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ABSTRACT

Routine and Ageing? The Intergenerational Divide in the Deroutinisation of Jobs in Europe*

This paper analyses the age dimension of changes in the task composition of jobs in 12 European countries between 1998 and 2014. We use the approach proposed by Autor et al. (2003) and Acemoglu & Autor (2011), and combine O*NET occupation content data with EU-LFS individual data to construct five task content measures: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical. We estimate occupation-level and worker-level regressions and find that the shift away from routine work and toward non-routine work occurred much faster among workers born between 1970 and 1989 than among workers born between 1950 and 1969. In the majority of countries, the ageing of the workforce occurred more quickly in occupations that were initially more routine-intensive, as the share of young workers in these occupations was declining. Individuals in these occupations were increasingly likely to be unemployed, especially if they were between the ages of 15 and 34.

JEL Classification: J21, J23, J24

Keywords: task content of jobs, routinisation, ageing, occupational change, O*NET

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NON-TECHNICAL SUMMARY

The shift away from routine work and toward non-routine work, the so called "deroutinisation of work", is one of the critical changes on labour markets around the world. Routine-biased technical change and offshoring are often identified as the factors behind these developments that reduce demand for middle-skilled labour and contribute to the polarisation of developed countries' labour markets. The literature on the rise of non-routine jobs and job polarisation has largely focused on changes in the distribution of skills and education across the workforce. The age and cohort dimension of deroutinisation has so far been overlooked, except for Autor & Dorn (2009) for the US. This dimension is, however, important because the impact of technical progress depends on workers' skills and adaptability to innovations, which in turn differ by age – older workers tend to have lower ICT-related and analytical skills (as evidenced by the PIAAC survey) and are also less likely to switch occupations than young workers. We wish to address this gap, and study 12 European countries (Austria, Belgium, Czechia, Denmark, Estonia, Germany, Greece, Hungary, Poland, Spain, Sweden, and the United Kingdom) between 1998 and 2014. We combine O*NET occupation content data and EU-LFS individual data, and follow Acemoglu & Autor (2011) in distinguishing between five task contents: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical.

We find substantial intergenerational differences behind the dominant shift from manual work to cognitive work, and from routine work to non-routine work. In Europe, these changes occurred much faster among younger workers: compared to workers born between 1950 and 1969, workers born between 1970 and 1989 experienced a much faster increase in the intensity of non-routine cognitive tasks, and a much faster decline in the intensity of manual tasks. The differences in the changes in the intensity of routine cognitive tasks were less pronounced, but were still noticeable.

Routine jobs were ageing faster in Europe. We find that in the majority of the countries studied, the age structures of the occupations with relatively high routine intensities of tasks in 1998 had aged more rapidly by 2010 than the occupations with the lower routine intensities. This finding was in turn related to a stronger relative decline in the share of young workers (aged 15–29) in the more routine-intensive occupations. On the other hand, the age structures of the occupations with relatively high non-routine cognitive content in 1998 had aged more slowly by 2010.

Individuals in routine-intensive occupations were increasingly likely to be unemployed, especially if they were aged between 15 and 34. The previous literature (Autor et al.; 2003, Michaels et al.; 2014, Goos et al.; 2014) showed that the hollowing-out of middle-skilled, routine jobs is likely to be driven by demand-side factors. Consequently, these factors may influence the unemployment risk of routine workers. Indeed, we found that in six out of the 12 countries we studied the more routine intensive an occupation was in 1998, the greater

the increase in the share of unemployed workers in this occupation was by 2010. At an individual level, a higher routine intensity was significantly related to a higher probability of unemployment in all of the countries studied, both in the late 1990s and in the 2010s. In most of the countries, this effect increased over time, and it was strongest for the younger workers (aged 15–34) in all countries except Greece.

Our findings have important policy implications. On the one hand, as older workers have so far been less affected by occupational changes than younger workers, and the age structures of routine-intensive occupations are ageing faster, older workers may be disproportionately affected if the shift away from routine work intensifies in the future. Life-long learning and on-the-job training are needed to address the challenges that older workers face, especially considering the European-wide gap in ICT skills between older and younger workers (as shown in the PIAAC survey). On the other hand, educational systems should be adapted to foster the development of the skills required to perform non-routine tasks, because young workers who enter more routine-intensive occupations face a relatively high unemployment risk, which has been increasing in recent years. Even if this effect can partly reflect the sorting of individuals with less human capital into more routine-intensive occupations (which we cannot account for using the EU-LFS data), it is still important that educational systems seek to impart the skills that will enable individuals to take non-routine jobs, as the failure to train people in these higher level skills may exacerbate inequalities in labour markets outcomes.

1. Introduction and motivation

One of the secular developments in the labour markets around the world over the past three decades has been the gross reallocation of labour from manual to cognitive work and the increasing importance of the non-routine content of jobs. Since the 1970s, middle-skilled, routine jobs in the US have been in decline, whereas the employment shares of high-skilled and low-skilled workers have grown (Autor et al., 2003; Autor & Price, 2013). Similar employment shifts, the "deroutinisation", have been occurring in Western European countries since the 1990s (Goos et al., 2014). Technological progress, especially if aimed at automating routine tasks that can be performed by machines following explicit rules, is often identified as the main reason for the hollowing-out of middle-skilled, routine employment and the polarisation of labour markets; as automation and computerisation reduce demand for workers to perform routine tasks (Autor et al., 2003; Autor et al., 2006; Acemoglu & Autor, 2011; Brynjolfsson & McAfee, 2014). Michaels et al. (2014) showed that in 11 OECD countries the growth of ICT has led to decreased demand for middle-educated workers, while it has resulted in increased demand for highly educated workers. Graetz & Michaels (2015) provided evidence that robots are crowding out low-skilled workers and, to a lesser extent, middle-skilled workers. Finally, the diffusion of ICT has intensified the shift away from routine work and towards analytical and interpersonal activities (Deming, 2015; Spitz-Oener, 2006; de la Rica & Gortazar, 2016). Offshoring is the second main factor that has contributed to the relative decline of routine-intensive, middle-skilled jobs, particularly in OECD countries (Goos et al., 2014, Hummels et al., 2016). The middle-income and the low-income countries have also been experiencing a shift away from manual work and towards cognitive work. However, routine employment, and especially routine cognitive employment, has either remained stable or even increased in the emerging South (Aedo et al., 2013), in Russia (Gimpelson & Kapeliushnikov, 2016), and in the transition economies of Central and Eastern Europe (Hardy et al., 2016). Hardy et al. (2016) attributed this evolution of routine work in emerging economies to structural change; specifically, to a gross reallocation of labour from (highly manual) agriculture to manufacturing (industrialised countries tend to have more routine-intensive labour markets; Marcolin et al., 2016) or services (which tend to be more cognitive-intensive than other sectors). Gimpelson & Kapeliushnikov (2016) found similar patterns in Russia.

The literature on the rise of non-routine jobs and job polarisation has largely focused on changes in the distribution of skills and education across the workforce. Other dimensions, such as age or gender, have rarely been studied. Still, Autor & Dorn (2009) found that in the US, the age structure of occupations that exhibited a relatively high degree of routine task intensity in 1980 had aged relatively quickly by 2005 (the average age of the workers had increased more than that of other occupations) and the employment shares of these occupations had decreased. Over this period in the US, only the youngest workers experienced mobility from routine to non-routine cognitive jobs; whereas flows in the opposite direction were more common in other age groups, regardless of the workers' education levels (Autor & Dorn, 2009). It has also been shown that the shares of inactive older workers in the US have been growing more in local labour markets that had relatively high initial shares of routine-intensive employment (Autor et al., 2015). Cortes (2016) found that since the 1990s in the US, the risk of unemployment has increased more among routine workers than among non-routine workers. Bosch & ter Weel (2013) showed that older workers in the Netherlands have been more likely than younger workers to end up in declining occupations with relatively low shares of high-skilled workers, to face a high risk of offshoring, and to perform more routine tasks.

Evidence has thus emerged that older people have a greater tendency than younger individuals to work in routine-intensive jobs which have declined in most countries. However, studies that have analysed the age differences in changes in the task content of jobs, and that have also accounted for unemployment, are scarce, especially in a cross-country setting. We wish to address this gap, and aim to answer two sets of questions. 1) Has the task content of jobs evolved differently among younger and older workers in Europe? Have workers in routine-intensive occupations been getting younger or older on average than other workers? 2) Since routine work is susceptible to automation, how has the relationship between the routine intensity of tasks and the unemployment risk changed over time? Has this relationship diversified by age? To answer these questions, we analyse 12 European countries – Austria, Belgium, Czechia, Denmark, Estonia, Germany, Greece, Hungary, Poland, Spain, Sweden, and the United Kingdom – between 1998 and 2014.[1] We follow Acemoglu & Autor (2011) in distinguishing between five task contents: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical.

The age dimension of occupational and task content changes is important because the impact of technical progress depends on workers' skills and adaptability to innovations, which in turn differ by age. OECD (2013) showed that older people tend to have lower ICT and analytical skills than younger individuals: the shares of adults aged 55-64 who were among the best performers (Level 2 or 3) in PIAAC tests of problem-solving in technology-rich environment were very low in all of the countries surveyed, and workers aged 55-64 were found to be 10 pp. less likely on average to use information-processing skills at work than workers aged 26-54. The skills gap observed among older workers may be attributed either to the depreciation of skills over the life-cycle (Desjardins & Warnke, 2012) or to cohort-specific effects. Some scholars have argued that the shift away from routine work and towards non-routine work is linked to the cohort-specific upskilling of the labour force, as younger workers are increasingly likely to be college or university graduates (Oesch, 2013; Salvatori, 2015; Hardy et al., 2016). Older workers tend to be offered fewer opportunities than younger workers to participate in training, as it is generally believed that older people are less willing to learn (Tempest & Coupland, 2016). They could be also more sceptical than younger workers about the usefulness of new technologies (Morris & Venkatesh, 2000). Aubert et al. (2006) showed that in French manufacturing firms, the introduction of new technologies reduces hiring opportunities more for older workers than for younger workers. Older workers also tend to have less between-occupation mobility than younger workers (Tempest & Coupland, 2016), which could make it difficult for them to switch to non-routine occupations. These findings raise serious concerns, as Acemoglu & Restrepo (2017) have found that the countries with the highest rates of automation through industrial robots are also the countries with the most rapidly ageing workforces.

The paper is structured as follows. In Section 2, we outline the methodology and the data used. In Section 3, we present the overall and the cohort-specific evolutions of the task content of jobs in the analysed countries. In Section 4, we analyse the relationship between the routine intensity of jobs and the ageing of workers in particular occupations. In Section 5, we study links between the routine task intensity (RTI) of occupations and the unemployment risk, allowing for differences between countries, age groups, and over time. In Section 6, we conclude and discuss our findings.

[1] We selected 12 countries that represent different economic and labour market models in Europe. In principle, any country covered by the EU-LFS can be analysed. The first year of our study reflects EU-LFS data availability.

2. Data and methodology

2.1. Data sources

We use the Occupational Information Network (O*NET) data and merge them with the EU-LFS data for 12 European countries – Austria, Belgium, Czechia, Denmark, Estonia, Germany, Greece, Hungary, Poland, Spain, Sweden, and the United Kingdom – in the period 1998-2014.[2] We apply the International Standard Classification of Occupations (ISCO) at the 3-digit level. Because the EU-LFS data for Poland include occupation codes at the 2-digit ISCO level, we instead use the LFS data provided by the Polish statistical office, which include occupations at the 3-digit ISCO level. In order to account for possible changes in the task content within occupations, we use the 2003 and the 2014 editions of O*NET.

We use crosswalks to match the O*NET task data for occupations (coded with an O*NET-specific extension of SOC classification of occupations) to the EU-LFS data (coded with an ISCO classification of occupations). For the Polish LFS data, we use additional crosswalks between the Polish classification (KZiS) and the ISCO classification.[3] As the EU-LFS data for our country sample contain a 3-digit level ISCO classification, we use the crosswalks for a 4-digit level of detail of the ISCO classification, and subsequently aggregate it into means of task items within a 3-digit level of detail.

The ISCO classification underwent a major revision in 2011 when the ISCO-88 was supplanted by the ISCO-08. This resulted in shifts in occupational time-series, since these two classifications are not entirely comparable. In general, we made three adjustments to achieve consistent data for the entire analysed period: a recoding of tasks items for farm workers (see also Aedo et al., 2013), a recoding of tasks for (selected) occupations in wholesale and retail trade, and a general rescaling aimed at removing the break between the 2010 and the 2011 data (discussed in the next subsection). The move from the ISCO-88 (COM) to the ISCO-08 classification led to shifts in the occupational time-series, since the classifications are not entirely comparable. In particular, in the farming occupations the non-routine cognitive task intensities are much higher in the ISCO-88 than in the ISCO-08. However, farming jobs are typically associated with routine and manual tasks (Arias et al., 2014), and involve relatively few non-routine cognitive tasks (Acemoglu & Autor, 2011). We therefore assumed that the ISCO-08 classification is more precise, and replaced the values of task items for some farming occupations in the ISCO-88 data with the task items in the ISCO-88 data. In each country separately, we selected at least three occupations that jointly represented at least 80% of the employment in agriculture (starting from the occupations with the largest shares) in 1998. For those ISCO-88 occupations, we matched the task items from the relevant occupations in the ISCO-08 (an average if more than one was matched).[4]

[2] Previous studies that use O*NET data merged with LFS data for other countries than the US include Arias et al. (2014), Goos et al. (2013), Goos et al. (2014), Dicarlo et al. (2016), and Hardy et al. (2016). Handel (2012) showed that US occupation-based and non-US skill survey-based measures lead to very similar outcomes for European countries. Cedefop (2013) confirmed that it is methodologically valid to use O*NET data to construct occupational measures in European countries.

[3] The complete set of crosswalks that we used is available online: ibs.org.pl/en/resources [accessed: 2017-01-27].

[4] We used the crosswalk available at the ILO website: http://www.ilo.org/public/english/bureau/stat/isco/isco08/ [accessed: 2017-01-30]

Table A1 in the appendix presents information on which occupations were updated in particular countries in order to ensure the consistency of the task data.

Corrections were also needed in the coding of occupations in the wholesale and retail trade sector. The ISCO-08 distinguishes between salespersons and supervisors within the group 522, whereas the ISCO-88 did not. This occupational group accounts for a large share of employment in wholesale and retail trade, and thus significantly influences the task composition in this sector. Since the EU-LFS occupational data are not coded at a 4-digit level, large shifts emerged in the intensity of routine cognitive tasks between 2010 and 2011 (the time of the transition to the ISCO-08). We therefore excluded occupations 5222 (shop supervisors) and 5221 (shop keepers) from our O*NET data; and from 2011 onwards, we assigned the mean task items of occupational group 5223 (shop sales assistants) to the occupational group 522 (shop salesperson). We found no other substantial differences in the ways in which occupations were coded in the ISCO-88 and the ISCO-08, but there are some breaks in the data that may be due to changes in country-specific classifications of occupations that are mapped into the ISCO in the EU-LFS.

2.2. Calculating the task content of jobs

In calculating the task content of occupations, we follow the procedure presented in Acemoglu & Autor (2011). Once the O*NET task items (from both 2003 and 2014 editions) are assigned to the EU-LFS data, we standardise the values of each task item over time, using the survey weights for each country separately. This approach follows the procedures used in the cross-country studies of Arias et al. (2014), Goos et al. (2014), Dicarlo et al. (2016), and Hardy et al. (2016). In the next step, we apply the Acemoglu & Autor (2011) definitions in order to construct five task content measures: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical. In the final step, we standardise the content measures over time using the survey weights for each country separately. As the standardisation of tasks measures is performed within countries, the estimated values of task contents allow for comparisons of task content levels over time within countries, but they do not allow for comparisons of task content levels between countries.

Because the ISCO transitioned from one classification another in 2011, the task intensity trends were inconsistent in that year. To account for this problem, we rescaled the period 1998-2010 so that the country-wide values and their standard deviations in 2010 equalled those in 2011. Our approach is similar to that of Goos et al. (2014). It removes any changes in the task intensities between 2010 and 2011, while ensuring that the changes that occurred between 1998-2010 and 2011-2014 are otherwise comparable.

Additionally, a few countries changed their national ISCO classifications over the period of the study. While the EU-LFS data contain uniform ISCO-88 (COM) and ISCO-08 classifications, the conversion of these data from national classifications does not fully account for the national changes. In 2001, the United Kingdom updated their classification to the SOC-00, which resulted in shifts in the task content intensities. We apply the above mentioned rescaling approach to the 1998-2000 period in the United Kingdom. Moreover, Poland introduced a new classification in 2002, in 2004 (2003 and 2005 in the Polish LFS data), and in 2007. While the most recent change did not affect the results (the changes did not affect the 4-digit level of classification), we applied the rescaling approach to the first two changes.

We apply a moving average to combine the task content measures based on the 2003 O*NET and the 2014 O*NET for each occupation. From 1998 to 2003, we use task indices based on O*NET 2003; for any year t in the period 2004-2014, we assign a weight $\frac{2014-t}{11}$ to task indices based on O*NET 2003, and a weight $\frac{t-2003}{11}$ to task indices based on O*NET 2014. The average level of task content calculated for a given population will be called task intensity. In order to have a common reference point, we shift the values of tasks so that the initial level of every average task intensity at the country level is equal to zero. For presentation purposes, we multiply all values by 100. The resulting values for any task intensity in any year range from -20.2 (routine manual for Spain in 2014) to 18.3 (non-routine cognitive analytical for Estonia in 2014), with a standard deviation of 7.8 for all calculated values (the smallest standard deviation is 5.7 in Germany and the largest standard deviation is 9.7 in the United Kingdom).

After calculating the task content intensities for workers, we assigned the same task content intensities to unemployed individuals based on the last they job held. For unemployed individuals who had never worked or did not provide the occupation code on their last job, the task contents are defined as missing.

2.3. Disaggregating the age groups and calculating the values for the birth cohorts

The EU-LFS data contain information on five-year age groups (15-19, 20-24,..., 60-64), but our interest here is in analysing five-year birth cohorts (born 1950-1954, 1955-1959,..., 1985-1989).[5] For the purposes of our analysis, we calculate the task contents for each year between 1998 and 2014 for each five-year age group. We then disaggregate the data to obtain task content measures for one-year age groups. Finally, we aggregate the relevant one-year age groups to the same five-year birth cohorts.

We use an algorithm implemented in R that takes a variable, a, described over a grid of ordered values with a specified frequency, a_j where $j \in J$ is a set of five-year age groups (15-19, 20-24, ..., 60-64), and recalculates them over a grid with a higher frequency , a_{ji} where $i = 1, \dots ,5$, identifies consecutive years within each five-year age group. The algorithm minimises the distances between every two consecutive disaggregated values, a_{ji}, with a criterion $min \sum_{j \in J} \sum_{i=1}^{5} \left(a_{ji} - a_{j(i-1)}\right)^2$ (where $a_{j(0)} = a_{(j-1)5}$), under the condition that, for every j, $a_j = \frac{1}{\max\{i\}} \left(\sum_i a_{ji}\right)$ if a variable a is an indicator (e.g., task content intensity); or under the condition that for every j, $a_j = \sum_i a_{ji}$ if a variable a is a population total (e.g., population or employment).

We use this algorithm to disaggregate task content intensities, population, and employment from five-year age groups to one-year age groups in each country and in each year studied. The aggregation of values for one-year age groups to values for five-year birth cohorts (born 1950-1954, 1955-1959,..., 1985-1989) is straightforward.

[5] We focus on the age groups of working ages, which are defined by Eurostat as 15-64 years for most of the period studied; and on cohorts who were of working ages in 2014.

2.4. Routine task intensity index

Following the literature, we also construct the routine task intensity (RTI) for each occupation as the relative intensity of routine tasks, using the formula:

$$RTI = \ln(r_{cog} + r_{man}) - \ln(nr_{analytical} + nr_{personal})$$

Our definition is consistent with definitions previously used in the literature (Autor & Dorn, 2009, 2013), and in line with Goos et al. (2014) we utilise task contents defined using the O*NET data (Acemoglu & Autor, 2011) instead of the DOT (previous occupational classification) values. This updated approach allows us to clearly distinguish between the routine and the non-routine tasks.[6] It also enables us to use two types of routine tasks – cognitive and manual – as indicators of the routine task intensity.[7] The RTI measure increases with the importance of routine tasks, and declines with the importance of non-routine tasks.

During the 1998-2010 period, the RTI index shows negative values for high-skilled occupations, like legislators, senior officials, managers, and professionals (average of -0.26 across all countries); low positive values for occupations like technicians and associate professionals (average of 0.18 across all countries); higher positive values for clerks, service workers, shop and market sales workers, skilled agricultural and fishery workers (an average of 0.66 across all countries); and the highest values for craft and related trades workers, plant and machine operators and assemblers, and workers in elementary occupations (an average of 1.36 across all countries). The distribution of the RTI index across the whole spectrum of ISCO occupations is presented in Figure A1 in the appendix. The RTI distribution is coherent across our entire sample, as the correlations of the RTI index across occupations in any two countries in our sample range from 95% to 100%.

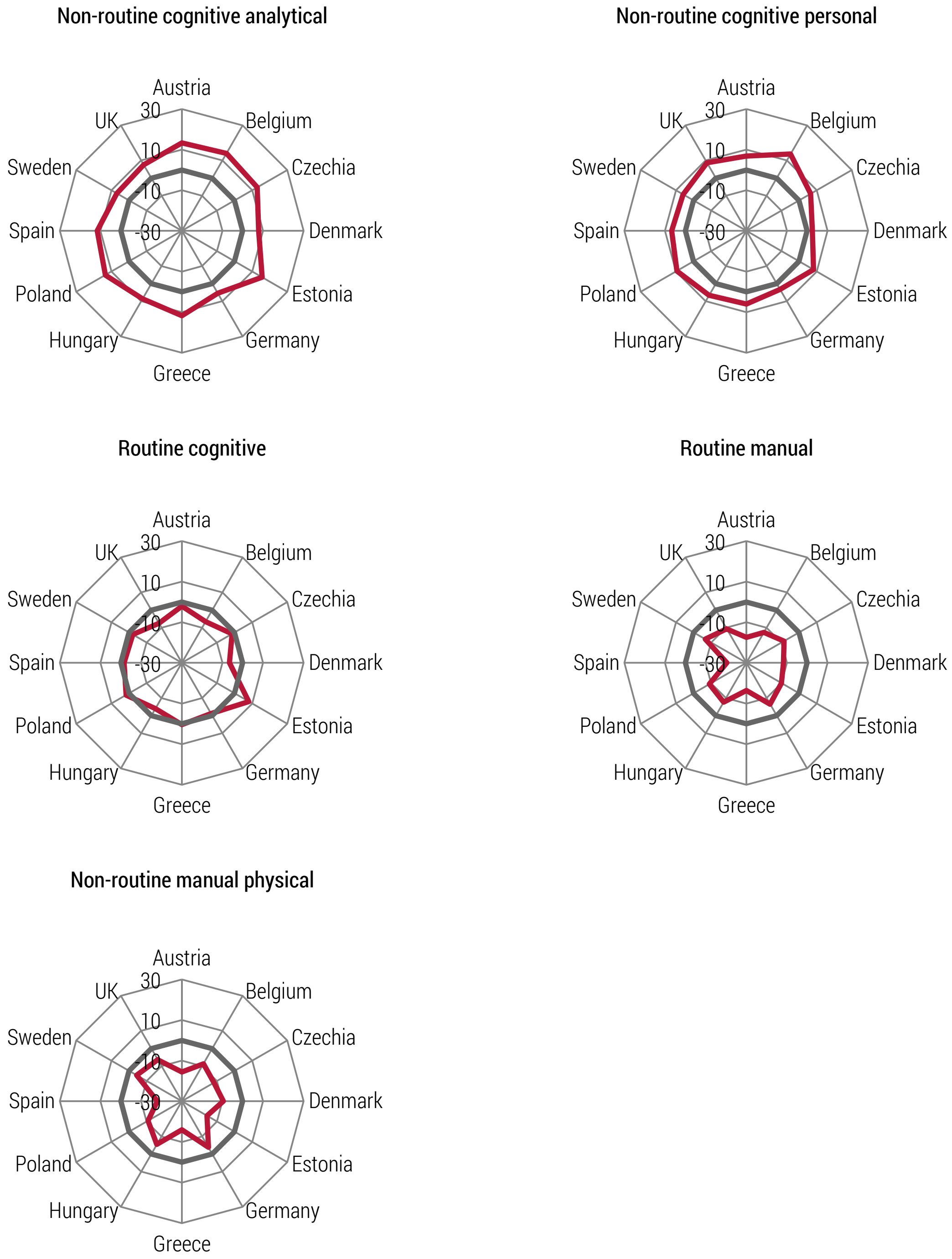
3. How did the task composition change?

The overall changes in tasks were quite similar across the analysed countries. In every country, the intensity of non-routine cognitive tasks rose substantially, in line with the findings of previous studies. At the same time, manual tasks, both routine and non-routine, shrank in all of the countries. However, the patterns of changes in routine cognitive tasks varied more across the countries. Figure 1 shows that in 10 out of the 12 analysed countries, the intensity of routine cognitive tasks contracted (to the greatest extent in Denmark, France, the UK, and Sweden) or held firm (e.g., in Czechia, Germany, and Spain). However, Poland and Estonia, two of the post-transition economies in our sample, saw an increase in the intensity of routine cognitive tasks. Hardy et al. (2016) found similar trends in four other CEE countries (Croatia, Latvia, Lithuania, Romania), and attributed these developments primarily to the patterns of structural change that these countries underwent.

[6] "Analytical", "manual", and "routine" tasks were available in DOT (Autor & Dorn, 2009, 2013).

[7] Since the intensity of routine manual tasks and the intensity of non-routine manual tasks are highly correlated (correlation ranging from 0.70 in Czechia to 0.82 in Sweden and Denmark), in our RTI measure we omit the non-routine manual content. Including these two measures would confound the RTI values. For the purposes of analysing routine-biased technological change, routine manual tasks seem more important than non-routine tasks, as there is no proof of technology directly influencing the demand for the latter.

Figure 1. Total change in the task intensity of jobs between 1998-2000 and 2012-2014 in selected European countries.



*Source: Own calculations based on EU-LFS and O*NET data.*

The pattern of the changes in the task content of jobs varied substantially across cohorts. Generally, the younger cohorts outperformed the older cohorts in the dynamics of task content changes in all of the countries in our sample. Figure 2 presents the estimated time-trend coefficients for task intensities by five-year cohorts born between 1950 and 1989 in all of the analysed countries. Clearly, the changes across time for the cohorts born before 1970 were rather flat in all of the countries. By contrast, the shifts for the cohorts born after 1970 were much more pronounced. Thus, we can see a gap between the older and the younger workers in the dynamics of the evolution of task content. The largest gap is in non-routine cognitive analytical tasks. In the 12 countries we studied, the yearly growth rate of these tasks between 1998 and 2014 averaged 0.43 for the cohorts born in 1950-1970 and averaged 4.2 for the cohorts born in 1970-1989. Reflecting the patterns observed for the non-routine cognitive tasks, we see that the younger cohorts experienced a deeper and a faster decline in the intensity of manual tasks. The average time trend coefficient for non-routine manual tasks was -0.40 for the cohorts born in 1950-1970, whereas it was -2.72 for the cohorts born in 1970-1989. Table 1 shows the time-trend coefficients estimated with fixed-effects panel regression. The results displayed in the table reaffirm the above findings: European countries experienced some kind of intergenerational divide in the changes in the task composition and deroutinisation of jobs.

The differences between the cohorts were less pronounced in the case of routine cognitive tasks: i.e., the averages of the estimated trend coefficients were -0.67 for the cohorts born in 1950-1969 and were -0.69 for the cohorts born in 1970-1989. Nearly all of the cohorts experienced a decline in the intensity of routine cognitive tasks, apart from the cohort born in 1985-1989, for whom the intensity of routine cognitive tasks generally rose (see Table 1). However, Figure 2 shows that the trend in question was positive in seven countries, and was significant in four countries only (it was largest in Poland at 9.5 and in Greece at 2.2; and it was also positively significant in Germany and Austria).[8]

Table 1. Time-trend coefficients from fixed-effects panel regressions on the task content intensities within cohorts

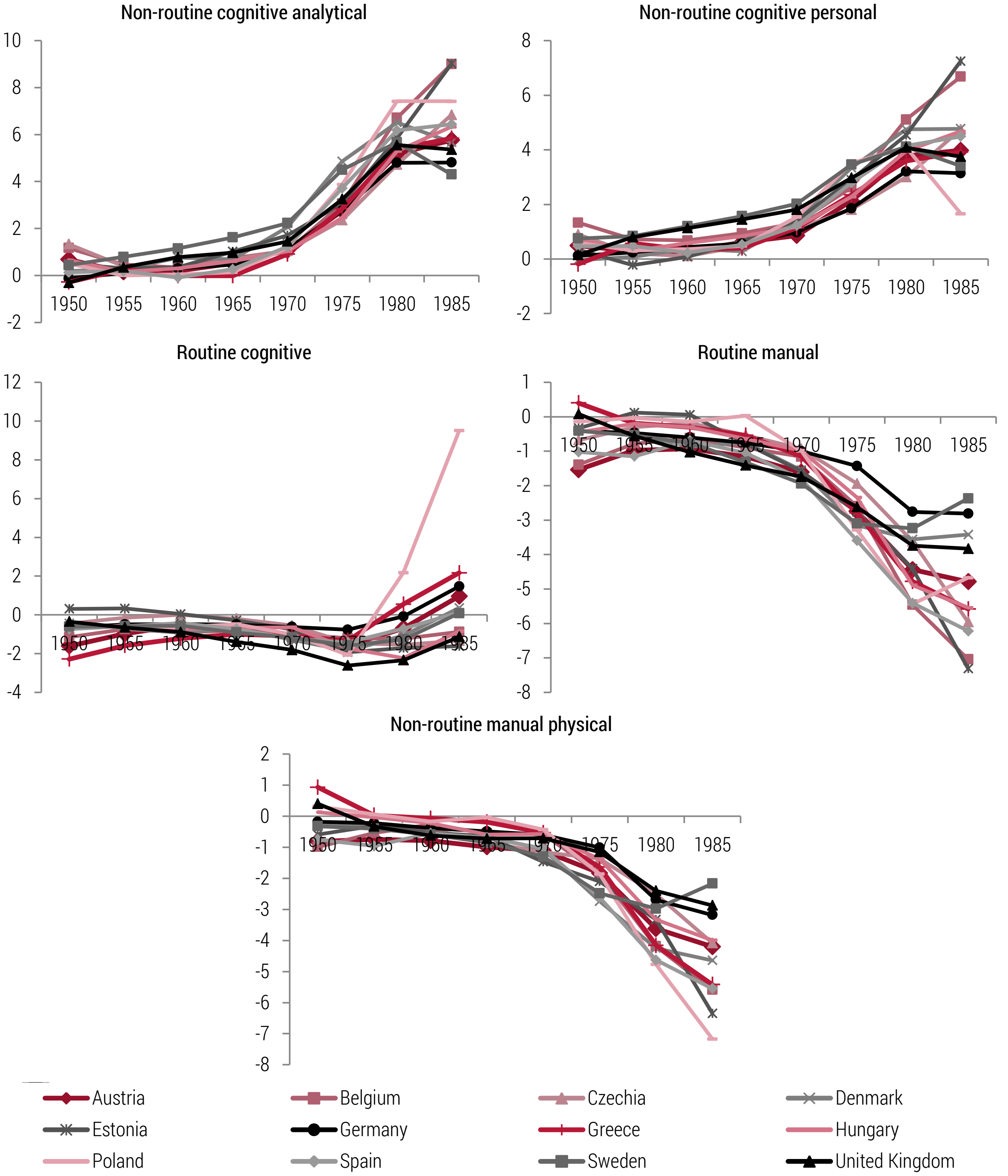
	1950-1954	1955-1959	1960-1964	1965-1969	1970-1974	1975-1979	1980-1984	1985-1989
Non-routine cognitive analytical	0.41***	0.28***	0.37***	0.64***	1.34***	3.30***	5.77***	6.39***
Non-routine cognitive personal	0.47***	0.38***	0.48***	0.73***	1.34***	2.67***	4.03***	4.36***
Routine cognitive	-0.77***	-0.61***	-0.61***	-0.70***	-1.02***	-1.63***	-0.84***	0.81***
Routine manual	-0.52***	-0.46***	-0.53***	-0.82***	-1.37***	-2.70***	-4.31***	-4.93***
Non-routine manual physical	-0.20***	-0.34***	-0.43***	-0.60***	-0.88***	-1.84***	-3.57***	-4.62***

*Note: Each coefficient comes from a separate panel regression with a specific task content measure (rows) as the explained variable and time-trend as the control variable, with the samples reduced to specific cohorts (columns). *** p<0.01.*

*Source: Own estimations based on EU-LFS and O*NET data.*

[8] The time-trend coefficients for routine cognitive tasks for the cohorts born in 1950-1965 in Estonia and for the cohorts born in 1980-1984 in Greece were also positive, but not statistically significant.

Figure 2. Linear time-trend coefficients estimated for the tasks intensities in the 1998-2014 period across cohorts.



Note: Each coefficient comes from a separate country-specific regression with a specific task content measure (rows) as the explained variable and time-trend as the control variable, with the samples reduced to specific cohorts (columns).
*Source: Own estimations based on EU-LFS & O*NET data.*

4. Ageing of routine occupations

In order to ascertain whether the age structure of routine jobs has been getting older, we follow the approach used by Autor & Dorn (2009). We regress the change in the mean age of a job on its routine task intensity (RTI, as defined in the subsection 2.4). We estimate the country-specific OLS regressions of the change in the mean age of workers in various occupations between 1998 and 2010 (at the ISCO-88 3-digit levels) on the initial (1998) RTI level in occupations and the changes in occupational employment shares between 1998 and 2010. We study the changes between 1998 and 2010. The period of analysis is shorter than in the previous section, because the changes within occupations can be analysed only for a period when a given classification of occupations was used It is not possible to fully and consistently map the ISCO-88 occupations (valid between 1998 and 2010) to the ISCO-08 occupations (valid between 2011 and 2014) at the 3-digit level. Therefore, we study the changes between 1998 and 2010 (the 2011-2014 period is too short to perform a credible analysis of the ageing of occupations).

Our results show that in eight out of 12 analysed countries, the higher the routine task intensity of an occupation was in 1998, the greater the change in the average age of the workers in this occupation was by 2010 (see Table 2). This pattern is similar to the pattern found by Autor & Dorn (2009) for the US. No significant relationship was observed in Austria, Greece, Sweden, or Estonia. Autor & Dorn (2009) also found a negative relationship between the change in the average age of the workers in an occupation and the change in the occupation's share of overall employment. In our sample, only Czechia and Estonia exhibited such a trade-off. In Austria, Denmark, Greece, and Poland, the change in the average age of the workers and the change in the employment share of a given occupation were positively related. In the remaining six countries, this relationship was not significant.

Table 2. Country-specific regressions of the changes in the mean ages of workers in occupations between 1998 and 2010, the changes in the RTI in 1998, and the changes in occupations' employment shares

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	United Kingdom
RTI	-0.61	0.90***	0.94**	0.75**	0.73	0.54**	0.15	0.87**	0.99***	0.79**	0.17	0.68**
ΔShare	0.63***	0.23	-0.73***	0.43*	-0.94**	-0.49	0.16**	0.04	0.22**	0.07	0.14	-0.35
No. of obs.	98	98	103	100	98	99	96	100	102	99	101	87
R^2	0.16	0.14	0.12	0.09	0.07	0.08	0.05	0.05	0.16	0.07	0.00	0.09

*Note: *** p<0.01, ** p<0.05, * p<0.1.*
*Source: Own estimations based on EU-LFS and O*NET data.*

The main reason why the age structure of routine jobs grew older more quickly was the declining share of workers in the youngest age groups in these occupations. In eight out of the 12 analysed countries, the higher the initial routine intensity of an occupation was, the more negative the change was in the share of workers in the youngest age group (aged 15-29) in this occupation (Table 3). Additionally, a higher initial RTI was associated with a growing share of workers aged 30-54 in several countries, and with a growing share of workers aged 55-64 in Czechia and Poland. These findings contrast with results for the US, which showed that the RTI-age relationship was mainly characterised by a decreasing share of the youngest workers and an increasing share of the oldest workers, but not by an increasing share of the prime-aged workers.

Table 3. The relationship between the RTI in 1998 and the changes in the shares of age groups within occupations. OLS regression results

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	United Kingdom
Δ 15-29	0.03	-0.020***	-0.039**	-0.019**	0.001	-0.023**	-0.034***	-0.035***	-0.021***	-0.053***	0.010	-0.013
Δ 30-54	0.13	0.014	0.024	0.020**	-0.030	0.025**	0.037***	0.025*	0.012	0.063***	-0.000	0.010
Δ 55-64	0.04	0.007	0.022***	0.001	0.018	0.002	-0.006	0.012	0.006*	-0.008	-0.011	-0.002
No. of obs.	98	98	103	100	98	99	96	100	102	99	101	87

*Note: The coefficients come from three OLS regressions per country, with the change in the share of workers of a specific age group within occupations as the explained variable, and with only the coefficients in addition to RTI reported in the table. All of the regressions included the variable indicating the change in the employment share of the occupation. *** p<0.01, ** p<0.05, * p<0.1.*
*Source: Own estimations based on EU-LFS and O*NET data.*

Complementing the previous results, we find that in several countries the change in the mean age of an occupation was negatively related to the intensity of non-routine cognitive tasks (both analytical and personal, cf. Table 4). This relationship was strongest in Czechia, Hungary, and Poland – three out of four of the post-transition economies in our sample – as well as in Denmark. For Greece, Sweden, and the United Kingdom we find no significant relationship between the changes in the age structure and the importance of non-routine cognitive tasks. Austria stands out as being the only country for which there was a positive relationship between these two variables.

Table 4. The relationship between the change in the mean occupation age and the intensity of non-routine cognitive tasks in 1998 within an occupation. OLS estimation, controlling for the change in the share of the occupation in employment

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	United Kingdom
Non-routine cognitive analytical	0.669***	-0.272*	-0.478**	-0.480*	-0.380	-0.251*	0.195	-0.858***	-0.568***	-0.364*	-0.116	-0.040
Non-routine cognitive personal	0.457**	-0.338**	-0.417**	-0.520**	-0.152	-0.316**	0.095	-0.682***	-0.530***	-0.208	-0.084	-0.157

*Note: Each coefficient was estimated in a separate regression with the change in the mean occupation age as the explained variable and the specific task content measure (rows) as the control variable. Regressions included the change in the share of occupation in employment as a control variable, which is not reported here. *** p<0.01, ** p<0.05, * p<0.1.*
*Source: Own estimations based on EU-LFS and O*NET data.*

5. Routine intensity and the risk of unemployment

In the previous sections, we showed that in European countries, the manual and the routine content of jobs declined between the late 1990s and the mid-2010s, and that the younger workers experienced these changes at a faster pace than the older workers. Because such occupational developments are often attributed to demand-side factors, such as routine-biased technological change or offshoring (Autor et al.; 2003, Michaels et al.; 2014, Goos et al.; 2014), they may be associated with an increase in the unemployment risk of routine workers. Using panel data, Cortes (2016) found evidence that this was indeed the case in the US. Unfortunately, panel datasets cannot be constructed using the EU-LFS, and are not available for the group of countries we are studying. Nevertheless, in this section we use the cross-section LFS data to analyse the relationship between the routine task intensity (RTI) of occupations and the unemployment risk. Our sample includes employed individuals and unemployed individuals who worked at least once in the past, and who provided the occupation code of their last job.[9]

5.1. Routine task intensity and occupation-specific unemployment rates

We define the annual occupation-specific unemployment rates as the share of the unemployed whose last job was in a given occupation in the labour supply in this occupation (i.e., the sum of unemployed individuals whose last job was in a given occupation and employed individuals currently working in this occupation). For each country, we regress the change in the occupation-specific unemployment rates between 1998 and 2010 on the RTI of an occupation in 1998 (see Table 5).

In six out of the 12 countries in our sample, the changes in the occupation-specific unemployment rates between 1998 and 2010 were significantly and positively associated with the occupation-specific routine intensities (RTIs) in 1998. In other words, the more routine the occupation was in 1998, the greater the change was in the occupation-specific unemployment rate over the next 16 years. In three of these countries – Estonia, Greece, and Sweden – this pattern was accompanied by rising unemployment rates across all occupations (as evidenced by a significant and positive constant). In the other three countries – Czechia, Denmark, and Spain – there was no general trend in the occupation-specific unemployment rates (the constant was insignificant). In Belgium and Germany, the relationship between the RTI in 1998 and the change in the occupation-specific unemployment rates was negative (Germany also recorded a significant decline in unemployment rates across all occupations). In the remaining four countries, there was no significant link between the RTI in 1998 and the change in the occupation-specific unemployment rates between 1998 and 2014.

Table 5. OLS regressions of the 1998-2010 change in the occupation-specific unemployment rates and the occupation's RTI in 1998[x]

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	United Kingdom
RTI	0.03	-0.71**	1.62***	2.33***	4.25***	-1.22***	1.97***	0.12	-0.34	4.26***	1.09***	-0.04
Constant	0.81**	0.48	-0.04	0.42	2.04*	-1.57***	2.10***	1.40***	-0.83*	-0.20	1.16***	0.93***
No. of obs.	98	99	104	103	98	101	97	101	102	100	101	88

Note: [x] Due to data availability, the changes in the 1999-2010 period and the RTI in 1999 are used for Germany and the United Kingdom, and the changes in the 2003-2010 period and the RTI in 2003 are used for Sweden. Occupation-specific unemployment rates are calculated by dividing the number of unemployed individuals whose last job was in a given occupation by the labour supply in a given occupation (the sum of employment in a given occupation and the number of unemployed individuals whose last job was in a given occupation). The regressions are weighted with the size of the occupational labour supply (sum of employed and unemployed individuals).
**** p<0.01, ** p<0.05, * p<0.1.*
*Source: Own estimations based on EU-LFS and O*NET data.*

[9] We might be concerned about potential omitted variable and selection issues related to the missing data on occupations. However, the shares of the unemployed who worked at least once and did not report the occupational code of their last job are small – below 2% in all countries (see Table A3 in the appendix). The unemployed individuals who had never worked were not surveyed about their occupations, so we had to exclude them as well. The underlying assumption is that an occupation can be assigned to a worker only if she or he has ever worked in that occupation.

5.2. Routine task intensity and individual unemployment risk

In the next step, we analyse the relationship between the routine task intensity, the risk of unemployment, and age. In order to study how this relationship evolved over time, we use individual EU-LFS data for the first three available years (1998-2000) and for the last three available years (at the time of writing, these years are 2012-2014). We estimate country-specific logit models with unemployment as the explained variable (relative to employment). In the first version of the model, we include the RTI and the time dummy for the 2012-2014 period as the explanatory variables. In the second version of the model, we add a standard set of socio-demographic controls (age, gender, marital status, education level). In the third version, we add two regional controls calculated using the Cambridge Econometrics European Regional Data. In order to account for the regional differences in the prevalence of routine jobs, we assign to each individual the regional employment share of industry (manufacturing and mining, the sector with the highest RTI values) at the time when the individual was in high school (aged 15-19), or the earliest available data.[10] We follow Fletcher & Sindelar (2009), who showed that the regional shares of blue-collar jobs affect the probability that an individual will decide to pursue a blue-collar occupation.[11] We also control for regional labour demand shocks with Bartik (1991) shocks. In the EU-LFS, the regional data are available on the NUTS2 or the NUTS1 level (see Table A4 in the appendix). In the fourth version of the model, we account for the heterogeneity of the RTI effects by age. To this end, we include interactions between the RTI and 10-year age group dummies. We include interactions between the RTI and a dummy variable for the period 2012-2014 in all of the regressions; and in the fourth version of the model we also interact the age-specific RTI variable with the 2012-2014 period dummy. The results of models 1-3 are presented in Table 6, and the results of model 4 are presented in Figure 3 and in Table A4 in the appendix.[12]

We find that in all of the countries studied the individuals in the more routine-intensive occupations were more likely to be unemployed. The odds ratios associated with the RTI in the simple model 1 are higher than one and are highly significant in all countries. Once we control for socio-demographic characteristics (model 2), the odds ratios associated with the RTI decline in all countries, but they remain highly significant in all countries except Spain. The inclusion of two regional controls (model 3) that account for past industrial structures and local labour demand shocks, respectively, does not substantially affect the general effect of the RTI. However, the odds ratio related to the effect of the RTI in the 2012-2014 period becomes positive and significant in Austria, and it increases in Spain. Once we factor out the regional labour demand effects, we find that the effect of the routine task intensity on unemployment increased over time in these two countries. Although the opposite was the case for the UK, the effect of the RTI in the UK was positive in both periods.

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[10] The Cambridge Econometrics European Regional Data covers the 1980-2014 period for the Western European countries, and the 1990-2014 period for the Central and Eastern European countries. Thus, we assign the 1980 shares to all of the individuals born before 1965 in Western European countries, and the 1990 shares to all of the individuals born before 1975 in the Central and Eastern European countries.

[11] Unlike Fletcher & Sindelar (2009), we do not have data on the respondent's place of residence at the age of 15-19 or on the respondent's parents that would have allowed us to create an instrument for early occupation choice.

[12] Model 4 accounts for the heterogeneity of the effects of RTI by age and therefore provides no average effect that could be directly compared with the estimates of models 1-3 presented in Table 6.

Table 6. The effect of the routine task intensity (RTI) on the probability of being unemployed, the estimated odds ratios from logit models 1-3

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	United Kingdom
Model 1												
RTI	1.67***	1.91***	1.83***	1.55***	1.71***	1.76***	1.6***	2.15***	2.14***	1.38***	1.76***	2.12***
RTI * period (2012-2014)	1.08	1.04	1.33**	1.17	1.03	1.08	1.03	0.96	1.12	1.33*	1.25**	0.99
Model 2												
RTI	1.43***	1.28**	1.40***	1.45***	1.45***	1.55***	1.34	1.59***	1.82***	1.03	1.43***	1.72***
RTI * period (2012-2014)	1.10	1.09	1.19	1.14	1.05	1.06	0.96	0.93	0.92	1.33**	1.25**	0.97
Model 3												
RTI	1.45***	1.37***	1.34***	1.45***	1.45***	1.55***	1.34	1.58***	1.83***	1.07	1.44***	1.73***
RTI * period (2012-2014)	1.13	1.03	1.21	1.15	1.05	1.09	0.96	0.93	0.91	1.31**	1.25**	0.97

Note: Model 1 – explanatory variables: RTI, time dummy (ref. 1998-2000[x]). Model 2 – explanatory variables: RTI, time dummy (ref. 1998-2000[x]) and personal characteristics (age, gender, marital status, education level). Model 3 – explanatory variables: RTI, time dummy (ref. 1998-2000[x]), personal characteristics (age, gender, marital status, education level) and regional controls (industry shares at the point in time when the worker was aged 17 or the earliest available shares, and Bartik (1991) local labour demand shocks). The standard errors are clustered at the occupation level. Only the results for the RTI are presented. The results for the other explanatory variables are available upon request.

Due to data availability, the reference period is 1999-2001 for Germany and the United Kingdom and is 2003-2005 for Sweden.

**** p<0.01, ** p<0.05, * p<0.1.*

*Source: Own estimations based on EU-LFS, O*NET, and Cambridge Econometrics European Regional Data.*

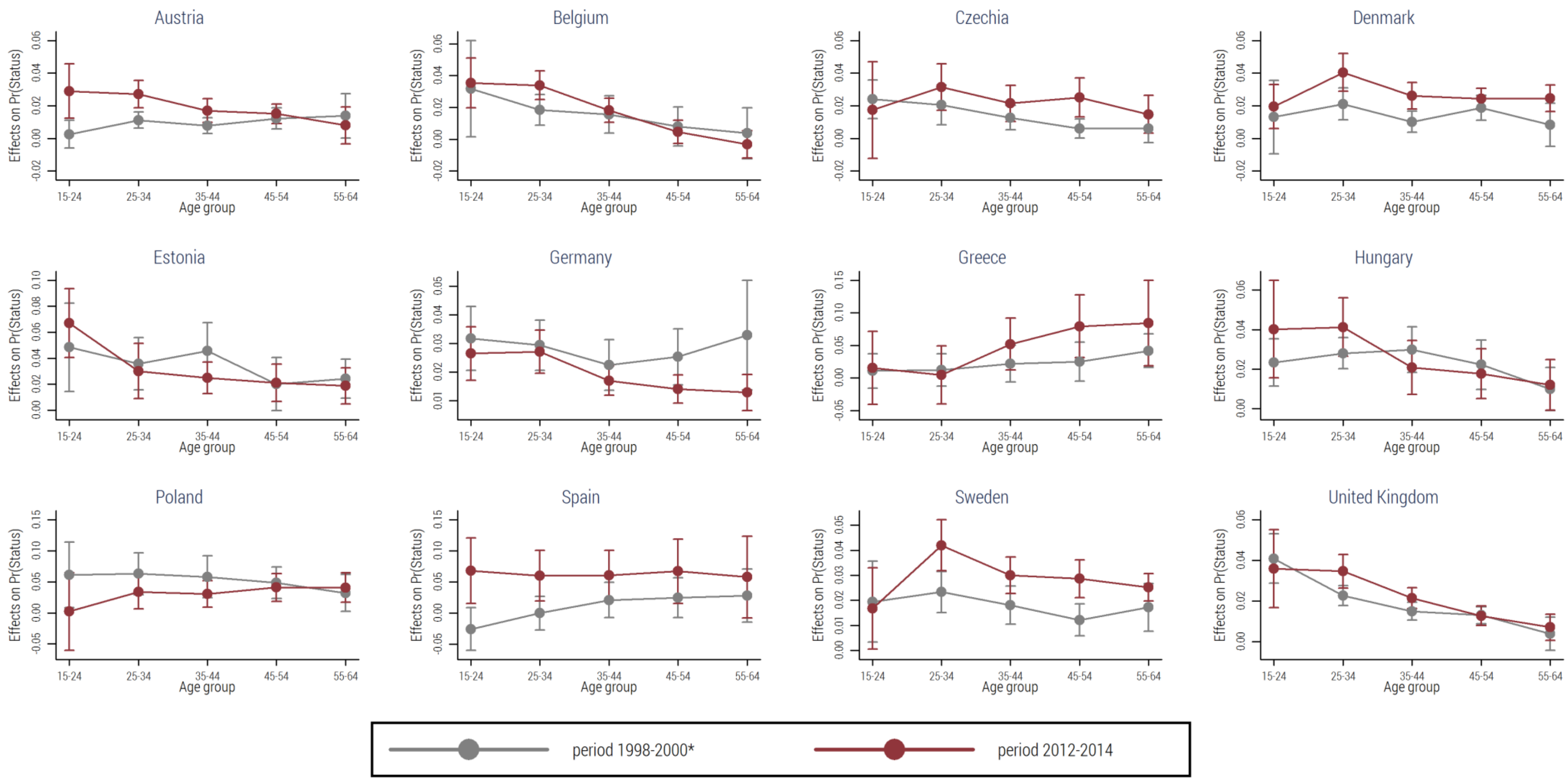
We find that in most countries the link between the RTI and unemployment was stronger in 2012-2014 than in 1998-2000. The only exceptions are Germany and Poland, the two countries where the overall labour market situation was much better in 2012-2014 than in 1998-2000. We reach this conclusion by using model 4 and calculating country-specific, aggregate marginal effects of the RTI on the unemployment probability for each 10-year age group in both periods, while holding other variables at their means (see Figure 3). This reinforces the findings from the OLS regressions presented in Table 5; namely, that the unemployment risk was rising more strongly in occupations with a higher relative routine intensity.

Age was an important factor in the effects of the routine intensity on the probability of unemployment (see Figure 3). In 1998-2000, the effect of a higher RTI on the unemployment risk was strongest among the young individuals (aged 15-24 or 25-34), and this effect decreased with age in seven out of 12 countries studied (Belgium, Czechia, Denmark, Estonia, Poland, Sweden, and the United Kingdom). The effect of the RTI was largest in Poland, where a small increase in the RTI for individuals aged 15-24 was associated with a 6.9 pp. increase in the unemployment risk. The opposite pattern is found for Austria, Germany, Greece, and Spain in 1998-2000. In these countries, the marginal effect of the RTI on the unemployment risk increased with age. Among individuals aged 55-64, a small increase in the RTI raised the probability of unemployment by 4.1 pp. in Greece, by 3.3 pp. in Germany, by 3.0 pp. in Spain, and by 1.3 pp. in Austria. Hungary stands out, as the effect of the RTI in this country displays a hump-shaped trajectory by age (the largest marginal effect, or 2.9 pp., is estimated among individuals aged 35-44).

Importantly, in the majority of the countries studied, the effect of the routine intensity of occupations on the unemployment risk became stronger over time among the younger individuals than among other age groups. This was particularly true for Austria and Spain, where the marginal effect among 15-24-year-olds was insignificant in the 1998-2000 period but became significant and noticeable (3.0 pp. and 5.9 pp., respectively) in the 2012-2014 period. In Belgium, Estonia, Germany, Hungary, and the UK, 15-24-year-olds were the most susceptible to unemployment related to the routine intensity of occupations (the marginal effects of the RTI varied from 2.6 pp. in Germany to 7.0 pp. in Estonia). In all of the countries except Germany, Poland, and Greece, the marginal effect of the routine intensity on the unemployment probability among people aged 25-34 also increased over time, most notably in Spain (see Figure 3). As a result, in 2012-2014, the effect of the routine task intensity on the unemployment risk was declining with age in nine out of the 12 countries studied.

Greece is the only country for which the marginal effects of the routine intensity on the unemployment risk were rising with age in both periods. Poland is the only other country for which the marginal effects of the routine intensity on the unemployment risk were rising with age in 2012-2014. But unlike in Greece, where the labour market situation deteriorated in the aftermath of the Great Recession, in Poland the overall labour market conditions were good and these effects were smaller than in the 1998-2000 period for all age groups.

Figure 3. The marginal effects of the routine task intensity (RTI) on the unemployment risk, by age, calculated from the country-specific logit regressions with heterogeneous effects of the RTI by age, 1998-2000* and 2012-2014.



Note: explanatory variables: RTI, time dummy (ref. 1998-2000[x]), personal characteristics (age, gender, marital status, education) and regional controls (regional industry shares when the worker was aged 15-19 or the earliest available shares, and Bartik (1991) local labour demand shocks), and interactions between the RTI and age. The standard errors clustered at the occupation level. All estimation results are in Table A4 in the appendix.

**Due to data availability, 1999-2001 for Germany and the United Kingdom, 2003-2005 for Sweden.*

*Source: Own estimations based on EU-LFS, O*NET, and Cambridge Econometrics European Regional Data.*

6. Conclusions and policy implications

In this paper, we analysed changes in the task composition of jobs in 12 European countries (Austria, Belgium, Czechia, Denmark, Estonia, Germany, Greece, Hungary, Poland, Spain, Sweden, and the United Kingdom) with a focus on the age and the cohort differences in the deroutinisation of jobs and the related unemployment risks between 1998 and 2014. We found important age differences behind the general shifts in the task composition. Compared to workers born between 1950 and 1969, workers born between 1970 and 1989 experienced a much faster increase in the intensity of non-routine cognitive tasks, and a much faster decline in the intensity of manual tasks. The differences in the changes in the intensity of routine cognitive tasks were less pronounced, but were still noticeable. In the majority of the countries studied, the age structures of the occupations with relatively high routine intensities of tasks in 1998 had aged more rapidly by 2010 than the occupations with the lower routine intensities. This finding was in turn related to a stronger relative decline in the share of young workers (aged 15-29) in the more routine-intensive occupations. On the other hand, the age structures of the occupations with relatively high non-routine cognitive content in 1998 had aged more slowly by 2010. The previous literature (Autor et al.; 2003, Michaels et al.; 2014, Goos et al.; 2014) showed that the hollowing-out of middle-skilled, routine jobs is likely to be driven by demand-side factors. Consequently, these factors may influence the unemployment risk of routine workers. Indeed, we found that in six out of the 12 countries we studied the more routine intensive an occupation was in 1998, the greater the increase in the share of unemployed workers in this occupation was by 2010. At an individual level, a higher routine intensity was significantly related to a higher probability of unemployment in all of the countries studied, both in the late 1990s and in the 2010s. In most of the countries, this effect increased over time, and it was strongest for the younger workers (aged 15-34) in all countries except Greece.

Our findings have important policy implications. On the one hand, as older workers have so far been less affected by occupational changes than younger workers, and the age structures of routine-intensive occupations are ageing faster, older workers may be disproportionately affected if the shift away from routine work intensifies in the future. Life-long learning and on-the-job training are needed to address the challenges that older workers face, especially considering the European-wide gap in ICT skills between older and younger workers (as shown in the PIAAC survey). On the other hand, educational systems should be adapted to foster the development of the skills required to perform non-routine tasks, because young workers who enter more routine-intensive occupations face a relatively high unemployment risk, which has been increasing in recent years. Even if this effect can partly reflect the sorting of individuals with less human capital into more routine-intensive occupations (which we cannot account for using the EU-LFS data), it is still important that educational systems seek to impart the skills that will enable individuals to take non-routine jobs, as the failure to train people in these higher level skills may exacerbate inequalities in labour markets outcomes.

In terms of directions for future research, we think that analyses of wage differences, conditional on age and tasks performed by workers, could shed light on the question of how the changes in task structures affect labour market inequalities. Unfortunately, the EU-LFS do not provide precise and comprehensive data on wages. Accounting for the heterogeneity of tasks within occupations is also an interesting avenue for future research. However, the surveys that collect such data, like the PIAAC for the OECD countries and the STEP for the developing countries, offer only one dataset per country. Thus, the analysis of changes over time will not be possible until the second waves of these surveys are completed.

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Appendix

Table A1. List of ISCO-88 occupations comprising at least 80% of agriculture in 1998, subsequently updated with matched ISCO-08 values, by country

Country	ISCO-88 occupations
Austria	611, 612, 613
Belgium	131, 611, 612
Czechia	321, 343, 611, 612, 613, 614, 723, 832, 833, 921
Denmark	611, 612, 613, 921
Estonia	321, 343, 612, 613, 614, 615, 832, 833, 834, 915, 921
Germany	321, 610, 611, 612, 614
Greece	611, 612, 613
Hungary	412, 611, 612, 613, 614, 722, 723, 832, 833, 914, 921, 932
Poland	6111, 6131 (KZiS; the classification was subsequently collapsed to the 3-digit level)
Spain	611, 613, 921
Sweden	611, 612, 613, 614, 833
United Kingdom	122, 131, 611, 613, 615, 833, 921

Note: The matched occupations from the ISCO-08 come from the ILO crosswalk: http://www.ilo.org/public/english/bureau/stat/isco/isco08/ [accessed: 2017-01-30]
Source: Own elaboration based on the EU-LFS data.

Table A2. Occupational and sectoral data issues (missing data or country-specific coding), by country

Country	Description
Germany	The data for 1998 do not contain information on the last occupation for the unemployed.
Poland	We used Polish LFS data instead of the EU-LFS datasets for improved accuracy. Due to national changes in classification, we rescaled the data near the breaks in the Polish classification of occupations (KZiS) in 2003, 2005 and 2011 (see Hardy et al., 2015 for more details on KZiS changes).
Sweden	There is no ISCO-88 information for previous occupations before 2000 or in 2001 or 2002. There is no NACE v1 information for previous industries before 2000 or in 2001, 2002, or 2008. The NACE v2 covers the year 2008.
United Kingdom	Due to national changes in classifications, we rescaled the data near the break in the classification of occupations (the transition to the SOC-00) in 2001. The data for 1998 do not contain information on the last occupation of unemployed individuals.

Source: Own elaboration based on the EU-LFS data.

Table A3. Occupational data non-response rate, by country

	The share of sample with missing occupational code
Austria	1.1
Belgium	1.1
Czechia	1.3
Denmark	0.3
Estonia	0.7
Germany	1.2
Greece	1.7
Hungary	0.7
Poland	2.0
Spain	1.5
Sweden	0.5
United Kingdom	0.8

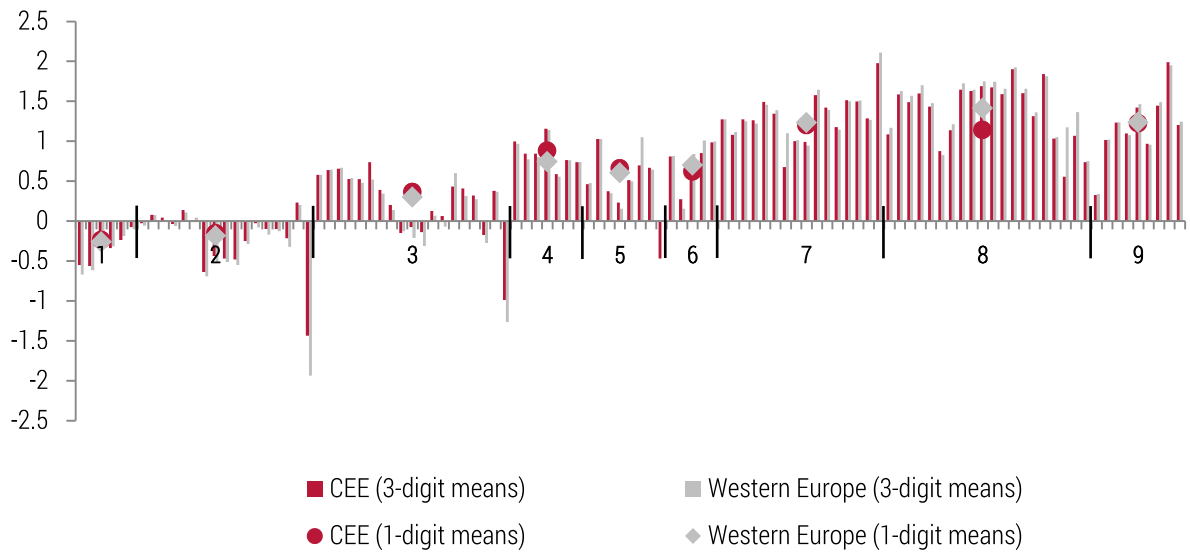
Source: Own elaboration based on the EU-LFS data.

Table A4. Regional data available in EU-LFS, by country

	1998-2000*	2012-2014
Austria	NUTS 1	NUTS 1
Belgium	NUTS 2	NUTS 2
Czechia	NUTS 2	NUTS 2
Denmark	regional data missing	NUTS 2
Estonia	NUTS 2	NUTS 2
Germany	regional data missing	NUTS 1
Greece	NUTS 2	NUTS 2
Hungary	NUTS 2	NUTS 2
Poland	NUTS 2	NUTS 2
Spain	NUTS 2	NUTS 2
Sweden	NUTS 2	NUTS 2
United Kingdom	NUTS 1	NUTS 1

Note:Due to data availability, 1999-2001 for Germany and the United Kingdom, 2003-2005 for Sweden.*
Source: Own elaboration based on the EU-LFS data.

Figure A1. Mean RTI values in Western European countries and in Central and Eastern European (CEE) countries between 1998 and 2010.



Note: The means for CEE do not include Poland due to a slightly different final occupation classification (Polish KZiS).
*Source: Own calculations based on EU-LFS and O*NET data.*

Table A4. Logit estimation results – on being unemployed (0-employed), odds ratios (model 4)

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	United Kingdom
RTI	1.10	1.55**	1.46***	1.26	1.67***	1.95***	1.15	1.40***	1.59**	0.85	1.21**	2.00***
Period(ref. 1998-2000[x])	0.98	0.96	2.58***	1.15	0.62	0.82	4.99***	1.34	1.32	1.73***	0.86	2.02***
period*RTI	1.60**	0.96	0.88	1.03	1.34	0.97	0.94	1.08	0.64	1.56***	0.97	0.77**
Age group (ref. 15-24)												
25-34	1.31	1.34	1.38**	1.04	1.52*	2.48***	1.46***	1.18	1.03	0.90	0.55***	0.98
35-44	2.05***	1.31	1.13	0.88	2.10***	3.65***	0.93	1.00	0.86	0.65***	0.42***	1.07
45-54	2.70***	1.27	1.00	1.05	1.86***	4.51***	0.83	0.77*	0.70	0.50***	0.32***	1.14
55-64	4.66***	1.01	0.90	1.50	0.91	8.91***	0.53	0.65	0.71	0.54**	0.41***	1.79***
Age group*RTI (ref. 15-24*RTI)												
25-34	1.50**	0.92	0.98	1.25	0.90	0.90	1.01	1.10	1.15	1.18*	1.24***	0.96
35-44	1.32	0.92	0.92	1.09	0.91	0.77**	1.27	1.21**	1.20	1.44**	1.26**	0.85*
45-54	1.39*	0.79	0.80**	1.29	0.74*	0.77**	1.35	1.18	1.19	1.54**	1.21*	0.80
55-64	1.25	0.73	0.84	0.95	0.90	0.70**	1.96*	0.98	1.01	1.55*	1.25	0.56***
Age group * period 2012-2014 (ref. age group = 15-24)												
25-34	1.25	0.74	0.66*	1.12	1.14	0.67***	1.05	0.77	0.80	0.84	0.79**	0.67***
35-44	1.07	0.83	0.83	1.07	0.73	0.57***	1.16	0.98	0.71	1.03	0.74**	0.67***
45-54	1.15	0.93	0.86	0.87	1.11	0.5***	1.03	1.27	0.66	1.25	0.97	0.70**
55-64	0.89	1.19	1.24	0.69	1.58	0.4***	1.67	1.62	0.64	1.14	0.93	0.59**
Age group * RTI * period 2012-2014 (ref. age group = 15-24)												
25-34	0.67**	1.27	1.44*	1.13	0.74	1.13	0.94	1.07	1.31	0.86	1.43***	1.46***
35-44	0.69*	1.07	1.36	1.27	0.74	1.14	0.97	0.76*	1.36	0.73*	1.50***	1.4***
45-54	0.65*	0.97	1.68**	1.05	0.81	1.08	1.09	0.75	1.70*	0.72	1.48**	1.17
55-64	0.57*	0.84	1.25	1.37	0.71	1.03	0.77	0.83	2.03**	0.69	1.21	1.4*
Gender (ref. male) and marital status (ref. single)												
Women	0.63***	0.55***	0.57***	0.71***	0.63***	0.63***	0.67***	0.6***	0.71***	0.74***	0.45***	0.75***
Married	0.60***	0.63***	0.55***	0.57***	0.71***	0.63***	0.63***	0.67***	0.6***	0.71***	0.74***	0.45***
Education (ref. secondary education)												
Higher	0.81***	0.56***	0.47***	0.94	0.68***	0.70***	0.58***	0.45***	0.53***	0.67***	0.93	0.83***
Primary	1.84***	1.79***	2.80***	1.26***	1.63***	1.49***	1.33***	1.97***	1.70***	1.52***	1.56***	1.54***
Regional controls												
Bartik shock	0.95	0.95	0.69***	0.92**	1.02	1.02**	1.01***	0.92***	0.95***	0.98***	1.17***	0.85***
Industry share at the age of 15-19	0.9***	0.95***	1.02***	0.99***	0.98	0.96***	1.01*	0.99***	1.00***	0.97***	1.00	0.99***
Constant	0.20***	0.19***	0.01***	0.05***	0.14**	0.07***	0.07***	0.09***	0.13***	0.43***	0.11***	0.06***
Observations	310,056	156,646	130,167	181,861	48,029	1,025,988	258,705	357,454	584,164	284,378	647,465	250,526

Note: Due to data availability, 1999-2001 for Germany and the United Kingdom, 2003-2005 for Sweden. The standard errors are clustered at the occupation level.

***** p<0.01, ** p<0.05, * p<0.1.*

*Source: Own estimations based on EU-LFS, O*NET, and Cambridge Econometrics European Regional Data.*