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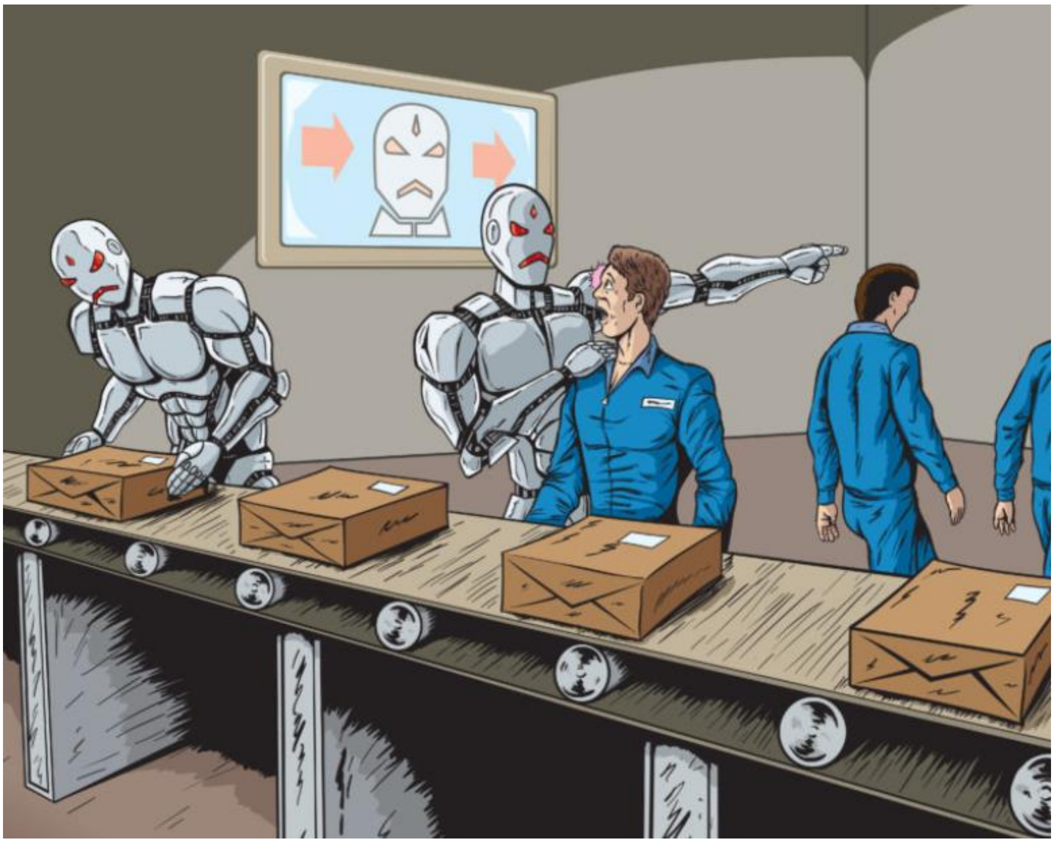
Automation and the Relatedness of Jobs in European Regions



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Abstract

Automation is changing the nature of work in the EU. This paper has taken a novel occupational-network approach to examine the impact of automation on the evolution of jobs in regions. We recognise two types of relatedness which mediates the impact of automation on regional job re-composition: geographical relatedness which makes jobs co-locate in the same region and complementary relatedness which makes jobs co-occur in the same industry. By using data from European labour force survey, Eurostat and the risk of automation from Frey and Osborne (2017), we calculate each of the relatedness and examine the impact of risk of automation with them on the evolution of the occupational structure of 221 EU NUTS2 regions for the period of 2014-2016. The main conclusion is that the impact of automation on geographical relatedness is associated with a higher probability of disappearance of an existing occupation specialisation on the one hand, and the impact of automation on complementarity relatedness is associated with a higher probability of entry of a new occupation specialisation. The policy relevancy of the study is that by revealing regional patterns in job dynamics in the face of automation policy makers can allocate educational resources more efficiently to equip people with up-to-date skills for employment outlook in the labour market.

Keywords: Automation; Occupation; European regions; Relatedness; Skills

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1. Introduction

In recent years, the expanded scope of automation has significantly changed the composition of employment in the labour market (Berger and Frey, 2016). The surge in computer-led automation of production and service provision has provoked ongoing debate about skill-biased and routine-biased job polarisation and growing inequalities. Acemoglu and Autor (2011) argue that automation is assumed to augment either high- or low-skill workers in the 1980s. However, with the prevalence of computer-skill complementarities, an alternative model introduced by Autor et al. (2003) suggests that computers tend to replace workers in routine tasks that are repetitive and rule-based. Namely, the labour market relative demand was in a "U" shape in preference to high-skilled labour and low-skilled labour over middle-skill labour. The reduction in demand of the middle level has reinforced competition for lower-paid jobs and may incur further polarisation in wage structure, indicating a potential inequality of income. (Spitz-Oener, 2006; Oesch and Menés, 2011; Frey and Osborne, 2013; Acemoglu and Restrepo, 2016).

However, given the absence of regional characteristics in the debate, increasing regional disparities in routine skills and occupations are overlooked. The far-ranging influence of automation offers regions new opportunities but also increases the divergence in labour market outcomes across regions. In the last decades before the ICT revolution, regions in the EU with abundant human capital had a comparative disadvantage in new job creation since those appearing routine tasks would be automated. After the 1980s, regions specialised in skilled work (non-routine, analytical tasks) gained comparative advantages in the new job creation. Economic historians argue that automation can create more rewarding jobs and accelerate productivity in the long-term to offset job loss in the short-term. However, this argument is suspect since many industrialised regions have experienced long-term labour redundant, but others revitalise themselves by attracting many high-skilled and knowledge-intensive labours. For instance, the computer revolution over the recent decades shaped US cities. The short-term routine job creation still warrants additional policy attention to the skill upgrading and retraining. Therefore, the importance is not only about creating jobs but helping regions to find and build on new sets of skills and knowledge in their economies (Hausmann and Rodrik, 2003). As McCann and Ortega-Argilés suggest (2016) that regional job dynamics could be regarded as an entrepreneurial process of self-discovery in the face of innovation and technology progress.

Many economic geographers have studied the 'creative destruction' process which was coined by Schumpeter to identify the economic growth (Schumpeter, 1939). They define the 'new' industries as the entry of industries that did not previously exist in a location (Frenken and Boschma, 2007; Neffke et al., 2011) which may indicate life-cycle patterns of industry diffusion (Berger and Frey, 2017). The recent progress has been towards the reasons that successful cities reinvent themselves to adopt digital revolution or failed cities become lagged for large unemployment (Berger and Frey, 2016; Berger and Frey, 2017). The importance of new occupations has been put into the central stage because the regional skill compositions may shape their economic trajectories over the course of automation (Berger and Frey, 2017). Farinha et al. (2018) firstly invent various measures of relatedness to capture the interdependence of occupations and its evolutionary nature. The ‘relatedness’ analytical framework might be a powerful tool to identify the paths of regional job re-composition affected by automation. For example, in a modern office setting, a CEO needs a secretary to administrate his or her daily schedules though these two occupations require different levels of knowledge and expertise. In a port city, the harbour transport workers usually co-locate with yacht-building engineers because they work in the same product chain. Occupations and skills are related when they require similar or complement knowledge or inputs (Hidalgo et al., 2018). Relatedness was shown to affect the entry and exit of occupations in US metropolitan regions through their pre-existing capabilities (Brachert 2016; Shutter et al., 2016; Farinha et al., 2018). Shutter et al. (2018) describe the relatedness of occupations as the strengths of interdependence between pairs of occupations. They find that urban population density increases superlinearly with the number of distinct occupations because of knowledge sharing. They also argue that occupational ‘network effect’ exists in the workplace when workers frequently communicate. Farinha et al. (2018) distinguish three network effects as complementairty (interdependent tasks), similarity (sharing similar skills) and local synergy (based on pure co-location) and find that the new jobs appearing in the US cities are positively related to the above three mechanisms ,and the pure co-location factor contributes the most in terms of diversification. The penetration of automation is also assumed to change the local skill pool and further influences the job creation and job loss. However, there is no study yet that has linked these two forces to investigate the job dynamic, without this link we might have an unclear mechanism that determine the co-evolution of the geography of jobs with automation.

The aim of this thesis is to research how does the risk of automation an effect regional labour market through their pre-existing and related occupations, with the consideration of regional characteristics. Thanks to the seminal paper from Farinha et al. (2018), we have this novel unpacking relatedness of occupations in cities. This thesis’s econometric models are mainly built from Farinha et al. (2018) meanwhile further develop their applications in automation literature. By using the aggregated regional data from European Labour Force Survey and occupation automatability from Frey and Osborne (2017), we examine two relatedness of occupations, namely, geographical relatedness and complementarity relatedness on the 211 European regions from 2014 to 2016. More specifically, we test the conditional probability of an occupational specialisation entering and exiting the regions under the risk of impact of automation, given the employment structure in the last year. We will confirm that the job creation or job destruction over time not only has been influenced by automation but also has been related to complementarity of skills and co-location of skills. The region that provides complementary tasks may experience fewer shocks from the impact of automation. We also find that the impact of automation on geographical relatedness is associated with the probability of disappearance of an existing occupation specialisation; the impact of automation on complementarity relatedness is associated with the probability of entry of a new occupation specialisation.

The next section develops a theoretical framework for the mechanisms of automation on the regional labour market. Section 3 introduces the variables and methods to obtain them. After presenting both descriptive and regressive results in Section 4, Section 5 concludes the article and points out the theoretical limitations and policy recommendation.

2. Automation and Job Recomposition

2.1 Impact of automation on the labour market

The nature of work is changing with the rise of automation. The recent breakthrough in artificial intelligence and industrial robotics have accelerated the race between human and machines. Most of the researches have reflected two narratives about the implications of automation. The first one is the destructive outcome of automation. Frey and Osborne (2013) suggest that nearly 50% of all jobs in the US face a high risk of being automated in the foreseeable future. The number is even more disturbing in developing countries, accounting for 70% of jobs at risks (Nedelkoska and Quintini, 2018). The second one is about job creation by automation. Michaels et al. (2013) show that jobs with communication and interpersonal tasks have become more prominent across occupations and industries, geographically concentrating in big cities.

Theoretically, automation's impact on labour market has reduced demand for certain routine-cognitive tasks but increased demand for cognitive tasks and interpersonal tasks, which induces job polarisation. For example, on the one hand, creative and professional classes have generated more returns through using digitalised tools to augment their creativity or decision-making; on the other hand, low-skilled jobs such as domestic, hotel and office cleaners and helpers resist automation because their physical dexterity or communication skills are still the bottlenecks to robotics and machine learning. Only those jobs requiring intermediate skill levels such as chemical and photographic products plant and machine operators have experienced job losses. Since high income groups are more willing to purchase personal care related services after their material demand have been reached. Consequently, highly paid skilled "lovely" jobs in turn raises the demand for poorly paid personal "lousy" jobs, reinforcing the polarisation of occupations (Goos and Manning, 2007; Autor and Dorn, 2013; Goos et al., 2014).

2.1.1 The timeline of automation

Every wave in the industrial revolution has been driven by the link between the human skilling and the level of technology status quo at the time. The first wave is the in the early 19 centuries, the manufacturing technology such as steam power demonstrates "deskilling" features by substituting artisan through simplification of tasks (James and Skinner, 1985; Katz and Goldin, 1996). Later, the continuous-flow processes had been deployed in a plant by Ford Motor Company to manufacture the T-Ford at a low price for its consumers in urban areas. The second wave is the electrification in the twentieth century. Electrification power allowed many stages of production process to be automated in a large establishment which contributes to a growing demand for managerial and clerking employee and relatively skilled blue-collar workers at the same time (Atack et al., 2008). The third wave is commonly referred to the computer revolution which began around the 1960s and deepened in the 1990s with the spread of internet and e-commerce (Nordhaus, 2007). Cash machines were spreading across financial industrials, and the same did bar-code scanners in retail industries in the 1980s (Gordon, 2012). The computer power at the initial stage was the word processing and spreadsheet function that allowed repetitive formatting and calculation, which leads to an increasing demand for office clerks. The current fourth wave is the general usage of artificial intelligence and industrial robots which takes the digital world to a new level. The algorism power mainly turns the old defined non-routine tasks into well-defined problems such as text mining and face recognition. Aided by big data, machine learning algorithms can discover hidden behaviour patterns in specific fields that generate raw data in real time (Brynjolfsson and Mcafee, 2011)

For example, the warehouse industry embraces automated storage and retrieval systems (AS/RS) dating back to the late 1960s, with computerised control systems for many tasks including sorting, picking and packing. In the Agri-food industry, self-learning robots are be applied in tractors to enable lean agriculture practices such as pixel farming with precise operations for seeding or vertical farming with artificial lighting system[1].

Figure 1. The robotic application in the agricultural Industry

Source: website picture from https://www.wur.nl/en/Research-Results

The recent growth in service industries such as e-commerce has accelerated the use of robots to support the massive tasks of picking high volumes of small and multi-line orders. In a study by DHL[2], it is shown that 20% of warehouse are mechanised or use fully installed advanced automated systems including robots. Research from the European Commission's digital unit (2014) shows app developers could earn four times higher, from €17.5 billion to €63 billion over the coming five years. Meanwhile, the spill-over effect on advanced production service

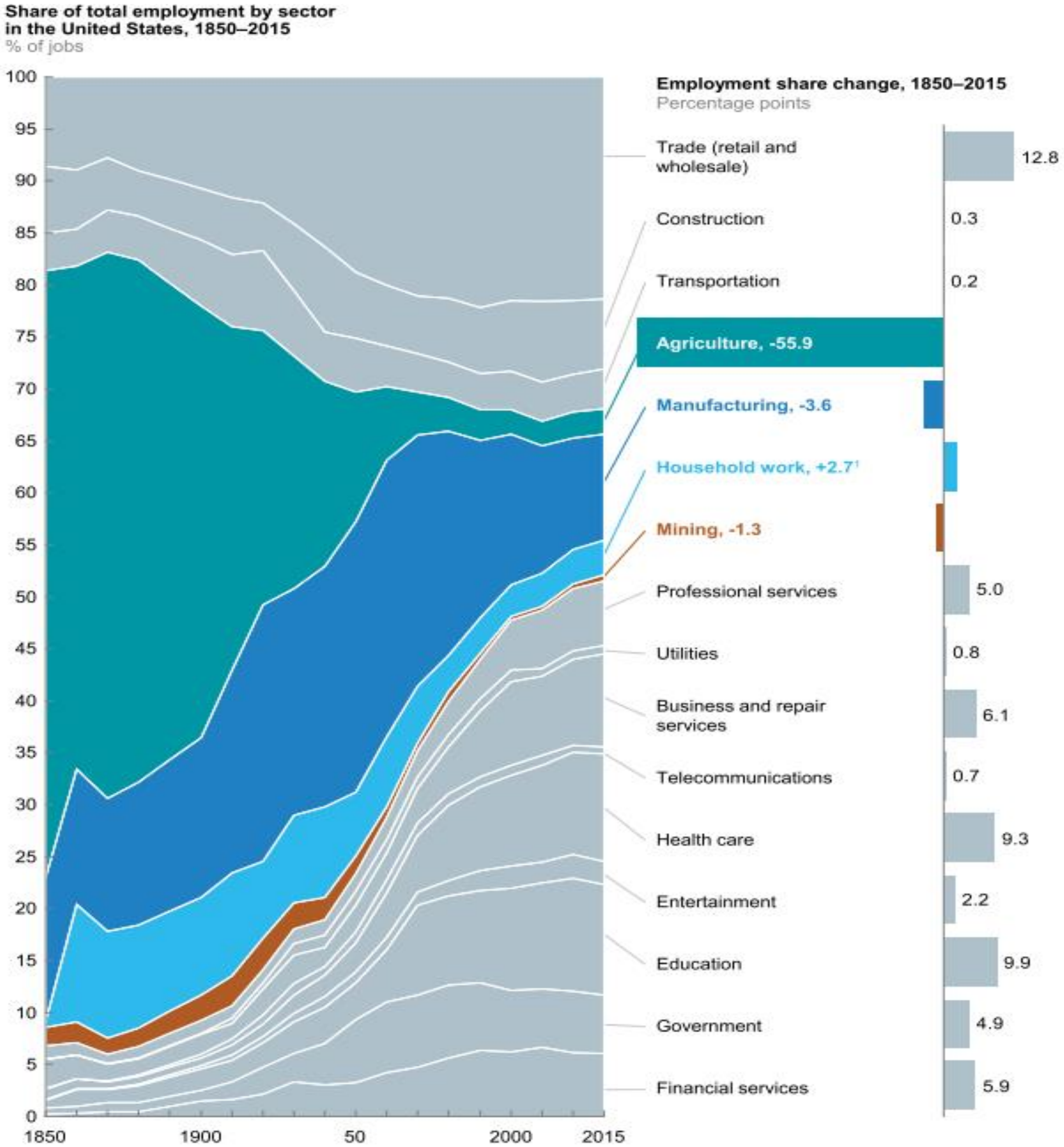
[1] https://www.wur.nl/en/Research-Results/Projects-and-programmes/Agro-Food-Robotics/show-agrofoodrobotics/Husky-Self-learning-robots.htm
[2] DHL, Robots in Logistics, March 2016

jobs such as marketing, financial and legal consultation is substantial as well, suggesting a growth to 4.8 million in 2018 from 2014 (Mulligan and Card, 2014)[3].

Throughout history, technological progress has vastly shifted the composition of employment, from agriculture and the artisan shop, to manufacturing and clerking, to service and management occupations. In the United States, for instance, the agriculture shares of employment declined from 58 percent of total employment in 1850 to 2.5 percent of employment today (Figure 2.). Between 1880 and 1920, the share of agricultural employment declined 25 percentage points, the share of miners and household workers, for example maids and servants, also declined, although these shifts affected fewer workers. Since 1960, when the third industrial revolution began, manufacturing fell from 27 percent of total US employment to 9 percent today, as automation transformed manufacturing and as demand for services exploded. What would be the future of jobs? The World Economic Forum (2018) conducts an extensive survey within Chief Human Resources and Chief Executive Officers of leading global companies which aims to give specificity to this question. Among the future landscape of jobs, Data Analysts and Scientists, Software and Applications Developers, and E-commerce and Social Media Specialists are in high demand for the continuous enhancement of Big Data and ML. Customer Service Workers, Sales and Marketing Professionals, Training and Development, People and Culture, and Organizational Development Specialists as well as Innovation Managers are also on the list given that their capacity to bring "human warmth" to the workplace.

Figure 2. The timeline of automation and employment change

[3] Mulligan, M., and Card, D. (2014). Sizing the EU app economy. *Retrieved January 10*, 2014.



Source: Author adopted from McKinney Global Institute (2017)

2.1.2 Theoretical thinking of the impact of automation

Neoclassical economists understand the consequences of technological progress on labour market through many mechanisms and one of them is: the intersection between skills and new technologies determines the elasticity of the labour demand. There are two theoretical frameworks which have been developed to explain the topic: The skill-biased technical change (SBTC) hypothesis is a competitive supply-demand framework for skilled and unskilled workers. The key insight of this framework assumes that the innovation augments the labour productivity of skilled workers by more than it does that of unskilled labour (Saint-Paul, 2008). Whereas, the skill-biased technological change (SBTC) model cannot account for two empirical paradoxes that are prevalent in European labour markets: non-monotonic shifts in employment and wages along the skill distribution (OECD, 2016). The routine-biased technological change (RBTC) hypothesis is based on the task assignment model of Acemoglu and Autor (2011). This model assumes that computers directly replace workers with the degree of task codifiability. The sorting mechanism that matches workers from a different level of skills into different level of tasks according to their comparative advantage (Acemoglu and Autor, 2011; Autor and Handel, 2013). The digital capital has a comparative advantage in doing middle-level tasks because these tasks are routine intensive and codifiable. Therefore, the RBTC predicts that *Digital Revolution* will lead to job polarisation in employment, rather than skill-upgrading as the statement the SBTC argues (Goos, 2018). The RBTC hypothesis is more suitable to explain the current U-shape of the labour market because it allows directly substitution of human labour.

To race with machines and not against them, there is a growing need to upgrade lagged occupations instead of only focusing on the unemployment. In the real world, employment in certain occupations would not disappear suddenly though we have enough technology to replace them. Erik Brynjolfsson (2014) argues that focusing on job loss is out of the central effect of automation, because automation never substitutes jobs entirely. Instead, we need to recognise the functional content of occupations and re-engineer or reinvent them to workers if the types of skills now demanded by employers do not match up with those existing labour force (Katz, 2010)[4]For example, facing growing ATM installation, bank cashiers still retain in the job category not because its irreplaceability but its role in maintaining customer relationships to business. The required skills shift from routinised clerk work to interpersonal caring. Truck drivers will be influenced relatively mild at least until 2030, but taxi drivers will be most affected by the autonomous cars in the coming years (Cotton, 2018). A bank cashier who has strong soft skills in working with managers in the business development department would be less likely to be replaced by cash machines. If it is the opposite, the job will be downgraded. Autor et al. (2000) describe this divergence of labour demand in a large bank which introduced an image processing technology. The downstairs deposit processing department suffers from low educated labours substituted by computers; the upstairs exceptions processing department enjoyed the integration of tasks which have been generated by the computers and developed demand for specific skills.

Previous studies have examined the impact of automation in a way of skill aggregates. However, Given the way automation subtly influencing workplace tasks and contextual skills it might also redefine the occupation status quo by changing its content. Although the RBTC framework's rational acknowledges the upgrading in skills since computerisation alters the relative demand of high- or low-skill labour, its dependence on *subjective occupation categories* (e.g. routine or not routine and cognitive or non-cognitive) fails to capture the redefinition of occupations and underestimates labour mobility between low- and middle-low occupation (Alabdulkareem et al., 2018).

Similarly, automation might cause an occupational structure change in a regional dimension. The labour market reactions to automation can be along the existing occupational specialisation in a region. For example, the impact of automation might change one of the specialised

[4] http://scholar.harvard.edu/files/lkatz/files/ long_term_unemployment_in_the_great_recession.pdf

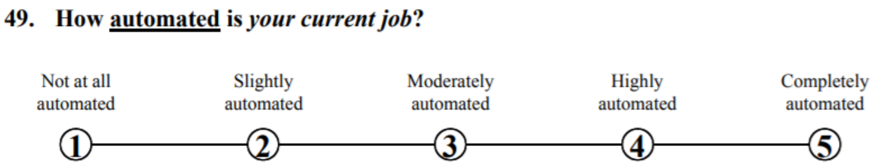
occupations from machinery operator to sales workers. In line with the old tradition of studying societal structural change induced by technological progress (Schumpeter, 1947; Pasinetti, 1981; Polanyi, 1984), some evolutionary economic geographers have joined this debate. They have studied how does regional diversification evolve over time and how does relatedness of activities impact the creative destruction process (Boschma 2017; Hidalgo et al., 2018). Diversification refers to the emergence of new activities, and they could be products, jobs, patent or firms (Saviotti and Pyka 2004). Take patent as an example, the intuition behind technologies relatedness is that the new technology is often embedded in or related to existing technologies(Boschma et al., 2015; Rigby, 2015). The same logic is also applied to skill, and jobs within a value chain sharing similar skill requirements (Neffke and Henning, 2014). Hence, some "smart technologies" are more likely to be adopted in advanced regions than lagged regions because of short proximity to existing ICT knowledge and compatible skillsets. This revealed path-dependency has been documented by many other scholars (Glaeser and Maré, 2002;2001; Bacolod et al., 2009; Mellander and Florida, 2012).

2.1.3 Objective and subjective measurement of automation

There is a difference in tasks that are evaluated by a designer or by workers of the system. According to Frey and Osborne (2017), their measurement of risk of automation focuses on the technological advances of Machine learning and Mobile Robotics. They use a Delphi method and invite an expert panel from the Oxford University Engineering Sciences Department to mark 70 out of 702 occupations that will certainly be replaced by the above two technologies. After a workshop, they identify three big categories of bottlenecks referred to tasks such as perception and manipulation, creativity and social intelligence and nine sub-attributes. In addition, they validate the 70 occupations subjective classification whether it is systematically related to the nine bottlenecks. Then FO run many probabilistic models to examine the power of these bottleneck-related attributes in predicting an occupation's automatibility. This automatibility is closer to an evaluation by a designer.

However, to evaluate the human-automation interaction, we also require an operator's subjective measure. Subjective response from workers reflects their perceptual task content and mental workload. A highly automated office job which also involves many tasks such as persuading, negotiating, and face-to-face communication might receive a lower rate because of its social dimension. By contrast, a textile machine operator might overestimate the automation effect simply because his or her workmates control the similar machines but neglect the fact that many tasks depend on manual dexterity. Subjective measures can rate the workload or effort experienced while a worker performing a task in an automated context. Unidimensional scale technique are often applied to ask one participant for rating for automation at a given point of time (Wierwille and Casali, 1983; Roscoe and Ellis, 1990). Each year The Bureau of Labour Statistics in the US will collaborate with O*NET research agency to collect new data by surveying job incumbents using standardised questionnaires. Generally, the O*NET data collection program provides several hundred ratings, based on responses by the sampled workers to the O*NET questionnaires. Specifically, surveyors use work context questionnaires to ask interviewees about their working conditions, its possible hazards, the pace of work, and interactions with other people. In terms of the automation question, the interviewee will be asked to put an **X** through the number for the answer that best describes his or hercurrent job. For example, figure 2 below shows a scale bar.

Figure 3. Questionnaires example



2.2 Mechanisms of automation on regional job re-composition

Currently, the diffusion of the fourth wave algorithm power is driving a substantial re-composition of job market (Wiegmann et al., 2017). The computer-skill complementarity happens across industries and regions. Given the fact that in reality, most automation is partial, researches simply calculate the employment loss is misleading (Bessen, 2015). Automation can lead to substitution of one occupation for another within industries (Bessen, 2016). For example, the loss of telephone operators in the office creates more receptionists in the front desks. Graphic designers using computers became more productive than typesetters, so automation facilitated the shift of work from typesetters to graphic designers.

Automation also affects occupational changes through job clusters in a region. The spatial trade-off between coordination and production costs varies across occupations. Some occupations would cluster with others to save on coordination cost and benefit from scale of economies.

The "Network Science" literatures use objective (unsupervised) data-driven clustering techniques to provide alternative insights about the economic complexity and occupation patterns (González et al., 2009; Hausmann and Hidalgo, 2011; Hidalgo, 2016; Balland et al., 2017; Alabdulkareem et al., 2018; Cicerone et al., 2019). This nuanced approach uses constructed skill network topology to answer the job polarisation question and propose regional strategies that reduce the negative effect of automation. Muneepeerakul et al. (2013) were the first to acknowledge the relevance of the occupational structure to analyse regional job re-composition. By using an occupation network, they found out co-located occupational clusters might determine the development path of urban economies. Following the work from Fernandes et al. (2018), we identify two mechanisms that automation might penetrate through in the local labour market and induce the entry or exit of occupational specialisations job re-composition.

2.2.1 Geographical relatedness of jobs

The geographical co-location of jobs might occur due to market demand, natural endowments or amenities (Florida, 2002; Moretti, 2012). What's more, the mix of occupations also generate local multiplier effect in which high-skill occupations will attract low-skill occupations into the same region, leading to a relatively high demand for low-wage jobs.

$$\mathrm{LQ}_{c,i} = \frac{employment_{c,i} \Big/ \sum_i employment_{c,i}}{\sum_c employment_{c,i} \Big/ \sum_{c,i} employment_{c,i}}$$

First, we identify the comparative advantage of occupation i in region c as location quotient $\mathrm{LQ}_{c,i}$, based on the weighed number of employments in i in region c in relation with the employment in occupation i in all selected European regions. By following Farinha (2018), we transform the matrix into a binary occupation-region matrix (N×M). Then we compute the geographical measure of relatedness between each pair of occupations based on their co-occurrences as comparative advantage in regions. More concretely, we use a conditional-probability-based measure developed by Van Eck and Waltman (2009) and reformulated by Steijn (2018)[5]. This results in a symmetric N×N occupation matrix, in which each cell (*i, j*) contains the geographical measure of relatedness (GeoRel) between occupation *i* and occupation *j*, i.e., the probability of a region *c* being specialized in occupation *i* given that it is also specialized in occupation *j*, as follows:

$$GeoRel(Cij, Si, Sj, T) = Cij/(m * ((Si/T) * Sj/(T - Sj) + (Sj/T) * (Si(T - Sj)))$$

where *Cij*, *Si*, and *Sj* are, respectively, the number of co-occurrences of i and j, the number of occurrences of occupation *i* and the number of occurrences of occupation *j*, as occupational specializations in regions. *T* is the sum of all region's occupational specializations, and *m* is the total number of co-occurrences. The geographical measure of relatedness indicates the probability of two occupations being together in the same region. *GeoRel* is lower bounded by zero (occupation *i* and *j* are never together as specializations in same region) but not upper bounded. A *GeoRel* higher than 1 means that two occupations co-locate in the same region more often than by chance (Fernandes et al., 2018).

2.2.2 Complementarity of relatedness of jobs

Skill transfer and skill sharing are amongst the most important prerequisites to activate synergies amongst firms located in the same region (Porter, 1985). The second mechanism identified by Farinha et al., (2018), referring to complementarity of skills between jobs in a same industry. Commonly, know-how knowledge is embedded within occupation and similar occupations need similar education attainment (Neffke, 2017). Hence, workers transit between occupations usually based on the similarity of their skillset or the skill qualifications required by certain industry. We will capture this complementarity by looking at pairs of occupations required in the same industry (employment-industry).

Jobs complementarity

Based on industry clusters' labour demand, we compute complementarity by looking at which pairs of occupations are jointly required in the same industry. We determine how often two occupations co-occur in the same industry cluster. We first compute each industry cluster's LQ

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[5] Balland, P. A. (2017). Economic Geography in R: Introduction to the EconGeo package.

in each occupation, i.e., each cluster employment shares in each occupation, compared to the average employment shares of all clusters (same LQ equation we used for occupations co-location measure, but based on the occupation-industry matrix). Then, we apply conditional probabilities for measuring jobs complementarity (equivalent to GeoRel equation but based on the occupation-industry matrix). So, we construct a symmetric N×N occupations matrix in which each cell (*i, j*) contains the jobs complementarity index between occupations *i* and *j*.

The example matrix will be shown in the Appendix as a supplement for easy understanding.

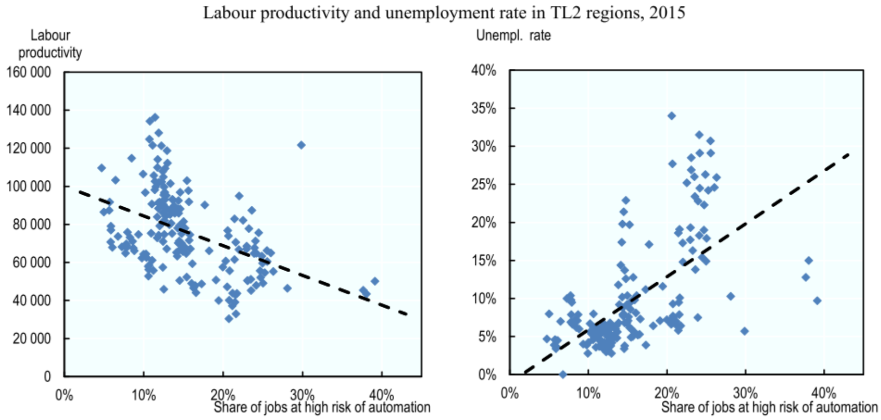
2.3 Automation on the EU regional labour market

These predictions not only theoretically intuitive, but also empirically precise in a spatial dimension. In European labour market, professional and managerial jobs expanded at the expense of the lower-middle class, eroding the jobs of production workers and office clerks (Oesch, 2014). Rahwan et al. (2018) show that regional specialisation influences the patterns of risk of automation in metropolitan area. The risk of automation is associated with the size, productivity, employment rate, or educational level.

Empirically, there are two relevant methods to estimate the outcome of automation of jobs. By adopting FO (referring to Frey and Osborne 2013) automatability approach in the US labour market, researchers estimate the share of jobs that are potential to be replaced to be around 35% in Finland and 59% in Germany (Pajarinen and Rouvinen, 2014; Brzeski and Burk, 2015). Bowles (2014) finds that automation in Europe range between 45% to more than 60%, with the southern European workforce facing the highest risk of automation. Arntz et al. (2016) criticise this method by treating same occupations with same identical task structures. The impact of technology on the skills required to perform a job is changing. Since the task structure differentiates within occupations, workers with the same occupation titles may be exposed to automation accordingly in different sectors (Autor and Handel, 2013). Hence, they use a revised task-based approach and conclude only 9% of jobs are automatable. Specifically, 10% of workers are employed in the five high-risk occupations: Food preparation assistants, drivers and mobile plant operators, labourers in mining, construction, manufacturing and transport, machine operators, and refuse collectors. They probably are the frontiers suffered from rapid automation.

The regional labour market impact of automation is also geographically uneven. Since 2011, most regions (60%) in EU have been able to create more jobs at lower risks of automation than those jobs lost in high automation risk sectors. The characteristics of core regions with a lower share of jobs at risk of automation, large amount of highly educated workers in knowledge-intensive service sectors and highly urbanised areas. Lagging regions which already have low productivity growth, high unemployment rate and low automation rate are likely fall into underperformance traps (OECD, 2018). The regional disparities display that the risk of automation is also highly correlated with regional economic performance and unemployment rate (see Figure 4). It shows that regions with higher unemployment levels have more jobs at risk of automation.

Figure 4. Regions highly affected by automation display higher unemployment and lower productivity



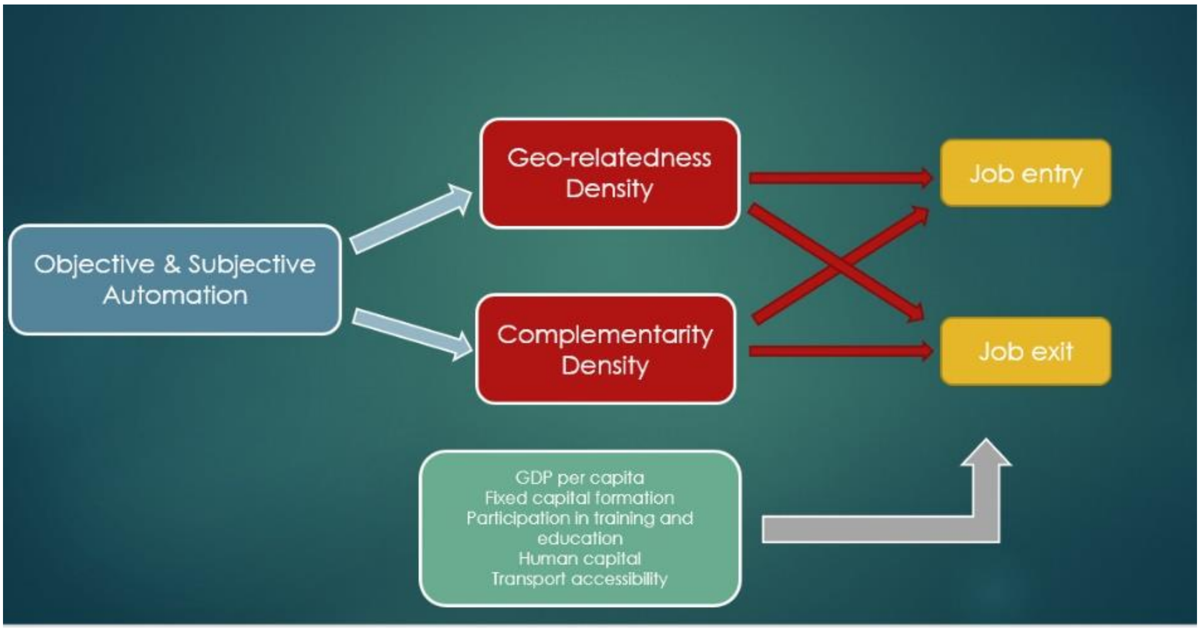
Source: Adopted from OECD (2018). Calculated from LFS 2015

Note: Data reported is from 2015 and corresponds to regions in Canada, the Czech Republic, Denmark, Estonia, Greece, Spain, Finland, Ireland, Italy, Norway, Poland, Sweden, Slovenia, the Slovak Republic, the United Kingdom, and the United States.

The number of industrial robots in use in the EU transition region stood at 41,000 in 2016, up from 1,500 in 1993 (based on data available for 22 transition countries). Most robots are deployed in manufacturing (particularly in the automotive sectors), but increasingly they are also being used in the production of plastic, chemicals, and metals (EBRD, 2018).

The EU seeks to promote the inclusive and smart growth. Employment issues are integrated into the Europe 2020 strategy as one of five headline targets, namely that 75 % of the 20–64 years old in the EU-28 should be employed by 2020. The OECD (2016a) report implies that the long-term structure transformation in labour market will be manifested by the rapidly increasing automation. The undergoing trend influences on the individuals' employment status but also on an aggregated regional level. Regions matter when we want to boost employment growth by identifying the competitive advantages of each region to draw investment in. Resilient regions are expected to sustain employment growth during shocks no matter it is the economic recession or technological revolution, and accumulate human capital to accelerate productivity growth (Garretsen et al., 2013; OECD, 2016b; van Dijk and Edzes, 2016).

Figure 5. Conceptual model



3. Data and Methodology

The article empirically addresses this issue by using regional data from the European Union Labour Force Survey (EU-LFS[6]), Eurostat regional statistics data and automation data from Frey and Osborne (2017) and O*NET. The combination of these sources enables us to create a cross-sectional dataset for European NUTS-II areas between 2014 and 2016. We examine 211 European regions in total[7] and 127 occupations on ISCO-08 3-digit level[8] and 21 industries on NACE 1-digit level. We only include full-time employee and exclude the unemployment because we mainly focus on the occupation mobility within full-time, first job and active participants in labour market. We also exclude the self-employed people (around 8%) because large amount of self-employment workers takes second job or work part-time not full-time. We think this activity more reflects the nature of work instead of an official job because work might be non-repeatedly scheduled and not fully compensated by money if we take the learning or joy of the experience into account. This involves with the flexibility outcome of digital economy (such as the gig economy) which we think it is unrelated to the focus of this thesis. The non-standard work is more related to the topic of labour's welfare and labour union. The people whose labour market participant age ranging from 22-65 years old is included. Immigrants and

[6] The EU-LFS is the largest European household sample survey, providing quarterly and annual data on labour participation of people aged 15 and over and on persons outside the labour force. It covers residents in private households (excluding conscripts) according to labour status. Each quarter, some 1.8 million interviews are conducted throughout the participating countries to obtain statistical information for some 100 variables. The sampling rates in the various countries vary between 0.2% and 3.3%.

[7] Because of the data availability, UK regions are in NUTS 1-digit level and Netherland will be treated as one region We excluded Poland, Slovenia, and Bulgaria because their occupation data are not on 3-digit level.

[8] Because Bulgaria, Poland and Slovenia are excluded because ISCO3D data are aggregated at the 2-digit level

people who work across borders are excluded. All the data aggregation uses the survey weight coefficient.

After that, we prepare two matrix datasets: weighted geographical relatedness (employment-ISCO-NUTS) and weighted job complementarity relatedness (employment-ISCO-NACE). After cleaning and rebalance, we compute the geographical density of relatedness and complementarity density. We will use the job complementarity relatedness dataset to calculate the between centrality of each occupation. The job space exploratory analysis uses *Minimum spanning tree* network representation algorithm in order to offer a visualization in which all jobs classes are included the network relates to minimum links possible. The colour of nodes will be clustered by *Modularity* algorism. We use Gephi 0.9.2 software to present the dynamic networks.

3.1 Dependent variables

We conceptualise the regional job re-composition as a dynamic process of job entry and job exit. Therefore, we first construct two dummy variables. Job entry (Entry) is computed as equal to one if the occupational specialisation of region c in time t-1 is lower than one, and it is larger than one in time t. Job exits (Exit) equals to one if the occupational specialisation of region c in time t-1 is higher than one, but it is lower than one in time t.

$$\text{Job entry}_{c,i,t} = 1, if\ LQ_{c,i,t} > 1\ and\ LQ_{c,i,t-1} \leq 1$$

$$\text{Job exit}_{c,i,t} = 1, if\ LQ_{c,i,t} \leq 1\ and\ LQ_{c,i,t-1} > 1$$

$$\mathrm{LQ}_{c,i} = \frac{employment_{c,i} / \sum_i employment_{c,i}}{\sum_c employment_{c,i} / \sum_{c,i} employment_{c,i}}$$

3.2 Independent variables

Geo-Relatedness Density

By following the R package *EconGeo* [9] provided by Balland (2017), we can compute geographical relatedness density (Geo-Relatedness Density) for each occupation *i* in region c in time t, which represents the relatedness of a new occupation specialization to the set of occupations the region is already specialized in, each year. This density measure is derived from the relatedness of occupation *i* to all other occupations *j* in which the region is specialized in, divided by the sum of relatedness of occupations *i* to all other occupations in EU at time t:

[9]Please see the installation and manuscript here, source: https://github.com/PABalland/EconGeo/blob/master/EconGeo.pdf

$$GeoRelatedness\ Density_{i,c,t} = \frac{\sum_{j \in c, j \neq i} GeoRe_{i,j}}{\sum_{j \neq i} GeoRe_{i,j}} * 100$$

Complementarity Density

We use the same density measure to calculate complementarity for each occupation *i* in region c. Complementarity Density measures the relatedness of an entry occupation specialisation to the status of jobs the region already has comparative advantage of, regarding to the complementary skills within the same industry sectors.

$$Complementarity\ Density_{i,c,t} = \frac{\sum_{j \in c, j \neq i} Complementarity_{i,j}}{\sum_{j \neq i} Complementarity_{i,j}} * 100$$

Subjective and objective Automation

Frey and Osborne (2017) data estimated the risk of job by their ML methods. This data-driven measure discards the subjective classification of tasks so we can use it to reveal the possible underlying risk of automation in a general sense. Also, we use the O*NET self-report degree of automation in the workplace to represent subjective automation. Currently, there is no study trying to research the impact of these two dimensions of automation on job creations and job losses. We use the share of employment of occupation i in region c as the weight to calculate the automation risk of occupation i in region c. We also normalised our two automation datasets to a notionally common scale to make it comparable in the regression session.

3.2 Control variables

Betweenness Centrality

The positioning of a region's tradeable sectors within trade patterns are argued to be critical for region's growth trajectories (Coniglio et al., 2018); Neffke et al., 2011). We borrow the idea from Cicerone, McCann and Venhorst (2019) in which degree of centrality of the related exports has been discussed in product space to our job space.

By following the estimation strategy of Guerrero and Axtell (2013)， we regard each occupation in a region as a node in a graph and draw edges between occupations if a worker has migrated between them. The overall graph of worker-region interactions is a matrix where occupation flows within a network. Then we connect the geo-relatedness as the matrix where the node is the occupation and the edge are the conditional probability of one job will co-locate with another. The betweenness centrality captures the potential influence of a specific occupation over the proximity of each occupations. For instance, an associated managerial occupation will serve as the bridge to connect the jobs clusters between basic office clerks and technicians therefore it has more power.

Regional GDP per capita

Regional growth is the guarantee for a high share of skilled worker (OECD, 2012). High Labour productivity also enhances the local economy of learning, sharing and matching (Duranton & Puga, 2014) These knowledge activities will attract knowledge-intensive workers to these regions. Therefore, we control the different levels of economic performance of regions.

Fixed Capital Formation

The fixed capital formation determines the physical volume of future automation deployment. The investment from private firms, government, and pure household sets the threshold of a region to automate its assets.

Participation in vocational education and training

Human capital is also accumulated on the jobs. Regions with high participation rate on the one hand means upskilling of professional and managerial workers; on the other hand it means reskilling of target people in jobs at the risk of automation. Re-training therefore can provide the "hollowing out" labour with necessary skills to re-entering the labour market. We compute the average share of employment attending training programmes to capture the job-specific human capital.

Accessibility (Air, Rail, and Road):

High accessibility of transport within a region can increase access to information about job opportunities available to workers and indirectly increase jobs (Oviedo, 2012). In addition, regions with high potential accessibility means more possibilities of reaching the market demand elsewhere, giving rise to an increase of job creation inside.

Regional transport accessibility is the amount of potential interaction destinations which, in the presented indicator, is observed as number of people in destination zones and the degree of geographic separation, observed by travel times (Frost and Spence, 1995; Geurs and van Wee, 2004).We use data from ESPON (2006) to calculate the air accessibility, rail accessibility, road accessibility[10].

Human capital: Territory education attachment has been an important influence on economic growth and labour productivity (Glaeser et al., 2004) Skill acquisition through explicit education can be costly and time consuming, so more commonly, workers transition between occupations based on the similarity of their skill set and the skill requirements of each occupation.

4. Results

[10] The potential accessibility measure is computed by an equation using current population counts in destination zones, the results of a function of travel time between two points and a zone-specific internal travel time. The origin points are equally distributed throughout Europe with roughly 15km intervals. The destination points are currently the centroids of the finest available zonal units in an area. Travel times are obtained using a shortest path algorithm assuming free-flow travel times.

We will discuss the results in two sections, descriptive results and regression results. The first section will use descriptive statistics to describe the job dynamics and regional responses under the threat of automation. The regression part will further investigate how does the two mechanisms (Geo-relatedness and Complementarity) facilitate the impact of subjective automation and objective automation on regional job re-composition.

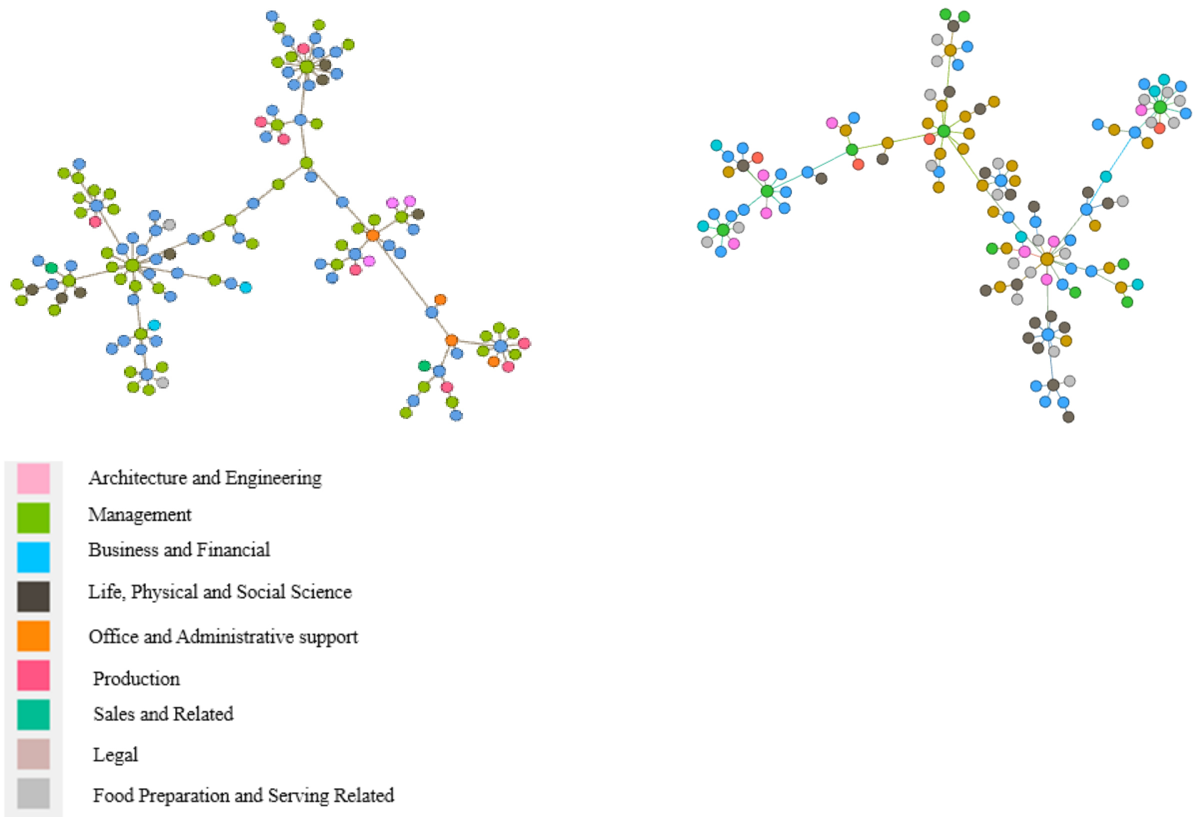
4.1 Descriptive results

4.1.1 Job dynamics during 2014-2016

Firstly, we use the network graph that illustrates the evolution of job relatedness during 2014 and 2016 in the EU regions. Given the aesthetic reason, we use *Minimum spanning tree* algorithm (Basuchowdhuri et al., 2014) to control the mapping of the main edges connecting all occupations (We only presents the edges if their calculated value is equal to one). Similarly, we apply the *Modularity* algorithm to decide the nodes' colors, which represents major groups of professions (1-dig occupational classification). Finally, we use *ForceAtlas 2* algorithm to present the visualization of networks (Jacomy et al., 2014).

The evolution of geo-relatedness of job space between 2014 and 2016 shows the features of job clusters moving from sparseness to concentration. The advanced professional job cluster is increasing (light black), which means that professional workers (such as in life science, engineering, and medicine) are more willing to co-locate with each other.

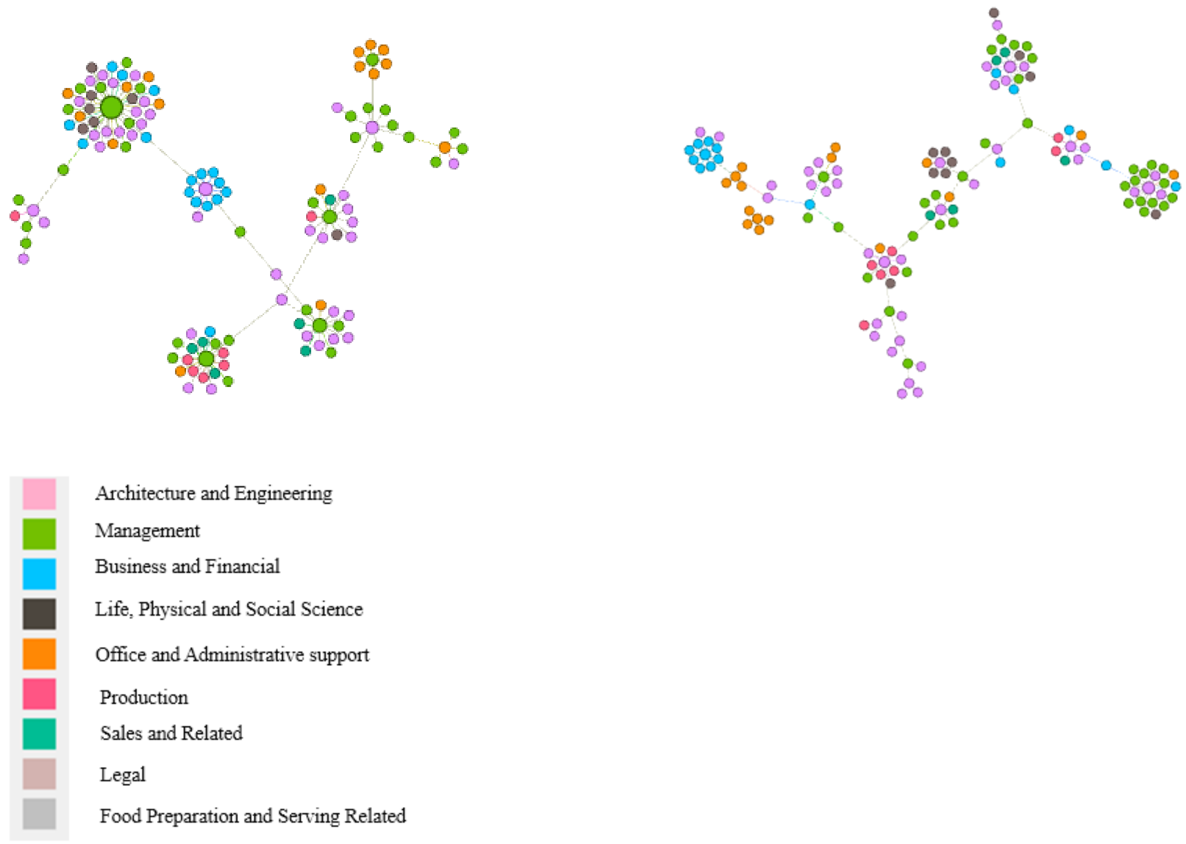
Figure 6. Geo-relatedness of job in 2014 (left) and 2016 (right)



Source: Author calcuated from LFS 2014 and 2016

It is easily to recognise that the complementarity of job relatedness network consists of several heterogeneously specialised clusters, compared to the more loose structure of geo-relatedness network (See Figure 5). Also, the evolution of complementarity of jobs features more from a big cluster-mix to a diversified cluster-mix.

Figure 7. Complementraity of job relatedness in 2014 (left) and 2016 (right)

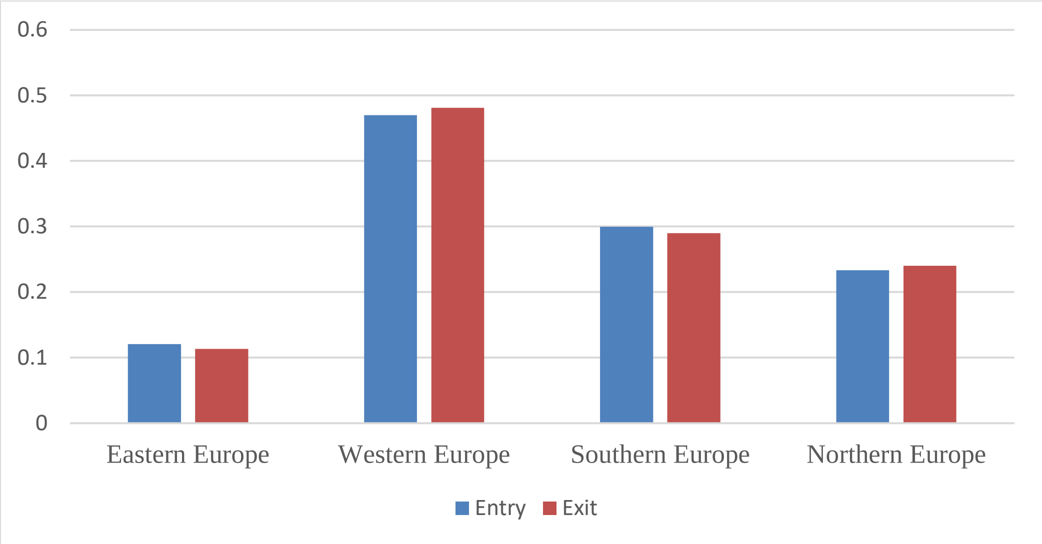


Source: Author calcuated from LFS 2014 and 2016

4.1.2 Regional responses to the threat of automation

From a geographical perspective (see Figure 7), Western Europe contributes the largest share of job dynamic which implies its resilience in the face of automation. The Eastern Europe contributes the least, but its share of job entry is larger than job exit, as the same with Southern Europe. Northern Europe is relatively stable.

Figure 8. The share of job entry and exit in EU four geographical regions during 2014-2016



Source: Author calculated from LFS 2014 and 2016.

We use two standards to evaluate the regional responses to automation, namely, job dynamic and its risk from automation in the future. Then, we classify occupation specialisations into four typologies (Table 1). Occupations are classified into job entry and exit in the period 2014-2016, and further divided according to the automatibility. Then we use ArcMap tool to visualise these occupational specialisations into four maps. The value of each region represents the numbers of occupational specialisation. The higher the value is, the more the region is diversified. This classification provides insights into the employment outlook of a region. The Top 20 regions in each category are reported in the appendix.

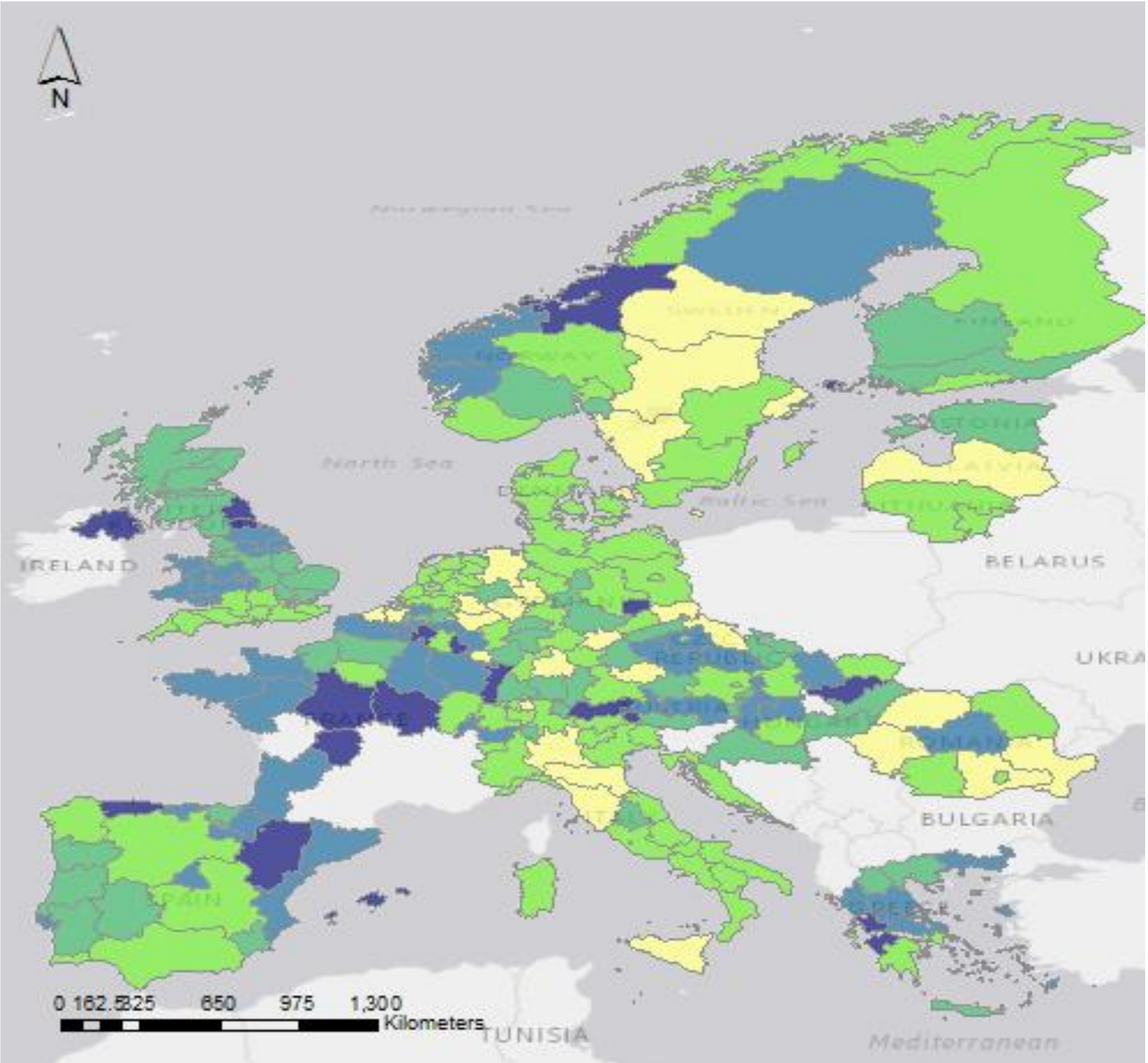
Table 1. An occupational specialisaiton typology for job creation in the face of technological disruption

Type of occupation specialisation	Description
Job entry in less risky occupations	Entry=1, Automation risk ≤ 0.7
Job entry in riskier occupations	Entry=1, Automation risk > 0.7
Job exit in less risky occupations	Exit=1, Automation risk ≤ 0.7
Job exit in riskier occupations	Exit=1, Automation risk > 0.7

* The automation risk rate is adopted from the Frey and Osborne (2013). We follow their research to set 0.7 as the cut-off value.

Regions that have job entry in occupations with a low risk of automation usually adopt the external shock in the short term and reduce their long-term risk of unemployment from automation (see Figure 8). By contrast, regions that create jobs in occupations at high risk of automation improve their job situation temporarily but might endure a potential risk of unemployment growth in the future (see Figure 9).

Figure 9. Regions with job entry at less risk of automation

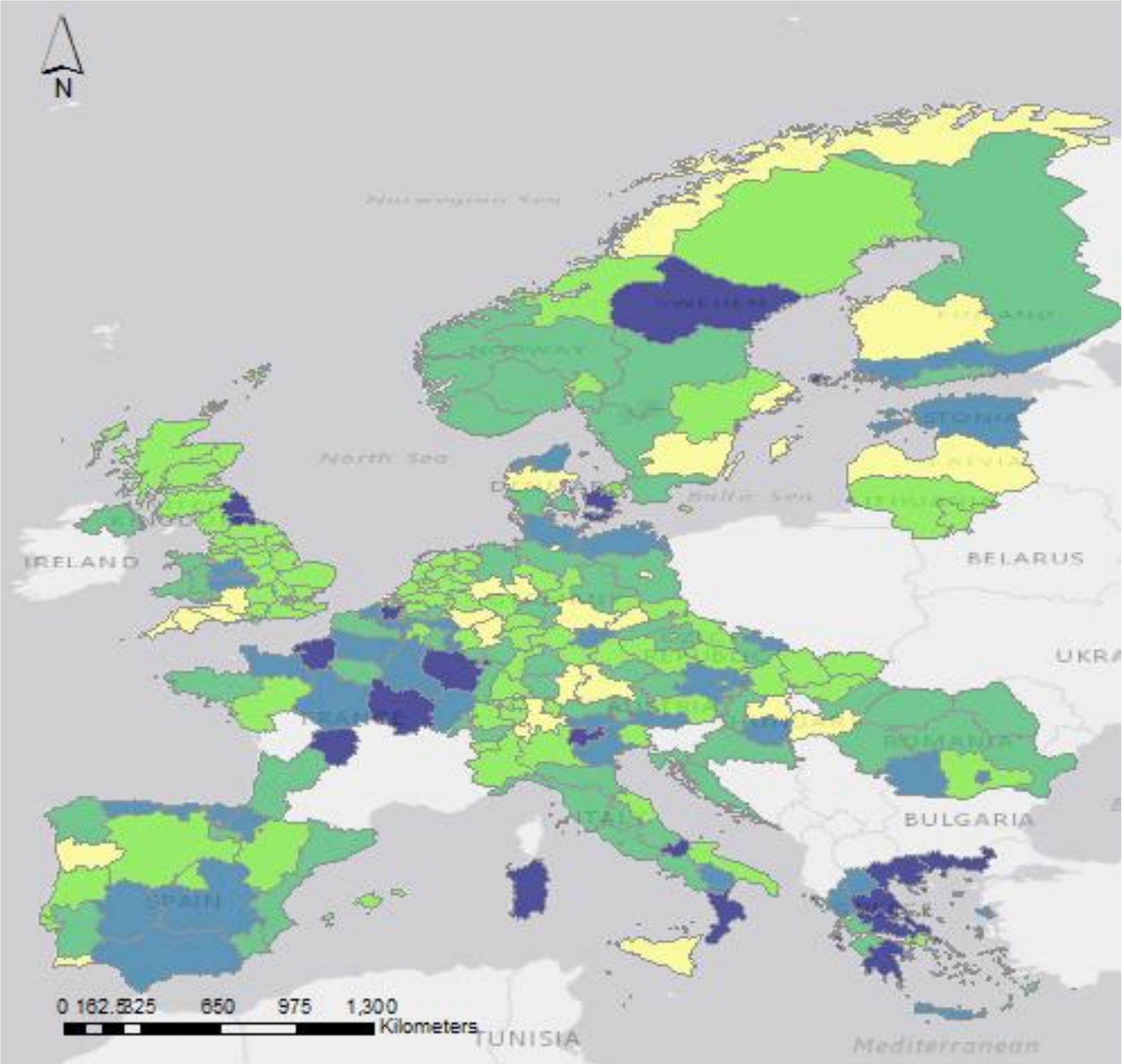


Numbers of entry occupational specialisation with less risk of automation

- 0 – 3
- 4 – 6
- 7 – 8
- 9 – 11
- 12 – 16

Source: The author calculated from LFS 2014 and 2016

Figure 10. Regions with job entry at high risk of automation

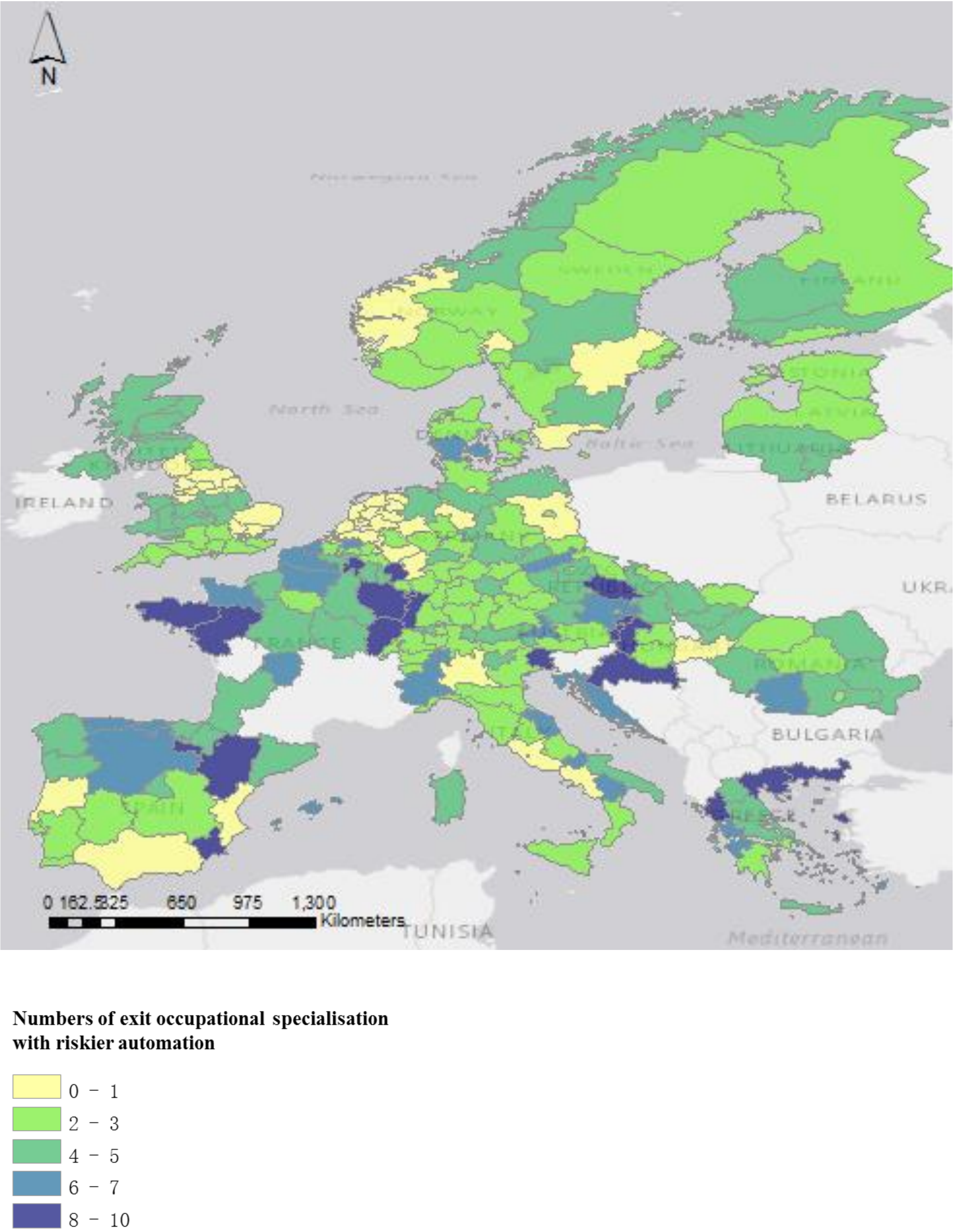


Numbers of entry occupation specialisation with riskier automation

0 - 1
2 - 3
4 - 5
6 - 7
8 - 10

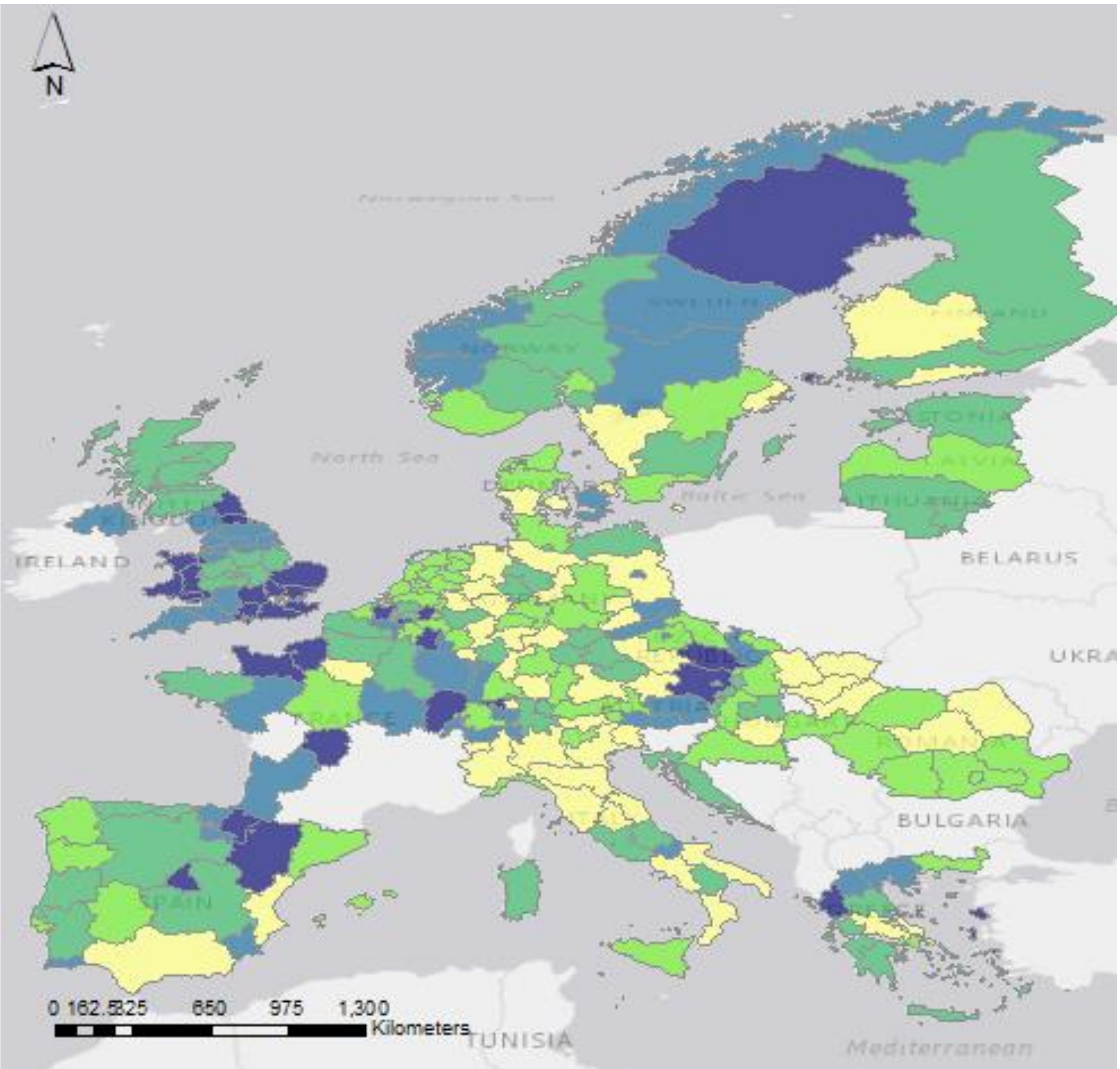
Source: The author calculated from LFS 2014 and 2016

Figure 11. Regions with job exit at high risk of automation



Source: The author calculated from LFS 2014 and 2016

Figure 12. Regions with job exit at less risk of automation



Numbers of exit occupation specialisation with less risk of automation

- 1 – 4
- 5 – 6
- 7 – 8
- 9 – 10
- 11 – 16

Source: The author calculated from LFS 2014 and 2016

Regions that have job exit in riskier occupations are challenged by structural change caused by automation. For example, in Figure 10, we have seen several regions in Austria, Belgium, and Spain. Lastly, regions that are losing jobs in less risky occupations need to take proactive actions immediately (see Figure 11). They suffer current job losses combined with an increasing risk of further job losses in the future due to automation. In this case, lagged regions like Attiki and Notio Aigaio is alarming to policy makers.

4.2 Regression results

The dataset includes 2 years and 127 occupations in 221 NUTS2 European regions. All the variables are lagged one year to reduce the potential endogeneity. All our relatedness density variables are centred around the mean for purposes of coefficients' interpretation. Table 3 below shows some descriptive statistics.

Table 2. Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Max
Entry	17941	0.1	0.3	0	1
Exit	10126	0.2	0.4	0	1
Geo-Relatedness Density	28067	35.9	5.7	13.4	100
Complementarity Density	28067	36.1	13.6	0	98.3
Objective Automation	23405	0	1	-0.7	13.7
Subjective Automation	24073	0	1	-0.8	14.6
Betweenness Centrality	28067	1.2	0.9	0	2.3
GDP per capita	25400	29281.4	13706.2	4600	89500
Fixed Capital Formation	22987	11539.8	13617.3	228.4	143142.4
Participation in Education and Training	25908	12.6	7.8	0.7	36
Airline Accessibility	23114	91.4	34.9	28.4	184.4
Rail Accessibility	23114	86.7	70.5	0	255.5
Road Accessibility	23114	91.2	72	0	217.5
High Education	28067	0.3	0.1	0.1	0.6
Middle Education	28067	0.5	0.1	0.2	0.8

Table 3 describes the correlations between core independent variables used in the model specifications, including relatedness density, automation, and betweenness centrality. The subjective and objective automation is highly correlated, so we need to separate them in the regression model. The geo-relatedness density and complementarity density is not highly correlated (0.3539) so we can test their combined effect in the second model, accounting for whether the spatially clustered industries also offering similar occupations. The features of these regions might have large concertation of nature resources or heavily industries.

Table 3. Correlation statistics

	Geo-Relatedness Density	Complementarity Density	Objective Automation	Subjective Automation	Betweenness Centrality
Geo-Relatedness Density	1				
Complementarity Density	0.3539	1			
Objective Automation	0.1583	0.0814	1		
Subjective Automation	0.2029	0.0947	0.8934	1	
Betweenness Centrality	-0.0319	0.0435	0.0943	0.0331	1

4.2.1 Entry and Exit Models-two mechanisms separate

In this section, we regress Entry or Exit of a new or existing occupation specialised in a region geo-relatedness density and complementarity density separately, with controls and betweenness centrality. The model specification is as follows:

$$Y_{i,c,t} = [Entry_{i,c,t}\ , Exit_{i,c,t}]$$

$$Automation_{i,c} = [Objective\ Automation_{i,c}, \qquad Subjective\ Automation_{i,c}]$$

$$\begin{aligned} Y_{i,c,t} = {} & \beta_1 GeoRelatedness\ Density_{i,c,t-1} + \beta_2 Automation_{i,c} \\ & + \beta_3 GeoRelatedness\ Density_{i,c,t-1} * Automation_{i,c} + \beta_4 Centrality \\ & + \beta_5 Controls_{c,t-1} + \varepsilon_{i,c,t} \end{aligned}$$

$$\begin{aligned} Y_{i,c,t} = {} & \beta_1 Complementarity\ Density_{i,c,t-1} + \beta_2 Automation_{i,c} \\ & + \beta_3 Complementarity\ Density_{i,c,t-1} * Automation_{i,c} + \beta_4 Centrality \\ & + \beta_5 Controls_{c,t-1} + \varepsilon_{i,c,t} \end{aligned}$$

In Table 4, we find that both geo-relatedness density and complementarity density have significantly positive effect or negative effect on the probability that a region specialises in a new occupation specialisation (Entry) or loses an existing occupation specialisation (Exit).

Both the influence of Objective automation and Subjective automation are significantly negative to Exit. One possible explanation is that if a region is already highly automated, automation also seems to prevent Exit of an existing occupation. GDP per capita is significant and negative to both Entry and Exit in most of the models. High GDP per capita means the high threshold of generating new occupation specialisation meanwhile the high threshold of losing existing occupation specialisations. This is in line with the literature showing that job polarisation caused by automation usually happens in advanced economies. Besides, many social inclusive policies also aim to prevent low-skilled workers to be unemployment. The same reasoning is also applied to fixed capital formation.

Participation in education and training is positive and statistically significant related to Entry and Exit in most models (1,3,4,5,6,7,8). This means regions with high rate of participation in vocational education and training is a double-edged sword. On one hand, it can create a ‘thick labour market' to generate more knowledge specialised jobs; On the other hand, its skill ecosystem might sort out a job class that is no longer suitable to the local economy.

The air accessibility and rail accessibility are both negative and statistically significant to Entry and Exit. For example, in model (5), air accessibility shows a negative coefficient of -0.0725, meaning that when air accessibility increases by 10 percentage points, the probability of entry a new job specialisation in the region decreases by 72.5%. When rail accessibility increases by 10 percentage points, the probability of entry a new job specialisation in the region decreases by 63%. By contrast, road accessibility is positive and statistically significant to Entry and Exit. For example, in model (5), road accessibility shows a positive coefficient of 0.105, meaning that when air accessibility increases by 1 standard deviation, the probability of entry a new job specialisation in the region increases by 10.5%. Road accessibility determines the efficiency and cost of workers' daily mobility. High road accessibility means denser road network which reduces the spatial cost of employment and vacancies' mismatch and further create the market which previously is disconnected. If a periphery region with relative high air accessibility and rail accessibility locates close to a metropolitan city, the "black hole" effect of agglomeration might deter the entry of a new job class because the new job class gains more return from the core city. It can also retain old job classes because it closes to a larger market with continuous demand.

Next, we focus on the interaction terms. In general, there is no large difference between the objective automation and subjective automation in terms of interaction terms. The signs and parameters of the interaction terms between geo-relatedness density with objective automation and geo-relatedness density with subjective automation are very identical. This is also applied to complementarity density. However, the parameters of interaction terms of subjective automation are always higher than their counterparts, implying the fact that people intend to overestimate their workplace automation degree and its effect on complementarily of skills between workers.

Regarding Entry, the intersection of complementarity density and subjective automation shows a significantly positive coefficient of 0.00250 in the entry model (6), meaning that when it increases by 10 percentage points, the probability of entry of a new job specialization in the city increases by 2.5%. This

Regarding Exit, the intersection of geo-relatedness density and subjective automation shows a significantly positive coefficient of 0.00966 in the entry model (4), meaning that when it increases by 10 percentage points, the probability of exit of a new job specialization in the city increases by 9.66%.

We can conclude that the impact of automation on geo-relatedness density is positively associated with the probability of exit of an existing occupation specialisation, suggesting a substitution effect overwhelming the protection effect; the impact of automation on complementarity density is positively associated with the probability of entry of a new occupation specialisation, implying automation enhancing the interdependency of occupations. Betweenness centrality is positive and significant to Entry as well as negative and significant to Exit, confirming the fact that an occupation has comparative advantage to bridge other occupations are more likely to generate jobs instead of diminishing jobs.

Table 4. Job entry and exit with geo-relatedness density and complementarity separately

	Entry=1	Entry=1	Exit=1	Exit=1	Entry=1	Entry=1	Exit=1	Exit=1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Geo-Relatedness Density	0.0175***	0.0177***	-0.0254***	-0.0255***				
	(15.76)	(15.64)	(-21.73)	(-21.73)				
Objective Automation	0.0658		-0.408***		0.0507		-0.110***	
	(1.05)		(-14.47)		(1.96)		(-11.55)	
Geo-Relatedness Density # Objective Automation	0.00109		0.00846***					
	(0.60)		(12.68)					
Subjective Automation		0.0687		-0.472***		0.0483		-0.113***
		(1.16)		(-17.53)		(1.84)		(-10.63)
Geo-Relatedness Density # Subjective Automation		0.00158		0.00966***				
		(0.94)		(14.95)				
Complementarity Density					0.00126**	0.00157***	-0.00240***	-0.00198***
					(3.12)	(3.45)	(-6.00)	(-5.04)
Complementarity Density # Objective Automation					0.00184**		0.000694**	
					(2.63)		(2.95)	
Complementarity Density # Subjective Automation						0.00250***		0.000294
						(3.43)		(1.10)
Betweenness Centrality	0.0202***	0.0227***	-0.0171**	-0.0230***	0.0184***	0.0199***	-0.00270	-0.0105
	(4.86)	(5.61)	(-3.17)	(-4.42)	(4.32)	(4.80)	(-0.48)	(-1.91)
GDP per capita	-0.00415	-0.00296	-0.0277***	-0.0261***	-0.0197***	-0.0182***	-0.0270***	-0.0231***

	(-0.91)	(-0.67)	(-4.71)	(-4.63)	(-4.33)	(-4.12)	(-4.48)	(-3.98)
Fixed Capital Formation	-0.00793***	-0.00708**	-0.00542	-0.00381	-0.00966***	-0.00883***	-0.0114**	-0.00916**
	(-3.31)	(-2.96)	(-1.57)	(-1.14)	(-3.96)	(-3.63)	(-3.19)	(-2.65)
Participation in Education and Training	0.00144*	0.00112	0.00274**	0.00236**	0.00232***	0.00198**	0.00368***	0.00323***
	(2.11)	(1.68)	(2.98)	(2.67)	(3.34)	(2.90)	(3.89)	(3.55)
Airline Accessibility	-0.0001***	-0.0609**	-0.0349	-0.0447	-0.0725***	-0.0634***	-0.0582*	-0.0660**
	(-3.68)	(-3.26)	(-1.39)	(-1.85)	(-3.71)	(-3.31)	(-2.28)	(-2.68)
Rail Accessibility	-0.0521*	-0.0503*	-0.0583	-0.0606	-0.0630*	-0.0609*	-0.0286	-0.0281
	(-2.04)	(-2.03)	(-1.68)	(-1.80)	(-2.40)	(-2.39)	(-0.80)	(-0.81)
Road Accessibility	0.108***	0.0987***	0.0945**	0.0961**	0.105***	0.0946***	0.0824*	0.0826*
	(4.23)	(4.00)	(2.74)	(2.87)	(3.98)	(3.71)	(2.31)	(2.38)
High Education	0.0506	0.0331	0.355***	0.407***	0.350***	0.322***	0.206*	0.259**
	(0.74)	(0.49)	(4.02)	(4.74)	(5.33)	(4.97)	(2.27)	(2.95)
Middle Education	-0.0577	-0.0578	0.0361	0.0547	-0.0157	-0.0191	-0.0993*	-0.0530
	(-1.70)	(-1.72)	(0.76)	(1.19)	(-0.46)	(-0.56)	(-2.08)	(-1.14)
_cons	-0.412***	-0.407***	1.169***	1.170***	0.0950**	0.102***	0.388***	0.354***
	(-9.30)	(-9.07)	(21.16)	(21.26)	(3.16)	(3.34)	(9.67)	(9.00)
N	9477	9764	6310	6471	9477	9764	6310	6471

**Coefficients are statistically significant at the ´p<0.1, * p<0.05, ** p<0.01, *** p<0.001 level. Standard errors in parentheses.*

4.2.2 Entry and Exit Models-two mechanisms combined

$$Y_{i,c,t} = [Entry_{i,c,t}\ , Exit_{i,c,t}]$$

$$Automation_{i,c} = [Objective\ Automation_{i,c}, \qquad Subjective\ Automation_{i,c}]$$

$$\begin{aligned} Y_{i,c,t} = \beta_1 Complementarity\ Density_{i,c,t-1} &+ \beta_2 GeoRelatedness\ Density_{i,c,t-1} \\ &+ \beta_3 Automation_{i,c} + \beta_4 Complementarity\ Dennity_{i,c,t-1} * Automation_{i,c} \\ &+ \beta_5 GeoRelatedness\ Density_{i,c,t-1} * Automation_{i,c} + \beta_6 Centrality \\ &+ \beta_7 Controls_{c,t-1} + \varepsilon_{i,c,t} \end{aligned}$$

The result in Table 7 shows that geo-relatedness density has a significant effect on the probability that a region specialises in a new occupation or loses an existing occupation. The complementarity density is not. The stronger effect on Entry comes from the joint effect of complementarity density and subjective automation, where an increase of 10 percentage points is associated with a 2.16% increase in the probability of entry. The joint effect of geo-relatedness density and subjective automation seems to be even stronger for Exit, with an increase of 10.2% on exit probability when the joint term increases by 10%.

Table 5. Job entry and exit with geo-relatedness and complementarity density

	Entry=1 (9)	Entry=1 (10)	Exit=1 (11)	Exit=1 (12)
Geo-Relatedness Density	0.0179*** (15.33)	0.0178*** (14.73)	-0.0254*** (-20.53)	-0.0257*** (-20.91)
Objective Automation	0.0506 (0.80)		-0.408*** (-14.99)	
Geo-Relatedness Density # Objective Automation	-0.000422 (-0.22)		0.00850*** (11.13)	
Subjective Automation		0.0601 (0.99)		-0.466*** (-17.32)
Geo-Relatedness Density # Subjective Automation		-0.000299 (-0.17)		0.0102*** (13.87)
Complementarity Density	-0.000364 (-0.87)	-0.000142 (-0.30)	0.00000391 (0.01)	0.000336 (0.84)
Complementarity Density # Objective Automation	0.00194** (2.63)		-0.0000579 (-0.19)	
Complementarity Density # Subjective Automation		0.00216**		-0.000714*

		(2.83)		(-2.32)
Betweenness Centrality	0.0201***	0.0224***	-0.0170**	-0.0221***
	(4.83)	(5.53)	(-3.05)	(-4.10)
GDP per capita/10000	-0.00390	-0.00272	-0.0277***	-0.0261***
	(-0.85)	(-0.61)	(-4.70)	(-4.61)
Fixed Capital Formation	-0.00812***	-0.00737**	-0.00542	-0.00387
	(-3.41)	(-3.11)	(-1.57)	(-1.16)
Participation in Education and Training	0.00153*	0.00127	0.00273**	0.00232**
	(2.25)	(1.89)	(2.97)	(2.62)
Airline Accessibility	-0.0722***	-0.0629***	-0.00348	-0.0436
	(-3.78)	(-3.36)	(-1.39)	(-1.80)
Rail Accessibility	-0.0507*	-0.0497*	-0.0586	-0.0624
	(-1.99)	(-2.01)	(-1.68)	(-1.85)
Road Accessibility	0.108***	0.100***	0.0946**	0.0966**
	(4.27)	(4.08)	(2.74)	(2.88)
High Education	0.0379	0.0163	0.356***	0.414***
	(0.56)	(0.24)	(4.01)	(4.81)
Middle Education	-0.0547	-0.0566	0.0366	0.0608
	(-1.61)	(-1.69)	(0.77)	(1.32)
_cons	-0.410***	-0.400***	1.168***	1.162***
	(-9.25)	(-8.86)	(21.15)	(21.08)
N	9477	9764	6310	6471

*Coefficients are statistically significant at the ´p<0.1, * p<0.05, ** p<0.01, *** p<0.001 level. Standard errors in parentheses.*

4.2.3 Robustness analysis

Testing for the impact of geographical heterogeneity on Entry and Exit

There are many reasons behind the co-location of jobs and one of them is geographical feature. In the above analysis, we find it is problematic if we include geo-relatedness and complementarity density in the same model regardless identifying the confounding variables. Therefore, we introduce the test of geographical heterogeneity to replace geo-relatedness density variable. After we control the geographical heterogeneity in our models, the impact of complementarity density on Entry and Exit is significant again. The other conclusion still holds and only minor effect changes.

Table 6. Job entry and exit with geography heterogeneity

	Entry=1 (13)	Entry=1 (14)	Exit=1 (15)	Exit=1 (16)
Subjective Automation		0.0214		-0.0892***
		(0.69)		(-6.23)
Objective Automation	0.0106		-0.100***	
	(0.35)		(-7.46)	
Complementarity Density	0.00134***	0.00162***	-0.00237***	-0.00193***
	(3.33)	(3.57)	(-5.90)	(-4.88)
Complementarity Density # Objective Automation	0.00186**		0.000582*	
	(2.66)		(2.53)	
Complementarity Density # Subjective Automation		0.00240***		0.0000652
		(3.32)		(0.24)
Geography:				
Western Europe	0.00364	0.00331	0.0317	0.0346
	(0.19)	(0.17)	(1.25)	(1.38)
Southern Europe	-0.00928	-0.0197	0.00842	0.00215
	(-0.37)	(-0.76)	(0.25)	(0.06)
Northern Europe	-0.153***	-0.148***	-0.148***	-0.150***
	(-5.95)	(-5.80)	(-4.49)	(-4.60)
Western Europe # Objective Automation	0.0625**		-0.0114	
	(2.80)		(-1.21)	
Southern Europe # Objective Automation	0.0705*		0.00323	
	(2.33)		(0.28)	
Northern Europe # Objective Automation	-0.0356		-0.00558	
	(-1.32)		(-0.45)	
Western Europe # Subjective Automation		0.0587**		-0.0274**
		(2.60)		(-2.91)
Southern Europe # Subjective Automation		0.0242		-0.00523

		(0.80)		(-0.41)
Northern Europe # Subjective Automation		-0.0413		0.00277
		(-1.52)		(0.24)
Betweenness Centrality	0.0189***	0.0205***	-0.00302	-0.0112*
	(4.45)	(4.96)	(-0.53)	(-2.04)
GDP per capita	-0.00439	-0.00239	-0.00101	-0.00631
	(-0.85)	(-0.75)	(-1.47)	(-0.94)
Fixed Capital Formation	-0.0129***	-0.0118***	-0.0161***	-0.0136***
	(-5.19)	(-4.75)	(-4.38)	(-3.83)
Participation in Education and Training	0.00470***	0.00427***	0.00574***	0.00530***
	(5.66)	(5.24)	(5.19)	(4.95)
Airline Accessibility	-0.0722***	-0.0637**	-0.0571*	-0.0639*
	(-3.52)	(-3.16)	(-2.10)	(-2.44)
Rail Accessibility	-0.0550*	-0.0516*	-0.0320	-0.0332
	(-2.04)	(-1.98)	(-0.87)	(-0.93)
Road Accessibility	0.0656*	0.0580*	0.0091	0.0330
	(2.39)	(2.19)	(0.78)	(0.92)
High Education	0.285***	0.262***	0.242*	0.271*
	(3.59)	(3.31)	(2.11)	(2.43)
Middle Education	-0.0165	-0.0156	-0.00471	0.0187
	(-0.28)	(-0.26)	(-0.05)	(0.22)
_cons	0.0933	0.0981	0.318***	0.299***
	(1.77)	(1.84)	(4.30)	(4.13)
N	9477	9764	6310	6471

*Coefficients are statistically significant at the ´p<0.1, * p<0.05, ** p<0.01, *** p<0.001 level. Standard errors in parentheses.*

5. Discussion and Conclusion

The co-evolution of automation and labour market has taken place for centuries. However, the recent applications of artificial intelligence and machine learning provoke our anxiety towards the changing nature of work. Whereas previously it was mostly low- and medium-skilled occupations that could be automated, the digital revolution brings the bad news as high-skilled occupations will be automated soon. Therefore, the traditionally analytical framework which treats regional job composition in an aggregated manner is outdated. The subtly influence of automation on skills will regenerate the composition of jobs in a region and leads to a different path of development based on regional characteristics. For example, some old manufacturing cities in the U.S. have struggled to reinvent themselves since they have many manual skilled workers who are vulnerable to the arrival of digital transformation (Glaeser and Saiz, 2004).

This paper has taken a novel occupational-network approach to examine the impact of automation on the evolution of occupational structures in regions (Shutter et al., 2016; Farinha et al., 2018). We shift the perspective about regional labour market from passively adapting external shocks to proactively seeking its development trajectories. Regions enter new occupational specialisations that are related to existing ones and exit existing jobs unrelated to existing ones in the face of automation. Following Farinha et al. (2018), we recognise two types of relatedness which mediate the impact of automation on regional job re-composition: geographical relatedness which makes jobs co-locate in the same region and complementary relatedness which makes jobs co-occur in the same industry. Our findings on the two density measures confirm the finds from Shutter et al (2018), where interdependency of workers does benefit the regions by diversifying jobs.

Our main conclusion is that the impact of automation on geographical relatedness is associated with a higher probability of disappearance of an existing occupation specialisation on the one hand, and the impact of automation on complementarity relatedness is associated with a higher probability of entry of a new occupation specialisation. Many previous literatures lay emphasis on the regional occupation heterogeneity as a key determinant of automation adoption. For example, regions with endowments of abstract skills are easily adapted to digitalisation by creating more new jobs (Berger and Frey, 2016). The previous studies also revealed that new technologies are closely related to regional pre-existing capabilities (Kogler et al., 2013; Rigby, 2015). Berger and Frey (2017) found that new industries mostly emerge from regions which specialise in demand for similar skills.

In addition, our regional automation approach also opens the black box of aggregated skill levels in mainstream economic empirical studies (Acemoglu and Autor, 2011). Moreover, we found the effect of subjective automation is stronger than the effect of objective automation.

The intersection of geographical relatedness and automation effect suggests that occupational specialisations benefit from economies of scale and knowledge pooling; the intersection of complementarity relatedness and automation effect suggests that the tendency of interdependent job tasks will brings new job specialisations because the increased labour productivity comes from co-workers or augmented skills from automation. Our contribution to

Farinha's paper is that we try to test the difference kinds of relatedness in an external shock, namely, the risk of automation. The relatedness theory has been criticised by narrowly discussing the interdependency of different regional elements within regions but hardly considering the external forces outside the regions or in a global scale (Zhu et al., 2017). The attempt of this thesis is a start to apply this theoretical approach to a contextual problem.

We find some other interesting results as well. Regions with a high rate of participation in vocational education and training is a double-edged sword to regional occupational specialisation. It can create a 'thick labour market' to generate more knowledge of specialised jobs. In contrast, its high-skill ecosystem might also sort out job classes that are no longer suitable to the local economy. The more air accessibility and rail accessibility, the more negatively related to entry of occupational specialisation. One possible explanation is rooted in the urban system theory. Combes et al. (2005) argue that the decrease in interregional transportation cost will increase the size of the agglomerated regions because of the home market effect. The home market effect pushes small regions more specialised in sectors (in this case it means less entry of new occupation specialisation) meanwhile absorbs new jobs in themselves. The more road accessibility, the more positively related to entry of occupational specialisation. This is in line with the finds from Bocarejoand and Oviedo (2012) that the local scale public transportation can increase the accessibility of information in labour market then indirectly increase the demand for new jobs. A high-speed train line between core-periphery regions often reinforces comparative advantages of core regions and leads to de-industrialisation of lagging regions, inducing a submissive *de facto* position to core regions (Puga, 2002).

Given the limitations of this paper, we could address the following points in further studies. We assume the occupation mobility matrix is a closed system based on probability, in real world, occupations will appear or disappear in this closed system constantly. We regard the content of occupation as static in the face of automation. However, the introduction of computerized machining tools radically changed the content of the "machinist" job from an emphasis on hand-eye coordination and steadiness to an emphasis on engineering and design, all without changing the job's name (Kemp and Clegg, 1987). In a research paper from McCrory et al. (2014), they point out the alternative way that labour racing with the machine. Machines can complement human skills and amplify the ability of humans to do work. Specialising more newly-differentiating skills to compete with machines will be regarded as a successful strategy. However, our limited data could not provide us the dynamic of skill changing. We only look at the full-time employee and exclude the self-employed workers. However, the emerging gig economy is prevalent in the online job market. People would like to take the second part-time job as a supplement to their first job. Therefore, the next step is to expand the analysis to the second and part-time jobs affected by digital development. We could include institutions in this framework as well, because the regional occupational structure change might also be affected by institutional requirements (Boschma and Capone, 2015). The mobility of workers between regional labour markets has been ignored in this study. We suggest that assigning workers to commuting zones in EU regions might reveal some new spatial patterns (Tolbert and Sizer, 1996).

Regional labour market policy should not be like a shopping list but rather a cooking recipe in which the decision makers know the trade-offs and complementarities of job creation. Creating jobs in occupations at high risk of automation merely defers the problem and increases the risk of higher future public expenditure to deploy displaced workers. Policy makers at all levels of government need to target more than just the availability of the numbers of jobs. It is increasingly important to create good quality and types of jobs in a digital era. This involves several dimensions of the working activity: salary, content and location of the workplace. Therefore, the equally important element of job quality and occupational type should be put on the agenda with the amount of job creation.

6. References

Acemoglu, D., & Autor, D. (2011). *Skills, tasks and technologies: Implications for employment and earnings*. *Handbook of Labor Economics* (Vol. 4). Elsevier Inc. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D., & Restrepo, P. (2016). The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment. *NBER Working Papers*, *22252*, 1–30. https://doi.org/10.3386/w22252

Arntz, M., Gregory, T., & Zierahn, U. (2016). The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis. *OECD Social, Employment and Migration Working Papers*, (189). https://doi.org/10.1787/5jlz9h56dvq7-en

Atack, J., Bateman, F., & Margo, R. A. (2008). Steam power, establishment size, and labor productivity growth in nineteenth century American manufacturing. *Explorations in Economic History*. https://doi.org/10.1016/j.eeh.2007.08.002

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US Labor Market. *American Economic Review*. https://doi.org/10.1257/aer.103.5.1553

Autor, D. H., & Handel, M. J. (2013). Putting Tasks to the Test : Human Capital, Job Tasks, and Wages. *Journal of Labor Economics*, *31*(2), 59–96. https://doi.org/10.1086/669332

Bacolod, M., Blum, B. S., & Strange, W. C. (2009). Skills in the city. *Journal of Urban Economics*. https://doi.org/10.1016/j.jue.2008.09.003

Berger, T., Chen, C., & Frey, C. B. (2017). Drivers of Disruption? Estimating the Uber Effect. *Journal of Retailing and Consumer Services*, *2018*(40), 295–298. https://doi.org/S0014292118300849

Berger, T., & Frey, C. B. (2016). Did the Computer Revolution shift the fortunes of U.S. cities? Technology shocks and the geography of new jobs. *Regional Science and Urban Economics*, *57*, 38–45. https://doi.org/10.1016/j.regsciurbeco.2015.11.003

Berger, T., & Frey, C. B. (2017). Industrial renewal in the 21st century: evidence from US cities. *Regional Studies*, *51*(3), 404–413. https://doi.org/10.1080/00343404.2015.1100288

Bessen, J. E. (2015). *How Computer Automation Affects Occupations: Technology, Jobs, and Skills*. *SSRN*. https://doi.org/10.2139/ssrn.2690435

Bocarejo S., J. P., & Oviedo H., D. R. (2012). Transport accessibility and social inequities: a tool for identification of mobility needs and evaluation of transport investments. *Journal* *of Transport Geography*. https://doi.org/10.1016/j.jtrangeo.2011.12.004

Boschma, R., Balland, P. A., & Kogler, D. F. (2015). Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, *24*(1), 223–250. https://doi.org/10.1093/icc/dtu012

Brynjolfsson, E., & Mcafee, A. (1981). Race Against The Machine: How The Digital Revolution Is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and The Economy. *InPharma*. https://doi.org/10.1016/S2213-8587(14)70016-6

Brzeski, C., & Burk, I. (2015). "Die Roboter kommen." Folgen der Automatisierung für den deutschen Arbeitsmarkt. *INGDiBa Economic Research*. https://doi.org/10.1365/s35764-011-0011-z

Cicerone, G., McCann, P., & Venhorst, V. (2017). *Promoting Regional Growth and Innovation: Relatedness, Revealed Comparative Advantage and the Product Space*. Retrieved from http://econ.geog.uu.nl/peeg/peeg.html

Coniglio, N. D., Vurchio, D., Cantore, N., & Clara, M. (2018). On the Evolution of Comparative Advantage: Path-Dependent Versus Path-Defying Changes. *SSRN Electronic Journal*, *3*(1), 1–35. https://doi.org/10.2139/ssrn.3136471

Dijk, J. Van, & Edzes, A. (2016). Towards inclusive and resilient regional labour markets : challenges for research and policy, *36*, 169–190.

Duranton, G., & Puga, D. (2014). The Growth of Cities. In *Handbook of Economic Growth*. https://doi.org/10.1016/B978-0-444-53540-5.00005-7

European Commission. (2014). Digital Inclusion and Skills. *Digital Agenda Scoreboard*. https://doi.org/10.3906/bot-1707-19

Fernandes, T. F., Balland, P.-A., Morrison, A., & Boschma, R. (2018). What Drives the Geography of Jobs in the US ? Unpacking Relatedness.

Frank, M. R., Sun, L., Cebrian, M., Youn, H., & Rahwan, I. (2018). Small cities face greater impact from automation. *Journal of the Royal Society Interface*, *15*(139). https://doi.org/10.1098/rsif.2017.0946

Frey, C., & Osborne, M. (2013). The future of employment: how susceptible are jobs to computerisation? *Sept*, 1–72. https://doi.org/10.1016/j.techfore.2016.08.019

Frost, M. E., & Spence, N. A. (2006). The Rediscovery of Accessibility and Economic Potential: The Critical Issue of Self-Potential. *Environment and Planning A: Economy and Space*. https://doi.org/10.1068/a271833

Garretsen, H., McCann, P., Martin, R., & Tyler, P. (2013). The future of regional policy. *Cambridge Journal of Regions, Economy and Society*, *6*(2), 179–186. https://doi.org/10.1093/cjres/rst013

Geurs, K. T., & van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: Review and research directions. *Journal of Transport Geography*. https://doi.org/10.1016/j.jtrangeo.2003.10.005

Glaeser, E. L., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2004). Do institutions cause growth? *Journal of Economic Growth*, *9*(3), 271–303. https://doi.org/10.1023/B:JOEG.0000038933.16398.ed

Glaeser, E. L., & Maré, D. C. (2002). Cities and Skills. *Journal of Labor Economics*.

https://doi.org/10.1086/319563

Goos, M. (2018). The impact of technological progress on labour markets: Policy challenges. *Oxford Review of Economic Policy*, *34*(3), 362–375. https://doi.org/10.1093/oxrep/gry002

Goos, M., & Manning, A. (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *The Review of Economics and Statistics*, *89*(1), 118–133. https://doi.org/10.1162/rest.89.1.118

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*. https://doi.org/10.1257/aer.104.8.2509

Gordon, R. J. (2012). Is US growth over? Faltering innovation faces six headwinds. *CEPR Policy Insight*.

Guerrero, O. A., & Axtell, R. L. (2013). Employment Growth through Labor Flow Networks. *PLoS ONE*. https://doi.org/10.1371/journal.pone.0060808

Heyman, F. (2016). Job polarization, job tasks and the role of firms. *Economics Letters*, *145*(1123), 246–251. https://doi.org/10.1016/j.econlet.2016.06.032

Hidalgo, C. A., Balland, P., Boschma, R., Delgado, M., Feldman, M., Frenken, K., … Delgado, M. (2018). *The Principle of Relatedness* (18 No. 30).

James, J. A., & Skinner, J. S. (1985). The Resolution of the Labor-Scarcity Paradox. *The Journal of Economic History*. https://doi.org/10.1109/ICOIN.2018.8343097

Katz, L. F., & Goldin, C. (1996). *The Origins of Technology-Skill Complementarity*. *SSRN*. https://doi.org/10.2139/ssrn.1537

McCann, P., & Ortega-Argilés, R. (2016). Smart specialisation: Insights from the EU experience and implications for other economies. *Investigaciones Regionales*, *2016*(36Speciali), 279–293.

Mellander, C., & Florida, R. (2012). The Rise of Skills: Human Capital, the Creative Class and Regional Development, (266), 1–26. https://doi.org/10.1007/978-3-642-23430-9

Nedelkoska, L., & Quintini, G. (2018). Automation, skills use and training. *OECD Social, Employment, and Migration Working Papers*. https://doi.org/http://dx.doi.org/10.1787/2e2f4eea-en

Neffke, F. (2017). *Coworker Complementarity*. *SSRN*. https://doi.org/10.2139/ssrn.2929339

Neffke, F., & Henning, M. (2014). SKILL RELATEDNESS AND FIRM DIVERSIFICATION, *316*(August 2012), 297–316. https://doi.org/10.1002/smj

Neffke, F., Henning, M. S., & Boschma, R. A. (2011). How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions. *Economic Geography*, *87*(3), 237–265. https://doi.org/10.1111/j.1944-8287.2011.01121.x

Nordhaus, W. D. (2007). Two centuries of productivity growth in computing. *Journal of Economic History*. https://doi.org/10.1017/S0022050707000058

OECD. (2018). Job Creation and Local Economic Development. Preparing for the Future of Work. https://doi.org/10.1787/9789264305342-en

Oesch, D. (2014). Occupational Change in Europe: How Technology and Education Transform the Job Structure. https://doi.org/10.1093/acprof

Oesch, D., & Menés, J. R. (2011). Upgrading or polarization? Occupational change in Britain, Germany, Spain and Switzerland, 1990-2008. *Socio-Economic Review*, *9*(3), 503–531.

https://doi.org/10.1093/ser/mwq029

Pajarinen, M., & Rouvinen, P. (2014). Computerization threatens one third of Finnish employment. *ETLA Brief*, *22*, 1–13. Retrieved from http://www.etla.fi/wp-content/uploads/ETLA-Muistio-Brief-22.pdf

Polanyi, K. (1984). The Great Transformation, 161–184. https://doi.org/10.2307/2144137

Puga, D. (2002) European regional policy in light of recent location theories. *Journal of Economic Geography* , 2: 373–406.

Rigby, D. L. (2015). Technological Relatedness and Knowledge Space: Entry and Exit of US Cities from Patent Classes. *Regional Studies*, *49*(11), 1922–1937. https://doi.org/10.1080/00343404.2013.854878

Roscoe, A. H., & Ellis, A. H. (1990). *A subjective rating scale for assessing pilot workload in flight: A decade of practical use*. *Royal Aerospace Establishment*.

Schumpeter, J. A. (1939). Business Cycles, Vol. 1. *Cambridge University Press*, Cambridge.

Schumpeter, J. A. (1947).The Creative Response in Economic History. *The Journal of Economic History*. https://doi.org/10.1017/S0022050700054279

Spitz-Oener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure. *Journal of Labor Economics*, *24*(2), 235–270. https://doi.org/10.1086/499972

Tolbert, C. M., & Sizer, M. (1996). US Commuting Zones and Labor Market Areas: A 1990 Update. *Economic Research Service Staff Paper* No. 9614. Washington, DC.

Wierwille, W. W., & Casali, J. G. (1983). A validated rating scale for global mental workload measurement applications. *Proceedings of the Human Factors Society*. https://doi.org/10.1177/154193128302700203

World Economic Forum. (2018). *The Future of Jobs Report*. *World Economic Forum* (Vol. 5). https://doi.org/10.1177/1946756712473437

Zhu, S., He, C., & Zhou, Y. (2017). How to jump further and catch up? Path-breaking in an uneven industry space. *Journal of Economic Geography*, 17(3), 521-545.

7. Appendix

Table 1. list of NUTS2 regions

NUTS2	Name
AT11	Burgenland
AT12	Niederösterreich
AT13	Wien
AT21	Kärnten
AT22	Steiermark
AT31	Oberösterreich
AT32	Salzburg
AT33	Tirol
AT34	Vorarlberg
BE10	Région de Bruxelles-Capitale / Brussels Hoofdstedelijk Gewest
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
CH01	Lake Geneva Region
CH02	Mittelland
CH03	Northwestern Switzerland
CH04	Zurich
CH05	Eastern Switzerland
CH06	Central Switzerland
CH07	Ticino
CY00	Κύπρος (Kypros)
CZ01	Praha
CZ02	Střední Čechy
CZ03	Jihozápad
CZ04	Severozápad
CZ05	Severovýchod
CZ06	Jihovýchod
CZ07	Střední Morava
CZ08	Moravskoslezsko
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
DK01	Hovedstaden
DK02	Sjælland
DK03	Syddanmark
DK04	Midtjylland
DK05	Nordjylland

EE00	Eesti
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	Comunidad Valenciana
ES53	Illes Balears
ES61	Andalucía
ES62	Región de Murcia
ES63	Ciudad Autónoma de Ceuta
ES70	Canarias
FI19	Länsi-Suomi
FI1B	Helsinki-Uusimaa
FI1C	Etelä-Suomi
FI1D	Pohjois- ja Itä-Suomi
FI20	Åland
FR10	Île de France
FR21	Champagne-Ardenne
FR22	Picardie
FR23	Haute-Normandie
FR24	Centre
FR25	Basse-Normandie
FR26	Bourgogne
FR30	Nord - Pas-de-Calais
FR41	Lorraine
FR42	Alsace
FR43	Franche-Comté
FR51	Pays de la Loire
FR52	Bretagne
FR53	Poitou-Charentes
FR61	Aquitaine
FR62	Midi-Pyrénées
FR63	Limousin
FR71	Rhône-Alpes
FR72	Auvergne
FR81	Languedoc-Roussillon

FR82	Provence-Alpes-Côte d'Azur
FR83	Corse
GR30	Anatoliki Makedonia, Thraki
GR41	Kentriki Makedonia
GR42	Dytiki Makedonia
GR43	Thessalia
GR51	Ipeiros
GR52	Ionia Nisia
GR53	Dytiki Ellada
GR54	Sterea Ellada
GR61	Peloponnisos
GR62	Attiki
GR63	Voreio Aigaio
GR64	Notio Aigaio
GR65	Kriti
HR03	Jadranska Hrvatska
HR04	Kontinentalna Hrvatska
HU10	Közép-Magyarország
HU21	Közép-Dunántúl
HU22	Nyugat-Dunántúl
HU23	Dél-Dunántúl
HU31	Észak-Magyarország
HU32	Észak-Alföld
HU33	Dél-Alföld
IE01	Border, Midland and Western
IE02	Southern and Eastern
IS00	Iceland
ITC1	Piemonte
ITC2	Valle d'Aosta/Vallée d'Aoste
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/Bozen
ITH2	Provincia Autonoma di Trento
ITH3	Veneto
ITH4	Friuli-Venezia Giulia

ITH5	Emilia-Romagna
ITI1	Toscana
ITI2	Umbria
ITI3	Marche
ITI4	Lazio
LT00	Lietuva
LU00	Luxembourg
LV00	Latvija
NL00	NEDERLAND
NO01	Oslo og Akershus
NO02	Hedmark og Oppland
NO03	Sør-Østlandet
NO04	Agder og Rogaland
NO05	Vestlandet
NO06	Trøndelag
NO07	Nord-Norge
PT11	Norte
PT15	Algarve
PT16	Centro (PT)
PT17	Área Metropolitana de Lisboa
PT18	Alentejo
PT20	Região Autónoma dos Açores
PT30	Região Autónoma da Madeira
RO11	Nord-Vest
RO12	Centru
RO21	Nord-Est
RO22	Sud-Est
RO31	Sud - Muntenia
RO32	Bucureşti - Ilfov
RO41	Sud-Vest Oltenia
RO42	Vest
SE11	Stockholm
SE12	Östra Mellansverige
SE21	Småland med öarna
SE22	Sydsverige
SE23	Västsverige
SE31	Norra Mellansverige
SE32	Mellersta Norrland
SE33	Övre Norrland
SK01	Bratislavský kraj
SK02	Západné Slovensko
SK03	Stredné Slovensko
SK04	Východné Slovensko
UKC0	North East England
UKD0	North West England
UKE0	Yorkshire and The Humber
UKF0	East Midlands
UKG0	West Midlands
UKH0	East of England
UKI0	Greater London
UKJ0	South East England
UKK0	South West England
UKL0	Wales
UKM0	Scotland
UKN0	Northern Ireland

Table 2. list of occupations

ISCO-08	Name
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 service 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 specialised secretaries
335	Regulatory government 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 technicians
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 service workers
952	Street vendors (excluding food)
961	Refuse workers
962	Other elementary workers

Table 3. list of industry

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 RECREATION
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

Table 4. Top 20 NUTS2 regions in the four classifications

Job entry in less risky occupations	Job entry in riskier occupations	Job exit in less risky occupations	Job exit in riskier occupations
Corse (FR)	Bourgogne (FR)	Attiki (GR)	Área Metropolitana de Lisboa (PT)
Voreio Aigaio (GR)	Peloponnisos (GR)	Notio Aigaio (GR)	Basilicata (IT)
Åland (FI)	Lorraine (FR)	Kärnten (AT)	Kärnten (AT)
Alsace (FR)	Attiki (GR)	Dél-Dunántúl (HU)	Niederösterreich (AT)
Limousin (FR)	Åland (FI)	Niederösterreich (AT)	Prov. Limburg (BE)
North East England (UK)	Limousin (FR)	Alsace (FR)	Länsi-Suomi (FI)
Principado de Asturias (ES)	Languedoc-Roussillon (FR)	Nord - Pas-de-Calais (FR)	Alsace (FR)
Languedoc-Roussillon (FR)	Haute-Normandie (FR)	Aragón (ES)	Principado de Asturias (ES)
Luxembourg (LU)	Calabria (IT)	Haute-Normandie (FR)	Östra Mellansverige (SE)
Trøndelag (NO)	Provincia Autonoma di Trento (IT)	Auvergne (FR)	Karlsruhe (DE)

Tirol (AT)	North East England (UK)	Prov. Oost-Vlaanderen (BE)	Prov. Brabant Wallon (BE)
Prov. Namur (BE)	Auvergne (FR)	País Vasco (ES)	Stredné Slovensko (SK)
Leipzig (DE)	Ipeiros (GR)	Corse (FR)	Cantabria (ES)
Aragón (ES)	Notio Aigaio (GR)	Prov. Brabant Wallon (BE)	Ticino (CH)
Illes Balears (ES)	Ionia Nisia (GR)	Rhône-Alpes (FR)	Comunidad Valenciana (ES)
Centre (FR)	Sjælland (DK)	Castilla-La Mancha (ES)	Champagne-Ardenne (FR)
Bourgogne (FR)	Molise (IT)	Bucureşti - Ilfov (RO)	Eastern Switzerland (CH)
Auvergne (FR)	Kriti (GR)	Prov. Limburg (BE)	Pays de la Loire (FR)
Észak-Magyarország (HU)	Sardegna (IT)	Rheinhessen-Pfalz (DE)	Aragón (ES)
Northern Ireland (UK)	Mellersta Norrland (SE)	Kontinentalna Hrvatska (HR)	Languedoc-Roussillon (FR)

Source: Author calculated.

Table 5. Intersection of air accessiblity with geo-density

	(1) Exit=1	(2) Entry=1
Geo Density	-0.0167***	0.00629**
	(-6.31)	(3.06)
Air Accessibility	0.00211	-0.00448***
	(1.96)	(-6.03)
Geo Density # Air Accessibility	-0.0000561*	0.000123***
	(-2.12)	(5.81)
Automation	-0.314***	0.195***
	(-5.60)	(4.28)
Geo Density2014 # Automation	0.00577***	-0.00186
	(4.20)	(-1.46)
Participation rate	0.00124	0.00843*
	(0.26)	(2.42)
Geo Density # Participation rate	0.00000281	-0.000290**
	(0.02)	(-2.98)
_cons	0.889***	0.0268
	(8.26)	(0.36)
N	7542	11041

t statistics in parentheses

="* p<0.05 ** p<0.01 *** p<0.001"

Table 6. Example of geographical relatedness matrix

	111	112	121	122	131	132	133	134	141	142
111	0	0.854372	1.035044	1.282691	1.16308	1.065997	1.363955	1.037092	0.820133	1.134822
112	0.854372	0	1.135181	1.302282	0.561266	0.62891	1.28221	0.818946	0.908946	0.529964
121	1.035044	1.135181	0	1.871786	1.21362	1.998539	2.118783	1.537798	1.564567	1.749059
122	1.282691	1.302282	1.871786	0	0.678493	1.736916	2.591628	1.769611	1.435297	1.281306
131	1.16308	0.561266	1.21362	0.678493	0	1.701334	0.937923	1.152017	1.438451	1.829875
132	1.065997	0.62891	1.998539	1.736916	1.701334	0	2.052175	2.002488	2.045766	2.120513
133	1.363955	1.28221	2.118783	2.591628	0.937923	2.052175	0	1.543978	1.847541	1.294359
134	1.037092	0.818946	1.537798	1.769611	1.152017	2.002488	1.543978	0	1.710173	1.858271
141	0.820133	0.908946	1.564567	1.435297	1.438451	2.045766	1.847541	1.710173	0	1.961884
142	1.134822	0.529964	1.749059	1.281306	1.829875	2.120513	1.294359	1.858271	1.961884	0

Table 7. Example of complementarity relatedness matrix

	111	112	121	122	131	132	133	134	141	142
111	0	0.579461	1.256084	0.877068	0	0	0	1.525156	0	0
112	0.579461	0	1.431756	1.332947	0	0.754065	1.642068	0.579461	0	2.422356
121	1.256084	1.431756	0	1.083522	0	0.408641	1.779739	1.256084	0	0
122	0.877068	1.332947	1.083522	0	0	0.570668	2.485436	0	0	3.66651
131	0	0	0	0	0	0	0	0	0	0
132	0	0.754065	0.408641	0.570668	0	0	0	0	0	0
133	0	1.642068	1.779739	2.485436	0	0	0	0	0	0
134	1.525156	0.579461	1.256084	0	0	0	0	0	0	0
141	0	0	0	0	0	0	0	0	0	0
142	0	2.422356	0	3.66651	0	0	0	0	0	0