	65694843	65694843	65694843	63330585	63330585	63330585	63330585
R2	0.008	0.006	0.006	0.006	0.007	0.006	0.004
R2 Adj.	0.008	0.006	0.006	0.006	0.006	0.006	0.004
R2 Within	0.000	0.002	0.001	0.001	0.002	0.001	0.003
R2 Within Adj.	0.000	0.002	0.001	0.001	0.002	0.001	0.003
AIC	−254147627.6	−254038460.3	−254016780.3	−242969590.9	−242991014.1	−242969660.1	−242863716.6
BIC	−254131803.1	−254030812.1	−254007356.0	−242960172.2	−242981579.5	−242960225.5	−242862439.5
RMSE	0.03	0.03	0.04	0.04	0.04	0.04	0.04
Std.Errors clustered	by: OCC & IND & Region	by: OCC & IND & Region	by: OCC & IND & Region	by: OCC & IND & Region	by: OCC & IND & Region	by: OCC & IND & Region	by: OCC & IND & Region
FE: Year	X	X	X	X	X	X	X
FE: Region	X	X	X	X	X	X	X
FE: OCC	X	X					
FE: IND	X		X	X	X	X	



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



Appendix 5: Development of Norwegian Industrial Specialisations (NACE)



Appendix 6: Development of Norwegian Occupational Specialisations (ISCO)