Economic Systems 44 (2020) 100816

Contents lists available at ScienceDirect

Economic Systems

journal homepage: www.elsevier.com/locate/ecosys

Ageing of routine jobs in Europe

Piotr Lewandowski[a,b,*], Roma Keister[a], Wojciech Hardy[a,c], Szymon Górka[a]

[a] Institute for Structural Research (IBS), Warsaw, Poland
[b] IZA, Bonn, Germany
[c] Faculty of Economics, University of Warsaw, Warsaw, Poland

ARTICLE INFO

JEL classification:
J21
J23
J24

Keywords:
Task content of jobs
Deroutinisation
Occupational change
Technological change
O*NET

ABSTRACT

We study how the de-routinisation of jobs affects workers at different ages in 12 European countries. We combine O*NET occupation content data with EU-LFS individual data for the 1998–2015 period to construct five task content measures: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical. We find that the shift away from routine work and toward non-routine work occurred much faster among workers aged between 25 and 44 than among older workers. 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 older workers in these occupations was rising and the share of young workers declining. At the same time, the unemployment risk related to the routine task intensity was increasing, especially among individuals between the ages of 15 and 34, and to a larger extent in countries with fast ICT capital growth and in countries not increasing their participation in global value chains.

1. Introduction and motivation

The shift away from manual and routine cognitive work, and towards non-routine cognitive work, has been a distinctive feature of labour markets in recent decades. Employment structures in the OECD countries have become polarised. In comparison to the second half of the 20th century, they are now characterised by lower shares of middle-skilled occupations that are rich in structured, routine tasks, and by higher shares of high-skilled occupations that are rich in abstract, non-routine tasks (Goos et al., 2014). The importance of non-routine tasks has also increased within occupations (Autor et al., 2003; Spitz-Oener, 2006). In the developed countries, this de-routinisation of work has been attributed to two factors. First, rapid technological progress in information and communication technologies (ICT), and robotics (Brynjolfsson and McAfee, 2014), and the introduction of these technologies into workplaces (Autor et al., 2003, 2006; Goos et al., 2014; Michaels et al., 2014). Second, the increasing fragmentation of production across countries involves routine-intensive jobs being offshored out of industrialised countries (Grossman and Rossi-Hansberg, 2008; Goos et al., 2014).

The literature on the de-routinisation of work and job polarisation has mainly been focused on changes in the distribution of skills and education across the workforce. Other dimensions, such as age or gender, remain under-researched. However, younger and older workers may be affected to a different extent by these trends, especially if de-routinisation is driven by factors on the labour demand side such as technological progress. According to the Programme for the International Assessment of Adult Competencies (PIAAC)

* Corresponding author.
E-mail addresses: piotr.lewandowski@ibs.org.pl (P. Lewandowski), roma.keister@ibs.org.pl (R. Keister), wojciech.hardy@ibs.org.pl (W. Hardy), szymon.gorka@ibs.org.pl (S. Górka).

https://doi.org/10.1016/j.ecosys.2020.100816
Received 24 July 2018; Received in revised form 6 March 2020; Accepted 11 March 2020
Available online 19 November 2020

data, older people (aged 55−64) in the OECD countries tend to have lower ICT and analytical skills, and are less likely to use information-processing skills at work than younger individuals. Older workers tend to be offered fewer opportunities to participate in training compared to younger workers, and tend to have less between-occupation mobility (Tempest and Coupland, 2016). The skills gap observed among older workers may be partly attributed to the depreciation of skills over the life-cycle, and partly to cohort-specific effects (Desjardins and Warnke, 2012). Younger workers in Europe are increasingly likely to be college or university graduates, which makes them better prepared to perform non-routine tasks (Oesch, 2013; Salvatori, 2018; Hardy et al., 2018). In the US, the average age of workers in more routine-intensive and declining occupations has increased faster than the average age of workers in less routine-intensive occupations (Autor and Dorn, 2009). On the other hand, younger workers are less likely to be unionised and protected by employment protection regulation than older workers, which in turn may make them more exposed to labour demand shocks (Bussolo et al., 2018). Indeed, there is some evidence that young workers could be more affected by technological change. The adoption of manufacturing robots in Germany had no effect on aggregate employment but reduced the hiring of labour market entrants (Dauth et al., 2017). In European countries, the decline of ICT prices has translated into job polarisation among young and middle-aged workers to a larger extent than among older workers (Jerbashian, 2019).

We present new evidence on the de-routinisation of European labour markets that reveals noticeable differences related to the age of workers. We follow Acemoglu and 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 account for changes driven by shifts in occupational structures, as well as for changes resulting from the evolution of task content within particular occupations. We study 12 European countries that represent different economic and labour market models in Europe and have detailed occupational data available in the EU-LFS survey – Austria, Belgium, Czechia, Denmark, Estonia, Germany, Greece, Hungary, Poland, Spain, Sweden, and the United Kingdom – between 1998 and 2015.[1]

Our first contribution is to document the diverging trends in the task content of jobs performed by young and older workers. We find that the shift away from manual tasks towards cognitive tasks, and from routine tasks towards non-routine tasks occurred much faster among the prime-aged (aged 25−44) and young (15−24) workers than among older (45−64) workers. Moreover, we find while the importance of routine cognitive tasks declined among the prime-age workers, it has increased among workers aged 55 or more years. In most countries, the average age of workers in the more routine-intensive occupations has increased faster than in the less routine occupations. The share of young workers was decreasing faster, and the share of older workers increasing faster in the more routine-intensive occupations.

Our second contribution is to establish the relationship between the routine intensity of jobs and the unemployment risk among various age groups of workers in European countries. The de-routinisation of work is 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). Hence, it may be associated with an increase in the unemployment risk of routine workers. There is evidence based on panel data that shows that this was indeed the case in the US (Cortes, 2016) or Germany (Bachmann et al., 2019). We find that higher routine intensity of jobs is associated with a higher unemployment risk in most European countries studied. We also provide evidence that this effect is stronger among young than among older workers, and that in many countries this gap has increased over time. In many European countries a large share of unemployment increase among young workers can be attributed to the increase in the unemployment risk related to routine task intensity. Using cross-country regressions, we show that the increase in this risk was larger in countries in which the stock of ICT capital per worker increased faster, and in countries which didn't increase their participation in global value chains. While the available cross-sectional data don't allow us to establish a causal link between routine intensity and unemployment risk, we are able to document these stylised facts in a cross-country setting, which, according to the authors' knowledge, hasn't been done before.

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 age-specific evolutions of the task content of jobs in the analysed countries. In Section 4, we analyse the relationship between the routine task intensity of jobs and workforce ageing in particular occupations. In Section 5, we study links between routine task intensity and unemployment risk, allowing for differences between countries, age groups, and over time. In Section 6, we conclude and discuss our findings.

2. Data and methodology

2.1. Data sources on tasks and labour market

We use Occupational Information Network (O*NET) data and merge them with the European Union Labour Force Survey (EU-LFS, European Commission, Eurostat, 2016; Statistics Poland, 2020) data for 12 countries – Austria, Belgium, Czechia, Denmark, Estonia, Germany, Greece, Hungary, Poland, Spain, Sweden, and the United Kingdom – over the period 1998–2015.[2] The O*NET data contain no information on worker characteristics and thus can be matched only at the level of occupations (cf. Goos et al., 2014; Hardy et al.,

[1] In principle, any country covered by the EU-LFS can be analysed. The first year of our study reflects the availability of the EU-LFS data in a synchronised form for a large number of countries.

[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. (2014); Dicarlo et al. (2016); Keister and Lewandowski (2017), and Hardy et al. (2018). 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.

Table 1
Total changes in the task intensity of jobs between 1998-2000 and 2013-2015 in selected European countries.

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	UK
NRCA	7.9	14.9	13.8	10.4	17.8	7.6	11.4	7.7	16.4	12.0	15.4	11.5
NRCP	6.0	14.2	9.5	3.3	13.6	7.1	6.9	6.5	12.7	8.4	12.8	14.6
RC	−2.7	−9.1	3.5	−2.9	8.6	−4.8	1.9	−2.1	4.8	1.7	−7.0	−12.0
RM	−9.5	−13.6	−8.3	−11.6	−12.7	−11.9	−18.6	−7.0	−12.4	−20.3	−15.5	−14.3
NRM	−9.3	−9.7	−11.9	−7.4	−18.3	−9.3	−17.5	−6.5	−15.6	−18.7	−11.4	−8.4

Notes: NRCA – non-routine cognitive analytical, NRCP – non-routine cognitive personal, RC – routine cognitive, RM –routine manual, NRM – non-routine manual.
Source: Own calculations based on EU-LFS and O*NET data.

2018). We apply the International Standard Classification of Occupations (ISCO) at the 3-digit level. We restrict our sample to employed individuals aged above 15, and unemployed individuals aged above 15 who worked at least once and provided their last occupation's code. Self-employed individuals are also included as long as their occupations are known. In order to account for possible changes in the task content within occupations, we use the 2003 and 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 the SOC classification of occupations) to the EU-LFS data (coded with an ISCO classification of occupations).[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. These two classifications are not entirely comparable (see also Aedo et al., 2013; Goos et al., 2014). In order to achieve consistent data for the entire analysed period, we recode task items for farm workers, and for selected occupations in the wholesale and retail trade (details are provided in Appendix A).

2.2. *Calculating the task content of jobs*

In calculating the task content of occupations, we follow the procedure of Acemoglu and Autor (2011), adapted to European data by Hardy et al. (2018). First, we assign the O*NET task items to the EU-LFS data. These task items describe the occupations in terms of the tasks typically performed on the job and the way they are performed (see Table A1 in the Appendix). Second, we standardise the task item scores to make them comparable. Thus, for each country c, we standardise the values t_j of each task item j in the set of task items J, using the country-specific means ($\bar{t}^0_{j,c}$) and standard deviations ($\delta^0_{j,c}$) calculated on the first three years of data:

$$\forall_{i,c}\ \forall_{j\in J}\ \ t^{std}_{i,j,c} = \frac{t_{i,j,c} - \bar{t}^0_{j,c}}{\delta^0_{j,c}}, \tag{1}$$

whereby i, c is a worker-level observation in the LFS data for country c. $t^{std}_{i,j,c}$ thus describes the task item intensity for each worker in each of the countries, with the values standardised so that their average across workers in the first three years of data is equal to 0 and the standard deviation to 1.

Third, we construct five composite task content measures: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual and non-routine manual physical. Each task content measure is calculated as a sum of constituent task items (see Table A1) and then again standardised to have a mean 0 and standard deviation 1 in the first three years in each country. We use three years as a reference period (rather than one year) so the standardisation is more robust (based on a larger sample and less dependent of occupational distribution in any given year). Double standardisation is required because particular task contents include various numbers of items (Table A1), which also have different ranges (Acemoglu and Autor, 2011). In line with Arias et al. (2014) and Dicarlo et al. (2016), we standardise within each country. The results can be used to analyse changes over time in particular countries, and a unit change in the mean values of task contents can be interpreted as a one standard deviation change since the beginning of the analysed period. They cannot, however, be used to compare levels of task content measures between countries.

Additional correction is required to account for the change of occupation classification from ISCO-88 (COM) to ISCO-08 in 2011. Our approach is similar to that of Goos et al. (2014). We equate the mean task values in the two years surrounding the classification changes and accordingly adjust the task levels from 2011. This removes any changes in the average values of task contents between 2010 and 2011, while ensuring that the changes that occurred between 1998–2010 and 2011–2015 are otherwise comparable. Rescaling is conducted separately for each country and for the two editions of O*NET that we use.

In order to account for task content changes within occupations, we assign the values from the 2003 and 2014 editions of O*NET, calculate the task content measures based on each edition, and then apply a weighted average. From 1998–2003, we use task measures 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; for the year 2015 we use task measures based on O*NET 2014.

[3] For the Polish LFS data, we use additional crosswalks between the Polish classification (KZiS) and the ISCO classification. All crosswalks that we used are available online: ibs.org.pl/en/resources [accessed: 2017−01-27].

Table 2
Time trend coefficients from panel regressions with country fixed effects on task content intensities in 5-year age groups.

	15–19	20–24	25–29	30–34	35–39	40–44	45–49	50–54	55–59	60–64
Non-routine cognitive analytical	−0.46***	−0.13*	0.93***	1.40***	1.27***	0.96***	0.60***	0.21***	0.36***	0.65***
	(0.14)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.08)	(0.11)
Non-routine cognitive personal	0.44***	0.39***	0.63***	0.80***	0.82***	0.72***	0.60***	0.30***	0.22***	−0.07
	(0.10)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.07)	(0.11)
Routine cognitive	0.23	−0.15**	−0.31***	−0.28***	−0.25***	−0.23***	−0.13***	0.15***	0.59***	1.31***
	(0.16)	(0.07)	(0.06)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.08)	(0.10)
Routine manual	−0.68***	−0.83***	−1.23***	−1.33***	−1.14***	−0.86***	−0.61***	−0.31***	−0.37***	−0.31***
	(0.13)	(0.08)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.08)	(0.09)
Non-routine manual physical	−0.38***	−0.28***	−0.88***	−1.18***	−1.12***	−0.90***	−0.59***	−0.39***	−0.69***	−0.83***
	(0.12)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.10)

Notes: Each coefficient was estimated in a separate panel regression with a particular task content intensity (rows) in a given age group (columns) as the explained variable and the time trend as the control variable. All regressions are for 216 annual observations of 12 countries. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own estimations based on EU-LFS and O*NET data.

Table 3
Changes in employment shares, unemployment rates and average worker age within particular task groups, between 1998-2000* and 2013-2015, by country.

Occupations		AT	BE	CZ	DK	EE	DE	GR	HU	PL	ES	SE	UK	AVG
Non-routine cognitive analytical	Δempl	3.6	−1.1	0.2	3.8	1.2	1.4	5.9	−1.7	2.0	−0.1	−0.8	4.0	1.5
	Δunemp	1.5	0.6	−0.7	0.8	−2.0	−1.9	9.7	−0.4	−1.0	3.7	−1.1	−0.1	0.7
	Δage	1.0	1.7	0.3	1.9	0.0	1.5	3.0	1.0	0.2	2.4	0.0	1.5	1.2
Non-routine cognitive personal	Δempl	1.1	0.6	6.0	−0.5	3.4	−2.9	−1.1	6.3	10.6	0.4	−4.3	−2.4	1.4
	Δunemp	1.4	0.3	−0.1	0.3	−3.1	−2.1	12.5	0.8	−0.2	6.7	−0.1	−0.5	1.3
	Δage	3.7	2.4	1.6	2.1	1.2	4.1	0.0	1.7	0.0	1.9	0.4	2.0	1.7
Routine cognitive	Δempl	0.8	0.6	−2.8	−5.6	0.2	5.6	10.3	−1.9	−5.2	4.7	−1.5	−3.0	0.2
	Δunemp	1.7	0.1	−0.8	1.3	−3.1	−4.3	13.8	−2.0	−4.2	4.7	−1.1	0.2	0.5
	Δage	3.1	3.7	3.3	2.2	2.7	2.2	5.0	3.8	2.2	6.2	0.6	3.0	3.2
Routine manual	Δempl	1.1	1.6	6.7	3.4	2.4	0.8	−3.9	3.3	−3.3	2.3	−0.5	−1.4	1.0
	Δunemp	4.0	0.1	1.1	1.8	−4.8	−3.9	19.4	2.6	−7.5	15.9	2.3	1.2	2.7
	Δage	4.7	3.8	3.6	1.7	2.9	4.3	2.2	5.0	4.0	4.7	0.6	1.1	3.2
Non-routine manual	Δempl	−6.5	−1.7	−10.1	−1.2	−7.2	−4.9	−11.1	−6.1	−4.0	−7.3	7.1	2.8	−4.2
	Δunemp	2.7	1.0	−0.4	0.9	−4.9	−3.1	21.7	0.4	0.0	15.0	0.5	−0.5	2.8
	Δage	2.3	2.7	3.1	2.9	1.4	2.6	0.7	3.6	2.6	3.8	0.0	1.2	2.2

Notes: *Due to data availability, 1999–2001 for Germany and the United Kingdom, 2003–2005 for Sweden. The AVG column presents an unweighted mean of the country-level changes. The changes in employment shares and unemployment rates are given in percentage points, while changes in average worker age are given in years.
Source: Own calculations based on EU-LFS and O*NET data.

The average level of task content calculated for a given population will be called task intensity. For presentation purposes, we multiply all values by 100. The resulting values for any task intensity in any year range from -21.8 (non-routine manual for Estonia in 2015) to 24.1 (non-routine cognitive analytical for Estonia in 2015), and with standard deviations varying from 8.4 in Austria to 11.7 in Czechia).

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

We also classify workers and unemployed into five groups according to the pre-dominant task of their occupation, as in Fonseca et al. (2018). For instance, we classify an occupation as routine manual if the routine manual task intensity of that occupation is higher than the intensities of other task content measures, as routine cognitive if the routine cognitive task intensity is the highest, and so forth.

Finally, we construct the routine task intensity (RTI) for each occupation, using the formula:

$$RTI = \ln\left(r_{cog} + r_{man}\right) - \ln\left(nr_{analytical} + nr_{personal}\right) \quad (2)$$

Our definition is consistent with definitions previously used in the literature (Autor and Dorn, 2009), and in line with Goos et al.

Table 4
The relationship between the routine intensity (RTI) in 1998 and changes in the mean age of workers in occupations between 1998 and 2010. Country-specific OLS regressions at the occupation level.

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	UK
RTI	−0.82*	0.74***	1.08***	1.08**	0.31	0.54**	0.16	1.48***	1.49***	0.63*	0.18	0.55
	(0.44)	(0.28)	(0.34)	(0.44)	(0.69)	(0.26)	(0.27)	(0.41)	(0.40)	(0.33)	(0.24)	(0.39)
ΔShare	0.64***	0.20	−0.51*	0.40*	−1.22***	−0.45	0.11	0.20	0.21*	0.08	−0.71*	−0.45**
	(0.16)	(0.19)	(0.27)	(0.23)	(0.43)	(0.31)	(0.07)	(0.23)	(0.11)	(0.25)	(0.40)	(0.22)
Constant	2.80***	2.03***	1.70***	1.48***	1.77***	1.77***	2.09***	2.38***	0.64*	1.99***	0.49***	1.96***
	(0.34)	(0.22)	(0.28)	(0.32)	(0.56)	(0.20)	(0.21)	(0.30)	(0.36)	(0.27)	(0.16)	(0.30)
No. of obs.	100	101	104	102	100	102	100	102	101	102	103	89
R^2	0.16	0.07	0.14	0.08	0.08	0.09	0.03	0.12	0.15	0.04	0.04	0.09

Notes: Each coefficient was estimated in a country-specific regression with the change in the average age of workers in a given occupation as the explained variable, and the initial (1998) RTI and the change in the share of the occupation in total employment as control variables. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own estimations based on EU-LFS and O*NET data.

Table 5

The relationship between routine intensity (RTI) in 1998 and changes in the shares of age groups within occupations (in pp.). Country-specific OLS regressions at the occupation level.

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	UK
Change in the occupation-specific share of workers aged 15–24												
RTI	1.15	−1.01*	−2.77***	−1.31	−1.40	−0.31	−3.87***	−4.38***	−2.20***	−6.10***	0.30	−1.27*
	(1.09)	(0.54)	(0.91)	(1.03)	(1.34)	(0.74)	(0.71)	(1.02)	(0.76)	(0.76)	(0.59)	(0.73)
const.	−0.93	−0.38	−5.89***	0.50	−2.81***	−0.11	−3.46***	−6.33***	−2.02***	−2.04***	0.13	−1.27**
	(0.83)	(0.43)	(0.76)	(0.76)	(1.04)	(0.59)	(0.53)	(0.82)	(0.64)	(0.62)	(0.40)	(0.57)
R^2	0.01	0.03	0.08	0.02	0.01	0.00	0.23	0.16	0.08	0.40	0.00	0.03
Change in the occupation-specific share of workers aged 25–44												
RTI	1.66	−3.10***	−1.51	−4.82***	0.75	−3.90***	5.81***	0.95	−4.48***	6.36***	−2.42***	−0.91
	(1.29)	(1.13)	(1.28)	(1.81)	(2.63)	(0.98)	(1.27)	(1.52)	(1.47)	(1.45)	(0.88)	(0.95)
const.	−9.85***	−7.62***	4.50***	−3.76***	−3.34	−6.58***	−4.03***	0.07	−1.32	−4.94***	0.02	−3.86***
	(1.00)	(0.89)	(1.07)	(1.35)	(2.05)	(0.77)	(0.94)	(1.23)	(1.24)	(1.19)	(0.59)	(0.74)
R^2	0.02	0.07	0.01	0.07	0.00	0.14	0.18	0.00	0.09	0.16	0.07	0.01
Change in the occupation-specific share of workers aged 45–64												
RTI	−2.81*	4.11***	4.28***	6.13***	0.66	4.21***	−1.94*	3.43**	6.68***	−0.26	2.12**	2.18*
	(1.48)	(1.15)	(1.25)	(1.88)	(2.61)	(0.99)	(1.10)	(1.52)	(1.43)	(1.42)	(0.91)	(1.22)
const.	10.78***	8.00***	1.39	3.26**	6.15***	6.69***	7.50***	6.26***	3.34***	6.97***	−0.15	5.13***
	(1.14)	(0.92)	(1.04)	(1.39)	(2.03)	(0.78)	(0.81)	(1.23)	(1.21)	(1.16)	(0.61)	(0.95)
R^2	0.04	0.11	0.10	0.10	0.00	0.15	0.03	0.05	0.18	0.00	0.05	0.04
No. of obs.	100	101	104	102	100	102	100	102	101	102	103	89

Notes: Each coefficient was estimated in a country-specific OLS regression with the change (1998–2010) in the share of a particular age group of workers in a given occupation as the explained variable (rows), and the initial (1998) RTI and the change in the share of occupation in total employment as control variables. For brevity, only the coefficients related to RTI are reported. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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

(2014) we utilise task contents defined with O*NET. This allows us to distinguish between routine and non-routine tasks, and to use two types of routine tasks – cognitive and manual – as indicators of the routine task intensity.[4] The task measures may take negative values. Hence, prior to calculating the RTI index, for each task content T_c in country c, we add the lowest value of T_c in a given country sample to the values of all individuals in this country sample, plus 1, to avoid non-positive values in the logarithm. By design, the RTI measure increases with the importance of routine tasks, and declines with the importance of non-routine tasks. The distribution of RTI across the spectrum of ISCO occupations is presented in Figure B.1 in the Appendix.

The RTI index shows negative values for high-skilled occupations, like legislators, senior officials, managers, and professionals (average of -0.30 across all countries); low positive values for occupations like technicians and associate professionals (average of 0.28 across all countries); higher positive values for clerks, service workers, shop and market sales workers, skilled agricultural and fishery workers (an average of 0.56 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 1.08 across all countries). 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 90 % to 95 %.

2.3. Econometric methodology

2.3.1. Trends in task intensities

In order to quantify age-specific changes in task intensities, we estimate linear time trends in the average intensity of each task content measure j among workers in specific age groups $a \in \{15-19,\ 20-24,\ 25-29,\ 30-34,\ 35-39,\ 40-44,\ 45-49,\ 50-54,\ 55-59,\ 60-64\}$:

$$\bar{t}_{j,a} = \beta_{0,j,a} + \beta_{1,j,a} time + \varepsilon_{j,a} \tag{3}$$

whereby *time* is expressed in years. The estimates of $\beta_{1,j,a}$ thus describe the linear relationships between time and the intensity of task j for age group a. We estimate a panel regression and a set of country-specific regressions.

2.3.2. Ageing of routine occupations

In order to quantify the differences in changes in age structures in more and less routine-intensive occupations, we follow the approach used by Autor and Dorn (2009). For each country c, we estimate an OLS regression:

$$y_{i,c} = \beta_{0,c} + \beta_{1,c} RTI_{i,c} + d_{freq_{i,c}} + \varepsilon_{i,c} \tag{4}$$

where $y_{i,c}$ is the change in the average age of a worker in occupation i (at the ISCO-88 3-digit level) between 1998 and 2010, $RTI_{i,c}$ is the initial (1998) routine task intensity in occupation i, and $d_{freq_{i,c}}$ is the change in the share of occupation i in total employment in country c between 1998 and 2010. We analyse the period when the ISCO-88 classification was valid (1998–2010) because it is not possible to completely map the ISCO-88 occupations to the ISCO-08 occupations (valid from 2011 on) at the 3-digit level.

We consider three modifications of model (4). First, to shed more light on the process of ageing of routine occupations, we estimate three variants of regression (4) with changes (between 1998 and 2010) in the shares of a particular age group (15−24, 25−44 or 45−54) in occupation i in country c as explained variables $y_{i,c}$. Second, we replace RTI in Eq. (5) with the initial (1998) intensity of non-routine cognitive tasks (either analytical or personal). Third, in order to verify if the above findings hold for changes over a longer period – between 1998 and 2015 – we re-estimate the regressions described above as pooled regressions at the 1-digit occupation level (nine occupations per country, 108 observations) with country fixed effects.[5]

2.3.3. Routine task intensity and occupation-specific unemployment risk

We analyse the relationship between the routine task intensity, age and unemployment at both the individual and the occupational level.

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 that 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 and the change in the share of the occupation in total employment, as in model (4).

At the worker level, we use individual EU-LFS data for the first three available years (1998−2000) and the last years in our sample (2013−2015). We estimate country-specific logit models with unemployment as the explained variable (relative to employment) on the sample without self-employed individuals. The models are described by the equation:

[4] Since the intensities of routine manual tasks and 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 both manual task measures would confound the RTI values. Moreover, the routine-replacing technological change hypothesis shows that routine manual tasks can be replaced by technology, while the effect on non-routine manual tasks is ambiguous.

[5] Occupations in ISCO-88 (valid until 2010) and ISCO-08 (valid since 2011) are entirely comparable only at the 1-digit level.

$$\Pr(y_i = 1) = \mathrm{F}\left(\beta_0 + \beta_1 RTI_i + \beta_2 RTI_i{*}period_{2013-2015} + \beta_3 X_i^{ind} + \beta_4 X_i^{reg} + \beta_5 X_i^{interact}\right) \tag{5}$$

where $F(Z) = \frac{e^Z}{1+e^Z}$, X_i^{ind} includes socio-demographic characteristics of individual i (age, gender, marital status, education level – three groups), X_i^{reg} includes 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), and $X_i^{interact}$ includes interactions between the RTI, 10-year age group dummies and the 2013−2015 period dummy.

In the first variant of the regressions (model 1), we only include the RTI and the time dummy for the 2013−2015 period as the explanatory variables (coefficients in vectors β_3, β_4, β_5 are fixed at zero). In the second variant (model 2), we add a standard set of socio-demographic controls (age, gender, marital status, education level). In the third variant (model 3), we add two regional controls calculated using the Cambridge Econometrics European Regional Data.

In the fourth variant (model 4), 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 2013−2015 in all the regressions; and in the fourth version of the model we also interact the age-specific RTI variable with the 2013−2015 period dummy.

In order to account for the selection of workers into routine-intensive occupations, we follow Fletcher and 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. In models 3 and 4, 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.[6] Unlike Fletcher and 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 occupational choice. Although we may overestimate the effect of routine task content on unemployment risk, it is unlikely that the selection of workers into occupations drives these effects entirely. For instance, Edin et al. (2019) use administrative panel data to analyse long-term effects of occupational declines in Sweden and show that only a small part of effects on wages and unemployment can be attributed to the selection of workers into occupations. We also control for regional labour demand shocks with Bartik (1991) shocks calculated at the NUTS2 or the NUTS1 level depending on the availability of regional data in the EU-LFS (see Table A4 in the Appendix).

As a robustness check, we estimate an alternative specification of models 3 and 4. We control for fixed effects of routine cognitive, routine manual and non-routine manual occupations, with non-routine cognitive occupations being the reference group, instead of a continuous RTI variable. We label these models 3′ and 4′.

2.3.4. Regression-based decomposition of changes in the unemployment rate

We use the estimated parameters of model 4 for each country c and age group y to decompose the change in the predicted unemployment rate between 1998−2000 and 2013−2015 into the contribution of change in the distribution of RTI, $D_{c,RTI}$, the contribution of change in the distributions of other explanatory variables, $D_{c,x}$, and the contribution of change in the coefficient expressing the effect of RTI on unemployment risk, $C_{c,RTI}$:

$$UR_{c,y,2013-2015} - UR_{c,y,1998-2000} = UR\left(\overline{RTI}^{15}_{c,y}, \overline{x}^{15}_{c,y}, coef^{15}_{RTI,c,y}\right) - UR\left(\overline{RTI}^{98}_{c,y}, \overline{x}^{98}_{c,y}, coef^{98}_{RTI,c,y}\right) = D_{c,y,RTI} + D_{c,y,x} + C_{c,y,RTI} \tag{6}$$

$$D_{c,y,RTI} = UR\left(\overline{RTI}^{15}_{c,y}, \overline{x}^{98}_{c,y}, coef^{98}_{RTI,c,y}\right) - UR\left(\overline{RTI}^{98}_{c,y}, \overline{x}^{98}_{c,y}, coef^{98}_{RTI,c,y}\right) \tag{7}$$

$$D_{c,y,x} = UR\left(\overline{RTI}^{15}_{c,y}, \overline{x}^{15}_{c,y}, coef^{98}_{RTI,c,y}\right) - UR\left(\overline{RTI}^{15}_{c,y}, \overline{x}^{98}_{c,y}, coef^{98}_{RTI,c,y}\right) \tag{8}$$

$$C_{c,y,RTI} = UR\left(\overline{RTI}^{15}_{c,y}, \overline{x}^{15}_{c,y}, coef^{15}_{RTI,c,y}\right) - UR\left(\overline{RTI}^{15}_{c,y}, \overline{x}^{15}_{c,y}, coef^{98}_{RTI,c,y}\right) \tag{9}$$

where

- $UR\left(\overline{RTI}^{t}_{c,y}, \overline{x}^{t}_{c,y}, coef^{t}_{RTI,c,y}\right)$ is the predicted unemployment rate calculated with the estimates of model 4 for country c and age group y in period t;
- $\overline{RTI}^{98}_{c,y}$, $\overline{RTI}^{15}_{c,y}$ are the average levels of RTI in 1998−2000 and 2013−2015, respectively;
- $\overline{x}^{98}_{c,y}$, $\overline{x}^{15}_{c,y}$ are the average levels of other explanatory variables in 1998−2000 and 2013−2015, respectively;
- $coef^{98}_{RTI,c,y}$, $coef^{15}_{RTI,c,y}$ are the coefficients on RTI estimated for 1998−2000 and 2013−2015, respectively.

[6] The Cambridge Econometrics European Regional Data cover the 1980−2014 period for the Western European countries, and the 1990−2014 period for the Central and Eastern European countries. We assign the 1980 shares to all individuals born before 1965 in Western European countries, and the 1990 shares to all individuals born before 1975 in the Central and Eastern European countries. We assign the 2014 shares to all individuals aged between 15 and 19 in 2015.

Table 6
The relationship between the intensity of non-routine cognitive analytical (NRCA) and non-routine cognitive personal (NRCP) tasks in 1998 and changes in the mean age of workers in occupations between 1998 and 2010. Country-specific OLS regressions at the occupation level.

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	UK
NRCA	0.68***	−0.23	−0.47**	−0.41*	−0.39	−0.24*	0.17	−0.76***	−0.58**	−0.32*	−0.09	−0.05
	(0.23)	(0.15)	(0.19)	(0.24)	(0.38)	(0.14)	(0.15)	(0.22)	(0.23)	(0.18)	(0.12)	(0.21)
R^2	0.21	0.03	0.12	0.05	0.09	0.08	0.03	0.11	0.09	0.03	0.04	0.07
NRCP	0.50**	−0.30*	−0.44**	−0.47**	−0.19	−0.31**	0.07	−0.65***	−0.62***	−0.23	−0.07	−0.14
	(0.23)	(0.15)	(0.18)	(0.24)	(0.38)	(0.14)	(0.14)	(0.23)	(0.22)	(0.18)	(0.12)	(0.22)
R^2	0.17	0.04	0.11	0.06	0.08	0.10	0.03	0.08	0.10	0.02	0.03	0.07
No. of obs.	100	101	104	102	100	102	100	102	101	102	103	89

Notes: Each coefficient was estimated in a country-specific regression with the change in the average age of workers in a given occupation as the explained variable, and the specific task content measure (rows) and the change in the share of the occupation in total employment as control variables. For brevity, only the coefficients related to the task content intensities are reported. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own estimations based on EU-LFS and O*NET data.

Table 7
The relationship between the routine intensity (RTI) in 1998 and the changes in the occupation-specific unemployment rates between 1998 and 2010. Country-specific OLS regressions at the occupation level.

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	UK
RTI	0.23 (0.45)	−1.44*** (0.45)	5.80*** (1.19)	4.09*** (0.68)	6.03*** (1.30)	−1.73*** (0.51)	3.04*** (0.64)	0.76 (0.66)	1.56 (2.11)	6.81*** (1.16)	1.93*** (0.52)	0.24 (0.42)
ΔShare	−0.07 (0.17)	−0.69** (0.30)	−2.85*** (0.91)	0.37 (0.35)	1.10 (0.80)	2.14*** (0.59)	0.81*** (0.17)	0.05 (0.38)	−0.46 (0.57)	−0.69 (0.87)	−0.14 (0.87)	0.25 (0.24)
Cons.	1.05*** (0.35)	0.50 (0.35)	−1.59 (0.96)	0.49 (0.50)	3.10*** (1.05)	−1.66*** (0.38)	2.70*** (0.48)	1.17** (0.49)	−0.83 (1.87)	0.30 (0.95)	1.15*** (0.35)	0.75** (0.32)
R^2	0.00	0.12	0.30	0.27	0.20	0.28	0.31	0.01	0.01	0.27	0.12	0.01
No. of obs.	100	101	104	102	100	102	100	102	102	102	103	89

Notes: Each coefficient is estimated in a country-specific OLS regression with the change (1998–2010) in the occupation-specific unemployment rate as the explained variable and the initial (1998) RTI and the change in the share of the occupation in total employment as a control variable. The regressions are weighted with the size of the occupational labour supply (sum of employed and unemployed individuals). Due to data availability, the reference period is 1999–2001 for Germany and the United Kingdom and 2003–2005 for Sweden. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own estimations based on EU-LFS and O*NET data.

Table 8
The marginal effect of the routine task intensity (RTI) on the probability of being unemployed, models 1-3.

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	United Kingdom
Model 1												
RTI	0.018***	0.042***	0.036***	0.025***	0.066***	0.049***	0.045***	0.055***	0.090***	0.047**	0.035***	0.038***
	(0.003)	(0.006)	(0.006)	(0.005)	(0.010)	(0.007)	(0.016)	(0.007)	(0.017)	(0.018)	(0.005)	(0.004)
RTI * period (2013–2015)	0.034***	0.043***	0.039***	0.038***	0.044***	0.028***	0.140***	0.053***	0.051***	0.161***	0.046***	0.042***
	(0.004)	(0.006)	(0.006)	(0.004)	(0.006)	(0.003)	(0.031)	(0.008)	(0.006)	(0.034)	(0.005)	(0.003)
Pseudo Rˆ2	0.0249	0.0187	0.0182	0.0157	0.0295	0.0290	0.0825	0.0295	0.0338	0.0395	0.0216	0.0300
No. of obs.	303,500	155,520	128,789	177,111	47,475	1,176,303	147,746	352,619	554,355	282,867	623,453	323,280
Model 2												
RTI	0.012***	0.013**	0.018***	0.021***	0.046***	0.034***	0.033*	0.031***	0.067***	0.008	0.021***	0.024***
	(0.003)	(0.006)	(0.004)	(0.004)	(0.008)	(0.006)	(0.018)	(0.006)	(0.015)	(0.016)	(0.004)	(0.003)
RTI * period (2013–2015)	0.024***	0.015***	0.019***	0.032***	0.032***	0.020***	0.101***	0.025***	0.029***	0.104***	0.032***	0.027***
	(0.003)	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.034)	(0.006)	(0.006)	(0.031)	(0.004)	(0.003)
Pseudo Rˆ2	0.0415	0.0496	0.0531	0.0286	0.0433	0.0431	0.0992	0.0512	0.0587	0.0626	0.0422	0.0581
No. of obs.	303,484	155,520	128,698	174,730	47,471	1,023,712	147,739	352,538	554,355	282,867	621,651	247,802
Model 3												
RTI	0.012***	0.017***	0.015***	0.021***	0.046***	0.035***	0.032*	0.031***	0.067***	0.014	0.021***	0.024***
	(0.003)	(0.005)	(0.004)	(0.004)	(0.008)	(0.006)	(0.018)	(0.006)	(0.015)	(0.015)	(0.004)	(0.003)
RTI * period (2013–2015)	0.026***	0.016***	0.018***	0.033***	0.032***	0.020***	0.100***	0.025***	0.029***	0.108***	0.032***	0.027***
	(0.003)	(0.006)	(0.004)	(0.004)	(0.005)	(0.003)	(0.034)	(0.006)	(0.006)	(0.032)	(0.004)	(0.003)
Pseudo Rˆ2	0.0527	0.0653	0.0586	0.0295	0.0434	0.0469	0.1006	0.0532	0.0602	0.0728	0.0427	0.0592
No. of obs.	303,484	155,520	128,698	174,730	47,471	946,367	147,739	352,538	554,355	282,867	621,651	247,802

Notes: Model 1 – explanatory variables: RTI, time dummy (ref. 1998–2000). Model 2 – explanatory variables: RTI, time dummy (ref. 1998–2000) and personal characteristics (age, gender, marital status, education level). Model 3 – explanatory variables: RTI, time dummy (ref. 1998–2000), 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 2003–2005 for Sweden. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own estimations based on EU-LFS, O*NET, and Cambridge Econometrics European Regional Data.

2.3.5. Correlates of cross-country differences in unemployment risk related to routine task intensity

In order to assess which factors are associated with the international differences in unemployment risk related to RTI, we estimate OLS regressions of the changes (between 1998−2000 and 2013−2015) in the average marginal effects of RTI on unemployment risk (Model 3) and of the changes in age-specific marginal effects (Model 4) against a range of macroeconomic and institutional variables. We focus on changes in marginal effects over time rather than their levels because the macroeconomic and institutional variables are plausibly exogenous to changes in the effects of interest. The levels of these effects, however, are likely to be affected by path dependence and shocks preceding our analysis period, which are also likely to have affected the macroeconomic and institutional variables. We account for two demand-side factors – technological change and globalization[7] – and for four labour market institutions: trade unions, the strictness of employment protection legislation, unemployment benefits, and active labour market policy (ALMP).[8] Formally, we estimate the following models:

$$\Delta ME^{A}_{RTI,c} = \beta_0 + \beta_1 X_{i,c} + \beta_2 VA_c \tag{10}$$

where $\Delta ME^{A}_{RTI,c}$ is the change in the marginal effects of RTI on unemployment risk for group A (total population or specific age groups) in country c. $X_{i,c}$ is one of the factors: ICT capital stock (average growth rate in 1998–2011), industrial robots (average growth rate 2004–2015), participation in global value chains (change in the foreign value added share in domestic output between 1998−2000 and 2013−2015), trade union density (average in 1998–2015), strictness of employment protection legislation (average in 1998–2015), unemployment benefits' replacement rate (average in 2001–2015), active labour market policy: public expenditure as a percentage of GDP divided by the share of participants in the working age population (average in 2004–2015). VA_c stands for the average value added growth in country c between 1998 and 2015.

We measure technological change with the average growth in ICT capital stock per worker, using Eden and Gaggl (2020) data, and with the average growth in the number of industrial robots per worker, using the International Federation of Robotics (IFR) data. We measure globalization with the change in the participation in global value chains (GVCs), using the backward-linkage index proposed by Wang et al. (2017) and provided by RIGVC UIBE (2016). We measure trade union density with the Visser (2019) data; the strictness of employment protection legislation with the OECD EPL index; the unemployment benefits with the OECD data on unemployment benefit replacement rates, and ALMP with normalised spending, i.e. spending per participant expressed as a share of GDP per capita, based on OECD data. For labour market institutions we use averages for the study period, as the changes in these institutions were probably endogenous to changes in unemployment. The data sources and precise definitions of variables are presented in Appendix A.1. As our country sample is quite small, we estimate separate models for each explanatory variable, while controlling for the average growth in GDP per capita in each regression. All explanatory variables are standardised across our country sample.

3. Changes in the task composition of jobs by age

Between the late 1990s and the mid-2010s, the intensity of non-routine cognitive tasks rose, while the intensity of manual tasks, both routine and non-routine, shrank in all countries studied (Table 1), in line with the findings of Goos et al. (2014); Hardy et al. (2018), or Bussolo et al. (2018). However, the patterns of changes in routine cognitive tasks varied. The intensity of routine cognitive tasks declined in the Western and Northern countries (to the greatest extent in the UK, Belgium and Sweden), but increased in Southern and Eastern countries (to a larger extent in Estonia and Poland and to a smaller extent in Greece and Spain).[9] These changes in average task intensities resulted from changes in the occupational structures, as well as changes in the task content of particular occupations. However, the former contributed much more: about 90 % of the changes in the average task contents can be attributed to changes in occupational structures, and about 10 % to changes of task contents within occupations (Hardy et al., 2018).

Next, we assess the change in the average intensity of each task content measure j among workers in specific age groups a, on the basis of estimated linear time trends (Eq. 3). The results for the panel regression are reported in Table 2, and the results for country-specific regressions in Fig. B2 in the Appendix.

We find substantial differences between age groups: the changes in the task content of jobs were much faster among prime-aged workers (aged 25−44) than among younger (15−24) or older workers (45−64). Prime-age workers (e.g. aged 25−44) recorded the fastest growth in the intensity of non-routine cognitive tasks, and the fastest shift away from routine cognitive tasks, as well as from manual tasks. Among workers aged 45−64, the changes were much slower. The growing trends of non-routine tasks were about half of those among prime-aged workers. The difference between the older and prime-aged workers was the largest in CEE countries (Estonia, Hungary, Poland).[10] Moreover, the intensity of routine cognitive tasks among older workers was increasing, even though it was

[7] These demand-side factors have been found to be instrumental for the de-routinisation of work (Autor et al., 2003; Goos et al., 2014; Michaels et al., 2014).

[8] These institutions have been found to be important determinants of labour markets adjustments (Blanchard and Wolfers, 2000; Bassanini and Duval, 2009).

[9] Hardy et al. (2018) attributed the increase in routine cognitive tasks in CEE and Southern European countries to patterns of structural change that these countries underwent, in particular to the gross reallocation of labour from agriculture or manufacturing (intensive in manual tasks) to services (rich in routine cognitive tasks).

[10] The United Kingdom was the only country where the intensity of both non-routine cognitive tasks grew faster among older workers than among prime-aged workers.

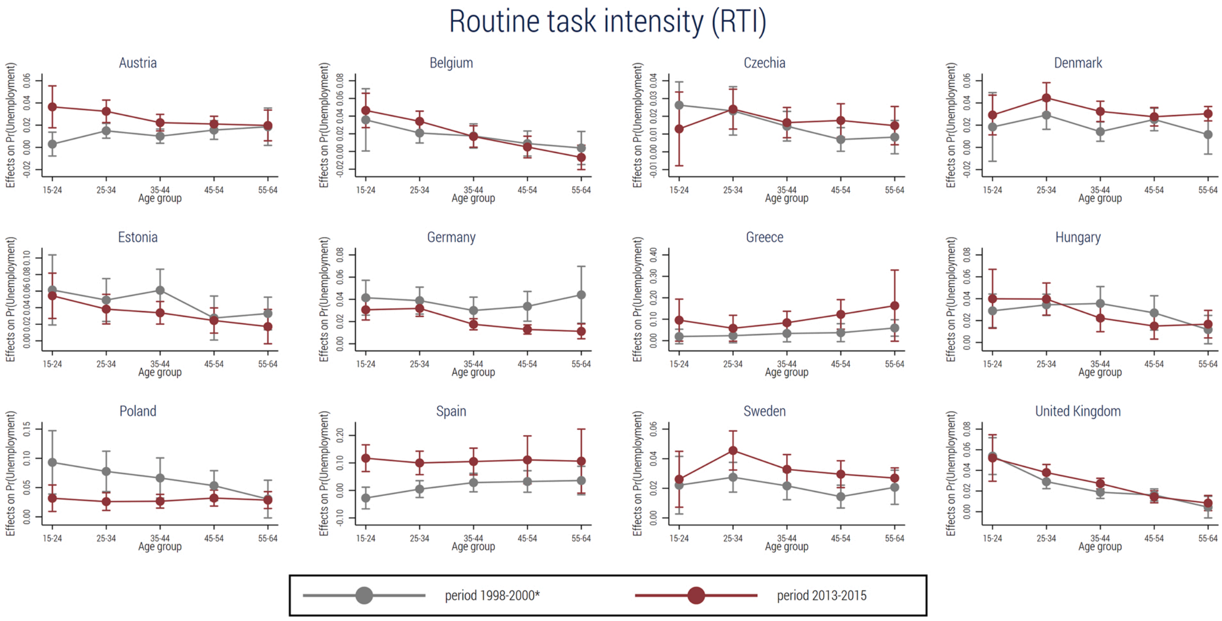

Fig. 1. The marginal effects of the routine task intensity (RTI) on unemployment risk, by age, calculated from the country-specific logit regressions with heterogeneous effects of the RTI by age, 1998-2000* and 2013-2015.

Notes: Explanatory variables: RTI, time dummy (ref. 1998−2000*), 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 are clustered at the occupation level. All estimation results are in Table B2 in the Appendix. Confidence intervals at 95 %.

*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.

declining overall and among prime-aged workers.[11] The decline in the importance of manual tasks was also slower than among prime-aged workers.[12] Among young workers (15−24), the intensity of non-routine cognitive analytical tasks was declining in a panel and in 7 out of 12 analysed countries, contrary to the overall trend. The intensity of non-routine cognitive personal tasks rose at a much slower pace than among prime-aged workers. The shift away from routine cognitive tasks or from manual tasks was also noticeably slower than among prime-aged workers (Table 2).

Between the late 1990s and the mid-2010s, the average age of workers in occupations in which routine tasks (either cognitive or manual) are pre-dominant has increased more than the average age of workers in occupations in which non-routine tasks, especially cognitive ones, are pre-dominant (Table 3). Moreover, in several countries the unemployment rate in routine occupations has increased relatively to the unemployment rate in non-routine occupations. Workers in the routine manual occupations were particularly affected.

Thus, the descriptive evidence suggests that the de-routinisation of jobs has been experienced mainly by prime-aged workers, while the jobs held by older workers became more routine-intensive. The average age of a worker in routine occupations increased, and the unemployment rate rose too.

4. Ageing of routine occupations

In this section, we provide econometric evidence that more routine-intensive occupations were ageing faster. We estimate country-specific regressions that relate the change in the average age of a worker, or a share of workers in a given age group, in occupation *i*, to the initial task intensity in occupation *i* (Eq. 4).

In seven out of 12 analysed countries, the higher the routine task intensity of an occupation was in 1998, the greater was the change in the average age of the workers in this occupation by 2010 (see Table 4). These effects were economically relevant. The difference of 1 unit of RTI, which is the difference between, e.g., secretaries (ISCO occupation 411) and social work associate professionals (ISCO occupation 346), or between industrial robot controllers (ISCO occupation 312) and pre-primary education teaching professionals (ISCO occupation 233), was associated with the increase of the average age of a worker in an occupation ranging from 0.6 years in

[11] Germany, Sweden and the United Kingdom are the only countries where the intensity of routine cognitive tasks among workers aged 45−64 was declining (Fig. B2 in the Appendix).

[12] In Czechia and Hungary, the intensity of manual tasks has even increased among workers aged over 55 (Fig. B2 in the Appendix).

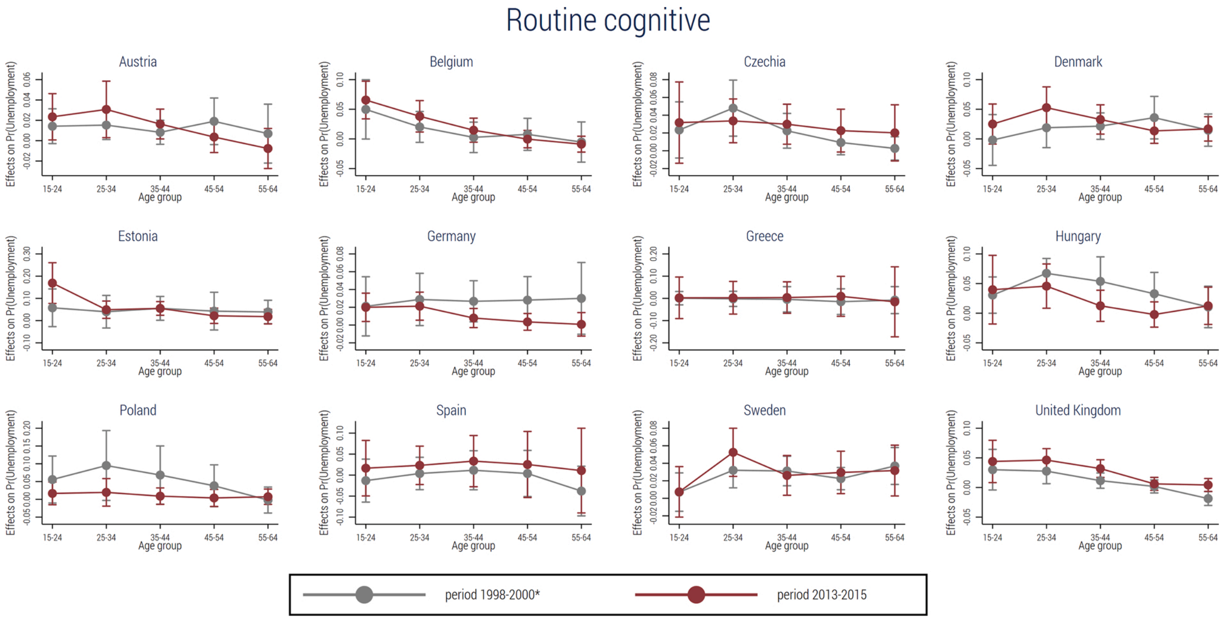

Fig. 2. The marginal effects of being in an occupation in which routine cognitive tasks are pre-dominant on unemployment risk, by age, calculated from the country-specific logit regressions with heterogeneous effects of tasks by age, 1998-2000* and 2013-2015.

Notes: Explanatory variables: task group fixed effects (routine cognitive, routine manual, non-routine manual, ref. non-routine cognitive analytical and personal), time fixed effect (ref. 1998−2000*), 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 task groups, age and time fixed effects. The standard errors are clustered at the occupation level. Confidence intervals at 95 %.

*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.

Spain to 1.5 year in Poland. This, in turn, was equivalent to 50 % (on average) of the recorded change in the mean worker age, which ranged from 0.5 year in Sweden to 2.8 years in Austria (constant in Table 4).

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 and the increasing share of older age groups in these occupations. In most countries, the higher the initial routine intensity of an occupation was, the more significantly negative was the change in the share of workers in the youngest age group (aged 15−24) in this occupation (Table 5). In Central and Eastern, and Southern European countries as well as in the UK, the effect related to a 1 unit difference in RTI was large and comparable to the overall decline in the employment share of young workers. Additionally, in most countries a higher initial RTI was associated with a significantly higher increase in the share of workers aged 45−64. Again, the effects related to a 1 unit difference in the RTI were strong, in many countries exceeding half the change in the share of a given group in total employment. Our findings are in line with Autor and Dorn's (2009) results for the US. Moreover, in five Western European countries a higher RTI was also associated with a significant decline in the share of workers aged 24–44, in each case replaced by a higher share of workers aged 45 or more. Greece and Spain stand out as the only countries where the more routine occupations were not ageing faster and recorded an increase in the share of prime-aged workers.

Next, we replace RTI in Eq. (4) with the initial (1998) intensity of non-routine cognitive tasks (either analytical or personal). We find that in several countries the higher the non-routine cognitive content was in 1998, the slower was the ageing of the workforce in this occupation (Table 6). This relationship was strongest in Czechia, Hungary, and Poland – three out of four of the post-transition economies in our sample.

Austria stands out as the only country in which the non-routine occupations were ageing as fast as the routine occupations, and the intensity of non-routine cognitive tasks was even positively correlated with the change in the average age of a worker in an occupation between 1998 and 2010. We think that Austria is an outlier in our sample because of early retirement reforms and the rise in retirement age implemented in the 2000s. These reforms made all types of workers remain in their jobs longer (Manoli and Weber, 2016), and were followed by a substantial increase in the labour force participation of older workers (from 30 % in 1998 to 48 % in 2015).

Finally, we verify if the above findings hold over a longer period (1998–2015) and re-estimate all regressions reported in Tables 4–6 as pooled regressions at the 1-digit occupation level with country fixed effects. The results of this robustness check are presented in Table B1 in the Appendix. They confirm our earlier findings: a higher routine intensity of an occupation in 1998 was associated with a larger increase in the average age of workers in a given occupation by 2015 (coefficient 0.83 significant at the 1% level), a stronger decline in the share of workers aged 15−24 (-2.01, 1% level) and a higher increase in the share of workers aged 45−64 (3.01, 1% level), while there was no significant association with the share of workers aged 25−44. The relationship between the intensity of particular non-routine cognitive tasks in occupations in 1998 and the increase in the average age of workers in a given occupation by

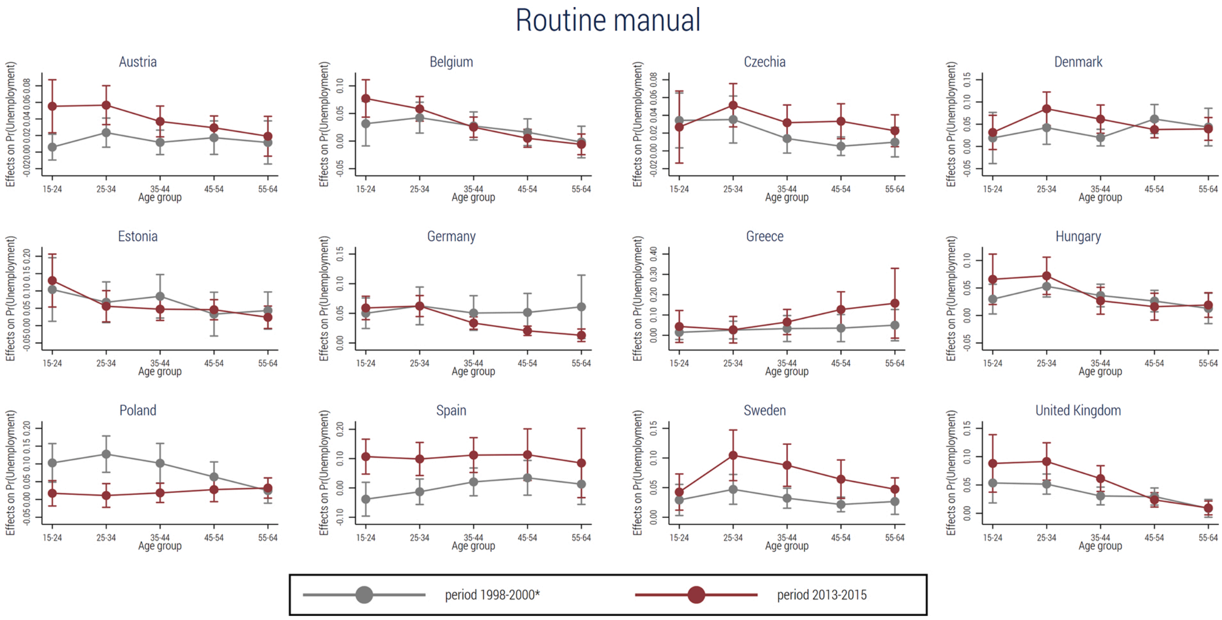

Fig. 3. The marginal effects of being in an occupation in which routine manual tasks are pre-dominant on unemployment risk, by age, calculated from the country-specific logit regressions with heterogeneous effects of tasks by age, 1998-2000* and 2013-2015.
Notes: Explanatory variables: task group fixed effects (routine cognitive, routine manual, non-routine manual, ref. non-routine cognitive analytical and personal), time fixed effect (ref. 1998–2000*), 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 task groups, age and time fixed effects. The standard errors are clustered at the occupation level. Confidence intervals at 95 %.
*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.

2015 was negative for both analytical and interpersonal tasks (-0.53 and -0.35, respectively, both significant at the 1% level). The more routine occupations were indeed ageing faster in Europe.

5. Routine task intensity and the risk of unemployment

The shift away from routine and towards non-routine work is 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). As such, it may be associated with an increase in the unemployment risk of routine workers.

We use the repeated cross-section LFS data to document the relationship between the routine task intensity (RTI) of occupations and the unemployment risk.[13] 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. The occupation data is missing for unemployed who had worked but didn't provide the occupation (non-response) and unemployed who had never worked.[14] In Appendix A we present evidence that the missing occupational information for these unemployed doesn't drive our findings.

5.1. Routine task intensity and occupation-specific unemployment rates

We find evidence that the more routine the occupation was in 1998, the greater the change was in the occupation-specific unemployment rate over the next dozen years. This was the case in six out of the 12 countries in our sample (Czechia, Denmark, Estonia, Greece, Spain and Sweden, see Table 7). 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, as shown by a negative constant). 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 2010.

[13] Studies for the US by Cortes (2016) and for Germany by Bachmann et al. (2019) used panel data to analyse this relationship. Unfortunately, panel datasets cannot be constructed using the EU-LFS, and are not available for the group of countries and time span that we are studying.
[14] The unemployed individuals who had never worked were not surveyed about their occupations. The underlying assumption is that an occupation can be assigned to a worker only if a worker has ever worked in that occupation.

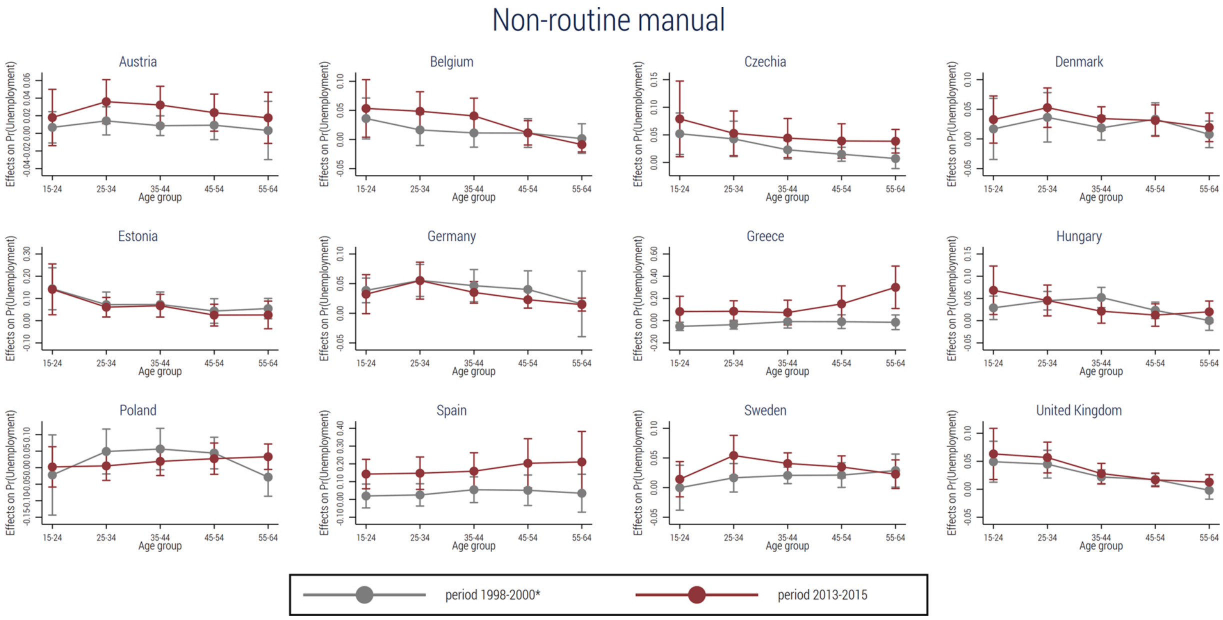

Fig. 4. The marginal effects of being in an occupation in which non-routine manual tasks are pre-dominant on unemployment risk, by age, calculated from the country-specific logit regressions with heterogeneous effects of tasks by age, 1998-2000* and 2013-2015.
Notes: Explanatory variables: task group fixed effects (routine cognitive, routine manual, non-routine manual, ref. non-routine cognitive analytical and personal), time fixed effect (ref. 1998–2000*), 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 task groups, age and time fixed effects. The standard errors are clustered at the occupation level. Confidence intervals at 95 %.
*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.

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 at the worker level, accounting for potential changes in these relationships over time. To this aim, we estimate several variants of regression (5).

Here we present the marginal effects of routine task intensity on unemployment risk, calculated while holding other variables at their means (models 1–3, Table 8) or age-specific means (models 4 and 4′, Figs. 1–4) in a given period. The complete results of the most elaborate specification (model 4) are presented in Table B2 in the Appendix. In the case of alternative specifications, we present the marginal effects pertaining to routine cognitive, routine manual and non-routine manual occupations estimated in the model with all individual and regional controls (model 3′, Table 9) and in the model with all interactions (model 4′, Figs. 2–4).

In all countries studied the individuals in the more routine-intensive occupations were more likely to be unemployed. The marginal effects on unemployment related to higher routine task intensity are positive and significant in all countries and specifications (Table 8). According to the simple specification (model 1), these marginal effects have also increased over time in 7 out of 12 countries studied, which suggests that the de-routinisation might have reduced job opportunities for some workers. Estonia, Germany and Poland were the only countries where the marginal effects of RTI on unemployment risk declined over time. These three countries recorded a secular improvement in labour market conditions between the late 1990s and the mid-2010s, and two of them (Estonia, Poland) also recorded an increase in the role of routine cognitive tasks related to the fast growth of services (Hardy et al., 2018).

Once we control for socio-demographic characteristics (model 2), the marginal effects associated with the RTI decline in all countries, but remain highly significant in all countries except Spain in 1998–2000. 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 effects of the RTI. Thus, the positive and significant effects of RTI on unemployment risk are not driven by the characteristics of local labour markets with more and less routine-intensive jobs, but presumably by the process of de-routinisation.

Allowing for heterogeneous effects of RTI by age (model 4), we find that in most countries the marginal effect of routine task intensity on unemployment risk was stronger among young than among older workers. The age-specific marginal effects are declining with age particularly strongly in Belgium, Germany (2013–2015), Hungary (2013–2015) and the United Kingdom – the countries

Table 9

The marginal effects of being in occupations in which routine cognitive, routine manual or non-routine manual tasks are pre-dominant on unemployment risk, model 3′.

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	United Kingdom
Routine cognitive	0.013*	0.012	0.023**	0.020*	0.044*	0.028**	−0.002	0.046***	0.062*	0.004	0.027***	0.013*
	(0.006)	(0.013)	(0.009)	(0.011)	(0.026)	(0.012)	(0.022)	(0.015)	(0.037)	(0.019)	(0.007)	(0.007)
Routine cognitive * (2013−2015)	0.016*	0.016*	0.027**	0.029***	0.047***	0.011*	0.004	0.018	0.013	0.026	0.032***	0.025***
	(0.008)	(0.009)	(0.011)	(0.010)	(0.011)	(0.006)	(0.035)	(0.014)	(0.013)	(0.029)	(0.010)	(0.007)
Routine manual	0.014**	0.027**	0.019***	0.038***	0.063***	0.053***	0.031	0.036***	0.095***	0.002	0.032***	0.035***
	(0.006)	(0.011)	(0.007)	(0.012)	(0.018)	(0.014)	(0.025)	(0.008)	(0.023)	(0.020)	(0.007)	(0.006)
Routine manual * (2013−2015)	0.041***	0.025***	0.034***	0.051***	0.051***	0.036***	0.075**	0.036***	0.021	0.106***	0.069***	0.052***
	(0.007)	(0.009)	(0.008)	(0.011)	(0.011)	(0.005)	(0.032)	(0.012)	(0.015)	(0.032)	(0.014)	(0.008)
Non-routine manual	0.009*	0.014	0.027***	0.027**	0.068***	0.042***	−0.023	0.036***	0.036	0.038	0.019**	0.027***
	(0.005)	(0.011)	(0.008)	(0.012)	(0.017)	(0.013)	(0.024)	(0.008)	(0.033)	(0.033)	(0.009)	(0.007)
Non-routine manual * (2013−2015)	0.028***	0.026**	0.046***	0.035***	0.051**	0.033***	0.120**	0.028**	0.018	0.176***	0.035***	0.033***
	(0.010)	(0.012)	(0.015)	(0.012)	(0.023)	(0.010)	(0.059)	(0.013)	(0.022)	(0.056)	(0.009)	(0.008)
Pseudo R^2	0.0519	0.0656	0.0606	0.0285	0.0429	0.0471	0.1027	0.0518	0.0597	0.0754	0.0444	0.0574
No. of obs.	303,484	155,520	128,698	174,730	47,471	946,367	147,739	352,538	554,355	282,867	621,651	247,802

Notes: Explanatory variables: task group fixed effects (routine cognitive, routine manual, non-routine manual; ref. non-routine cognitive analytical and personal), time fixed effect (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 task group fixed effects and time fixed effects. The standard errors are clustered at the occupation level. Only the results for the task group fixed effects 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. Standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

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

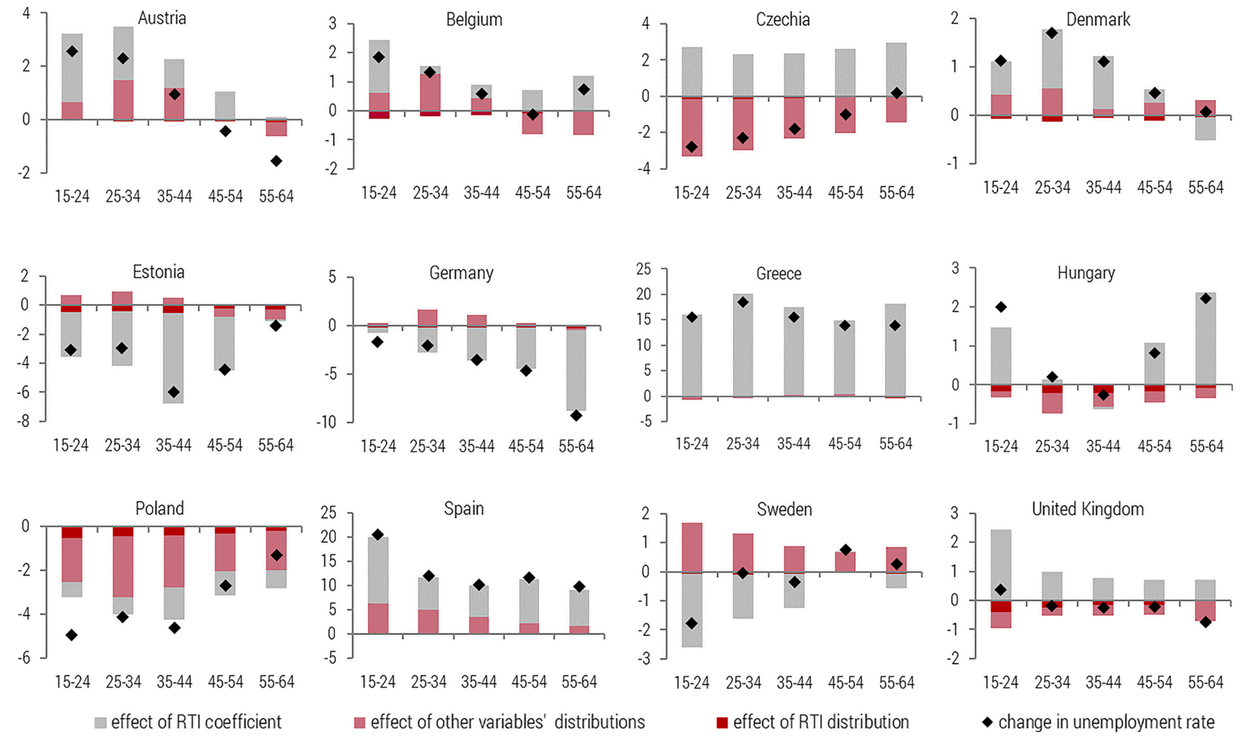

Fig. 5. The contributions of changes in the effect of routine task intensity (RTI), in the distribution of RTI and other characteristics to changes in the unemployment rate between 1998-2000* and 2013-2015, by age (in pp.).
Notes: Effects calculated using the estimation results of model 4, see Table B2 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.

where the overall decline in the intensity of routine tasks was the most pronounced (Table 1). In Austria (2013–2015), Denmark (2013–2015), Estonia, Poland (1998–2000), and Sweden the effects of routine task intensity on unemployment risk were also larger among young than among older workers, but the differences were less pronounced. Moreover, in Austria, Denmark, Hungary, and Sweden, the marginal effects of RTI among young workers (aged 15–24 or 25–34) increased over time to a larger extent than among older age groups. On the other hand, Greece and Spain are the only two countries where the effects of routine task intensity on unemployment risk were not highest among young workers. Greece and Spain are the only countries in our sample in which the more routine-intensive occupations were not ageing faster (Table 4) and which recorded a secular increase in unemployment between the late 1990s and the mid-2010s.

The results of an alternative specification in which we control for the effects of routine cognitive, routine manual and non-routine manual occupations instead of a continuous RTI measure show that the age-specific effects on unemployment are robust. However, these results also provide additional insights on the relationship between routine task content and unemployment. First, in all countries the effects pertaining to routine manual occupations are stronger than those pertaining to routine cognitive occupations (Table 9 and Figs. 2–3). This is particularly the case in countries in which the average intensity of routine manual tasks has declined substantially between the late 1990s and the mid-2010s (Table 1), such as Austria, Germany, Spain, Sweden and the UK. This finding, although not causal, is consistent with the argument that de-routinisation is driven by factors on the labour demand side such as automation or offshoring rather than by factors on the labour supply side such as educational upgrading of workers (Goos et al., 2014; Fonseca et al., 2018). Second, although the effects pertaining to non-routine manual occupations are positive and significant in eight out of 12 countries we study, they are generally smaller than those pertaining to routine manual occupations.

5.3. Decomposition of unemployment rate changes over time

In order to quantify the economic significance of the relationship between RTI and unemployment, we use the model 4 parameters estimated for each country c and age group y to decompose the change in the predicted unemployment rate between 1998–2000 and 2013–2015 in line with Eq.s (6)–(9). The results are presented in Fig. 5 and compared with the actual changes in unemployment rates in the relevant age groups in particular countries.

A noticeable share of unemployment increases in European countries between the late 1990s and the mid-2010s can be attributed to an increase in the unemployment risk related to the routine task intensity of occupations. This contribution was especially high among young workers – in countries such as Austria, Belgium, Denmark, Hungary, and the United Kingdom it amounted to more than

Table 10
Associations between changes in marginal effects of RTI on unemployment and technology, participation in global value chains and labour market institutions.

	ICT capital stock per 10,000 workers	Industrial robots per 10,000 workers	Participation in global value chains	Trade union density	Strictness of employment protection legislation	Unemployment benefits' replacement rate	Active labour market policy
Marginal effect of RTI on unemployment risk							
effect	0.014	−0.012	−0.020**	−0.007	0.013	−0.004	−0.011
	(0.010)	(0.013)	(0.008)	(0.010)	(0.009)	(0.010)	(0.009)
R^2	0.45	0.25	0.60	0.38	0.46	0.36	0.44
Marginal effect of RTI on unemployment risk in population aged 15−24							
effect	0.014	−0.011	−0.028*	−0.012	0.016	−0.003	−0.02
	(0.016)	(0.021)	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)
R^2	0.37	0.22	0.55	0.36	0.39	0.31	0.46
Marginal effect of RTI on unemployment risk in population aged 25−34							
effect	0.003	−0.010	−0.019**	−0.001	0.007	0.003	−0.01
	(0.011)	(0.013)	(0.008)	(0.010)	(0.010)	(0.010)	(0.009)
R^2	0.26	0.32	0.55	0.29	0.32	0.29	0.37
Marginal effect of RTI on unemployment risk in population aged 35−44							
effect	0.008	−0.013	−0.016**	−0.002	0.008	0.000	−0.007
	(0.009)	(0.011)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
R^2	0.42	0.41	0.65	0.43	0.48	0.42	0.48
Marginal effect of RTI on unemployment risk in population aged 45−54							
effect	0.020*	−0.012	−0.019*	−0.008	0.017*	−0.011	−0.01
	(0.009)	(0.012)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
R^2	0.57	0.15	0.53	0.32	0.48	0.37	0.35
Marginal effect of RTI on unemployment risk in population aged 55−64							
effect	0.029***	−0.008	−0.016	−0.01	0.013	−0.015	−0.009
	(0.007)	(0.012)	(0.010)	(0.011)	(0.010)	(0.009)	(0.010)
R^2	0.76	0.05	0.452	0.35	0.41	0.45	0.35
No. of obs.	11	11	12	12	12	12	12

Notes: ICT capital stock – average growth rate in 1998–2011, data from Eden and Gaggl (2020). Industrial robots – average growth rate 2004–2015, data from IFR. Participation in global value chains – change in the foreign value added share in domestic output between 1998−2000 and 2013−2015, data based on WIOD provided by RIGVC UIBE (2016). Trade union density – average in 1998–2015, data from Visser (2019). Strictness of employment protection legislation – average in 1998–2015, OECD data. Unemployment benefits' replacement rate – average in 2001–2015, OECD data. Active labour market policy: public expenditure as a percentage of GDP divided by the share of participants in working age population – average in 2004–2015, OECD data. In each regression we control for average value added growth between 1998 and 2015, measured with EU KLEMS data. In each case, the period used reflects data availability. Data sources and definitions are explained in detail in Appendix A1. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own estimations based on EU-LFS, O*NET, OECD, International Federation of Robotics, and Eden and Gaggl (2020) data.

half of the observed increase of the unemployment rate among workers aged between 15 and 34 years. At the same time, in most countries the contribution of unemployment risk related to RTI to changes in the unemployment rate among older workers (aged over 45) was rather small.

Overall, we find that the increase in the unemployment risk related to routine task intensity has contributed positively to changes in the unemployment rate in all countries except Estonia, Germany, Poland (three countries that recorded secular improvements in the labour market situation between the late 1990s and the mid-2010s) and Sweden.[15] This effect was to a certain extent counterbalanced by changes in the distribution of RTI across workers that in all countries contributed negatively to the changes in the unemployment rate. Hence, we find that the de-routinisation of European labour markets has strengthened the effect of higher routine task intensity of occupations on unemployment, but also reduced the number of workers exposed to high RTI. The former effect on unemployment rates was much stronger than the latter.

We also account for the contribution of changes in all observable characteristics, regional controls and labour markets shocks (effect of other variables' distributions in Figure 6). In countries that experienced a substantial educational expansion, in particular increasing tertiary education enrolment among successive cohorts, such as the Czech Republic or Poland, this effect is negative because better educated workers are less likely to be unemployed. Besides, these effects of other control variables can be largely attributed to changes in labour demand shocks, which capture differences in the overall labour market conditions between the late 1990s and the mid-2010s (e.g. improvement in Estonia and Germany, deterioration in Greece and Spain).

5.4. Factors associated with cross-country differences in unemployment risk related to routine task intensity

In order to shed light on factors associated with international differences in unemployment risk related to RTI, we estimate OLS regressions (10) of the changes in average marginal effects of RTI on unemployment risk (Model 3 in Table 8) and of the changes in age-specific marginal effects (Model 4 in Fig. 1) against a range of macroeconomic and institutional variables. The results are presented in Table 10.

We find that faster growth in routine-replacing technologies, in particular ICT capital, was associated with a larger increase in the marginal effect of RTI on unemployment risk, especially among older workers who usually possess lower technology-related skills. The effects pertaining to robotization are small and insignificant. At the same time, the change in participation in GVCs is negatively associated with the change in the marginal effects of RTI on unemployment risk. This effect was the strongest among young workers, weaker among prime-aged workers, and insignificant among workers aged 55–64. This means that in countries that increased their participation in GVCs (e.g. Belgium, Czech Republic, Poland), the increases in the unemployment risk related to routine task intensity were smaller than in countries in which this participation remained flat (e.g. Greece, Spain, Sweden). This finding is consistent with theories of global value chains arguing that routine tasks are more likely to be traded between countries involved in GVCs and off-shoring (Grossman and Rossi-Hansberg, 2008). It also suggests that sectors involved in this trade are more likely to employ younger workers.

The results pertaining to labour market institutions are in line with previous findings (Blanchard and Wolfers, 2000; Bassanini and Duval, 2009), but mostly insignificant. Higher trade union density and higher normalised spending on ALMP are associated with a lower increase in the marginal effect of RTI on unemployment risk, especially among young workers, although these effects are not statistically significant. The effects associated with unemployment benefit replacement rates are virtually zero. Finally, countries with stricter employment protection legislation were characterised by higher increases in the marginal effects of RTI on unemployment risk, but this effect is significant only for workers aged 45–54.

In general, our results suggest that cross-country differences in changes of unemployment risk related to performing routine intensive jobs were associated mainly with demand-side factors such as technology adoption and participation in global value chains.

6. Conclusions and policy implications

In this paper, we studied 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) between 1998 and 2015, with a focus on the differences between young, prime-aged and older workers. These differences related to age are relevant because older workers usually have lower skill levels, especially regarding ICT use, and lower occupational mobility than younger workers. On the other hand, the declining importance of routine jobs may reduce the supply of entry-level jobs for young workers.

We have found that the shift away from routine and toward non-routine work occurs differently among various age groups. First, it happened much faster among workers aged between 25 and 44 years than among those aged between 15 and 24 years and between 45 and 64 years. Second, in the majority of countries studied, occupations with higher routine task intensities (in 1998) aged more rapidly over the next dozen or so years than occupations with lower routine task intensities: the share of young workers (aged 15–24) decreased, while the share of older workers (aged 45–64) and the average age of workers increased more strongly in the more routine-intensive occupations. Our findings are in line with those of Siliverstovs et al. (2011), who associated population ageing with an employment shift from agriculture, manufacturing, construction and mining sectors towards community, social and personal services as well as the financial sector. Our research shows that job routine intensity, which differs between sectors, could be one of the factors

[15] In the case of countries where the labour market deteriorated substantially (Greece and Spain), this contribution is probably overestimated as the coefficient on RTI is the only one we allow to vary over time.

underlying this shift.

Third, we found that the risk of unemployment is higher in more routine-intensive occupations, especially among young workers. It has also increased over time, to a larger extent in countries in which de-routinisation was more pronounced, in countries in which the growth of ICT capital stock per worker was the fastest, and in countries that didn't increase their participation in global value chains. Our findings are consistent with the conjecture that the hollowing-out of middle-skilled, routine jobs is driven by demand-side factors, as indeed argued in the previous literature (Autor et al., 2003; Michaels et al., 2014; Goos et al., 2014). So far, the main focus in the literature was on job polarisation and the related wage inequality. Our findings suggest that the de-routinisation of jobs may also have contributed to the secular rise of unemployment among young people in many European countries.

Several policy implications stem from our findings. 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 Europe-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, 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 market 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 changes in task structures affect labour market inequalities. Unfortunately, the EU-LFS does 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, surveys that collect such data, like PIAAC for OECD countries and STEP for 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.

Acknowledgements

We thank the participants of the EALE Conference 2017 in. St. Gallen, the IBS Jobs Conference 2017 in Warsaw, the ASSA 2018 Annual Meeting in Philadelphia, and the Jobs and Development Conference 2018 in Bogotá for their insightful comments. This paper was financially supported by the Network for Jobs and Development under the auspices of the World Bank. This paper uses Eurostat data and Statistics Poland data. Eurostat has no responsibility for the results and the conclusions, which are those of the authors. The usual disclaimers apply. All errors are ours.

Appendix A. Additional information on data and methods

Construction of task content measures

Table A1

The ISCO-88 (used in the EU-LFS data until 2010) and ISCO-08 (used from 2011 on) classifications are not entirely comparable, which affects the calculated task intensities. In particular, the non-routine cognitive task intensities of farming occupations are much higher in the ISCO-88 than in the ISCO-08. Farming jobs are typically associated with routine and manual tasks (Arias et al., 2014), and involve relatively few non-routine cognitive tasks (Acemoglu and Autor, 2011). We therefore assumed that the ISCO-08 classification

Table A1
Construction of task contents measures based on O*NET data.

Task content measure (*T*)	Task items (*J*)
Non-routine cognitive analytical	Analysing data/information
	Thinking creatively
	Interpreting information for others
Non-routine cognitive interpersonal	Establishing and maintaining personal relationships
	Guiding, directing and motivating subordinates
	Coaching/developing others
Routine cognitive	The importance of repeating the same tasks
	The importance of being exact or accurate
	Structured vs. unstructured work
Routine manual	Pace determined by the speed of equipment
	Controlling machines and processes
	Spending time making repetitive motions
Non-routine manual physical	Operating vehicles, mechanized devices, or equipment
	Spending time using hands to handle, control or feel objects, tools or controls
	Manual dexterity
	Spatial orientation

Source: Own elaboration based on Acemoglu and Autor (2011).

Table A2
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

Notes: 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 EU-LFS data.

Table A3
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., 2018 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 EU-LFS data.

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) using the crosswalk provided by ILO.[16] Table A2 shows which occupations were updated in particular countries.

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 group 522, whereas the ISCO-88 did not. As a result, the task content values for this group, in particular of routine cognitive tasks, differ substantially between classifications. 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).

A few countries changed their national occupational classifications over the period of the study. In the United Kingdom, the classification used was updated to the SOC-00 in 2001 In Poland, the Polish classification of occupations (KZiS) was modified in 2003, 2005, 2011 and 2015 (see Hardy et al., 2018, for more details on KZiS changes). In Austria, the LFS was converted to a continuous survey (covering all weeks of the year) in 2004. In all these cases, we apply the same rescaling method that we apply to the classification change from ISCO-88 (COM) to ISCO-08. Our adjustments overlap with those applied by Goos et al. (2014) (Table A3).

Availability of regional data in the EU-LFS

Table A4

[16] http://www.ilo.org/public/english/bureau/stat/isco/isco08/ [accessed: 2017−01-30]

Table A4
The level of regional data available in the 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 EU-LFS data.

Dealing with non-response pertaining to occupations

We provide evidence that missing occupational information for some unemployed doesn't drive our findings presented in Section 5.

First, 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 (Table A5). We tested if the fractions of particular sub-groups by age, education, gender, or marital status are significantly different among the unemployed who reported occupations and among those who did not. Only 57 out of 708 possible tests showed that differences in fractions are significant at the 10 % level.[17]

Second, we impute the task content values for the unemployed with missing occupation data, and compare the distribution of RTI among them with the observed distribution of RTI among unemployed and workers. We use country-specific regressions of RTI regressed against individual characteristics (age, education (also interacted), gender, marital status) and regional controls (as in regression 5, see Subsection 2.3).[18] The distributions of RTI among these three groups are presented in Fig. A1. In each country, the distribution of imputed RTI among the unemployed with no occupation data is closely aligned with the distribution of RTI among the unemployed. It is shifted towards higher RTI than among workers: the mean and median of RTI imputed among the unemployed with no occupation data are higher than the mean and median of RTI among workers. It is also unlikely that the unemployed who have never worked possess unobservable traits which would make them perform less routine-intensive tasks than those performed by individuals with similar observable characteristics who have worked in the past. Hence, we conclude that missing occupational

Table A5
Occupational data non-response rate, by country (%).

	The share of unemployed who had worked but did not provided occupation 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.
Notes: Boxplots identify median, first and third quartile, minimum and maximum of RTI. Outside values are excluded. RTI for unemployed with now occupations are imputed based on country-specific models of RTI regressed against individual characteristics – age, education (also interacted), gender and marital status – year fixed effects and regional controls (Bartik shocks, past industry employment shares).
*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.

[17] Due to the high number of tests, the results are not presented here and are available upon request.
[18] The estimation results of these models are available upon request.

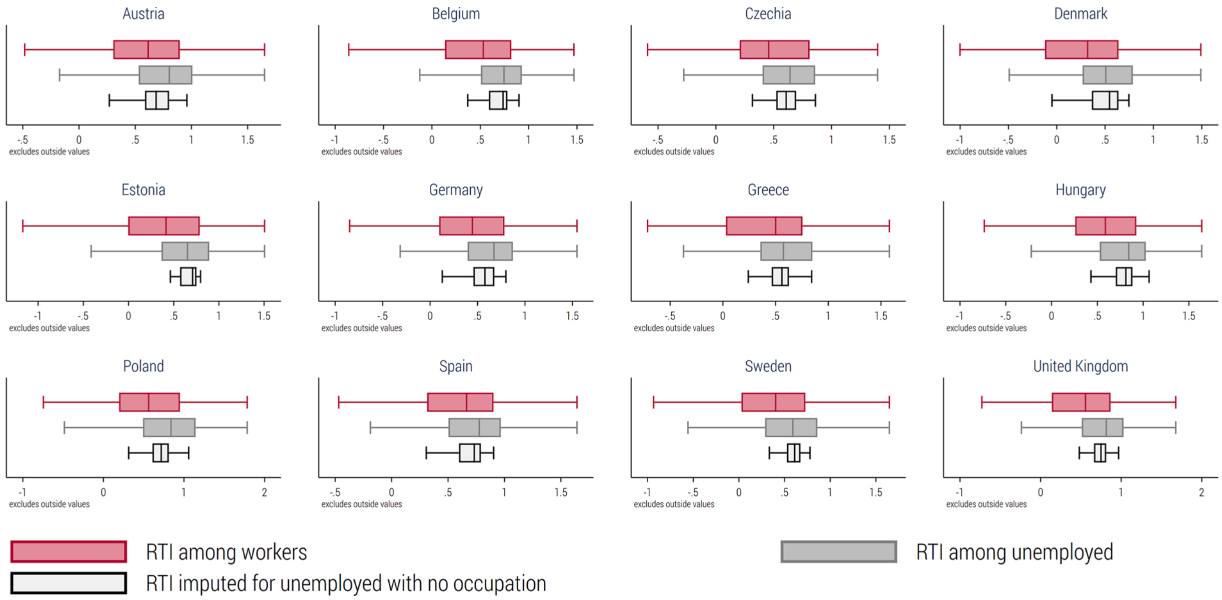

Fig. A1. The distribution of RTI among workers, unemployed (based on last occupation held) and RTI imputed for the unemployed who have never worked or provided no previous occupation.

Notes: boxplots identify median, first and third quartile, minimum and maximum of RTI. Outside values are excluded. RTI for unemployed with now occupations are imputed based on country-specific models of RTI regressed against individual characteristics – age, education (also interacted), gender and marital status – year fixed effects and regional controls (Bartik shocks, past industry employment shares).

*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.

information is not driving the potential relationship between routine task intensity and unemployment risk.

Data on technology, global value chains and labour market institutions

The data on ICT capital stock are taken from Eden and Gaggl (2020) and are available for the period 1998–2011. We combine them with Eurostat data on total employment to calculate ICT capital stock per 10,000 workers.

The data on industrial robots come from the International Federation of Robotics [IFR] (2017). From 2004, data are available for all countries in our sample except Estonia. Following Graetz and Michaels (2018); Dauth et al. (2017) and Acemoglu and Restrepo (2020), we use data on the operational stock of robots and combine them with Eurostat data on total employment to calculate the stock of robots per 10,000 workers.

The data on the participation in global value chains come from the RIGVC UIBE (2016) database. We use the backward linkage-based measure, defined as the foreign value added share in the production of final goods and services (Wang et al., 2017). We use the variables based on WIOD.

The data on trade union density come from Visser (2019) and are available for the period 1998–2015.

The data on strictness of employment protection legislation come from the OECD and are available for the period 1998–2015. We use the indicator pertaining to regulations for individual dismissals. As a robustness check, we use the indicator that accounts for regulations for collective dismissals, and the indicator of regulations for temporary contracts. The results are qualitatively the same and are available upon request.

The data on the replacement rate of unemployment benefits come from the OECD and are available for the period 2001–2015. We calculate the average replacement rate across all wage levels (minimum wage, 67 % of average wage, average wage), all household types and all unemployment durations. As a robustness check, we use replacement rates calculated for particular wage levels (averaged across household types and unemployment durations). The results are qualitatively the same and are available upon request.

The data on the active labour market policy rate come from the OECD and are available for the period 2004–2015. We calculate the normalised spending on ALMP by dividing the public expenditure as a percentage of GDP over the share of participants in working age population.

The data on value added come from EU KLEMS.

Appendix B. Additional Results

Tables B1 and B2

Table B1
The relationship between the routine (RTI), non-routine cognitive analytical (NRCA) and non-routine cognitive personal (NRCP) intensity in 1998, and the changes in the mean ages of workers and change in the share of workers aged 15-24, 25-44, 45-64 in occupations between 1998 and 2015. Pooled regressions at the 1-digit occupation level with country dummies.

Explanatory variable of interest	RTI	RTI	RTI	RTI	NRCA	NRCP
Explained variable	Δ age	Δ 15−24	Δ 25−44	Δ 45−64	Δ age	Δ age
Coefficient of interest	0.83***	−2.01***	−1.00	3.01***	−0.53***	−0.35***
	(0.23)	(0.56)	(0.91)	(0.89)	(0.12)	(0.12)
ΔShare	−0.02	−0.03	0.14	−0.11	−0.01	−0.03
	(0.03)	(0.07)	(0.11)	(0.10)	(0.03)	(0.03)
Austria	0.47	−1.18	−0.23	1.41	0.42	0.38
	(0.53)	(1.31)	(2.12)	(2.06)	(0.52)	(0.54)
Belgium	0.40	−1.22	0.78	0.44	0.37	0.45
	(0.53)	(1.30)	(2.11)	(2.06)	(0.52)	(0.54)
Czechia	−0.17	−6.89***	16.14***	−9.25***	−0.19	−0.09
	(0.54)	(1.31)	(2.12)	(2.06)	(0.52)	(0.54)
Denmark	−0.25	−0.22	3.52*	−3.31	−0.36	−0.26
	(0.53)	(1.31)	(2.11)	(2.06)	(0.52)	(0.54)
Estonia	−1.19**	−2.36*	9.90***	−7.54***	−1.25**	−1.16**
	(0.53)	(1.31)	(2.11)	(2.06)	(0.52)	(0.54)
Spain	1.46***	−6.95***	7.24***	−0.29	1.27**	1.40**
	(0.53)	(1.31)	(2.11)	(2.06)	(0.52)	(0.54)
Greece	0.83	−6.76***	8.49***	−1.73	0.73	0.78
	(0.53)	(1.31)	(2.11)	(2.06)	(0.52)	(0.54)
Hungary	0.95*	−7.38***	10.45***	−3.06	0.92*	0.88
	(0.53)	(1.31)	(2.12)	(2.06)	(0.52)	(0.54)
Poland	−0.31	−3.63***	8.93***	−5.30**	−0.50	−0.31
	(0.53)	(1.31)	(2.11)	(2.06)	(0.52)	(0.54)
Sweden	−2.70***	1.52	10.23***	−11.75***	−2.89***	−2.79***
	(0.54)	(1.31)	(2.12)	(2.07)	(0.52)	(0.55)
United Kingdom	−0.61	−1.10	5.84***	−4.73**	−0.68	−0.63
	(0.53)	(1.31)	(2.11)	(2.06)	(0.52)	(0.54)
Constant	2.41***	0.38	−11.94***	11.56***	4.38***	3.74***
	(0.40)	(0.97)	(1.58)	(1.53)	(0.50)	(0.48)
R-squared	0.55	0.62	0.57	0.53	0.58	0.54

Notes: Each coefficient was estimated in a pooled regression at the 1-digit occupation level (108 observations) with country dummies. The change in the average age of workers, or a change in the share of workers aged 15−24, 25−44, 45−64 in a given occupation are the explained variables in particular regressions. The initial (1998) RTI or the initial (1998) intensity of non-routine cognitive analytical (NRCA) or the initial (1998) intensity of non-routine cognitive personal (NRCP) tasks serve as variables of interest in particular regressions. All regressions include the change in the share of the occupation in total employment as a control variable. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own estimations based on EU-LFS and O*NET data.

Table B2
Logit estimation results – on being unemployed (0-employed), odds ratios (model 4, as described in Section 5.2).

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	United Kingdom
RTI	1.98***	1.49***	1.5***	1.88***	1.74***	2.1***	1.32	1.7***	2.07***	1.04	1.61***	2.31***
	(0.37)	(0.17)	(0.19)	(0.32)	(0.3)	(0.24)	(0.27)	(0.16)	(0.42)	(0.12)	(0.15)	(0.21)
Period(ref. 1998–2000[x])	1.64***	0.98	1.77***	1.19	0.59**	0.6***	4.18***	0.95	1.1	1.12	0.69**	1.25*
	(0.29)	(0.15)	(0.26)	(0.23)	(0.15)	(0.07)	(0.64)	(0.1)	(0.28)	(0.12)	(0.11)	(0.14)
period*RTI	0.93	1.15	1.09	1.12	1.07	1.04	1.01	1.16	0.69*	1.59***	1.41**	1.15
	(0.19)	(0.15)	(0.14)	(0.21)	(0.22)	(0.14)	(0.22)	(0.15)	(0.15)	(0.2)	(0.2)	(0.13)
Age group (ref. 25–34)												
15–24	0.74*	0.76	0.73**	0.96	0.67	0.43***	0.71**	0.86	0.87	1.13	1.75***	1.06
	(0.13)	(0.15)	(0.1)	(0.17)	(0.17)	(0.04)	(0.1)	(0.09)	(0.17)	(0.1)	(0.12)	(0.11)
35–44	1.6***	0.98	0.8**	0.85	1.38*	1.44***	0.63*	0.87	0.87	0.74***	0.78***	1.04
	(0.24)	(0.12)	(0.08)	(0.17)	(0.27)	(0.06)	(0.15)	(0.1)	(0.09)	(0.08)	(0.06)	(0.08)
45–54	2.11***	0.95	0.72***	1.01	1.28	1.77***	0.57*	0.66***	0.72***	0.58***	0.59***	1.12
	(0.4)	(0.16)	(0.09)	(0.23)	(0.25)	(0.17)	(0.17)	(0.1)	(0.09)	(0.11)	(0.07)	(0.14)
55–64	3.58***	0.76	0.62**	1.45	0.6**	3.52***	0.35**	0.56**	0.71	0.64*	0.75*	1.75***
	(0.81)	(0.24)	(0.14)	(0.34)	(0.14)	(0.52)	(0.15)	(0.14)	(0.2)	(0.17)	(0.12)	(0.33)
Age group*RTI (ref. 25–34*RTI)												
15–24	0.57***	1.1	1.01	0.74	1.1	1.14	0.97	0.89	0.97	0.81**	0.77***	1.07
	(0.12)	(0.27)	(0.14)	(0.19)	(0.25)	(0.15)	(0.15)	(0.09)	(0.17)	(0.08)	(0.07)	(0.13)
35–44	0.83	1	0.93	0.83	1.01	0.82***	1.34	1.11	0.99	1.27**	1.02	0.84**
	(0.14)	(0.12)	(0.09)	(0.15)	(0.2)	(0.04)	(0.35)	(0.13)	(0.09)	(0.14)	(0.1)	(0.06)
45–54	0.88	0.84	0.8*	1.03	0.77	0.81**	1.45	1.09	0.95	1.37*	0.97	0.78**
	(0.17)	(0.16)	(0.1)	(0.22)	(0.16)	(0.08)	(0.44)	(0.19)	(0.1)	(0.26)	(0.13)	(0.09)
55–64	0.79	0.76	0.88	0.69	1.01	0.72**	2.35*	0.85	0.77	1.36	1.01	0.49***
	(0.19)	(0.24)	(0.17)	(0.18)	(0.22)	(0.11)	(1.03)	(0.21)	(0.22)	(0.33)	(0.18)	(0.08)
Age group * period 2013–2015 (ref. age group = 25–34)												
15–24	0.87	1.28	1.22	0.91	1.05	1.54***	0.78	1.26	1.05	1.16	1.11	1.36*
	(0.18)	(0.26)	(0.26)	(0.18)	(0.32)	(0.19)	(0.15)	(0.21)	(0.23)	(0.15)	(0.11)	(0.23)
35–44	0.81	1.16	1.23	0.97	0.77	0.76***	1.17	1.15	0.81*	1.14	0.98	0.95
	(0.13)	(0.15)	(0.18)	(0.2)	(0.19)	(0.04)	(0.31)	(0.14)	(0.09)	(0.12)	(0.1)	(0.12)
45–54	0.84	1.31	1.32*	0.89	0.92	0.62***	0.92	1.58***	0.79	1.45**	1.29*	1.09
	(0.18)	(0.26)	(0.21)	(0.23)	(0.25)	(0.07)	(0.31)	(0.25)	(0.13)	(0.28)	(0.19)	(0.16)
55–64	0.61*	1.78	1.69**	0.62*	1.85*	0.43***	1.6	1.96**	0.74	1.28	1.25	0.95
	(0.17)	(0.63)	(0.42)	(0.16)	(0.63)	(0.06)	(0.76)	(0.57)	(0.22)	(0.36)	(0.27)	(0.18)
Age group * RTI * period 2013–2015 (ref. age group = 25–34)												
15–24	1.79***	0.89	0.76	0.98	1.06	0.84	1.31	0.93	0.98	1.22	0.75**	0.72*
	(0.4)	(0.23)	(0.17)	(0.28)	(0.33)	(0.13)	(0.31)	(0.16)	(0.19)	(0.18)	(0.1)	(0.14)

(*continued on next page*)

Table B2 (*continued*)

	Austria	Belgium	Czechia	Denmark	Estonia	Germany	Greece	Hungary	Poland	Spain	Sweden	United Kingdom
35−44	1.12	0.82	0.97	1.28	0.96	0.99	0.89	0.71**	1.16	0.88	1.02	1.13
	(0.22)	(0.11)	(0.15)	(0.25)	(0.24)	(0.07)	(0.25)	(0.1)	(0.13)	(0.11)	(0.13)	(0.14)
45−54	1.08	0.79	1.16	0.89	1.08	0.92	1.09	0.63***	1.33*	0.84	0.99	0.79
	(0.27)	(0.17)	(0.2)	(0.22)	(0.3)	(0.11)	(0.37)	(0.11)	(0.22)	(0.21)	(0.15)	(0.12)
55−64	1.15	0.64	0.97	1.43	0.75	0.91	0.79	0.81	1.62	0.85	0.79	0.98
	(0.38)	(0.24)	(0.24)	(0.41)	(0.26)	(0.15)	(0.44)	(0.25)	(0.51)	(0.31)	(0.16)	(0.19)
Gender (ref. male) and marital status (ref. single)												
Women	0.93	1.15*	1.38***	1.34***	0.9	0.95	1.27**	0.91*	1.33***	1.23**	0.91**	0.77***
	(0.05)	(0.09)	(0.14)	(0.08)	(0.08)	(0.06)	(0.12)	(0.05)	(0.1)	(0.13)	(0.04)	(0.03)
Married	0.57***	0.64***	0.55***	0.58***	0.73***	0.61***	0.6***	0.67***	0.6***	0.71***	0.75***	0.46***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)	(0.01)
Education (ref. secondary education)												
Higher	0.82***	0.56***	0.48***	0.98	0.69***	0.74***	0.64***	0.45***	0.47***	0.72***	0.91	0.84***
	(0.06)	(0.05)	(0.06)	(0.1)	(0.05)	(0.04)	(0.06)	(0.04)	(0.05)	(0.05)	(0.08)	(0.04)
Primary	1.85***	1.81***	2.83***	1.32***	1.57***	1.52***	1.25***	1.94***	1.78***	1.47***	1.62***	1.52***
	(0.09)	(0.07)	(0.24)	(0.07)	(0.13)	(0.08)	(0.11)	(0.15)	(0.16)	(0.1)	(0.07)	(0.05)
Regional controls												
Bartik shock	1.24***	1.09**	0.69***	0.95	0.99	1.01	0.98***	0.92***	0.94***	0.95***	1.15***	0.85***
	(0.09)	(0.05)	(0.02)	(0.05)	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.06)	(0.02)
Industry share at the age of 15−19	0.91***	0.95***	1.02***	0.98***	0.97	0.97***	1.02***	0.99***	1.00***	0.97***	1.00	0.99***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.17***	0.18***	0.02***	0.06***	0.23	0.12***	0.09***	0.11***	0.12***	0.43***	0.07***	0.05***
	(0.05)	(0.03)	(0.00)	(0.01)	(0.25)	(0.02)	(0.02)	(0.01)	(0.03)	(0.06)	(0.01)	(0.01)
Pseudo R^2	0.0538	0.0664	0.0598	0.0305	0.0452	0.0508	0.1021	0.0544	0.0606	0.0738	0.0439	0.0610
Observations (thousand)	303.48	155.52	128.70	174.73	47.47	946.37	147.74	352.54	554.36	282.87	621.65	247.80

Notes: Due to data availability, 1999–2001 for Germany and the United Kingdom, 2003–2005 for Sweden. Observation numbers reported in thousands. The standard errors are clustered at the occupation level. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Own estimations based on EU-LFS, O*NET, and Cambridge Econometrics European Regional Data.

Figs. B1and B2

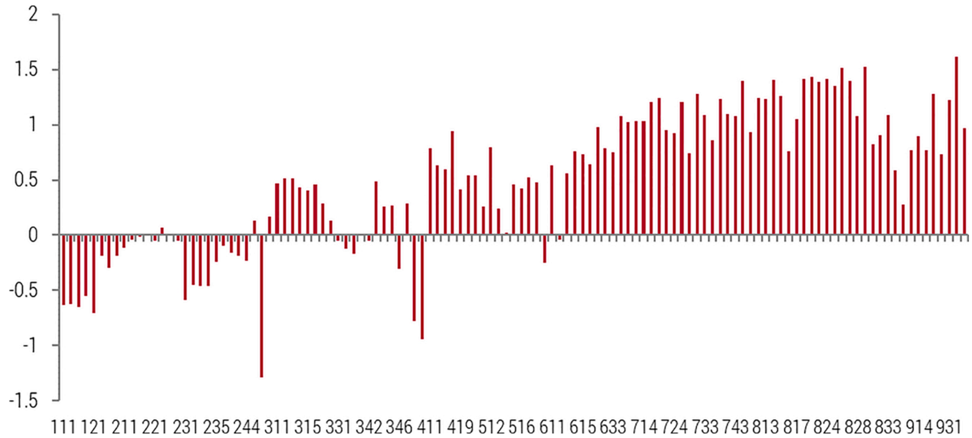

Fig. B1. Average RTI values between 1998 and 2010, by 3-digit ISCO occupation groups, in all countries.
Source: Own calculations based on EU-LFS and O*NET data.

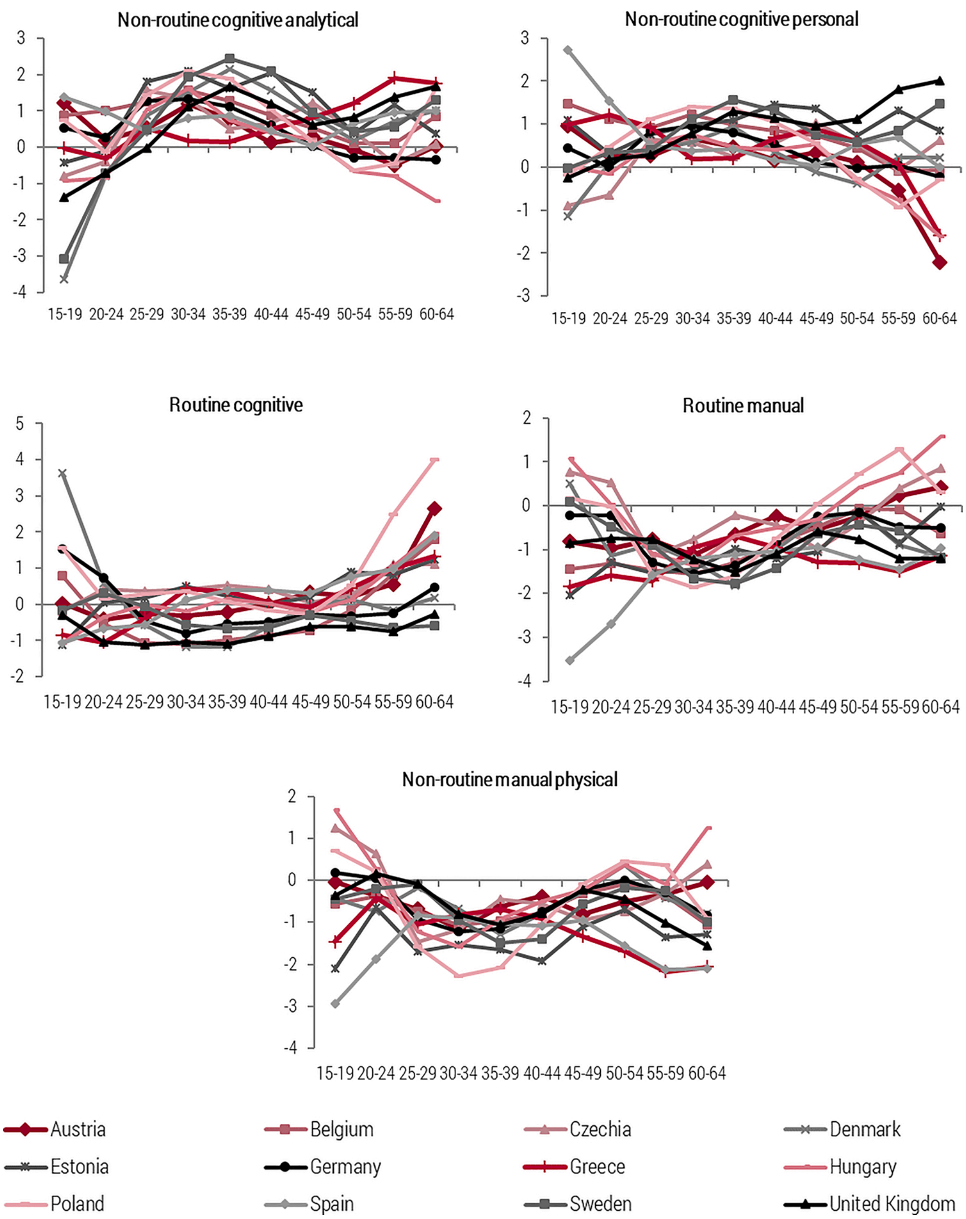

Fig. B2. Linear time-trend coefficients from unweighted regressions estimated for task intensities in the 1998-2015 period across age groups.
Notes: Each coefficient estimated in a separate country-specific regression with a particular task content intensity in a given age group as the explained variable and the time trend as the control variable.
Source: Own estimations based on EU-LFS and O*NET data.

References

Acemoglu, D., Autor, D.H., 2011. Skills, tasks and technologies: implications for employment and earnings. In: Card, D., Ashenfelter, O. (Eds.), Handbook of Labor Economics. Elsevier, Amsterdam, pp. 1043–1171.

Acemoglu, D., Restrepo, P., 2020. Robots and jobs: evidence from US labor markets. J. Polit. Econ. 128 (6), 2188-2244.

Aedo, C., Hentschel, J., Moreno, M., Luque, J., 2013. From Occupations to Embedded Skills: a Cross-country Comparison. World Bank Policy Research Working Paper No. 6560.

Arias, O.S., Sánchez-Páramo, C., Dávalos, M.E., Santos, I., Tiongson, E.R., Gruen, C., de Andrade Falcão, N., Saiovici, G., Cancho, C.A., 2014. Back to Work: Growing With Jobs in Eastern Europe and Central Asia, Europe and Central Asia Reports. The World Bank, Washington, DC.

Autor, D.H., Dorn, D., 2009. This job is "Getting old": measuring changes in job opportunities using occupational age structure. American Economic Review: Papers and Proceedings 99 (2), 45–51.

Autor, D.H., Levy, F., Murnane, R., 2003. The skill content of recent technological change: an empirical exploration. Q. J. Econ. 118, 4.

Autor, D.H., Katz, L.F., Kearney, M.S., 2006. The polarization of the U.S. Labor market. American Economic Review Papers and Proceedings 96, 2.

Bachmann, R., Cim, M., Green, C., 2019. Long-run patterns of labour market polarization: evidence from german Micro data. Br. J. Ind. Relat. 57 (2), 350–376. https://doi.org/10.1111/bjir.12419.

Bartik, T.J., 1991. Who Benefits From State and Local Economic Development Policies? *Books from Upjohn Press*, W.E. Upjohn Institute for Employment Research number wbsle, 06.

Bassanini, A., Duval, R., 2009. Unemployment, institutions, and reform complementarities: re-assessing the aggregate evidence for OECD countries. Oxford Rev. Econ. Policy 25 (1), 40–59.

Blanchard, O., Wolfers, J., 2000. The role of shocks and institutions in the rise of european unemployment: the aggregate evidence. Econ. J. 110, 1–33.

Brynjolfsson, E., McAfee, A., 2014. The Second Machine Age: Work Progress, and Prosperity in a Time of Brilliant Technologies. W. W. Norton and Company., New York.

Bussolo, M., Davalos, M.E., Peragine, V., Sundaram, R., 2018. Toward a New Social Contract: Taking on Distributional Tensions in Europe and Central Asia. Europe and Central Asia Studies. World Bank. © World Bank, Washington, DC. License: CC BY 3.0 IGO. https://openknowledge.worldbank.org/handle/10986/30393.

Cedefop, 2013. Quantifying Skill Needs in Europe Occupational Skills Profiles: Methodology and Application. Cedefop, Thessaloniki.

Cortes, G.M., 2016. Where have the middle-wage workers gone? A study of polarization using panel data. J. Labor Econ. 34 (1), 63–105.

Dauth, W., Findeisen, S., Südekum, J., Wößner, N., 2017. German Robots - the Impact of Industrial Robots on Workers. CEPR Discussion Paper 12306.

Desjardins, R., Warnke, A.J., 2012. Ageing and Skills: A Review and Analysis of Skill; Gain and Skill Loss Over the Lifespan and Over Time, OECD Education Working Papers, No. 72.

Dicarlo, E., Bello, S.L., Monroy-Taborda, S., Oviedo, A.M., Sanchez-Puerta, M.L., Santos, I., 2016. The Skill Content of Occupations Across Low and Middle Income Countries: Evidence From Harmonized Data. IZA Discussion Paper No. 10224.

Eden, M., Gaggl, P., 2020. Do poor countries really need more IT? World Bank Econ. Rev. 34 (1), 48–62.

Edin, P.-A., Evans, T., Graetz, G., Hernnäs, S., Michaels, G., 2019. Individual Consequences of Occupational Decline, IZA Discussion Papers 12434. Institute of Labor Economics (IZA).

European Commission, Eurostat, 2016. European Union Labour Force Survey 1998-2015. European Commission, Eurostat, Brussels.

Fletcher, J., Sindelar, J., 2009. Estimating Causal Effects of Early Occupational Choice on Later Health: Evidence Using the PSID, NBER Working Papers 15256. National Bureau of Economic Research, Inc.

Fonseca, T., Lima, F., Pereira, S., 2018. Job polarization, technological change and routinization: evidence for Portugal. Labour Econ. 51, 317–333.

Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: routine-biased technological change and offshoring. Am. Econ. Rev. 104, 2509–2526.

Graetz, G., Michaels, G., 2018. Robots at work. Rev. Econ. Stat. 100 (5), 753-768.

Grossman, G., Rossi-Hansberg, E., 2008. Trading tasks: a simple theory of offshoring. Am. Econ. Rev. 98 (5), 1978–1997.

Handel, M.J., 2012. Trends in Job Skill Demands in OECD Countries, OECD Social, Employment and Migration Working Papers No. 143.

Hardy, W., Keister, R., Lewandowski, P., 2018. Educational upgrading, structural change and the task composition of jobs in Europe. Econ. Transit. 26 (2), 201–231.

Jerbashian, V., 2019. Automation and job polarization: on the decline of middling occupations in Europe. Oxf. Bull. Econ. Stat. 81, 1095–1116.

Keister, R., Lewandowski, P., 2017. A routine transition in the digital era? The rise of routine work in Central and Eastern Europe. Transf. Eur. Rev. Labour Res. 23 (3), 263–279.

Manoli, D.S., Weber, A., 2016. The Effects of the Early Retirement Age on Retirement Decisions, NBER Working Papers 22561. National Bureau of Economic Research, Inc.

Michaels, G., Natraj, A., Van Reenen, J., 2014. Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. Rev. Econ. Stat. 96, 60–77.

Oesch, D., 2013. Occupational Change in Europe. How Technology and Education Transform the Job Structure. Oxford University Press.

RIGVC UIBE, 2016. UIBE GVC Index. Research Institute for Global Value Chains. University of International Business and Economics.

Salvatori, A., 2018. The anatomy of job polarisation in the UK. J. Labour Mark. Res. 52 (8).

Siliverstovs, B., Kholodilin, K.A., Thiessen, U., 2011. Does aging influence structural change? Evidence from panel data. Econ. Syst. 35, 244–260.

Spitz-Oener, A., 2006. Technical change, job tasks, and rising educational demands: looking outside the wage structure. J. Labor Econ. 24, 235–270.

Statistics Poland. Labour Force Survey data, annual data 1998-2015. Warsaw: GUS.

Tempest, S., Coupland, C., 2016. Lost in time and space: temporal and spatial challenges facing older workers in a global economy from a career capital perspective. Int. J. Hum. Resour. Manag. 1–25.

Visser, J., 2019. ICTWSS Database. Version 6.1. Amsterdam. Amsterdam Institute for Advanced Labour Studies (AIAS), University of Amsterdam.

Wang, Z., Wei, S., Yu, X., Zhu, K., 2017. Measures of Participation in Global Value Chains and Global Business Cycles. *NBER Working Paper* No. 23222. National Bureau of Economic Research, Inc.