The relation between Urbanization and Job Polarization in the European Labour Market between 1998 and 2018

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Abstract

This paper examines the relation between urbanization and job polarization between 1998 and 2018, considering nine European countries. Job polarization is characterized by a decrease in the share of middle-skill occupations with a simultaneous increase in the share of low- and high-skill occupations over time. The general consensus in literature is that job polarization has been an ongoing process in Europe during the last couple of decades. However, research on job polarization on different levels of urbanization is limited. In this research data of the European Union Labour Force Survey, supplemented with data from Eurostat, was used to I) explore potential job polarization patterns in cities, towns and suburbs and rural areas for a selection of nine European countries, and to II) analyse whether these differences could be significantly explained by urbanization on a regional level, accounting for several alternative explanatory aspects such as technology and sectoral composition.

The exploration of occupational changes in the nine European countries showed distinct patterns of job polarization for all levels of urbanization. Cities and towns and suburbs polarization patterns demonstrated a strong resemblance, experiencing a larger decrease in middle-skill occupations and a larger increase in high-skill occupations compared to rural areas. The addition of alternative explanatory variables to test the significance of urbanization in explaining these occupational changes for different occupational skill levels on a regional scale generated mixed results. Urbanization was roughly able to explain the changes in the low- and middle-skill occupations, but had no clear relation with high-skill occupational changes. The results also revealed that rural regions tend to experience a replacement bias of the middle-skill occupations toward low-skill occupations.

Future research could aim to include a greater number of countries as a means to enhance the generalizability to Europe as a whole, to see whether a different approach would result in a clear relation between urbanization and high-skill occupational change, and to improve knowledge of the relation between urbanization and job polarization in general.

Key words: Job Polarization, Urbanization, Routine Biased Technological Change

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1 - Introduction

1.1 - Background & Research questions

Job polarization has been an ongoing phenomenon in the more developed economies for a while now. As the global economy develops, the occupational structure is ever-changing. Job polarization is characterized by a particular shift in this occupational structure, namely the decrease in middle-skilled jobs with a simultaneous increase in (predominantly) high-skilled and low-skilled jobs, which is the result of several mechanisms. Routine-biased technological change could be highlighted as one of the main drivers, which favours the low- and high-end occupations more so than middle-skilled occupations. The former being better complemented by mechanisation and technological innovations, resulting in a labour replacement bias of routine middle-skilled labour (Autor, 2019; Goos et al., 2014).

The occurrence and effects of job polarization have been researched and described by several scholars and on different scales. Research on this topic is predominantly conducted on a national scale (e.g., US - Autor 2019, United Kingdom - Goos and Manning 2007, France - Davis et al. 2020). Alternatively, sub-national and 'European' approaches have also been considered, looking at cities and local labour markets, as well as selections of European countries. Goos et al. (2009) have researched whether job polarization can be observed in Europe, using data from 1993 until 2006, considering 16 European countries. Their results showed that, similarly to the US and the United Kingdom, Europe has been experiencing job polarization since the 1990s (Goos et al., 2009). In the assessment of job polarization, research take different contextual factors and mechanisms that are expected to have an effect on occupational changes into consideration. Urbanization, education, offshorability and routine task intensity are examples of such aspects.

Even though urbanization is a variable that has been considered, rural and urban differentiations, or the rural as a research subject, are still lacking in the literature on job polarization. This might be because high-skilled and -paid jobs tend to be limitedly available in rural areas, which in turn limits the occurrence of the standard polarizing effects observed when considering countries or cities. Yet the rural is becoming increasingly connected through ICT infrastructure, facilitating potential (high-skill) growth and development (Oju & Onyebuka, 2016). Furthermore, the European Union also has an ongoing European Regional Development Fund, which aims to reduce economic disparities and improve connectivity of underdeveloped regions (European Commission, 2022; Camagni & Capello, 2017). This further highlights the potential for rural areas to accommodate high-skill occupations. Dauth (2014) and Davis et al. (2020) both concluded, in a German and French context respectively, that job-polarization is predominantly an urban phenomenon. Researching the relation between urbanization and occupational change, and its generalizability to Europe as a whole, can provide insights into whether the ongoing decline in middle-skill occupations is just as strong in rural areas. This in turn could give direction to initiatives, such as the European Regional Development Fund, to warrant occupational and economic stability for rural regions.

Analysing potential differences in job polarization between rural and urban areas could prove to be a valuable addition to the body of literature on job polarization. This will be done by considering changes in the occupational structure between 1998 and 2018, evaluating the pervasiveness of job polarization in Europe in relation to various levels of urbanization. Furthermore, through knowledge on whether job polarization is experienced differently for various levels of urbanization, policy makers will be able to more effectively compensate for- and enact upon the observed trends.

The following two research questions are introduced to give an answer to these aspects, and to guide the thesis and analysis. The first research question aims to gain insights into the recent (polarized) occupational changes in the European labour force as a whole. The second sub-question addresses the nature of the potential relation between various levels of urbanization and these occupational changes over time.

I) *How has the European occupational structure changed between 1998 and 2018, and are these changes consistent with job polarization patterns?*

II) *To what extent does urbanization affect the changes in the European occupational structure between 1998 and 2018 considering all occupations, as well as for low-, medium- and high-skill occupations in isolation.*

1.2 - Thesis Structure

The structure of the research is as follows. First, the theoretical framework will provide the background information and context of job polarization. Here, the underlying mechanisms of job polarization will be discussed, which will be complemented by an overview of relevant literature on job polarization in practice. The theoretical framework will conclude with the conceptual model and hypotheses, focussing on urbanization and its relation to changes in different occupational skill levels. Second, the methodology will describe the data that has been used in the analysis, including the operationalization of the variables, as well as the country selection. Additionally, the methodology will discuss the analysis and statistics that will be carried out. The results and analysis will be presented third, which will explore and discuss potential job polarization in nine EU countries in relation to urbanization. This will be followed by the conclusion, in which the primary findings will be presented and future research topics will be proposed.

2 - Theoretical framework

2.1 - Background

Having a grasp on the specifics and details of one's occupational structure as a (regional) government or organisation has been considered valuable knowledge. Relevant from a city- to a continental scale, comprehension of its occupational structure can function as a proxy for many economic dimensions, such as economic growth and income inequality (Hauser & Warren, 1997). An occupational structure describes a population on the basis of their occupational status. Occupational status includes information on the specific occupation a person performs, which reflects social standing in a societal and cultural context. Additionally, demographic information such as age, gender, income and education are frequently collected and linked to these occupational characteristics. Combined, this information can provide a comprehensive overview and estimate of economic activity in that region. Furthermore, this intelligence can play a key role in tailormade (economic) development and policies. Examples of such as investments are investing in high-skill occupations to retain high-educated youth to stay regionally competitive, or to provide reschooling and guidance to people who are (previously) employed in occupations that are currently losing relevance and are expected to partially disappear.

A 'snapshot' of a particular occupational structure at any given point in time is valuable on its own. This knowledge could for example be utilized in regional comparisons, as well as for the assessment of comparative advantages and potential weaknesses -of and dependencies -on certain sectors in a region. For example, a region that has a large occupational share in tourism is likely able to attract tourists to their region due to their investments in utilities aimed to tailor the needs of tourists. At the same time, this region also becomes dependent on the tourism sector, which makes the region vulnerable to external factors such as climate, (national) policies or potential pandemics as these aspects could drastically alter the number of tourists visiting this region.

Nevertheless, without taking the changes in occupational structure over time that have resulted in a particular situation into account, one lacks context and nuance to describe the (stability) of that occupational structure, let alone predict future changes. But when one *does* consider the changes in occupational structure over time, one is able to do these very things. For example, in a region at a point in time, certain (type of skill- and paying-) occupations are disproportionately underrepresented. As a response to this 'data', policymakers might be eager to make investments or enforce policies in order to increase labour in these occupations. Yet analysis of the same scenario, but this time also taking occupational structure data of the prior 10 years into account, could very well show that these occupations are already at a healthy upward trend (or are diminishing at an alarming rate for that matter). Consequently, the prior strategy to affect the underrepresented occupations might be reconsidered, amplifying the importance of the consideration of occupational changes over time.

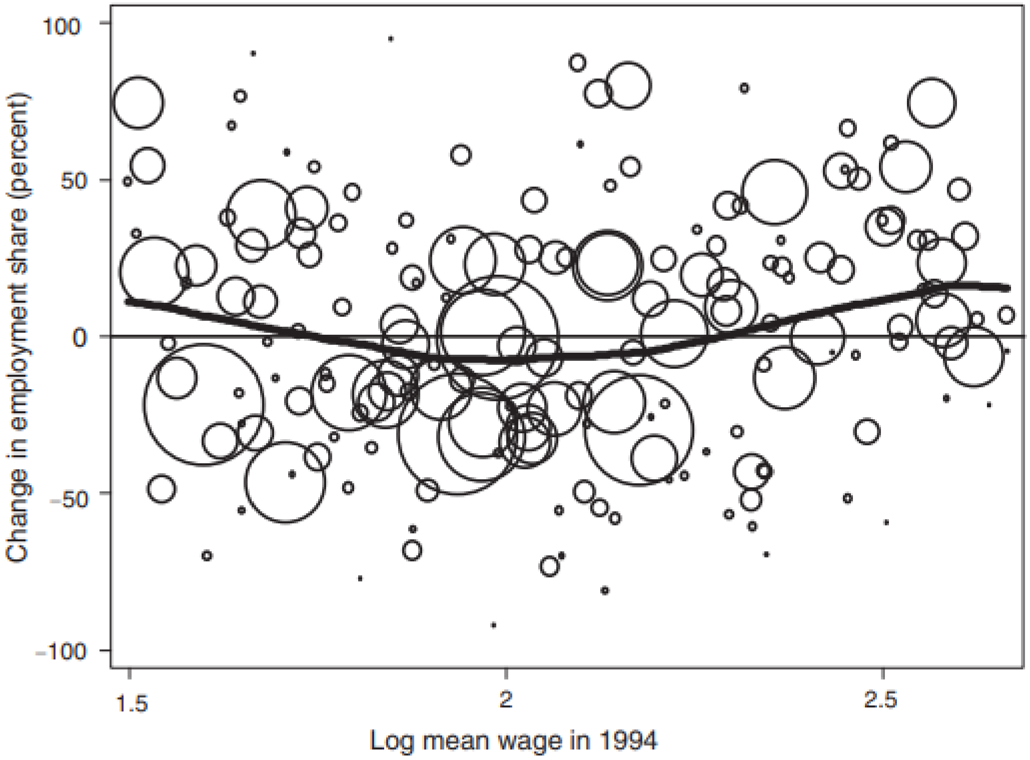
Job polarization

Occupational structures are ever-changing, adapting to the needs of society. Particularly evident in studies of western economies, these labour market changes tend to follow a particular pattern, for which Goos and Manning (2007) have introduced the now commonly used term Job Polarization. Job polarization is characterized by a decrease in middle-skill jobs, paired with an increase in the high- and low-skilled jobs over time. Figure 1 shows an example of such pattern, showing occupational changes of 16 European countries between 1993 and 2016 (Goos et al., 2009). Here, a clear upward trend in the low- and high-wage occupations, and a downward trend in the middle-wage occupations can be observed. To review this phenomenon, a method to differentiate between the level of skill that a job requires is needed. This occupational categorization of the low-middle-high skilled jobs is frequently based on wage, where the considered occupations are ranked by wage, and then grouped in the three respective skill-categories accordingly (as can be observed in Goos et al. (2014)). This results in the characterization of low-skill occupational categories as service and manual oriented occupations, such as health, personal cleaning and security, operators and laborers. The middle-skilled occupations are sales, production and administrative oriented, whereas the high-skilled end tends to include technical, professional and managerial occupations (Autor, 2019; Mishel et al., 2013).

Within the job polarization literature, papers tend to focus on different aspects, which can be reduced to either the fundamentals of job polarization (i.e. what are the changes in occupational structure and why), or focussing on the consequences and implications of the job polarization (i.e. socio-economic inequalities and discrepancies).

In this research, the main purpose will be addressing the current occupational changes in European regions, with an additional focus on the influence of urbanization on these changes. The why-aspect of job polarization, the main mechanisms as for why job polarization occurs, will not be researched in this paper. Nevertheless, knowledge of these underlying mechanisms as for why shifts in occupational structures occur, and in extension potential polarization of the labour market, can provide context to patterns of occupational change discussed in the analysis.

Figure 1 – Percentage changes in employment shares between 1993 and 2016 in 16 EU countries, for jobs ranked by their 1994 log wage.



Source – Goos et al. (2009)

2.2 - Determining factors of job polarization

Remarkably, research on this topic put forward several different underlying mechanisms that would help explain why job polarization occurs. These reasonings are not necessarily mutually exclusive, as they each have their own distinctive characteristics in explaining the phenomena. In the following paragraphs, an overview of two prominent mechanisms in explaining changes in occupational structure will be outlined and discussed.

Skill-biased technological change

Skill-biased technological change (SBTC) is one of these relevant aspects in explaining and researching job polarization. SBTC describes the ongoing increasing demand for skilled workers, especially prominent in cities, because of technological advancements. These technological developments are associated with computer related technologies, resulting in a shift toward analytical and interactive activities (Spitz, 2004). High-skilled and -educated workers are more likely to use computers at their jobs and are therefore better and more experienced in doing so (Card & DiNardo, 2002). Additionally, the supply of high-skilled workers has increased rapidly in recent decades. This has further accelerated the development of high-skill complementary technologies (Acemoglu, 2000). Due to technological change, progressively more jobs and tasks become (high-) skill-oriented, thereby increasing its demand. Furthermore, individuals who are 'skilled' (e.g., better educated or more experienced) have a (productivity) premium over the ones that do not fall in this skilled category (Giannone, 2017). In short, SBTC is expected to increase the demand for 'skilled' occupations relative to 'unskilled' occupations (Goos & Manning, 2007).

SBTC appears to only explain the shift from the middle-skilled jobs and workers to the high-end jobs, whereas job polarization also entails the change from the middle- to low-skilled jobs (Goos et al, 2009; Goos & Manning, 2007). Even though SBTC provides a limited explanation of job polarization, it contributes to the skill-upgrading mechanisms experienced in job polarization.

Routine-biased technological change

Routine-biased technological change (RBTC) considers advancements in technology, design and costs wise, that substitute routine tasks. These routine tasks tend to be a part of cognitive and manual middle-skill occupations, such as clerical work, bookkeeping, and machine operators (Acemoglu & Autor, 2011; Mishel at al., 2013). The main characteristics of these occupations are the well-defined and precise procedures that are carried out. These tasks are increasingly getting codified in software and carried out by machines, which result in replacement of workers in these occupations. Furthermore, these advancements also enable the offshoring of the information-based routine tasks to foreign countries (Acemoglu & Autor, 2011). At the same time, the technological advancements and computerization are poor substitutes for non-routine -cognitive and -manual tasks, which tend to be tasks in low- and high-skill occupations.

RBTC appears to be a better fit in explaining job polarization in the sense that middle-skilled occupations and workers both shift towards the lower and higher end jobs, rather than a general shift from unskilled to skilled occupations observed with SBTC. Additionally, skill upgrading associated to SBTC is predominantly linked to within-industry changes, whereas RBTC also facilitates between-industry shifts (Goos et al., 2014). RBTC (also mentioned as routinization) entails that due to the continuous technological change, increasingly more jobs will become available in the high end, and to some extent the lower end of the spectrum. This is because these technological advancements, such as automation and computerization, are complementary to the high-skill interactive abstract tasks (Autor et al., 2006; Dauth, 2014). Simultaneously the routine tasks, which are often situated in the middle-skill occupations, tend to get substituted, or at the very least don't benefit as much as the low- and high-skilled jobs. Low-skill non-routine labour is also able to benefit from the technological advancement due to the, albeit less so than the high-skilled jobs, complementarity. Dauth (2014) also states that the growth of jobs and occupations due to automation and computerization are paired with an increase in demand for services, which tend to be present in low-skilled low-paid jobs. Additionally, Dauth (2014) concludes that the benefits from RBTC for the high-skilled jobs tend to cluster in city and urban like areas, which will be further reviewed in following sections. RBTC thus is better able to account for the patterns seen in job polarization.

2.3 - Job Polarization in practice

The general consensus in literature is that job polarization has been an ongoing process during the last couple of decades. Furthermore, through analysing changes in occupational structures over time at sub-national levels such as labour markets and cities, one can more precisely identify characteristics resulting in, or being the result of, job polarization. The United States has been a country in which labour market polarization and its implications has been regularly investigated and discussed on a national scale, studying different aspects of job polarization. Autor & Dorn (2013) for example have focused particularly on the growth of service-oriented low-skill jobs. They find that labour markets that focus or specialize in routine tasks and jobs tend to be prone to experiencing employment and wage polarization. This is because, partly due to computerization, routine tasks are increasingly being substituted, consequently resulting in the reallocation of low-skill workers who were previously employed in those routine tasks towards low-skill service jobs. Autor also contributed towards research on the consequences and implications of job polarization in the context of the United States. Autor (2019) in his paper takes a closer look at how different educational groups in the United States, more specifically non-college versus college-educated, experience occupational polarization differently. Data over roughly four decades, from 1970 to 2016, suggests that the shift of job structure has resulted in a somewhat evenly relocation of middle-skill occupations towards high- and low-skill jobs for college graduates, whereas this is not the case for non-college workers. Non-college workers (those with high school or lower education) saw a very different effect over the same period: non-college employment in middle-skill jobs decreased by 14 percent point, from 43 percent, their employment in high-skill jobs increased with 1.4 percent point to 16.4 percent, while employment in low-skill occupations among non-college workers grew with 12.3 percent point towards a share of 54.3 percent (Autor, 2019). Thus, non-college workers have disproportionately reallocated towards low-skill jobs in the United States.

Job Polarization has also been discussed in a European context. Here, studies have considered both a collection of European countries, as well as focussing on individual countries' labour markets and cities. Goos et al. (2014) found convincing evidence that within the timeframe they considered (1993 to 2010), Western European countries have experienced occupational polarization. They concluded that technological change is biased towards replacing middle-skill routine jobs, bringing about growth in high-paid high-skill and low-paid low-skill employment and occupations. The study of Goos et al. (2014) can be considered more general, whereas Micheals et al. (2014), for example, take a more specific approach within the European context. They researched the potential polarizing effect of ICT, rather than technology in general, in Japan, the US and nine European countries. Micheals et al. (2014) find that ICT's complementarity of non-routine cognitive tasks, and a simultaneous substitutability of routine tasks, result in a shift from the middle-skill and -wage occupations towards the higher end. ICT appears to have little effect on changes of non-routine manual occupation and wage structures. Based on these findings, they conclude that industries with the fast growth in ICT tend to experience a strong decrease in demand for the intermediate educated and middle-skilled, with a simultaneous strong demand for highly educated high skilled workers, related to SBTC skill-upgrading (Micheals et al., 2014).

Overall, research on job polarization in a western context shows convincing patterns of occupational growth in low- and high skill occupations, with a simultaneously decrease in middle-skill occupations. These polarization effects and its underlying mechanisms appear to affect workers with different levels of education differently. Autor (2019) concludes us that in the US, non-college workers priorly occupying middle-skill jobs are more likely to substitute towards low-skilled occupations due to job polarization than their college-educated counterparts. Considering western European countries, Goos et al. (2014) found that the decrease in middle-skill occupations is strongly related to RBTC, which complements abstract and interactive tasks in high-skill occupations and service tasks in low-skill occupations and tend to replace routine tasks in middle-skill occupations. Next to the exploration of job polarization in Europe as a whole, it is worthwhile to explore the effects of urbanization of job polarization

Urbanisation

On a smaller scale, job polarization has also been considered and studied within individual European countries. For example, Dauth (2014) has researched the extent in which local labour markets (LLM) of Western Germany have been experiencing job polarization between 1980 and 2010. Of the considered 204 functional labour markets, 144 shown to be significantly polarized. Upon further examination, Dauth identified that job polarization appears to be a predominantly urban phenomenon. His results reveal that a major city (100.000+) is located in 67% (96) of the polarized LLM, whereas this is only the case for 17% (10) of the not polarized LLM.

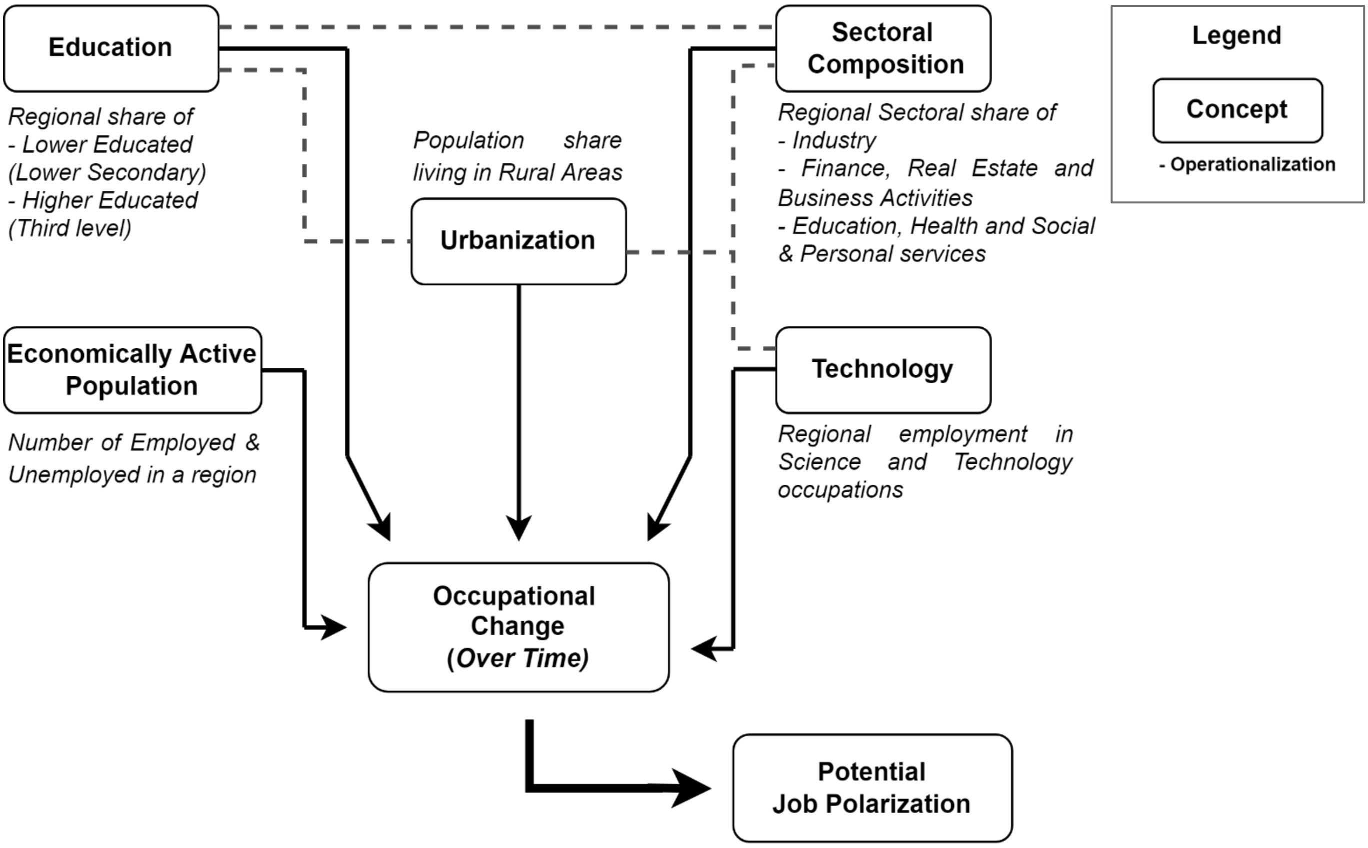
Davis et al. (2020) in their paper, similarly to Dauth, discussed job polarization in cities. In the assessed timeframe 1994-2015, French cities show clear signs of labour market polarization. The ratio of employment shares of low-, medium- and high-paid occupations increased from ‘’one-eighth, three-quarters, and one-eighth’’ to ‘’one-fifth, three-fifths and one-fifth’’ from 1994 to 2015. Most of the decrease of jobs in the middle-paid category consists of MRO-jobs (maintenance, repair and overhaul), which are the occupations that are strongest exposed to offshoring and automation (Davis et al., 2020). In the assessment of occupational changes in 117 of France largest cities, Davis et al. (2020) distinguished three key features of labour market polarization in individual cities. Firstly, the occupational shift is pervasive in virtually all cities; of the 117 cities studied, 115 cities experienced a decrease in middle-paid jobs over the period 1994-2015, whilst also experiencing an increase in the share of both low- and high-income occupations. Secondly, city size is significantly related to the decline of middle-paid jobs; overall, larger cities tend to lose more middle-paid jobs. Thirdly, city size also influences the type of substitution for the diminishing middle-paid occupations. In larger cities, replacement of lost jobs tends to favour high-paid occupations, whereas in smaller cities the middle-skilled jobs are more likely to be substituted with low-paid jobs. Their findings add to Dauth’s accentuation of the relevance of urbanisation in assessing job polarization.

To conclude, one aspect that has become evident through analysis of changes in occupational structure on smaller scales, is that level of urbanization has the potential to influence the direction as well as the strength of job polarization. It would therefore be interesting to analyse the rural-urban distinction for Europe as a whole, to assess whether this will result in similar patterns.

2.3 - Conceptual model

Figure 2 depicts the conceptual model, representing the general overview of the thesis and analysis. The figure shows several concepts that are expected to influence *occupational change* over time. These changes in turn could potentially show patterns resembling job polarization. Additionally, the conceptual model shows the operationalization of each of the independent concepts.

Figure 2 – Conceptual model.



Source – Own work

The first part of the analysis, visualized at the bottom of the conceptual model, will investigate how the occupational structure of nine EU countries has changed between 1998 and 2018, and whether these changes can be perceived as job polarization. This evaluation is related to the first research question. Additionally, an urbanization distinction is added to see whether these patterns change when considering different levels of urbanization, which will be further investigated in the second part of the analysis.

The arrows directed at *occupational change* in the conceptual model show the relations that will be considered in the second section of the analysis. *Urbanization* in relation to *occupational change* is the main relation that will be examined and discussed in the analysis, related to the second research question. *Education, sectoral composition, economically active population* and *technology* are other main concepts that are expected to influence occupational change.

Education is added to the conceptual model as a regional education distribution is expected to affect the replacement bias of the middle-skill occupations toward either low- or high-skill occupations. Non-college educated tend to get disproportionately replaced toward low-skill occupations, whereas college educated relocations tend to be divided rather evenly between low- and high-skill occupations (Autor, 2019).

The economically active population of a region is likely to influence occupational change akin to how urbanization affects occupational change. In both instances, the high end of the scale (i.e. a relatively large number of regional economically active population and a predominantly urban region) is expected to experience stronger occupational changes over time. The urbanization variable considers the regional population share living in rural areas (areas that are thinly populated, the operationalization is further discussed in chapter 3.2.2). The economically active population regards the number of people participating in a labour market on a regional level. As (regional) population size is closely related density, it would be valuable to explore whether the addition of the variable economically active population affects the relation between urbanization and occupational change.

The concepts sectoral composition and employment share in science and technology are two concepts that are expected to influence occupational change in a similar manner. Due to a range of mechanisms, among which RBTC, certain sectors and occupations are expected to experience growth or decline in their share over time. Generally, labour markets experience a decline in sectors and occupations related to manufacturing, and a growth services (Cirillo, 2018).

These additional concepts can provide insights on the importance and relevance of urbanization in explaining occupational changes, through accounting for alternative explanatory mechanisms and concepts. The dotted lines are included to indicate the prominent interrelations between the variables, both within and outside the job-polarization context. The interrelations visualized by the dotted lines are included to provide context and understanding of the underlying relations but will not be directly researched in the analysis.

2.4 – Hypothesis

Rooted in the theoretical framework and the conceptual model, I hypothesize that:

(I) The changes in occupational structure between 1988 and 2018 in the nine European countries will show distinct patterns of job polarization across all levels of urbanization.
(II) Urban regions will experience larger changes in the low-, middle- and high-skill occupations than rural regions between 1998 and 2018, and will show a replacement bias of middle-skill occupations towards high-skill occupations.

3 - Methodology

3.1 - Data description

This research will use data from the European Union Labour Force Survey (EULFS) to study job polarization in a European context. The EULFS contains data suitable for (household) labour market analysis. EULFS currently consists of 35 countries, namely the member states of the European Union, three EFTA countries (Norway, Iceland and Switzerland), four EU candidate countries (Montenegro, North Macedonia, Serbia and Turkey) and the United Kingdom (Eurostat, 2021a). Data is collected quarterly or annually, depending on the employment status. This is done by the participating countries, which Eurostat collects and combines. Due to this centralized and collective approach, Eurostat can provide comprehensive data with matching concepts, guidelines and classifications across countries. Consequently, the data is well suited for conducting research, as the data is comparable over time and across countries. Of the 35 countries, 9 countries are used in this research: Austria, Belgium, Czechia, Greece, Spain, Finland, Hungary, Italy and Portugal. This selection is chosen because these countries contain data on the variables of interest on a regional level between 1998 to 2018. Chapter 3.3 will elaborate on the country selection.

3.2 – Operationalization

Tables 1 through 3 provide a general indication of the included observations from the EULFS. These tables show the weighted number of cases in the respective categories of each variable. Table 1 shows the distribution of cases between the nine selected countries. In table 2, one can examine the number of cases belonging to the different occupational categories. Considering all years, the high skill occupations (*International Standard Occupational Classification* (ISCO) *codes 100, 200 and 300*) together have a share of 36.2%, the medium skill occupations (*ISCO codes 400, 700 and 800*) 37,1% and the low skill occupations (*ISCO codes 500 and 900*) 26,4%. The cases are relatively evenly divided across the considered years 1998, 2008 and 2018, as can be observed in table 3.

Occupations and skill-level

Potential occupational polarization of the European labour market will be determined and visualized through analysing changes in occupational employment shares among working-age adults over time. The occupational categories used in the analysis correspond to the 1-digit ISCO codes, part of the EULFS. Armed forces and skilled agricultural, forestry and fishery workers are excluded from the analysis. These occupational categories were dropped because of the limited occupational share, and limited data availability across years, adopted from Holm et al. (2017) and Goos et al. (2011) who similarly drop these occupational groups in researching job polarization. Based on the classifications of Goos et al (2014) and Cirillo (2018), the remaining eight mutually exclusive occupation groups are categorized by wage, from lowest to highest. These are (from lowest to highest) *Elementary occupations, Service and sales workers, Plant and machine operators & assemblers, Craft and related trade workers, Clerical support workers, Technicians and associated professionals, Professionals* and *Managers.* This method relates to the majority of studies that also use changes in employment shares in relation to occupational wage and skill in order to research job polarization. The average wage of an occupational category highly correlates with the skill level needed for these occupations. Therefore, grouping the occupational categories based on low-, middle- and high wages can also be perceived as low-, middle- and high-skill occupational categories (Autor, 2019). Analysing how the shares of these occupational skill clusters change over time then provides insights on potential job polarization (Autor

2019). The adaptation of Author his (2019) skill-groups categorisation to the occupational classifications of Goos et al (2014) and Cirillo (2018) result in the following three skill-groups. The low-skill occupations are service and sales workers and elementary occupations. The middle-skill occupations are operators and assemblers, and clerical support and craft workers. The high-skill occupations include the technical, professional, and managerial occupations. Changes in the shares of these above-mentioned classifications and occupation groups represent changes in the low-skill and paid, middle-skill and -paid and high-skill and -paid occupations, and therefore can be used as an indication for job polarization. As the content of the analysis predominantly revolves around changes in the three *grouped* occupational skill-categories, 1-digit ISCO codes are used, as opposed to the 2- to 4-digit ISCO codes. Furthermore, 1-digit ISCO codes are able to show and explain patterns job polarization (Cirillo, 2018; Holm et al., 2017), which makes it suitable for the goal of this research: discussing general patterns of job polarization in relation to urbanization.

Table 1 - Frequency table nine selected EU countries, 1998 - 2018.

	Frequency	Percent
Austria	11322	6,1
Belgium	12598	6,8
Czechia	14737	8,0
Greece	10673	5,8
Spain	40478	21,9
Finland	6796	3,7
Hungary	11722	6,3
Italy	63456	34,3
Portugal	13350	7,2
Total	185132	100,0

Source - European Union Labour Force Survey 1998 – 2018.

Table 2 – Frequency table 1-digit ISCO occupational codes, nine EU countries, 1998 - 2018.

	Frequency	Percent
100 - *Managers*	12530	6,8
200 - *Professionals*	26841	14,5
300 - *Technicians and associated professionals*	28183	15,2
400 - Clerical support workers	20885	11,3
500 - *Service and Sales workers*	29472	15,9
700 - *Craft and related trade workers*	30183	16,3
800 - *Plant and machine operators & assemblers*	17655	9,5
900 - *Elementary occupations*	19383	10,5
Total	185132	100

Source – European Union Labour Force Survey 1998 – 2018.

Table 3 – Frequency table included years, nine EU countries, 1998 - 2018.

	Frequency	Percent
1998	56350	30,4
2008	64486	34,8
2018	64296	34,7
Total	185132	100

Source – European Union Labour Force Survey 1998 – 2018.

3.2.2 - Urbanisation

In exploring the extent to which rural areas differ from urban areas in job polarization, an urbanisation distinction is made. For this distinction between rural and urban areas, the classifications used by the EULFS will also be used in this research. In the dataset the level of urbanization is divided into three categories; *cities* (densely populated areas: at least 50% of the population lives in urban centres), *towns and suburbs* (intermediate density areas: less than 50% of the population lives in rural grid cells and less than 50% of the population lives in urban centres) *and rural areas* (thinly populated areas: more than 50% of the population lives in rural grid cells). These categories are the result of a classification by a body of European institutions, among which the OECD, using population density and geographical contiguity (Eurostat, 2021b). In the analysis, the degree of urbanisation in 1998 will function as the baseline on which the rural and urban comparison will be based. In doing so, one is able to assess the changes in the occupational structure of the *then* rural and urban areas, and in extension determine whether (potential) job polarization has been influenced by these categories differently.

Regional descriptive statistics

Table 4 includes the descriptive statistics of the variables of interest for the regression analysis. In the analysis, the relation between urbanization and occupational change will be further analysed, controlling for several other characteristics and concepts. The variables are all aggregated on a regional NUTS-2 (nomenclature of territorial units for statistics) level.

Table 4 – Descriptive statistics on a regional level (NUTS-2), based on nine EU countries, 1998-2018.

Data Source	Variables	Included Years	N	Minimum	Maximum	Mean	Std. Deviation
EULFS	Share living in Rural Area's	1998, 2008, 2018	185132	0	0,840	0,2564	0,18822
	Share Lower Education	1998, 2008, 2018	185132	0,032	0,696	0,3314	0,15338
	Share Middle Education	1998, 2008, 2018	185132	0,166	0,810	0,4190	0,17548
	Share Higher Education	1998, 2008, 2018	185132	0,092	0,516	0,2491	0,08803
	Gender ratio (F/M)	1998, 2008, 2018	185132	0,350	0,510	0,4349	0,03578
	Average Age	1998, 2008, 2018	185132	39,470	44,600	41,9571	1,25670
Eurostat	GDP	2000	185132	807,46	259.861,46	66.795,21	63893,41412
	Ln GDP	2000	185132	6,690	12,470	10,6090	1,10504
	Economically Active Population	1999*	185132	12	4023	1451,5	1004,66590
	Ln Economically Active Population	1999*	185132	2,50	8,30	7,0108	0,79186
	Technology [occupational share]	1999*	185132	0,079	0,427	0,2135	0,05747
	Industry [Sectoral share - C_F]	1999*	185132	0,104	0,479	0,3178	0,08168
	Financial intermediation; Real estate [Sectoral share - J_K]	1999*	184377	0,034	0,200	0,0937	0,03448
	Public administration and community services [Sectoral share - L_Q]	1999*	185132	0,155	0,521	0,2624	0,05906

Source – European Union Labour Force Survey 1998 - 2018, Eurostat (2021c, 2022a, 2022b, 2022c). GDP in millions. Economically active pop in thousands. The variables Industry, Financial intermediation; Real estate and Public administration and community services are based on NACE (revision 1.1) codes, corresponding NACE codes in parentheses.

** These variables have missing data of 5 to 7 regions in 1999. For these regions, data of 2005 and 2013 were used as substitute, as these years were the first available years with valid data for these regions.*

Data from the European Union Labour Force Survey

The top halve of table 4 depicts the descriptive statistics of the variables adopted from the EULFS (corresponding gender, age, education and degree of urbanization frequency tables can be found in the appendix, table 14 through 17). The urbanization variable that will be used is the *Share living in Rural Areas.* The operationalization is adopted from the EULFS, aggregated to a regional level. An individual is living in a rural area when the considered area is thinly populated (more than 50% of the population lives in rural grid cells). The regional share living in rural areas ranges from 0% to 84,0%, with a mean of 25,64%.

Table 4 also shows the share of people in a region having completed lower (lower secondary), middle (higher secondary) or higher (third level) education. The average proportion of low-middle-high educated in a region is 32,9% - 41,8% - 25,3% (table 15, appendix). In the analysis, the three education variables cannot be included simultaneously due to collinearity. The regional share of lower and higher educated will be used in the analysis to cover both ends of the spectrum. Including the high- and low-end of the education categories makes that the results can compared job polarization literature regarding predictions and outcomes related to education (such as Autor, 2019).

The gender ratio shows the share of the population that is *female*. On average, a region's female to male ratio is 43,5%. The average age of the working population of a region in the dataset is 42, with a standard deviation of 1,26. Age, Gender, education and degree of urbanization frequency tables can be found in the appendix, table 14 through 17.

External data from Eurostat

The remainder of the variables in table 4 were retrieved from Eurostat. These independent variables were added to the data as they are predicted to have an impact on occupational change. Several combinations of the variables in table 4 are included in the analysis, to monitor potential change in the explanatory capabilities of urbanization on occupational change. All the variables, similar to the EULFS data, include data on a regional (NUTS-2) level. The variables describe the regions' economy and labour market in the year 1999 or 2000, depending on data-availability, as data was not available for the year 1998. These variables function as contextual factors that control for the occupational changes between 1998 and 2018.

The mean *GDP* of the included regions is 66.795,29 million, with a range from 807,46 to 259.861,00 million (Eurostat, 2022c). *Economically active population* is also included in the regression analysis. An economically active population consist of the employed and unemployed, including those who seek work for the first time (OECD, 2002). The region with the least economically active people has 12.000 workers (Åland, Finland), the region with the highest economically active population has 4.023.000 workers (Lombardy, Italy) (Eurostat, 2022a). In the analysis, the logarithmic adaptation of GDP and economically active population are used, as these variables were strongly skewed on the high end of the distribution. The logarithmic transformation results in a normal distribution of the variables and reduces skewness in the standard error estimates (Lütkepoh & Xu, 2009).

Table 4 also includes the variable *Technology,* which measures the regional share of professionals and technicians employed in science and technology occupations. This variables was included to control for technology in the analysis, as the stock of human resources in science and technology can be used as an indicator for the presence of technology in that region (Eurostat, 2021c). In the data, the share of these occupations on a regional level ranges from 7,9% to 42,7% (table 4).

The remaining three variables describe the sectoral compositions of the included regions, using NACE-codes (revision 1.1). The three categories, I) *Industry,* II) *Financial intermediation; Real estate* and lll) *Public administration and community services* are adopted from the Eurostat categorization (Eurostat, 2022b). The sectoral share of *Industry* (NACE-codes C to F) in the included regions ranges from 10,4% to 47,9%, the share of *Financial intermediation; Real estate* (NACE-codes J to K) from 3,4% to 20,0% and the share of *Public administration and community services* (NACE-codes L to Q) from 15,5% to 52,1%.

Lastly (not included in table 4), the percent point changes in occupational share between 1998 and 2018 are averaged per region and ISCO category, to regress and test its relation with urbanization and the other additional regional variables of table 4.

3.3 - Country selection

To do the assessment of the occupational structures and the changes therein, it is necessary for countries to have data on the subset of variables of interest. These are 1-digit ISCO codes, the region (at NUST-2 level) of the household and the degree of urbanization. Occupational ISCO data is required to analyse the occupational changes over time. A regional variable is included for the geographical distinction required in the regression analysis. The urbanization variable is added to analyse the expected rural-urban differences in occupational change and job polarization. Additionally, data on age, gender, education and the weighting coefficient are included. Countries are omitted due to missing data on one or more of these variables in the years 1998, 2008 or 2018. Of the 35 countries in the EULFS, 15 countries were omitted because of absence of data in the ISCO, weighing coefficient and / or NUTS-2 variable. Additionally, 11 countries were omitted due to missing data in the urbanization variable. This resulted in the subset of 9 countries: Austria, Belgium, Czechia, Greece, Spain, Finland, Hungary, Italy and Portugal.

The degree of urbanization of the *living* place of the households appeared to be the strongest limiting variable in the country selection. This degree of urbanization in the EULFS data is determined per household's, based on one's residential location. The degree of urbanization (cities, towns and suburbs and rural areas) depends on the population density of 1km2 raster cells using criteria of population density and contiguity, in combination with the share of local population living in urban centres and clusters in local administrative units (LAU) (Eurostat, 2021b).

As this research aims to describe and make findings that are 'representative' of Europe, an alternative variable of urbanization was considered which would result in the inclusion of 6 additional countries (Switzerland, Ireland, Lithuania, Poland, Slovenia, Slovakia), and hence would improve the representativeness. The alternative method adds urbanization data from Eurostat to the region variable of the EULFS dataset. Importantly, the degree of urbanization in Eurostat is aggregated on NUTS-3 level, whereas the region variable of the EULFS dataset is on a larger scale, namely NUTS-2 level. (A single NUTS-2 region consists of a few, up to many NUTS-3 regions. As an indication: in 2021 there were 242 regions at NUTS 2 and 1166 regions at NUTS 3 (Eurostat, 2022d).) The necessary compression of many (NUTS 3) regions to one (NUTS 2), to match the Eurostat urbanization data to the regional data (of the dependent variables) of the households in the EULFS, results in a strong generalization of the degree of urbanization.

To compare these effects of the different degree of urbanization variables, in the following section referred to as *EULFS urbanization* and *Eurostat urbanization*, differences in results between these two methods were assessed using a test of a small subset of 3 countries. These countries (Belgium, Portugal and Greece) were selected based on consistent regional classifications across the three years of interest, 1998, 2008 and 2018, as well as having degree of urbanization data across the three years.

The comparison in table 8 (Appendix) shows that for the three countries combined, the Eurostat urbanization results in a significantly lower share of households living in cities compared to the corresponding EULFS urbanization numbers, 8,7% versus 47,8% respectively. (Note that these numbers are skewed by the absence of NUTS-2 regions that are characterized as cities after the generalisation from NUTS-3 regions in Greece, as of the 13 NUTS-2 regions, 12 are rural areas, and one is towns and suburbs.)

Table 9 and 10 (appendix) show the percentage point changes in occupational employment shares per skill category, for the three degrees of urbanization between 1998 and 2018, both for the EULFS and Eurostat urbanization. Next to the three urbanization categories, there is also a 'baseline' included, which shows the changes in occupational share without the urbanization distinction. As the urbanization variable is the only variable that differs in the assessment of the two 'methods', the baseline scenario is the same for both tables. Table 10 reveals that, looking at the percentage point changes between 1998 and 2018 for Eurostat urbanization, cities not only experience an (expected) decrease in the medium-skill category but also in the low-skill category, which strongly contrasts with the growth of low-skill occupations present in both the corresponding EULFS urbanization category, as well as in the baseline scenario. Furthermore, following the Eurostat urbanization, the rural areas experience a much stronger(larger) shift compared to the respective EULFS urbanization (with a difference of 4,0 - 5,5 and 1.2 percentage points in the respective skill categories, low, medium and high).

Due to the loss of nuance using the *Eurostat urbanization* (as a 'degree of urbanization' is assigned to a region, rather than to an individual or household, which is the case with *EULFS urbanization*), and the consequential effects on the occupational changes over time observed in the tables 12 and 13, the analysis of this research will not include additional countries using urbanization data from Eurostat.

The sum of variable parameters results in a set of 7 countries: Austria, Belgium, Greece, Spain, Finland, Italy and Portugal. In an attempt to increase the country total, the other countries in the EULFS data were examined in order to find countries that had: (I) limitations in one or more variables at one of the three considered years, but (II) no limitations in a year close to the year where data was incomplete. Data (of all variables) of that year would then substitute the 'missing' year. Following this method, two countries were added to the dataset, namely Czechia and Hungary. Both countries were missing urbanization data in the year 1998, but had available urbanization data in 2002 and 2001 respectively.

3.4 - Analysis

The upcoming analysis will focus on two distinct aspects. The first segment will consider changes in occupational structure on a European level as an indication of job polarization. This will be done through calculating percent point changes in ten- and twenty-year intervals between 1998 and 2018, using the ISCO occupational data of the EULFS. Processing and visualizing this information will give an indication of the persuasiveness of job polarization during the last two decades. Next, an additional selection based on degree of urbanization will uncover potential differences between the three levels of urbanization. These will be the theme of the second segment. Here, a set of regressions are executed to test the significance of the observed differences in occupational change over time of the different levels on urbanization on a regional level. In preparation of these regressions, individual data was aggregated to regional characteristics. This was necessary as the data does not follow individuals over time, thus respondents' characteristics (such as age and occupation) have no influence on the occupations held by past or future respondents. A region's gender ratio, age, share of low-, medium- and high-educated and average occupational change on the other hand *are* able to interact with one another. In the regressions, additional variables regarding the economy and labour market of a region (from Eurostat) were added to the dataset to explore their effect on the relation between urbanization and occupational change.

The use of weights

The weighting variable included in the EULFS dataset is applied in the descriptive statistics. Weighting is not applied in the regression models. As the sampling weight consists of the variables that are used in the models, unweighted estimates are preferred as they produce less biased parameter estimates and smaller standard errors (Winship & Radbill, 1994). Furthermore, the construct of the weighting variable across countries is also inconsistent. Countries in the EULFS do not use the same (number of) key variables, weighting method and reference population for weighting (Eurostat, 2019). This consequently also results in inconsistent parameter estimations when the weighting variable is used (Solon et al. 2013). Gender and age-group are two variables that are consistent across countries in determining the weighting coefficient. These are also included in the regression models. Importantly, interpretation of these variables must be done with caution, as they also correct for the bias in the population.

3.5 – Limitations

Generalizability

While researching job polarization on a European level can provide insightful patterns, and moreover show the relevance and magnitude of job polarization in Europe, it also has its limitations. Even though this research used a composition of European countries, this does not automatically make at an accurate representation of Europe as a whole. The country selection used in the coming analysis do not include some major European countries such as France, Germany and The United Kingdom due to limitations on data, which limits the generalizability of the included countries to Europe as a whole.
Also, because the variables are pooled across countries, certain nuance in the variables is lost. For example, an education distinction between college and non-college educated can result in two categories, grouped across countries. A college degree can be (objectively) be more appraised or 'worth' (i.e., higher educated) in one country than in another. But because all the college educated are pooled into one category, all the college educated are regarded 'the same' in analysis using this variable. Because of the selection of countries and certain loss of nuance through grouping the variables across countries, conclusions of the results and the generalizations to Europe should be made with caution.

Self-selection bias

People tend to live in, or more importantly, move to the 'location' where they expect to find or have their job matching their skill and occupational preferences (Tervo, 2016). This results in a 'self-selection bias'. Unfortunately, it is difficult to predict the extent to which this bias influences occupational changes in the analysis. The research design uses three cross-sectional samples of ten-year intervals. This entails that the dataset doesn't involve the same respondents over time, and in extension doesn't track one's changes in (urbanization) habitat and occupation. This means that data doesn't *allow for* statistical analysis on the effects of this self-selection bias on the changes in occupational structure. Nevertheless, as the research design assesses the nine European countries in 10-year intervals, it is sensible to assume that a portion of the changes in the occupational shares in the respective urbanization categories is due to this bias. Differences in occupational changes among different levels of urbanization should thus be interpreted with caution.

4 - Results & Analysis

4.1 – The occupational structure over time

Before taking a closer look into the relation between urbanization and job polarization, the presumable persuasiveness of job polarization in Europe will first be explored. This is done through the examination of changes in the occupational composition of the included countries between 1998 and 2018. Table 5 shows the average employment shares for the eight occupational categories, for the three studied years (1998, 2008 and 2018). Here, the occupational categories are divided by their mean wage ranking into high-, middling- and low-paying occupational groups as a proxy for the skill categories (low-medium-high) central to job polarization. Additionally, the percent point changes of each occupational category between 1998 - 2008, 2008 - 2018 and 1998 – 2018 is also shown in table 5.

Table 5 - Levels and changes in Occupational Employment Shares in nine EU countries, 1998-2018.

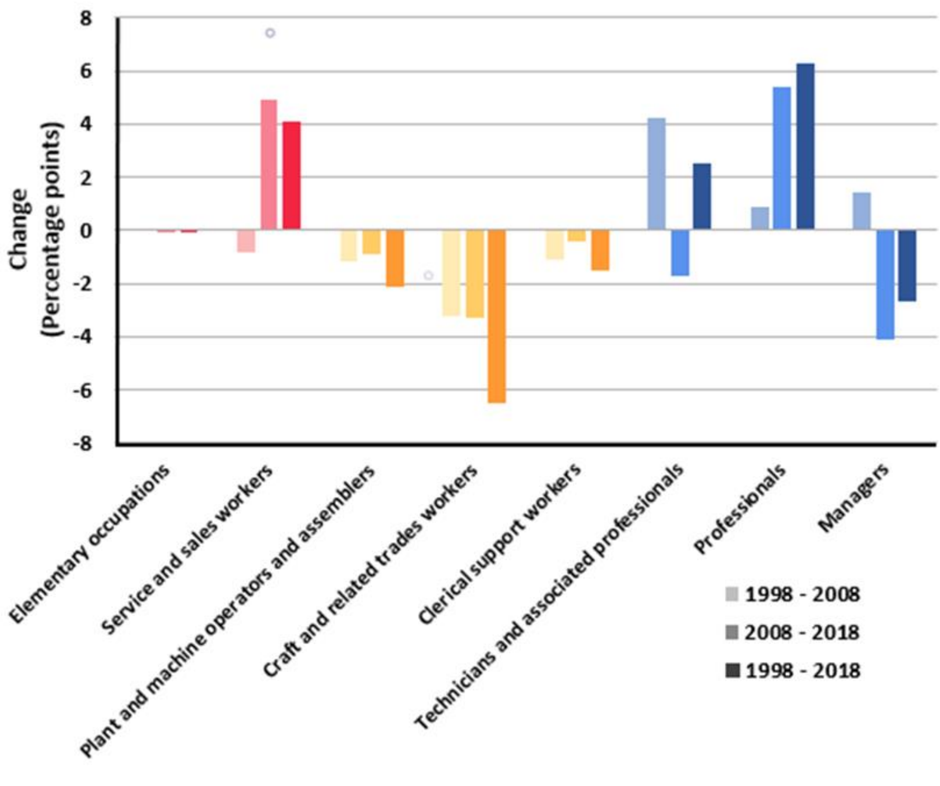
Occupations ranked by mean European wage	Average employment share in 1998 (in percent)	Average employment share in 2008 (in percent)	Average employment share in 2018 (in percent)	Percentage point change 1998 - 2008	Percentage point change 2008 - 2018	Percentage point change 1998 - 2018
High-paying occupational groups	**32,1**	**38,6**	**38,2**	**6,5**	**-0,4**	**6,1**
Managers	7,2	8,6	4,5	1,4	-4,1	-2,7
Professionals	12	12,9	18,3	0,9	5,4	6,3
Technicians and associated professionals	12,9	17,1	15,4	4,2	-1,7	2,5
Middling occupational groups	**42,6**	**37,1**	**32,5**	**-5,5**	**-4,6**	**-10,1**
Clerical support workers	12,2	11,1	10,7	-1,1	-0,4	-1,5
Craft and related trades workers	19,7	16,5	13,2	-3,2	-3,3	-6,5
Plant and machine operators and assemblers	10,7	9,5	8,6	-1,2	-0,9	-2,1
Low-paying occupational groups	**25,3**	**24,5**	**29,3**	**-0,8**	**4,8**	**4**
Service and sales workers	14,8	14	18,9	-0,8	4.9	4,1
Elementary occupations	10,5	10,5	10,4	0	-0,1	-0,1

Notes: Occupational groups are ordered based on mean wage rankings used by Goos et al. (2014) and Cirillo (2018). Employment shares and percentage point changes are based on 9 European countries from EULFS, pooled. Included countries: Austria, Belgium, Czechia, Greece, Spain, Finland, Hungary, Italy and Portugal. Occupational groups are derived from ISCO-1 digit codes, excluding armed forces & skilled agricultural, forestry and fishery workers.
Source – Own calculations based on European Union Labour Force Survey 1998 – 2018.

It becomes evident that the three middle skill occupations combined experienced a substantial decrease in occupational share. The grouped middle-skill occupations experienced a decrease of 10,1 percent point between 1998 and 2018, from an occupational share of 42,6% in 1998 to a share of 32,5% in 2018. In 1998, the middling occupations accounted for the largest occupational share with a share of 42,6%, compared to a share of 25,3% and 32,1% of the low and high skill occupations respectively. In following 20 years, these proportions experienced a substantial shift from the middling occupations to the high- and low-skill occupations. The middling occupations in 2018 account for a share of 32,5%, just slightly larger than the low-skill occupations with a share of 29,3%. Following the trends observed in the table 5, the share of low-skilled occupations is highly likely to exceed the share of middle-skill occupations in the years to come. The high-skill occupations already surpassed the middle-skill occupations as the largest occupational category, with an occupational share of 38,2% in 2018.

Figure 3 visualizes the data presented in table 5, which provides a clarification of the occupational changes of the nine EU countries between 1998 and 2018, related to the first research-question. Occupational categories are likewise ordered from lowest to highest paying 1-digit ISCO occupations, with the lower paying occupations on the left-hand side, and the highest on the right-hand side. The general colours each represent a skill category, with red, yellow and blue representing the low-, middle- and high-skill occupations respectively. Through the visualization a general U-shaped pattern becomes evident, in line with a 'job polarizing' occupational shift. When taking a closer look at the low skill occupations several aspects stand out. Firstly, *elementary occupations* virtually didn't experience changes in their occupational share between 1998 and 2018, balancing around an occupational share of 10,5%. This means that, looking at the aggregate of the nine countries, the *nett* growth of workers in low-skill occupations can be attributed to *service and sales occupations*. These findings are in line with the expected effect of RBTC in explaining job polarization. RBTC predicts that the non-routine low-skill and high-skill occupations will benefit from the technological advancements. Additionally, the growth in high-skill occupations is likely to result in an increased demand for services, which tend to be present in low-skill jobs (Dauth, 2014). Figure 3 shows that the elementary occupations, -

Figure 3 – Percentage point changes in occupational employment shares in nine EU countries, 1998 – 2018.



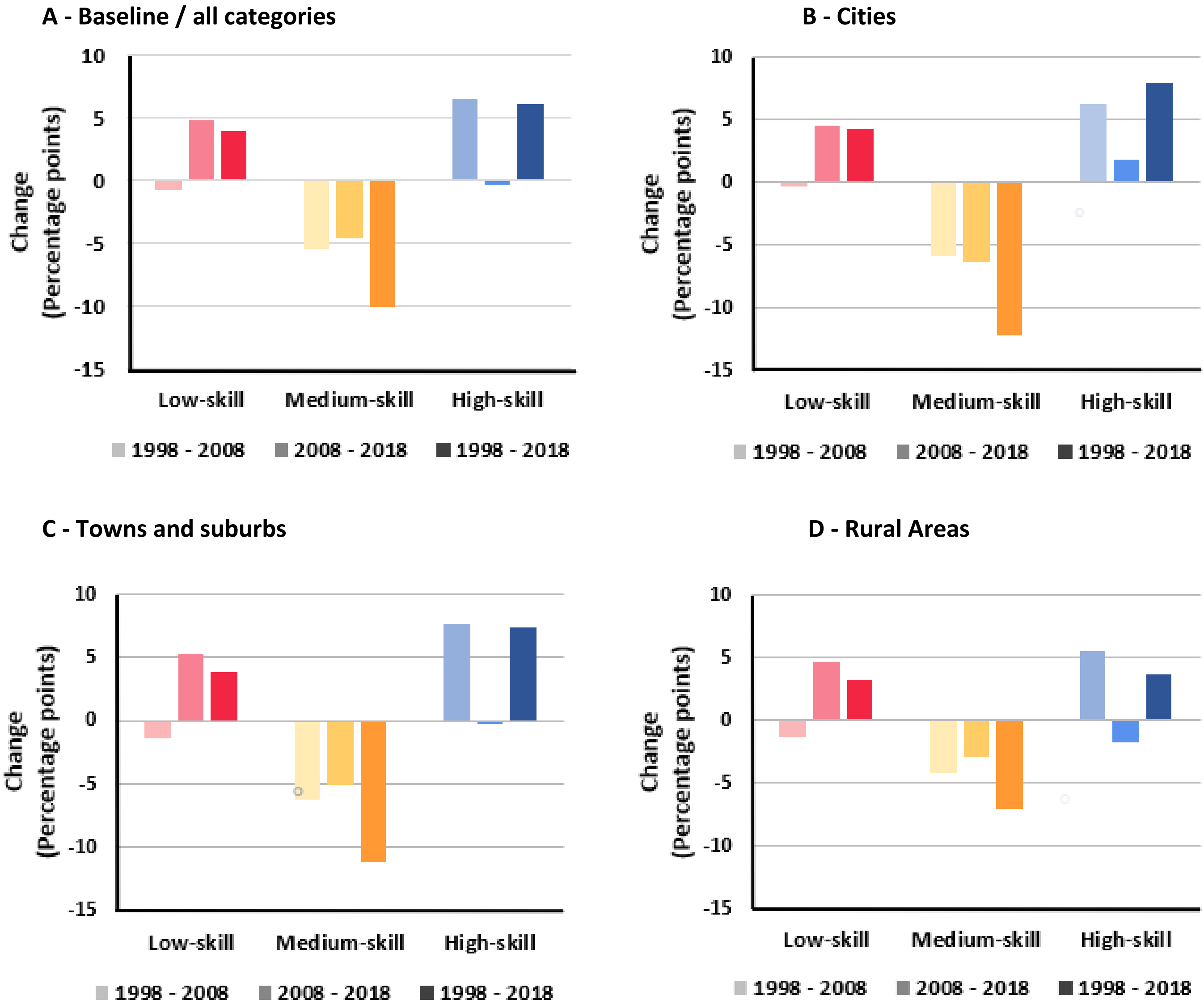
Source – Own visualization based on European Union Labour Force Survey 1998 – 2018.

- characterized by simple and routine physical tasks, are not able to benefit as much from the technological advancements as the service and sales occupations. Interestingly, the growth in service and sales occupations happened solely between 2008 and 2018. The decrease in middle-skill occupations is distinct across all the three occupational groups for both decades, with *craft and related trade workers* undergoing the strongest decline. The share of all the high skill occupations grew between 1998 and 2008. This growth did not persevere between 2008 and 2018. In the second decade, only *professionals* increased its relative occupational share, whereas both *technicians and associated professionals* and *managers* experienced a decline. Nevertheless, it can be established that between 1998 and 2018, the data shows patterns of job polarization, characterized by the decline in middle-skill occupations with an increase in the low- and high-skill occupations.

4.2 – Adding Urbanization to the equation

The process of analysing potential job polarization patterns can be enhanced by making an additional distinction between degree of urbanization, to look at its influence on the occupational changes over time. Figure 4A displays the occupational employment share percent point changes of 'all' the cases, which is a simplified representation of the data in table 5 and figure 3. Figure 4B up to 4D likewise -

Figure 4 - Percentage point changes in occupational employment shares per skill-category, for different urbanization 'levels', nine EU countries, 1998 – 2018.



Source – Own visualization based on European Union Labour Force Survey 1998 – 2018.

- showcase the experienced occupational changes, but adapted by looking just at cities, towns and suburbs or rural areas rather than the combination of the three (figures 4 B,C and D are derived from table 11 to 13, appendix). Note that figure 4 uses the combined low-, medium- and high-skill occupational ISCO categories. Visualizing the changes over time in this manner allows for effectively identifying general differences between the different degrees of urbanization and the baseline. Nevertheless, only general conclusions can be derived from this figure. As for example figure 3A shows that between 2008 and 2018 the high skill occupations *together* experienced very little change in occupational share, though this does not imply that the three high-skill occupations groups experienced no change at all (as can be seen in figure 3), they just happen to even each other out.

When comparing the three urbanization levels, a couple of things stand out. Firstly, figure 4 shows that for all levels of urbanization, job polarization occurs in the nine European countries between 1998 and 2018, supporting the first hypothesis. Secondly, the bar figures of *Cities* (4B) and *Towns and suburbs* (4C) show a strong resemblance. This can be seen by the respective high-, medium- and low-skill percent point changes between 1998 and 2018, which are +8,0% / -12,2% / +4,2% for cities and +7,4 / -11,2% / +3,9% for towns and suburbs. These numbers are a large contrast to the +3,7% / -7,1% / +3.3% between 1998 and 2018 for the *Rural Areas* (4D). Here it becomes evident that when grouping the occupational changes by skill level that I) *Cities* and *Towns and Suburbs* compared to *Rural Areas* experience stronger changes overall. Additionally, II) these differences particularly manifest in a smaller decrease amongst the middle skill occupations and smaller increase in high skill occupations for the rural area's (-7,1 percent point vs -12,2 & -11,2 and +3,3 percent point vs +8,0 and +7,4 respectively). These findings are in line with the expectations discussed in the theoretical framework of urbanization its effects on job polarization (Davis et al, 2020). The following sections will further investigate whether these findings are also *significant.*

The exploration of Job Polarization thus far has been based on how the occupational compositions have changed between 1998 and 2018 in Europe as a whole. The coming analysis will similarly consider these percent point change of the eight occupations, but now on a regional level. As an individual and its characteristics (i.e. gender, age, occupation, etc.) at a point of time have no direct effect on the occupational changes occurred prior or after that point in time, the analysis will use these characteristics averaged on a regional level for each of the three years (1999, 2008, 2018) instead.

4.3 – The significance of Urbanization

With the aim to analyse the relation between urbanization and job polarization, variations of the same model for each respective occupational skill category have been explored, providing insights into the second research question. The constants in these models are the dependent variable *occupational percent point change* (per region), the independent control variables *gender ratio* and *average age* on a regional scale and the independent variable of interest *urbanization.* As the intention of these regressions is to analyse the extent the rural experiences job polarization differently than towns & suburbs and cities, *regional share living in rural areas* will be used as the urbanization variable. Additionally, dummies of the considered regions were included.

These variables are then complemented by a combination of variables related to education, economy and labour force, technology, and sectoral composition. These are regressed using a selection of either the cases with low-skill occupations (*1-digit ISCO codes 500 and 900, service and* *sales workers and elementary occupations respectively),* middle-skill occupations (*1-digit ISCO codes 400, 700 and 800, clerical support workers, craft and related trades workers and plant and machine operators and assemblers respectively*) or high-skill occupations (*1-digit ISCO codes 100, 200 and 300, managers, professionals and technicians and associated professionals respectively*). The distinction between the different occupational skill-levels is required to test whether urbanization can explain the more moderate decrease in middle-skilled occupations and smaller increase in high-skill occupations in rural areas opposed to cities and towns and suburbs, observed in figure 4.

Middle-skill occupations

Table 6 shows the first model, portraying the standardized coefficients of the five subsets of independent variables explaining occupational percent point changes in middle-skill occupations between 1998 and 2018. The model in table 6 is discussed in the context portrayed and discussed in figure 4. Overall, a decrease in the share of the middle-skill occupations between 1998 and 2018 takes place. The estimates in table 6 imply whether the variables significantly reduce or amplify the occupational decrease in the middle-skill occupations.

First, the relation between urbanization and middle-skill occupational change is tested in isolation (1), whereafter additional independent variables are added to observe potential changes in the urbanization estimates. In the second variation education is introduced (2), followed by economic and labour force characteristics in the third variation (3). In the next variation (4) three overarching sectoral composition variables are introduced, containing information on the share of these respective sectors on a regional level. In variation (5), the share of people employed in science and technology occupations is added to explore the relation between technology and occupational change. With the addition of the technology variable (5) to the explanatory variables in the fourth variation, the control variable *gender-ratio* gets omitted due to collinearity with the other included variables. As the *gender-ratio* variable is required to compensate for the bias in the data (together with *regional average age* functioning as the weight of the dataset), several subsets of independent variables with the inclusion of technology *and* both the control variables age and sex were explored. This has resulted in the exclusion of the sectoral NACE categories *Financial Intermediation and Real Estate*, and *Public Administration and Community Services* in the fifth variation in order to preserve the variable *gender-ratio*.

The estimates of the different variations in table 6 hint at an overall positive relation between urbanization, the share of the population living in rural areas, and middle-skill occupational change. Variations (1) and (2) in table predict a significant and notable positive relation between a higher rural share and occupational change. This entails that when a region has a larger share of rural residents, that region tends to experience a smaller decrease in middle-skill occupations between 1998 and 2018. When adding GDP and the economically active population variables to the equation (3), the urbanization estimate remains positive, yet becomes smaller, and thereby loses explanatory capacity. Simultaneously, a larger regional share of the lower educated (lower secondary) shows to have a strong negative influence on the occupational change, which translates to a stronger decrease in middle-skill occupations between 1998 and 2018 for regions with a relatively high share of lower educated. With the addition of the variables describing the regional sectoral composition (4), the positive coefficient of urbanization experienced a substantial increase.

Table 6 – Explaining occupational change in middle-skill occupations, standardized coefficients and significance, nine EU countries, 1998 – 2018. *(Dependent variable - Occupational percent point change 1998-2018).*

		(1)	(2)	(3)	(4)	(5)
Urbanization	Share living in Rural Areas	0,214 0,000**	0,152 <0,001**	0,097 <0,001**	0,380 <0,001**	-0,027 0,059
Education Share	Low	__	-0,384 0,000**	-0,552 <0,001**	-0,554 <0,001**	-0,005 0,862
	High	__	-0,013 0,064	-0,095 <0,001**	-0,255 <0,001**	-0,287 <0,001**
Economy and labour force	GDP	__	__	0,081 <0,001**	-0,009 0,867	-0,583 <0,001**
	Economically Active Population	__	__	-0,178 <0,001**	0,152 <0,001**	0,364 <0,001**
Employment Share	Technology	__	__	__	__	0,802 <0,001**
Sectoral Share *(NACE)*	**C-F** - Industry	__	__	__	-0,166 <0,001**	-0,023 0,000**
	J-K - Financial Intermediation; Real Estate	__	__	__	0,082 0,001**	__
	L-Q -Public Administration and Community Services	__	__	__	0,377 <0,001**	__
	R^2	0,231	0,234	0,234	0,229	0,237

Notes: Dependent variable – Percent point change (of occupations per region). All models include region dummies. All models also include gender-ratio and average age on a regional level. The variables GDP and Economically Active Population are logarithmic scaled. Case selection - Middle skill occupations (1-digit ISCO codes 400, 700 and 800, clerical support workers, Craft and related trades workers and plant and machine operators and assemblers respectively). Source - European Union Labour Force Survey 1998 – 2018.

*** Significant at the 1 percent level. * Significant at the 5 percent level.*

With the addition of Technology (5), measured by the regional occupational share in science and technology, multiple variables experience a large shift in their coefficients. Urbanization is now showing a *small negative* influence on occupational change and is slightly outside of the 5% significance range with a p-value of 0,059. The estimate of lower education, which had the largest coefficient in the variations 1 through 4, has lost virtually all explanatory power (-0,005) and is no longer significant. The variables that show the largest estimates are GDP (-0.583), which in the prior variations showed little impact, and technology, showing a strong significant positive relation (0,802).

Overall, urbanization appears to be a relevant aspect in explaining regional occupational change in middle-skill occupations between 1998 and 2018. The first four variations in the first model show positive and significant estimates for the urbanization variable. A region being more rural tend to have a significant positive relation with middle-skill occupational change. This entails that the more rural a region is, the smaller the *decrease* in the share of middle-skill occupations between 1998 and 2018. This relation is strongest when considering education, economy and labour force dimensions and sectoral composition (variation 4). However, with the addition of technology to the subset explanatory variables in variation 5, the share living in rural areas no longer significantly influenced middle-skill occupational change between 1998 and 2018. Additionally, the share living in rural areas variable in the fifth variation has a small negative coefficient. These results indicate that, due to the addition of the explanatory variable technology 'regional share of professionals and technicians employed in science and technology occupations', a positive and significant relation between urbanization and middle-skill occupational change is not consistent across all variations in model 1. This entails that even though regions being more *urban* can be interpreted as an aspect that tends to strengthen the decrease in middle-skill occupations, and therefore inducing job polarization patterns, its relevance when considering alternative explanatory variables is not without question.

High-skill occupations

The second model dives into the relation between urbanization and occupational change in the high-skill occupations. Table 7 shows the second model, which uses the same approach as the first model. The same combinations of variables are introduced, resulting in 5 variations.

Once again, the model is discussed and interpreted from the perspective discussed in figure 4. Overall, an increase in the share of the high skill occupations between 1998 and 2018 takes place. The estimates in model 2 imply whether the variables significantly reduce or amplify the occupational increase in high-skill occupations. The first two variations in table 7 show comparable results with regard to the urbanization variable. The significant negative urbanization estimates (-0,080 and -0.096 respectively) in the first two variations indicate that the more rural a region is, the smaller the increase in the high-skill occupations between 1998 and 2018. Education is also added in the second variation, where -

Table 7 – Explaining occupational change in high-skill occupations, standardized coefficients and significance, nine EU countries, 1998 – 2018. *(Dependent variable - Occupational percent point change 1998-2018)*

		(1)	(2)	(3)	(4)	(5)
Urbanization	Share living in Rural Areas	-0,080 <0,001**	-0,096 <0,001**	0,076 <0,001**	-0,463 <0,001**	0,044 0,012**
Education	Low	—	0,478 0,000**	0,151 <0,001**	0,004 0,940	-0,646 <0,001**
	High	—	-0,060 <0,001**	-0,020 0,016**	-0,017 0,521	0,161 <0,001**
Regional Characteristics	GDP	—	—	0,362 <0,001**	0,535 <0,001**	1,270 0,000**
	Economically Active population	—	—	-0,070 <0,001**	-0,593 <0,001**	-0,814 <0,001**
Employment Share	Technology	—	—	—	—	-0,676 <0,001**
Sectoral Share *(NACE)*	**C-F** - Industry	—	—	—	0,401 <0,001**	0,309 <0,001**
	J-K - Financial Intermediation; Real Estate	—	—	—	0,101 <0,001**	—
	L-Q -Public administration and community services	—	—	—	-0,510 <0,001**	—
	R^2	0,207	0,212	0,213	0,209	0,215

Notes: Dependent variable – Percent point change (of occupations per region). All models include region dummies. All models also include gender-ratio and average age on a regional level. The variables GDP and Economically Active Population are logarithmic scaled. Case selection - High skill occupations (1-digit ISCO codes 100, 200 and 300, Managers, Professionals and Technicians and associated professionals respectively). Source - European Union Labour Force Survey 1998 – 2018.

*** Significant at the 1 percent level.*

** Significant at the 5 percent level.*

- the share of lower educated shows a strong positive relation with the percent point occupational change in high skill occupations on a regional level. This entails that a larger share of lower educated on a regional level amplifies the expected growth in high-skill occupations between 1998 and 2018. The estimates of the regional share in lower education shifts substantially with the addition of the other regional characteristics in variation three to five, going from a strong positive influence to a strong negative influence on high-skill occupational change.

When the regional characteristics GDP and economically active population are introduced in variation 3, urbanization no longer appears to have a negative relation with high-skill occupational change. The positive and significant 'share living in rural areas' coefficient (0,076) in variation 3 indicate that a more rural region tends to experience a larger growth in the high-skill occupational share. This relation is counterintuitive to the job polarization literature in relation to urbanization, as well as to the second hypothesis (Dauth, 2014; Davis et al, 2020)..

With the addition of the sectoral composition variables (4), urbanization shows a strong and significant standardized coefficient (-0,463). This means that a more rural region tends to experience a *smaller growth* in the high-skill occupational share between 1998 and 2018 compared to regions that exhibit a higher rural share.

Though when technology (regional employment share in science and technology occupations) is added to the model (5), the degree of rurality suddenly experiences a substantial decrease in explanatory power on high-skill occupational change compared to variation 4. In variation 5, urbanization shows a small positive relation with high-skill occupational change, with an estimate of 0,044. When the variable *technology* is accounted for, it seems as if the technology variable takes over the underlying relation between urbanization and high-skill occupational change. As technology is expected to cluster in city and urban like areas (Malecki, 1997), the technology estimate (-0,676) in table 7 can be interpreted as the more *urban* (higher share of technology occupations) the region, the *smaller* the increase in high-skill occupational share between 1998 and 2018. This is contradictory to the relation between rurality and high-skill occupational change, where the more *rural* the region, the *smaller* the increase in high-skill occupational share between 1998 and 2018. Meaning that the technology variable does not take over the urbanization mechanism, on the contrary, its relation with occupational change is the exact opposite. This relation is counterintuitive, as well as in stark contrast with the job polarization literature (Dauth, 2014; Davis et al, 2020). Nevertheless, the urbanization variable is significant in variation 5, and the R^2 did not decrease after the addition of the technology variable. Therefore, the variation remains relevant in the assessment of the relation between urbanization and occupational change. Though the implied relations in variation 5 remain difficult to interpret and explain.

Overall, the model in table 7 illustrates mixed results regarding the relation between urbanization and high-skill occupational change between 1998 and 2018. Three out of five variations (1,2,4) show negative coefficients, indicating that a more rural region tends to experience a smaller increase in high-skill occupations compared to more urban regions. This is in line with the expected relation between urbanization and high-skill occupational change according to job polarization literature and the hypotheses. However, variation 1 and 2 are two of these three variations, which are the variations with the least additional explanatory variables. The urbanization coefficients in variation 3 and 5, in which a larger subsets of explanatory variables are included, predict an opposite and counterintuitive relation between urbanization and high-skill occupational change. Namely that the rurality of a region has a positive relation with high-skill occupational change, meaning that a more rural region tends to experience a stronger growth in high-skill occupations over time. This entails that, based on the results of the second model, urbanization does not have a clear relation with high-skill occupational change between 1998 and 2018 on a regional level.

It is unclear as for why urbanization does not have a distinct relation with high-skill occupational change in the regression analysis, as figure 4 showed such an substantial difference in high-skill occupational growth between rural areas on one hand and cities and towns and suburbs on the other. There are two major aspects that are different in the regression analysis in chapter 4.3 opposed to the exploration of occupational changes in the three levels of urbanization in chapter 4.2. In the regression analysis, occupational changes are considered on a regional level rather than the pooled nine EU countries. Additionally, alternative explanatory variables are introduced and accounted for.

The change in the considered scale from the aggregate nine EU countries to a regional level has likely not affected the relation between urbanization and high-skill occupational change. Firstly, NUTS-2 regions are used as the regional dimension. These regions are substantial in size, entailing that high-skill occupational changes are evident in these regions, and therefore should not be a reason as for why the regressions on a regional scale did not produce results in line with the observed patterns in the exploration of the nine EU countries, as the regions are part of these very countries (as an indication, there are currently 242 NUTS-2 regions in the European Union and the UK (Eurostat, 2022d)). Secondly, the *share* living in rural areas is used as the urbanization variable in the regression analysis, rather than the alternative method of assigning a single urbanization level (rural area, towns and suburbs or city area) to a region. Utilizing the rural share thus ensures that the regional rurality is an accurate representation of the rurality of the individual and grouped countries. Therefore, conducting the analysis on a regional scale is likely not the reason for the different results regarding the relation between urbanization and high skill occupational change.

The remaining aspect that is inherently different in the regression analysis opposed to the prior exploration is the inclusion of alternative explanatory variables. In job polarization literature, these variables have a clear connection to occupational change over time, therefore having the potential to influence the relevance of urbanization in explaining occupational changes. The estimates of urbanization in table 7 are significant in all five variations, and show both a positive (two out of five variations) and a negative (three out of five variations) relation. Yet theoretically, it would make more sense that the addition of other explanatory variables would only alter the strength and relevance of urbanization in relation to high-skill occupational change, not the nature of the relation. Additionally, some of the alternative explanatory variables shown counterintuitive results, as has been discussed in the case of technology. It remains unclear as for why the alternative independent variables partially show counterintuitive results, and how these affect the relation between urbanization and high skill-occupational change. Because of lack in clarity on the connection between the inclusion of the additional variables and urbanization, it cannot be concluded that the addition of these variables is the main cause of the different patterns regarding high-skill occupational change in the exploration and regression analysis. Nevertheless, the addition of the alternative explanatory variables is one of the two prominent differences between the exploration and regression analysis, next to the regional dimension, the latter being unlikely to have affected the differences. Therefore, an influence of the additional variables in the regression analysis on the inconsistent relation between urbanization and high-skill occupational change cannot be ruled out either.

Education and occupational change

When taking a closer look at the relation between *share of lower educated* and occupational change between 1998 and 2018 on a regional level (table 6, 7 and 18), it becomes evident that regions with a higher share of lower educated tend to experience a replacement bias of the middle-skill occupations toward low-skill occupations. Table 6 illustrates that regions with a high share of lower educated have a negative relation with middle-skill occupational change, thereby strengthening the 'polarizing' decrease in middle-skill occupations. Table 18 (appendix) shows the third model, describing the relations between the independent explanatory variables with low-skill occupational change. Here it can be observed that in the third to fifth variation, the lower share education variable shows a strong positive influence on the low-skill occupational change between 1998 and 2018. This implies that a region with a high share of lower educated tend to experience a larger growth in the low-skill occupations between 1998 and 2018 compared to regions with a smaller share of lower educated. However, in the second variation the lower education coefficient is negative rather than positive. Although this variation includes less explanatory variables, this still indicates that the relationship between urbanization and low-skill occupational change is not unquestionably positive based on the model in table 18.

When looking at the influence of the regional share of lower educated on changes in the high-skill occupations between 1998 and 2018 in table 7, variations two and three show a positive relation between share lower education and occupational growth in high-skill occupations. This means that a region with a larger share of lower educated tend to experience a larger high-skill occupational change between 1998 and 2018 compared to regions with a smaller share of lower educated. Yet the estimate of the fourth variation is insignificant, and the estimate in the fifth variation is negative rather than positive. Therefore, lower education does not have a clear and transparent (positive) relation with high-skill occupational change.

Overall, the regional share lower educated has a moderate positive relation with low-skill occupational change, and no clear relation with high-skill occupational change. These results, albeit cautiously, hints that regions in the nine EU countries with a higher share of lower educated (lower secondary education) tend to experience a replacement bias of the middle-skill occupations toward low-skill occupations between 1998 and 2018. This is in line with the findings of Autor (2019) in a US-context, concluding that the decline in middle-skill occupations between 1970 and 2016 has been disproportionately redirected toward low-skill jobs for non-college educated compared to college graduates.

To summarize, the exploration of the occupational changes in the nine EU countries between 1998 and 2018 resembled patterns of job polarization. The occupational changes in the nine EU countries is characterized by a shift from middle-skill occupations toward high-skill occupations in the first decade, and a shift from middle-skill occupations toward low-skill occupations in the second decade. Adding an additional urbanization distinction revealed that the job polarization patterns are persistent on all urbanization levels, in line with the first hypotheses. The occupational changes in the different degrees of urbanization revealed clear differences between cities and towns and suburbs on the one hand, and rural areas on the other. The most prominent differences between the two are the stronger decrease in middle-skill occupations and the stronger growth in the high-skill occupations between 1998 and 2018 in cities and towns & suburbs. These findings relate to the findings of Davis et al. (2020), which found similar patterns in their study, researching the relation between urbanization and job polarization in French cities. They concluded that city size is significantly related to the decline in middle-skill occupations, and that the lost jobs in the larger cities tend to get substituted in favour of the high-skill occupations (Davis et al 2020). Likewise, these patterns are similar to the observed occupational changes in the different levels of urbanization, namely a larger decrease in middle skill occupations and larger increase in high skill occupations in cities opposed to rural areas.

When further looking into the significance of these findings through the analysis of the relation between urbanization and alternative explanatory variables on the one hand, and regional occupational changes in either low-, middle- or high-skill occupations in the other, some mixed results came to light. Overall, the variable *share living in rural areas* roughly accounted for a larger growth in the low-skill occupations and a smaller decrease in the middle-skill occupations. The results did not support the expected job polarizing relation between urbanization and high-skill occupational changes (I.e. a higher regional *share living in rural areas* resulting in a smaller high-skill occupational growth between 1998 and 2018). In other words, a region being more *rural* tend to result in a smaller decrease in the share of middle-skill occupations and a larger increase in the share of low-skill occupations over time. A region having a higher share living in rural areas had no decisive influence on high-skill occupational change. These findings contradict with the second hypothesis. Of the changes in the three occupational skill-levels between 1998 and 2018, only the changes in middle-skill occupations tend to be stronger in *urban* regions opposed to rural regions, whereas the hypothesis predicted larger changes in urban regions all across the board (i.e. a larger increase in the share of low- and high-skill occupations, and a larger decrease in middle-skill occupations). Furthermore, as the degree of regional rurality could not significantly predict high-skill occupational changes between 1998 and 2018, a replacement bias from middle-skill occupations toward high-skill occupations in *urban* regions of the nine EU countries could not be concluded. Interestingly, as the share living in rural areas roughly accounted for the growth in the low-skill occupations (4 out of 5 variations, table 6) and showed a significant relation with the middle-skill occupational changes, a replacement bias from middle-skill occupations toward low-skill occupations in *rural* regions could cautiously be concluded.

The addition of the technology variable *regional occupational share in science and technology* produced counterintuitive results. Following theory, technology was expected to impact job polarization in a comparable manner as urbanization variable *share living in rural areas* (Micheals et al., 2014). But when technology was added in the second model, considering changes in high-skill occupations, share living in rural areas lost relevance in explaining occupational changes. Rather than taking over the relation, the variable technology showed an relation in the opposite direction, predicting a smaller increase in high skill occupations for urban regions compared to rural regions rather than a stronger increase. Additional research should further analyse and assess the characteristics and aspects of urbanization, beyond population density, to improve understanding of the different patterns on job polarization experienced by the different levels of urbanization.

5 - Conclusion

Key findings

In this research, job polarization has been discussed in relation to urbanization in a European context. Data of the EULFS and from Eurostat were used to analyse changes in the occupational structure of nine European countries between 1998 and 2018, for different levels of urbanization. The nine European countries that were part of the analysis showed distinct patterns of job polarization. These countries experienced a decrease in the share of middle-skill occupations, with a simultaneous increase in low- and high-skill occupations. This is in line with Goos et al. (2009, 2014) their results, who similarly analysed job polarization patterns in a European context. When an additional distinction based on urbanization level was introduced, isolating the occupational changes between 1998 and 2018 for cities, towns and suburbs and rural areas, the results showed occupational changes in line with job polarization patterns for all categories. Cities and towns & suburbs showed very similar occupational changes, characterized by a larger decrease in middle-skill occupations and a larger increase in high-skill occupations compared to rural areas.

To evaluate whether these differences in occupational changes between cities and towns & suburbs opposed to rural are significant, occupational changes between 1998 and 2018 in the three occupational skill-categories were analysed in relation to the urbanization variable population *share living in rural areas*, on a regional scale. In this analysis, several independent variables that are expected to have an influence on occupational change were included to explore the persuasiveness of the relation between urbanization and occupational change, such as education and sectoral composition (Autor, 2019; Cirillo, 2018). The results showed that urbanization did not have the expected relation with changes in low- and high-skill occupations. When accounting for several other explanatory variables, rurality roughly predicted a smaller decrease in middle-skill occupations. This is in line with the prior exploration that specified a smaller decrease in the share of middle-skill occupations for rural areas. The analysis showed that a higher regional share of rural areas tend to predict a larger increase in low-skill occupational change between 1998 and 2018, implying a replacement bias toward low-skill occupations in rural regions. Strikingly, the assessment of the estimates of the regional share living in rural areas did not result in a decisive positive nor negative relation with high-skill occupational change. Further examination of both the estimates and the contextual factors of the regression analysis did not result in a clear theory as for why this relation between urbanization and high-skill occupational change, or the lack thereof, was found.

Generalizability & limitations

Even though the aforementioned conclusions are based on data of 9 countries with a substantial number of cases (1.645.008), the generalization of the results to Europe as a whole is limited. This is because three countries with a major economic presence and relevance in the European context (i.e. France, Germany and the United Kingdom) are not included, and thus not represented in the data. Additionally, the data of the EULFS uses random sampled households, entailing that individuals in the dataset are not tracked over time. Changes in one’s personal occupation in relation to other characteristics, such as recently attained education or changes in residence, are not included and therefore cannot be accounted for.

Future Research

The results of the nine European countries showed different job polarization patterns when considering different levels of urbanization between 1998 and 2018. The analysis revealed that urbanization was roughly able to explain the regional occupational changes in the low- and middle-skill occupations. Though when accounting for different subsets of alternative explanatory variables, urbanization did not show a distinct relation with high-skill occupational change. Future research could aim to include more European countries using a similar research design, to research whether the job polarization patterns of different levels of urbanization would change with the addition of more countries, and to improve representativeness of- and generalizability to Europe as a whole. Additionally, future research on the characteristics and aspects of urbanization beyond population density could improve the understanding of the different job polarization patterns in urban and rural regions. This could support policy makers and (local) governments in addressing-, and if needed, compensating for these trends.

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Appendix

Urbanization comparison

Table 8 – Urbanization distribution per country, in percent, by EULFS and Eurostat urbanization.

Country	Category	EULFS Urbanization (N - Observations)	Eurostat Urbanization (N - Observations)	NUTS-2 regions ** (Eurostat)
Belgium	1 (Cities)	45,0 (40.291)	11,8 (10.689)	1
	2 (Towns and suburbs)	44,3 (40.291)	76,8 (69.840)	8
	3 (Rural areas)	10,7 (9698)	11,4 (10.361)	2
	Total	100 (90.890)	100 (90.890)	11
Portugal	1	37,3 (55.566)	17,9 (26.600)	1
	2	35,7 (53.059)	18,9 (28.189)	2
	3	27,0 (40.186)	63,2 (94.022)	4
	Total	100 (148.811)	100 (148.811)	7
Greece	1	57,3 (108.171)	0 (0)	0
	2	21,5 (40.587)	31,2 (58817)	2
	3	21,2 (40.001)	66,1 (124.831)	12
	Missing	-	2,7 (5.111)	
	Total	100 (188.759)	100 (188.759)	14
Combined	1	47,8 (204.638)	8,7 (37.289)	2
	2	31,3 (133.937)	36,6 (156.846)	12
	3	21,0 (89.885)	53,5 (229.214)	18
	Missing	-	1,2 (5.111)	
	Total	100,0 (428.460)	100 (428.460)	32
Combined Weighted	1	50,4 (18.471)	13,4 (4.923)	2
	2	34,7 (12.697)	43,5 (15.917)	12
	3	14,9 (5.452)	42,7 (15.632)	18
	Missing	-	0,4 (149)	
	Total	100 (36.621)	100 (36.621)	32

Notes – Data from Eurostat is aggregated from NUTS-3 regions to NUTS-2 regions. All observations of a particular NUTS-2 region from Eurostat have the same ''urbanization category'', whereas the observations of a particular NUTS-2 region from the EULFS include all three types of urbanization.

*** The distribution of the NUTS-2 regions corresponds with the aggregated Eurostat urbanization distribution. Only the 'total' NUTS-2 value is relevant for both EULFS and Eurostat.*

Source - European Union Labour Force Survey 1998 – 2018.

Table 9 – Percentage point changes in occupational employment shares per skill-category, for different urbanization levels, Belgium, Portugal, Greece, 1998 - 2018. **EULFS URBANIZATION.**

		1998 - 2008	2008 - 2018	1998 – 2018 (total)
Baseline	Low-skill	1,7	3,5	5,2
	Medium-skill	-4,6	-7,3	-11,9
	High-skill	2,9	3,8	6,7
Cities	Low-skill	2	4,1	**6,1**
	Medium-skill	-5	-9,1	-14,1
	High-skill	3	5,1	8,1
Towns and Suburbs	Low-skill	2,1	1,9	4
	Medium-skill	-5	-8,9	-13,9
	High-skill	-0,1	7	6,9
Rural Area's	Low-skill	-0,4	3,6	3,2
	Medium-skill	-1,7	-6,3	-8
	High-skill	1,9	2,8	4,7

Source - European Union Labour Force Survey 1998 - 2018

Table 10 – Percentage point changes in occupational employment shares per skill-category, for different urbanization levels, Belgium, Portugal, Greece, 1998 – 2018. **EUROSTAT URBANIZATION.**

		1998 - 2008	2008 - 2018	1998 – 2018 (total)
Baseline	Low-skill	1,7	3,5	5,2
	Medium-skill	-4,6	-7,3	-11,9
	High-skill	2,9	3,8	6,7
Cities	Low-skill	-0,9	-0,9	**-1,8**
	Medium-skill	-4,5	-9,7	-14,2
	High-skill	5,3	10,6	15,9
Towns and Suburbs	Low-skill	1,9	3,2	5,1
	Medium-skill	-4,1	-5,5	-9,6
	High-skill	2,2	2,2	4,4
Rural Area's	Low-skill	2,2	5	7,2
	Medium-skill	-5,2	-8	-13,2
	High-skill	2,8	3,1	5,9

Source - European Union Labour Force Survey 1998 - 2018

Changes in occupational employment share for different levels of Urbanization

Table 11 - Levels and changes in Occupational Employment Shares in **cities**, nine EU countries, 1998-2018.

Occupations ranked by mean European wage	Average employment share in 1998 (in percent)	Average employment share in 2008 (in percent)	Average employment share in 2018 (in percent)	Percentage point change 1998 - 2008	Percentage point change 2008 - 2018	Percentage point change 1998 - 2018
High-paying occupational groups	**37,4**	**43,6**	**45,4**	**6,2**	**1,8**	**8**
Managers	7,8	8,7	4,9	0,9	-3,8	-2,9
Professionals	15,1	16,6	24,3	1,5	7,7	9,2
Technicians and associated professionals	14,5	18,3	16,2	3,8	-2,1	1,7
Middling occupational groups	**38,6**	**32,7**	**26,4**	**-5,9**	**-6,3**	**-12,2**
Clerical support workers	14,2	12,5	11,4	-1,7	-1,1	-2,8
Craft and related trades workers	16	13	9,3	-3	-3,7	-6,7
Plant and machine operators and assemblers	8,4	7,2	5,7	-1,2	-1,5	-2,7
Low-paying occupational groups	**24**	**23,7**	**28,2**	**-0,3**	**4,5**	**4,2**
Service and sales workers	14,5	13,9	18,3	-0,6	-0,6	3,8
Elementary occupations	9,5	9,8	9,9	0,3	0,3	0,4

Notes for table 11, 12 and 13: Occupational groups are ordered based on mean wage rankings used by Goos et al. (2014) and Cirillo (2018). Employment shares and percentage point changes are based on 9 European countries from EULFS, pooled. Included countries: Austria, Belgium, Czechia, Greece, Spain, Finland, Hungary, Italy and Portugal. Occupational groups are derived from ISCO-1-digit codes, excluding armed forces & skilled agricultural, forestry and fishery workers.
Source – Own calculations based on European Union Labour Force Survey 1998 – 2018.

Table 12 – Levels and changes in Occupational Employment Shares in **towns and suburbs**, nine EU countries, 1998-2018.

Occupations ranked by mean European wage	Average employment share in 1998 (in percent)	Average employment share in 2008 (in percent)	Average employment share in 2018 (in percent)	Percentage point change 1998 - 2008	Percentage point change 2008 - 2018	Percentage point change 1998 - 2018
High-paying occupational groups	**28,9**	**36,6**	**36,3**	**7,7**	**-0,3**	**7,4**
Managers	6,3	8,7	4,6	2,4	-4,1	-1,7
Professionals	10,1	10,7	16	0,6	5,3	5,9
Technicians and associated professionals	12,5	17,2	15,7	4,7	-1,5	3,2
Middling occupational groups	**45,9**	**39,7**	**34,7**	**-6,2**	**-5**	**-11,2**
Clerical support workers	11,5	10,7	10,7	-0,8	0	-0,8
Craft and related trades workers	22,5	18,6	14,6	-3,9	-4	-7,9
Plant and machine operators and assemblers	11,9	10,4	9,4	-1,5	-1	-2,5
Low-paying occupational groups	**25,1**	**23,7**	**29**	**-1,4**	**5,3**	**3,9**
Service and sales workers	14,7	13,5	18,8	-1,2	-1,2	4,1
Elementary occupations	10,4	10,2	10,2	-0,2	-0,2	-0,2

Notes – see notes table 11.

Table 13 - Levels and changes in Occupational Employment Shares in **rural areas**, nine EU countries 1998-2018.

Occupations ranked by mean European wage	Average employment share in 1998 (in percent)	Average employment share in 2008 (in percent)	Average employment share in 2018 (in percent)	Percentage point change 1998 - 2008	Percentage point change 2008 - 2018	Percentage point change 1998 - 2018
High-paying occupational groups	**25,8**	**31,3**	**29,5**	**5,5**	**-1,8**	**3,7**
Managers	7,2	8,4	4	1,2	-4,4	-3,2
Professionals	8,3	8,6	11,9	0,3	3,3	3,6
Technicians and associated professionals	10,3	14,3	13,6	4	-0,7	3,3
Middling occupational groups	**46**	**41,8**	**38,9**	**-4,2**	**-2,9**	**-7,1**
Clerical support workers	8,9	8,7	9,5	-0,2	0,8	0,6
Craft and related trades workers	23,5	20,4	17,3	-3,1	-3,1	-6,2
Plant and machine operators and assemblers	13,6	12,7	12,1	-0,9	-0,6	-1,5
Low-paying occupational groups	**28,2**	**26,9**	**31,5**	**-1,3**	**4,6**	**3,3**
Service and sales workers	15,4	14,9	19,9	-0,5	-0,5	4,5
Elementary occupations	12,8	12	11,6	-0,8	-0,8	-1,2

Notes - see notes table 11.

Frequency tables

Table 14 – Frequency table gender, nine EU countries, 1998 – 2018.

	Frequency	Percent
Male	106037	57,3
Female	79095	42,7
Total	185132	100

Source - European Union Labour Force Survey 1998 - 2018.

Table 15 – Frequency table education, nine EU countries, 1998 – 2018.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Low	60853	32,9	32,9	32,9
	Middle	77233	41,7	41,8	74,7
	High	46849	25,3	25,3	100
	Total	184935	99,9	100	
Missing	System	197	0,1		
Total		185132	100		

Notes: Low education = lower secondary, Middle education = higher secondary, High education = third level.
Source - European Union Labour Force Survey 1998 - 2018.

Table 16 – Frequency table age, nine EU countries, 1998 – 2018.

	Frequency	Percent	Cumulative Percent
17	2622	1,4	1,4
22	12306	6,6	8,1
27	20676	11,2	19,2
32	24304	13,1	32,4
37	25532	13,8	46,2
42	26696	14,4	60,6
47	24970	13,5	74,1
52	22149	12	86
57	15775	8,5	94,5
62	7483	4	98,6
67	1750	0,9	99,5
72	573	0,3	99,8
77+	297	0,2	100
Total	185132	100	

Source - European Union Labour Force Survey 1998 - 2018.

Table 17 – Frequency table Degree of Urbanization, nine EU countries, 1998 - 2018

	Frequency	Percent	Cumulative Percent
Cities	80205	43,3	43,3
Towns and Suburbs	62831	33,9	77,3
Rural Areas	42097	22,7	100
Total	185132	100	

Source - European Union Labour Force Survey 1998 - 2018.

Regression analysis

Table 18 – Explaining occupational change in low-skill occupations, standardized coefficients and significance, nine EU countries, 1998 – 2018. *(Dependent variable - Occupational percent point change 1998-2018)*

		(1)	(2)	(3)	(4)	(5)
Urbanization	Share living in Rural Areas	0,080 <0,001**	0,070 <0,001**	-0,060 <0,001**	0,765 <0,001**	0,113 <0,001**
Education	Low	—	-0,488 0,000**	0,763 <0,001**	0,425 <0,001**	1,379 0,000**
	High	—	0,040 <0,001**	0,279 <0,001**	0,637 <0,001**	0,194 <0,001**
Regional Characteristics	GDP	—	—	-0,965 0,000**	-0,545 <0,001**	-1,666 0,001**
	Economically Active population	—	—	0,783 0,000**	1,129 0,000**	1,395 0,001**
Employment Share	Technology	—	—	—	—	0,290 <0,001**
Sectoral Share *(NACE)*	**C-F** - Industry	—	—	—	-0,361 <0,001**	-0,419 <0,001**
	J-K - Financial Intermediation; Real Estate	—	—	—	-0,482 <0,001**	—
	L-Q -Public administration and community services	—	—	—	0,759 <0,001**	—
	R^2	0,393	0,398	0,403	0,439	0,405

Notes: Dependent variable – Percent point change (of occupations per region). All models include region dummies. All models also include gender-ratio and average age on a regional level. The variables GDP and Economically Active Population are logarithmic scaled. Case selection - Low skill occupations (1-digit ISCO codes 500 and 900, Service and Sales workers and Elementary Occupations respectively). Source – own calculations based on EULFS data. Source - European Union Labour Force Survey 1998 - 2018.

*** Significant at the 1 percent level.*

** Significant at the 5 percent level.*