HKUST IEMS
INSTITUTE FOR EMERGING MARKET STUDIES

TECHNOLOGY OR UPSKILLING? TRENDS IN THE TASK COMPOSITION OF JOBS IN CENTRAL AND EASTERN EUROPE

Wojciech HARDY

Roma KEISTER

Piotr LEWANDOWSKI

HKUST IEMS Working Paper No. 2016-40

December 2016

Originally part of IBS Working Paper series, Issue 01/2016 (July)

HKUST Institute for Emering Market Studies
The Hong Kong University of Science and Technology
Clear Water Bay, Kowloon, Hong Kong
T: +852 3469 2215 E: iems@ust.hk W: iems.ust.hk

TECHNOLOGY OR UPSKILLING? TRENDS IN THE TASK COMPOSITION OF JOBS IN CENTRAL AND EASTERN EUROPE

Wojciech HARDY, Roma KEISTER, Piotr LEWANDOWSKI

HKUST IEMS Working Paper No. 2016-40
December 2016

Abstract

In this paper we analyse the changes in the task content of jobs in Central and Eastern European countries between 1998 and 2013. We link the O*NET data on occupational characteristics with EU-LFS, following the approach of Autor, Levy and Murnane (2003), and Acemoglu and Autor (2011). We find that the CEE countries witnessed similar trends of rising intensity of non-routine cognitive tasks, and a decreasing intensity of manual tasks, although they differed with regards to changes in the routine cognitive task content. We assess the relative role played by education and technology in the development of task contents. We also decompose the observed changes into the contributions of sectoral, educational and occupational changes as well as the interaction between them. Our results show that workforce upskilling was the major factor behind the evolution of non-routine cognitive and manual tasks in CEE, whereas structural changes and shifts towards work with lower speed of de-routinisation have shaped routine cognitive tasks.

Keywords: task content of jobs, routinization, job polarization, Central and Eastern Europe
JEL: J21, J23, J24, I25

Author's contact information

Wojciech Hardy

Institute for Structural Research[1] (IBS)
Faculty of Economics, University of Warsaw
E: wojciech.hardy@ibs.org.pl

Roma Keister

Institute for Structural Research (IBS)
E: roma.keister@ibs.org.pl

Piotr Lewandowski

Institute for Structural Research (IBS)
Institute for Labor Economics[2] (IZA)
E: piotr.lewandowski@ibs.org.pl

[1] *Instytut Badań Strukturalnych*, Warsaw, Poland
[2] *Forschungsinstitut zur Zukunft der Arbeit,* Bonn, Germany

The authors would like to thank Szymon Górka for his excellent research assistance, as well as the participants of: the IBS Jobs Conference 2015, the Conference on Urbanization, Structural Change, and Employment at the Hong Kong University of Science and Technology, the ETUC/ETUI Shaping the New World of Work conference and WIEM 2016 for their insightful comments. This paper was originally supported financially by the Network for Jobs and Development initiative under the auspices of the World Bank. This paper uses Central Statistical Office of Poland data. Eurostat has no responsibility for the results and conclusions which are those of the authors. Usual disclaimers apply. All errors are the authors'.

1. Introduction and motivation

Recent research highlights a progressing shift of employment from low and middle-skilled occupations towards high-skilled occupations in many countries around the world. Machin and Van Reenen (1998) identified this occupational upgrading in the United States and six other OECD countries, and attributed it to 'skill-biased technological change', i.e. a demand shift towards high-skilled labour due to new technologies increasing its relative productivity. The refined 'routine-biased technological change' hypothesis (RBTC) argues that recent technological progress has increased demand for high-skilled workers who can perform non-routine cognitive work (which to date cannot be replaced by machines, e.g. architects, IT specialists, managers), while it has decreased the demand for middle-skilled workers performing routine work (already replaceable by machines, e.g. bookkeepers, clerks, assemblers). It also indirectly increases employment in simple, yet unstructured, jobs (e.g. drivers, waiters and waitresses, hairdressers). Machines are, so far, unable to replace people performing non-routine manual tasks, at a price justifying a replacement, while the supply of workers willing to perform such jobs may rise as job opportunities in routine jobs decline. Autor et al. (2003) provided evidence that, between 1960 and 1998, computerisation in the US was associated with a reduced labour input of routine manual and routine cognitive tasks and an increased labour input of non-routine cognitive tasks, within industries, occupations and education groups. Autor and Price (2013) showed that the decline of routine tasks continued in the US in the 2000s, while non-routine manual tasks grew in comparison to the 1990s, in line with RBTC.

Moreover, several authors (e.g. Acemoglu and Autor 2011; Autor 2014; Goos et al. 2014) showed that over the last three decades there has been a growing job polarisation (the share of middle-wage / middle-skilled workers has declined) and wage polarisation (rising relative wages of high-skilled workers) in the US and Western European countries. Michaels et al. (2014) analysed 11 OECD countries in the period 1980-2004 and provided additional evidence for the "routinisation hypothesis" of RBTC. Graetz and Michaels (2015) studied 14 industries in 17 OECD countries and found that industries with a higher share of routine tasks in 1980 had been more likely to adapt to industrial robots, and as a result experienced higher productivity growth. Deming (2015) showed, again for the US, that high-skilled, difficult-to-automate jobs increasingly require social skills which is consistent with RBTC, as computers are increasingly better in dealing with codifiable challenges while progress in automating social interactions has been poor (Brynjolfsson and McAfee, 2014). Machin and van Reenen (1998) also showed that R&D intensity was a major driver of the demand for skilled workers in the most developed countries. De la Rica and Gortazar (2016) found that differences in ICT adoption explain a large part of differences in de-routinisation of jobs in the OECD countries, The link between technology and occupational changes is supported by a growing body of research, largely studying the most developed countries. However, some authors suggested that developments of skills and task structures if employment may be driven by supply-side changes. Salvatori (2015) argued that the decline in the share of middle-skilled jobs in the UK since 1979 was mostly fuelled by a decreasing number of non-graduates and to a lesser extent by technological progress. Oesch (2013) showed that in the UK, Germany, Spain and Switzerland, occupational upgrading and job polarisation were driven by factors both on the demand side (like technology) and on the supply side (educational expansion, migration), as well as labour market institutions. The lack of growth in non-routine cognitive tasks in the US in the 2000s (Autor and Price, 2013) is also at odds with RBTC, as ICT continues to improve. These findings suggest that routinisation and polarisation are more complex and need to be studied further, taking into account more, also middle and low-income, countries.

The aim of this paper is to quantify the evolution of the task content of jobs in to 10 Central and Eastern European (CEE) countries[1] between 1998 and 2013,[2] and identify the labour demand and labour supply side factors contributing to this evolution. We apply the task approach of Autor et al. (2003) and Acemoglu and Autor (2011) using O*NET and EU-LFS data, and distinguish five tasks: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual and non-routine manual physical. To the best of our knowledge, the CEE labour markets have, so far, not been comprehensively studied from that perspective, except for Hardy et al. (2015) for Poland. The CEE countries seem particularly interesting to study developments along the cognitive vs. manual and routine vs. non-routine dimension of jobs. That's because both the demand for labour and its structure in terms of occupation and skills, as well as their supply have changed considerably (IBS, 2014), while economies moved from lower to upper middle (Bulgaria, Romania) or high income status (remaining of the CEE 10).

In particular, the CEE countries followed a common pattern of sectoral changes over the period 1998-2013. Employment shares in agriculture have declined and converged across the region, although in 2013 they still exhibited large differences between the analysed countries (see Tables A2-A3 in the Appendix).[3] In 1998, the share of workers employed in manufacturing ranged from 19% in Latvia and Lithuania to 32% in Slovenia, and by 2013 it has declined by approx. 2-5 pp. The share of services rose in all countries. Employment shares of services such as financial, insurance and real estate activities; administrative and support activities; public administration and defence; health, social work; education; arts and entertainment, recorded a particularly big increase (by approx. 6-9 pp.). Commerce, accommodation and food activities (15-19% of employment in CEE in 1998) and transport, storage and communication (5-9%) also grew noticeably (Table A2). On the labour supply side, the main improvement was related to a rising educational attainment. In 1998, the average share of workers with tertiary education (ISCED 5-8) attained in the CEE equalled 17%, and the share of workers with primary education (ISCED 0-2) was 18% (see in Table A4 in the Appendix for data by country). Since the middle 1990s, all CEE countries have enjoyed a thriving increase in tertiary education. Latvia, Lithuania, Poland and Slovenia were the irrefutable leaders – employment share of tertiary graduates grew by 15-19 pp. in these countries. In 2013, the average CEE employment share of tertiary and primary educated amounted to 28% and 10%, respectively. Finally, CEE countries were converging to the most advanced countries in terms of ICT capital stock, but the gap remained large (Figure A1 in the Appendix). In 1998, the ICT capital stock per worker ranged from 2% of the US level in Romania to 23% in Czechia. In 2013, it ranged from 7% to 30%, respectively in Romania and Czechia.

We aim to contribute to two fields of literature. On the one hand, we test whether evolutions of the task content of jobs in a group of European upper-middle income countries are consistent with those observed in the most advanced economies and often attributed to the RBTC. We find it important to develop the empirical evidence on routine vs. non-routine structures of jobs in countries at various development level, especially as it argued that majority of jobs around the world are susceptible to automation (WDR, 2016). On the other, we offer a novel look

---

[1] Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia.

[2] We use the 1998-2013 period due to the availability of data (see Section 2). Unless stated otherwise, all data used in this section comes from the EU-LFS datasets.

[3] In 1998, the employment share of agriculture ranged from 6-8% in Czechia, Hungary and Slovakia, and 19-20% in Latvia, Lithuania and Poland, to 42% in Romania. In 2013 these shares amounted to 3-5% in Czechia, Hungary and Slovakia, 8% in Latvia, Lithuania, 12% in Poland and 28% in Romania.

on secular changes in the post-transition economies of Central and Eastern Europe that allows joint analysis of demand- and supply-side changes in the task content of jobs framework.

2. Data & methodology

2.1. Data

We use the Occupational Information Network (O*NET) database as a source of information on the task content of occupations, applying the framework of Acemoglu and Autor (2011).[4] In applying O*NET data from the US to middle-income European countries we follow Aedo et al. (2013) and Arias and Sánchez-Páramo (2014). We use two distinct editions of O*NET (2003 and 2014) to account for possible changes of the task content within occupations. We utilise EU-LFS data to calculate the employment structure in CEE countries (people aged 15 or above). Since EU-LFS data is unavailable for several countries before 1998, we start our analysis period in 1998, with the exception of Croatia, which enters our sample in 2003. We drop Bulgaria from the sample as we have encountered severe inconsistencies in the Bulgarian EU-LFS data.[5] We also found some inconsistencies related to the encoding of education levels in the Lithuanian EU-LFS, which we address in the Appendix A1.

Although the assumption of task content equivalence between CEE countries and the US may seem strong, Handel (2012) showed that US occupation-based and non-US skill survey-based measures lead to very similar outcomes for European countries. Moreover, Cedefop (2013) showed that two surveys based on O*NET and recently conducted in Italy and Czechia (*Indagine sulle professioni* and *Kvalifikace 2008*, respectively) yielded results that correlated highly (mostly around 0.8) with those of O*NET. Cedefop (2013) argue that it is therefore methodologically valid to use O*NET data to construct occupational measures in European countries. Finally, we do not assume the equivalence of jobs in CEE countries and US *per se*, but rather use the US data as an approximation of the general task intensity distribution across occupations.

In the EU-LFS data, occupations are coded coherently, although the level of detail varies between countries: some are coded at a 3-digit level, some at a 2-digit level. We used the highest level of detail available in each country, which is predominantly 3-digit (see Table 1). In Romania 3-digit level codes were available in 1998, 1-digit level codes from 1999 to 2004 and 3-digit codes from 2005 onwards. For Romania we mapped all occupations into a 1-digit level over the entire period in order to avoid inconsistencies in the data.[6] In the O*NET data occupations are coded using ONET-SOC,[7] whereas in the EU-LFS data ISCO is used, and the ISCO coding is derived from the

---

[4] See Acemoglu and Autor (2011) for a detailed description of the method, and Hardy et al. (2015) for a related case of applying it to the Polish LFS data.

[5] Bulgaria was excluded due to the inconsistencies in encoding occupations. Between 2003 and 2006 we observed parallel shifts of similar magnitudes in public administration, where the number of "other associate professionals" curbed by 50 thousand and the number of "personal and protective workers" grew by approx. 40 thousand. We think that these occurring inaccuracies in the methodology of encoding occupations possibly resulted from Eurostat changing the coding guidelines.

[6] For countries with available 3-digit and 2-digit ISCO codes, we found that codes at different level may provide slightly different values of our variables of interest, but resulting time series are highly correlated and exhibit the same trends. Results at 2-digit levels for countries which provided 3-digit codes, are available upon request.

[7] The ONET-SOC is built upon the SOC classification, however it is more detailed than its predecessor.

country-specific classifications.[8] To estimate the task content of jobs, we first mapped O*NET task items to the corresponding occupations in SOC and afterwards, using the official ILO crosswalk, we translated all SOC-based occupations into ISCO.[9] Both the SOC and ISCO have undergone several revisions during the 1998-2013 period. A major one occurred in 2011 – ISCO-88 (COM) was revised and supplanted by the newer ISCO-08 – which resulted in shifts in occupational time-series since these two classifications are not entirely comparable. In practice, adjustments of crosswalks were required for two types of occupations – one of farming workers (see also Aedo et al., 2013), the other of wholesale and retail trade workers. We discuss this in detail in Appendix A1.

Table 1. The ISCO level of detail for analysed countries.

Level of detail	Country
1-digit	Romania
2-digit	Slovenia
3-digit	Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia

Note: These are the levels available in EU- LFS datasets. For consistency reasons, in the case of Romania we used the 1-digit level for the whole period and the highest available level for other countries.
Source: Own elaboration based on EU-LFS data.

2.2. Calculating task contents

Having assigned the O*NET task items to the EU-LFS data, we standardised the values of each task item within countries to make them comparable over time, in line with Arias and Sánchez-Páramo (2014) and Dicarlo et al. (2015). Then, using the Acemoglu and Autor (2011) methodology, we constructed five task content measures, namely: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual and non-routine manual physical.

As mentioned in section 2.1, we used relevant crosswalks to ascribe the task items to both ISCO-88 and ISCO-08, although the two standards are not fully comparable which leads to some inconsistent shifts in task content structure between 2010 and 2011. Our main tool for dealing with these conversions is the rescaling approach, previously applied in Hardy et al. (2015). The rescaling equates the mean task values in the two years surrounding the classification changes, and allows us to study the overall changes in a consistent manner. The main goal is to fit the post-revision data so that, firstly, it starts with the level reached in the previous period and, secondly, the inner variance of the data remains comparable with the earlier periods. Note that rescaling was conducted separately for each country. In all the countries studied, we corrected the data for shifts related to the ISCO-88 (COM)/ISCO-08 conversion, which took place between 2010 and 2011. We also, however, identified a large change in the classification of occupations in Slovakia (KZAM) that occurred in 2002 due to KZAM-2001 replacing the previous classification. We additionally rescaled the 1998-2001 period in Slovakia to ensure that data before and after the classification are consistent. In Poland we rescaled the data in accordance with the breaks of Polish classification of occupations (KZiS) in 2003, 2005 and 2011 (see Hardy et al., 2015 for more details on KZiS changes).

[8] Before 2011 the EU-LFS data was coded with the EU-specific classification - the ISCO-88 (COM). However, the differences between ISCO-88 (COM) and ISCO-88 are negligible.

[9] The crosswalks sometimes yield ambiguous mapping between two classifications. In such cases we followed the solution described in detail in Hardy et al. (2015).

Although we calculate changes in the task content intensity over time, one should remember that the standardisation of tasks measures is performed within countries, thus the estimated values of task intensities between countries are not comparable. However, we are able to interpret them within countries in relative terms (i.e. in comparison to previous and subsequent years) as the mean intensity of performing given tasks per worker in a given year. We can also derive information on the dynamics of task content changes and compare them to the dynamics in other countries. However, the greater increase of task content intensity in one country does not imply that this country's economy is more abundant in a given type of task than other countries.

For the sake of a common reference point (i.e. the initial level) and as the values of the task contents can only be interpreted in relationship to values from other years, we have shifted the country values of tasks so that the starting level is equal to zero and multiplied all values by 100. The resulting values for any task in any year, range from -28.8 (non-routine manual physical for Lithuania in 2011) to 29.0 (non-routine cognitive analytical for Slovenia in 2013), with a standard deviation of 10.2 for all calculated values (the smallest standard deviation is 5.8 in Croatia and the largest is 15.4 in Slovenia).

3. Task content of jobs in CEE

3.1. Overall changes

We find that trends in the evolution of task content structures were similar across the CEE countries. Firstly, all of them recorded a significant increase in the average intensity of non-routine cognitive tasks. Among the countries considered, it was Slovenia that experienced the largest growth (relatively to its task structure in 1998) in non-routine cognitive tasks: between 1998 and 2013 the intensity of non-routine cognitive analytical and personal tasks increased by 29 and 25, respectively. Slovakia experienced the smallest growth in the non-routine cognitive analytical (by 5) and personal tasks (by 7). Secondly, a prevalent increase in non-routine cognitive tasks went hand-in-hand with a substantial decline in the average intensity of manual tasks, both routine and non-routine. Non-routine manual tasks declined most in Lithuania (by 29), while routine manual tasks fell most in Slovenia (by 28). At the same time, the smallest decline of routine manual tasks was recorded by Estonia (by 8) and the smallest drop in non-routine manual tasks – by Hungary (by 7). This is in line with trends identified for the most developed countries (Autor et al., 2003; Autor and Price, 2013; Spitz-Oener, 2006) and selected middle-income economies (Aedo et al., 2013; Arias and Sánchez-Páramo, 2014).

A more diversified picture emerges with respect to routine cognitive tasks, which also proved more enigmatic in previous literature – Autor et al. (2003) and Spitz-Oener (2006) found declining routine cognitive tasks in the US and Germany, while Jaimovich and Siu (2012) and Acemoglu and Autor (2011) found diverse trends for specific periods of time or gender. In general, three patterns can be distinguished regarding the evolution of the average intensity of routine cognitive tasks in CEE:

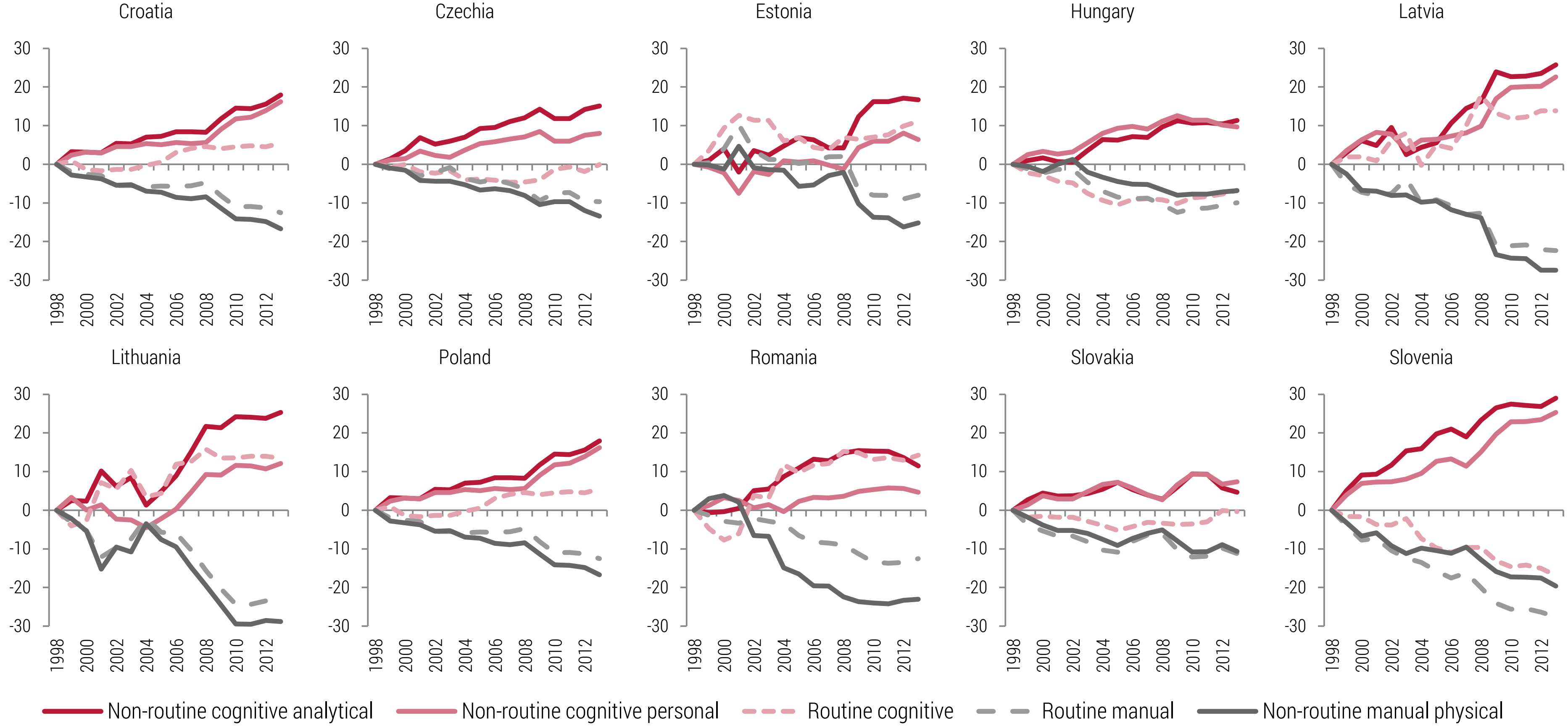
(1) In Czechia and Slovakia it was rather stable and close to 0

(2) In Croatia, Estonia, Latvia, Lithuania, Poland and Romania the average intensity of routine cognitive tasks grew considerably (the change ranges from 5 in Poland to 14 in Latvia and Romania). Romania stood out as the only country with higher increase in the average intensity of routine cognitive tasks (14) than in non-routine cognitive tasks (11 for analytical, 5 for personal).

(3) In Hungary and Slovenia routine cognitive tasks decreased, and the drop in Slovenia (by 17) was more than double that in Hungary (by 7).

Overall, our results show that the CEE countries recorded a substantial shift from manual to cognitive tasks, with a varying degree of non-routine content among the latter.

Figure 1. Evolution of the task content of jobs in the CEE countries between 1998 and 2013.



*Note: A moving average was used to combine the derived mean task content measures from the 2003 and 2014 O*NET data sets. To make the results comparable the task indices were rescaled so that the initial value of all of them was 0.*

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

3.2. Educational attainment, technology and task content of jobs in CEE

Previous literature indicates that changes in task content or occupational structures are affected by both demand-side factors, in particular technology proxied by computerisation (Autor et al., 2003, Autor and Dorn, 2013, Bessen, 2016), ICT use (de la Rica and Gortazar, 2016) or R&D spending (Machin and van Reenen, 1998; Michaels et al., 2014), but also supply side factors, in particular the educational attainment of the workforce (Oesch, 2013, Salvatori, 2015). In this subsection we analyse to what extent changes of task content intensities in CEE were related to factors on the supply and demand-side of the labour market. We use a fixed-effects panel regression to control unobservable country-specific factors and estimated the model for each j-th task content, where $j \in J$ and $J = \{1, \dots, 5\}$, in the following formula:

$$\forall_{j \in J}\, y_{ijt} = u_i + \beta_1 H_{it} + \beta_2 M_{it} + \beta_3 RD_{it} + \varepsilon_{it}\,, \tag{1}$$

whereby:

- y_{ijt} is the overall change in mean *j* task content intensity during the period $t \in T$ in country $i \in C$, where *C* is the set of countries and *T={1998,..., 2012}*;
- β_k are the estimated coefficients for independents variables (for *k*=1,2,3);
- H_{it} is the share of workers with tertiary education attained in employment in time *t* and country i;
- M_{it} is the share of workers with secondary education attained in employment in time *t* and country i;
- RD_{it} is the research and development expenditure as a percentage of GDP in time *t* and country i;
- u_i is the unknown intercept for each country i;
- ε_{it} is the error term for country i in time *t*.

Following Autor et al. (2003), we estimate separate regressions for particular tasks. Following Machin and van Reenen (1998) and Goos et al. (2015), we use R&D spending as a proxy for technological progress, as we face a shortage of data about the value of ICT capital and investment in CEE. Data collected by Eden and Gaggl (2015) allows calculating ICT stock per worker but only for six CEE countries (Czechia, Hungary, Poland, Romania, Slovakia, Slovenia) and only until 2011, which is a much smaller sample than the one we study. However, R&D spending as percent of GDP (see Figure A2 in the Appendix) correlates well with the ICT stock per worker in the subsample for which the ICT data are available (see Table A5 in the Appendix), which supports using R&D in the entire sample.[10] We use the EU-LFS data to calculate the shares of workers with a particular educational level (primary – ISCED 0-2, secondary – ISCED 3-4, tertiary – ISCED 5-8). The data used covers the 1998-2012 period except for Croatia (2003-2012). The year 2013 was dropped due to the lack of data on R&D spending. Table 2

[10] Foreign Direct Investment could be an alternative proxy for technology. In converging economies, FDI could be the leading source of technology adoption and progress. However, we find that FDI does not correlate with the ICT stock per worker in CEE (Table A6 in the Appendix) so it does not seem a good proxy for technology adoption in CEE. According to Eurostat indicators on high-tech industry and knowledge–intensive services, on the average in Czechia, Estonia, Poland, Slovakia and Slovenia (the only CEE countries with available data), only 50% of FDI was either in high-tech industry or knowledge–intensive services. Therefore, we find R&D a better proxy for technology in CEE and use it as our main variable in the panel regression. Nevertheless, we re-estimate models with FDI variable and find that it fails to explain any of the changes in the task content intensities (Table A7 in the Appendix).

presents the estimation results. Note that the reference variable for the educational structure is the share of workers with primary education.

We find that the non-routine cognitive analytical task content intensity was significantly, positively related to workforce upskilling, i.e. the rising share of workers with relatively better educational attainment. Across CEE, a 1 pp. increase in the share of workers with secondary education was associated with an increase in the intensity of non-routine cognitive analytical tasks by 0.7. For tertiary education the effect was twice as large (1.5). In the case of non-routine cognitive personal tasks, it was the share of workers with tertiary education that mattered – its increase by 1 pp. was associated with the intensity of these tasks higher by 0.8 – while we find no significant difference between workers with secondary and primary education.

At the same time, we find no significant relationship between the routine cognitive task intensity and the educational attainment structure of the workforce. In the next subsection we use the shift-share decomposition to shed more light on factors influencing routine cognitive tasks, which seems not driven by the evolution of educational structure of the workforce in CEE.[11]

We also find that the shift towards tertiary education was driving the decline of both routine and non-routine manual tasks in CEE: a 1 pp. increase in the share of workers with tertiary education was associated with a lower task intensity of 1.2 and 1.7 respectively. In the case of routine manual tasks, changes in the share of workers with secondary education at the expense of those with primary education didn't matter. For non-routine manual tasks, however, a 1 pp. increase in the share of workers with secondary education at the expense of primary education was associated with a 1.2 decrease in the task intensity, with no, statistically significant difference between the impact of the share of tertiary and secondary education attainment.[12]

Table 2. Panel fixed-effects regressions of task content measures in the CEE, 1998-2012

	Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Routine manual	Non-routine manual physical
Share of workers with tertiary education	1.49*** (0.15)	0.82*** (0.15)	0.74 (0.44)	-1.18*** (0.16)	-1.74*** (0.29)
Share of workers with secondary education	0.71*** (0.20)	0.01 (0.32)	0.60 (0.84)	-0.33 (0.21)	-1.17* (0.53)
R&D expenditure as a percentage of GDP	3.73* (1.73)	3.04* (1.57)	-4.71 (3.78)	-3.01* (1.38)	-1.81 (2.99)
Observations	145 (10 countries)	145 (10 countries)	145 (10 countries)	145 (10 countries)	145 (10 countries)
R^2 (overall)	0.22	0.11	0.06	0.14	0.08
R^2 (within)	0.84	0.75	0.20	0.80	0.82
R^2 (between)	0.01	0.01	0.03	0.00	0.04

*Notes: Data from 2003 used for Croatia. All regressions include country-level fixed-effects and robust standard errors. * p<0.1; ** p<0.05; *** p<0.01.*
*Source: Own estimations based on EU-LFS, O*NET and World Bank data.*

[11] At least at the 3-class disaggregation of education, which is the only available for all years and observations of the EU-LFS data between 1998 and 2013.

[12] The Wald test does not allow for the rejection of the hypothesis of equal coefficients at any viable level (p-value of 0.19).

The R&D spending, a proxy for technological progress, was positively and significantly related to the intensity of non-routine cognitive tasks, and negatively to the intensity of routine manual tasks. A 1 pp. increase in the R&D spending to GDP ratio was associated with a growth in non-routine cognitive analytical and personal task intensity by 3.7 and 3.0 respectively. A 1 pp. increase in the R&D spending was also associated with a drop in routine manual task intensity by 3.0. The R&D coefficients in routine cognitive and non-routine manual tasks equations are negative, but not statistically significant. Altogether, R&D may replace routine manual work, but complement non-routine cognitive work (which is in line with the findings of e.g. Michaels et al., 2014).

In the next step, we calculate the contributions of each explanatory variable to the total change in the intensity of particular task content between 1998 and 2012. Given *C* is the set of countries and *J* is the set of five task content measures, the change in task content intensities may be approximated by the formula below:

$$\forall_{i\in C, j\in J}\ T_i^{2012} - T_i^{1998} \approx \hat{\beta}_1 \Delta H_i + \hat{\beta}_2 \Delta M_i + \hat{\beta}_3 \overline{RD_\iota}\,, \qquad (2)$$

whereby:

- T_j^{2012} and T_j^{1998} are the economy-wide task content intensities in 2012 and 1998, respectively;
- $\hat{\beta}_k$ are the estimated coefficients (Table 2) for independent variables (*k*=1,2,3) from equation (1);
- ΔH_i is the change in share of workers with tertiary education in country i between 1998 and 2012;
- ΔM_i is the change in share of workers with secondary education in country i between 1998 and 2012;
- $\overline{RD_\iota}$ is the mean R&D expenditure (as a percentage of GDP in country i) between 1998 and 2012.[13]

The shares of workers with secondary and tertiary education are expressed in levels in regression (2), therefore ΔH_i and ΔM_i reflect the magnitude of changes between 1998 and 2012 consistently with the variables used in the estimation. R&D is measured in terms of flows, so we use the mean R&D expenditure between 1998 and 2012 as an approximation of R&D spending, distinguishing 2012 from 1998 in each country.[14] As all the parameters in the regression for routine cognitive tasks are insignificant, we do not discuss the decomposition for these tasks.

The growth of non-routine cognitive tasks was mostly driven by workforce upskilling (see Figure 2). Since the increase of the share of tertiary educated workers, on average across the CEE, was four times larger (11 pp.) than the drop in the share of workers with secondary education (3.6 pp.), the rise in tertiary attainment was the main factor behind the growth of non-routine cognitive tasks. The contribution of tertiary (secondary) education attainment averaged 17 (-3) and 10 (0) for analytical and personal tasks, respectively. Latvia, Lithuania and Poland witnessed the largest increases in the share of tertiary attainment and at the same time enjoyed the largest contribution of this factor to the change of non-routine cognitive analytical tasks, equal to 92%, 91% and 91% of the total positive input, respectively. Moreover, only Slovenia experienced a larger overall increase in non-routine cognitive analytical tasks between 1998 and 2012 than these three countries. Slovenia saw tertiary education attainment rise at a slightly slower pace, although it recorded rather higher average R&D spending, hence the largest growth of non-routine cognitive tasks. Croatia, Hungary and Slovakia are the countries where

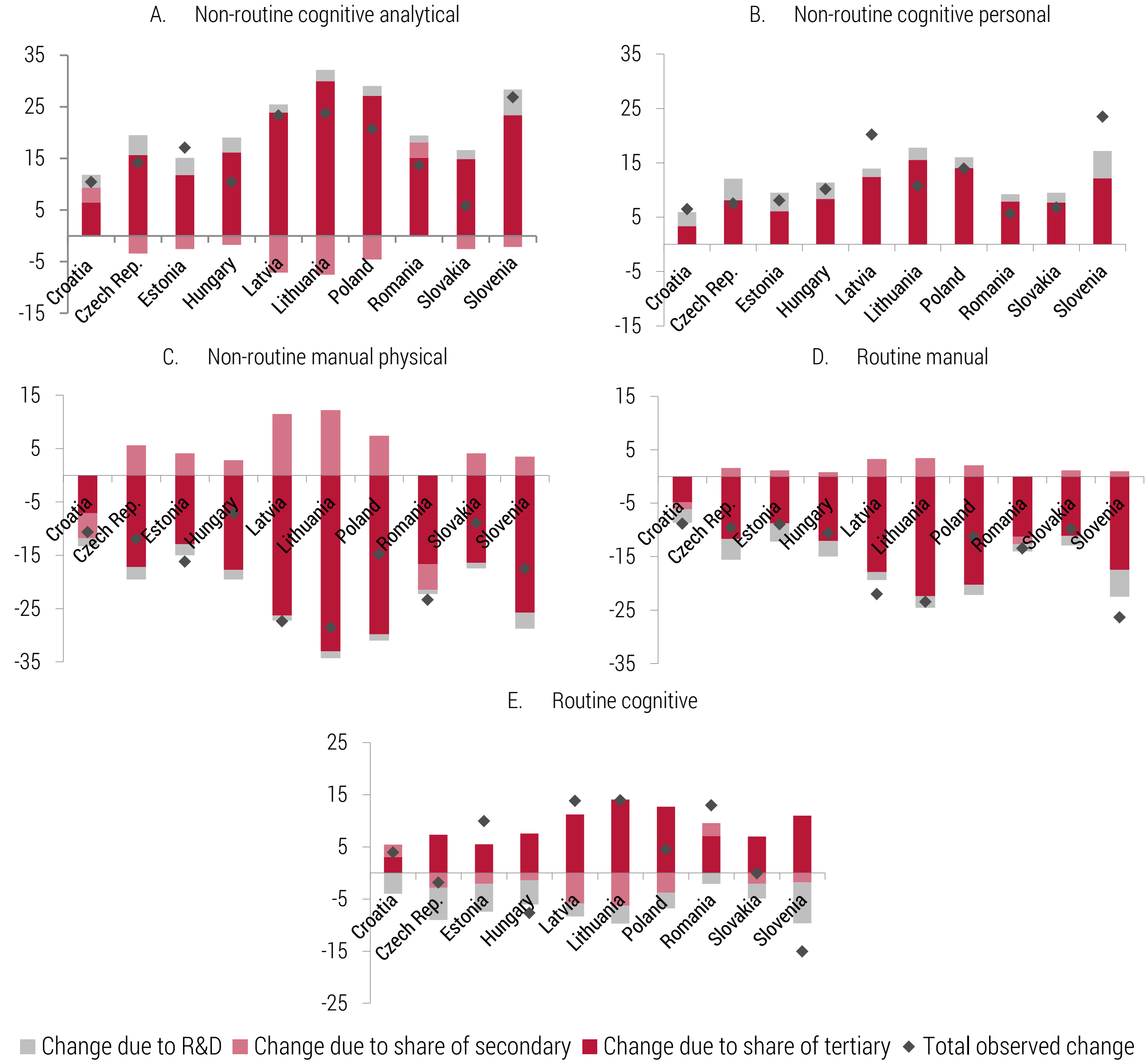
[13] For Croatia the period analysed is 2003-2012.

[14] This specification of decomposition (2) is equivalent to analysing the difference between hypothetical t_0 and t_1 where in t_0 each country exhibits the task contents and workforce education structures as per 1998, while in t_1 – the task contents and workforce education structures as per 2013, and R&D spending (as a share of GDP) in t_1 equals the country-specific average R&D spending over the period studied.

the increase in analytical tasks was the smallest. In Hungary and Slovakia analytical tasks grew rather modestly and less than implied by the changes in educational structure and R&D spending. Table A8 in the Appendix shows that the growth of non-routine cognitive analytical tasks in these countries was hampered by the negative contribution of education sector.

At the same time, the increase in the tertiary attainment of workers contributed to the decrease in routine manual tasks, and its contribution to the overall estimated change was even more pronounced than in the case of non-routine cognitive tasks. In Latvia, Lithuania and Poland it accounted, respectively, for 92%, 92% and 91% of the total negative input to the change in routine manual intensity. Mirroring the changes of non-routine cognitive analytical tasks, Slovenia experienced the largest drop in routine manual tasks, which was larger than implied by the model and additionally fuelled by an extraordinary drop in the employment share of manufacturing (we study the sectoral factors in the next section). Latvia and Lithuania likewise saw routine manual tasks plummeting more than would be implied by the model. These two countries stood out as agriculture experienced a decrease in routine manual tasks, hence putting more downward pressure on routine manual tasks than implied by changes in education structure and R&D.

Figure 2. Decomposition of changes in task contents between 1998 and 2013 into contributions of workforce upskilling and R&D.



Source: Own calculations based on the results of the estimation presented in Table 2, EU-LFS and World Bank data.

The results of the estimation (Table 5) suggest that the share of workers with secondary education was most important correlate of non-routine manual tasks and this is reflected in the decomposition. In most CEE countries the share of workers with secondary education declined, which pushed the non-routine manual tasks up. However, that was outweighed by the rising tertiary attainment. Still, the workforce upskilling cannot solely explain the extraordinary drop in non-routine manual tasks in the Baltic States and Romania. In these countries the reduction of non-routine manual tasks was additionally fuelled by the steep decline in agricultural employment – in the Baltic States and Romania the decline in agriculture averaged 10 pp., whereas in other countries it amounted to 4 pp.

3.3. Task content of jobs and structural changes

The majority of recent studies on the most developed economies indicates automation and computerisation as the main factors shaping the task composition of jobs. However, our panel regressions show that large share of task content changes in CEE can be attributed to changes in educational structure of the workforce, and a small share to R&D which approximates technology adoption. Routine cognitive tasks are an exception as none of these factors proved significant. To delve further into factors driving changes in particular tasks, we use a shift-share decomposition. We decompose total changes in task intensities between 1998-2000 and 2011-2013 into the contributions of: (i) changes in the sectoral structure (structural effect), BS_i; (ii) changes in the educational structure (educational effect), BE_i;(iii) changes in the occupational structure and within-occupational task content (occupational effect), OC_i; and (iv) the interaction between all these effects, INT_i.[15] For each country we distinguish 42 education-sector cells, and for each task i we use the following formula:

$$\forall_{i\in T}(TI_i^{2013} - TI_i^{1998}) = (\sum_{j\in S}\sum_{k\in E} t_{i,j,k,14}^{13} h_{j,k}^{13} - \sum_{j\in S}\sum_{k\in E} t_{i,j,k,03}^{98} h_{j,k}^{98}) = BS_i + BE_i + OC_i + INT_i, (3)$$

$$\forall_{i\in T}\ BS_i = \sum_{j\in S} t_{i,j,03}^{98}(h_j^{13} - h_j^{98}), (4)$$

$$\forall_{i\in T}\ BE_i = \sum_{j\in S}\left[\sum_{k\in E} t_{i,j,k,03}^{98}\ \left(\frac{h_{j,k}^{13}}{h_j^{13}} - \frac{h_{j,k}^{98}}{h_j^{98}}\right)\right] h_j^{98}, (5)$$

$$\forall_{i\in T}\ OC_i = \sum_{j\in S}\sum_{k\in E}(t_{i,j,k,14}^{13} - t_{i,j,k,03}^{98})\ h_{j,k}^{98}, (6)$$

$$\forall_{i\in T}\ INT_i = \sum_{j\in S}\sum_{k\in E}(t_{i,j,k,14}^{13} - t_{i,j,k,03}^{98})\ (h_{j,k}^{13} - h_{j,k}^{98}) + \sum_{j\in S}\sum_{k\in E} t_{i,j,k,03}^{98}\left(h_{j,k}^{13}\left(1 - \frac{h_j^{98}}{h_j^{13}}\right) + h_{j,k}^{98}\left(1 - \frac{h_j^{13}}{h_j^{98}}\right)\right), (7)$$

whereby:

- TI_i^{1998} and TI_i^{2013} are the average intensities of task i in 1998-2000 and 2011-2013, respectively;
- $t_{i,j,k,14}^{y}$ and $t_{i,j,k,03}^{y}$ are the average values of task content i for workers in "sector j, education k" cell in period y, calculated using O*NET 2014 and O*NET 2003, respectively, variables omitting subscript k represent sectoral averages, and $y = \{1998, 2013\}$ represents 1998-2000 and 2011-2013, respectively;

[15] The interaction term is positive (negative) if the task content i increases more (less) than is implied by changes in the sectoral structure, by changes in educational structure within sectors and by changes in the task content of occupations held by workers at a given education level in a given sector.

- $h^{98}_{j,k}$ and $h^{13}_{j,k}$ are the employment shares of workers "sector j, education k" cell in 1998-2000 and 2011-2013, respectively, and variables omitting subscript k represent sectoral employment shares;
- T is the set of five task content measures;
- S is the set of 14 different sectors at the NACE one-digit level;[16] and E is the set of three different educational levels (based on ISCED).

Table 3. Shift-share decomposition of task content changes between 1998-2000 and 2011-2013 in CEE countries

Non-routine cognitive analytical	Croatia	Czechia	Estonia	Hungary	Latvia	Poland	Romania	Slovakia	Slovenia
Structural effect	7	5	5	5	9	6	12	3	10
Educational effect	4	11	5	12	11	19	11	11	17
Occupational effect	-1	-5	4	-7	-1	-12	-13	-11	-2
Interaction	0	0	1	0	2	1	4	1	-2
Total change	11	11	15	9	21	13	15	3	23
Non-routine cognitive personal	Croatia	Czechia	Estonia	Hungary	Latvia	Poland	Romania	Slovakia	Slovenia
Structural effect	3	3	3	3	5	0	1	1	8
Educational effect	2	9	4	10	9	16	9	10	14
Occupational effect	-2	-5	-1	-3	1	-8	-18	-4	-1
Interaction	4	-2	2	-2	2	3	14	-1	0
Total change	7	5	7	8	18	11	5	5	21
Routine cognitive	Croatia	Czechia	Estonia	Hungary	Latvia	Poland	Romania	Slovakia	Slovenia
Structural effect	4	1	-1	0	5	8	18	2	-4
Educational effect	1	-6	-1	-4	-4	-10	-4	-6	-8
Occupational effect	-1	2	5	-4	12	6	0	0	-7
Interaction	-1	3	1	3	-1	3	4	5	5
Total change	3	0	5	-5	12	7	19	1	-14
Routine manual	Croatia	Czechia	Estonia	Hungary	Latvia	Poland	Romania	Slovakia	Slovenia
Structural effect	-6	-4	-5	-6	-9	-5	-4	-3	-12
Educational effect	-2	-7	-3	-8	-7	-15	-7	-7	-12
Occupational effect	0	6	1	7	4	12	7	6	1
Interaction	-2	-2	-2	-1	-5	-1	-9	-3	1
Total change	-10	-7	-9	-8	-17	-8	-13	-7	-23
Non-routine manual physical	Croatia	Czechia	Estonia	Hungary	Latvia	Poland	Romania	Slovakia	Slovenia
Structural effect	-6	-5	-4	-5	-9	-5	-22	-4	-8
Educational effect	-1	-8	-4	-8	-9	-14	-8	-8	-11
Occupational effect	0	4	-4	9	-2	9	3	5	7
Interaction	-4	-1	-1	-1	-3	-2	1	-1	-3
Total change	-11	-10	-13	-5	-23	-12	-27	-8	-15

Note: Lithuania is omitted due to education data coding issues (see Appendix A1).

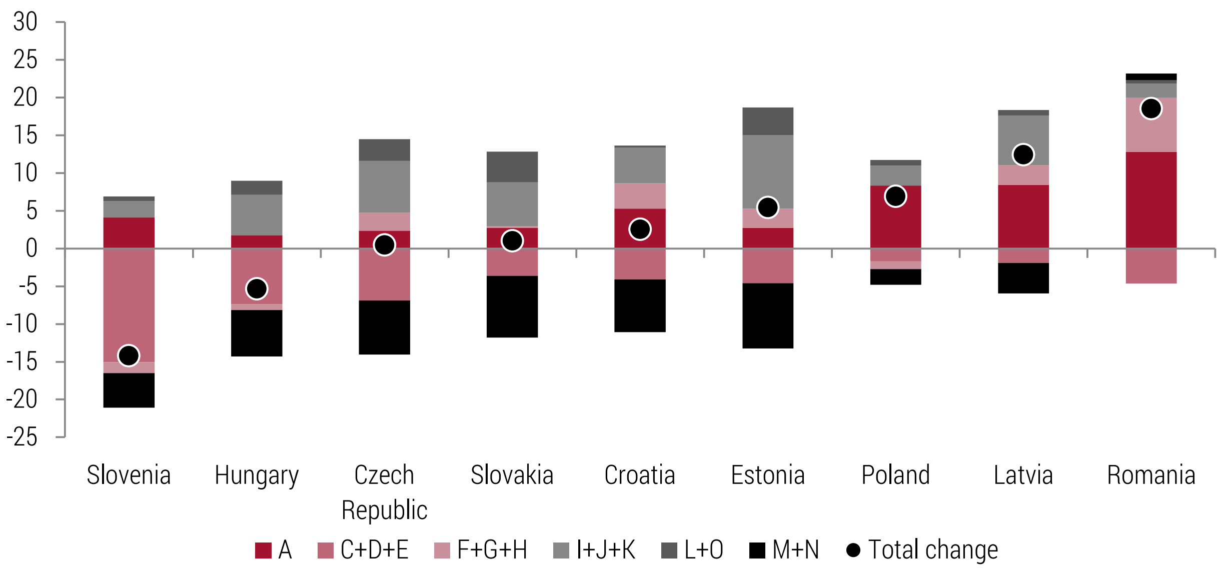
*Source: Own calculations based on O*NET and EU-LFS data.*

[16] Due to the NACE revision in 2007 (from NACE 1.1 to NACE 2.0), we mapped all NACE 2.0 sectors to the previous classification (except for the sector B in NACE 1.1, which had been coupled with sector A, and hence we decided to exclude it from the decomposition). Therefore, the decomposition is performed for 14 economic sectors in accordance with NACE 1.1.

The structural effect quantifies changes in task content intensities which would happen if only the sectoral composition of employment changed, but educational and occupational structures within sectors remained constant. The educational effect quantifies changes in task content intensities which would happen if only the educational composition of employment in particular sectors changed, but sectoral structure and occupational structure within sectors remained constant. The occupational effect quantifies changes in task content intensities which would happen if the occupational structure and within-occupational task content of workers at a given education level in particular sectors changed, but sectoral structure and educational structure within sectors remained constant.[17] Table 3 presents the decomposition results.

The decomposition corroborates the econometric findings with regard to the role played by workforce upskilling. Table 3 illustrates that the educational effect was responsible for most of the task content changes in the CEE countries between 1998-2000 and 2011-2013. It drove the growth of non-routine cognitive tasks, and compressed the other tasks, including routine cognitive ones (except for Croatia). Poland evidenced the largest contribution of the educational effect, while Croatia evidenced the smallest. In Czechia, Hungary, Poland and Slovakia the changes in non-routine cognitive tasks implied by upskilling were larger than the total observed change of these tasks. Regarding the routine cognitive tasks, the rising workforce share of graduates (who were performing jobs with the lowest average routine cognitive content among all educational groups) was the main factor behind the negative educational effect.

Figure 3. Contributions of sectors to changes of routine cognitive tasks between 1998-2000 and 2011-2013 in CEE.



Note: Contribution of as given sector is calculated as a sum of structural, educational, occupational and interaction effect in that sector. Countries are sorted by the country-level task content change. Sectors: A - Agriculture, C - Mining and quarrying, D – Manufacturing, E - Electricity, gas and water supply, F – Construction, G - Wholesale and retail trade, H - Hotels and restaurants, I - Transport, storage and communication, J - Financial intermediation, K - Real estate, L - Public administration and defence, M – Education, N - Health and social work , O - Other community, social and personal activities.
Sectors B – Fishing, P – Activities of households, Q – Extra-territorial organizations and bodies were excluded due to too small samples.Data for Croatia is for 2003 and 2013. Lithuania is omitted due to data issues (see Appendix A1).
Source: Own calculations based on EU-LFS and ONET data.

[17] The occupational effect can be viewed as a measure of the impact of technology on the nature of jobs, in line with Autor et al. (2003). However, occupational changes can also result from changes in the matching of workers skills with jobs tasks. The UE-LFS data don't allow us to identify and separate these different effects.

Structural effect was the second most powerful factor behind the educational effect. It contributed positively to the change of all cognitive tasks, including routine ones, and negatively to the change of all manual tasks. Its contribution was largest in countries that witnessed vast reallocation of labour from agriculture (Romania, Poland, Latvia) or from manufacturing (Slovenia). Importantly, in all countries which recorded growth of routine cognitive tasks (except Estonia), the contribution of structural effect was positive. Figure 3 shows that in these countries agriculture contributed most to routine cognitive tasks' growth (in Estonia transport, storage and communication contributed most).[18] It was due to declining employment share of agriculture, a sector poor in routine cognitive tasks, and gross reallocation of workers to other sectors more suffused with such tasks. On the other hand, in countries where the intensity of routine cognitive tasks declined (Slovenia and Hungary), it was largely thanks to manufacturing (Figure 3) – both the gross reallocation of workforce out of manufacturing, and de-routinisation of jobs in this sector played a role.

The contributions of structural and educational effects to the change of non-routine cognitive tasks were to some extent offset by the occupational changes within particular sector-education cells, i.e. negative occupational effect (Table 3). At the same time, occupational effect increased the routine cognitive content of jobs in Czechia, Estonia, Latvia and Poland. This means, that within sectors, workers with specific levels of education in 2011-2013 performed less non-routine cognitive work than their counterparts in 1998-2000. This was particularly the case for such sectors as education, wholesale and trade, hotels and restaurants. Finally, in all countries, except Latvia and Croatia, the interaction term in routine cognitive tasks was positive. This means that employment structure was shifting towards those educational-sectoral groups which at the same time recorded increasing routine cognitive content due to occupational effects.

Overall, the decomposition confirms that workforce upskilling contributed most to the shift from routine and manual to non-routine cognitive jobs in the CEE countries. Structural shifts also contributed to these changes, mostly through the outflow from agriculture to other sectors. They were crucial for the growth of routine cognitive tasks which was unexplained in the panel regression. In countries where routine cognitive tasks rose most, it can be largely attributed to gross reallocation of the workforce from agriculture to services.

Conclusions

In this paper we study the evolution of 10 Central and Eastern European labour markets in the period 1998-2013 using the task-based approach of Acemoglu and Autor (2011) and distinguishing between non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical tasks. To the best of our knowledge this is the first task-oriented analysis of this region. We use O*NET data from 2003 and 2014 and combine it with EU-LFS data, using mostly a 3-digit occupation classification. We analyse the economy-wide changes in the task content of jobs, and their educational and structural components. We search for interactions between task content dynamics, workforce upskilling and R&D via fixed-effect panel regressions.

We find that all CEE countries witnessed an increase in non-routine cognitive tasks and a decrease in manual tasks, which is line with the previous literature on the most developed economies (e.g. Acemoglu and Autor, 2011;

[18] Results of structural, educational and occupational effect by sectors are available upon request. Contributions of sectors to changes in other tasks are presented on Figures A3-A6 in the Appendix A2.

Autor et al., 2003; Spitz-Oener, 2006). However, routine cognitive tasks increased in six CEE countries, remained stable in two and declined in two, contrary to the patterns found in the US and Western European countries, and at odds with RBTC. Using the shift-share decomposition we conclude that diverse developments in routine cognitive tasks can be attributed to diverse patterns of structural changes in the CEE. Countries such as Romania, Latvia and Poland which in the 1990s had higher agriculture shares of employment and which saw these shares decline more substantially, experienced higher increase in routine cognitive tasks. On the other hand, routine cognitive tasks were compressed by the workforce upskilling in CEE countries – rising tertiary attainment was the main facet of upskilling and graduates were performing jobs with lower intensity of routine tasks than less educated workers. Structural shifts were also important for the increase in non-routine analytical tasks, and the fall in manual tasks, yet these were mainly educational effects that contributed to these changes.

Our panel regressions confirm a link between the evolution of the task content of jobs, and education attainment changes and identify the link with R&D spending (a proxy for technology adoption). We find a positive and statistically significant relationship between both non-routine cognitive task intensities and the share of workers with tertiary education attained. There is also a positive correlation between the intensity of non-routine cognitive analytical tasks and the share of secondary educated workers. The most profound impact of educational expansion occurred for Latvia, Lithuania and Poland, where on average this factor explained 91% of the estimated growth in non-routine cognitive analytical tasks. Manual tasks are found negatively related to the share of workers with tertiary education. However, for routine manual tasks we find no significant difference between workers with secondary and primary education. The R&D spending was positively and significantly correlated with the intensity of non-routine cognitive tasks, and negatively with the intensity of routine manual tasks. At the same time, we find no significant relationship between the routine cognitive task intensity and the educational structure of the workforce or R&D, suggesting that demand-side factors (structural shifts) were of greater importance for the evolution of these tasks.

Several implications stem from our findings. Workforce upskilling played a major role in the evolving task structure of jobs in CEE. In previous studies, workforce upskilling was often perceived as inferior to routine-biased technology progress. We find that educational change remains a major determinant of the labour market structure evolution in upper-middle / newly established high income countries. In particular, the rapidly increasing tertiary education attainment was a crucial component of CEE educational boom as it had the largest impact on the task content structure. We also find that structural changes, which in CEE followed a standard pattern of declining agriculture and rising share of services, can largely explain why some CEE countries experienced an increase in routine cognitive tasks, which have been declining in the most developed economies. We think that low and middle-income countries which experience a reallocation of labour from the primary sector should not expect a fast de-routinisation of the labour market, especially if manufacturing employment shares are stable or peak at middle-income stage (Rodrik, 2016) and its services sector which accommodates the gross reallocation of labour from agriculture. In the CEE case, further convergence with the most advanced economies might however lead to the de-routinisation and increase the risk of hollowing out of routine-intensive jobs. Arntz et al. (2016)[19] show that workers in CEE countries (Czechia, Poland, Slovakia) were to a larger extent concentrated in

[19] The approach of Arntz et al. (2016) differs from our approach, as they used PIACC 2012 data, which allowed them to account for differences in the actual tasks within an occupation, but did not allow them to analyse time series.

occupations at high risk of automation than workers in the US (in 2012), but they were more often performing duties which are relatively hard to automate, which reduced the risk of automation. The opposite was the case in most EU15 countries, so if work organisation in CEE became more EU15-like, the risk of automation would rise.

We also provide evidence that the shift towards non-routine cognitive jobs is also positively correlated (albeit to a smaller degree) with R&D spending, which proxies for technological improvements. The interaction between expenditure on research and development, technology adoption and sectoral change should be taken into account by the policy makers responsible for both labour market and R&D policies. However, further research is needed on understanding the interplay between technology adoption, task content of jobs and employment, in particular in CEE, other transition and middle income countries. At the moment, the available data for the CEE allows only a tentative analysis at the aggregate level.

References

Acemoglu, D., Autor, D., *Skills, Tasks and Technologies: Implications for Employment and Earnings*. In: Handbook of Labor Economics. Elsevier, pp. 1043–1171, 2011

Aedo, C., Hentschel, J., Moreno, M., Luque, J., *From occupations to embedded skills: a cross-country comparison*. World Bank Policy Research Working Paper, 2013

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., *Back to work: growing with jobs in Eastern Europe and Central Asia, Europe and Central Asia reports*. The World Bank, Washington, DC, 2014

Arntz, M., Gregory T., Zierahn U., The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis, OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing, Paris, 2016

Autor, D., *Polanyi's Paradox and the Shape of Employment Growth*, Working Paper No. 20485. National Bureau of Economic Research, 2014

Autor, D., Dorn D., *The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market*, American Economic Review, 103(5): 1553-97, 2013

Autor, D., Levy, F., Murnane, R., *The Skill Content of Recent Technological Change: An Empirical Exploration*. Quarterly Journal of Economics 118, 4, 2003

Autor, D., Price, B.M., *The Changing Task Composition of the US Labor Market: An Update of Autor, Levy and Murnane*. (2003), MIT Monograph, 2013

Bessen, J., *How Computer Automation Affects Occupations: Technology, Jobs, and Skills*, Boston Univ. School of Law, Law and Economics Research Paper No. 15-49, 2016

Boeri, T., Keese, M., *Labour markets and the transition in Central and Eastern Europe*. OECD Economic Studies 18, 133–163, 1992

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

Cedefop, *Quantifying skill needs in Europe occupational skills profiles: methodology and application*. Cedefop, Thessaloniki, 2013

Central Statistical Office of Poland, Labour Force Survey data*, annual data 1998-2013* de la Rica, S., Gortazar, L., *Differences in Job De-Routinization in OECD Countries: Evidence from PIAAC*, IZA Discussion Paper No. 9736, 2016

Deming, D., *The Growing Importance of Social Skills in the Labor Market*, NBER Working Paper No. 21473, 2015

Dicarlo, E., Lo Bello, S., Monroy, S., Oviedo, A.M., Puerta, M.L.S., Santos, I., *The skill content of occupations across low and middle income countries: evidence from harmonized data*. *Mimeo*, 2015

Eden, M., Gaggl P., *Do poor countries really need more IT? The role of relative prices and industrial composition*. Policy Research Working Paper Series 7352, The World Bank, 2015

European Commission, Eurostat, *European Union Labour Force Survey, annual data 1998-2013*

Goos, M., Manning, A., Salomons, A., *Explaining Job Polarization: Routine-Biased Technological Change and Offshoring*. American Economic Review 104, 2509–2526, 2014

Goos, M., Konings, J., Vandeweyer, M., *Employment Growth in Europe: The Roles of Innovation, Local Job Multipliers and Institutions*, SSRN Scholarly Paper No. 2671765. Social Science Research Network, 2015

Graetz, G., Michaels, G., *Robots at Work*, CEP Discussion Papers dp1335, Centre for Economic Performance, LSE, 2015

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

Hardy, W., Keister, R., Lewandowski, P., *Do entrants take it all? The evolution of task content of jobs in Poland*, IBS Working Paper 10/2015, 2015

IBS,. Employment in Poland 2013. *Labour in the Age of Structural Change*, Books and Reports published by IBS. Instytut Badań Strukturalnych, 2014

Jaimovich, N., Siu, H.E., *The trend is the cycle: Job polarisation and jobless recoveries*. National Bureau of Economic Research, 2012

Machin, S., Van Reenen, J., *Technology and changes in skill structure: evidence from seven OECD countries*. Quarterly Journal of Economics 1215–1244, 1998

Michaels, G., Natraj, A., Van Reenen, J., *Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years*. Review of Economics and Statistics 96, 60–77, 2014

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

Rodrik, D., *Premature Deindustrialization,* Journal of Economic Growth, 21: 1, 2016

Salvatori, A., *The Anatomy of Job Polarisation in the UK*. IZA Discussion Papers 9193, 2015

Spitz-Oener, A., T*echnical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure*. Journal of Labor Economics 24, 235–270, 2006

World Bank, *World Development Report 2016: Digital Dividends. Washington*, DC: World Bank. License: Creative Commons Attribution CC BY 3.0 IGO, 2016

Appendix

A1. Data

We have encountered two major problems with exploited data. First one stems from changes of the ISCO classification, while the second one is related to the change in encoding educational levels in Lithuania. In 2011 – ISCO-88 (COM) was revised and supplanted by the newer ISCO-08 – which caused shifts in occupational time-series since these two classifications are not entirely comparable. In particular, the non-routine cognitive task content in several agricultural occupations proved much higher in the data with ISCO-88 classification than in the data with ISCO-08. This higher intensity of non-routine cognitive analytical seems implausible as agriculture is typically associated with routine and manual tasks (Arias and Sánchez-Páramo, 2014), while non-routine cognitive tasks are typical for occupations which are rare in agriculture (Acemoglu and Autor, 2011). Assuming a higher precision of the more recent classifications, we therefore imputed the values of task items from selected ISCO-08 occupations to data with ISCO-88 occupations. In each country separately, we ranked the ISCO-88 occupations by the shares in agricultural employment in 1998 and identified those that jointly constituted at least 80% of agricultural employment (starting with the occupations with the largest shares). For these country-specific subsets of ISCO-88 occupations, we ascribed the task items from relevant ISCO-08 occupations (average values of several occupations if required) – see Table A1 below. This procedure improved the consistency of data before and after the ISCO change, allowing us to disaggregate the data by sectors in a reliable way. At the same time, it had a negligible impact on country-level results: the correlation of the corrected and uncorrected yearly task content values ranges from 0.95 (non-routine cognitive analytical) to 1.00 (non-routine manual physical).

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

Country	ISCO-88 (ISCO-08)
Croatia	613 (613); 611 (611); 612 (612)
Czechia	612 (612); 833 (834); 614 (621); 723 (723); 921 (921); 832 (832, 833); 611 (611); 321 (314, 321); 343 (331, 334); 613 (613)
Estonia	613 (613); 612 (612); 833 (834); 921 (921); 614 (621); 615 (622); 832 (832, 833); 321 (314, 321); 915 (962); 343 (331, 334); 834 (835)
Hungary	612 (612); 611 (611); 613 (613); 833 (834); 723 (723); 921 (921); 832 (832, 833); 614 (621); 412 (431); 722 (722); 914 (910, 912); 932 (932)
Latvia*	600 (6**); 613 (613); 921 (921); 833 (834); 611 (611); 512 (512, 513, 515); 612 (612)
Lithuania	613 (613); 921 (921); 612 (612); 833 (834); 610 (610, 611, 612, 613)
Poland	6111 (6111); 6131 (6130); the classification was subsequently collapsed to a 3-digit level
Romania	6 (6)
Slovakia	921 (921); 612 (612); 833 (834); 832 (833, 832); 723 (723); 614 (621); 915 (962); 611 (611); 321 (321, 314); 343 (331, 334); 814 (817); 413 (432)
Slovenia	61 (61)

*Note: * Despite being mostly coded at a 3-digit level, the Latvian dataset contains some observations with occupation coded as 600 and that jointly form a significant part of Agriculture. In this case, we ascribed the mean of tasks in all occupations in the '6' group of ISCO-08.*

Source: Own elaboration based on EU-LFS data.

We also identified similar shifts in the wholesale and retail trade sector. ISCO-08 distinguishes between salespersons and supervisors within the group 522, whereas its predecessor ISCO-88 did not. This occupational group accounted for a large share of employment in wholesale and retail trade, and significantly influenced the task composition in this sector. Since the EU LFS occupational data are not coded at a 4-digit level, we are not able to properly map this group of occupations, which results in large shifts of intensity of routine cognitive tasks between 2010 and 2011 (the time of switching to the ISCO-08). Therefore, we excluded occupations 5222 (shop supervisors) and 5221 (shop keepers) from our O*NET data and from 2011 onwards, assigned the mean task items of occupational group 5223 (shop sales assistants) to the occupational group 522 (shop salesperson). No other sectors exhibited substantial differences between ISCO-88 and ISCO-08, although there are some breaks in the data which may be due to changes in country-specific classifications of occupations which are mapped into ISCO in the EU-LFS.

The data on education in Lithuania evidences a large break between the years 2000 and 2001 with a shift of around 20 pp. from tertiary to secondary education, mainly due to a change in school classification with no later breaks. We captured the magnitude of the shift with a simple OLS regression of the share of tertiary education on years and a dummy indicating the years before the shift. We then deducted the coefficient attached to the dummy from the shares of tertiary educated and added it to the shares of secondary educated before 2001. We report the corrected values in the Table A3 and use them for the analyses in further sections (apart from the decomposition in the section 3.3).

A2. Tables & Figures

Table A2. Employment shares by sector in 1998, by country (in %)

SECTOR	HR*	CZ	EE	HU	LV	LT	PL	RO	SK	SI
Agriculture	17	6	9	7	19	20	19	42	8	12
Mining	1	2	1	1	0	0	2	2	2	1
Manufacturing	20	28	22	25	19	19	21	21	26	32
Energy, gas and water supply	2	2	3	3	2	3	2	2	2	1
Construction	8	10	7	6	6	7	7	4	9	6
Commerce, accommodation and food activities	19	17	16	16	16	16	15	10	15	17
Transport, storage and communication	6	8	9	8	8	7	6	5	8	6
Other services	27	28	32	33	30	29	27	15	30	26

*Note: *2003 for Croatia, due to data availability. Other services include financial, insurance and real estate activities; administrative and support activities;*
public administration and defence; health, social work; education; arts and entertainment.
Source: Own elaboration based on EU LFS data.

Table A3. Changes in employment shares by sector, by country between 1998 and 2013 (in percentage points)

SECTOR	HR*	CZ	EE	HU	LV	LT	PL	RO	SK	SI
Agriculture	-6	-3	-5	-2	-11	-11	-7	-13	-5	-4
Mining	0	-1	0	-1	0	0	-1	-1	-1	0
Manufacturing	-3	-1	-3	-4	-5	-4	-2	-3	-3	-9
Energy, gas and water supply	1	0	-1	0	0	-1	0	0	0	1
Construction	-1	-1	2	0	2	1	1	3	1	0
Commerce, accommodation and food activities	1	-1	0	2	2	5	1	5	3	1
Transport, storage and communication	2	1	1	1	3	2	2	2	1	3
Other services	6	6	6	4	9	8	6	6	5	9

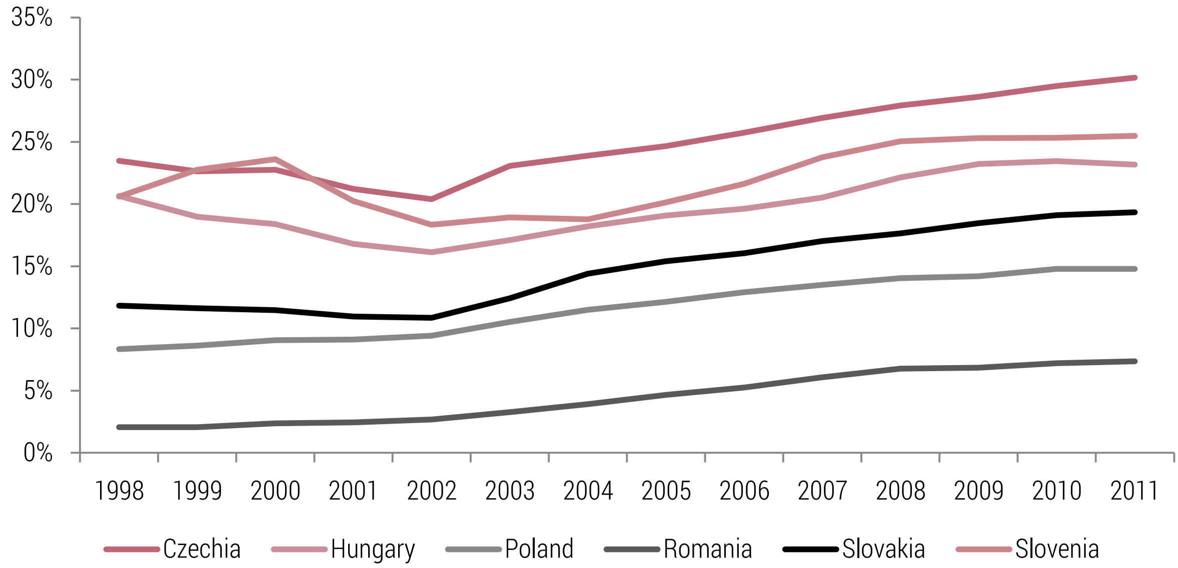
*Note: *2003 for Croatia, due to data availability. Other services include financial, insurance and real estate activities; administrative and support activities;*
public administration and defence; health, social work; education; arts and entertainment.
Source: Own elaboration based on EU LFS data.

Table A4. Educational attainment in the employment, in 1998 and 2013

	Share of workers with primary education (ISCED 0-2) attained			Share of workers with secondary education (ISCED 3-4) attained			Share of workers with tertiary education (ISCED 5-8) attained		
	1998	2013	Δ	1998	2013	Δ	1998	2013	Δ
Croatia*	0.23	0.15	-0.08	0.58	0.62	0.04	0.19	0.23	0.04
Czechia	0.09	0.04	-0.05	0.79	0.75	-0.05	0.11	0.21	0.10
Estonia	0.12	0.08	-0.04	0.56	0.53	-0.04	0.32	0.39	0.07
Hungary	0.19	0.11	-0.08	0.65	0.63	-0.02	0.16	0.26	0.10
Latvia	0.14	0.09	-0.05	0.67	0.57	-0.10	0.19	0.34	0.15
Lithuania	0.13	0.04	-0.09	0.66	0.56	-0.10	0.21	0.40	0.19
Poland	0.18	0.07	-0.11	0.70	0.64	-0.06	0.12	0.30	0.17
Romania	0.36	0.23	-0.14	0.55	0.59	0.04	0.08	0.18	0.10
Slovakia	0.10	0.04	-0.06	0.78	0.75	-0.04	0.12	0.21	0.09
Slovenia	0.23	0.11	-0.12	0.62	0.59	-0.03	0.15	0.30	0.15

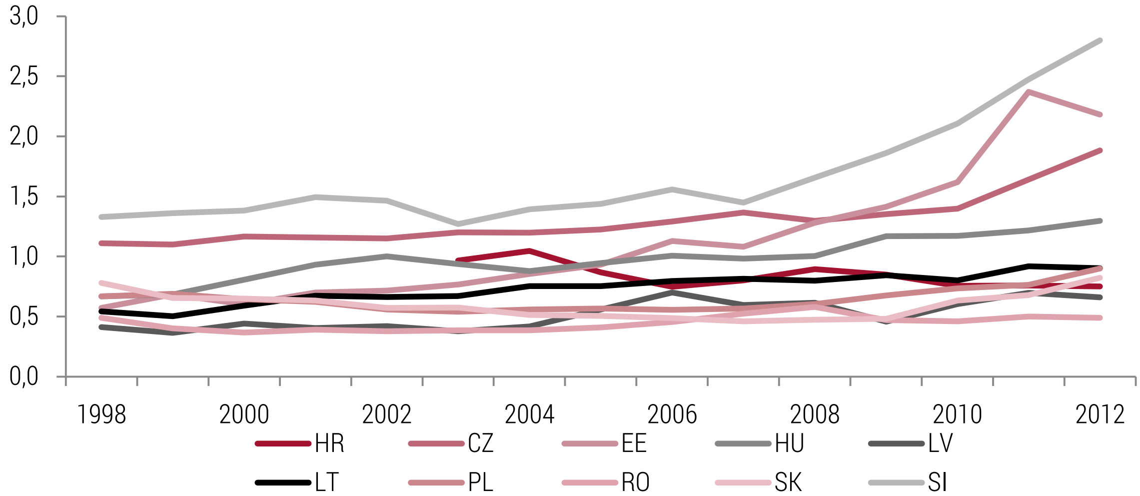
*Note: *Data for Croatia is for 2003 and 2013. Data for Lithuania are adjusted as described in the Appendix A1.*
Source: Own elaboration based on EU-LFS data.

Figure A1. ICT Stock per Worker relative to the US (in %) in selected CEE countries, 1998-2011.



Source: Own calculations on Eden and Gaggl (2015) data on ICT capital stock and Eurostat data on employment.

Figure A2. R&D expenditure as % of GDP in CEE countries.



Source: Own elaboration based on the World Bank data.

Table A5. Panel fixed-effects regressions of log ICT stock per worker on R&D expenditure in the CEE, 1998-2011

	Coefficient	Std. err.	R^2 within	R^2 between	Correlation
R&D expenditure as a percentage of GDP	118.87**	39.55	0.17	0.59	0.73
Constant	-0.63	0.36			
Observations	84 (6 countries)				

*Notes: The countries included are: Czechia, Hungary, Poland, Romania, Slovakia, Slovenia. The last column reports a simple correlation measure between all values of R&D expenditure and all values of ICT stock per worker. All regressions include country-level fixed-effects and robust standard errors. * p<0.1; ** p<0.05; *** p<0.01.*

Source: Own estimations based on World Bank data and data from Eden and Gaggl (2015).

Table A6. Panel fixed-effects regressions of log ICT stock per worker on Foreign Direct Investment in the CEE, 1998-2011

	Coefficient	Std. err.	R^2 within	R^2 between	Correlation
FDI as a percentage of GDP	0.003	0.35	0.00	0.03	0.05
Constant	0.451***	0.02			
Observations	83 (6 countries)				

*Notes: The countries included are: Czechia, Hungary, Poland, Romania, Slovakia, Slovenia. The last column reports a simple correlation measure between all values of FDI and all values of ICT stock per worker. All regressions include country-level fixed-effects and robust standard errors. * p<0.1; ** p<0.05; *** p<0.01.*

Source: Own estimations based on World Bank data and data from Eden and Gaggl (2015).

Table A7. Panel fixed-effects regressions of task content measures in the CEE 1998-2012 on education and FDI

	Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Routine manual	Non-routine manual physical
Share of workers with tertiary education	1.58*** (0.14)	0.89*** (0.18)	0.63 (0.49)	-1.26*** (0.17)	-1.79*** (0.28)
Share of workers with secondary education	0.62*** (0.18)	-0.07 (0.30)	0.72 (0.82)	-0.25 (0.19)	-1.12* (0.52)
FDI as a percentage of GDP	-0.002 (0.008)	0.009 (0.014)	-0.04 (0.023)	0.005 (0.021)	0.010 (0.010)
Observations	145 (10 countries)	145 (10 countries)	145 (10 countries)	145 (10 countries)	145 (10 countries)
R^2 (overall)	0.19	0.07	0.005	0.12	0.09

Notes: Data from 2003 used for Croatia. All regressions include country-level fixed-effects and robust standard errors. * p<0.1; ** p<0.05; *** p<0.01.

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

Figure A3. Contributions of sectors to changes of non-routine cognitive analytical tasks between 1998-2000 and 2011-2013 in CEE.

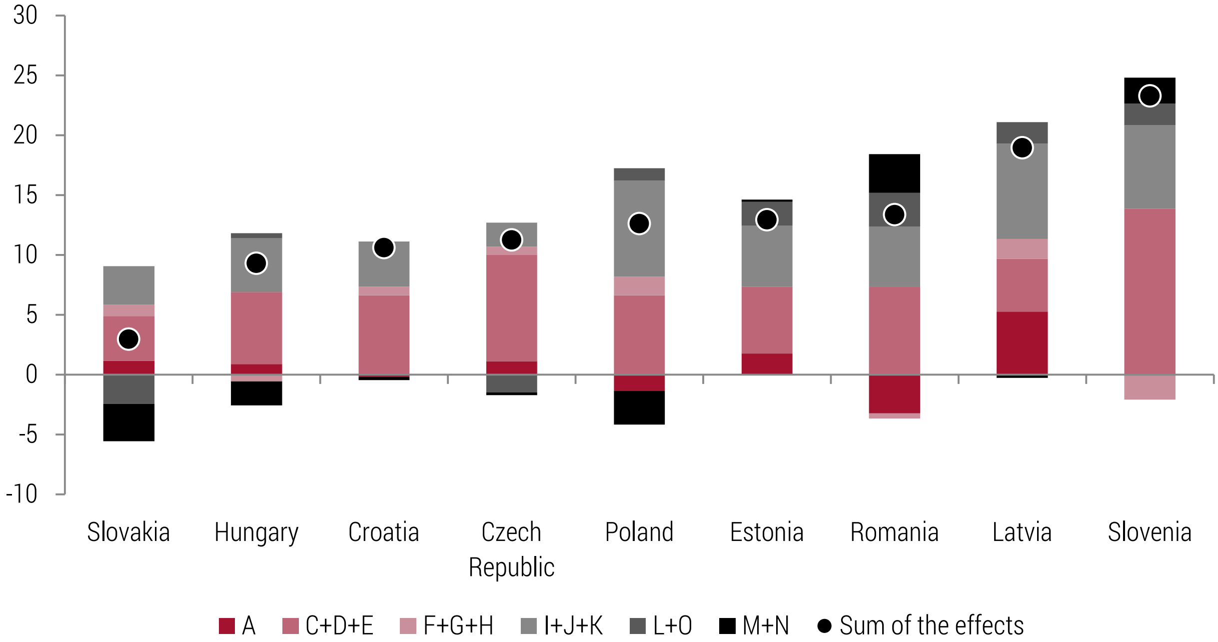
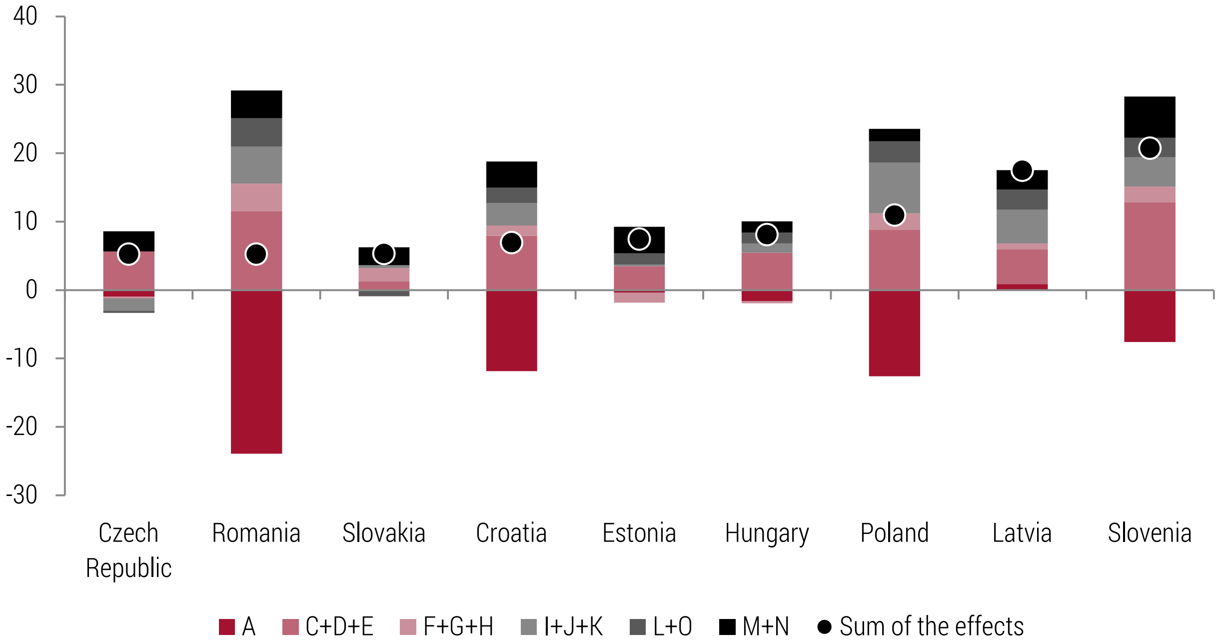


Figure A4. Contributions of sectors to changes of non-routine cognitive personal tasks between 1998-2000 and 2011-2013 in CEE.



Note: Contribution of as given sector is calculated as a sum of structural, educational, occupational and interaction effect in that sector. Countries are sorted by the country-level task content change. Sectors: A - Agriculture, C - Mining and quarrying, D – Manufacturing, E - Electricity, gas and water supply, F – Construction, G - Wholesale and retail trade, H - Hotels and restaurants, I - Transport, storage and communication, J - Financial intermediation, K - Real estate, L - Public administration and defence, M – Education, N - Health and social work , O - Other community, social and personal activities.
Sectors B – Fishing, P – Activities of households, Q – Extra-territorial organizations and bodies were excluded due to too small samples.
**Data for Croatia is for 2003 and 2013. Lithuania is omitted due to data issues (see Appendix A1).*
Source: Own calculations based on EU-LFS and ONET data.

Figure A5. Contributions of sectors to changes of routine manual tasks between 1998-2000 and 2011-2013 in CEE.

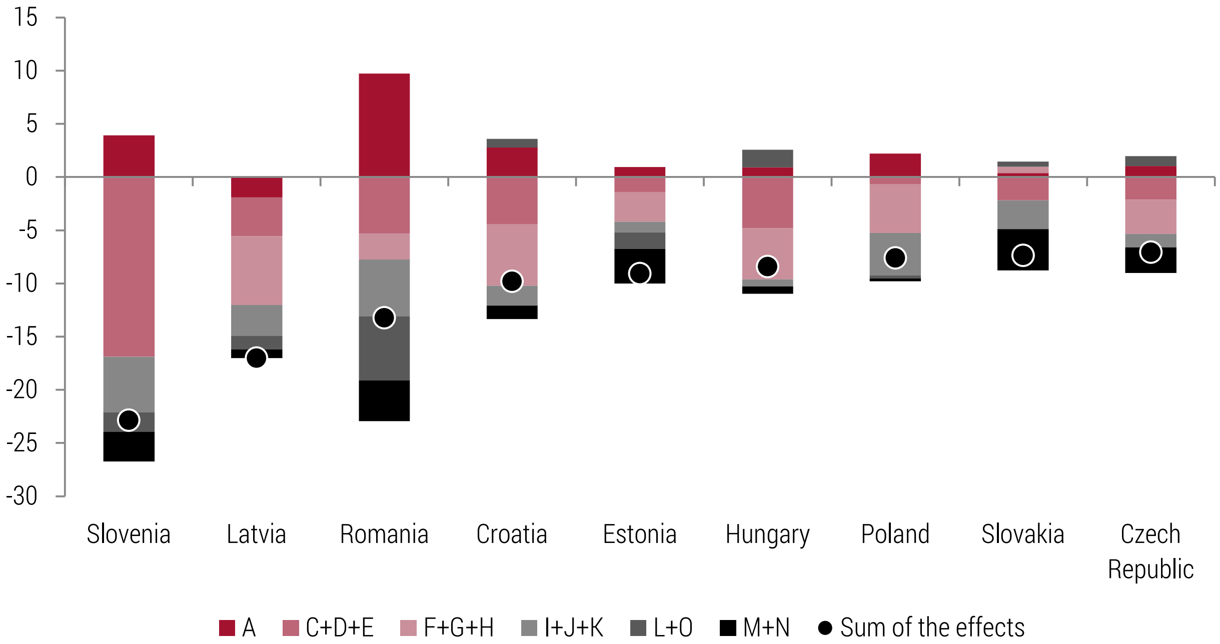
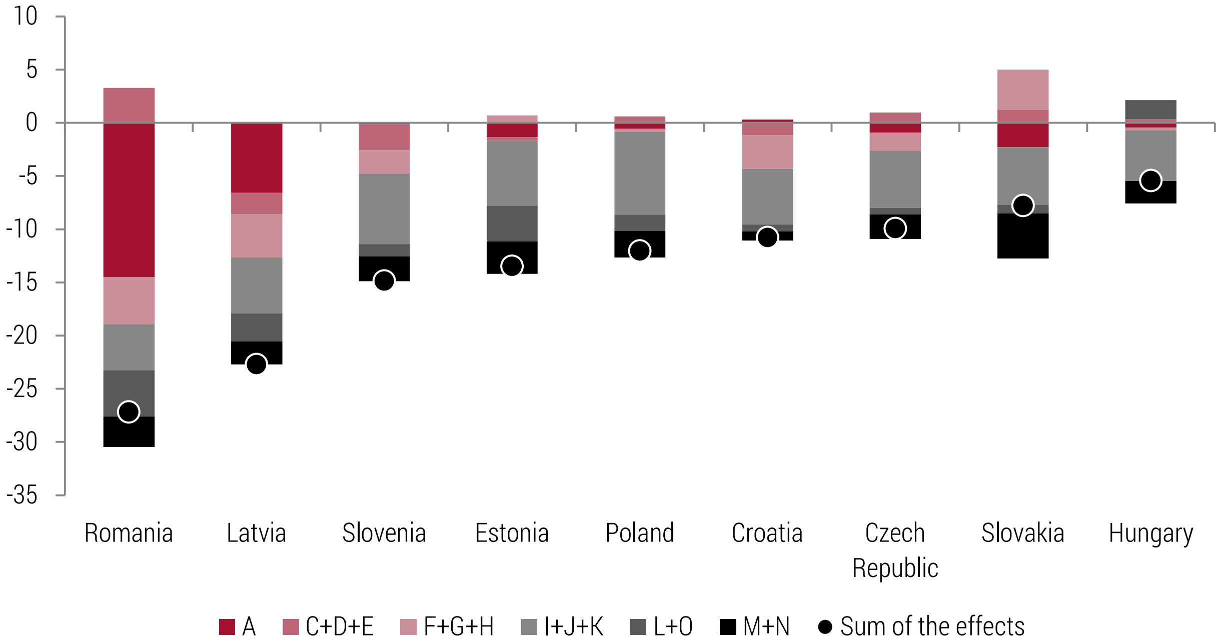


Figure A6. Contributions of sectors to changes of non-routine manual physical tasks between 1998-2000 and 2011-2013 in CEE.



Note: Contribution of as given sector is calculated as a sum of structural, educational, occupational and interaction effect in that sector. Countries are sorted by the country-level task content change. Sectors: A - Agriculture, C - Mining and quarrying, D – Manufacturing, E - Electricity, gas and water supply, F – Construction, G - Wholesale and retail trade, H - Hotels and restaurants, I - Transport, storage and communication, J - Financial intermediation, K - Real estate, L - Public administration and defence, M – Education, N - Health and social work , O - Other community, social and personal activities.
Sectors B – Fishing, P – Activities of households, Q – Extra-territorial organizations and bodies were excluded due to too small samples.
**Data for Croatia is for 2003 and 2013. Lithuania is omitted due to data issues (see Appendix A1).*
Source: Own calculations based on EU-LFS and ONET data.