The future geography of industries and occupations

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PILLARS – Pathways to Inclusive Labour Markets:

The future geography of industries and occupations

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Summary

Abstract

In this report we evaluate the opportunities for regional diversification in Europe over the last decade. We use microdata from the European Labour Force Survey to empirically test the entry and exit of occupational specializations at the regional level. Our results show that NUTS 2 regions are more likely to diversify into new occupations that are related to their existing local labour markets. So, the new opportunities for diversification are path-dependent, that is, they depend on the previous (occupational) production structure of the regions. Relatedness is especially important for diversifying toward complex occupations, thus increasing the potential economic benefits of the regions. However, there are significant regional heterogeneities in this related diversification process. Relatedness is positively associated with occupational specialization, but it loses strength as GDP per capita increases among European regions. Finally, we point out some policy orientations that can guide the paths of occupational diversification for European regions.

1. Introduction

The future geography of occupations and industries in Europe critically depends on the capability of regions to diversify into new activities and to maintain their existing strongholds, especially those that bring about relatively high economic benefits.

In recent years, the literature on regional diversification has emphasized the importance of existing local capabilities for the economic future of regions and their diversification opportunities (Balland *et al.* 2019; Boschma 2017; Hidalgo *et al.* 2018). In this literature, there is strong evidence that regions are more likely to diversify from an existing occupation (or industry, product, technology) to a new occupation (or industry, product, technology) with similar capabilities. The more related a potential new occupation is to the existing occupations in a region, the lower the costs (and thus less risky) to diversify into this new occupation (Balland *et al.* 2022; Farinha *et al.* 2019; Jacobs 1969; Wixe & Andersson 2017).

In addition, it has been found that different occupations might be associated with different potential economic benefits. Recent literature on economic complexity sheds light on the difficulty and benefit associated with an occupation (Galetti *et al.* 2022; Mealy *et al.* 2019). Occupations with a sophisticated skills combination have the potential to generate high economic benefits for regions because they involve workers with higher educational level, higher salaries, and distinctive skills that are better able to overcome a crisis in the labour market (in contrast to routine occupations that may be easily replaced). However, it might be more difficult for regions to diversify into these occupations, especially when regions do not possess relevant capabilities.

It is well recognized that there are significant regional heterogeneities in diversification opportunities. Diversified regions with complex capabilities (like advanced regions) might have more chances to diversify than regions with less capabilities (like peripherical regions), especially into those complex occupations. This creates a perverse challenge where policies encouraging smart growth might increase regional disparity.

This report presents the main findings of Deliverable D4.1 of the PILLARS project on the future geography of occupations, including a policy brief. The key objective is to assess the effects of regional labour markets on the occupation dynamics of regions during the period

2011-2019. We present an empirical study leveraging the microdata from the European Labour Force Survey to evaluate the diversification opportunities of NUTS 2 regions in Europe at the three-digit level of ISCO-08.

The report is structured as follows. Section 2 gives a short literature review on the regional occupation dynamics to evaluate the diversification opportunities for regions in Europe. Section 3 discusses the data and variables we used in this report, including quality checks of the micro-data of the European Labour Force Survey, and explains how we calculate the relatedness between occupations, the complexity of occupations and regions, and our baseline econometric specification. Section 4 presents the results, including the profile of occupations and regions from the point of view of complexity, the dynamic of occupational specialization, and how relatedness and complexity affect the labour market at NUTS 2 regions in Europe, accompanied by a detailed analysis of the diversification opportunities of regions. We conclude in Section 5 and provide a policy brief in Section 6.

2. Specialization, occupational relatedness and regional labour market

In the last decade, there has been a growing literature discussing the role of the capabilities of regions and how they lay the foundations for the development new activities. Local capabilities can give birth to new activities by providing a pool of local resources, such as similar knowledge, skills, and institutions. However, at the same time, they also set limits to what can be achieved in this diversification process. If a region does not possess the capabilities required for a new activity, it will be much harder and riskier to develop it. Therefore, one expects regions to diversify into new activities related to existing local activities, to build on their local capabilities. By contrast, unrelated diversification requires a complete transformation of local capabilities, accompanied by high transition costs and high risks of failure, and, thus less likely to happen (Balland & Boschma 2021; Boschma 2017; Hidalgo 2021).

Recent literature on economic complexity further highlights the different requirements of capabilities in different activities. Complex activities tend to require more sophisticated capabilities than less complex ones. Combining such capabilities is difficult. As a result, complex activities are less likely to be imitated by others and, therefore, can provide a source of high economic rents (Hausmann *et al.* 2013; Hidalgo & Hausmann 2009). There is a positive association between the complexity of activities in regions and their economic performance since the most complex activities concentrate in the wealthiest cities (Antonelli *et al.* 2022; Balland *et al.* 2020; Balland & Rigby 2017; Davies & Maré 2020; Mewes & Broekel 2020; Rigby *et al.* 2022).

Despite that relatedness has been found to play a very important role (Boschma 2017; Hidalgo 2021), there are significant regional heterogeneities in diversification opportunities, which may lead us to under or overestimate its effect. Galetti *et al.* (2021) (2021)'s study of Brazilian regions revealed that entry is more likely in large regions and depends less on relatedness in advanced and middle-income regions. Skill relatedness plays a role in preventing exit from small regions and enhancing employment growth in larger regions. The regional disparity is even more prominent in diversifying into complex activities. Pinheiro *et al.* (2022) found that diversification opportunities in more complex technologies and industries tend to be higher in high-income regions than in low-income regions. Thus, how regions can develop complex activities is essential for the future of regions. Coniglio *et al.* (2018; 2021) showed that countries focusing on related diversification tend to have weaker economic performances. Pinheiro *et al.* (2022b) showed that related diversification is more frequent for countries at low levels of development but becomes less frequent as countries climb the complexity ladder. Petralia *et al.* (2017) pointed out that countries also climb the ladder of technological development by building up new capabilities gradually; at early stages of development, the diversification is more heavily constrained by related capabilities, and at later stages, countries can develop new technologies less related to their previous knowledge bases.

Another gap in the literature is that most existing regional diversification studies focused mainly on product and industry diversification or technological diversification. What these studies take up, especially those using patent data, are technological capabilities and specifically high-tech capabilities (Balland & Boschma 2019). However, to get a more comprehensive picture of the diversification potentials of regions in the EU, there is a need to broaden the capability measure and go beyond patents. Such effort is also needed to capture better capabilities in peripheral regions that patent only to a limited extent and are focused more on low/medium-tech and low complex activities (Tessarin & Azzoni 2022).

Occupations, in turn, provide complementary insight into the local capabilities (Muneepeerakul et al. 2013; Brachert 2016; Farinha *et al.* 2019; Neffke & Henning 2013; Tessarin & Azzoni 2022), especially with the increasing importance of human capital and skills in the age of digitalization (Acemoglu & Restrepo 2018). Scholars have been applying occupation data from linked employer-employee data or national labour force surveys to study the diversification of regions in individual countries, e.g. Fitjar & Timmermans (2017) on Norwegian regions, Farinha *et al.* (2019) on US cities, and Galetti *et al.* (2021; 2022) on Brazilian regions. These studies all confirm the importance of relatedness in the entry of new occupations in regions.

Our study is the first one to leverage the micro-data from the European Labour Force Survey to study the occupation dynamics of regions in Europe. In order to shed light on the disparity of regional diversification opportunities, especially in complex activities, we adopt an analytical framework proposed by Balland *et al.* (2019). This framework is based on two concepts: relatedness and complexity. Relatedness provides an indicator of the cost of diversifying from existing activities to a new activity in a region. Complexity provides a way of assessing the potential economic benefits of diversifying into a new activity: the higher the economic complexity of this activity, the higher the potential economic benefits, as illustrated in Figure 1 below.

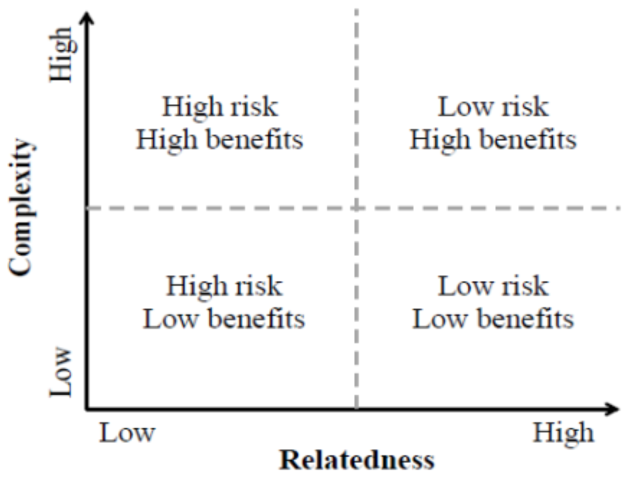

Figure 1. Typology of future diversification opportunities based on Balland et al. (2019)

3. Data and methods

3.1 Data source

We are using Labour Force Survey (LFS), from Eurostat, a national household survey conducted by European countries to produce official national statistics following the same statistical regulation. This database has information on individuals indicating occupation (by ISCO-08), industry (by NACE revision 2) and place of work (by NUTS level 2).

We had access to the LFS database in the scope of the PILLARS Project, so we were able to access disaggregated information from occupations and NUTS regions to conduct this study.

Data period

To analyse the recent changes in the labour market, we work with information from the last decade (2011 to 2019). We did not consider 2020 due to the Covid-19 crisis, which affected regions, especially occupations with distinct magnitudes throughout that year, so we avoid capturing shocks unrelated to structural change.

We were also concerned with selecting a period in which all countries had already become members of the European Union. The entry event of a new member country could disturb the results, suggesting that there was specialization from one year to the next, while other countries would proportionally lose specialization just by the statistical effect of a new member. Therefore, we chose a period in which the set of member countries is balanced throughout the period.

In addition, data for occupation in the latest classification starts in 2011 (ISCO-08, 2008 version), which allowed us to adopt a single occupational classification throughout the period.

Option for the individual's region of work

Since we are interested in active workers, we selected only individuals who claimed to be employed in the year of survey collection. To identify the worker's location, we used the variable indicating the individual's region of work (as opposed to residency) since we are focusing on labour market dynamics.

Regional, occupational, and industrial breakdown

The LFS database has occupation information at the 3-digit level at ISCO-08 (available from 2011 onwards), which covers 130 exclusive codes. Appendix C -Table C.1 displays the 130 ISCO-08 occupations.

LFS provides information for 32 European countries detailed at 1- and 2-digit NUTS region. We chose to work with the most disaggregated version at the 2-digit NUTS level; however, we had to exclude five countries due to the limitation that arose after evaluating the granularity of the data by region of work and occupation. Bulgaria, Malta, Poland, and Slovenia have no 3-digit occupation information and therefore we dropped them from the database. The Netherlands was also excluded because it does not provide information at the subnational level (in this case, there is only country-level information).

The United Kingdom was also included in the analysis, but it has regional disaggregation only at the 1-digit NUTS level.

Table 1 exhibits the 27 study countries (22 EU countries, 4 EFTA and the UK) and the number of NUTS regions of each country, totalling 217 NUTS regions at 2-digits and 12 regions NUTS at 1-digit to the United Kingdom). Appendix C – Table C.2 displays the codes and names of all 229 NUTS regions of the study.

Table 1: Countries and numbers of NUTS regions of the study

Countries	NUTS breakdown	Number of NUTS regions
Austria	2	9
Belgium	2	11
Cyprus	2	1
Czech Republic	2	8
Germany	2	38
Denmark	2	5
Estonia	2	1
Spain	2	19
Finland	2	5
France	2	26
Greece	2	13
Croatia	2	2
Hungary	2	8
Ireland	2	3
Iceland	2	1
Italy	2	21
Liechtenstein	2	1
Lithuania	2	2
Luxembourg	2	1
Latvia	2	1
Norway	2	7
Portugal	2	7
Romania	2	8
Sweden	2	8
Switzerland	2	7
Slovakia	2	4
United Kingdom	1	12

Source: Authors using the Labour Force Survey (LFS).

As for industrial classification, we are working with NACE revision 2 at 1-digit, which means 21 codes, as shown in Appendix C – Table C.3.

Data cleaning and treatment

Since the description of regions and occupations names vary in some survey years (for instance, region names recorded in English or the local language) and the codes of some NUTS regions have changed over the period, we have thoroughly matched names and codes in the classification. Additionally, we did a deep cleaning of the database for information without comparable codes for ISCO occupation and/or NUTS region and dropped the workers without occupational or regional identification; We also dropped workers from work regions not belonging to the 27 European countries in the study. In the end, proportionally to the total, little information was lost in the cleaning process.

After cleaning and treating the data, we dropped only 4% of the workers. In total, our dataset covers 15.7 million workers between the period 2011 to 2019, about 1.6 million workers per year.

Verification of LFS regional employment distribution

As LFS is a national household sample survey conducted by European countries, verifying whether the regional distribution of employment is similar to that reported by the Eurostat statistics based on administrative records and additional checks from various sources is essential. We want to verify whether the national surveys are well-balanced and represent the large and small regions well. Thus, we compare each country's regional employment distribution from the LFS with the Eurostat regional employment data[1]. Tables 2 to 6 display the five countries (Germany, United Kingdom, France, Italy, and Spain) that generate the most jobs in Europe. The comparison of other countries can be seen in the Tables in Appendix E.

[1] We consulted the Eurostat tables [lfst_r_lfe2eftpt] to compare with the national statistics data released in the LFS.

The high Pearson correlation in the last row of the following five tables and in Appendix E confirms that the regional distribution of LFS employment is very similar to the one from Eurostat in the vast majority of countries. We also compared some traditional indicators built from LFS with those reported by Eurostat. The correlation was also very high; for example, the correlation of the manufacturing share in total regional employment for all regions in the study was 99%. Therefore, it gives more credibility to continue with statistical analysis and econometric exercises.

Table 2: Regional employment share's correlation between LFS and Eurostat: Germany

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
DE11	5.6	5.5	5.6	5.1	5.2	5.3
DE12	3.4	3.5	3.6	3.4	3.5	3.5
DE13	2.8	2.8	2.8	2.9	2.9	2.8
DE14	2.2	2.3	2.4	2.3	2.3	2.4
DE21	6.8	6.6	6.5	5.9	6.0	6.1
DE22	1.8	1.6	1.6	1.6	1.6	1.6
DE23	1.6	1.5	1.4	1.4	1.4	1.4
DE24	1.4	1.4	1.3	1.4	1.3	1.3
DE25	2.5	2.5	2.3	2.2	2.2	2.2
DE26	1.6	1.7	1.7	1.7	1.7	1.7
DE27	2.4	2.4	2.3	2.3	2.3	2.4
DE30	4.6	4.7	4.7	4.0	4.2	4.4
DE40	2.6	2.5	1.9	3.1	3.0	3.0
DE50	1.0	1.1	1.1	0.8	0.8	0.8
DE60	2.8	2.7	2.9	2.2	2.3	2.3
DE71	4.9	5.0	5.2	4.8	4.8	4.9
DE72	1.3	1.2	1.2	1.3	1.3	1.2
DE73	1.6	1.5	1.5	1.5	1.5	1.5
DE80	1.6	1.7	1.7	1.9	1.9	1.8
DE91	1.9	2.0	2.0	1.9	1.9	1.8
DE92	2.8	2.6	2.6	2.5	2.5	2.5
DE93	1.6	1.7	1.7	2.0	2.1	2.0
DE94	2.9	3.0	3.1	3.0	3.0	3.1
DEA1	6.0	5.9	6.1	6.0	6.0	6.0
DEA2	4.6	4.8	5.2	5.1	5.2	5.3
DEA3	2.7	2.7	2.9	3.1	3.1	3.1
DEA4	2.2	2.3	2.5	2.5	2.5	2.4
DEA5	3.9	4.0	4.0	4.1	4.1	4.1
DEB1	1.7	1.6	1.7	1.8	1.8	1.8
DEB2	0.6	0.6	0.6	0.7	0.7	0.7
DEB3	2.1	2.3	2.3	2.5	2.5	2.4
DEC0	1.3	1.2	1.1	1.2	1.2	1.1
DED2	1.9	2.0	1.9	1.9	1.9	1.9
DED4	1.8	1.8	1.7	1.8	1.7	1.6
DED5	1.2	1.2	1.3	1.2	1.2	1.2
DEE0	2.6	2.5	2.3	2.7	2.6	2.5
DEF0	3.0	2.9	3.0	3.4	3.4	3.4
DEG0	2.6	2.6	2.4	2.8	2.6	2.5
Total	100.0	100.0	100.0	100.0	100.0	100.0

Pearson Correlation	0.98	0.99	0.98			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table 3: Regional employment share's correlation between LFS and Eurostat: UK

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
UKC	3.9	3.9	4.0	3.8	3.8	3.8
UKD	11.1	11.3	11.2	10.8	10.7	10.8
UKE	9.2	8.9	8.7	8.1	8.1	8.0
UKF	7.3	7.4	7.2	7.2	7.2	7.1
UKG	8.3	8.3	8.7	8.5	8.4	8.5
UKH	9.1	9.2	8.8	9.6	9.5	9.4
UKI	12.6	12.9	12.1	13.5	14.1	14.4
UKJ	13.2	12.9	12.3	14.2	14.1	14.1
UKK	8.5	8.7	9.1	8.4	8.4	8.5
UKL	4.3	4.4	4.4	4.6	4.5	4.5
UKM	8.7	8.4	8.1	8.5	8.4	8.3
UKN	3.8	3.6	5.4	2.7	2.7	2.6
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.99	0.99	0.96			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table 4: Regional employment share's correlation between LFS and Eurostat: France

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
FR10	19.3	16.4	17.3	19.9	19.9	20.1
FRB0	3.8	3.5	3.6	3.9	3.8	3.8
FRC1	2.7	2.3	2.3	2.5	2.4	2.4
FRC2	2.2	2.0	1.9	1.8	1.8	1.8
FRD1	2.6	2.4	2.5	2.2	2.2	2.2
FRD2	2.9	2.7	2.8	2.8	2.7	2.7
FRE1	6.2	5.6	5.5	5.7	5.6	5.5
FRE2	2.7	2.5	2.4	2.9	2.8	2.8
FRF1	3.2	3.0	3.1	3.1	3.0	3.1
FRF2	3.0	2.8	2.8	2.0	1.9	1.8
FRF3	3.3	3.1	2.9	3.5	3.4	3.4
FRG0	6.3	5.9	5.7	5.7	5.8	5.8
FRH0	5.2	5.2	5.2	5.0	5.1	5.0
FRI1	5.0	4.5	4.8	5.0	5.1	5.2
FRI2	2.3	2.2	2.1	1.1	1.1	1.1
FRI3	3.0	2.9	2.6	2.7	2.6	2.6
FRJ1	3.4	3.2	3.0	3.6	3.7	3.8
FRJ2	4.3	4.1	3.9	4.7	4.6	4.7
FRK1	2.1	1.9	1.8	2.0	2.0	2.0
FRK2	9.7	9.0	9.3	10.2	10.3	10.6
FRL0	6.6	6.1	5.8	7.4	7.3	7.1
FRM0	0.3	0.3	0.3	0.3	0.3	0.5
FRY1	-	1.8	1.9	0.5	0.5	0.4
FRY2	-	1.9	1.9	0.5	0.5	0.5
FRY3	-	1.8	1.8	0.2	0.2	0.2

FRY4	-	2.7	2.6	0.9	1.0	1.0
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.99	0.99	0.99			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table 5: Regional employment share's correlation between LFS and Eurostat: Italy

NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
ITC1	9.0	8.2	8.1	8.0	8.0	7.9
ITC2	2.4	3.5	3.4	0.2	0.2	0.2
ITC3	2.8	3.0	3.0	2.7	2.7	2.6
ITC4	14.7	14.6	14.5	18.7	19.0	19.2
ITF1	2.1	1.9	2.1	2.2	2.1	2.1
ITF2	1.5	1.1	1.2	0.5	0.5	0.5
ITF3	5.3	5.8	6.0	7.1	7.1	7.2
ITF4	4.6	4.1	4.0	5.4	5.2	5.3
ITF5	2.5	2.5	2.5	0.8	0.8	0.8
ITF6	3.3	2.0	2.1	2.4	2.3	2.3
ITG1	6.8	6.4	6.5	6.2	6.0	5.9
ITG2	3.0	2.8	2.7	2.6	2.5	2.5
ITH1	3.1	3.4	3.7	1.1	1.1	1.1
ITH2	3.8	3.1	2.9	1.0	1.0	1.0
ITH3	5.8	5.4	5.6	9.3	9.2	9.2
ITH4	3.0	3.4	3.4	2.2	2.2	2.2
ITH5	8.0	8.7	8.8	8.5	8.5	8.6
ITI1	6.5	6.5	6.7	6.8	6.8	6.8
ITI2	2.3	2.6	2.5	1.6	1.6	1.5
ITI3	3.0	3.2	3.1	2.8	2.8	2.7
ITI4	6.5	7.6	7.4	9.9	10.3	10.3
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.95	0.95	0.95			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table 6: Regional employment share's correlation between LFS and Eurostat: Spain

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
ES11	12.5	11.9	11.5	5.9	5.7	5.5
ES12	2.7	2.8	2.7	2.2	2.1	2.0
ES13	2.5	2.4	2.2	1.3	1.3	1.2
ES21	5.4	5.2	5.1	5.1	4.9	4.8
ES22	2.6	2.5	2.4	1.5	1.5	1.5
ES23	1.7	1.8	1.7	0.7	0.7	0.7
ES24	4.3	4.4	4.8	3.0	3.0	3.0
ES30	6.8	7.0	7.6	15.8	15.6	15.5
ES41	9.5	9.3	9.3	5.4	5.3	5.1
ES42	5.9	6.1	6.1	4.2	4.1	4.2
ES43	3.0	3.2	2.9	2.0	2.0	2.0
ES51	10.8	11.1	11.0	17.3	17.4	17.4
ES52	7.5	7.8	7.9	10.3	10.5	10.6
ES53	2.6	2.8	2.6	2.7	2.8	2.9
ES61	14.2	13.8	14.4	15.1	15.4	15.7
ES62	2.8	3.0	2.9	3.0	3.0	3.1
ES63	0.3	0.4	0.4	0.1	0.2	0.1

ES64	0.3	0.3	0.4	0.1	0.1	0.1
ES70	4.4	4.3	4.1	4.2	4.4	4.5
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.78	0.80	0.82			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

3.2 Methodology

We employed three years average non-overlapping time periods (2011-2013; 2014-2016; 2017-2019) to avoid capturing sporadic shocks to specific occupations or regions over the last decade. Thus, all variables were calculated considering the 3-year periods.

Occupational relatedness and relatedness density

To measure occupational relatedness between ISCO-08 occupations for a given time period, we adopt the co-occurrence approach – industry-occupation matrix, based on NACE (1-digit) and ISCO (3-digit), normalizing using the association measure (Eck & Waltman 2009). Occupational relatedness in a period is, therefore, a standardized measure of the frequency with which two occupations appear in the same industry. High values of relatedness indicate that two occupations are more frequently combined, while low values of relatedness suggest that the occupation pairs are relatively independent.

To link occupational relatedness with the economic structure of NUTS regions, we calculated the occupational relatedness density index following (Hidalgo *et al.* 2007), which represents the distance between an occupation and the existing occupational structure in a NUTS region.

Entry and exit measures

We calculate several measures of entry and exit - that is, gain or loss of occupational specialization in the regions - in addition to the measures commonly used in the specialized literature. The reason for several measures is to test the robustness of the results under more restrictive entry and exit conditions. We describe the conditions devised for entry and exit measurements in the following.

a) Traditional entry (and exit)

Traditional entry – or gain in the occupational specialization – occurs when the LQ < 1 at time t and > 1 at time t+1. The traditional exit - or loss of occupational specialization - occurs when the LQ > 1 at time t and < 1 at time t+1.

b) Traditional entry (and exit) with absolute employment growth (decline)

Now we will consider as an entry (exit) the traditional measure of the previous item plus the condition of an absolute increase (decline) in employment between two periods. In this way, we capture only pairs of regions-occupations that have gained (lost) specialization in absolute terms (and not just relative to the others).

The idea is that some regions may become specialized (lose specialization) due to the reduction (increase) in the share of other regions in the complete set. In this way, the LQ values are rebalanced, and some regions gain specialization (lose specialization) even without having an absolute increase (decline) in employment. As the locational quotient is a ratio of the local share in the European Union total, variations in the numerator as well as in the denominator can impact the result.

c) New entry (and new exit)

The new entry (exit) condition requires an increase (decrease) in the Locational Quotient of at least two-tenths. Thus, the new entry requires LQ < 0.8 at time t, and > 1 at time t+1 the new exit requires LQ >1.2 at time t, and < 1 at time t+1.

We understand that many cases in which a change in the locational quotient makes a region specialized – or leads to a loss of specialization – are concentrated very near to 1. However, minor marginal variations may reflect a dynamic that does not lead to long-term structural changes, that is, small marginal variations that can easily be reversed in the following period. We, therefore, establish a condition requiring a more considerable variation in the LQ (of at least 2-tenths) to consider that a region has gained or lost specialization. In our understanding, such a condition allows us to capture long-lasting gains or losses of specialization.

d) New entry (and new exit) with absolute employment growth (decline)

In this option, we add to the conditions defined in the previous item a restrictive condition of an absolute increase (decline) in employment in the region between two periods to be considered an entry (exit).

e) Entry (and exit) defined by bootstrap technique

Understanding that some occupations are by nature rarer than others, one might expect the LQ value for considering a region specialized in such an occupation to be lower than that of another occupation widely present in almost all regions. Thus, the value of the LQ for considering a regional specialization is not necessarily fixed; instead, the LQ may vary according to the frequency (rarity/abundance) of an occupation. To consider this, we applied a bootstrap method (Boschma *et al.* 2022; Cortinovis *et al.* 2017; Tian 2013) to define the individual cut-offs for each occupation.

To do so, we use two techniques; the first involves the traditional technique, which determines the cut-off value based on the standardized location quotient (SLQ), following a normal distribution. Alternatively, we followed Tian (2013), that adopted the bootstrap method without any assumption about the statistical distribution to obtain the cut-off value based on logarithmic transformation and standardization of the LQ (referred to as SLLQ hereafter). Then, we get the cut-off values of the SLQ and SLLQ from the bootstrap method for all ISCO-08 occupations.

As for the first bootstrap technique, there is occupational specialization gain (entry) when SLQ at time t < cut-off e SLQ at time t+1 > cut-off. And there is a loss of occupational specialization (exit) in the opposite situation: SLQ at time t > cut-off e SLQ at time t+1 < cut-off. As for the second bootstrap technique, just replace SLQ with SLLQ.

Furthermore, all entry and exit measures were calculated only for regions with 10 or more workers in each occupation in each period (i.e. occupation-region-time pairs greater than 10). We did this to capture occupations that are minimally well represented in a region and to avoid impacting the results with regions that are very sensitive to small variations, especially in smaller regions. In very small regions, a tiny increase in the number of occupations may indicate a structurally weak specialization gain, so we drop occupation-region-time pairs below 10 jobs. In this way, we focus on more representative relative specialization gains/losses.

For the organizational purpose of the report (as well as for space limit), we will show the econometric results for measures (c) and (d) in the results section - which we will simply call entry and exit. We will include the econometric tests with the remaining conditions for entries and exits in the Tables in Appendix A as robustness tests.

Econometric model

We applied a three-way fixed-effect model by time, region and occupation. The dependent variable is the entry or exit of occupational specialization.

To control the characteristics of the regions, we selected the following variables from the LFS tables or data available on Eurostat: the share of the population with tertiary education (EducThir); firm size given by the percentage of workers employed in firms with less than 10 employees (SmallSize); population density by persons per square kilometre (PopDens); gross domestic product per capita (GDPpc), and unemployment rate (Unemploy). All the independent variables are lagged by one period and are mean-centred. The correlation tables between the variables can be seen in the Appendix F.

Table 7: Descriptive statistics of variables

Variables	*Mean*	*SD*	*Min*	*Max*
Entry1	0.05920	0.23601	0	1
Entry2	0.05805	0.23384	0	1
Exit1	0.03647	0.18747	0	1
Exit2	0.03427	0.18193	0	1
Entry3	0.12381	0.32937	0	1
Entry4	0.11316	0.31679	0	1
Exit3	0.13148	0.33794	0	1
Exit4	0.11744	0.32195	0	1
Entry5	0.02302	0.14996	0	1
Entry6	0.02334	0.15099	0	1
Exit5	0.02279	0.14922	0	1
Exit6	0.02172	0.14578	0	1
RelDens	38.77941	12.82833	0	94.85
CompOcc	59.53666	19.73160	0	100
CompReg	50.98740	24.13345	0	100
EducThir	0.36586	0.32277	0.0011655	1
SmallSize	0.34550	0.25116	0	1
PopDens	346.882	860.234	3.200	7,473.267
GDPpc	28,431	11,001	8,333	79,233
Unemploy	8.748	5.742	1.433	33.567

Note: GDPpc at Purchasing Power Standard (PPS, EU27 from 2020), per inhabitant.

We are using cluster-robust standard errors (heteroskedasticity-robust) clustered at region and occupation levels, which gives greater robustness to the model.

To understand how relatedness density is associated with the gain or loss of regional occupational specialization, we assess how complexity relates to occupational specialization. To do so, we calculate the complexity of occupations and the complexity of regions following the method of reflection by Hidalgo and Hausmann (2009). It is more difficult or rare to find complex occupations and regions; however, more complex occupations or complex regions have better conditions to raise the level of regional development.

Our baseline models can be described as follows:

$$
\begin{aligned}
Entry_{ort} = \beta_1 + \; & \beta_2\, RelDens_{ort-1} + \; \beta_3\, CompOcc_{ot-1} + \beta_4\, CompReg_{rt-1} \\
& + \; \beta_5\, RelDens_{ort-1} * CompOcc_{ot-1} \; + \; \beta_6\, RelDens_{ort-1} * CompReg_{rt-1} \\
& + \; \Theta_{rt-1} + \varphi_o + \alpha_r + \; \gamma_t + \; \varepsilon_{ort}
\end{aligned}
$$

where the dependent variable $Entry_{ort}$ represents the entry of an occupation *o* in a region *r* at time *t* or, alternatively, $Exit_{ort}$ represents the exit of an occupation *o* in a region *r* at time *t*. $CompOcc_{ot-1}$ is the complexity index by occupation *o* at time t-1; $CompReg_{rt-1}$ is the complexity index by region *r* at time *t-1*; Θ_{rt-1} represents the control variables by region at time *t-1*. Finally, φ_o is the occupation-fixed effect, α_r is the region-fixed effect, γ_t is the time-fixed effect; and ε_{ort} is a regression residual.

We are primarily interested in understanding the association between occupational density relatedness and regional specialization gains/losses. Is entry (and exit) associated with occupational relatedness density?

In addition, we are also interested in understanding the role of occupational complexity and regional complexity on the entry and exit of occupational specializations in regions. Is the existence of complex occupations associated with the gain (or loss) of regional specialization related or not to the previous regional occupational structure? Moreover, do complex regions play a role in fostering (discouraging) new entries (exits) related or unrelated to occupational specializations? We seek to answer these questions in the results section below.

4. Regional labour market dynamics in EU NUTS-2 regions

The following sections present the results found in this study. Section 4.1 offers a ranking of occupations and regions' complexity, allowing a more comprehensive idea of the profile and diversification possibilities for the EU NUTS regions, including occupations linked to all activities. Section 4.2 illustrates the future diversification opportunities of regions using occupational relatedness among the EU regions. In section 4.3, we present the regional labour market dynamics in EU NUTS-2 regions and an evaluation of regions with different income levels.

4.1 A perspective of occupations and regions in the EU

Complexity of occupations and complexity of regions

We follow the method of reflection from Hidalgo & Hausmann (2009) employed in many studies (Hidalgo 2021) to measure the knowledge complexity of occupations and regions in Europe. For regions, for example, the method of reflection considers the diversity and ubiquity of occupations present in a region. The method captures that many regions can use less complex occupations (mostly linked to traditional activities such as agriculture, retail trade, accommodation, and food service), but only a few can use complex occupations (mostly linked to complex industries such as aerospace, machinery, and computer programming) requiring a high level of education, specialization and training. Complex regions, in general, are diversified regions that host occupations with a high level of education and training necessary in a few less spatially ubiquitous industries.

Some studies have shown that complex industries concentrate in large, highly diversified cities (Balland *et al.* 2020; Balland & Rigby 2017; Pintar & Scherngell 2020). In turn, it should be noted that complex occupations are easier spotted in complex industries, but not only that, they are also present in low complex industries to a lesser extent - for instance, a manager in a hotel or a sales manager in a department store.

Table 8 shows the top 40 most complex occupations calculated using the LFS data. The common determinant in all of them is the high intensity of cognitive skills and the high level of education required, and for some occupations, social skills are also relevant. Unlike the ranking of industry or technology complexity, where at the top predominates high-tech manufacturing activities and some knowledge-intensive services, in the top 40 most complex occupations there are occupations typical of several manufacturing and service industries. In fact, the first decile of most complex occupations – 13 out of 130 ISCO-08 codes at 3-digit – exhibit more typical service occupations than manufacturing occupations.

We can see that the top of the rank shows creative, management and leading administration professionals [2] together with STEM occupations (science, technology, engineering, and math). This distribution can be a portrait of advanced European regions with strong service economies based on advanced knowledge. Additionally, it sheds light on the fact that some service sectors have the ability to positively assist regional development by demanding complex occupations.

Table 8: Top 40 occupations most complex

Rank	ISCO-08 codes	ISCO-O8 names	Complexity
1	223	Traditional and Complementary Medicine Professionals	100.00
2	112	Managing Directors and Chief Executives	99.31
3	251	Software and Applications Developers and Analysts	98.17
4	242	Administration Professionals	95.67
5	243	Sales, Marketing and Public Relations Professionals	90.66
6	212	Mathematicians, Actuaries and Statisticians	90.22
7	432	Material Recording and Transport Clerks	89.31
8	264	Authors, Journalists and Linguists	88.97
9	252	Database and Network Professionals	87.36
10	122	Sales, Marketing and Development Managers	86.53
11	265	Creative and Performing Artists	86.25
12	334	Administrative and Specialized Secretaries	84.29
13	121	Business Services and Administration Managers	84.25
14	214	Engineering Professionals (excluding Electrotechnology)	83.36
15	133	Information and Communications Technology Services Managers	82.89
16	413	Keyboard Operators	82.76
17	341	Legal, Social and Religious Associate Professionals	82.40
18	232	Vocational Education Teachers	79.88
19	515	Building and Housekeeping Supervisors	79.53
20	325	Other Health Associate Professionals	79.27
21	742	Electronics and Telecommunications Installers and Repairers	79.26
22	263	Social and Religious Professionals	79.10
23	311	Physical and Engineering Science Technicians	78.88
24	335	Government Regulatory Associate Professionals	78.88
25	226	Other Health Professionals	77.43
26	231	University and Higher Education Teachers	76.53
27	215	Electrotechnology Engineers	76.50
28	343	Artistic, Cultural and Culinary Associate Professionals	76.08
29	323	Traditional and Complementary Medicine Associate Professionals	75.82
30	262	Librarians, Archivists and Curators	75.39
31	412	Secretaries (general)	74.59
32	312	Mining, Manufacturing and Construction Supervisors	74.39
33	321	Medical and Pharmaceutical Technicians	74.10

[2] Administration professionals (ISCO-08 251) covers management and organization analysts; policy administration professionals; personnel and careers professionals; and training and staff development professionals.

34	732	Printing Trades Workers	73.90
35	216	Architects, Planners, Surveyors and Designers	73.80
36	754	Other Craft and Related Workers	72.20
37	333	Business Services Agents	70.67
38	324	Veterinary Technicians and Assistants	70.23
39	134	Professional Services Managers	69.90
40	933	Transport and Storage Labourers	69.20

Note: Complexity calculated for the 2017-2019 period. Source: Authors.

Table 9 shows the bottom 40 fewer complex occupations. They are linked to traditional activities such as agriculture, low-tech manufacturing, retail trade, construction, transport, and food service. Such occupations demand predominantly manual skills, and some also demand social skills. In addition, such occupations require a much lower level of training and education than complex occupations – usually secondary education or lower – and tend to be well distributed among regions. Table D.1 in the Appendix D displays the 50 remaining occupations with intermediate complexity.

Table 9: Bottom 40 occupations less complex

Rank	ISCO-08 codes	ISCO-08 names	Complexity
91	524	Other Sales Workers	42.13
92	835	Ships Deck Crews and Related Workers	40.83
93	912	Vehicle, Window, Laundry and Other Hand Cleaning Workers	40.55
94	711	Building Frame and Related Trades Workers	40.03
95	131	Production Managers in Agriculture, Forestry and Fisheries	39.55
96	411	General Office Clerks	39.49
97	817	Wood Processing and Papermaking Plant Operators	39.48
98	962	Other Elementary Workers	38.86
99	313	Process Control Technicians	38.81
100	142	Retail and Wholesale Trade Managers	38.48
101	911	Domestic, Hotel and Office Cleaners and Helpers	38.37
102	833	Heavy Truck and Bus Drivers	37.70
103	523	Cashiers and Ticket Clerks	37.46
104	811	Mining and Mineral Processing Plant Operators	37.26
105	951	Street and Related Services Workers	36.07
106	512	Cooks	35.68
107	821	Assemblers	34.29
108	931	Mining and Construction Labourers	34.10
109	832	Car, Van and Motorcycle Drivers	34.00
110	233	Secondary Education Teachers	32.87
111	814	Rubber, Plastic and Paper Products Machine Operators	30.25
112	612	Animal Producers	29.44
113	021	Non-commissioned Armed Forces Officers	28.95
114	541	Protective Services Workers	28.32
115	513	Waiters and Bartenders	24.71
116	622	Fishery Workers, Hunters and Trappers	24.07
117	631	Subsistence Crop Farmers	23.70
118	521	Street and Market Salespersons	21.35

119	751	Food Processing and Related Trades Workers	20.56
120	611	Market Gardeners and Crop Growers	20.41
121	224	Paramedical Practitioners	19.56
122	613	Mixed Crop and Animal Producers	18.37
123	952	Street Vendors (excluding Food)	16.97
124	753	Garment and Related Trades Workers	14.22
125	815	Textile, Fur and Leather Products Machine Operators	12.86
126	961	Refuse Workers	12.28
127	633	Subsistence Mixed Crop and Livestock Farmers	11.23
128	632	Subsistence Livestock Farmers	10.19
129	921	Agricultural, Forestry and Fishery Labourers	7.48
130	634	Subsistence Fishers, Hunters, Trappers and Gatherers	0.00

Note: Complexity calculated for the 2017-2019 period. Source: Authors.

On the other hand, Tables 10 and 11 show the 50 most and least complex European regions (calculated using the last data period, 2017-2019), respectively. The complexity index of the remaining 129 regions can be consulted in Appendix D - Tables D.2 to D.4.

Germany is the country with the largest number of complex regions leading the ranking of regional complexity, confirming the strength of the German economy in the European context. Other regions from Sweden, Switzerland, France, Finland, United Kingdom, Austria, Belgium, Denmark, and Luxembourg – all of them high-income regions – are also among the top 50.[3]

Table 10: Top 50 European regions' most complex

Rank	NUTS codes	NUTS names	Complexity
1	DE11	Stuttgart	100.00
2	DE25	Mittelfranken	97.52
3	DE71	Darmstadt	94.90
4	DE60	Hamburg	94.51
5	DE30	Berlin	93.86
6	DE12	Karlsruhe	93.23
7	DE21	Oberbayern	93.23
8	DEA2	Köln	91.94
9	CH04	Zürich	91.49
10	DE50	Bremen	90.22
11	DE91	Braunschweig	90.03
12	DEA1	Düsseldorf	89.77
13	DED5	Leipzig	87.84
14	DEB3	Rheinhessen-Pfalz	86.79
15	DE27	Schwaben	86.44
16	DEA4	Detmold	85.94
17	CH03	Nordwestschweiz	85.55

[3] It is noteworthy that the Dutch regions were left out of the study due to the lack of occupational data detailed by NUTS regions.

18	DEA5	Arnsberg	84.88
19	DE92	Hannover	83.94
20	DEF0	Schleswig-Holstein	83.81
21	DE14	Tübingen	83.16
22	SE11	Stockholm	82.81
23	CH06	Zentralschweiz	81.92
24	DE26	Unterfranken	81.61
25	CH01	Région lémanique	81.60
26	DED2	Dresden	81.01
27	DEA3	Münster	80.09
28	DEC0	Saarland	79.69
29	CH02	Espace Mittelland	78.54
30	DE72	Gießen	78.33
31	NO01	Oslo og Akershus	77.86
32	DE13	Freiburg	77.81
33	DE73	Kassel	77.40
34	FR10	Île de France	77.20
35	FI1B	Helsinki-Uusimaa	76.49
36	DE40	Brandenburg	76.31
37	CH07	Ticino	76.28
38	DEB2	Trier	76.10
39	AT13	Wien	75.67
40	DEB1	Koblenz	75.17
41	DE24	Oberfranken	74.49
42	UKI	London	74.13
43	SE22	Sydsverige	73.84
44	LU00	Luxembourg	73.80
45	CH05	Ostschweiz	73.41
46	DE23	Oberpfalz	72.58
47	BE10	Région de Bruxelles-Capitale	72.49
48	DEG0	Thüringen	72.43
49	DK01	Hovedstaden	72.06
50	SE23	Västsverige	71.66

Note: Complexity calculated for the 2017-2019 period. Source: Authors.

The least complex regions are in the most backward areas of Europe, mainly in Greece, Romania, Portugal, Italy, Spain, Hungary, Lithuania, and Slovakia (see Table 11).

Table 11: Bottom 50 European regions less complex

Rank	NUTS codes	NUTS names	Complexity
180	HU33	Dél-Alföld	27.53
181	SK02	Západné Slovensko	27.22
182	SK04	Východné Slovensko	27.04
183	ITF2	Molise	26.82
184	ITH1	Provincia Autonoma di Bolzano	26.51
185	HU32	Észak-Alföld	25.62
186	ES64	Ciudad de Melilla	25.17
187	LT02	Vidurio ir vakaru Lietuvos regionas	24.83
188	ES70	Canarias	24.67
189	ITI1	Toscana	24.40
190	ES61	Andalucía	23.34
191	RO42	Vest	23.02

192	ES24	Aragón	22.84
193	ITI3	Marche	22.67
194	ITI2	Umbria	22.35
195	PT15	Algarve	22.25
196	HU22	Nyugat-Dunántúl	21.73
197	PT30	Região Autónoma da Madeira	21.69
198	HU23	Dél-Dunántúl	21.69
199	EL52	Kentriki Makedonia	20.66
200	ITF1	Abruzzo	19.35
201	RO22	Sud-Est	18.99
202	ITG1	Sicilia	18.52
203	ES42	Castilla-la Mancha	18.12
204	ITF4	Puglia	17.65
205	ES41	Castilla y León	17.60
206	ITG2	Sardegna	17.38
207	RO12	Centru	17.12
208	PT20	Região Autónoma dos Açores	16.90
209	ITF5	Basilicata	16.84
210	PT11	Norte	16.51
211	ITF3	Campania	15.89
212	ES43	Extremadura	15.33
213	EL64	Sterea Ellada	13.93
214	EL61	Thessalia	13.58
215	RO31	Sud - Muntenia	13.41
216	RO11	Nord-Vest	12.70
217	EL54	Ipeiros	12.33
218	PT16	Centro (PT)	12.16
219	EL65	Peloponnisos	11.28
220	ITF6	Calabria	10.79
221	EL41	Voreio Aigaio	10.65
222	EL53	Dytiki Makedonia	8.67
223	EL42	Notio Aigaio	8.21
224	RO41	Sud-Vest Oltenia	6.15
225	PT18	Alentejo	5.85
226	EL43	Kriti	5.01
227	RO21	Nord-Est	3.60
228	EL51	Anatoliki Makedonia, Thraki	0.48
229	EL63	Dytiki Ellada	0.00

Note: Complexity calculated for the 2017-2019 period. Source: Authors.

4.2 Future diversification opportunities of regions

In this section, we will explore future diversification opportunities of regions based on the analytical framework in Section 2. Figure 2 shows the complexity of regions over the period of 2017-2019. There is a clear core-periphery divide at the European level, as well as at the national level of each country. At the European level, regions in Germany, Switzerland, the United Kingdom, and Nordic countries have higher complexity than regions in Southern and Eastern European countries. At the national level, the capital region tends to have higher complexity than others, e.g. Madrid in Spain, Vienna in Austria, Bratislava in Slovakia, and Sostinės in Lithuania.

Figure 3 shows the aggregated future diversification opportunities of regions in complex occupations. We adopted the complexity potential indicator by Mealy & Teytelboym (2022), which measures how related on average a regions' occupation structure is to those complex occupations they haven't specialize yet. The higher value complexity potential of a region, more future diversification opportunities the region has in those complex occupations because it already poses the required capabilities.

On average, regions with higher complexity tend to have lower diversification opportunities because they already specialized in most of the complex activities. The occupations that they haven’t specialized in are therefore on average less complex. In turn, regions with lower complexity tend to have higher diversification opportunities. However, there are many exceptions where regions have both less complex local labour market and fewer diversification opportunities towards complex occupations. These regions are primarily in periphery regions in Greece and Romania. It will be challenging for those regions to upgrade their labour market since they don’t have the necessary capabilities to diversify into complex occupations.

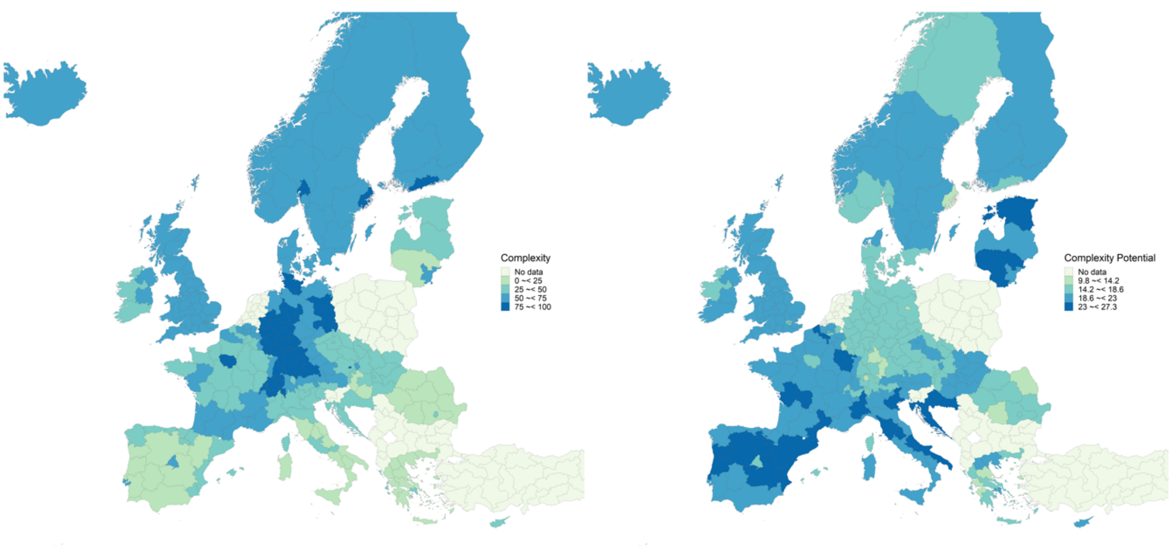

Figure 2. The complexity (left panel) and the aggregated future diversification opportunities (right panel) of European regions over the period of 2017-2019.

We then demonstrate future diversification opportunities for different types of regions in Europe: metropolitan, industrial, mining, and periphery regions. We focus on different types of occupations based on three dimensions: 1) whether the focal region has a revealed comparative advantage in the occupation (orange circle 1<RCA<=2: specialized; red circle RCA>2: very specialized) or not (blue circle 0.5<RCA<=1: potential diversification opportunities); 2) the extent to which the focal occupation is related the focal region (the risk of future diversification); and 3) the complexity of the focal occupation (the benefit of future diversification).

Figure 3 and Figure 4 show the future diversification opportunities for metropolitan regions (Ile de France and Brussels) and advanced industrial regions (Stuttgart and Dusseldorf), respectively. All those regions already specialized in many highly complex occupations that are, in many cases, also significantly related to their existing local labour markets (red and orange circles in the figure). For the Ile-de-France region, Database and Network Professional is the occupation with the largest chance to be added to its future specialization (low risk and high benefit). Although it is not as complex as other potential occupations like Traditional and Complementary Medicine Professional, or Managing Directors and Chief Executives, it is more related to the existing labour market in the region.

In the case of the advanced industrial regions (Figure 4), it is still possible to see that the possibilities of diversification into complex occupations are feasible, but compared to the metropolitan regions, such occupations are less related to the existing structure of the region (mainly Stuttgart).

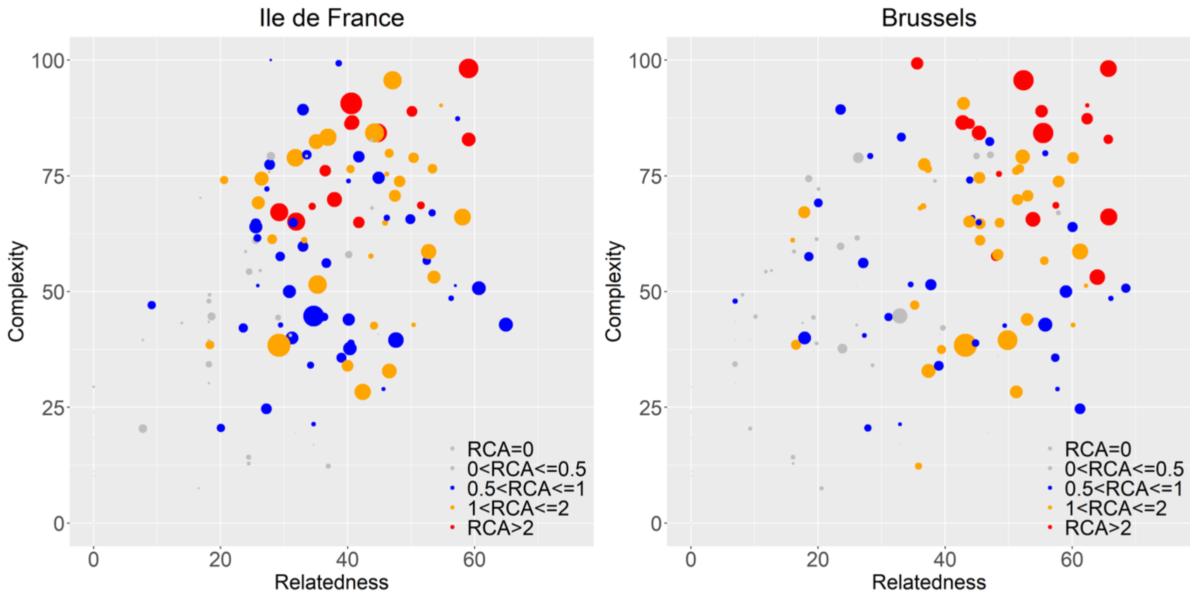

Figure 3: This Figure shows the future diversification opportunities for Ile de France and Brussels using occupation data. Colours indicate occupations' Revealed Comparative Advantages in the region

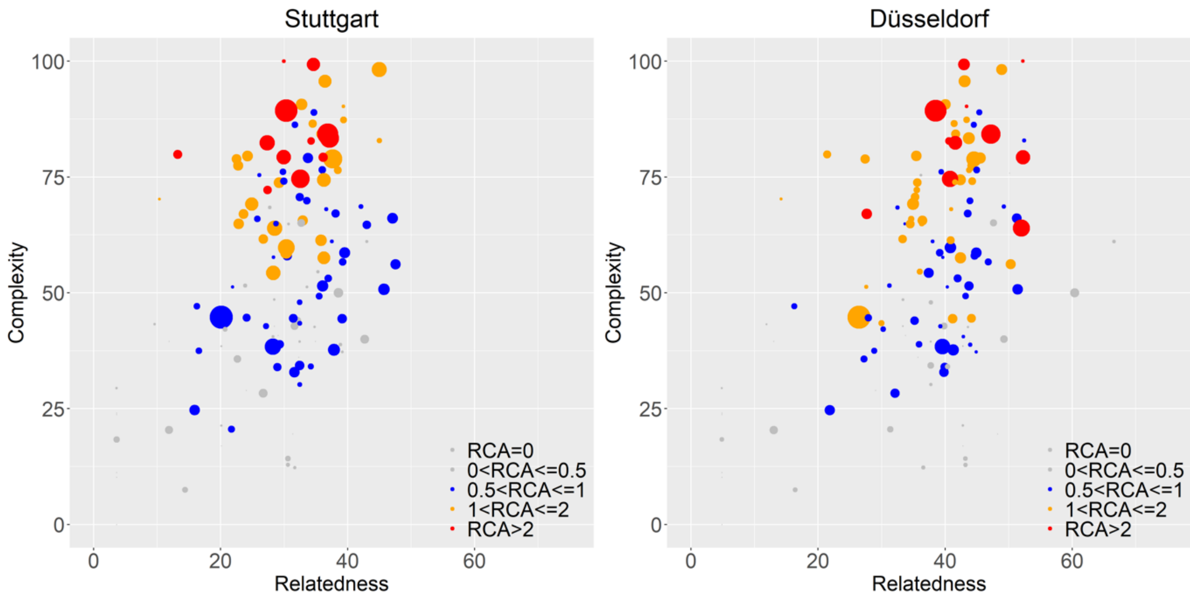

Figure 4: This Figure shows the future diversification opportunities for Stuttgart and Dusseldorf using occupation data. Colours indicate occupations' Revealed Comparative Advantages in the region

Figure 5 shows the future diversification opportunities for two of the representative old industrial regions in Europe (Nord Pas de Calais region in France and Piemonte region in Italy). They tend to specialize in less complex occupations. There are some diversification opportunities in complex occupations; however, they are less related to their existing labour markets. This means it will be uncertain for them to develop those complex occupations.

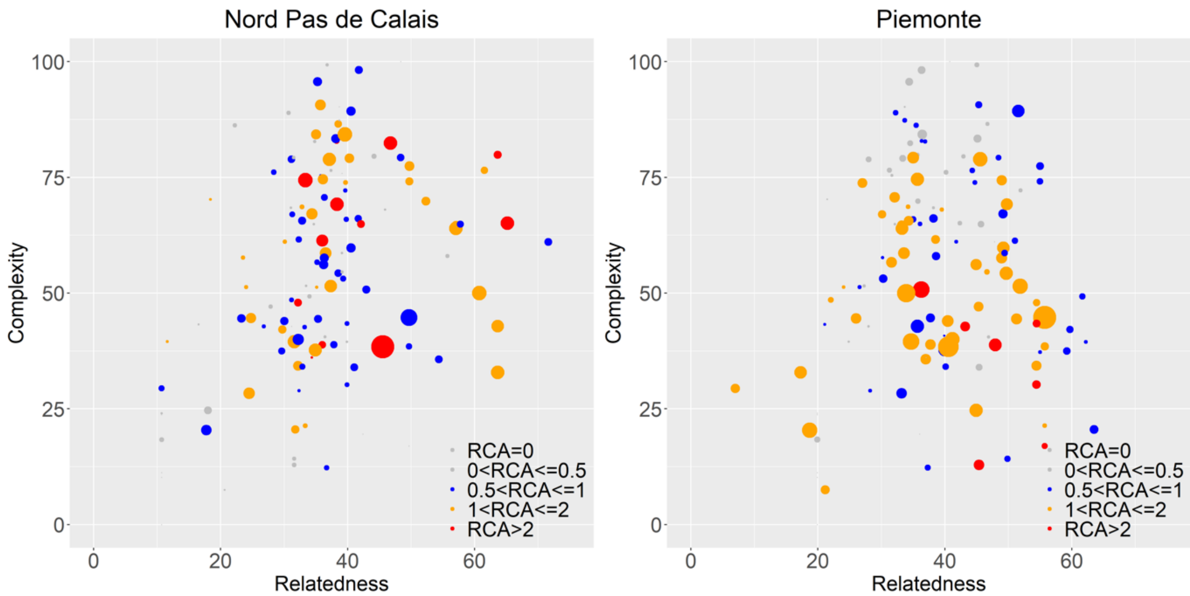

Figure 5: This Figure shows the future diversification opportunities for Piemonte and Nord pas de Calais using occupation data. Colours indicate occupations' Revealed Comparative Advantages in the region

Figure 6 shows the future diversification opportunities of two mining regions in Europe. Both were included in the "Initiative for coal regions in transition of European Commission". The Sud Vest Oltenia region in Romania, is also located in the periphery of Europe. The Severozapad region is an industrial region in the northern part of the Czech Republic. Although both are coal mining regions, they have a very different diversification profile from each other. While the Severozapad region has more diversification possibilities in the sense of related occupations (several of them towards complex occupations), the Romanian region of Sud Vest Oltenia is practically an empty space of related occupations.

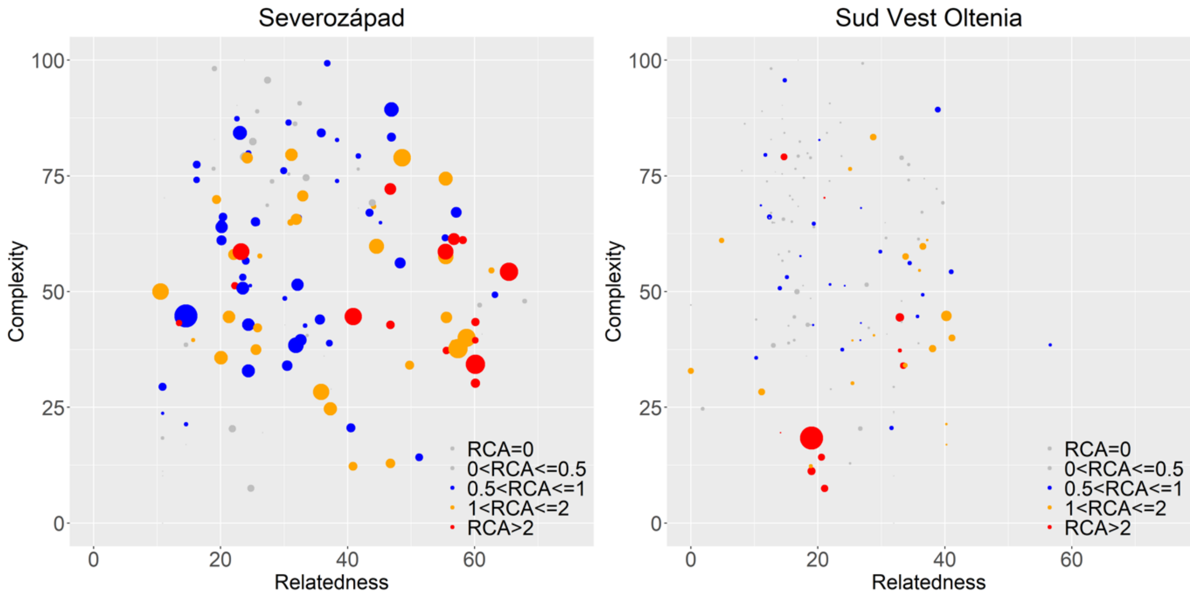

Figure 6: This Figure shows the future diversification opportunities for Severozapad and Sud Vest Oltenia using occupation data. Colours indicate occupations' Revealed Comparative Advantages in the region

Figure 7 shows the future diversification opportunities of two periphery regions (Dytiki Ellada in Greece and Nord Est region in Romania). The main occupations in these two regions are agricultural jobs that are less complex (Market Gardeners and Crop Growers, Animal Producers and Mixed Crop and Animal Producers). Most of the complex jobs are less related to their local labour markets. Thus, it will remain a challenge for them to diversify into activities that will bring potential economic benefits.

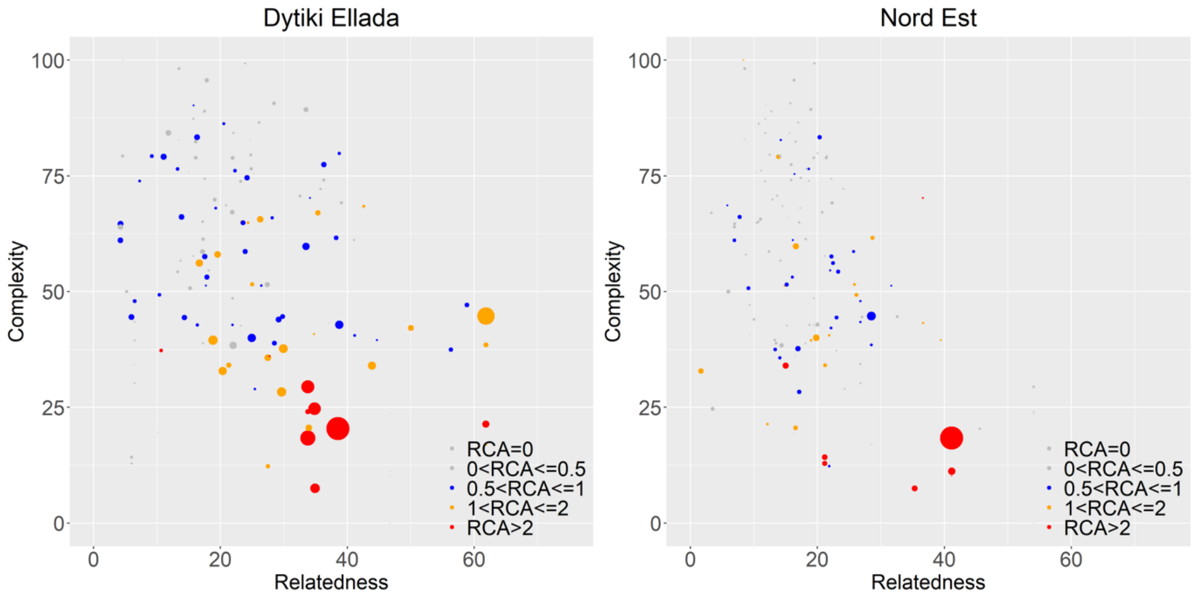

Figure 7: This Figure shows the future diversification opportunities for Dytiki Ellada and Nord Est using occupation data. Colours indicate occupations' Revealed Comparative Advantages in the region

Next, we present the occupation space elaborated from the 130 ISCO occupations (Figure 8). We followed Hidalgo et al. (2007) to present a max spanning tree network. The network is visualized using Force Altas 2 layout in the software Gephi. Each node represents an ISCO 3 digit occupation (minor group). The size of nodes measures the complexity of occupations and the colour of nodes represents the ISCO major group that each 3 digit ISCO minor group belongs to. The advantage of this occupation space is that we can better capture relations between occupations across ISCO major groups. We can observe several clusters of nodes of the same colour together with some supporting managers, professionals, and technicians. These clusters are mostly divided around industrial sectors, like agricultural, manufacturing, transport, health care and ICT services, etc.

For example, the light blue nodes that are close to each other are Skilled Agricultural, Forestry and Fishery Workers. These occupations are less complex. The nodes closely connected to those light blue nodes (Skilled Agricultural, Forestry and Fishery Workers) are Life Science Technicians and Related Associate Professionals and Veterinary Technicians and Assistants (light green nodes), and Life Science Professionals (blue node), and

Managers in Agricultural Sectors (pink node). These occupations tend to be more complex than those agricultural occupations.

Another example is the cluster of blue nodes in the upper right part of the network. These complex occupations are mostly advanced technology services such as Administrative Professionals, Database and Network Professionals, and Software Application Developers and Analysts. The occupations connected to them are ICT Operations and User Support Technicians (green node) and ICT Services Managers (pink node).

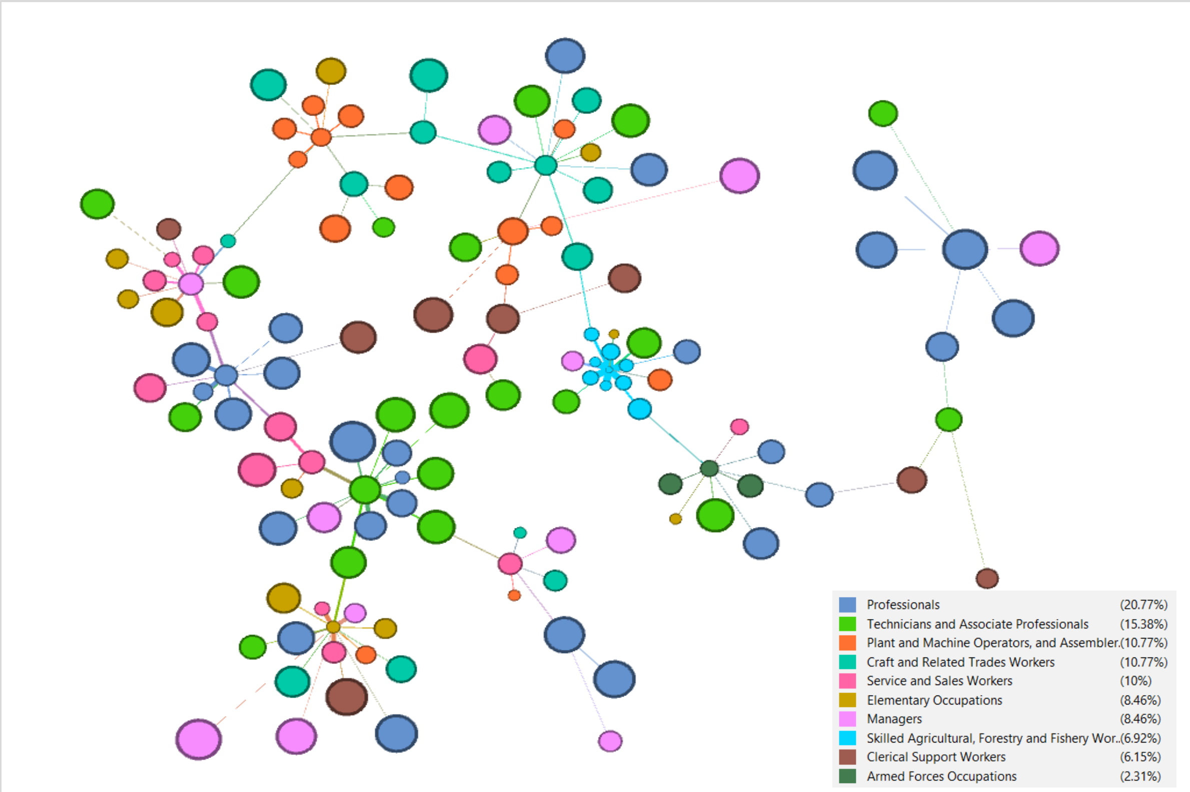

Figure 8: Network of occupation-space (ISCO 3D, 2017-19)

4.3 Regional labour market dynamics in EU NUTS-2 regions

Next, we present the results of the econometric analysis for the models where a region becomes specialized (loses specialization) if it has a positive (negative) variation of at least 2-tenths in LQ between consecutive periods – this means a variation in LQ from < 0.8 at time *t* to > 1 at time *t+1* for entry; and a variation in LQ from >1.2 at time *t* to LQ <1.0 at time *t+1* for exit. In this way, we eliminate marginal gains of regional specialization from the analysis, as previously mentioned.

Table 12 presents the findings for entries (gain in occupational specialization). Relatedness density (RelDens) shows a positive and significant coefficient, indicating that an increase in relatedness density is associated with new entries.

As for the complexity indicators, both occupational and regional were not individually significant. However, interacting the relatedness density with complexity becomes significant and positive only for occupational complexity. Such results indicate that the more the occupation complexity and relatedness density increase, the greater the chance of a region becoming specialized in that occupation. On the other hand, an increase in relatedness density tied to more complex regions does not produce significant results on the gain of regional occupational specialization. In this way, it seems that the occupation's complexity helps explain the specialization gains more than the region's complexity.

Furthermore, when interacting the complexity of occupation with the complexity of the region, we also obtain a statistically significant and positive coefficient. This indicates that the presence of more complex occupations in more complex regions is a factor that tends to promote regional specialization.

Table 12: Entry Models – increase in Locational Quotient of at least 2-tenths

	Entry1							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.01853***	0.01854***	0.01851***	0.02043***	0.01811***	0.01963***	0.02046***	0.01868***
	(0.00479)	(0.00479)	(0.00479)	(0.00430)	(0.00442)	(0.00459)	(0.00473)	(0.00480)
t_lag_CompOcc		-0.00499		0.00074	0.00552	-0.00666	-0.00624	-0.00408
		(0.02758)		(0.02805)	(0.02840)	(0.02820)	(0.02920)	(0.02951)
t_lag_CompReg			0.03436	0.02988	0.02935	0.02971	0.04190	0.04073
			(0.02764)	(0.02782)	(0.02787)	(0.02935)	(0.03258)	(0.03268)
t_lag_EducThir						-0.01087	-0.01012	-0.00740
						(0.00960)	(0.00970)	(0.00986)
t_lag_SmallSize						-0.01552**	-0.01593**	-0.01622**
						(0.00781)	(0.00803)	(0.00800)
t_lag_ln_PopDens							-0.00417	-0.00446
							(0.00688)	(0.00681)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_ln_GDPpc							0.03801	0.03719
							(0.03370)	(0.03364)
t_lag_Unemploy							-0.02574	-0.02522
							(0.02317)	(0.02316)
t_lag_RelDens x t_lag_CompOcc				0.01742***	0.01592***	0.01649***	0.01609***	0.01499***
				(0.00380)	(0.00425)	(0.00364)	(0.00390)	(0.00434)
t_lag_RelDens x t_lag_CompReg				-0.00042	-0.00248	-0.00227	-0.00120	-0.00278
				(0.00379)	(0.00387)	(0.00412)	(0.00437)	(0.00444)
t_lag_CompOcc x t_lag_CompReg					0.01398***			0.01134***
					(0.00402)			(0.00425)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,453	11,453	11,453	11,453	11,453	10,669	9,935	9,935
R^2	0.13959	0.13960	0.13992	0.14259	0.14474	0.14789	0.15187	0.15319
Adjusted R^2	0.11318	0.11311	0.11345	0.11596	0.11809	0.11949	0.12282	0.12410
Residual Std. Error	0.22225	0.22226	0.22222	0.22190	0.22163	0.21720	0.22031	0.22015

Note: The variables are mean-centred. The standard errors are clustered on the regional and occupational levels. Entry condition: LQ < 0.8 at time t, and > 1 at time t+1. Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level.

To check the robustness of the results in Table 12, besides the increase in the LQ of at least 2-tenths, we include an additional condition of absolute growth in the number of jobs between periods for the region-occupation pairs (measure *d*). The results are shown in Table 13.

Table 13: Entry Models – absolute employment growth and increase in Locational Quotient of at least 2 tenths

	Entry2							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.01785***	0.01787***	0.01782***	0.01974***	0.01744***	0.01902***	0.01976***	0.01798***
	(0.00474)	(0.00474)	(0.00474)	(0.00428)	(0.00440)	(0.00454)	(0.00469)	(0.00477)
t_lag_ CompOcc		-0.01041		-0.00472	0.00002	-0.01277	-0.01295	-0.01082
		(0.02647)		(0.02703)	(0.02742)	(0.02691)	(0.02778)	(0.02812)
t_lag_ CompReg			0.03543	0.03088	0.03034	0.02986	0.04327	0.04210
			(0.02779)	(0.02798)	(0.02803)	(0.02907)	(0.03168)	(0.03180)
t_lag_EducThir						-0.01131	-0.01062	-0.00791

						(0.00963)	(0.00973)	(0.00989)
t_lag_SmallSize						-0.01473*	-0.01512*	-0.01540*
						(0.00783)	(0.00806)	(0.00803)
t_lag_ln_PopDens							-0.00537	-0.00566
							(0.00760)	(0.00753)
t_lag_ln_GDPpc							0.03855	0.03773
							(0.03353)	(0.03352)
t_lag_Unemploy							-0.01842	-0.01792
							(0.02256)	(0.02257)
t_lag_RelDens x t_lag_CompOcc				0.01717***	0.01567***	0.01599***	0.01547***	0.01436***
				(0.00375)	(0.00420)	(0.00362)	(0.00386)	(0.00430)
t_lag_RelDens x t_lag_CompReg				0.00003	-0.00202	-0.00187	-0.00087	-0.00245
				(0.00379)	(0.00388)	(0.00412)	(0.00438)	(0.00445)
t_lag_CompOcc x t_lag_CompReg					0.01390***			0.01132***
					(0.00400)			(0.00423)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,439	11,439	11,439	11,439	11,439	10,658	9,924	9,924
R^2	0.13860	0.13862	0.13896	0.14157	0.14373	0.14908	0.15296	0.15431
Adjusted R^2	0.11221	0.11215	0.11250	0.11495	0.11710	0.12070	0.12392	0.12522
Residual Std. Error	0.22033	0.22034	0.22030	0.21999	0.21972	0.21530	0.21833	0.21817

Note: The variables are mean-centred. The standard errors are clustered on the regional and occupational levels. Entry condition: regions with an absolute increase in jobs and LQ < 0.8 at time t, and > 1 at time t+1. Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level.

In general, results correspond to those found in the previous table. However, the magnitude of the coefficients is slightly smaller than those in Table 12 (as expected, since here there is a restriction condition, considering an absolute increase in employment). The results show that an increase in relatedness density tends to promote gains in occupational specialization in the regions.

Changes in occupational complexity and regional complexity have no impact on the gain of new occupational specializations. However, as in the previous model, when we interact relatedness density with occupation complexity, we found a positive and significant association, meaning that the occupation complexity positively reinforces the traditional role of relatedness density in promoting regional specialization.

We obtain again a statistically significant and positive coefficient for the interaction term between the region's complexity and the occupation's complexity.

Next, we will assess the results for the exit, which means the loss of occupational specialization in the regions (Tables 14 and 15).

Table 14: Exit Models – decrease in Locational Quotient of at least 2-tenths

	Exit1							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.00790***	0.00790***	0.00785***	0.00805***	0.00659***	0.00771***	0.00680***	0.00554**
	(0.00219)	(0.00219)	(0.00220)	(0.00223)	(0.00227)	(0.00230)	(0.00248)	(0.00251)
t_lag_CompOcc		0.00013		0.00198	0.00566	0.00080	0.00530	0.00718
		(0.01901)		(0.01892)	(0.01843)	(0.02056)	(0.02192)	(0.02165)
t_lag_CompReg			0.02760	0.02708	0.02575	0.03208	0.03416	0.03240
			(0.02325)	(0.02319)	(0.02277)	(0.02546)	(0.02995)	(0.02956)
t_lag_EducThir						-0.02766***	-0.02903***	-0.02666***
						(0.00736)	(0.00735)	(0.00749)
t_lag_SmallSize						-0.00794**	-0.00802*	-0.00855**
						(0.00371)	(0.00407)	(0.00402)
t_lag_ln_PopDens							0.00484	0.00492
							(0.00521)	(0.00517)
t_lag_ln_GDPpc							0.05150**	0.05109**
							(0.02415)	(0.02410)
t_lag_Unemploy							0.00374	0.00357
							(0.01446)	(0.01445)
t_lag_RelDens x t_lag_CompOcc				0.00275	0.00175	0.00250	0.00333	0.00263
				(0.00202)	(0.00219)	(0.00209)	(0.00223)	(0.00243)
t_lag_RelDens x t_lag_CompReg				0.00004	-0.00123	-0.00012	-0.00089	-0.00193
				(0.00182)	(0.00186)	(0.00189)	(0.00185)	(0.00191)
t_lag_CompOcc x t_lag_CompReg					0.01152***			0.00994***
					(0.00220)			(0.00228)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,495	21,495	21,495	21,495	21,495	20,197	18,620	18,620
R^2	0.06702	0.06702	0.06736	0.06746	0.06993	0.07736	0.08003	0.08182
Adjusted R^2	0.05162	0.05158	0.05193	0.05189	0.05435	0.06090	0.06302	0.06479
Residual Std. Error	0.18257	0.18257	0.18254	0.18254	0.18230	0.18219	0.18145	0.18128

Note: The variables are mean-centred. The standard errors are clustered on the regional and occupational levels. Exit condition: LQ >1.2 at time t to LQ <1.0 at time t+1. Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level.

Table 14 presents the findings for exit using the restriction condition that a region loses occupational specialization only if there is a negative variation in LQ of at least 2-tenths between two periods (measure *c*).

In that case, we have found a result different from the expected. In this condition, the loss of regional occupational specialization is positively associated with occupational relatedness density, but the expected result would be a negative association. However, the coefficients size of the relatedness density in the exit models (Table 14) are much smaller - two to four times smaller - than the coefficient in the entry models (Table 12). Therefore, we can sustain that the relatedness density is more strongly associated with gaining rather than losing occupational specialization.

For the exit models, the complexity of the occupation or the region does not show a statistically significant coefficient. We did not find significant results for the interaction term between relatedness density and both complexity measures as well. Therefore, we cannot state that the complexity of the region or occupation has the capacity to retain the exit of occupational specialization, nor say that complexity of occupation or region are associated with a loss of specialization.

In the same way we presented in the entry models, we included a more restrictive condition for the exit models. So, in Table 15, we consider the loss of occupational specialization across regions when there is a decrease in LQ of at least 2-tenths (LQ > 1.2 at time t and < 1.0 at time t+1) and additionally an absolute decline in the number of jobs in the region-occupation pairs between periods (measure *d*). In this model, the pattern remains the same, confirming the previous results' robustness (Table 14).

Table 15: Exit Models – absolute decline in employment and decrease in Locational Quotient of at least 2-tenths

	Exit2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.00742***	0.00741***	0.00741***	0.00755***	0.00640***	0.00725***	0.00624**	0.00534**
	(0.00216)	(0.00216)	(0.00216)	(0.00218)	(0.00222)	(0.00225)	(0.00245)	(0.00247)
t_lag_CompOcc		0.00433		0.00476	0.00767	0.00408	0.00937	0.01070
		(0.01886)		(0.01895)	(0.01859)	(0.02050)	(0.02180)	(0.02162)
t_lag_CompReg			0.00465	0.00427	0.00329	0.00656	0.00123	0.00006
			(0.01326)	(0.01334)	(0.01324)	(0.01363)	(0.01404)	(0.01399)
t_lag_EducThir						-0.03041***	-0.03180***	-0.03011***
						(0.00726)	(0.00725)	(0.00734)
t_lag_SmallSize						-0.00848**	-0.00853**	-0.00890**
						(0.00364)	(0.00399)	(0.00396)
t_lag_ln_PopDens							-0.00275	-0.00273
							(0.00401)	(0.00398)
t_lag_ln_GDPpc							0.04792**	0.04764**
							(0.02356)	(0.02354)
t_lag_Unemploy							-0.00933	-0.00941
							(0.01260)	(0.01262)
t_lag_RelDens x t_lag_CompOcc				0.00256	0.00178	0.00229	0.00301	0.00252
				(0.00195)	(0.00209)	(0.00201)	(0.00214)	(0.00231)
t_lag_RelDens x t_lag_CompReg				-0.00077	-0.00177	-0.00103	-0.00198	-0.00273
				(0.00174)	(0.00180)	(0.00181)	(0.00176)	(0.00184)
t_lag_CompOcc x t_lag_CompReg					0.00909***			0.00708***
					(0.00193)			(0.00198)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,446	21,446	21,446	21,446	21,446	20,148	18,571	18,571
R^2	0.06593	0.06594	0.06594	0.06606	0.06768	0.07629	0.07951	0.08047
Adjusted R^2	0.05048	0.05044	0.05045	0.05043	0.05204	0.05976	0.06244	0.06338
Residual Std. Error	0.17728	0.17728	0.17728	0.17728	0.17713	0.17659	0.17529	0.17521

Note: The variables are mean-centred. The standard errors are clustered on the regional and occupational levels. Exit condition: regions with an absolute decrease in jobs and LQ >1.2 at time t to LQ <1.0 at time t+1. Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level.

Similar to the previous results, relatedness density in Table 15 positively correlates with the loss of regional occupational specialization. When comparing the size of the relatedness density coefficients in the entry and exit models following the exact specification (Tables 13 and 15), we note that, although both return positive coefficients, in the exit model the coefficient ranges from 2.4 to 3.5 times lower than those found in the entry model. Thus, the interpretation is the same; a higher occupational relatedness density is more strongly associated with gain than a loss of specialization.

In Table 15, the complexity of either occupation or region is also not statistically significant, not even in the case of interaction with relatedness density.

As a complementary robustness check, in Appendix A we include the results tables with all the other entry and exit conditions mentioned in the methodology. In general, the results follow the same direction as those found above.

4.4 A regional perspective by income level

There is growing literature on regional diversification that focuses on the development of new activities in regions and how they build local capabilities based on related industries, occupations, or technologies. However, the opportunities that regions have to promote new activities are limited. For example, it is known that high-income regions tend to diversify more and especially into more complex activities, those that bring greater economic benefit (Boschma 2022; Galetti *et al.* 2021; Pinheiro *et al.* 2022a; Rigby *et al.* 2022). In turn, low-income regions generally concentrate on low-complex activities. They, therefore, face more significant obstacles in moving towards non-related activities that typically require more complex industries, occupations, or technologies than those existing in the region.

Seeking to understand how this dynamic of diversification opportunities performs in European regions, we will assess the relationship between relatedness and occupational specialization in NUTS 2 regions by different per capita income levels. We also want to understand whether occupation complexity plays any role in the diversification of regions by different per capita income levels.

To this end, we test how the effect of related diversification varies at different stages of economic development. We are interested in the relatedness density coefficient and complexity measures in three types of regions: low-income, middle income and high-income regions in the European context. We divided the 229 NUTS 2 regions into equal tertiles of per capita income for each period (in this way, each income tertile has approximately 76 regions).

Here we also apply a three-stage fixed effects model (by occupation, region, and time), all the variables are lagged in one period, and all the independent variables are mean-centred. We are using three regions' dummies by per capita income level in the econometric tests. Such dummies are interacting either with relatedness density or with occupation complexity.

In the following, we bring the results of two econometric specifications: first, with the specialization condition of LQ variation of at least 2-tenths between two consecutive periods, and second, the same variation on LQ together with absolute employment variation for each region-occupation pair (measures c and d). The econometric tests with all additional conditions to the entry and exit measures are also presented in Appendix B as robustness exercises.

Entry results are shown in Tables 16 and 17. The interaction between relatedness density and regional dummies by per capita income level has distinct dimensions. The higher the GDP per capita of the region, the lower the coefficient of such an interaction. Thus, relatedness density is positive, significant, and higher in regions with lower GDP per capita than regions with higher GDP per capita. This result is in line with convergence theory[4], in which the role of relatedness density is positive for entries of new occupational specialization, but it loses strength as GDP per capita increases. According to our interpretation, high-income regions depend less on relatedness density because they are more able to engage in not necessarily related occupational diversification.

However, we do not find significant coefficients regarding the complexity of occupations in regions at different per capita income levels. The complexity of occupations has a positive and significant coefficient when interacting with relatedness density. In this case, we can state that the higher the occupational relatedness density of a region, the greater the chances of developing related and complex occupational specializations.

[4] Positive but decreasing returns as per capita GDP increases.

Table 16: Entry Models by per capita income level – increase in Locational Quotient of at least 2-tenths

	Entry1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.01853***		0.02769***			0.03295***	0.01698***
	(0.00287)		(0.00510)			(0.00667)	(0.00300)
CompOcc				-0.00610		0.00034	
				(0.01974)		(0.01974)	
CompReg					0.04588***	0.04280**	
					(0.01742)	(0.01745)	
RelDens x GDPpcLow		0.02769***		0.02770***	0.02748***		
		(0.00510)		(0.00510)	(0.00510)		
RelDens x GDPpcMid		0.01897***	-0.00872	0.01897***	0.01906***	-0.01119	
		(0.00525)	(0.00736)	(0.00525)	(0.00525)	(0.00877)	
RelDens x GDPpcHigh		0.01055**	-0.01714**	0.01056**	0.01049**	-0.02310**	
		(0.00466)	(0.00704)	(0.00466)	(0.00466)	(0.00998)	
RelDens x CompOcc						0.01687***	
						(0.00314)	
RelDens x CompReg						0.00646*	
						(0.00385)	
GDPpcLow x CompOcc							-0.02730
							(0.02010)
GDPpcMid x CompOcc							0.00018
							(0.01998)
GDPpcHigh x CompOcc							0.00573
							(0.02004)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,453	10,883	10,883	10,883	10,883	10,883	10,883
R^2	0.13959	0.14232	0.14232	0.14233	0.14289	0.14531	0.14425
Adjusted R^2	0.11318	0.11592	0.11592	0.11585	0.11642	0.11866	0.11782
Residual Std. Error	0.22225	0.22411	0.22411	0.22412	0.22405	0.22376	0.22387

Note: The variables are mean-centred. Entry condition: LQ < 0.8 at time t, and > 1 at time t+1. Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level.

Table 17: Entry Models by per capita income level - increase in Locational Quotient of at least 2-tenths and absolute employment growth

	Entry2						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.01785***		0.02556***			0.03032***	0.01623***
	(0.00285)		(0.00507)			(0.00662)	(0.00298)

CompOcc				-0.01174		-0.00534	
				(0.01958)		(0.01958)	
CompReg					0.04723***	0.04395**	
					(0.01728)	(0.01731)	
RelDens x GDPpcLow		0.02556***		0.02558***	0.02534***		
		(0.00507)		(0.00507)	(0.00507)		
RelDens x GDPpcMid		0.01870***	-0.00686	0.01870***	0.01880***	-0.00881	
		(0.00521)	(0.00730)	(0.00521)	(0.00520)	(0.00871)	
RelDens x GDPpcHigh		0.01076**	-0.01480**	0.01079**	0.01070**	-0.01999**	
		(0.00462)	(0.00699)	(0.00462)	(0.00462)	(0.00991)	
RelDens x CompOcc						0.01659***	
						(0.00312)	
RelDens x CompReg						0.00602	
						(0.00382)	
GDPpcLow x CompOcc							-0.03274
							(0.01994)
GDPpcMid x CompOcc							-0.00606
							(0.01982)
GDPpcHigh x CompOcc							0.00034
							(0.01988)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,439	10,869	10,869	10,869	10,869	10,869	10,869
R^2	0.13860	0.14120	0.14120	0.14123	0.14181	0.14419	0.14326
Adjusted R^2	0.11221	0.11481	0.11481	0.11476	0.11536	0.11755	0.11685
Residual Std. Error	0.22033	0.22214	0.22214	0.22214	0.22207	0.22179	0.22188

Note: The variables are mean-centred. Entry condition: regions with an absolute increase in jobs and LQ < 0.8 at time t, and > 1 at time t+1. Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level.

Next, we will evaluate the possibilities of exit, whether the relationship between relatedness density and loss of specialization differs in regions at distinct per capita income levels.

When interacting the relatedness density with the regions' dummies by per capita income level, we found a positive and significant coefficient (Tables 7 and 8) in accordance with the baseline models (without segmentation by income level per capita) presented in Section 4.2.

Compared to the entry models (Table 16), the coefficients' size is quite smaller (see models 3 and 6 in Tables 16 and 18). However, as the region's per capita income increases, the coefficient's size decreases considerably (approaching zero in high-income regions). Thus, the role of relatedness density in avoiding exits is stronger in high-income regions, followed by middle-income regions, compared to low-income regions. As for the occupation complexity, we do not find significant coefficients.

Table 18: Exit Models by per capita income level – decrease in Locational Quotient of at least 2-tenths

	Exit1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.00790***		0.01452***			0.01991***	0.00631***
	(0.00166)		(0.00290)			(0.00372)	(0.00173)
CompOcc				0.00424		0.00576	
				(0.01141)		(0.01142)	
CompReg					0.02821***	0.02834***	
					(0.01040)	(0.01043)	
RelDens x GDPpcLow		0.01452***		0.01452***	0.01440***		
		(0.00290)		(0.00290)	(0.00290)		
RelDens x GDPpcMid		0.00460	-0.00992**	0.00460	0.00457	-0.01534***	
		(0.00304)	(0.00418)	(0.00304)	(0.00304)	(0.00486)	
RelDens x GDPpcHigh		0.00143	-0.01309***	0.00142	0.00138	-0.02207***	
		(0.00279)	(0.00408)	(0.00279)	(0.00279)	(0.00566)	
RelDens x CompOcc						0.00255	
						(0.00190)	
RelDens x CompReg						0.00562**	
						(0.00230)	
GDPpcLow x CompOcc							-0.00521
							(0.01165)
GDPpcMid x CompOcc							0.00661
							(0.01159)
GDPpcHigh x CompOcc							0.00975
							(0.01160)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,495	20,230	20,230	20,230	20,230	20,230	20,230
R^2	0.06702	0.06786	0.06786	0.06787	0.06821	0.06856	0.06813
Adjusted R^2	0.05162	0.05231	0.05231	0.05227	0.05261	0.05283	0.05254
Residual Std. Error	0.18257	0.18180	0.18180	0.18181	0.18177	0.18175	0.18178

Note: The variables are mean-centred. Exit condition: LQ >1.2 at time t to LQ <1.0 at time t+1. Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level.

Table 19: Exit Models by per capita income level - decrease in Locational Quotient of at least 2-tenths and absolute employment decline

	Exit2						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.00742***		0.01383***			0.01754***	0.00580***
	(0.00162)		(0.00281)			(0.00361)	(0.00168)
CompOcc				0.00880		0.00891	
				(0.01107)		(0.01108)	
CompReg					0.00155	0.00184	
					(0.01022)	(0.01024)	
RelDens x GDPpcLow		0.01383***		0.01383***	0.01383***		
		(0.00281)		(0.00281)	(0.00281)		
RelDens x GDPpcMid		0.00427	-0.00956**	0.00427	0.00427	-0.01320***	
		(0.00295)	(0.00406)	(0.00295)	(0.00295)	(0.00471)	
RelDens x GDPpcHigh		0.00092	-0.01291***	0.00090	0.00091	-0.01894***	
		(0.00270)	(0.00396)	(0.00270)	(0.00270)	(0.00550)	
RelDens x CompOcc						0.00234	
						(0.00185)	
RelDens x CompReg						0.00382*	
						(0.00223)	
GDPpcLow x CompOcc							-0.00083
							(0.01130)
GDPpcMid x CompOcc							0.01239
							(0.01124)
GDPpcHigh x CompOcc							0.01327
							(0.01125)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,446	20,181	20,181	20,181	20,181	20,181	20,181
R^2	0.06593	0.06685	0.06685	0.06688	0.06685	0.06709	0.06718
Adjusted R^2	0.05048	0.05124	0.05124	0.05123	0.05120	0.05129	0.05153
Residual Std. Error	0.17728	0.17614	0.17614	0.17614	0.17614	0.17613	0.17611

Note: The variables are mean-centred. Exit condition: regions with an absolute decrease in jobs and LQ >1.2 at time t to LQ <1.0 at time t+1. Coefficients are significant at *p < 0.10; **p < 0.05; ***p < 0.01 level.

5. Conclusion

Related activities draw on similar capabilities tend to enhance knowledge spillovers and the probability of learning from each other, providing opportunities for knowledge recombination and the emergence and disappearance of activities over time (Boschma *et al.* 2013).

In this context, occupational relatedness is derived from sharing similar knowledge, skill content, tasks and other factors associated with local agglomeration economies (Balland *et al.* 2022; Farinha *et al.* 2019; Wixe & Andersson 2017). Relatedness between occupations influences the region's structural change through a branching process (Galetti *et al.* 2022) in which, on the one hand, new occupations grow out of existing occupations and on the other hand, unrelated occupations decline due to the lack of similarity with the local productive structure. Thus, possibilities for future diversification will be linked to the profile of existing occupations in a region.

In addition, a greater diversity of occupations also positively influences regional diversification (Balland *et al.* 2019; Xiao *et al.* 2018), since there are more possible combinations to be made, and more occupations can lead to related occupations. However, a group of occupations can promote even more significant economic benefits, the complex occupations, which demand high skills and a higher educational level (Balland *et al.* 2020; Mealy *et al.* 2019; Wixe & Andersson 2017). Thus, complex occupations in a region can stimulate the attraction of other complex occupations along with ancillary occupations that are not complex but are essential to maintain the activities where the complex occupations are seen.

This report makes some contributions to the literature. First, we present a broad view of relatedness between occupations for the European Union. Due to the difficulty in finding data that allow this analysis, previous work has been based mainly on individual countries (such as Italy, Norway, and Sweden). By treating the LFS microdata we were able to provide an overview of the 229 NUTS regions of the 27 European countries. Second, evaluating occupations at ISCO 3D (130 occupations) allowed us to identify occupations related to manufacturing and also to the service activities. Previous studies concentrate on the product or technology space, which follow an approach focused on goods and technological services. Based on our results it is also possible to identify many occupations directly involved in service activities (both complex and less complex occupations) in addition to an approach based on goods. This is relevant because many EU countries have economies strongly based on service activities. Third, we elaborated a regions' complexity rank based on the occupations found in each NUTS region and an occupations' complexity rank as well. Thus, besides the approach based on technologies or goods, we also identify regions and occupations related to administrative headquarters of public and private institutions (and that demand highly qualified professionals); creative and cultural activities; education and health workers; in addition to knowledge intensive service. Still, occupations associated with industrial regions - which due to changes in the allocation of supply chain activities have lost their prominence - also appear in different positions in the complexity rank, giving new clues about how regional specialization is taking form. Fourth, we have documented the dynamics of related diversification at different stages of economic development (starting from the level of per capita income) and verified the role of complexity of occupations and regions in related diversification.

The results of this report show that the space of occupations composed of mixed clusters. High complexity occupations are surrounded mainly by medium complexity ones. In turn, low complexity occupations are at the edges of the network but are also present in some high and medium complexity clusters. This reinforces that an occupation is not only related to other similar occupations, it requires other complementary occupations that are not as complex as itself, but that are vital to perform its task.

As for the gain in occupational specialization (entry), results indicating that an increase in relatedness density tends to promote gains in occupational specialization in the regions. We also found that the more the occupation complexity and relatedness density increase, the greater the chance of a region becoming specialized in that occupation.

As for the loss of specialization, although the results show a positive relation of relatedness density and exit, when we compare both entry and exit, its association with new entries is greater than its effect supporting exits. So, we can say that a higher occupational relatedness density is more strongly associated with gain than a loss of specialization.

From a perspective by regional income level, we have seen that the specialization dynamic varies at different stages of economic development. We found that the role of relatedness density is positive for entries of new occupational specialization, but it loses strength as GDP per capita increases. We understand that high-income regions depend less on relatedness density because they are more able to engage in not necessarily related occupational diversification. As for the role of relatedness density in avoiding exits, we found that it is stronger in high-income regions, followed by middle-income regions, compared to low-income regions. Besides, we also identified that the higher the complexity of occupation, the greater the chances of developing related and complex occupational specializations. These results are robust to several econometric specifications based on various more restrictive entry and exit conditions than those traditionally employed in the literature.

6. Policy brief

To conclude this report, we prepared a short policy brief to bring together some insights from our report and reflect on those in terms of possible policy implications.

Seeking to understand the factors that lead regions to follow vibrant trajectories or to be stuck in low growth trajectories, the evolutionary economic geography built a theoretical and empirical framework (Boschma & Frenken 2018). This literature argues that the prior knowledge base and competencies established in a region will determine the future paths that the region can follow, that is, path dependence matters (Neffke *et al.* 2011). On the one side, regions not much diversified and with a few complex activities tend to perpetuate a trajectory of low technological dynamism for a long time. On the other side, diversified regions with complex activities have a wider range of knowledge and technologies that can be recombined, resulting in new specializations (Rigby *et al.* 2022). Diversification tends to occur more frequently for related activities, i.e. towards activities that involves knowledge, technologies, skills, infrastructure or similar institutions (Boschma 2017).

How do region diversify over time has been a core topic of the regional diversification literature. Empirical studies in the last decade have convincingly shown that relatedness is an important driver behind industrial dynamics at the regional level that new industries are more likely to emerge and develop in a region when these are related to existing industries in a region, while existing industries are more likely to exit a region when unrelated to other local industries (Boschma 2017; Hidalgo 2021).

However, most regional diversification studies focused on product and industry diversification or technological diversification. What these studies take up, especially those using patent data, are technological capabilities and specifically high-tech capabilities (Balland & Boschma 2019). To get a broad picture of the diversification potentials of regions in the EU, there is a need to broaden the capability measure and go beyond patents and products. Such effort is also needed to capture better capabilities among regions with different occupational portfolio, such as highly diversified ones that concentrate complex occupations, regions with an intermediate degree of diversification or regions that are not very diversified and not very complex. This would be key information for policy makers when setting priorities in their Smart Specialization policies (D'Adda et al. 2019; Marrocu et al. 2020).

Occupations can provide complementary insight into the local capabilities (Farinha *et al.* 2019; Neffke & Henning 2013; Tessarin & Azzoni 2022), especially with the increasing importance of human capital and skills in the age of digitalization (Acemoglu & Restrepo 2018). Previous studies confirm the importance of relatedness in the entry of new occupations in a region - Fitjar & Timmermans (2017) on Norwegian regions, Farinha et al. (2019) on US cities, and Galetti et al. (2021; 2022) on Brazilian regions. This report aims to more comprehensively shed light on the disparity in regional diversification opportunities and the occupation dynamics by NUTS 2 regions in Europe, using microdata from European Labour Force Survey. Knowing this dynamic of the regional diversification process, we are also able to suggest policies that can guide the paths of occupational diversification for European regions.

Results from our report on NUTS 2 regions and ISCO-08 three-digit occupations show that European regions with a more coherent occupational structure are likely to experience more opportunities for diversification, especially into complex occupations. Thus, possibilities for future occupational diversification will be linked to the profile of existing occupations in a region. However, not every region has the same capacity to diversify into new occupations. At this point, the policy can make a difference in the sense of promoting investment from outside, lifting training and professional education, even the capacity of local firms to promote the professional updating of their employees, and establishing collaborations with other regions, among other actions.

It is good to realize that related diversification in regions is far from a natural process but it needs to be activated and promoted by public policy, as there might be significant bottlenecks in regions, such as a lack of funding, low education, lack of entrepreneurial attitude, weak regulations, corruption. The more challenging task for policy is to ensure that regions can evolve out of their low complexity trap, especially when this requires regions to make jumps in the more unknown. One way to accomplish this is to upgrade the local knowledge infrastructure (science and education) to enhance the ability of regions to move into more complex activities. Another way is to establish inter-regional linkages (Miguelez and Moreno 2018; Trippl et al. 2018; Balland and Boschma 2021), such as attracting skilled migrants (Caviggioli et al. 2020) and external firms (Neffke et al. 2018), and establishing research collaborations (De Noni et al. 2018; Uyarra et al. 2018). Improving institutional governance in regions is also crucial, especially tackling low quality of government (Kroll 2015; Rodríguez-Pose and Di Cataldo 2015) and bonding social capital that lower diversification opportunities in regions (Cortinovis et al. 2017).

Our results also indicate that the highest ranked complex occupations include creative, management and leading administration professionals together with STEM occupations (science, technology, engineering, and math). The common determinant here is the high intensity of cognitive skills and high level of education required, and for some occupations, social skills are also relevant. In this sense, policies that focus on moving towards complex occupations promote gains for a region in terms of attracting more skilled workers, higher wages, and sophisticated tasks. Ultimately, this type of professional promotes knowledge spillovers, especially among related occupations. Thus, the stock of knowledge in the region and the ability to specialize in other activities that demand related occupations increases.

Regarding the unequal potential of regions to diversify, our results show that higher income European regions are more likely to diversity into occupations that are less related to their existing labour markets compared to lower income regions. We argued that high-income regions depend less on relatedness density because they are more able to engage in not necessarily related occupational diversification. Overall, high-income regions have more diversified and complex productive activities that require occupations of several types (from more complex to less complex), so they have a wide range of diversification options. In contrast, lower per capita income regions, which are poorly diversified and generally specialize in less complex activities, tend to diversify more into related occupations. Thus, the occupational profile of lower income regions is more standardized and its knowledge is easier to find, which makes it difficult to expand the knowledge stock and regional specializations range in order to extrapolate such path dependence. To narrow this divergence among European regions, it is necessary to take advantage of a region's prior conditions to promote related but not identical diversification. This means policies aimed at attracting workers with close but also additional skills, so as to enlarge the regional knowledge stock. Therefore, new activities that demand new knowledge and workers can also be encouraged, especially thinking about occupations that are able to deal with new technologies, which can shape the future of the labour market.

Our results showed that as occupation complexity increases, the greater the chances of developing related and complex occupational specializations in a region. Considering that we are in an era of rapid penetration of digital and automation technologies and that they tend to be more complex in nature (Balland & Boschma 2021), future diversification policies must be in line with these new technologies. The impact on the labour market is not yet precise; while digital technologies can replace routine and traditional tasks, new technologies can also require different human skills as well as new tasks that complement the functionality of such new technology. In this sense, education and professional training policies must be tuned to such changes. Thereby, the diversification toward complex occupations points to a labour market better able to soften shocks arising from digital technologies.

Having said this, it is still on the research agenda to advance the discussion to understand impact of digital and automation technologies on the future geography of occupations and industries in Europe. Outstanding issues still need to be deepened, such as whether emerging digital and automation technologies will change the relatedness between occupations to enable new diversification opportunities, and whether they will change the industry competitiveness across European regions in the global economy. These issues will be investigated further in our work package in the PILLARS project.

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8. Appendices

Appendix A – Additional Results Tables

The following tables are intended to check the robustness of the results. The different entry and exit conditions are described in each table, as well as a brief comparison between the results found.

In general terms, the results of the models with different entry and exit conditions follow the same direction as the results presented previously. The entry models confirm that an increase in relatedness density is associated with occupational specialization gains in the regions.

In the exit models, it is noted that in the traditional specification - without additional restrictions on a region to lose specialization - the relatedness density coefficient returns a statistically significant and negative result, as expected. However, in the other specifications with restrictive conditions for loss of specialization we again have statistically significant and positive results. As with the models presented previously in the results section, the size of the relatedness density coefficient in the exit models is smaller than in the entry models (which are also significant and positive).

Table A.1: Entry traditional

	Entry3							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.03208***	0.03212***	0.03208***	0.03343***	0.02913***	0.03165***	0.03257***	0.02840***
	(0.00599)	(0.00599)	(0.00599)	(0.00545)	(0.00572)	(0.00555)	(0.00551)	(0.00582)
t_lag_CompOcc		-0.03445		-0.03324	-0.02300	-0.04816	-0.04052	-0.03401
		(0.02713)		(0.02744)	(0.02812)	(0.02924)	(0.02854)	(0.02937)
t_lag_CompReg			0.00157	-0.00486	-0.00683	-0.01228	-0.00452	-0.00936
			(0.02473)	(0.02499)	(0.02520)	(0.02677)	(0.02905)	(0.02933)
t_lag_EducThir						-0.02007**	-0.01830*	-0.01132
						(0.00958)	(0.00941)	(0.00956)
t_lag_SmallSize						-0.02490***	-0.02779***	-0.02902***
						(0.00876)	(0.00911)	(0.00901)
t_lag_ln_PopDens							0.03850***	0.03871***
							(0.00863)	(0.00868)

t_lag_ln_GDPpc							0.06602	0.06504
							(0.04115)	(0.04080)
t_lag_Unemploy							-0.01823	-0.01737
							(0.02735)	(0.02710)
t_lag_RelDens x t_lag_CompOcc				0.01852***	0.01572**	0.01665***	0.01641***	0.01405**
				(0.00534)	(0.00615)	(0.00567)	(0.00560)	(0.00653)
t_lag_RelDens x t_lag_CompReg				-0.00370	-0.00734	-0.00370	-0.00229	-0.00580
				(0.00540)	(0.00528)	(0.00604)	(0.00640)	(0.00629)
t_lag_CompOcc x t_lag_CompReg					0.03027***			0.03007***
					(0.00480)			(0.00491)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,149	18,149	18,149	18,149	18,149	16,968	15,704	15,704
R^2	0.09404	0.09417	0.09404	0.09584	0.10127	0.09873	0.10212	0.10733
Adjusted R^2	0.07627	0.07636	0.07622	0.07790	0.08339	0.07958	0.08237	0.08763
Residual Std. Error	0.31656	0.31655	0.31657	0.31628	0.31534	0.31478	0.31375	0.31285

Note: The variables are mean centred. The standard errors are clustered on the regional and occupational level. Entry condition: LQ < 1 at time t and > 1 at time t+1. Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

In the Table A.1 relatedness density shows a positive and significant coefficient using the traditional specialization measure, indicating a positive association between relatedness density and entries.

Changes in occupational complexity and regional complexity have no association on the entry of new occupational specialization. Otherwise, when we interact relatedness density and occupational complexity, we found positive and significant association, meaning that the influence of relatedness density is positively reinforced in regions where there are complex occupations.

The coefficient of interaction between occupational complexity and regional complexity is positive and significant, indicating that more complex occupations located in more complex regions tend to be associated with new entries of regional specialization, thus contributing to the regional diversification process.

Table A.2: Entry traditional with absolute employment growth

	Entry4							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.03072***	0.03077***	0.03073***	0.03209***	0.02788***	0.03059***	0.03081***	0.02675***
	(0.00575)	(0.00575)	(0.00575)	(0.00523)	(0.00550)	(0.00533)	(0.00535)	(0.00565)
t_lag_CompOcc		-0.03939		-0.03845	-0.02841	-0.05375**	-0.04844*	-0.04220
		(0.02469)		(0.02504)	(0.02568)	(0.02564)	(0.02570)	(0.02653)
t_lag_CompReg			-0.00290	-0.00940	-0.01128	-0.01803	-0.00533	-0.00998
			(0.02491)	(0.02533)	(0.02553)	(0.02679)	(0.02838)	(0.02874)
t_lag_EducThir						-0.02047**	-0.01855*	-0.01175
						(0.00979)	(0.00946)	(0.00953)
t_lag_SmallSize						-0.02285***	-0.02461***	-0.02577***
						(0.00844)	(0.00881)	(0.00875)
t_lag_ln_PopDens							0.03576***	0.03600***
							(0.00794)	(0.00807)
t_lag_ln_GDPpc							0.04974	0.04858
							(0.04862)	(0.04836)
t_lag_Unemploy							-0.01026	-0.00972
							(0.02819)	(0.02796)
t_lag_RelDens x t_lag_CompOcc				0.01874***	0.01596***	0.01690***	0.01718***	0.01489**
				(0.00512)	(0.00590)	(0.00541)	(0.00529)	(0.00616)
t_lag_RelDens x t_lag_CompReg				-0.00254	-0.00609	-0.00232	-0.00129	-0.00466
				(0.00514)	(0.00502)	(0.00574)	(0.00604)	(0.00595)
t_lag_CompOcc x t_lag_CompReg					0.02954***			0.02898***
					(0.00467)			(0.00483)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,931	17,931	17,931	17,931	17,931	16,765	15,511	15,511
R^2	0.09025	0.09044	0.09025	0.09221	0.09784	0.09527	0.09842	0.10370
Adjusted R^2	0.07225	0.07239	0.07219	0.07404	0.07972	0.07587	0.07839	0.08373
Residual Std. Error	0.30513	0.30511	0.30514	0.30484	0.30390	0.30327	0.30191	0.30103

Note: The variables are mean centred. The standard errors are clustered on the regional and occupational level. Entry condition: absolute increase in jobs and LQ < 1 at time t and > 1 at time t+1. Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

In Table A.2, we consider as occupational specialization gain the traditional approach plus the condition of an absolute increase of employment between two periods.

In general, the results also remain like the previous ones. An increase in relatedness density is associated with specialization gains in the regions. In this case, the coefficients are quite similar to those found in the traditional entry model (Table A.1).

As for the complexity measures, occupation complexity becomes significant in only two specifications, not allowing us to generalise the result. However, the interaction between relatedness density and occupation complexity returns coefficients similar to the previous ones (positive and significant), reinforcing that a higher occupational complexity associated to a higher relatedness density tends to promote the gain of regional specialization in this type of occupation.

Table A.3: Entry by bootstrap technique using standard distribution

	Entry5							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.00918***	0.00918***	0.00917***	0.00926***	0.00786***	0.00883***	0.00824***	0.00672***
	(0.00157)	(0.00157)	(0.00157)	(0.00146)	(0.00138)	(0.00146)	(0.00150)	(0.00139)
t_lag_CompOcc		0.00338		0.00311	0.00593	0.00327	-0.00298	-0.00089
		(0.00952)		(0.00947)	(0.00937)	(0.01011)	(0.00805)	(0.00798)
t_lag_CompReg			0.00779	0.00688	0.00554	0.00541	0.00342	0.00187
			(0.00770)	(0.00762)	(0.00757)	(0.00750)	(0.00705)	(0.00702)
t_lag_EducThir						-0.00944**	-0.00984***	-0.00736**
						(0.00365)	(0.00357)	(0.00357)
t_lag_SmallSize						-0.00531	-0.00598*	-0.00674**
						(0.00343)	(0.00345)	(0.00333)
t_lag_ln_PopDens							0.00274*	0.00285*
							(0.00147)	(0.00147)
t_lag_ln_GDPpc							0.00097	0.00040
							(0.01093)	(0.01102)
t_lag_Unemploy							-0.00050	-0.00107
							(0.00631)	(0.00624)
t_lag_RelDens x t_lag_CompOcc				0.00435***	0.00399***	0.00438***	0.00349**	0.00328**
				(0.00144)	(0.00133)	(0.00149)	(0.00151)	(0.00136)
t_lag_RelDens x t_lag_CompReg				-0.00137	-0.00211	-0.00141	-0.00206	-0.00283**
				(0.00129)	(0.00130)	(0.00135)	(0.00140)	(0.00141)
t_lag_CompOcc x t_lag_CompReg					0.00907***			0.00940***
					(0.00140)			(0.00147)

Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,802	33,802	33,802	33,802	33,802	31,850	29,072	29,072
R^2	0.02743	0.02744	0.02747	0.02792	0.03049	0.02708	0.02710	0.02999
Adjusted R^2	0.01720	0.01717	0.01721	0.01758	0.02014	0.01605	0.01558	0.01848
Residual Std. Error	0.14866	0.14866	0.14866	0.14863	0.14844	0.14755	0.14525	0.14504

Note: The variables are mean centred. The standard errors are clustered on the regional and occupational level. Entry condition: LQ defined by bootstrap technique using standard distribution (SLQ). Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

In Table A.3 we applied the bootstrap technique by SLQ (with standard distribution). In this case the LQ that define whether a region is specialized (or not) should vary according to the cut-offs that the bootstrap technique determines.

The results also follow the same previous pattern, with a positive and significant association between relatedness density and new entries. But the size of the relatedness density coefficients is much smaller.

Complexity also does not appear significant individually, but when we interact relatedness density and occupation complexity, we find a positive and significant association as in the previous models. For the complexity of the region, there is no significant coefficients.

Table A.4: Entry by bootstrap technique using logarithmic distribution

	Entry6							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.00960***	0.00960***	0.00959***	0.00975***	0.00841***	0.00960***	0.00931***	0.00782***
	(0.00165)	(0.00165)	(0.00165)	(0.00154)	(0.00150)	(0.00157)	(0.00162)	(0.00158)
t_lag_CompOcc		0.00300		0.00260	0.00532	0.00163	-0.00587	-0.00383
		(0.00722)		(0.00726)	(0.00739)	(0.00781)	(0.00694)	(0.00712)
t_lag_CompReg			0.00468	0.00347	0.00216	0.00260	0.00385	0.00230
			(0.00856)	(0.00847)	(0.00837)	(0.00796)	(0.00867)	(0.00858)
t_lag_EducThir						-0.00833**	-0.00917**	-0.00668*
						(0.00373)	(0.00377)	(0.00380)
t_lag_SmallSize						-0.00274	-0.00227	-0.00299
						(0.00313)	(0.00317)	(0.00302)

t_lag_ln_PopDens							0.00557***	0.00569***
							(0.00143)	(0.00139)
t_lag_ln_GDPpc							0.00672	0.00624
							(0.01442)	(0.01457)
t_lag_Unemploy							0.00819	0.00768
							(0.00769)	(0.00771)
t_lag_RelDens x t_lag_CompOcc				0.00576***	0.00538***	0.00581***	0.00492***	0.00469***
				(0.00151)	(0.00146)	(0.00153)	(0.00158)	(0.00150)
t_lag_RelDens x t_lag_CompReg				-0.00107	-0.00181	-0.00118	-0.00158	-0.00236
				(0.00132)	(0.00138)	(0.00141)	(0.00143)	(0.00147)
t_lag_CompOcc x t_lag_CompReg					0.00891***			0.00941***
					(0.00146)			(0.00144)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,844	33,844	33,844	33,844	33,844	31,888	29,097	29,097
R^2	0.03163	0.03163	0.03164	0.03237	0.03481	0.03041	0.03177	0.03460
Adjusted R^2	0.02142	0.02140	0.02141	0.02206	0.02449	0.01940	0.02029	0.02312
Residual Std. Error	0.14936	0.14937	0.14937	0.14932	0.14913	0.14820	0.14661	0.14640

Note: The variables are mean centred. The standard errors are clustered on the regional and occupational level. Entry condition: LQ defined by bootstrap technique using logarithmic distribution (SLLQ). Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

In Table A.4 we use a second bootstrap technique applying logarithmic transformation on the LQ (called SLLQ). The results also follow very closely the previous model (Table A.3), with a positive and significant association between relatedness density and new entries.

Complexity also does not appear significant individually, but when we interact relatedness density and occupation complexity, we find a positive and significant association as in the previous models. For the complexity of the region, there is no significant result as well.

Below are the results concerning the exit, that is, loss of occupational specializations, following the same econometric specifications as the entry models.

Table A.5: Exit traditional

	Exit3							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	-0.02488***	-0.02490***	-0.02507***	-0.02427***	-0.01996***	-0.02403***	-0.02749***	-0.02277***
	(0.00601)	(0.00600)	(0.00601)	(0.00616)	(0.00599)	(0.00625)	(0.00635)	(0.00607)
t_lag_CompOcc		-0.03007		-0.03620	-0.05113	-0.03380	-0.02437	-0.03955
		(0.03608)		(0.03728)	(0.04160)	(0.03804)	(0.04375)	(0.04776)
t_lag_CompReg			0.06141*	0.06502**	0.07726**	0.07410**	0.07839**	0.08827**
			(0.03166)	(0.03285)	(0.03246)	(0.03303)	(0.03883)	(0.03821)
t_lag_EducThir						-0.02150	-0.02879*	-0.03345**
						(0.01431)	(0.01512)	(0.01459)
t_lag_SmallSize						0.00434	0.00817	0.01296
						(0.01377)	(0.01447)	(0.01442)
t_lag_ln_PopDens							0.00698	0.00499
							(0.00426)	(0.00426)
t_lag_ln_GDPpc							0.01417	0.01791
							(0.04918)	(0.04876)
t_lag_Unemploy							-0.03757	-0.03059
							(0.02515)	(0.02513)
t_lag_RelDens x t_lag_CompOcc				-0.01285*	-0.01034	-0.01326*	-0.01100	-0.00889
				(0.00678)	(0.00624)	(0.00699)	(0.00734)	(0.00670)
t_lag_RelDens x t_lag_CompReg				0.00886	0.00733	0.00879	0.00506	0.00327
				(0.00587)	(0.00564)	(0.00600)	(0.00612)	(0.00592)
t_lag_CompOcc x t_lag_CompReg					-0.05091***			-0.05600***
					(0.00877)			(0.00936)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,322	18,322	18,322	18,322	18,322	17,445	15,604	15,604
R^2	0.06066	0.06075	0.06117	0.06194	0.06910	0.06468	0.07141	0.07998
Adjusted R^2	0.04194	0.04198	0.04241	0.04303	0.05028	0.04486	0.05047	0.05918
Residual Std. Error	0.33077	0.33077	0.33069	0.33059	0.32933	0.32937	0.33149	0.32997

Note: The variables are mean centred. The standard errors are clustered on the regional and occupational level. Exit condition: LQ > 1 at time t and < 1 at time t+1. Coefficients are significant at *p< 0.10; **p< 0.05; ***p0< 0.01 level.

Now, assessing the results for the traditional exit (Table A.5) there is a negative association between relatedness density and exit which indicates that occupational specializations tend to be retained in regions that have related occupations.

The complexity of the region shows a positive and significant association with the traditional exit, that is, more complex regions are associated with higher occupational specialization loss. In general, more complex regions are also more diversified and dynamic, so there is a greater flow of workers; while less complex regions are less dynamic, i.e. they have greater structural rigidity and show little change. The complexity of occupation, on the other hand, has no significant effect.

In addition, when interacting the complexity variables with RD, practically none of the two – occupational or regional – becomes significant.

Finally, the interaction between occupation complexity and region complexity is negative and significant, making it difficult for complex occupation-region pairs to exit.

Table A.6: Exit traditional with absolute decline in employment

	Exit4							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.02526***	0.02537***	0.02515***	0.02559***	0.02146***	0.02471***	0.02173***	0.01784***
	(0.00602)	(0.00602)	(0.00602)	(0.00603)	(0.00629)	(0.00613)	(0.00617)	(0.00645)
t_lag_CompOcc		-0.06247*		-0.05859*	-0.04700	-0.05225	-0.04022	-0.03358
		(0.03417)		(0.03447)	(0.03282)	(0.03597)	(0.03639)	(0.03534)
t_lag_CompReg			0.05484**	0.05055**	0.04703*	0.05904**	0.04568*	0.04043*
			(0.02477)	(0.02469)	(0.02425)	(0.02563)	(0.02431)	(0.02407)
t_lag_EducThir						-0.06140***	-0.06086***	-0.05410***
						(0.01227)	(0.01202)	(0.01260)
t_lag_SmallSize						-0.02340***	-0.02171***	-0.02308***
						(0.00722)	(0.00806)	(0.00807)
t_lag_ln_PopDens							-0.01324*	-0.01371*
							(0.00770)	(0.00752)
t_lag_ln_GDPpc							0.08471*	0.08326*
							(0.04532)	(0.04525)
t_lag_Unemploy							-0.03676	-0.03660
							(0.02488)	(0.02504)
t_lag_RelDens x t_lag_CompOcc				0.00369	0.00110	0.00292	0.00109	-0.00077
				(0.00561)	(0.00631)	(0.00588)	(0.00583)	(0.00654)
t_lag_RelDens x t_lag_CompReg				0.00055	-0.00307	-0.00011	-0.00383	-0.00699
				(0.00389)	(0.00411)	(0.00427)	(0.00433)	(0.00463)

t_lag_CompOcc x t_lag_CompReg					0.03030***			0.02809***
					(0.00500)			(0.00519)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,018	18,018	18,018	18,018	18,018	16,876	15,593	15,593
R^2	0.10285	0.10332	0.10329	0.10376	0.10933	0.11319	0.11710	0.12174
Adjusted R^2	0.08513	0.08555	0.08552	0.08585	0.09148	0.09424	0.09754	0.10222
Residual Std. Error	0.30794	0.30787	0.30788	0.30782	0.30687	0.30695	0.30416	0.30337

Note: The variables are mean centred. The standard errors are clustered on the regional and occupational level. Exit condition: absolute decrease in jobs and LQ > 1 at time t and < 1 at t+1. Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

In Table A.6, in addition to the traditional approach (LQ > 1 at time t and < 1 at t+1) we consider only region-occupation pairs that had an absolute decline in the number of workers between periods.

The association of relatedness density with the loss of occupational specialization is positive and statistically significant - contrary to what was expected -, that is, an increase in relatedness density is associated with a loss of occupational specialization of the regions. Note that the relatedness density coefficients for exit are a little bit smaller than the coefficients of entry models using the same specification (Table A.2 and Table A.6).

Here only region complexity is statistically significant and positive in all specifications, reinforcing the previous result that more complex regions tend to show a greater loss of occupational specialization.

When considering the interaction term between relatedness density and complexity of the region or occupation, the coefficients are also not significant.

The interaction term between occupation complexity and region complexity is positive and significant, thus facilitating the exits.

Table A.7: Exit by bootstrap technique using standard distribution

	Exit5							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.00870***	0.00870***	0.00869***	0.00905***	0.00745***	0.00927***	0.00901***	0.00725***
	(0.00167)	(0.00167)	(0.00167)	(0.00171)	(0.00168)	(0.00174)	(0.00173)	(0.00170)
t_lag_CompOcc		0.00644		0.00580	0.00907	0.00678	0.00809	0.01057

		(0.00717)		(0.00715)	(0.00749)	(0.00756)	(0.00810)	(0.00839)
t_lag_CompReg			0.00510	0.00386	0.00234	0.00556	0.01339	0.01156
			(0.01555)	(0.01539)	(0.01534)	(0.01699)	(0.01764)	(0.01747)
t_lag_EducThir						-0.01465***	-0.01324***	-0.01037***
						(0.00376)	(0.00400)	(0.00386)
t_lag_SmallSize						-0.00406	-0.00347	-0.00441
						(0.00319)	(0.00342)	(0.00333)
t_lag_ln_PopDens							-0.00073	-0.00064
							(0.00178)	(0.00174)
t_lag_ln_GDPpc							0.00504	0.00448
							(0.02116)	(0.02086)
t_lag_Unemploy							0.01649*	0.01585
							(0.00968)	(0.00962)
t_lag_RelDens x t_lag_CompOcc				0.00569***	0.00525***	0.00576***	0.00432**	0.00405**
				(0.00192)	(0.00188)	(0.00196)	(0.00185)	(0.00184)
t_lag_RelDens x t_lag_CompReg				0.00152	0.00068	0.00133	0.00150	0.00063
				(0.00120)	(0.00131)	(0.00130)	(0.00132)	(0.00145)
t_lag_CompOcc x t_lag_CompReg					0.01042***			0.01084***
					(0.00149)			(0.00174)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,794	33,794	33,794	33,794	33,794	31,869	29,098	29,098
R^2	0.03289	0.03292	0.03291	0.03374	0.03717	0.03706	0.03835	0.04205
Adjusted R^2	0.02272	0.02271	0.02270	0.02346	0.02689	0.02615	0.02698	0.03069
Residual Std. Error	0.14752	0.14752	0.14752	0.14746	0.14720	0.14862	0.14719	0.14691

Note: The variables are mean centred. The standard errors are clustered on the regional and occupational level. Exit condition: LQ defined by bootstrap technique using standard distribution (SLQ). Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

Table A.7 uses the bootstrap technique by SLQ (with standard distribution) to set the occupation specialization cut-offs. The relatedness density coefficients continue positive and significant, but they have small size compared to most previous models.

However, in these models the complexity coefficients do not follow the pattern of the previous models since they are not statistically significant for both region and occupation. Only when we interact relatedness density and occupation complexity is there a positive and significant coefficient.

Furthermore, here also the interaction between occupation complexity and region complexity is positive and significant.

Table A.8: Exit by bootstrap technique using logarithmic distribution

	Exit6							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_lag_RelDens	0.00855***	0.00855***	0.00855***	0.00895***	0.00745***	0.00933***	0.00920***	0.00762***
	(0.00162)	(0.00162)	(0.00162)	(0.00163)	(0.00157)	(0.00171)	(0.00173)	(0.00167)
t_lag_CompOcc		-0.00223		-0.00296	0.00022	-0.00173	-0.00082	0.00146
		(0.00739)		(0.00740)	(0.00745)	(0.00746)	(0.00829)	(0.00836)
t_lag_CompReg			0.00355	0.00229	0.00084	0.00325	0.00763	0.00597
			(0.01619)	(0.01599)	(0.01591)	(0.01775)	(0.01993)	(0.01978)
t_lag_EducThir						-0.01531***	-0.01255***	-0.00991**
						(0.00434)	(0.00445)	(0.00421)
t_lag_SmallSize						-0.00155	-0.00014	-0.00098
						(0.00318)	(0.00338)	(0.00324)
t_lag_ln_PopDens							0.00007	0.00015
							(0.00123)	(0.00140)
t_lag_ln_GDPpc							0.00724	0.00673
							(0.02407)	(0.02379)
t_lag_Unemploy							0.01168	0.01116
							(0.00939)	(0.00933)
t_lag_RelDens x t_lag_CompOcc				0.00594***	0.00549***	0.00614***	0.00461**	0.00435**
				(0.00179)	(0.00171)	(0.00190)	(0.00187)	(0.00180)
t_lag_RelDens x t_lag_CompReg				0.00226*	0.00141	0.00217	0.00246*	0.00163
				(0.00122)	(0.00129)	(0.00133)	(0.00138)	(0.00146)
t_lag_CompOcc x t_lag_CompReg					0.00997***			0.00995***
					(0.00152)			(0.00168)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,788	33,788	33,788	33,788	33,788	31,864	29,068	29,068
R^2	0.03203	0.03204	0.03204	0.03305	0.03634	0.03554	0.03686	0.04017
Adjusted R^2	0.02182	0.02179	0.02180	0.02272	0.02601	0.02461	0.02546	0.02878
Residual Std. Error	0.14418	0.14419	0.14418	0.14412	0.14387	0.14547	0.14308	0.14284

Note: The variables are mean centred. The standard errors are clustered on the regional and occupational level. Exit condition: LQ defined by bootstrap technique using logarithmic distribution (SLLQ). Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

Table A.8 applyes the SLLQ bootstrap technique. The results persist, a positive and significant association between relatedness density and exit (occupational specialization loss), with the size of the relatedness density coefficients being like previous models (Table A.7).

Here the complexity of either occupation or region are also not statistically significant. But when we interact relatedness density and occupation complexity, the coefficients are positive and significant, in the same way as the previous test (Table A.7). This confirms that more complex occupations reinforce the role of relatedness density, leading to a loss of occupational specialization in the regions.

Again, the interaction between occupation complexity and region complexity is positive and significant.

Appendix B – Additional results by income level per capita

This appendix exhibits the results of the additional entry and exit measures by per capita income level to highlight the robustness of the prior results. The entry and exit measures are described below each table.

Table B.1: Traditional entry by GDPpc level

	Entry3						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.03208***		0.04710***			0.05166***	0.02995***
	(0.00314)		(0.00548)			(0.00711)	(0.00327)
CompOcc				-0.02966		-0.02793	
				(0.02156)		(0.02158)	
CompReg					0.00447	-0.00020	
					(0.01964)	(0.01968)	
RelDens x GDPpcLow		0.04710***		0.04713***	0.04708***		
		(0.00548)		(0.00548)	(0.00548)		
RelDens x GDPpcMid		0.02822***	-0.01888**	0.02819***	0.02822***	-0.02138**	
		(0.00576)	(0.00793)	(0.00576)	(0.00576)	(0.00932)	
RelDens x GDPpcHigh		0.02228***	-0.02482***	0.02234***	0.02227***	-0.03037***	
		(0.00523)	(0.00769)	(0.00523)	(0.00523)	(0.01085)	
RelDens x CompOcc						0.01848***	
						(0.00357)	
RelDens x CompReg						0.00587	
						(0.00435)	
GDPpcLow x CompOcc							-0.06216***
							(0.02195)
GDPpcMid x CompOcc							-0.02062
							(0.02185)
GDPpcHigh x CompOcc							-0.00804
							(0.02190)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,149	17,143	17,143	17,143	17,143	17,143	17,143
R^2	0.09404	0.09642	0.09642	0.09652	0.09642	0.09801	0.09919
Adjusted R^2	0.07627	0.07857	0.07857	0.07862	0.07852	0.07997	0.08134
Residual Std. Error	0.31656	0.31531	0.31531	0.31530	0.31531	0.31507	0.31483

Note: The variables are mean centred. Entry condition: LQ < 1 at time t and > 1 at time t+1. Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

Table B.2: Entry traditional with absolute employment growth by GDPpc level

	Entry4						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.03072***		0.04466***			0.05000***	0.02786***
	(0.00306)		(0.00532)			(0.00692)	(0.00318)
CompOcc				-0.03646*		-0.03463*	
				(0.02093)		(0.02095)	
CompReg					0.00387	-0.00102	
					(0.01901)	(0.01905)	
RelDens x GDPpcLow		0.04466***		0.04469***	0.04465***		
		(0.00532)		(0.00532)	(0.00532)		
RelDens x GDPpcMid		0.02598***	-0.01869**	0.02594***	0.02598***	-0.02196**	
		(0.00559)	(0.00771)	(0.00559)	(0.00559)	(0.00906)	
RelDens x GDPpcHigh		0.02045***	-0.02421***	0.02054***	0.02044***	-0.03114***	
		(0.00507)	(0.00747)	(0.00507)	(0.00507)	(0.01055)	
RelDens x CompOcc						0.01899***	
						(0.00346)	
RelDens x CompReg						0.00678	
						(0.00421)	
GDPpcLow x CompOcc							-0.06756***
							(0.02130)
GDPpcMid x CompOcc							-0.02950
							(0.02121)
GDPpcHigh x CompOcc							-0.01441
							(0.02125)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,931	16,933	16,933	16,933	16,933	16,933	16,933
R^2	0.09025	0.09241	0.09241	0.09258	0.09241	0.09429	0.09528
Adjusted R^2	0.07225	0.07431	0.07431	0.07443	0.07426	0.07601	0.07719
Residual Std. Error	0.30513	0.30361	0.30361	0.30359	0.30361	0.30333	0.30313

Note: The variables are mean centred. Entry condition: absolute increase in jobs and LQ < 1 at time t and > 1 at time t+1. Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

Table B.3: Entry by bootstrap technique using standard distribution by GDPpc level

	Entry5						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.00918***		0.01157***			0.01080***	0.00784***
	(0.00103)		(0.00171)			(0.00217)	(0.00107)
CompOcc				-0.00281		-0.00302	
				(0.00749)		(0.00749)	
CompReg					0.00707	0.00636	
					(0.00681)	(0.00682)	
RelDens x GDPpcLow		0.01157***		0.01156***	0.01155***		
		(0.00171)		(0.00171)	(0.00171)		
RelDens x GDPpcMid		0.00740***	-0.00417*	0.00740***	0.00738***	-0.00315	
		(0.00191)	(0.00253)	(0.00191)	(0.00191)	(0.00288)	
RelDens x GDPpcHigh		0.00686***	-0.00471*	0.00686***	0.00684***	-0.00328	
		(0.00176)	(0.00249)	(0.00176)	(0.00176)	(0.00338)	
RelDens x CompOcc						0.00331***	
						(0.00118)	
RelDens x CompReg						-0.00098	
						(0.00146)	
GDPpcLow x CompOcc							-0.01274*
							(0.00763)
GDPpcMid x CompOcc							-0.00065
							(0.00760)
GDPpcHigh x CompOcc							0.00331
							(0.00760)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,802	31,549	31,549	31,549	31,549	31,549	31,549
R^2	0.02743	0.02736	0.02736	0.02737	0.02740	0.02765	0.02866
Adjusted R^2	0.01720	0.01692	0.01692	0.01690	0.01693	0.01709	0.01820
Residual Std. Error	0.14866	0.14676	0.14676	0.14676	0.14676	0.14674	0.14666

Note: The variables are mean centred. Entry condition: LQ defined by bootstrap technique using standard distribution (SLQ). Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

Table B.4: Entry by bootstrap technique using logarithmic distribution by GDPpc level

	Entry6						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.00960***		0.01257***			0.01289***	0.00834***
	(0.00104)		(0.00172)			(0.00218)	(0.00107)
CompOcc				-0.00289		-0.00320	
				(0.00751)		(0.00751)	
CompReg					0.00331	0.00239	
					(0.00684)	(0.00684)	
RelDens x GDPpcLow		0.01257***		0.01256***	0.01256***		
		(0.00172)		(0.00172)	(0.00172)		
RelDens x GDPpcMid		0.00735***	-0.00522**	0.00735***	0.00734***	-0.00519*	
		(0.00192)	(0.00254)	(0.00192)	(0.00192)	(0.00288)	
RelDens x GDPpcHigh		0.00705***	-0.00552**	0.00705***	0.00704***	-0.00593*	
		(0.00177)	(0.00250)	(0.00177)	(0.00177)	(0.00339)	
RelDens x CompOcc						0.00468***	
						(0.00119)	
RelDens x CompReg						0.00014	
						(0.00146)	
GDPpcLow x CompOcc							-0.01239
							(0.00766)
GDPpcMid x CompOcc							-0.00102
							(0.00762)
GDPpcHigh x CompOcc							0.00290
							(0.00763)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,844	31,576	31,576	31,576	31,576	31,576	31,576
R^2	0.03163	0.03309	0.03309	0.03309	0.03310	0.03359	0.03417
Adjusted R^2	0.02142	0.02269	0.02269	0.02266	0.02266	0.02307	0.02375
Residual Std. Error	0.14936	0.14747	0.14747	0.14747	0.14747	0.14744	0.14739

Note: The variables are mean centred. Entry condition: LQ defined by bootstrap technique using logarithmic distribution (SLLQ). Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

Table B.5: Exit traditional by GDPpc level

	Exit3						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	-0.02488***		-0.03976***			-0.04397***	-0.02527***
	(0.00329)		(0.00515)			(0.00652)	(0.00344)
CompOcc				-0.01819		-0.02262	
				(0.02386)		(0.02403)	
CompReg					0.06522***	0.06918***	
					(0.02116)	(0.02130)	
RelDens x GDPpcLow		-0.03976***		-0.03982***	-0.03976***		
		(0.00515)		(0.00515)	(0.00515)		
RelDens x GDPpcMid		-0.01407**	0.02570***	-0.01405**	-0.01451**	0.02855***	
		(0.00606)	(0.00760)	(0.00606)	(0.00606)	(0.00843)	
RelDens x GDPpcHigh		-0.02490***	0.01486*	-0.02491***	-0.02514***	0.02229**	
		(0.00594)	(0.00781)	(0.00594)	(0.00594)	(0.01026)	
RelDens x CompOcc						-0.01090***	
						(0.00419)	
RelDens x CompReg						-0.00184	
						(0.00512)	
GDPpcLow x CompOcc							0.03180
							(0.02445)
GDPpcMid x CompOcc							-0.02802
							(0.02434)
GDPpcHigh x CompOcc							-0.04941**
							(0.02433)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,322	16,796	16,796	16,796	16,796	16,796	16,796
R^2	0.06066	0.06536	0.06536	0.06539	0.06590	0.06645	0.06918
Adjusted R^2	0.04194	0.04605	0.04605	0.04602	0.04654	0.04693	0.04989
Residual Std. Error	0.33077	0.33231	0.33231	0.33231	0.33222	0.33216	0.33164

Note: The variables are mean centred. Exit condition: LQ > 1 at time t and < 1 at time t+1. Coefficients are significant at *p< 0.10; **p< 0.05; ***p0< 0.01 level.

Table B.6: Exit traditional with absolute decline of employment by GDPpc level

	Exit4						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.02526***		0.02527***			0.02149***	0.02018***
	(0.00310)		(0.00541)			(0.00696)	(0.00320)
CompOcc				-0.05331**		-0.05028**	
				(0.02090)		(0.02094)	
CompReg					0.04631**	0.04272**	
					(0.01944)	(0.01949)	
RelDens x GDPpcLow		0.02527***		0.02526***	0.02505***		
		(0.00541)		(0.00541)	(0.00541)		
RelDens x GDPpcMid		0.01975***	-0.00552	0.01985***	0.01976***	-0.00112	
		(0.00560)	(0.00777)	(0.00560)	(0.00560)	(0.00909)	
RelDens x GDPpcHigh		0.02188***	-0.00339	0.02201***	0.02178***	0.00306	
		(0.00512)	(0.00755)	(0.00511)	(0.00512)	(0.01057)	
RelDens x CompOcc						0.00184	
						(0.00350)	
RelDens x CompReg						-0.00328	
						(0.00425)	
GDPpcLow x CompOcc							-0.08245***
							(0.02128)
GDPpcMid x CompOcc							-0.04202**
							(0.02120)
GDPpcHigh x CompOcc							-0.03673*
							(0.02124)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,018	16,994	16,994	16,994	16,994	16,994	16,994
R^2	0.10285	0.10420	0.10420	0.10455	0.10451	0.10487	0.10717
Adjusted R^2	0.08513	0.08635	0.08635	0.08665	0.08661	0.08682	0.08932
Residual Std. Error	0.30794	0.30533	0.30533	0.30528	0.30529	0.30525	0.30484

Note: The variables are mean centred. Exit condition: absolute decrease in jobs and LQ > 1 at time t and < 1 at t+1. Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

Table B.7: Exit by bootstrap technique using standard distribution by GDPpc level

	Exit5						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.00870***		0.01045***			0.01373***	0.00733***
	(0.00102)		(0.00170)			(0.00216)	(0.00106)
CompOcc				0.00735		0.00696	
				(0.00746)		(0.00746)	
CompReg					0.00987	0.00912	
					(0.00675)	(0.00676)	
RelDens x GDPpcLow		0.01045***		0.01047***	0.01043***		
		(0.00170)		(0.00170)	(0.00170)		
RelDens x GDPpcMid		0.00279	-0.00766***	0.00278	0.00276	-0.01073***	
		(0.00190)	(0.00252)	(0.00190)	(0.00190)	(0.00286)	
RelDens x GDPpcHigh		0.00995***	-0.00050	0.00994***	0.00993***	-0.00605*	
		(0.00175)	(0.00247)	(0.00175)	(0.00175)	(0.00336)	
RelDens x CompOcc						0.00393***	
						(0.00117)	
RelDens x CompReg						0.00337**	
						(0.00145)	
GDPpcLow x CompOcc							-0.00106
							(0.00760)
GDPpcMid x CompOcc							0.00761
							(0.00757)
GDPpcHigh x CompOcc							0.01425*
							(0.00757)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,794	31,547	31,547	31,547	31,547	31,547	31,547
R^2	0.03289	0.03418	0.03418	0.03421	0.03424	0.03483	0.03508
Adjusted R^2	0.02272	0.02381	0.02381	0.02381	0.02385	0.02434	0.02469
Residual Std. Error	0.14752	0.14604	0.14604	0.14604	0.14604	0.14600	0.14598

Note: The variables are mean centred. Exit condition: LQ defined by bootstrap technique using standard distribution (SLQ). Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

Table B.8: Exit by bootstrap technique using logarithmic distribution by GDPpc level

	Exit6						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RelDens	0.00855***		0.01003***			0.01419***	0.00728***
	(0.00100)		(0.00166)			(0.00210)	(0.00103)
CompOcc				-0.00136		-0.00178	
				(0.00725)		(0.00724)	
CompReg					0.00665	0.00591	
					(0.00656)	(0.00656)	
RelDens x GDPpcLow		0.01003***		0.01003***	0.01002***		
		(0.00166)		(0.00166)	(0.00166)		
RelDens x GDPpcMid		0.00211	-0.00792***	0.00211	0.00209	-0.01187***	
		(0.00185)	(0.00245)	(0.00185)	(0.00185)	(0.00278)	
RelDens x GDPpcHigh		0.01077***	0.00074	0.01077***	0.01076***	-0.00635*	
		(0.00170)	(0.00240)	(0.00170)	(0.00170)	(0.00327)	
RelDens x CompOcc						0.00421***	
						(0.00114)	
RelDens x CompReg						0.00438***	
						(0.00141)	
GDPpcLow x CompOcc							-0.01001
							(0.00738)
GDPpcMid x CompOcc							-0.00032
							(0.00735)
GDPpcHigh x CompOcc							0.00518
							(0.00735)
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,788	31,520	31,520	31,520	31,520	31,520	31,520
R^2	0.03203	0.03386	0.03386	0.03386	0.03389	0.03468	0.03468
Adjusted R^2	0.02182	0.02345	0.02345	0.02342	0.02345	0.02415	0.02425
Residual Std. Error	0.14418	0.14181	0.14181	0.14181	0.14181	0.14176	0.14175

Note: The variables are mean centred. Exit condition: LQ defined by bootstrap technique using logarithmic distribution (SLLQ). Coefficients are significant at *p< 0.10; **p< 0.05; ***p< 0.01 level.

Appendix C – Classification lists

Table C.1: List of occupations by ISCO-08

ISCO-08 codes	ISC0-08 names
011	Commissioned Armed Forces Officers
021	Non-commissioned Armed Forces Officers
031	Armed Forces Occupations, Other Ranks
111	Legislators and Senior Officials
112	Managing Directors and Chief Executives
121	Business Services and Administration Managers
122	Sales, Marketing and Development Managers
131	Production Managers in Agriculture, Forestry and Fisheries
132	Manufacturing, Mining, Construction and Distribution Managers
133	Information and Communications Technology Services Managers
134	Professional Services Managers
141	Hotel and Restaurant Managers
142	Retail and Wholesale Trade Managers
143	Other Services Managers
211	Physical and Earth Science Professionals
212	Mathematicians, Actuaries and Statisticians
213	Life Science Professionals
214	Engineering Professionals (excluding Electrotechnology)
215	Electrotechnology Engineers
216	Architects, Planners, Surveyors and Designers
221	Medical Doctors
222	Nursing and Midwifery Professionals
223	Traditional and Complementary Medicine Professionals
224	Paramedical Practitioners
225	Veterinarians
226	Other Health Professionals
231	University and Higher Education Teachers
232	Vocational Education Teachers
233	Secondary Education Teachers
234	Primary School and Early Childhood Teachers
235	Other Teaching Professionals
241	Finance Professionals
242	Administration Professionals
243	Sales, Marketing and Public Relations Professionals
251	Software and Applications Developers and Analysts
252	Database and Network Professionals
261	Legal Professionals
262	Librarians, Archivists and Curators
263	Social and Religious Professionals
264	Authors, Journalists and Linguists
265	Creative and Performing Artists
311	Physical and Engineering Science Technicians
312	Mining, Manufacturing and Construction Supervisors
313	Process Control Technicians
314	Life Science Technicians and Related Associate Professionals
315	Ship and Aircraft Controllers and Technicians
321	Medical and Pharmaceutical Technicians
322	Nursing and Midwifery Associate Professionals
323	Traditional and Complementary Medicine Associate Professionals
324	Veterinary Technicians and Assistants
325	Other Health Associate Professionals
331	Financial and Mathematical Associate Professionals
332	Sales and Purchasing Agents and Brokers

333	Business Services Agents
334	Administrative and Specialized Secretaries
335	Government Regulatory Associate Professionals
341	Legal, Social and Religious Associate Professionals
342	Sports and Fitness Workers
343	Artistic, Cultural and Culinary Associate Professionals
351	Information and Communications Technology Operations and User Support
352	Telecommunications and Broadcasting Technicians
411	General Office Clerks
412	Secretaries (general)
413	Keyboard Operators
421	Tellers, Money Collectors and Related Clerks
422	Client Information Workers
431	Numerical Clerks
432	Material Recording and Transport Clerks
441	Other Clerical Support Workers
511	Travel Attendants, Conductors and Guides
512	Cooks
513	Waiters and Bartenders
514	Hairdressers, Beauticians and Related Workers
515	Building and Housekeeping Supervisors
516	Other Personal Services Workers
521	Street and Market Salespersons
522	Shop Salespersons
523	Cashiers and Ticket Clerks
524	Other Sales Workers
531	Child Care Workers and Teachers Aides
532	Personal Care Workers in Health Services
541	Protective Services Workers
611	Market Gardeners and Crop Growers
612	Animal Producers
613	Mixed Crop and Animal Producers
621	Forestry and Related Workers
622	Fishery Workers, Hunters and Trappers
631	Subsistence Crop Farmers
632	Subsistence Livestock Farmers
633	Subsistence Mixed Crop and Livestock Farmers
634	Subsistence Fishers, Hunters, Trappers and Gatherers
711	Building Frame and Related Trades Workers
712	Building Finishers and Related Trades Workers
713	Painters, Building Structure Cleaners and Related Trades Workers
721	Sheet and Structural Metal Workers, Moulders and Welders, and Related Workers
722	Blacksmiths, Toolmakers and Related Trades Workers
723	Machinery Mechanics and Repairers
731	Handicraft Workers
732	Printing Trades Workers
741	Electrical Equipment Installers and Repairers
742	Electronics and Telecommunications Installers and Repairers
751	Food Processing and Related Trades Workers
752	Wood Treaters, Cabinet-makers and Related Trades Workers
753	Garment and Related Trades Workers
754	Other Craft and Related Workers
811	Mining and Mineral Processing Plant Operators
812	Metal Processing and Finishing Plant Operators
813	Chemical and Photographic Products Plant and Machine Operators
814	Rubber, Plastic and Paper Products Machine Operators
815	Textile, Fur and Leather Products Machine Operators
816	Food and Related Products Machine Operators
817	Wood Processing and Papermaking Plant Operators
818	Other Stationary Plant and Machine Operators
821	Assemblers

831	Locomotive Engine Drivers and Related Workers
832	Car, Van and Motorcycle Drivers
833	Heavy Truck and Bus Drivers
834	Mobile Plant Operators
835	Ships Deck Crews and Related Workers
911	Domestic, Hotel and Office Cleaners and Helpers
912	Vehicle, Window, Laundry and Other Hand Cleaning Workers
921	Agricultural, Forestry and Fishery Labourers
931	Mining and Construction Labourers
932	Manufacturing Labourers
933	Transport and Storage Labourers
941	Food Preparation Assistants
951	Street and Related Services Workers
952	Street Vendors (excluding Food)
961	Refuse Workers
962	Other Elementary Workers

Source: Authors.

Table C.2: Countries and NUTS regions

Country code	Country	NUTS codes	NUTS region
AT	Austria	AT11	Burgenland (AT)
		AT12	Niederösterreich
		AT13	Wien
		AT21	Kärnten
		AT22	Steiermark
		AT31	Oberösterreich
		AT32	Salzburg
		AT33	Tirol
		AT34	Vorarlberg
BE	Belgium	BE10	Région de Bruxelles-Capitale
		BE21	Prov. Antwerpen
		BE22	Prov. Limburg (BE)
		BE23	Prov. Oost-Vlaanderen
		BE24	Prov. Vlaams-Brabant
		BE25	Prov. West-Vlaanderen
		BE31	Prov. Brabant wallon
		BE32	Prov. Hainaut
		BE33	Prov. Liège
		BE34	Prov. Luxembourg (BE)
		BE35	Prov. Namur
CH	Switzerland	CH01	Région lémanique
		CH02	Espace Mittelland
		CH03	Nordwestschweiz
		CH04	Zürich
		CH05	Ostschweiz
		CH06	Zentralschweiz
		CH07	Ticino
CY	Cyprus	CY00	Kypros
CZ	Czech Republic	CZ01	Praha
		CZ02	Strední Cechy
		CZ03	Jihozápad
		CZ04	Severozápad
		CZ05	Severovýchod
		CZ06	Jihovýchod
		CZ07	Strední Morava
		CZ08	Moravskoslezsko
DE	Germany	DE11	Stuttgart
		DE12	Karlsruhe
		DE13	Freiburg
		DE14	Tübingen
		DE21	Oberbayern
		DE22	Niederbayern
		DE23	Oberpfalz
		DE24	Oberfranken
		DE25	Mittelfranken
		DE26	Unterfranken
		DE27	Schwaben
		DE30	Berlin
		DE40	Brandenburg
		DE50	Bremen
		DE60	Hamburg
		DE71	Darmstadt
		DE72	Gießen
		DE73	Kassel
		DE80	Mecklenburg-Vorpommern
		DE91	Braunschweig
		DE92	Hannover

		DE93	Lüneburg
		DE94	Weser-Ems
		DEA1	Düsseldorf
		DEA2	Köln
		DEA3	Münster
		DEA4	Detmold
		DEA5	Arnsberg
		DEB1	Koblenz
		DEB2	Trier
		DEB3	Rheinhessen-Pfalz
		DEC0	Saarland
		DED2	Dresden
		DED4	Chemnitz
		DED5	Leipzig
		DEE0	Sachsen-Anhalt
		DEF0	Schleswig-Holstein
		DEG0	Thüringen
DK	Denmark	DK01	Hovedstaden
		DK02	Sjælland
		DK03	Syddanmark
		DK04	Midtjylland
		DK05	Nordjylland
EE	Estonia	EE00	Eesti
ES	Spain	ES11	Galicia
		ES12	Principado de Asturias
		ES13	Cantabria
		ES21	País Vasco
		ES22	Comunidad Foral de Navarra
		ES23	La Rioja
		ES24	Aragón
		ES30	Comunidad de Madrid
		ES41	Castilla y León
		ES42	Castilla-la Mancha
		ES43	Extremadura
		ES51	Cataluña
		ES52	Comunitat Valenciana
		ES53	Illes Balears
		ES61	Andalucía
		ES62	Región de Murcia
		ES63	Ciudad de Ceuta
		ES64	Ciudad de Melilla
		ES70	Canarias
FI	Finland	FI19	Länsi-Suomi
		FI1B	Helsinki-Uusimaa
		FI1C	Etelä-Suomi
		FI1D	Pohjois- ja Itä-Suomi
		FI20	Åland
FR	France	FR10	Île de France
		FRB0	Centre - Val de Loire
		FRC1	Bourgogne
		FRC2	Franche-Comté
		FRD1	Basse-Normandie
		FRD2	Haute-Normandie
		FRE1	Nord-Pas-de-Calais
		FRE2	Picardie
		FRF1	Alsace
		FRF2	Champagne-Ardenne
		FRF3	Lorraine
		FRG0	Pays-de-la-Loire
		FRH0	Bretagne
		FRI1	Aquitaine

		FRI2	Limousin
		FRI3	Poitou-Charentes
		FRJ1	Languedoc-Roussillon
		FRJ2	Midi-Pyrénées
		FRK1	Auvergne
		FRK2	Rhône-Alpes
		FRL0	Provence-Alpes-Côte d'Azur
		FRM0	Corse
		FRY1	Guadeloupe
		FRY2	Martinique
		FRY3	Guyane
		FRY4	La Réunion
EL	Greece	EL30	Attiki
		EL41	Voreio Aigaio
		EL42	Notio Aigaio
		EL43	Kriti
		EL51	Anatoliki Makedonia, Thraki
		EL52	Kentriki Makedonia
		EL53	Dytiki Makedonia
		EL54	Ipeiros
		EL61	Thessalia
		EL62	Ionia Nisia
		EL63	Dytiki Ellada
		EL64	Sterea Ellada
		EL65	Peloponnisos
HR	Croatia	HR03	Jadranska Hrvatska
		HR04	Kontinentalna Hrvatska
HU	Hungary	HU11	Budapest
		HU12	Pest
		HU21	Közép-Dunántúl
		HU22	Nyugat-Dunántúl
		HU23	Dél-Dunántúl
		HU31	Észak-Magyarország
		HU32	Észak-Alföld
		HU33	Dél-Alföld
IE	Ireland	IE04	Northern and Western
		IE05	Southern
		IE06	Eastern and Midland
IS	Iceland	IS00	Ísland
IT	Italy	ITC1	Piemonte
		ITC2	Valle d'Aosta
		ITC3	Liguria
		ITC4	Lombardia
		ITF1	Abruzzo
		ITF2	Molise
		ITF3	Campania
		ITF4	Puglia
		ITF5	Basilicata
		ITF6	Calabria
		ITG1	Sicilia
		ITG2	Sardegna
		ITH1	Provincia Autonoma di Bolzano
		ITH2	Provincia Autonoma di Trento
		ITH3	Veneto
		ITH4	Friuli-Venezia Giulia
		ITH5	Emilia-Romagna
		ITI1	Toscana
		ITI2	Umbria
		ITI3	Marche
		ITI4	Lazio
LI	Liechtenstein	LI00	Liechtenstein

LT	Lithuania	LT01	Sostines regionas
		LT02	Vidurio ir vakaru Lietuvos regionas
LU	Luxembourg	LU00	Luxembourg
LV	Latvia	LV00	Latvija
NO	Norway	NO01	Oslo og Akershus
		NO02	Innlandet
		NO03	Sør-Østlandet
		NO04	Agder og Rogaland
		NO05	Vestlandet
		NO06	Trøndelag
		NO07	Nord-Norge
PT	Portugal	PT11	Norte
		PT15	Algarve
		PT16	Centro (PT)
		PT17	Área Metropolitana de Lisboa
		PT18	Alentejo
		PT20	Região Autónoma dos Açores (PT)
		PT30	Região Autónoma da Madeira (PT)
RO	Romania	RO11	Nord-Vest
		RO12	Centru
		RO21	Nord-Est
		RO22	Sud-Est
		RO31	Sud - Muntenia
		RO32	Bucuresti - Ilfov
		RO41	Sud-Vest Oltenia
		RO42	Vest
SE	Sweden	SE11	Stockholm
		SE12	Östra Mellansverige
		SE21	Småland med öarna
		SE22	Sydsverige
		SE23	Västsverige
		SE31	Norra Mellansverige
		SE32	Mellersta Norrland
		SE33	Övre Norrland
SK	Slovakia	SK01	Bratislavský kraj
		SK02	Západné Slovensko
		SK03	Stredné Slovensko
		SK04	Východné Slovensko
UK	United Kingdom	UKC	North East (UK)
		UKD	North West (UK)
		UKE	Yorkshire and The Humber
		UKF	East Midlands (UK)
		UKG	West Midlands (UK)
		UKH	East of England
		UKI	London
		UKJ	South East (UK)
		UKK	South West (UK)
		UKL	Wales
		UKM	Scotland
		UKN	Northern Ireland (UK)

Source: Authors.

Table C.3: Codes and description of NACE Revision 2

NACE codes	NACE Description
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply, sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreat
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organisations and bodies

Source: Authors.

Appendix D: Ranking of complexity

Table D.1: Complexity of occupations – Rank from 41 to 90

Rank	ISCO-08 codes	ISCO-08 names	Complexity
41	352	Telecommunications and Broadcasting Technicians	68.61
42	511	Travel Attendants, Conductors and Guides	68.40
43	211	Physical and Earth Science Professionals	68.05
44	132	Manufacturing, Mining, Construction and Distribution Managers	67.14
45	421	Tellers, Money Collectors and Related Clerks	67.03
46	241	Finance Professionals	66.13
47	342	Sports and Fitness Workers	65.97
48	441	Other Clerical Support Workers	65.62
49	531	Child Care Workers and Teachers Aides	65.07
50	516	Other Personal Services Workers	64.96
51	941	Food Preparation Assistants	64.90
52	315	Ship and Aircraft Controllers and Technicians	64.88
53	221	Medical Doctors	64.66
54	322	Nursing and Midwifery Associate Professionals	63.95
55	713	Painters, Building Structure Cleaners and Related Trades Workers	61.61
56	818	Other Stationary Plant and Machine Operators	61.35
57	831	Locomotive Engine Drivers and Related Workers	61.14
58	222	Nursing and Midwifery Professionals	61.08
59	723	Machinery Mechanics and Repairers	59.75
60	431	Numerical Clerks	58.65
61	932	Manufacturing Labourers	58.65
62	235	Other Teaching Professionals	58.02
63	111	Legislators and Senior Officials	57.68
64	741	Electrical Equipment Installers and Repairers	57.58
65	351	Information and Communications Technology Operations and User Support Technicians	56.64
66	712	Building Finishers and Related Trades Workers	56.20
67	813	Chemical and Photographic Products Plant and Machine Operators	54.56
68	722	Blacksmiths, Toolmakers and Related Trades Workers	54.31
69	261	Legal Professionals	53.09
70	213	Life Science Professionals	51.55
71	332	Sales and Purchasing Agents and Brokers	51.49
72	225	Veterinarians	51.29
73	314	Life Science Technicians and Related Associate Professionals	51.29
74	331	Financial and Mathematical Associate Professionals	50.75
75	532	Personal Care Workers in Health Services	49.98
76	752	Wood Treaters, Cabinet-makers and Related Trades Workers	49.31
77	031	Armed Forces Occupations, Other Ranks	48.57
78	816	Food and Related Products Machine Operators	47.97
79	141	Hotel and Restaurant Managers	47.07
80	522	Shop Salespersons	44.74
81	834	Mobile Plant Operators	44.60
82	514	Hairdressers, Beauticians and Related Workers	44.51
83	721	Sheet and Structural Metal Workers, Moulders and Welders, and Related Workers	44.39
84	422	Client Information Workers	43.98
85	812	Metal Processing and Finishing Plant Operators	43.46
86	621	Forestry and Related Workers	43.25
87	234	Primary School and Early Childhood Teachers	42.83
88	011	Commissioned Armed Forces Officers	42.82
89	731	Handicraft Workers	42.78
90	143	Other Services Managers	42.66

Note: Complexity of the 2017-2019 triennium. Source: Authors.

Table D.2: Complexity of the European regions – Rank 51 to 100

Rank	NUTS codes	NUTS names	Complexity
51	DE93	Lüneburg	70.43
52	DE22	Niederbayern	70.06
53	CZ01	Praha	70.01
54	DE94	Weser-Ems	69.93
55	SE12	Östra Mellansverige	69.00
56	DEE0	Sachsen-Anhalt	68.93
57	DE80	Mecklenburg-Vorpommern	68.81
58	UKJ	South East (UK)	68.57
59	LI00	Liechtenstein	68.04
60	UKE	Yorkshire and The Humber	67.94
61	BE24	Prov. Vlaams-Brabant	67.80
62	SK01	Bratislavský kraj	67.58
63	UKM	Scotland	67.14
64	SE33	Övre Norrland	66.48
65	DK04	Midtjylland	66.25
66	SE32	Mellersta Norrland	66.00
67	BE21	Prov. Antwerpen	65.92
68	UKF	East Midlands (UK)	65.09
69	UKH	East of England	64.70
70	NO03	Sør-Østlandet	64.62
71	DED4	Chemnitz	64.31
72	FRK2	Rhône-Alpes	64.26
73	HU11	Budapest	63.90
74	UKG	West Midlands (UK)	63.80
75	BE31	Prov. Brabant wallon	63.61
76	UKC	North East (UK)	63.60
77	SE31	Norra Mellansverige	63.35
78	UKL	Wales	63.32
79	FRJ2	Midi-Pyrénées	63.29
80	ES30	Comunidad de Madrid	62.78
81	NO06	Trøndelag	62.73
82	UKD	North West (UK)	62.59
83	UKK	South West (UK)	62.18
84	NO04	Agder og Rogaland	61.38
85	DK03	Syddanmark	61.18
86	IS00	Ísland	60.45
87	BE23	Prov. Oost-Vlaanderen	59.58
88	NO05	Vestlandet	59.56
89	FI1C	Etelä-Suomi	59.14
90	NO02	Innlandet	58.61
91	NO07	Nord-Norge	58.41
92	FI19	Länsi-Suomi	57.46
93	SE21	Småland med öarna	57.22
94	FRL0	Provence-Alpes-Côte d'Azur	55.99
95	UKN	Northern Ireland (UK)	55.99
96	IE06	Eastern and Midland	55.86
97	BE22	Prov. Limburg (BE)	55.64
98	FI1D	Pohjois- ja Itä-Suomi	55.55
99	DK02	Sjælland	55.07
100	FI20	Åland	54.65

Note: Complexity of the 2017-2019 triennium. Source: Authors.

Table D.3: Complexity of the European regions – Rank 101 to 150

Rank	NUTS codes	NUTS names	Complexity
101	FRE1	Nord-Pas-de-Calais	54.65
102	AT31	Oberösterreich	54.53
103	LT01	Sostines regionas	54.22
104	PT17	Área Metropolitana de Lisboa	52.54
105	FRJ1	Languedoc-Roussillon	51.13
106	BE33	Prov. Liège	50.79
107	AT32	Salzburg	50.62
108	FRF1	Alsace	50.30
109	AT22	Steiermark	50.30
110	FRI1	Aquitaine	50.29
111	DK05	Nordjylland	50.29
112	FRG0	Pays-de-la-Loire	50.19
113	AT33	Tirol	50.04
114	RO32	Bucuresti - Ilfov	49.87
115	EE00	Eesti	49.38
116	FRF3	Lorraine	49.23
117	AT34	Vorarlberg	48.88
118	AT12	Niederösterreich	48.13
119	BE32	Prov. Hainaut	48.09
120	AT21	Kärnten	48.02
121	BE35	Prov. Namur	47.96
122	CZ02	Strední Cechy	47.83
123	FRB0	Centre - Val de Loire	47.76
124	FRH0	Bretagne	47.59
125	AT11	Burgenland (AT)	47.48
126	ES21	País Vasco	47.18
127	FRI2	Limousin	46.62
128	FRC2	Franche-Comté	46.39
129	FRF2	Champagne-Ardenne	45.47
130	FRI3	Poitou-Charentes	45.46
131	BE34	Prov. Luxembourg (BE)	44.91
132	FRD2	Haute-Normandie	44.68
133	CZ08	Moravskoslezsko	44.60
134	BE25	Prov. West-Vlaanderen	43.79
135	FRD1	Basse-Normandie	43.50
136	CY00	Kypros	43.35
137	FRC1	Bourgogne	43.21
138	ES22	Comunidad Foral de Navarra	43.19
139	FRY2	Martinique	42.71
140	CZ05	Severovýchod	42.30
141	FRM0	Corse	42.06
142	ITI4	Lazio	41.55
143	CZ06	Jihovýchod	41.53
144	CZ07	Strední Morava	41.21
145	IE05	Southern	40.92
146	FRE2	Picardie	40.26
147	FRY1	Guadeloupe	40.01
148	ES51	Cataluña	39.80
149	ITC4	Lombardia	39.13
150	FRY3	Guyane	38.51

Note: Complexity of the 2017-2019 triennium. Source: Authors.

Table D.4: Complexity of the European regions – Rank 151 to 179

Rank	NUTS codes	NUTS names	Complexity
151	IE04	Northern and Western	38.21
152	FRK1	Auvergne	38.02
153	EL30	Attiki	37.83
154	FRY4	La Réunion	36.90
155	ES53	Illes Balears	35.83
156	HU12	Pest	35.73
157	ES63	Ciudad de Ceuta	35.20
158	ITH4	Friuli-Venezia Giulia	34.41
159	LV00	Latvija	34.21
160	ITH2	Provincia Autonoma di Trento	34.17
161	ES13	Cantabria	33.14
162	HU31	Észak-Magyarország	32.93
163	CZ03	Jihozápad	31.99
164	ITC3	Liguria	31.71
165	ES12	Principado de Asturias	31.58
166	HR03	Jadranska Hrvatska	31.39
167	CZ04	Severozápad	30.47
168	ITH5	Emilia-Romagna	30.22
169	SK03	Stredné Slovensko	30.20
170	ITH3	Veneto	30.01
171	ES52	Comunitat Valenciana	29.57
172	HR04	Kontinentalna Hrvatska	29.53
173	HU21	Közép-Dunántúl	28.98
174	ITC2	Valle d'Aosta	28.85
175	EL62	Ionia Nisia	28.74
176	ES23	La Rioja	28.58
177	ES11	Galicia	28.47
178	ES62	Región de Murcia	27.99
179	ITC1	Piemonte	27.78

Note: Complexity of the 2017-2019 triennium. Source: Authors.

Appendix E – Correlation tables of employment share by NUTS regions

Table E.1: Regional employment share's correlation between LFS and Eurostat: Austria

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
AT11	5.2	5.0	4.9	3.3	3.2	3.2
AT12	11.5	11.2	11.3	19.2	19.2	19.0
AT13	15.4	15.8	16.0	19.2	19.5	20.0
AT21	9.9	9.6	9.8	6.3	6.2	6.1
AT22	11.0	11.6	11.9	14.3	14.1	14.1
AT31	13.4	13.2	12.7	17.6	17.6	17.5
AT32	11.6	11.3	10.9	6.6	6.6	6.6
AT33	11.8	11.7	11.8	8.9	9.0	8.9
AT34	10.2	10.6	10.7	4.6	4.7	4.7
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.74	0.74	0.76			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.2: Regional employment share's correlation between LFS and Eurostat: Belgium

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
BE10	17.5	19.2	18.0	9.2	9.6	9.7
BE21	11.7	11.8	11.2	16.6	16.7	16.9
BE22	8.3	7.1	7.1	8.2	8.1	8.1
BE23	11.0	10.5	10.4	14.4	14.4	14.4
BE24	9.7	9.6	9.3	10.8	10.8	10.7
BE25	10.9	10.7	11.6	11.2	11.2	11.2
BE31	4.2	4.6	4.7	3.5	3.5	3.5
BE32	7.8	8.3	8.6	10.4	10.2	10.1
BE33	9.1	9.6	9.5	9.1	8.8	8.7
BE34	4.8	4.2	4.6	2.5	2.5	2.5
BE35	5.1	4.5	5.0	4.2	4.2	4.1
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.65	0.62	0.63			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.3: Regional employment share's correlation between LFS and Eurostat: Bulgaria

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
BG31	11.9	10.3	10.1	9.8	9.1	8.6
BG32	10.9	10.5	10.8	10.8	10.8	10.7
BG33	12.1	12.5	12.0	12.6	13.2	13.0
BG34	13.2	12.6	14.3	14.2	14.0	14.3
BG41	31.4	31.5	30.4	33.2	33.0	33.5
BG42	20.5	22.6	22.5	19.5	19.9	20.0
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.99	0.98	0.98			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.4: Regional employment share's correlation between LFS and Eurostat: Czech Republic

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
CZ01	10.2	10.7	10.3	13.0	12.8	13.1
CZ02	11.1	11.4	11.4	12.7	12.8	12.9
CZ03	15.0	14.1	13.9	11.8	11.7	11.5
CZ04	9.8	9.5	9.1	10.3	10.2	10.2
CZ05	15.4	16.0	15.4	14.1	14.2	14.0
CZ06	16.4	16.8	17.3	15.8	16.0	15.8
CZ07	11.4	10.9	11.3	11.3	11.3	11.3
CZ08	10.8	10.7	11.3	11.1	11.1	11.1
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.73	0.84	0.79			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.5: Regional employment share's correlation between LFS and Eurostat: Denmark

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
DK01	30.6	32.7	33.0	32.3	33.4	33.4
DK02	12.0	11.3	11.0	14.0	13.6	13.5
DK03	21.9	21.4	21.2	20.9	20.3	20.4
DK04	24.8	24.3	24.7	22.9	22.7	22.9
DK05	10.8	10.3	10.2	10.0	10.1	9.8
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.98	0.99	0.99			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.6: Regional employment share's correlation between LFS and Eurostat: Finland

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
FI19	25.1	24.8	24.8	24.5	24.4	24.3
FI1B	30.7	31.5	32.7	32.3	32.9	33.2
FI1C	20.2	19.4	18.7	20.6	20.1	20.1
FI1D	22.5	22.7	22.4	22.0	22.0	21.7
FI20	1.5	1.6	1.5	0.6	0.6	0.6
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	1.00	1.00	1.00			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.7: Regional employment share's correlation between LFS and Eurostat: Greece

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
EL30	24.9	24.2	22.5	37.8	37.4	36.6
EL41	2.3	2.6	2.9	1.8	1.8	1.8
EL42	2.3	2.5	4.0	3.4	3.5	3.4
EL43	8.3	8.0	8.4	6.0	5.9	6.4
EL51	6.8	8.4	9.8	5.2	5.5	5.5
EL52	14.4	15.7	14.6	16.0	16.5	16.8
EL53	3.0	2.9	3.1	2.2	2.3	2.2
EL54	6.9	6.2	4.8	3.0	2.9	2.8
EL61	6.8	6.2	6.5	6.5	6.3	6.4
EL62	2.9	2.5	3.3	2.1	2.0	2.0
EL63	7.0	6.1	6.5	5.8	5.7	5.6
EL64	6.6	6.6	6.0	4.8	4.9	5.0
EL65	7.8	8.2	7.5	5.3	5.3	5.4
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	**0.97**	**0.96**	**0.96**			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.8: Regional employment share's correlation between LFS and Eurostat: Croatia

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
HR03	31.1	37.4	33.7	32.1	32.4	32.2
HR04	68.9	62.6	66.3	67.9	67.6	67.8
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	1.00	1.00	1.00			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.9: Regional employment share's correlation between LFS and Eurostat: Hungary

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
HU11	14.6	13.2	11.7	19.0	19.1	18.8
HU12	7.5	8.4	7.8	13.0	12.9	13.4
HU21	11.4	11.8	12.3	11.5	11.4	11.2
HU22	11.4	11.8	11.8	10.8	10.7	10.7
HU23	10.7	10.7	10.5	8.8	8.6	8.3
HU31	13.4	13.6	13.9	10.5	10.7	10.8
HU32	16.1	16.0	16.9	13.9	14.1	14.3
HU33	14.9	14.6	15.2	12.5	12.5	12.5
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.40	0.29	0.10			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.10: Regional employment share's correlation between LFS and Eurostat: Ireland

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
IE04	15.7	16.0	17.4	17.3	17.1	16.9
IE05	38.5	34.5	34.2	33.3	32.7	32.0
IE06	45.8	49.5	48.5	49.4	50.2	51.1
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.96	1.00	0.99			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.11: Regional employment share's correlation between LFS and Eurostat: Lithuania

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
LT01			33.2			32.0
LT02			66.8			68.0
Total			100.0			100.0
Pearson Correlation			1.00			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.12: Regional employment share's correlation between LFS and Eurostat: Norway

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
NO01	23.6	25.3	26.3	24.8	25.4	26.0
NO02	7.1	7.1	6.9	7.1	7.1	7.0
NO03	17.4	16.5	16.2	18.3	17.8	17.8
NO04	16.1	15.9	15.9	14.9	14.8	14.4
NO05	16.5	16.4	16.2	17.2	17.1	16.9
NO06	8.9	9.1	8.9	8.6	8.7	8.8
NO07	10.4	9.7	9.7	9.1	9.1	9.0
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.99	0.99	0.99			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.13: Regional employment share's correlation between LFS and Eurostat: Poland

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
PL21	6.8	6.1	4.4	8.4	8.3	8.7
PL22	8.4	7.8	7.6	12.3	11.4	11.5
PL41	7.3	6.6	5.7	8.8	8.7	9.8
PL42	4.6	4.5	4.8	3.7	3.7	4.2
PL43	4.2	4.5	6.4	2.6	2.6	2.6
PL51	5.7	5.5	4.4	6.8	7.2	7.5
PL52	6.3	6.6	5.5	2.2	2.4	2.4
PL61	5.0	5.7	8.4	4.9	5.2	5.3
PL62	5.5	5.4	4.8	3.4	3.4	3.4
PL63	6.0	6.1	6.4	5.8	6.0	6.2
PL71	7.0	6.6	4.5	8.0	7.5	6.7
PL72	5.6	5.8	6.3	3.5	3.5	3.1
PL81	6.7	6.7	6.2	6.1	6.0	5.3
PL82	6.1	6.2	7.6	5.1	5.0	5.1
PL84	5.9	6.1	6.4	2.9	3.0	3.0
PL91	4.7	5.2	5.9	8.7	9.0	8.7
PL92	4.1	4.6	4.8	6.8	7.2	6.5
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.57	0.43	-0.03			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.14: Regional employment share's correlation between LFS and Eurostat: Portugal

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
PT11	25.9	26.7	26.7	35.3	34.8	35.1
PT15	10.8	10.2	10.1	4.2	4.3	4.4
PT16	17.9	17.2	16.7	22.5	22.3	21.7
PT17	16.6	17.9	18.4	26.4	27.0	27.3
PT18	11.2	10.9	10.7	6.8	6.7	6.6
PT20	8.6	8.6	8.3	2.3	2.4	2.4
PT30	9.0	8.5	9.2	2.5	2.5	2.5
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.97	0.97	0.98			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.15: Regional employment share's correlation between LFS and Eurostat: Romania

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
RO11	13.2	14.3	15.3	13.5	13.7	13.7
RO12	11.2	10.5	9.5	10.5	10.9	11.0
RO21	18.4	19.3	18.9	17.2	17.8	17.7
RO22	11.6	10.8	10.5	11.6	11.3	11.1
RO31	15.3	14.7	14.5	14.8	14.8	14.7
RO32	9.2	9.7	9.5	12.9	13.1	13.6
RO41	12.1	11.5	12.4	10.4	9.5	9.6
RO42	9.1	9.2	9.3	9.1	8.9	8.6
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.86	0.87	0.80			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.16: Regional employment share's correlation between LFS and Eurostat: Sweden

NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
SE11	22.5	23.6	24.9	23.8	24.3	24.7
SE12	15.4	15.8	15.3	16.0	16.1	16.1
SE21	9.7	9.6	9.3	8.5	8.4	8.3
SE22	13.9	13.7	13.4	14.3	14.3	14.1
SE23	20.1	20.0	19.9	20.2	20.3	20.4
SE31	8.3	7.6	7.5	8.3	7.9	7.9
SE32	4.7	4.6	4.8	3.7	3.6	3.6
SE33	5.4	5.1	5.0	5.2	5.2	4.9
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	1.00	1.00	1.00			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.17: Regional employment share's correlation between LFS and Eurostat: Switzerland

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
CH01	16.7	19.3	20.0	17.2	17.3	17.5
CH02	20.2	20.1	21.0	22.5	22.4	22.2
CH03	12.4	12.6	12.5	13.7	13.6	13.6
CH04	21.3	19.2	19.2	18.3	18.5	18.6
CH05	12.1	12.1	12.3	14.5	14.4	14.3
CH06	12.8	11.6	9.8	10.1	10.2	10.1
CH07	4.5	5.1	5.2	3.7	3.7	3.6
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.93	0.96	0.96			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.18: Regional employment share's correlation between LFS and Eurostat: Slovenia

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
SI03	49.6	51.6	48.2	52.6	52.2	52.1
SI04	50.4	48.4	51.8	47.4	47.8	47.9
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	-1.00	1.00	-1.00			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Table E.19: Regional employment share's correlation between LFS and Eurostat: Slovakia

	Employment share from LFS			Employment share from Eurostat		
NUTS	2011-2013	2014-2016	2017-2019	2011-2013	2014-2016	2017-2019
SK01	17.1	15.1	15.1	13.4	13.1	13.1
SK02	32.4	34.0	32.4	35.7	35.4	34.9
SK03	23.5	22.7	23.4	24.3	24.4	24.5
SK04	27.0	28.2	29.1	26.6	27.1	27.4
Total	100.0	100.0	100.0	100.0	100.0	100.0
Pearson Correlation	0.99	0.99	0.98			

Source: Authors' calculations from LFS and Eurostat [lfst_r_lfe2eftpt].

Appendix F – Correlation tables between variables of the econometric model

Table F.1: Correlation of variables from model (Entry1)

	Entry1	*t_lag_RelDens*	*t_lag_CompOcc*	*t_lag_CompReg*	*t_lag_EducThir*	*t_lag_SmallSize*	*t_lag_ln_PopDens*	*t_lag_ln_GDPpc*
t_lag_RelDens	0.080***							
t_lag_CompOcc	0.015	0.121***						
t_lag_CompReg	-0.048***	0.122***	-0.352***					
t_lag_EducThir	0.015	0.086***	0.433***	-0.179***				
t_lag_SmallSize	-0.01	-0.159***	-0.127***	-0.147***	-0.096***			
t_lag_ln_PopDens	-0.057***	0.053***	-0.114***	0.410***	-0.101***	-0.097***		
t_lag_ln_GDPpc	-0.040***	0.180***	-0.234***	0.729***	-0.167***	-0.063***	0.434***	
t_lag_Unemploy	0.054***	-0.006	0.205***	-0.564***	0.116***	0.230***	-0.124***	-0.433***

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.2: Correlation of variables from model (Entry2)

	Entry2	*t_lag_RelDens*	*t_lag_CompOcc*	*t_lag_CompReg*	*t_lag_EducThir*	*t_lag_SmallSize*	*t_lag_ln_PopDens*	*t_lag_ln_GDPpc*
t_lag_RelDens	0.077***							
t_lag_CompOcc	0.014	0.121***						
t_lag_CompReg	-0.046***	0.123***	-0.352***					
t_lag_EducThir	0.015	0.086***	0.434***	-0.179***				
t_lag_SmallSize	-0.008	-0.158***	-0.127***	-0.148***	-0.096***			
t_lag_ln_PopDens	-0.057***	0.053***	-0.115***	0.410***	-0.102***	-0.097***		
t_lag_ln_GDPpc	-0.040***	0.180***	-0.234***	0.729***	-0.168***	-0.063***	0.434***	
t_lag_Unemploy	0.052***	-0.006	0.205***	-0.564***	0.116***	0.231***	-0.125***	-0.433***

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.3: Correlation of variables from model (Exit1)

	Exit1	*t_lag_RelDens*	*t_lag_CompOcc*	*t_lag_CompReg*	*t_lag_EducThir*	*t_lag_SmallSize*	*t_lag_ln_PopDens*	*t_lag_ln_GDPpc*
t_lag_RelDens	0.042***							
t_lag_CompOcc	0.019**	0.090***						
t_lag_CompReg	-0.01	0.113***	-0.184***					
t_lag_EducThir	-0.014	0.066***	0.412***	-0.093***				
t_lag_SmallSize	-0.018*	-0.153***	-0.138***	-0.175***	-0.127***			
t_lag_ln_PopDens	-0.018*	0.065***	-0.066***	0.400***	-0.058***	-0.094***		
t_lag_ln_GDPpc	-0.017*	0.173***	-0.126***	0.705***	-0.087***	-0.087***	0.422***	
t_lag_Unemploy	0.020**	-0.017*	0.109***	-0.577***	0.095***	0.226***	-0.122***	-0.454***

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.4: Correlation of variables from model (Exit2)

	Exit2	*t_lag_RelDens*	*t_lag_CompOcc*	*t_lag_CompReg*	*t_lag_EducThir*	*t_lag_SmallSize*	*t_lag_ln_PopDens*	*t_lag_ln_GDPpc*
t_lag_RelDens	0.038***							
t_lag_CompOcc	0.011	0.089***						
t_lag_CompReg	-0.024***	0.112***	-0.186***					
t_lag_EducThir	-0.020**	0.065***	0.412***	-0.094***				
t_lag_SmallSize	-0.014	-0.152***	-0.137***	-0.175***	-0.127***			
t_lag_ln_PopDens	-0.026***	0.065***	-0.067***	0.399***	-0.058***	-0.095***		
t_lag_ln_GDPpc	-0.018*	0.173***	-0.127***	0.707***	-0.086***	-0.087***	0.421***	
t_lag_Unemploy	0.024**	-0.017*	0.110***	-0.577***	0.094***	0.226***	-0.121***	-0.454***

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.5: Correlation of variables from model (Entry3)

	Entry3	*t_lag_RelDens*	*t_lag_CompOcc*	*t_lag_CompReg*	*t_lag_EducThir*	*t_lag_SmallSize*	*t_lag_ln_PopDens*	*t_lag_ln_GDPpc*
t_lag_RelDens	0.104***							
t_lag_CompOcc	0.014	0.105***						
t_lag_CompReg	-0.037***	0.116***	-0.241***					
t_lag_EducThir	0.019*	0.075***	0.418***	-0.125***				
t_lag_SmallSize	-0.012	-0.154***	-0.131***	-0.167***	-0.117***			
t_lag_ln_PopDens	-0.030***	0.057***	-0.085***	0.399***	-0.073***	-0.092***		
t_lag_ln_GDPpc	-0.019*	0.171***	-0.157***	0.713***	-0.106***	-0.081***	0.424***	
t_lag_Unemploy	0.031***	-0.016*	0.142***	-0.574***	0.098***	0.231***	-0.120***	-0.447***

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.6: Correlation of variables from model (Entry4)

	Entry4	*t_lag_RelDens*	*t_lag_CompOcc*	*t_lag_CompReg*	*t_lag_EducThir*	*t_lag_SmallSize*	*t_lag_ln_PopDens*	*t_lag_ln_GDPpc*
t_lag_RelDens	0.095***							
t_lag_CompOcc	0.016*	0.106***						
t_lag_CompReg	-0.037***	0.116***	-0.243***					
t_lag_EducThir	0.020*	0.074***	0.420***	-0.128***				
t_lag_SmallSize	-0.005	-0.151***	-0.130***	-0.167***	-0.116***			
t_lag_ln_PopDens	-0.028***	0.056***	-0.084***	0.402***	-0.074***	-0.093***		
t_lag_ln_GDPpc	-0.023**	0.171***	-0.158***	0.713***	-0.110***	-0.079***	0.425***	
t_lag_Unemploy	0.034***	-0.015	0.144***	-0.574***	0.100***	0.231***	-0.121***	-0.447***

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.7: Correlation of variables from model (Exit3)

	Exit3	*t_lag_RelDens*	*t_lag_CompOcc*	*t_lag_CompReg*	*t_lag_EducThir*	*t_lag_SmallSize*	*t_lag_ln_PopDens*	*t_lag_ln_GDPpc*
t_lag_RelDens	-0.062***							
t_lag_CompOcc	0.014	0.037***						
t_lag_CompReg	-0.025**	0.051***	0.466***					
t_lag_EducThir	0.003	0.027***	0.379***	0.150***				
t_lag_SmallSize	0.030***	-0.103***	-0.255***	-0.279***	-0.175***			
t_lag_ln_PopDens	-0.033***	0.151***	0.191***	0.394***	0.109***	-0.121***		
t_lag_ln_GDPpc	-0.044***	0.106***	0.321***	0.684***	0.178***	-0.154***	0.430***	
t_lag_Unemploy	0.006	-0.017*	-0.303***	-0.610***	0.028***	0.275***	-0.120***	-0.486***

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.8: Correlation of variables from model (Exit4)

	Exit4	*t_lag_RelDens*	*t_lag_CompOcc*	*t_lag_CompReg*	*t_lag_EducThir*	*t_lag_SmallSize*	*t_lag_ln_PopDens*	*t_lag_ln_GDPpc*
t_lag_RelDens	0.089***							
t_lag_CompOcc	0.005	0.098***						
t_lag_CompReg	-0.051***	0.117***	-0.245***					
t_lag_EducThir	-0.034***	0.067***	0.421***	-0.125***				
t_lag_SmallSize	0.001	-0.152***	-0.134***	-0.167***	-0.117***			
t_lag_ln_PopDens	-0.044***	0.058***	-0.085***	0.397***	-0.074***	-0.095***		
t_lag_ln_GDPpc	-0.020*	0.177***	-0.161***	0.716***	-0.114***	-0.080***	0.425***	
t_lag_Unemploy	0.044***	-0.020*	0.145***	-0.572***	0.102***	0.229***	-0.115***	-0.448***

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.9: Correlation of variables from model (Entry5)

	Entry5	*t_lag_RelDens*	*t_lag_CompOcc*	*t_lag_CompReg*	*t_lag_EducThir*	*t_lag_SmallSize*	*t_lag_ln_PopDens*	*t_lag_ln_GDPpc*
t_lag_RelDens	0.043***							
t_lag_CompOcc	0.007	0.073***						
t_lag_CompReg	-0.007	0.088***	0.045***					
t_lag_EducThir	-0.007	0.040***	0.391***	-0.013*				
t_lag_SmallSize	-0.017**	-0.133***	-0.180***	-0.213***	-0.141***			
t_lag_ln_PopDens	-0.014*	0.092***	0.023***	0.393***	-0.002	-0.106***		
t_lag_ln_GDPpc	-0.009	0.146***	0.019**	0.696***	-0.004	-0.110***	0.419***	
t_lag_Unemploy	0.011	-0.009	-0.050***	-0.591***	0.071***	0.244***	-0.123***	-0.468***

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.10: Correlation of variables from model (Exit5)

	Exit5	t_lag_RelDens	t_lag_CompOcc	t_lag_CompReg	t_lag_EducThir	t_lag_SmallSize	t_lag_ln_PopDens	t_lag_ln_GDPpc
t_lag_RelDens	0.044***							
t_lag_CompOcc	0.001	0.073***						
t_lag_CompReg	0.009	0.090***	0.048***					
t_lag_EducThir	-0.004	0.043***	0.393***	-0.012*				
t_lag_SmallSize	-0.01	-0.133***	-0.181***	-0.215***	-0.142***			
t_lag_ln_PopDens	-0.001	0.093***	0.025***	0.394***	-0.001	-0.107***		
t_lag_ln_GDPpc	-0.008	0.148***	0.020***	0.696***	-0.004	-0.112***	0.419***	
t_lag_Unemploy	0.01	-0.009	-0.050***	-0.592***	0.070***	0.243***	-0.123***	-0.467***

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.11: Correlation of variables from model (Entry6)

	Entry6	t_lag_RelDens	t_lag_CompOcc	t_lag_CompReg	t_lag_EducThir	t_lag_SmallSize	t_lag_ln_PopDens	t_lag_ln_GDPpc
Entry6								
t_lag_RelDens	0.043***							
t_lag_CompOcc	0.002	0.075***						
t_lag_CompReg	-0.01	0.090***	0.045***					
t_lag_EducThir	-0.015**	0.042***	0.390***	-0.014*				
t_lag_SmallSize	-0.003	-0.134***	-0.181***	-0.213***	-0.141***			
t_lag_ln_PopDens	-0.016**	0.092***	0.024***	0.394***	-0.002	-0.106***		
t_lag_ln_GDPpc	-0.017**	0.147***	0.020***	0.696***	-0.003	-0.111***	0.419***	

Note: Computed correlation used Pearson-method with listwise-deletion.

Table F.12: Correlation of variables from model (Exit6)

	Exit6	t_lag_RelDens	t_lag_CompOcc	t_lag_CompReg	t_lag_EducThir	t_lag_SmallSize	t_lag_ln_PopDens	t_lag_ln_GDPpc
t_lag_RelDens	0.039***							
t_lag_CompOcc	0	0.075***						
t_lag_CompReg	0.012*	0.093***	0.047***					
t_lag_EducThir	-0.009	0.045***	0.392***	-0.013*				
t_lag_SmallSize	-0.008	-0.135***	-0.180***	-0.215***	-0.142***			
t_lag_ln_PopDens	0.001	0.095***	0.025***	0.395***	0	-0.107***		
t_lag_ln_GDPpc	-0.01	0.150***	0.021***	0.696***	-0.003	-0.112***	0.420***	
t_lag_Unemploy	0.008	-0.01	-0.049***	-0.591***	0.071***	0.242***	-0.122***	-0.466***

Note: Computed correlation used Pearson-method with listwise-deletion.