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OCCUPATIONAL CHANGE, ARTIFICIAL INTELLIGENCE AND THE GEOGRAPHY OF EU LABOUR MARKETS

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We study the nature and geography of occupational change in 24 European Union countries from 2002 to 2016. We evaluate how the composition of skills in the labour force depends on new technologies enabled by artificial intelligence and machine learning, and on institutional variables including educational attainment, labour legislation and product market regulations. We find that on average, EU countries have been through an upgrading of the skills of their occupational structures, rather than a pervasive polarisation. However, job polarisation is significant for workers without university degrees. Moreover, the European debt crisis has led to some job polarisation, which is particularly evident in urban centres. The changes in occupational structures appear to vary substantially across European Union regions. Cities, followed by suburban areas and towns, have suffered the largest declines in mid-skilled jobs. On the potential impact of new technologies, we find that low-skill mid-skill jobs are significantly exposed. Occupational changes caused by these technologies are likely to be more concentrated in cities and suburban areas. Last but not least, countries with high degrees of labour flexibility, high quality science education and less pervasive product market regulations tend to have higher skill-oriented occupational structures.

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1 Introduction

The impact of technology on skills and occupations has attracted the attention of economists and has generated significant contributions in the last three decades. Based on quantitative evidence and case studies, the first important conclusion has been the so-called skill-biased technical change (SBTC) hypothesis, according to which technology favours skilled over unskilled labour by increasing its relative productivity and, therefore, the relative demand for it. This skill-upgrading hypothesis was used to explain the rise of wage inequality in the US which started in early 1980s, shortly after the adoption of personal computers, suggesting that this new technology played a role in the divergence in the wages of different worker skill groups (Katz, 1999). High-skill workers and those with some years of schooling were more likely to use computers for job tasks (Krueger, 1993). As computers improved the efficiency of workers, there was a rise in demand for high-skill and highly-educated workers, which led to an increase in their wage relative to unskilled workers.

Criticism of this hypothesis appeared in the early 2000s. For example, Card and Di Nardo (2002) pointed out that wage inequality remained relatively stable during the 1990s, despite the continuing advances in computer technologies. They also concluded that SBTC fails to explain gender and racial wage gaps, or the return to education for different age groups.

Autor *et al* (2003) showed that computer capital substitutes for workers in performing routine cognitive and manual tasks, but complements workers in performing non-routine problem solving and complex communications tasks. Routine tasks include manual craft jobs that require precision and, hence, were never the lowest-paid jobs on the labour market, but are rather in the middle of the skill spectrum. Non-routine tasks include skilled professional and managerial jobs that tend to be in the upper part of the wage distribution. But they also include low-skill and low-wage jobs including personal service, cleaning or other work that requires a degree of dexterity or a set of inter-personal skills that robots do not have.

The implication of this routine biased technical change (RBTC) hypothesis, therefore, is that there is a more nuanced relationship between technology, skills and occupations that goes beyond the predictions of SBTC. The routinisation hypothesis provides an alternative explanation, according to which technology leads to job polarisation (Goos and Manning, 2007). It leads to rising relative demand for well-paid skilled jobs, typically requiring non-routine cognitive skills, and for low-paid least-skilled jobs requiring non-routine manual skills. This in turn, leads to falling relative demand for middle-skilled jobs that have typically required routine manual and cognitive skills. Autor and Dorn (2013) provided a unified theory that explains job polarisation which does not only involve the RBTC hypothesis, but also task offshoring (which is itself partially influenced by technological change) through the reallocation of low-skilled labour to service occupations. Goos *et al* (2009, 2014) provided evidence of pervasive job polarisation in 16 Western European advanced economies from 1993 to 2010. In Germany, Spitz-Oener (2006) has shown that greater use of ICT by workers has reduced the importance of routine work.

Other authors are more critical of the RBTC hypothesis. Fernandez-Macias and Hurley (2017), argued that the concept of routine occupations is elusive, making any evaluation of routine jobs hard to achieve. They also argued that routine tasks are not associated with skills in the non-linear polarised way predicted by RBTC, or with the observed cases of job polarisation in Europe from 1995 to 2007. Oesch and Piccitto (2019), covering a more limited sample of EU countries between 1992 and 2015, found evidence of occupational upgrading rather than polarisation. They based this conclusion on a wide set of measures and ranked occupations beyond income, notably by also including prestige, education and job satisfaction. However, one could argue that these measures are not better suited than income alone to measure the skill intensity of occupations.

The first objective of our paper is to evaluate the nature of occupational change in 24 EU countries from 2002 to 2016. To our knowledge, we are the first to consider a nearly EU-wide study, which also captures the aftermath of the prolonged European debt crisis. Previous studies have only focused on industrialised EU countries (Oesch and Piccitto, 2019; Cirillo, 2018; Goos *et al*, 2014) or on the older member states excluding newer EU members (Fernandez-Macias and Hurley, 2017).

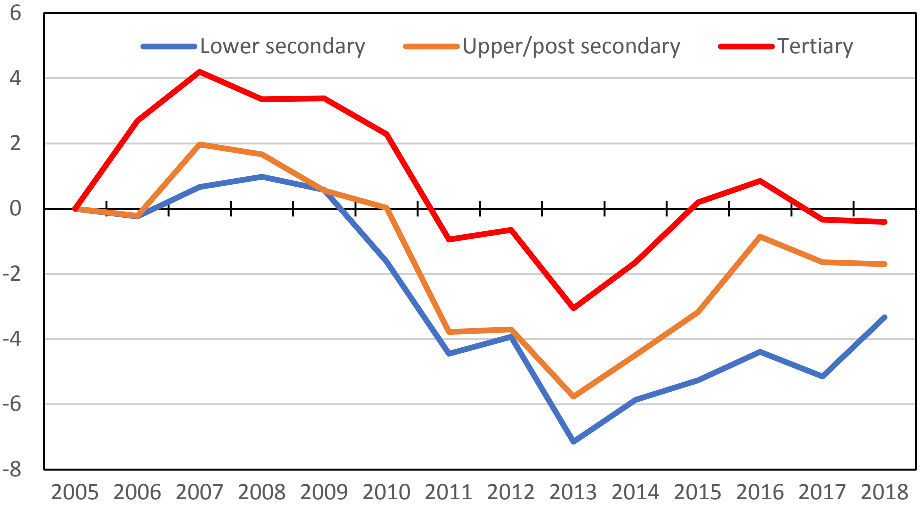
We also add a geographical differentiation aspect to the study of occupational change in the EU. We are specifically interested in capturing how skills evolve in regions of different population density and different organisational structures. Finally, we make inferences about the potential risks new technologies, such as machine learning and artificial intelligence (AI), would create for labour markets, as they might be the next technological disruptive force after digitalisation. To do so, we use the probability-of-automation score created by Nedelkoska and Quintini (2018), which measures the probability and the potential of new technologies to replicate work tasks. We also compare how the countries in our sample perform on this score. We construct an index of skill upgrading for each country (upskilling index) and we examine the relationship between this index and the probability-of-automation score for the countries of our sample. We also compare this relationship with the correlation between our upskilling index and the average of the occupational intensity of ICT in each country.

Lastly, we study how our upskilling index depends on institutional variables in each country, such as the flexibility of work (as it is computed for national labour legislation), the quality of education and how pervasive product market regulations are.

Our methodology is inspired by Autor (2019) who dealt with the paradox of the sustained fall in the real wages of less-educated workers, leading to increased wage inequality. Because of the rapid increase in the educational attainment of the US labour force, one would expect that the less-educated, who are in shorter supply, would see their wages rising to reach a market clearing supply and demand equilibrium. However, available evidence suggests the opposite. The wage differential between more- and less-educated workers has sharply increased over recent decades. Autor (2019) provided a new avenue for explaining this paradox that relies on the observation that polarisation has not unfolded evenly in different geographical areas.

Over the period 2005 to 2016, we observe that overall, for all educational groups, the post-2009 period saw real wage declines initially, followed by a mild recovery from 2013. Over the whole period, from 2005 to 2016, real wages tended to stagnate in EU countries. Differentiating by educational attainment groups, we observe that workers with different levels of educational attainment faced different real wage dynamics over the studied period (Figure 1). Notably, higher educated workers experienced positive real wage growth between 2005 and 2018, with a 1.9% increase. Upper and post-secondary educated workers saw their real wages increase less, by 1.5% over the same period. The real wages of lower secondary educated workers were constant. A common characteristic in each educational group is that during the recovery from the crisis, the cumulative growth of real wages has not reached pre-crisis levels (which peaked in 2007). We seek to investigate whether the aforementioned developments in wages match changes in occupational structures of the sample as a whole and for different educational groups. We do not argue that these changes are the sole driver of the wage differentials observed in Figure 1. But they might have played a role.

Figure 1: Cumulative percentage changes in real yearly wages by educational attainment in selected EU counties, 2005-2018



Source: Bruegel. Note: Data obtained from Eurostat based on EU-SILC and adjusted using country level inflation data from Eurostat, the data is aggregated using population weights obtained from Eurostat. The data used is the equivalised median income per educational category on a country level. To take into account the impact of differences in household size and composition, the total disposable household income is 'equivalised'. The equivalised income attributed to each member of the household is calculated by dividing the total disposable income of the household by the equivalisation factor. The country level series are created using the country level CPI and then aggregated using population weights. Then, the cumulative percentage change is calculated.

We find that on average, over the whole period considered, the EU countries of our sample experienced an upskilling of their occupational structures rather than a polarisation, though this finding is modified by a trend towards some polarisation after 2009. Mid-skill jobs declined substantially between 2002 and 2016, and especially after 2009. The opposite trend is observed for high-skill occupations, for which we see sharp increases. Nevertheless, low-skill jobs have on average only slightly increased. Whether this can be referred to as polarisation is debatable as there is no clear criterion for such a qualification. Furthermore, the rise in low-skill jobs accelerated after the financial crisis, raising concerns about a long-lasting negative impact of the economic downturn. Another important factor to be considered is education. We provide evidence that a large part of the skill upgrading of occupations in the EU labour market might have been driven by a large increase in the educational attainment of the EU labour force.

The changes in occupational structures also appear to vary substantially across geographies. We study these changes with respect to population densities in European regions and also by comparing cities with suburbs and rural areas. Our findings suggest that interregional inequalities in terms of occupational structures did not increase over the studied period. However, cities, followed by suburban areas and towns, suffered the largest declines in mid-skilled jobs.

On the technology side and the potential impact of AI and machine learning, we find that our measure, the probability-of-automation score, is particularly high for low-skill and middle-skill occupations, while it is rather low for the high-skill occupations. Moreover, technology related occupational changes are likely to be more concentrated in cities and suburban areas. We also find that not all European countries are exposed to these changes to the same degree, as countries with large shares of high-skill jobs tend to be less affected.

Our analysis at the country level reveals that the number of countries with polarised trends across the different skill groups increased from 2009, suggesting that bad economic downturns trigger some degree of job polarisation, which is observed even in the recovery phase. New machine learning technologies seem to interact in a similar way with the occupational ICT intensity. Moreover, countries with high degrees of labour flexibility, high quality science education and less-pervasive product market regulations tend to have higher skill-oriented occupational structures.

Our paper is structured as follows: in the second section we introduce the data and methodology we employed to measure occupational change. In the third section, we look at the EU labour market overall and examine what type of occupational change occurred between 2002 and 2016, differentiating between educational groups. In the fourth section we evaluate occupational change across geographies. In the fifth, we look at the potential impact of machine learning technologies on occupational change. In the sixth section we evaluate the country-level changes in occupational structures, exposure to machine learning technology and correlations between upskilling and institutional variables. In the seventh section, we conclude.

2 Data and methodology

We rely on the European Union Labour Force Survey (EU-LFS), which is a large household survey providing quarterly results on labour participation of people aged 15 and over, as well as on persons outside the labour force, covering the whole of the European Union. In our sample, employment comprises all persons of working age who during the given year, have worked for at least a week either full-time or part-time, as employees or self-employed. We also use the European Union Statistics on Income and Living Conditions (EU-SILC) survey to obtain average wages associated with each occupation category, in order to rank them. The EU-SILC is an instrument aiming at collecting timely and comparable cross-sectional and longitudinal multidimensional microdata on income, poverty, social exclusion and living conditions in the EU over time.

The countries of our sample are 24 EU countries: all members except Bulgaria, Croatia, Malta and Romania. The pre-Brexit United Kingdom is part of our sample[1, 2].

The definition of high, middle and low-skill occupations is based on Autor (2019)[3], which is in turn based on the work of Autor and Dorn (2013). In these papers, the authors divided occupations into 12 categories which they define as having similar properties based on characteristics including routine intensity of the work, average educational attainment of the workers, and employment dynamics[4]. Similarly, we rank occupational categories, based on average monthly income, using EU-SILC data for

[1] Because of data limitations, Poland, Slovakia, Estonia, Slovenia, Ireland and Lithuania are not included in the part of our analysis which relies on the variable ‘degree of urbanisation’.
[2] For Figure 8, the Netherlands, Denmark and Finland are each treated as one region because of the lack of regional information in their data.
[3] We also check for robustness using another ranking method, notably based on the PIAAC survey of the OECD, to create a non-income-based measure of skills (OECD, 2015). As such we ranked occupations based on their average score for 6 composite PIAAC variables: reading, writing, numeracy, ICT, influencing and planning, and organising. This ranking leads to a similar ranking of occupations with the difference of transportation and material moving occupations falling under the low skill category and the sales occupations under the mid skill category. Using the PIAAC occupational ranking leads to similar overall results with the income-based ranking described above.
[4] We use 11 categories because the EU service sector occupation classification is too aggregated to split these occupations into three categories. We therefore split them into two categories: 1) Food prep, buildings and grounds, cleaning; and 2) Personal care and personal services.

2005 (Table 1)[5]. To account for differences in skill intensity of occupational categories in different countries, a different ranking is used for each country in the analysis based on local wage information. We assumed here, in line with previous literature (see relevant discussion in the introduction), that wages are reflective of the skill intensity of occupations. In line with this, the distribution of occupational categories is split between high, middle and low-skill by considering that the three first categories are high skill, the next four are middle skill and the last four are low-skill occupations.

Table 1: Occupational categories rankings of high, middle and low-skill workers[6]

Occupational Title	Average monthly income in 2005 (EUR)
Managers	€ 45,713.00
Professionals	€ 31,196.00
Technicians	€ 26,446.00
Office and admin	€ 20,339.00
Mechanics and repairers and construction workers	€ 19,824.00
Transportation and material moving occupations	€ 19,156.00
Precision production and machine operators	€ 17,331.00
Food prep, buildings and grounds, cleaning	€ 16,357.00
Personal care and personal services	€ 14,026.00
Agriculture	€ 12,595.00
Sales	€ 11,296.00

Source: EU SILC.

Employment in each skill group as a share of total employment is calculated for each given year. In addition, employment shares and average wages are calculated for three different categories of educational attainment provided in EU-LFS and EU-SILC. The first category, lower secondary and primary educated workers, typically refers to workers who left education at an age of around 16 years old, after having completed compulsory primary and secondary education, with either a qualification allowing them to continue to an upper secondary programme or without a secondary qualification at all. Upper/post-secondary educational attainment usually refers to workers who left formal education around the age of 18. Typically, upper/post-secondary educated workers have a vocational educational degree or a general upper secondary degree giving them access to tertiary education. Tertiary educated workers have completed a diploma of higher education, typically a university degree such as a bachelor or master's degree, or an advanced vocational degree.

[5] We use data from 2005 since it allows us to rank occupations at a country level, as data from years prior to 2005, like the European Community Household Panel (ECHP), only covers a subset of countries in our sample. We nonetheless checked if using older data would have had a significant impact on the occupational category ranking. Using data for 1995 from seven countries (Denmark, Belgium, Luxembourg, France, United Kingdom, Ireland and Portugal) we concluded with exactly the same skill categories.

6 Our analysis required several crosswalks between occupational classifications to be made. First, from 2011 onwards the EU-LFS classifies occupations according the ISCO08 standard, whereas before that year it used ISCO88. To make our results comparable over time we therefore used the ISCO88 – ISCO08 crosswalk provided by ILO, to convert the crosswalk of ISCO88 occupations to the Autor and Dorn (2013) occupational categories to the ISCO08 standard. While these crosswalks are done at a 3-digit level, there is still some loss of information since some ISCO88 occupations are not matched by a single ISCO08 occupation. We decided to use the most prevalent ISCO08 occupation in that case. Also, in the special case of ISCO88 occupation 'Managers of small enterprises', which translates into several very different ISCO08 occupations, we decided to drop this occupation altogether to reduce the bias its mapping to a single ISCO08 occupation could cause. Also, since the occupational categories of Autor and Dorn (2013) were linked to the US Census Standard Occupational Classification 1990 (US SOC 1990) system, a conversion of those to ISCO was required. For this purpose, we employed the crosswalk created by Ganzeboom and Treiman (2019) between ISCO88 and US SOC 1990.

Table 2: Educational categories

Education level	Acronym	ISCED level
Lower secondary and primary	L Sec	0-2
Upper/post-secondary	U/P Sec	3-4
Tertiary	Uni	5-8

We also link employment with regional differences in EU countries. Employment shares in each local labour market were derived at a NUTS2 level and then aggregated into population density bins by taking their average, weighted by the total employment in the region. The regional data on population densities was obtained from Eurostat's regional database of population densities and then matched to the regional information from the EU-LFS. This procedure was performed such that each bin represents approximately 5% of the EU employed population in a given year[7]. The employment shares that result from this procedure were then adjusted by subtracting the overall employment share of each skill group level in 2002 (first year of the analysis), irrespective of the population density, to shed light on variations in employments share per skill level for each density. As NUTS2 level is still quite aggregated, extending well beyond the city level, we also developed an alternative approach in which we rely on a 3-category discretionary scale of the degree of urbanisation, provided by EU-LFS. The degree of urbanisation scale is measured at the respondent's local administrative unit level, which is the most granular scale available for European countries and may refer to a range of different administrative units, including municipalities, communes, parishes or wards. The degree of urbanisation of the respondent's local administrative unit is based on a criterion of geographical contiguity in combination with a minimum population threshold based on population grid square cells of 1 square kilometre. Respondents' places of residence are reported in three categories of population density: low (rural areas), medium (towns and suburb areas) or high (cities). We use the degree of urbanisation index to help us to study the geographical aspect of job polarisation.

Furthermore, we study how skills are related to AI and machine learning. We use the probability-of-automation score developed by Nedelkoska and Quintini (2018) to assess the exposure to machine learning of tasks and occupations using the OECD Survey of Adult Skills (PIAAC) database. We compute the probability-of-automation score at EU-LFS level for European occupations. The higher the probability-of-automation score of a given occupation is, the greater its potential exposure to machine learning and AI. At the same time, we use the information provided by the occupation-level PIAAC database to construct a variable that measures the ICT intensity of work in different countries (OECD, 2015). We define the ICT skill intensity of an occupation as the weighted average ICT skill intensity across all PIAAC countries in our sample. We take the average of all countries in our sample participating in PIAAC, since country-level occupational samples are too small to be representative and certain countries in our sample are not covered by the PIAAC dataset.

Finally, to compare our results with certain institutional variables reflective of labour market flexibility and production market openness, we employ two off-the-shelf indexes. Firstly, we use the labour market flexibility index created by Schwab and Sala-i-Martín (2018) as the 7th pillar of its Global Competitiveness Index. Labour market flexibility is measured as a composite index based to a large extent on an Executive Opinion Survey of the World Economic Forum, which includes, for example, measures of cooperation in labour-employer relations, flexibility of wage determination, capacity to retain talent, and also quantitative measures such as average redundancy costs and female participation in the labour force. To measure rigidities in the goods market, we employ the OECD's

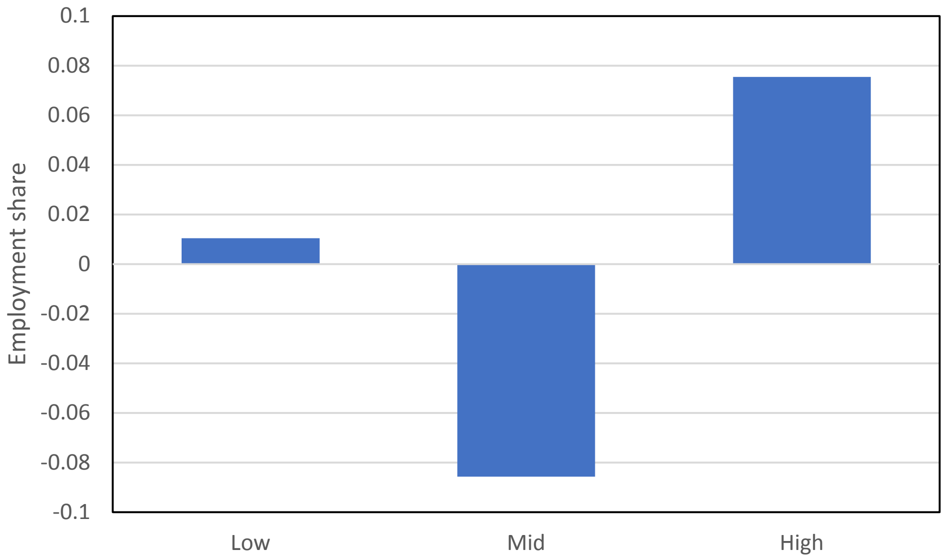
[7] We used population bins for visualisation purposes, plotting the data at a regional unit level leads to the same results.

Product Market Regulation index for the year 2018 (OECD, 2018). The PMR index is an indicator of regulatory barriers to firm entry and competition in a broad range of key policy areas, ranging from licensing and public procurement, to governance of state-owned enterprises, price controls, evaluation of new and existing regulations, and foreign trade. The index is constructed using a self-evaluation questionnaire issued to the participating countries. Finally, we use the OECD's PISA 2009 science score to measure the quality of education in STEM (science, technology, engineering and maths) in the different countries in our sample (OECD, 2010). The PISA science score is based on the standardised testing of 15-year-old students in all the countries covered by the programme.

3 Job polarisation and educational attainment in EU labour markets

Looking at how average employment shares of low, middle and high-skill groups changed between 2002 and 2016 in our sample of 24 countries, we observe a tendency in labour markets to upgrade with respect to occupational distribution. Nevertheless, the low-skill employment share also increased over the studied period, showing a tendency for the labour market to polarise as well (Figure 2). Between 2002 and 2016, the employment share of middle-skill occupations declined by 8.5 percentage points, while, in contrast, the shares increased for low-skill occupations by 1.0 percentage points, and for high-skill occupations by 7.5 percentage points.

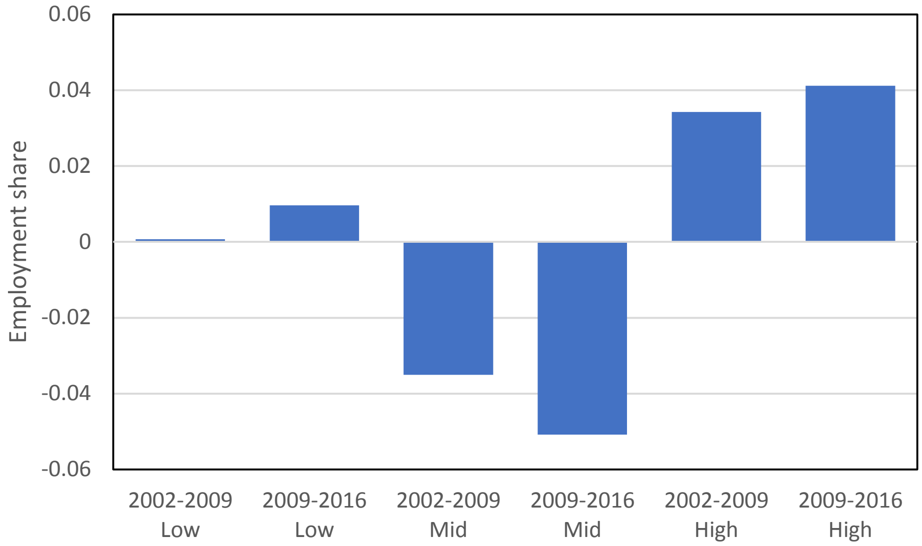
Figure 2: Change in employment shares (%) for low-, middle-, and high-skilled workers for EU countries between 2002 and 2016



Source: Bruegel. Note: This figure is based on EU-LFS data, where the employment share is calculated for 2002and 2016 as the total number of persons employed in each skill level as a share of the total number of persons employed in our sample. The change in employment shares between 2016 and 2002 is obtained by subtracting the share for 2002 from the share in 2016. The number of persons employed in each skill level is obtained by assigning the occupation of each respondent to the corresponding broad category defined in Table 1, these broad categories are then grouped into three skill levels. The data is adjusted using the EU-LFS sampling weights to be representative of the EU labour force.

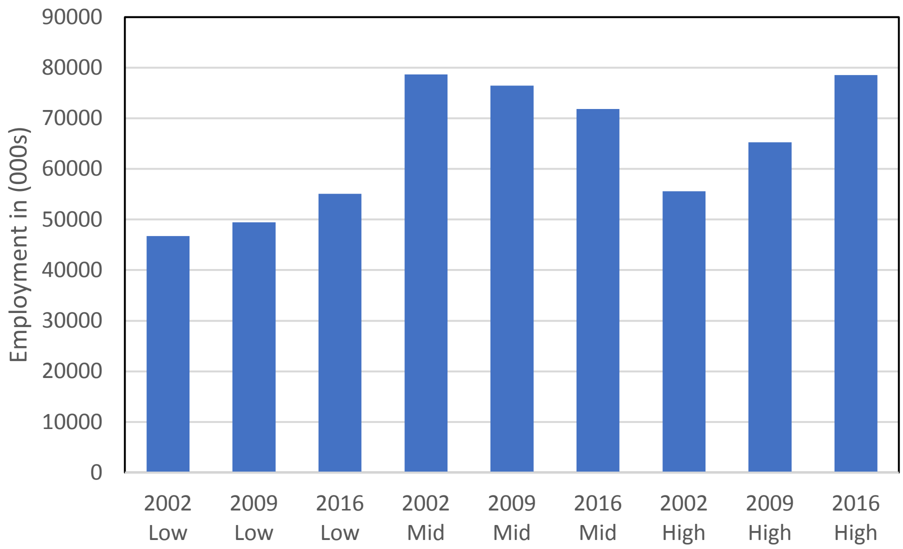
Looking at how occupational structures evolved in our two subperiods, between 2002 and 2009, and 2009 and 2016 (Figure 3), we observe some job polarisation in the second subperiod, corresponding to the European debt crisis and the subsequent recovery, which is biased towards high-skill occupations. Indeed, between 2002 and 2009, the European labour force tended to upskill, as reflected by the decline in the mid-skill employment share being almost fully compensated for by an increase in the high-skill share during that period. But, after 2009 the story was different. In the second period, the reduction in mid-skill jobs accelerated and so did the rise in high-skill jobs, but the low-skill employment share rose as well. Looking at absolute values rather than employment shares, we see that the number of workers in high-skill and low-skill occupations rose both between 2002 and 2009 as well as between 2009 and 2016, while the number of workers in mid-skill occupations declined in those same time periods (Figure 4).

Figure 3: Change in employment shares (%) for low-, middle-, and high-skilled workers in selected EU countries for 2002, 2009 and 2016



Source: Bruegel. Note: For method and data refer to the note of Figure 1. In this case, we subtract the shares per skill level of 2002 from the shares per skill level of 2009 and shares of 2009 from the shares of 2016.

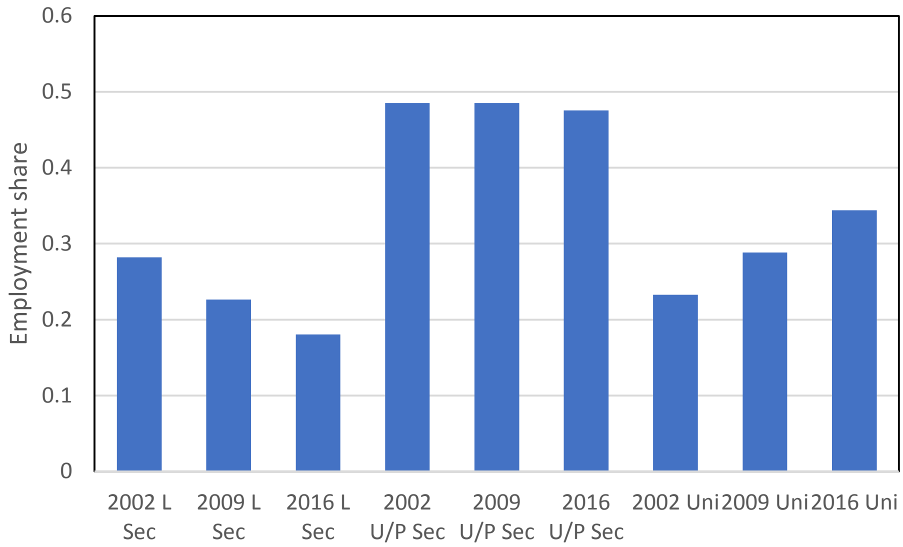
Figure 4: Number of low-, middle-, and high-skilled workers in selected EU countries for 2002, 2009 and 2016



Source: Bruegel. Note: The number of persons employed in each skill level is obtained by assigning the occupation of each respondent to the corresponding broad category defined in Table 1, these broad categories are then grouped into three skill levels for each given year. The data is weighted using EU-LFS sampling weights.

Over time, EU workers have become more educated on average (Figure 5). The share of workers with only primary or lower secondary education has steadily declined, while the share of those with tertiary education has increased. Between 2002 and 2016, the share of tertiary educated workers rose by 11 percentage points, that of upper/post-secondary educated workers declined by 1 percentage point, and the share of workers with lower secondary education or less declined by 10 percentage points. The decline in the share of workers with only primary or lower secondary educational attainment might be due to two factors: first and most obviously, an upskilling of the EU labour force, and second, the major increase in unemployment this educational category experienced during the crisis (Hoftijzer and Gortaza, 2018). Meanwhile, the share of employees with upper and post-secondary education remained relatively constant over the years. This leads us to the question of whether improvements in educational attainment drove the up-skilling of employment in the EU labour force.

Figure 5: Employment shares at different levels of education for selected EU countries, 2002-2016



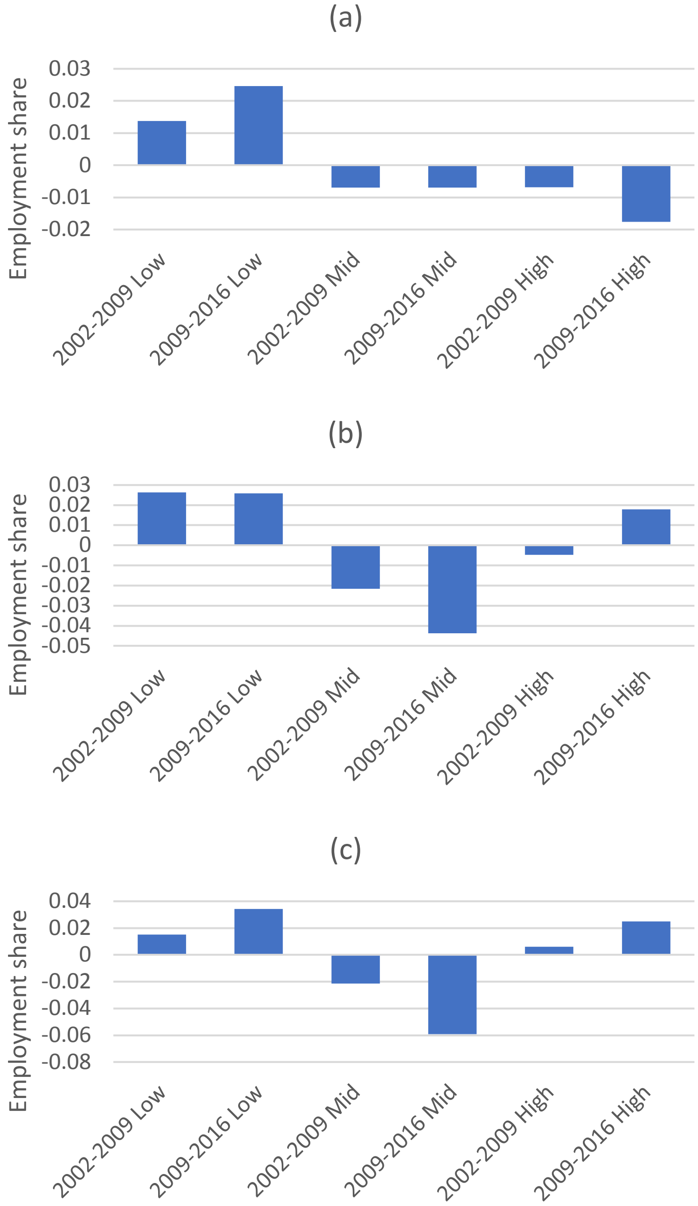
Source: Bruegel. Note: This figure refers to the educational attainment of the labour force dividing education in three categories outlined in Table 2. The employment share refers here to the share of the labour force with a given level educational attainment. The data is weighted using EU-LFS sampling weights.

As more workers obtained a tertiary degree, given that these workers are more likely to have a high-skill job (about 70% of them), the employment share of high-skill workers increased as well. This becomes clear from Figure 6, in which we keep educational categories constant. From Figure 6 c), we notice that workers with university education experienced a relatively mild but still significant skill downgrading, which was particularly prominent from 2009 onwards. We notice from Figure 7 c) that this was not caused by a decline in the number of university graduates taking high-skill jobs but rather by the relative increase in the number of those working in low-skill jobs. This result implies that while the number of university graduates increased, the chance that these workers would find themselves in low-skill jobs also increased. In other words, relative overqualification has increased for university graduates, accelerating during the crisis. The debt crisis led to an increase in overqualification in the EU, as the labour market's demand for skills could not keep up with the rising supply of university graduates (see also Cedefop, 2015). However, the skill downgrading experienced by university graduates was too small in size to counteract the compositional change effect of their rising number on the overall high-skill employment share (Figure 3).

For upper/post-secondary educated workers, there appears overall to have been a down-skilling, for both periods considered (Figure 6 (b)). The share of those workers employed in low-skill jobs increased between 2002 and 2009 and between 2009 and 2016, as did their absolute numbers (Figure 7 (b)). The number of upper/post-secondary educated workers in high-skill occupations also increased in those periods, but to a lesser extent. Therefore, given that the number of workers in mid-skill occupations remained constant, their share diminished overall. The number of primary and lower secondary educated workers decreased by a large amount over the period considered (Figure 7 (a)). Given that their decline in mid-skill occupations was greater than their decline in low-skill occupations, the overall picture is that of a polarisation of their employment shares (Figure 6 (a)).

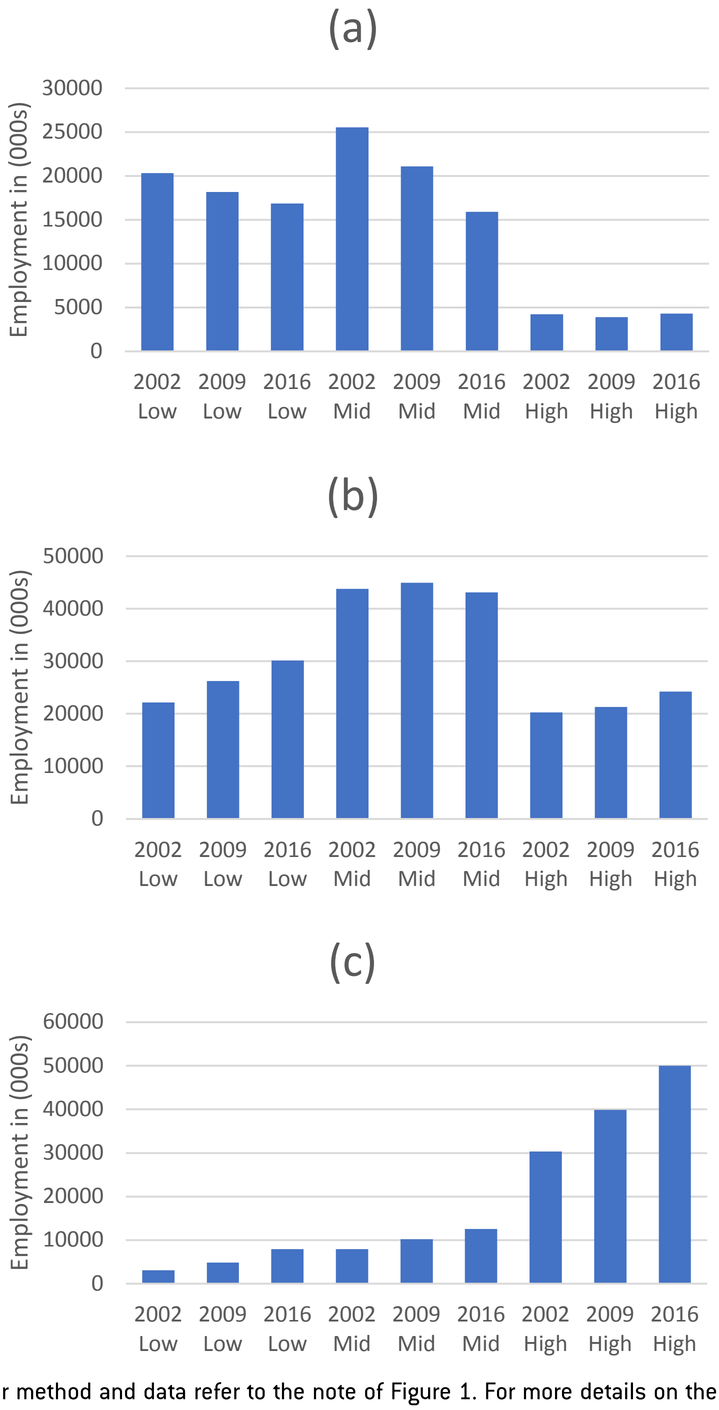
By comparing the results of Figure 6 with the real wage development in Figure 1, we note relatively small changes in the employment shares of university educated workers compared to the two other educational subcategories. Workers with lower secondary education as their highest educational attainment experienced the most negative wage developments during the crisis. They are also the group that faced the largest decline in their mid-skill employment share (6.0 percentage points) and the largest rise in their low-skill employment share (3.5 percentage points). Finally, upper/post-secondary educated workers, for whom intermediate real wage developments compared to the two other groups, experienced a 4.3 percentage points decline in their share of employment in mid-skill jobs between 2009 and 2016. Although occupational change cannot be considered the only driver of wage growth differentials between educational cohorts, we nevertheless think that the above-mentioned trends played a role in the dynamics we observe in Figure 1.

Figure 6: Change in employment shares for low-, middle-, and high-skilled workers in selected EU countries for (a) workers without post-secondary education, (b) workers with some upper or post-secondary education and (c) workers with university degrees



Source: Bruegel. Note: For method and data refer to the note of Figure 1. For more details on the educational attainment levels refer to Table 2.

Figure 7: Change in employment for low-, middle-, and high-skilled workers in selected EU countries for (a) workers without post-secondary education, (b) workers with some upper or post-secondary education and (c) workers with university degrees



Source: Bruegel. Note: For method and data refer to the note of Figure 1. For more details on the educational attainment levels refer to Table 2.

4 Geographical differential impact of occupational change

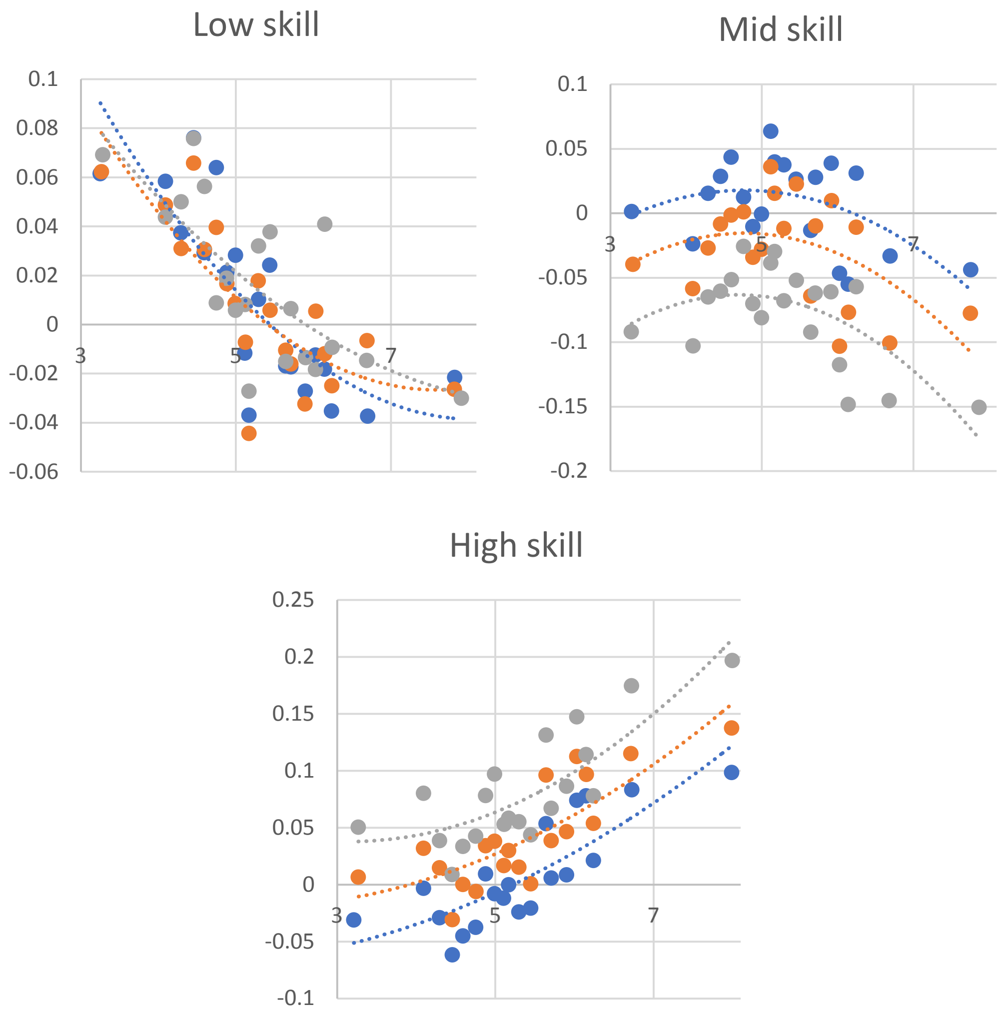
Occupational change has been shown to have geographical differential impacts in US labour markets (Autor, 2019). We examine in this section if similar dynamics are at play in the EU, although we study developments in the EU labour market over a much shorter period.

Studying how employment shares changed in relation to population density, in the three different skill groups in our sample, in 2002, 2009 and 2016 (Figure 8), leads to several observations. First, it is clear that the employment share of middle-skill occupations has dropped over the years for every value of population density. This drop was greater between 2009 and 2016 and was rather constant over population densities. On average the reduction was 5 percentage points in the least-densely populated regions and 7 percentage points in the most-densely populated regions. Mid-skill jobs are more concentrated in intermediate population density regions, while, their share of employment is lowest in regions of high population density[8]. High-skill occupations are more concentrated in metropolitan regions with high population densities. In 2016, the difference between the least-densely populated region and the most-densely populated region in our sample in terms of employment share of high-skill jobs was 15 percentage points, 2 percentage points more than in 2002. Regarding the dynamic aspect of high-skill occupations, we see their share of employment increasing consistently for every population density over time. There appears to be, nevertheless, a more rapid increase in the employment share of high-skill occupations in the highest density regions, with 10 percentage point increases over the period studied. For low-skill occupations, the pattern shows a decreasing relationship with population density: less-densely populated regions tend to have higher shares of low-skill occupations than regions that are more densely populated. The dynamic trend in the distribution of low-skill jobs over time appears to be flat.

The overall picture that emerges from Figure 8 is that jobs are not evenly distributed across densities in the EU. There is a clear pattern of geographic polarisation in the EU with high-skill jobs concentrated in metropolitan, high-density regions, while low-skill jobs and, to some degree, mid-skill jobs are more concentrated in the middle and low ends of the density distribution. This finding matches Busetti *et al* (2017), who distinguished highly competitive knowledge economy-based regions, which include the largest metropolitan areas in Europe and offer the best labour market and socio-economic conditions in the EU. Busetti *et al* (2017) noted that while knowledge economy activities tend to concentrate in technologically advanced regions and in capital cities, less-developed and rural areas often lack the infrastructure and human capital needed to support knowledge dissemination and innovation. We find nonetheless that between 2002 and 2016, in terms of distribution of skilled jobs, inequality between regions of different densities did not necessarily increase in the EU.

[8] We checked for robustness by removing the three most extreme points on each side of the density distribution; the same inverted u-shape pattern emerges for mid-skill occupations.

Figure 8: Relative employment shares for different skill categories by population density



Source: Bruegel. Note: For this figure, which include population densities, employment shares in each local labour market where derived at a NUTS2 level from EU-LFS data and then aggregated in population density bins by taking their average, weighted by the total employment in the region. The regional data on population densities are obtained from the Eurostat regional database on population densities and then matched to the regional information of the EU-LFS. This procedure was performed such that each bin approximately represents 5% of the employed population. The employment shares that resulted from this procedure were then adjusted by subtracting the overall employment share of each skill level in 2002 (first year of the analysis), irrespective of the population density, to shed light on variations of employments share per skill level across densities. Population densities are expressed in natural logarithms and the overall method for deriving these figures is based on Autor (2019).

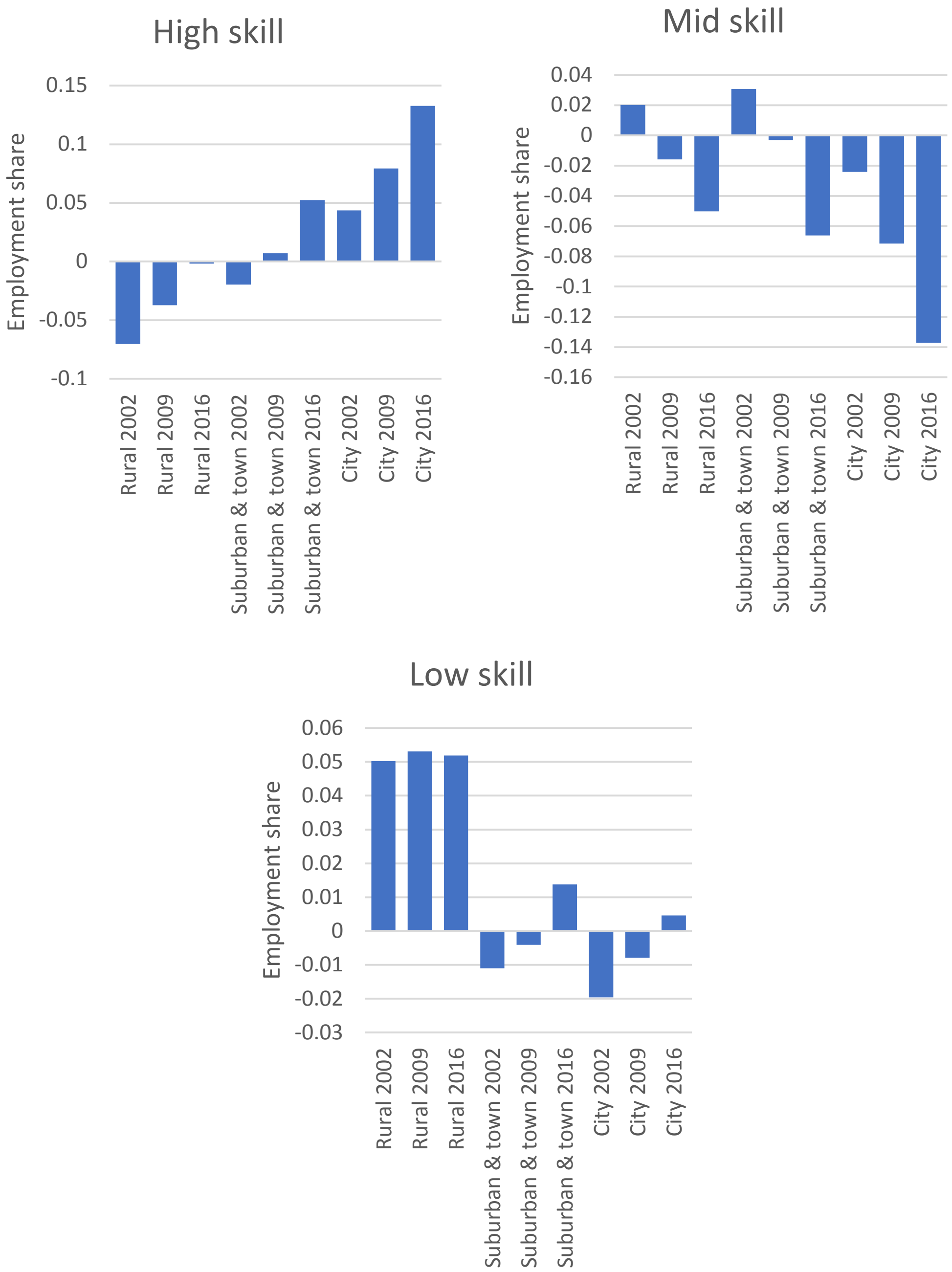
We now turn to the degree-of-urbanisation measure. It allows us to study employment shares with respect to work in cities, suburban areas and towns, and rural areas (Figure 9). Our reason for going to this level of precision stems from the limitations associated with the aggregate nature of the NUTS2 regions used in Figure 8. At NUTS2 level, a distinction can be made between metropolitan areas and more remote areas in the EU.. In least-densely populated regions, such as northern Sweden or Lapland, we can expect economic activities to be rather homogeneous, as they are nearly entirely rural areas. But for other regions the distinction might be less clear cut. For instance, the NUTS2 region of Oberbayern in Germany, which includes Munich, is not very densely populated, but includes large cities combined with more remote rural areas. So, given the degree of heterogeneity within NUTS2 regions, by looking separately at cities, suburban areas and towns, and rural areas, we might be able to obtain new insights into how occupational structures vary with geography in the EU.

First, we observe from Figure 9 that mid-skill jobs have declined the most in cities and suburban areas. Between 2002 and 2016, mid-skill jobs declined by 12 percentage points in cities and by 10 percentage points in suburban areas; in rural areas the decline was 7 percentage points. This led mid-skill jobs to be 9 percentage points less prevalent in cities than in rural areas by 2016, compared with a 4-percentage point difference in 2002. Also, while mid-skill occupations were more prevalent in suburbs and towns than in rural areas in 2002, this was no longer the case in 2016. In the meantime, a large part of the decline in mid-skill employment was compensated for by increases in high-skill employment across all geographies, reflecting the up-skilling of workers. Nevertheless, it must be noted that some of the decline in mid-skill occupations was compensated for by a rising share of low-skill jobs, notably in suburban areas and cities, while the share of low-skill jobs in rural areas remained constant. The aforementioned trends reflect the increasing geographical polarization of employment in the EU between 2002 and 2016, with a strong shift from mid-skill jobs towards high-skill jobs, which was particularly marked in cities and suburban areas, accompanied by, to a lesser degree, a shift towards low-skill employment.

However, we know from Figure 4 that the rise in high-skill employment occurred in tandem with a strong increase in the educational attainment of the European labour force. As noted, improvements in the educational attainment of the EU labour force explain the up-skilling trend we capture in Figure 10. We nevertheless wish to observe how geographic disparities in skilled employment evolved for different educational groups. For this reason, we reproduce Figure 9 but distinguish workers by their educational attainment, thereby controlling for education; Figure 10 shows the results. Here we notice that upper/post-secondary and lower secondary workers experienced the greatest declines in mid-skill employment in cities and suburban areas, where both groups experienced declines ranging from 12 to 8 percentage points. For these educational cohorts, the largest part of these declines was compensated for by rises in low-skill employment, and to a much lesser extent, by minor rises in high-skill employment shares. Thus, for lesser-educated workers, declines in mid-skill employment in cities and suburban areas were compensated for by rises in low-skill employment in those same areas. These results remind us of the findings of Autor (2019) for the US, where an apparent upskilling of occupations hid a down-skilling trend for lesser-educated workers, which was mostly concentrated in cities and suburban areas.

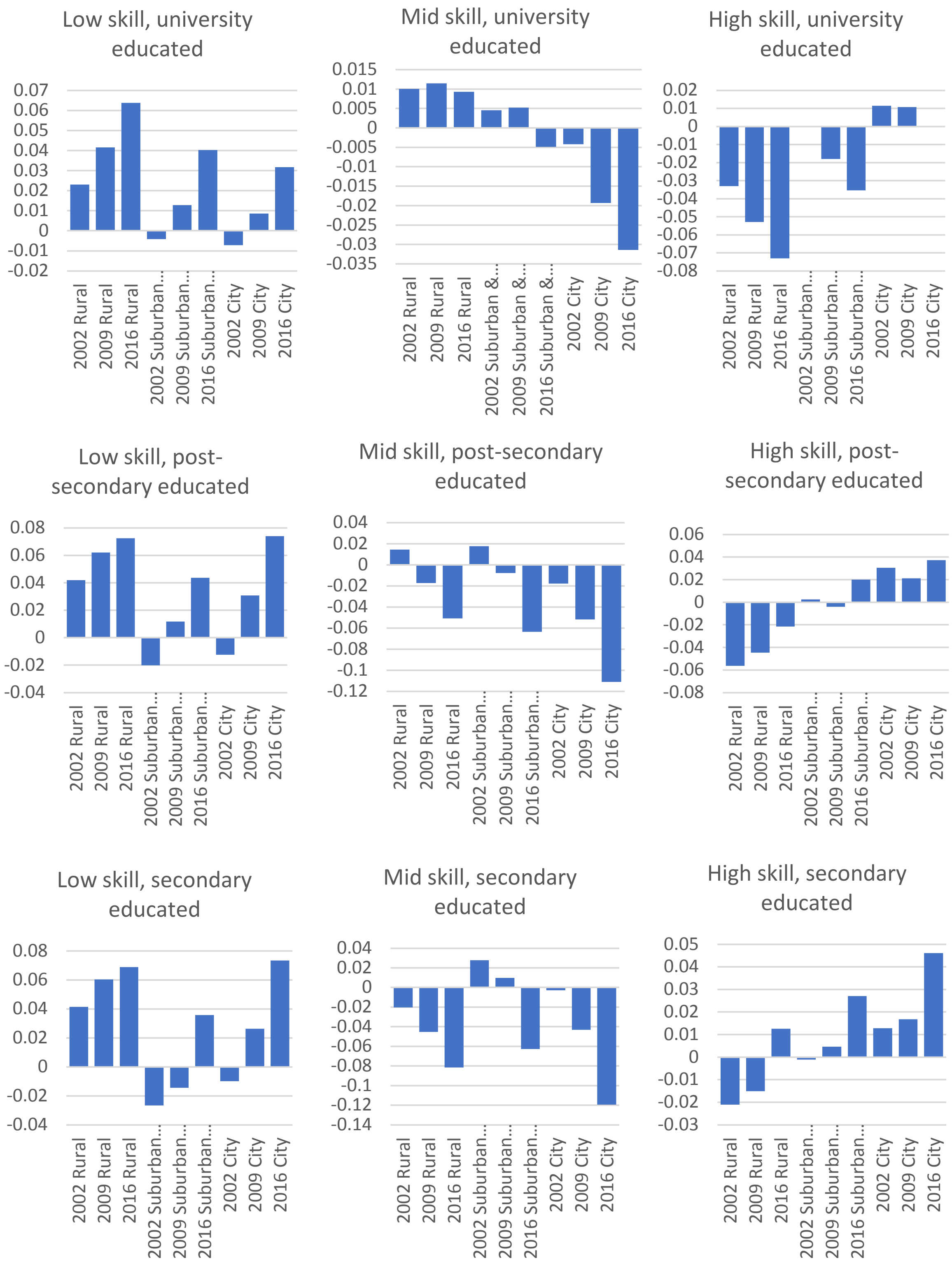
The abovementioned trends led to a change in the geographical distribution of employment for different educational groups. In 2002, for upper/post-secondary and lower-secondary educated workers performing low-skill jobs, the shares of employment in rural areas were, respectively, 3 and 5 percentage points higher than in cities. In 2016, the share of workers with a similar educational attainment performing low-skill jobs was slightly higher in cities than in rural areas. This indicates the down-skilling of these workers in cities, where most of the workers from these educational categories moved from a mid-skill job to a low-skill job. The situation for lower-educated workers is not all negative however, as we notice that across all three geographies, a much smaller, but non-negligible share of mid-skill employment was reallocated to high-skill occupations. Focusing now on tertiary-educated workers, we find that employment shares in high-skill jobs declined in all three geographical categories, but the trend was more marked in rural areas and in suburban areas than in cities. This strengthens our view that higher-educated workers in cities enjoyed much better employment opportunities, including during the economic crisis, than any other group in our study. In contrast to their lesser-educated counterparts, for tertiary-educated workers, the geographical structure of occupations stayed constant over time; most tertiary-educated workers in low-skill jobs were in rural areas, while for those in high-skill occupations, most were located in cities.

Figure 9: Relative employment shares by degree of urbanisation



Source: Bruegel. Note: This figure shows variations of employment shares per skill level across degrees of urbanisation, a 3-category discretionary scale. The variable of the EU-LFS employed, Degree of Urbanisation, divides respondents' places of residence into three categories: low, medium or high degree of urbanisation. The employment shares obtained for each year and category were adjusted by subtracting the overall employment share of each skill level in 2002 (first year of the analysis), irrespective of the degree of urbanisation, to shed light on variations of employment share per skill level across degrees of urbanisation.

Figure 10: Relative employment shares by degree of urbanisation and education



Source: Bruegel. Note: For this figure refer to the note of Figure 9. For more details on the educational attainment levels refer to Table 2.

5 Artificial intelligence and occupational change

Since approximately 2010, there have been new advancements based on machine-learning techniques that enable AI systems to perform tasks in a very efficient way. AI systems are able to perform tasks that involve decision-making, changing the impact of automation on the workforce. Machine learning enables computer programs to acquire knowledge and skills, and even improve their own performances. Big data provides the raw material for machine learning, and offers examples that computer programs can use for 'practice' in order to learn, exercise and ultimately perform their assigned tasks more efficiently.

Software and AI-powered technologies can now retrieve information, coordinate logistics, handle inventories, prepare taxes, provide financial services, translate complex documents, write business reports, prepare legal briefs and diagnose diseases. They are set to become much better at these tasks in the next few years (Brynjolfsson and McAfee, 2014; Ford, 2015). Currently, to assess the impact of these technologies on the labour market, we can only underline the main characteristics of these technologies and apply speculative feasibility tests to the potential job tasks that will be created and displaced.

While AI systems have already managed to perform better than humans at certain tasks, it should not be overlooked that workers perform a variety of different tasks. As machines automate some of these tasks, the remaining tasks that are non-automatable might become more valuable (Brynjolfsson and Mitchell, 2017). For example, in legal contexts, AI can perform well in classification tasks, such as sorting large amounts of documents, but cannot replace lawyers in formulating legal strategies (Levy and Remus, 2017). Machines are unable to represent clients in court. Lawyers can therefore allocate more time to preparation for the court and can become more efficient. We are still far from artificial general intelligence that would match humans in all cognitive areas[9].

Based on the work of Frey and Osborn (2017), who identified engineering bottlenecks through interviews with AI experts and, based on these bottlenecks, identified hard-to-automate tasks, Nedelkoska and Quintini (2018) developed a measure of the probability of automation of different occupations[10]. They assessed the engineering bottlenecks (perception and manipulation, creative intelligence, and social intelligence) and linked these with specific PIAAC (OECD Survey of Adult Skills) variables. They identified 10 PIAAC variables that reflect these bottlenecks, and used these to derive the probability of automation of different occupations, in line with Frey and Osborn (2017).

[9] However, young trainees in law firms whose primary task is to classify documents may find it harder to get a position and gain some experience.

[10] For the interpretation of this measure of automation, it is important to clarify that it refers to the probability that some tasks within each occupation are automated, not to the probability that whole occupations are automated. Brynjolfsson *et al* (2018) showed that there is a great variation across the tasks involved in each occupation in terms of their probability of automation, so the likelihood that whole occupations will be automated is very small. So, the measure we adopt here should be better viewed as the potential of automation to transform occupations and not to eliminate them.

Table 3: European occupations with the highest and lowest probabilities of automation.

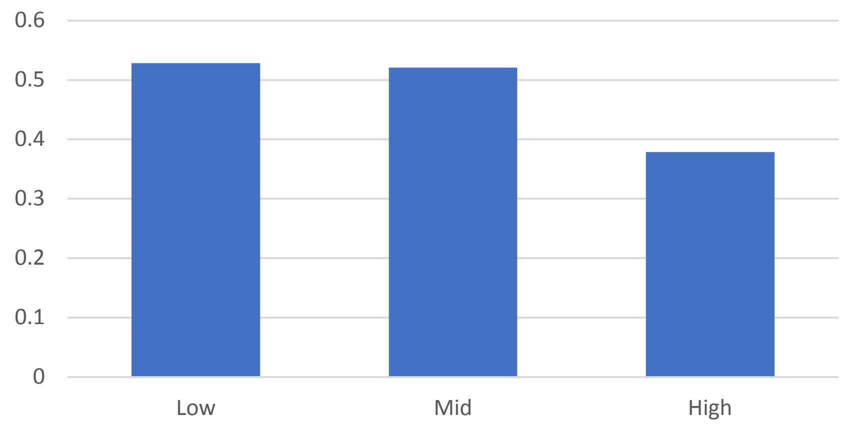
Occupations with the lowest probability of automation	Occupations with the highest probability of automation
Teaching professional	Food preparation assistants
Production, specialised services managers	Cleaners and helpers
Chief executives, senior officials, legislators	Labourers in mining, construction, manuf, transport
Administrative and commercial managers	Assemblers
Hospitality, retail, other services managers	Drivers and mobile plant operators

Source: Nedelkoska and Quintini (2018).

One of the major causes of job polarisation is the adoption of computer technologies (Autor *et al*, 2003). Most of the criteria used to derive the probability-of-automation score can also be seen through the lens of routine intensiveness and therefore also have a meaning in explaining the results we have obtained on the decline of mid-skilled employment. In Figure 11, we report the average exposure or probability-of-automation score per occupation skill group for 2016. Exposure to automation is particularly prominent for the middle- and low-skill groups, while it is quite low for the high-skill group. High-skill occupations involve non-routine problem-solving skills and advanced communication skills that are difficult to automate, making these job consequently less exposed to such developments, as shown by their probability-of-automation scores.

The probability-of-automation score is also forward looking and includes criteria that are uniquely related to exposure to machine-learning technologies. The results shown in Figure 11 suggest that, in the future, low-skill employment might be more at risk of being exposed and affected as well. The fact that low-skill jobs also have a high risk of automation suggests that a new era of technological development related to machine learning might have a different impact to the development and adoption of computer technologies.

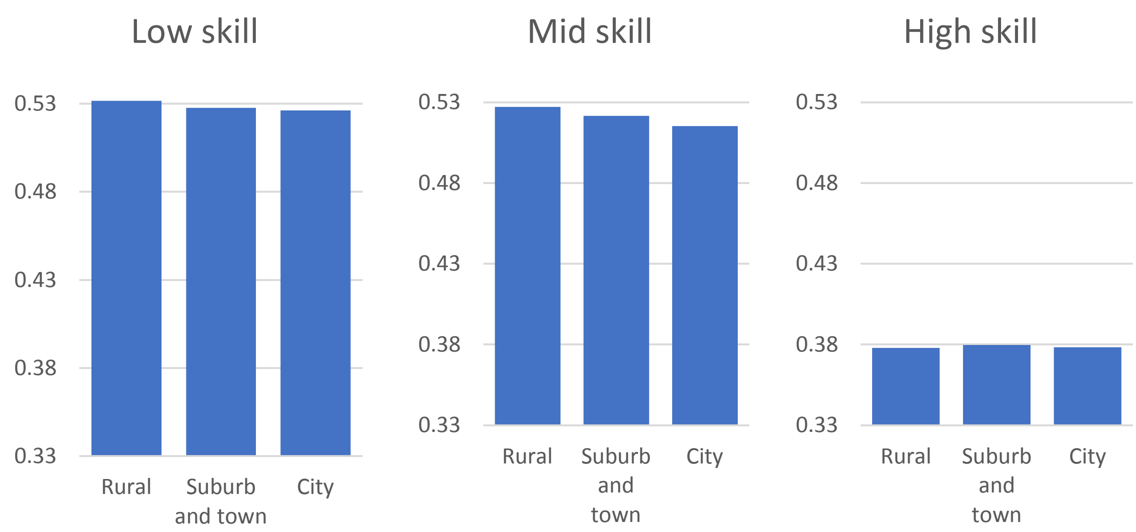
Figure 1: Probability of exposure to automation of different skill groups



Note: This figure refers to the average exposure to automation of the individuals in each skill groups. The average exposure is defined by the occupations individuals in each group have and their number. The exposure of each occupation is defined by the scale created by Nedelkoska and Quintini (2018).

Decomposing the exposure to automation by geographies (Figure 12) sheds light on which geographical areas are most exposed to automation and may also help to explain the results obtained in this paper. We notice from Figure 12 that for low-skill and mid-skill workers, the average exposure to automation is greatest in rural areas, followed by suburban areas, and is lowest in cities, although differences across geographies are small. The high level of exposure in rural areas is in part driven by the prevalence of agricultural workers who have a relatively high probability of automation. For high-skill workers, we notice no variation across geographies.

Figure 12: Exposure to automation of skill groups by degree of urbanisation



Source: Bruegel. Note: This figure refers to the average exposure to automation of the individuals in each skill groups by degree of urbanisation. The average exposure is defined by the occupations individuals in each group have and their number. The exposure of each occupation is defined by the scale created by Nedelkoska and Quintini (2018). The variable of the EU-LFS employed, Degree of Urbanisation, divides respondents' places of residence into three categories: low, medium or high degree of urbanisation.

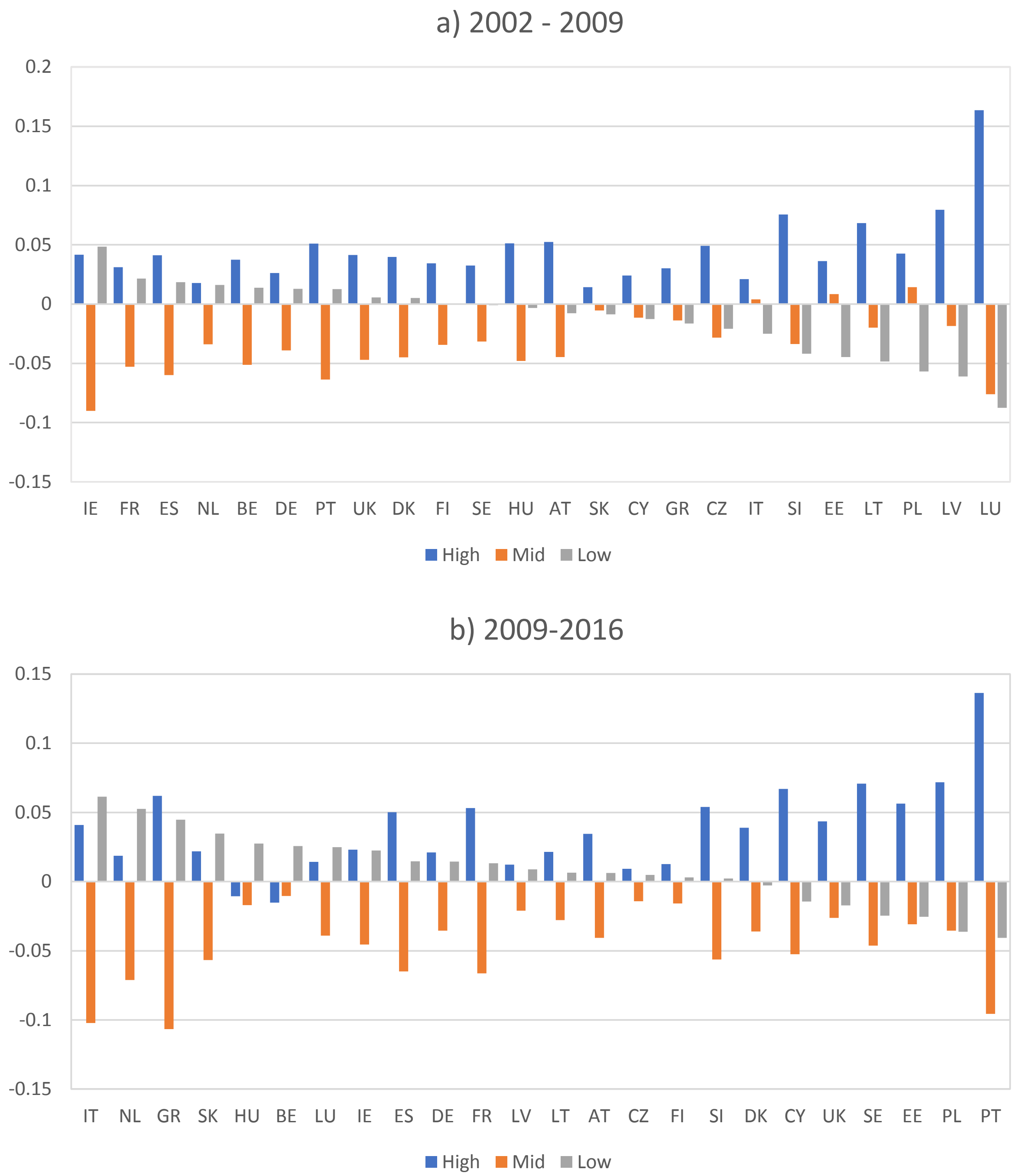
6 Job polarisation and skill upgrading in EU countries

So far, we have examined the EU averages of employment shares of different skill and education groups and how they interact with time and geography. We now study how occupational change evolves at the country level. Figure 13 shows employment shares for different skill groups for each country in our sample for two different time periods, 2002-2009 and 2009-2016. Countries are ranked by the change in the low-skill share of employment they experienced during the given time period. On the left-hand side we see the countries that exhibited some degree of job polarisation (meaning that the share of low-skill employment has increased), while on the right-hand side we have the group of countries that exhibit skill upgrading (the share of low-skill employment declined). While the period from 2002 to 2009 was marked by upskilling in many countries, the number of countries that exhibited some degree of job polarisation from 2009 to 2016 increased substantially. Overall, it is noticeable that European countries had very different experiences of occupational change between 2002 and 2016. Some saw an upskilling pattern in their labour market structures, others a polarisation and a few, mostly after 2009, even saw a down-skilling. In an exploratory way, we will compare how different degrees of upskilling of labour markets relate to certain structural and institutional variables we believe to be relevant.

From Figure 14, in which we compare the country's mean probability-of-automation scores with an index of upskilling, which is defined as the difference between the employment shares of high-skill and low-skill workers in 2016. We notice that these two tend to be strongly correlated. Countries that display high degrees of upskilling, meaning that most of their labour force is concentrated in high-skill occupations, appear to be less at risk of automation. Yet the relationship is not exactly one to one. Sweden, Estonia and Luxembourg have the highest upskilling indexes. Nevertheless, on average, workers in Sweden are less exposed than Estonian or Luxembourgish workers to automation. This difference can be explained by the type of occupations Swedish workers perform compared to Estonian or Luxembourgish workers, which are less exposed to automation overall. Similarly, exposure to automation can also be substantial for certain high-skill occupations, and therefore having a high upskilling index does not always equate with a low exposure-to-automation score. Nevertheless, countries are likely to benefit by having an upskilled occupational structure in terms of dealing with automation related to the implementation of machine learning. For this reason, the recent trend of countries seeing polarisation of their labour markets, compared to upskilling prior to the crisis, is a source of concern.

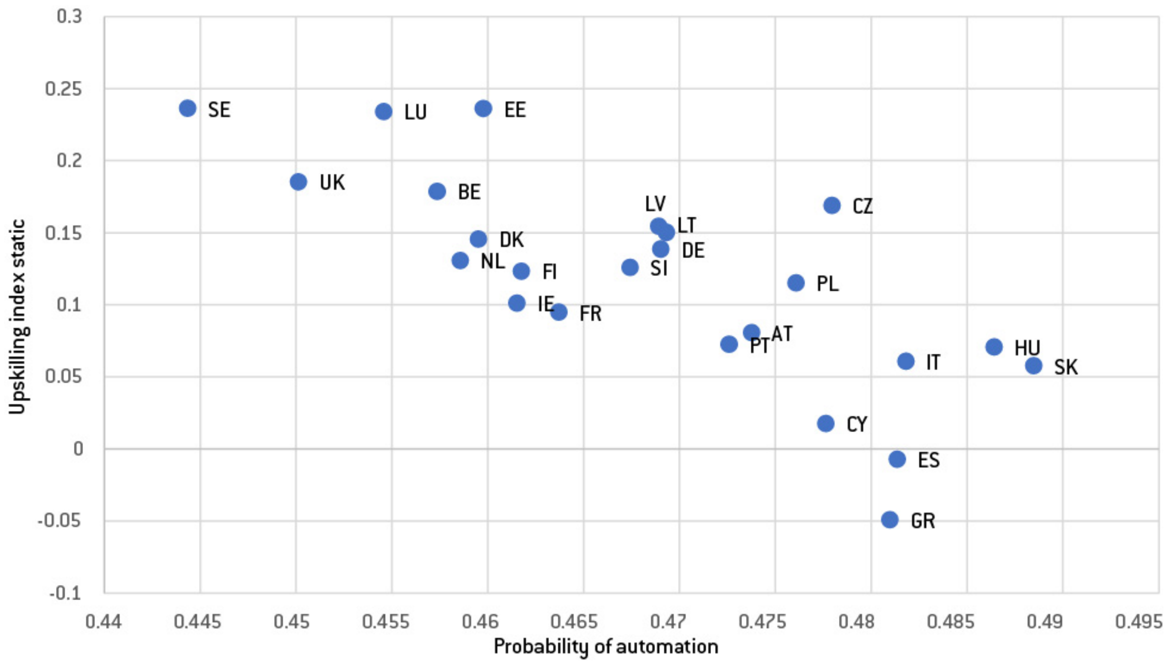
In Figure 15 we compare each country's ICT intensity of work, measured as the average ICT intensity of the country's occupational structure, with the upskilling index. We find that their relationship is positive. Countries with deeper penetration of ICT technologies in their jobs and occupations also display more skill-oriented occupational structures. Higher skill jobs tend to require more ICT usage. It is worth noting that some countries, while having similar degrees of ICT occupational intensity, have different degrees of upskilling. This suggests that some countries have more ICT-intensive middle and low-skill occupations. This is the case for example for Estonia and the Netherlands. Although they share a similar degree of average ICT intensity of work, the Netherlands' occupational structure is less upskilled than Estonia's.

Figure 13: Changes in employment shares at country level



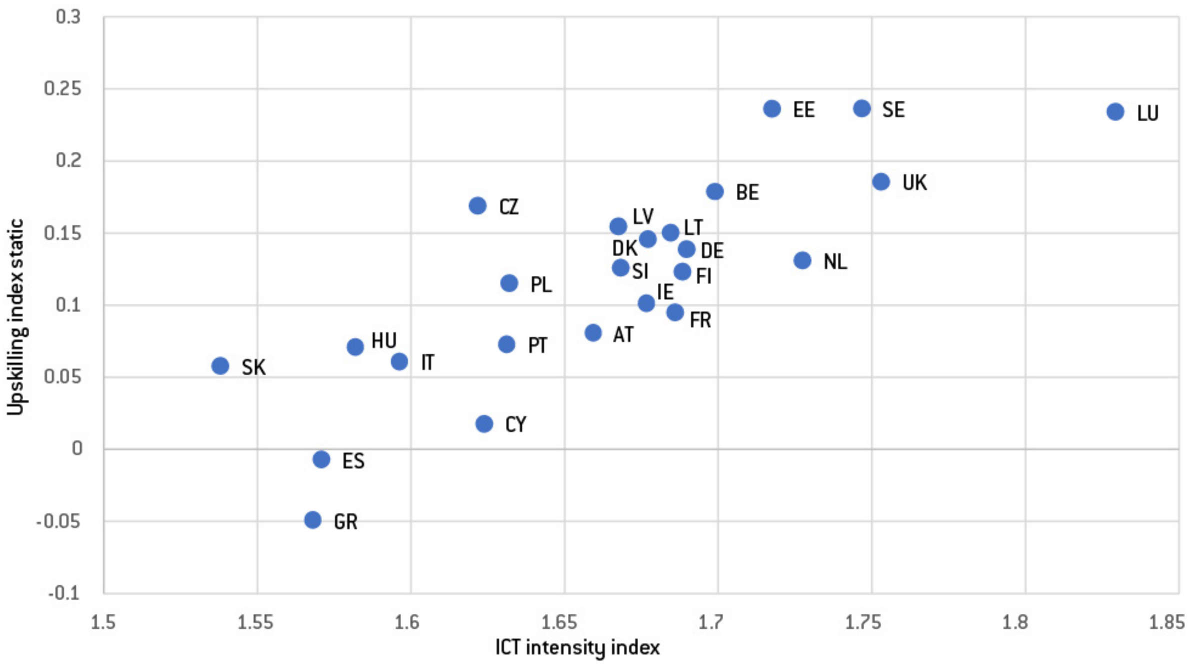
Source: Bruegel. Note: These figures display the changes in occupational employment shares between the given years at a national level for selected EU countries. The countries are divided in each figure between those where the share of low-skill employment is increasing over the given period (on the right) and the countries where the share of low skill employment has decreased over the given period (on the left).

Figure 14: Probability of automation score vs. upskilling index



Source: Bruegel. Note: The probability of automation score is based on Nedelkoska and Quintini (2018) and is the average score of all workers per country for the year 2016. The upskilling index is based on the index of concentration at the extremes by Krieger *et al* (2016), it takes the value of 1 if the whole population of the country is working in high-skill occupations and -1 if the whole population of the country is working in low-skill occupations. The year used to measure the upskilling index is 2016.

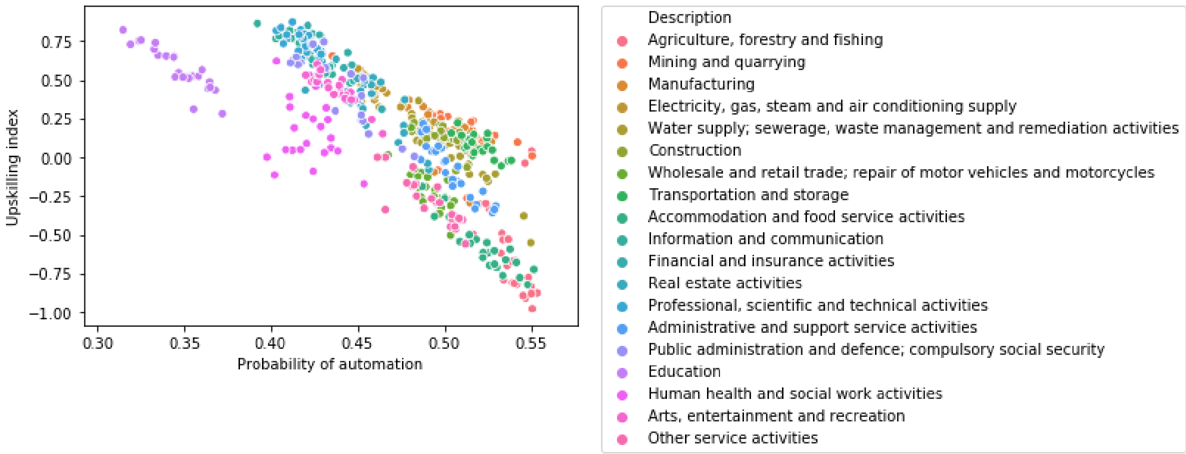
Figure 15: ICT intensity vs. upskilling index



Source: Bruegel. Note: The ICT intensity index derived from the OECD's (2015) PIAAC microdata and is the average ICT work intensity of all workers per country for the year 2016. The upskilling index is based on the index of concentration at the extremes by Krieger et al (2016), it takes the value of 1 if the whole population of the country is working in high-skill occupations and -1 if the whole population of the country is working in low-skill occupations. The year used to measure the upskilling index is 2016.

Figure 16 reports the probability-of-automation score and the upskilling index for each country and industry. For most industries, this relationship across different countries tends to be negatively correlated. In education, we find relatively small probability-of-automation scores and high upskilling index values. Transportation and storage are found in the opposite corner (south-east) where again a negative correlation is reported. This result is in line with that of Figure 14: industries with less-skilled workers are more likely to be transformed by the adoption and diffusion of new technologies. However, we also see some particular industries for which the upskilling index is relatively low or high (in comparison to the average value of the upskilling index across industries), given a certain probability-of-automation score. For example, human health and social work activities tend to have a probability-of-automation score that is relatively low in relation to its level of upskilling, in comparison to construction or transportation and storage. This reflects that this industry, while a mid-skill industry, will be relatively unaffected by AI technologies. The opposite is also found. For instance the mining and quarrying industry faces a relatively high level of exposure to AI technology relative to its level of upskilling.

Figure 16: Probability of automation vs. upskilling index for each industry and country

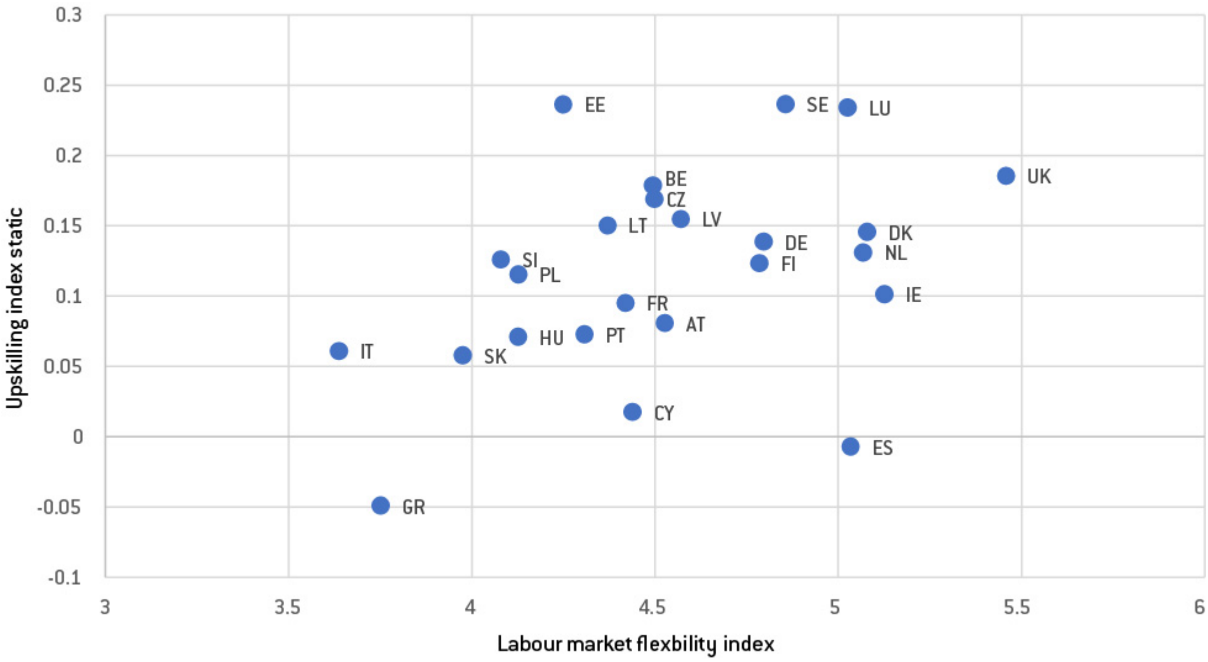


Source: Bruegel. Note: The probability of automation score is based on Nedelkoska and Quintini (2018) and is the average score of all workers per country-industry for the year 2016. The upskilling index is based on the index of concentration at the extremes by Krieger *et al* (2016), it takes the value of 1 if the whole population of the country-industry is working in high-skill occupations and -1 if the whole population of a country-industry is working in low-skill occupations. The year used to measure the upskilling index is 2016. The industries used are classified using the NACE rev. 2 classification.

Our data on skills across EU countries allows us also to investigate the relationship between our upskilling index and institutional variables at the country level. Institutions are believed to play a crucial role in the formation of skills and investment in human capital. However, there is a great variety of institutions and market structures across the countries considered here, even if they all participate in a common, single EU market. By capturing the relationship between different institutions and market structures and skills, we can assess the types of public policies that can contribute to the minimisations of concern about the labour implications of new technologies. As we have shown, the probability of automation is negatively correlated with the upskilling of the labour force. We evaluate now which policy variables can be effective in achieving high upskilling index values. We consider in particular, labour market regulations for which we use an index of labour flexibility an index of product market regulations and for the quality of education the PISA science score.

In relation to labour market flexibility, which we measure using the index created by the World Economic Forum (WEF), we notice a positive correlation between labour market flexibility and upskilling in an economy (Figure 17). Labour market flexibility is measured as a composite index based to a large extent on an executive opinion survey, which includes, for example, measures of cooperation in labour-employer relations, flexibility of wage determination, capacity to retain talent and quantitative measures, such as average redundancy costs and female participation in the labour force. Countries including Sweden, Luxembourg and the UK have the highest labour market flexibility scores and have high upskilling indexes. Countries including Greece and Italy have low levels of labour market flexibility and also display low upskilling indexes.

Figure 17: Labour market flexibility vs upskilling index, 2016

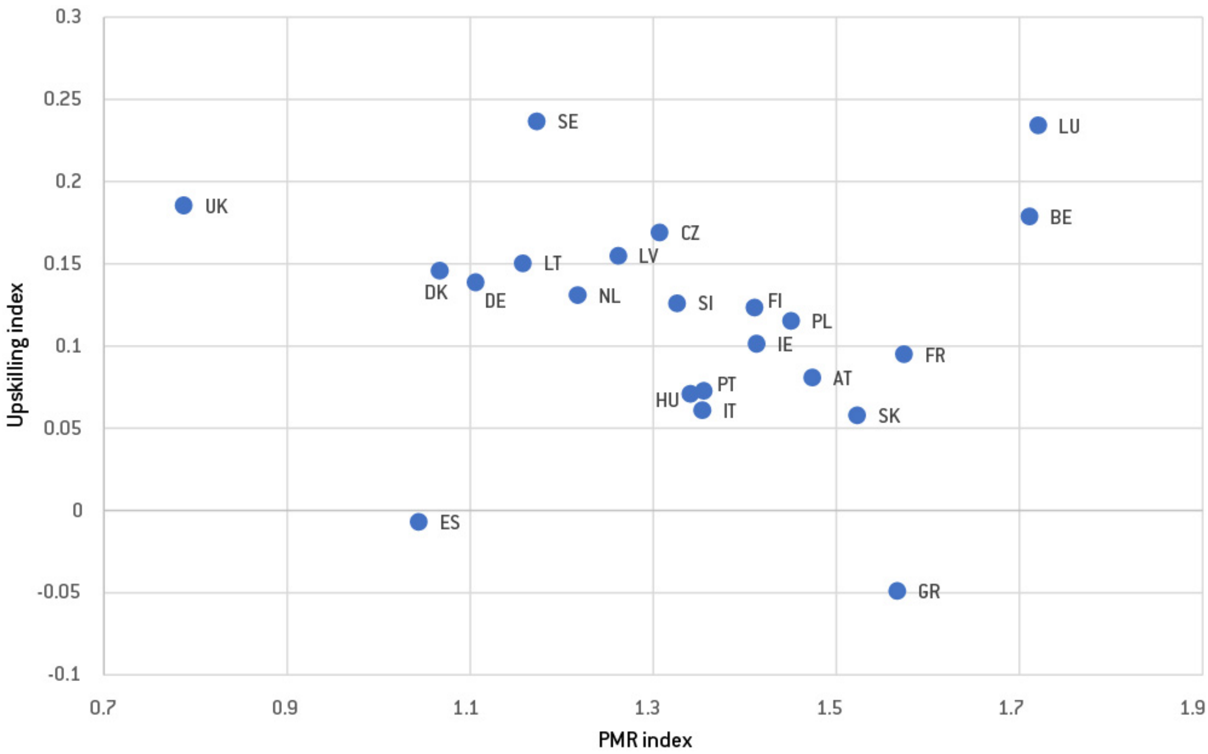


Source: Bruegel. Note: The upskilling index is based on the index of concentration at the extremes by Krieger *et al* (2016). It takes the value of 1 if the whole population of the country is working in high-skill occupations and -1 if the whole population of a country is working in low-skill occupations. The labour market flexibility index from Schwab & Sala-i-Martín (2018), the index takes values between 1 and 7, where 7 is the most flexible and 1 the least. It is a composite index created applying a min-max transformation, to preserves the order of, and the relative distance between, country scores.

We also consider the relationship between the openness of markets and our measure of upskilling (Figure 18). To make this comparison we use the OECD's Product Market Regulation Index for 2018[11]. A higher PMR score indicates a more regulated product market. We use the measure from 2018 since the last measurement before 2018 was 2013 and thus this measure is closer to our final year of analysis. The PMR index measures the regulatory barriers to firm entry and competition in a broad range of key policy areas, ranging from licensing and public procurement, to governance of SOEs, price controls, evaluation of new and existing regulations, and foreign trade. There appears to be a negative correlation between the PMR index and the upskilling index. Overall, countries with a freer product market tend to display a higher upskilling index. There are however significant outliers. Spain for instance, has a low product market regulation level but also a low degree of upskilling. On the other hand, Belgium and Luxembourg display high levels of product market regulation but also highly-skilled occupational structures.

[11] Results are qualitatively the same if we consider the PMR index less the most recent years.

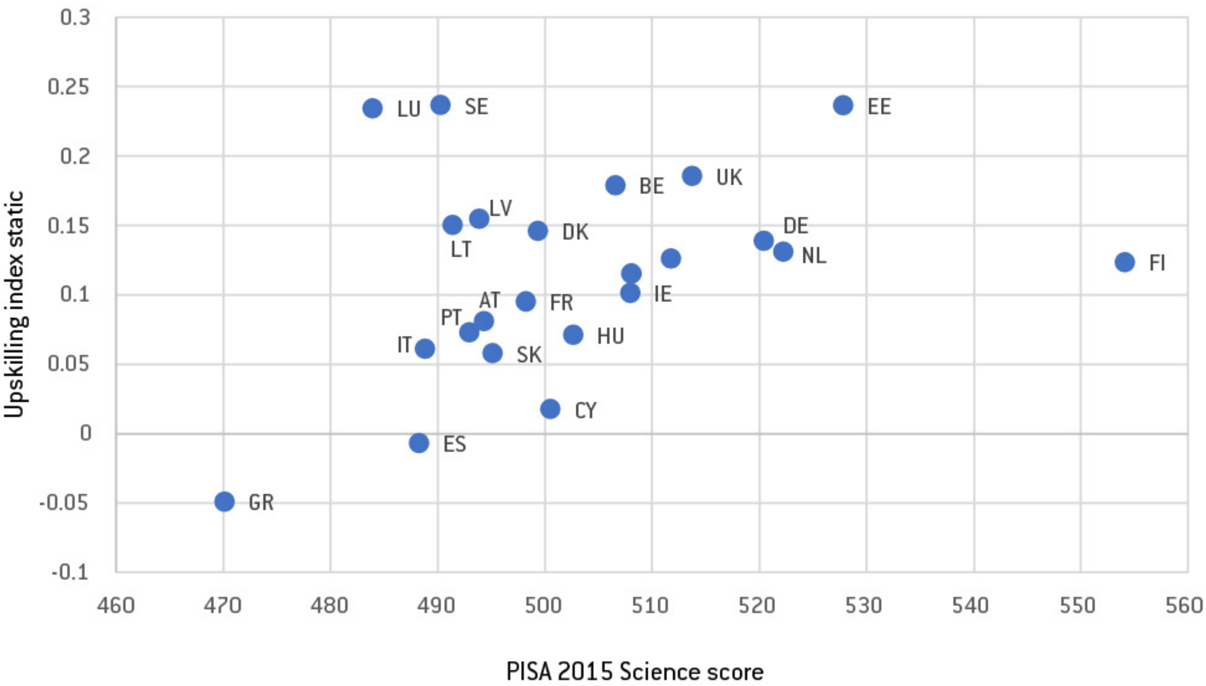
Figure 18: Product market regulation score vs upskilling index, 2016



Source: Bruegel. Note: The upskilling index is based on the index of concentration at the extremes by Krieger et al. (2016), it takes the value of 1 if the whole population of the country is working in high-skill occupations and -1 if the whole population of a country is working in low-skill occupations. The PMR index created by the OECD (2018), is constructed using the 2018 PMR questionnaire. The questionnaire includes over 1000 questions on economy-wide or industry-specific regulatory provisions and is filled in by relevant national institutions.

We also considered the relationship between quality of education and the degree of upskilling of a country's labour market. To do so, we compared each sample country's upskilling index for 2016 with the quality of science education of that country in 2009. As a measure of the quality of science education in a country for the year 2009 we employ the OECD's Programme of International Student Assessment (PISA) score in the field of science. We use data for 2009 to account for the time lag educational outcomes have on the labour market, although we are aware that the students who took the test in 2009 had just entered the labour market in 2016. Nevertheless, we believe that the quality of an educational system changes only slowly and thus the country scores tend to be correlated over time. We observe from Figure 18 that there appears to be a positive correlation between the PISA Science score and the upskilling index. Estonia has one of the highest PISA scores and has a highly skilled occupational structure. Greece, however, displays a low PISA science score and a low level of upskilling. We nevertheless also identify outliers including Luxembourg, Sweden and Finland.

Figure 19: PISA 2009 Science score vs upskilling index, 2016



Source: Bruegel. Note: The upskilling index is based on the index of concentration at the extremes by Krieger *et al* (2016). It takes the value of 1 if the whole population of the country is working in high-skill occupations and -1 if the whole population of a country is working in low-skill occupations. The PISA 2009 Science score (OECD, 2010) is a measure ranging from 0 to 1000 based on microdata from the OECD PISA test. The PISA test is a standard test administered to 15-year-old high school students across the countries participating in the programme.

7 Conclusion

In our analysis, we have evaluated several aspects of occupational change in the EU labour market and potential job polarisation, with a special focus on educational attainment, geography and the potential effects from the transformative nature of AI. The starting point for our analysis is that real wages appeared to have diminished in the aftermath of the financial crisis, after having been on a rising trend prior to that. Real wage developments between 2005 and 2016 were different for different educational groups. Tertiary educated workers' wages declined the least, while lower secondary educated workers' wages declined the most. We wanted to assess if occupational changes contributed to these trends. We evaluated in this paper the occupational changes in a selection of 24 EU countries between 2002 and 2016, using an approach developed by Autor and Dorn (2013) and enhanced by Autor (2019). We obtained the following results.

First, looking at the whole sample, there appears to be little evidence of pervasive job polarisation. Mid-skill employment dropped this but was mostly compensated for by a rise in high-skill employment. However, the first decomposition we make between two subperiods, 2002 to 2009, and 2009 to 2016, already shows a different picture. The first period could be referred to as a period of upskilling for the EU labour force, but the period post-2009 saw a significant increase in low-skill occupations. Furthermore, we observe that over the whole period considered, the average educational attainment of EU workers improved substantially. We find this to be an important driver of the upskilling of the EU labour force, as the share of tertiary-educated workers, who tend to have high-skill jobs, rose by 11 percentage points between 2002 and 2016. The employment share of high-skill occupations rose as well. For specific groups of educational attainment, a different picture emerges. Tertiary-educated workers tend to be more likely to have lower skill occupations, although the changes are small. Upper/post-secondary workers and lower secondary workers appear to be significantly polarised, as they have been displaced to low-skill jobs to a greater extent than to high-skill jobs. This trend is especially strong for lower secondary educated workers after 2009. We believe that this might be linked to the wage dynamics of these educational groups over the period considered.

The second part of our analysis relates to the linkages between urbanisation and occupational change. We first look at how the prevalence of skilled employment relates to population densities in the EU. We find that high-skill jobs are concentrated in high population-density regions, mid-skill jobs in the middle of the density distribution and low-skill occupations in low-density regions. We do not, however, over the period of our study, find significant changes in these structures. We also evaluated if there were significant changes in employment structures at a less-aggregate level, comparing cities with suburban areas and towns, and rural areas. There, we found that cities followed by suburban areas were most affected by declines in mid-skill occupations, and that non-tertiary educated workers were mostly shifting to low-skill occupations in these areas. These results match to some degree the findings of Autor (2019) for the United States.

The third part of this paper is a more forward looking one: the potential impact of AI on occupational structures. We use the probability-of-automation score created by Nedelkoska and Quintini (2018) and apply it to our data. In the new wave of technological development that is machine learning, mid-skill occupations are still most likely to be negatively affected, but low-skill occupations are also highly exposed. High-skill jobs are far less exposed to machine-learning technologies. Both for low-skill and mid-skill occupations, rural areas appear to be where exposures are the highest. By comparing the probability-of-automation score across EU countries, we find that they are heterogeneously exposed. Countries with the most upskilled employment structures face limited exposure, but there are differences even for countries with similar shares of high-skill employment. Our finding that countries moved on average from upskilling to polarisation during the financial crisis is therefore a reason for concern.

Finally, we consider the correlation of our upskilling index with the probability of automation score and several institutional variables for exploratory purposes. We notice that EU countries with upskilled labour markets also tend to be less exposed to the rise of AI technologies. Furthermore, we see significant variations between EU countries in that regard. Comparing exposure to AI across country-industries is instructive as well. Overall, the results match those of the country-level analysis. However, some industries appear relatively more or less exposed, given their levels of upskilling. In addition, it appears that upskilling is also corelated with market openness and labour market flexibility. Countries with less regulated markets also appeared to have higher degrees of upskilling. Finally, we observe that countries with high quality science education have tended to have higher skill-oriented occupational structures.

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