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Educational upgrading, structural change and the task composition of jobs in Europe[1]

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Abstract

We analyze the changes in the task content of jobs in 24 European countries between 1998 and 2015. We link the O*NET occupational data with the European Union Labour Force Survey (EU-LFS), and use the methodology of Acemoglu and Autor (2011). We find that the intensity of non-routine cognitive tasks grew in all countries, while the intensity of manual tasks declined. Workforce upskilling was the major factor contributing to these developments. The intensity of routine cognitive tasks grew in most Central and Eastern European countries, but it declined in Western European countries. This difference is

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attributed to the contrasting patterns of structural changes in these groups of countries.

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JEL classifications: J21, J23, J24, I25.

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 (Acemoglu and Autor, 2011; Autor, 2014; Michaels *et al.*, 2014), often accompanied by wage polarization – rising relative wages of high-skilled workers (Goos *et al.*, 2014). These changes have been attributed to 'routine-biased technological change' hypothesis (RBTC) which 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, for instance architects, IT specialists, managers), while it has decreased the demand for middle-skilled workers performing routine work (already replaceable by machines, for instance bookkeepers, clerks, assemblers). It also indirectly increases employment in simple, yet unstructured, jobs (for instance, drivers, waiters and waitresses, hairdressers).[2] Autor *et al.* (2003) and Autor and Price (2013) provided evidence that since the 1960s, computerization 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. Spitz-Oener (2006) showed that the higher use of ICT reduced the importance of routine work in Germany.

The majority of existing research on the task content of jobs is focused on the most developed OECD countries while studies of emerging economies are rare. Aedo *et al.* (2013) showed that, between the early 1990s and the middle 2000s, non-routine cognitive tasks grew at the expense of manual tasks in seven emerging economies around the world. Hardy *et al.* (2016) found that the cognitive task content of jobs, especially the non-routine one, has been steadily increasing in Poland, while the manual task content has been declining. Gimpelson and Kapeliushnikov (2016) found that employment in transitionary Russia was shifting towards better-skilled occupations. However, cross-country studies covering a range of emerging or transition economies, and using methodologies which were used in the seminal studies of the most developed economies, are lacking.

[2] 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.

In this paper, we try to answer two questions. First, what are the similarities and differences in the evolution of task content of jobs in the post-transition European countries and in the more advanced Western European countries? Second, what structural forces can these similarities and differences be attributed to? With this aim, we quantify the task content of jobs in 10 CEE countries which joined the European Union since 2004 (CEE10) and in 14 'old' EU Member States between 1998 and 2015 (EU14). 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. We focus on two structural forces – sectoral developments and educational upgrading – and use a shift-share decomposition to quantify their contribution to the changes in the task content of jobs.

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 levels, especially as it is often argued that the majority of jobs around the world are susceptible to automation (World Bank, 2016). On the other, we offer a novel look at 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.

The EU-LFS data do not allow us to test the RBTC hypothesis as they do not contain information on technology use in the workplace. Following the literature, we study whether the changes in the task content of jobs are consistent with the implications of RBTC. Deming (2017) showed that high-skilled, difficult-to-automate jobs in the US increasingly require social skills which is consistent with RBTC, as computers are increasingly better at dealing with codifiable challenges while progress in automating social interactions has been poor (Brynjolfsson and McAfee, 2016). Autor and Dorn (2013) showed that the falling cost of automation of routine tasks contributed to the growth of simple services jobs and employment polarization in the US. Machin and Van Reenen (1998) provided evidence that R&D intensity was a major driver of the demand for skilled workers in the most developed countries, although Kuku *et al.* (2007) showed that in some transition countries (e.g., Armenia, Belarus, Russia) in the early 2000s the firm costs of computer adoption suppressed the worker returns to their usage. De La Rica and Gortazar (2016) found that differences in ICT adoption explain a large part of differences in deroutinization of jobs in the OECD countries, while Akçomak *et al.* (2015) showed that technology affects both the types of task performed within occupations and the demand for particular jobs. However, some authors suggested that developments of skills and task structures of 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 polarization 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.

To the best of our knowledge, the task content of jobs in the CEE labour markets has, so far, not been comprehensively studied, except for Hardy *et al.* (2016) for Poland. The CEE countries seem particularly interesting to study developments along the cognitive vs. manual and routine vs. non-routine dimensions of jobs for two main reasons: they experienced considerable changes in the demand and supply of labour, as well as in the occupational and skills structure (IBS, 2014) and they moved from lower to upper middle- (Bulgaria, Romania) or high-income status (the remainder of the CEE10).[3] In particular, the CEE countries followed a common pattern of sectoral changes over the 1998–2015 period. Employment shares in agriculture have declined and converged across the region, but in 2015 they were still much higher than in the EU14 (with the exception of Hungary and Slovenia; see Tables A1 and A2 in the Appendix). Likewise, in 1998, the share of workers employed in industry in the CEE was higher than in the EU14 (it ranged from 22 percent in Latvia to 34 percent in Slovenia, and from 16 percent in Greece to 26 percent in Italy and Germany). By 2015, industrial employment shares in CEE shrank by a few percentage points, but most of the EU14 countries recorded even stronger declines. The share of services rose in all CEE countries, but remained lower than in the EU14 countries. Only the shares of construction, wholesale and retail trade, and hotels and restaurants in CEE10 have converged with the EU14. Although the employment shares of financial, insurance and real estate activities, as well as the shares of transport, storage and communication have increased the most among services sectors in the CEE10, in 2015 they were still noticeably lower than in most of the EU14 countries. Moreover, the differences between the CEE10 and the EU14 in the employment shares of education, and health and social work have widened (Tables A1 and 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 percent, and the share of workers with primary education (ISCED 0-2) was 18 percent (see Table A3 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 16–23 percentage points in these countries. In 2015, the average CEE employment share of tertiary and primary educated amounted to 31 and 9 percent, respectively. Over the same time, the average share of primary educated employment in EU14 decreased from

[3] Although it would be interesting to analyze other CEE countries (which have not joined the EU), we are not able to do this because of data availability – the synchronized EU-LFS which allows consistent occupation-based analysis in particular countries, is not available for the non-EU countries.

36 percent to 21 percent and the average share of tertiary educated employment increased from 23 percent to 36 percent. In 2015, there was still a gap in the share of tertiary educated employment between the CEE and EU14 countries. However, there were far fewer primary educated workers in CEE countries than in EU14 countries.

Section 2 describes the data and its conversion to European occupational classification standards. Section 3 presents the results of the evolution of task content of jobs in particular countries, and of the shift-share decomposition of these changes in contributions of structural and educational shifts. Section 4 comprises a discussion of our findings, compares them with the previous state of knowledge and highlights our contributions to the literature.

2. Data and methodology

2.1 Data

We use the Occupational Information Network (O*NET) database as a source of information on the task content of occupations, and we merge it with individual EU-LFS data on the basis of occupations. We use two distinct editions of O*NET (2003 and 2014) to account for possible changes of the task content within occupations. Since EU-LFS data are unavailable for several countries before 1998, we start our analysis period in 1998, with the exception of Croatia, which enters our sample in 2002. Data for Germany, Ireland and the UK lack information on educational attainment in 1998, therefore, all analyses involving educational data for these countries are done from 1999 onwards. We drop Bulgaria from the sample as we encountered severe inconsistencies in the Bulgarian EU-LFS data.[4] We also found some inconsistencies related to the encoding of education levels in the Lithuanian EU-LFS, which we address in Appendix A1. In order to facilitate the comparative perspective of our paper, we also included 14 Western European countries in our sample.[5] We restricted our sample to employed individuals aged above 15 years. Self-employed individuals are also included as long as their occupations are known. Sample sizes largely increased from 2005 onwards, when Eurostat started to disseminate all four quarterly samples (Eurostat, 2014).[6] Final sample sizes are presented in Table A4 in the

[4] 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' decreased by 50,000 and the number of 'personal and protective workers' grew by approx. 40,000. We think that these inaccuracies resulted from changes in the implementation of Eurostat coding guidelines.

[5] They overlap with the EU countries studied in Goos *et al.* (2014), with the exception of Luxembourg which we excluded because of small sample sizes in the LFS data.

[6] Eurostat (2014) also provides a comprehensive summary of a sampling design of EU-LFS data.

Appendix, together with some basic summary statistics of the sample (cf. Tables A1–A3 in the Appendix).

In applying O*NET data from the US to European countries we follow Aedo *et al.* (2013), Arias *et al.* (2014) and Goos *et al.* (2014). Although the assumption of task content equivalence between European countries, especially the 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 Czech Republic (*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 European countries and the 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 three-digit level, some at a two-digit level. We used the highest level of detail available in each country, which is predominantly a three-digit level (see Table 1). In Romania three-digit level codes were available in 1998, one-digit level codes from 1999 to 2004 and three-digit codes from 2005 onwards. For Romania we mapped all occupations into a one-digit level over the entire period in order to avoid inconsistencies in the data.[7] In the O*NET data occupations are coded using ONET-SOC,[8] whereas in the EU-LFS data ISCO is used, and the ISCO coding is derived from the country-specific classifications.[9] 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.[10] Both the SOC and ISCO have undergone several revisions during the 1998–2015 period. A major one occurred in 2011 when ISCO-88 (COM) was revised and supplanted by the newer ISCO-08. This 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 – farming workers (see also Aedo *et al.*, 2013) and retail trade workers. We discuss this in detail in Appendix A1.

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

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

[9] Before 2011, the EU-LFS data were coded with the EU-specific classification – the ISCO-88 (COM). The differences between ISCO-88 (COM) and ISCO-88 are negligible.

[10] The crosswalks sometimes yield ambiguous mapping between two classifications. In such cases we followed the solution described in detail in Hardy *et al.* (2016).

Table 1. The ISCO level of detail for analyzed countries

Level of detail	Country
1-digit	Romania
2-digit	Slovenia
3-digit	Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia + all EU 14 countries (Old Member States)

Note: These are the levels available in EU-LFS datasets. For consistency reasons, in the case of Romania we used the one-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 created task content measures following the approach and task typology of Acemoglu and Autor (2011).[11] We first standardized the values of each task item using the country-specific means and standard deviations calculated on the first 3 years of data in every country. Next, using these standardized task items, we created five composite task content measures: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual and non-routine manual physical (see Table 2 for the list of task items used for the creation of each task content measure). Each composite task content measure is calculated as a sum of constituent task items (see Appendix A1 for the detailed description) which in the next step is again standardized to have a mean 0 and standard deviation 1 in the first 3 years in every country. This allows us to achieve a mean of 0 and a standard deviation of 1 over the first 3 years available for each country, and interpret a unit change in the mean values of task contents as a one standard deviation change since the beginning of the analyzed period. Three years were chosen to reduce the impact of potential outliers. Standardization is also required because particular task contents use various numbers of items which also have different ranges (Acemoglu and Autor, 2011). In line with Arias *et al.* (2014) and Dicarlo *et al.* (2016) standardization is done within each country so the results can be used to analyze changes over time in particular countries, but they cannot be used to compare levels of task content measures between countries.

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. We removed the level shifts by equating the mean task values in the 2 years surrounding the classification changes, which allows us to study the overall changes in a consistent manner. The adjustments for breaks in occupational

[11] See Acemoglu and Autor (2011) for a detailed description of the method, and Hardy *et al.* (2016) for a related case of applying it to the Polish LFS data.

Table 2. Construction of task contents measures

Task content measure (*T*)	**Task items (*J*)**
Non-routine cognitive analytical	Analyzing 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).

employment were also applied in Goos *et al.* (2014; see the online Appendix to that article). 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 data around that period in Slovakia to ensure that data before and after the classification are consistent. Similarly, we corrected the UK data where in 2001 the classification was updated to the SOC-00, which resulted in shifts in the task content intensities. In Poland, we rescaled the data in accordance with the breaks of Polish classification of occupations (KZiS) in 2003, 2005, 2011 and 2015 (see Hardy *et al.*, 2016 for more details on KZiS changes). In Finland, we rescaled the data according to the change of classification in 2002 (Ammattiluokitus 1997 to Ammattiluokitus 2001). In France, we rescaled the data due to an introduction of a continuous survey in 2003 and also due to a large survey change in 2013. In Austria, we rescaled the data due to a conversion of the survey to a continuous one in 2004. Finally, we rescaled the data for Italy, due to a change in the definitions of occupations in 2004. In general, our adjustments overlap with those performed by Goos *et al.* (2014).

We apply a weighted average to combine the task content measures based on the 2003 O*NET and the 2014 O*NET for each occupation. From 1998 to 2003, we use task 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 measures based on O*NET 2003, and a weight $\frac{t-2003}{11}$ to task measures based on O*NET 2014; and for 2015 we use task measures based on O*NET 2014. The average level of task content calculated for a given population will be called a task intensity. For presentation purposes, we shift the values of tasks so that the initial level of every average task intensity at the country level is equal to zero, and multiply all values by 100 so the results can be interpreted as percentages of standard deviation of a particular task content in the initial period.

3. The evolution of task content of jobs in Europe

3.1 Overall changes

Trends in the evolution of task content structures were similar across the CEE countries. Firstly, all CEE countries recorded a large increase in the average intensity of non-routine cognitive tasks, with the intensity expressed as the percentage of initial (1998–2000) standard deviation of a task in each country. Among the CEE countries considered, it was Slovenia and Latvia that experienced the largest growth (relative to its task structure in 1998) in non-routine cognitive tasks: between 1998 and 2015[12] the intensity of non-routine cognitive analytical and personal tasks in Slovenia increased by 26 and 24, respectively, and in Latvia by 26 and 25, respectively. Slovakia experienced the smallest growth in the non-routine cognitive analytical tasks (by 2) and personal tasks (by 6). 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 Romania (by 29), while routine manual tasks fell most in Slovenia (by 23). At the same time, the smallest decline of routine manual task intensity was recorded by Slovakia (by 7) and of non-routine manual task intensity by Hungary (by 7). These trends in the changes of non-routine cognitive and manual tasks largely resembled those present in the EU14 countries (Figure 1), and bore out previous findings for the most developed countries (Autor and Price, 2013; Autor *et al.*, 2003; Spitz-Oener, 2006) and selected middle-income countries (Aedo *et al.*, 2013; Arias *et al.*, 2014). However, the pace of these changes was faster among CEE countries than among the EU14 countries, with the exception of routine manual tasks which declined at a similar pace in both groups of countries.

[12] In order to increase the robustness of our findings, these changes in task content intensities are calculated as the change between 3-year averages at the beginning and at the end of the analysis period. However, for the sake of simplicity, in the main text we refer to them as the change between 1998 and 2015.

Figure 1. Evolution of the task content of jobs in the CEE and EU14 countries between 1998 and 2015.

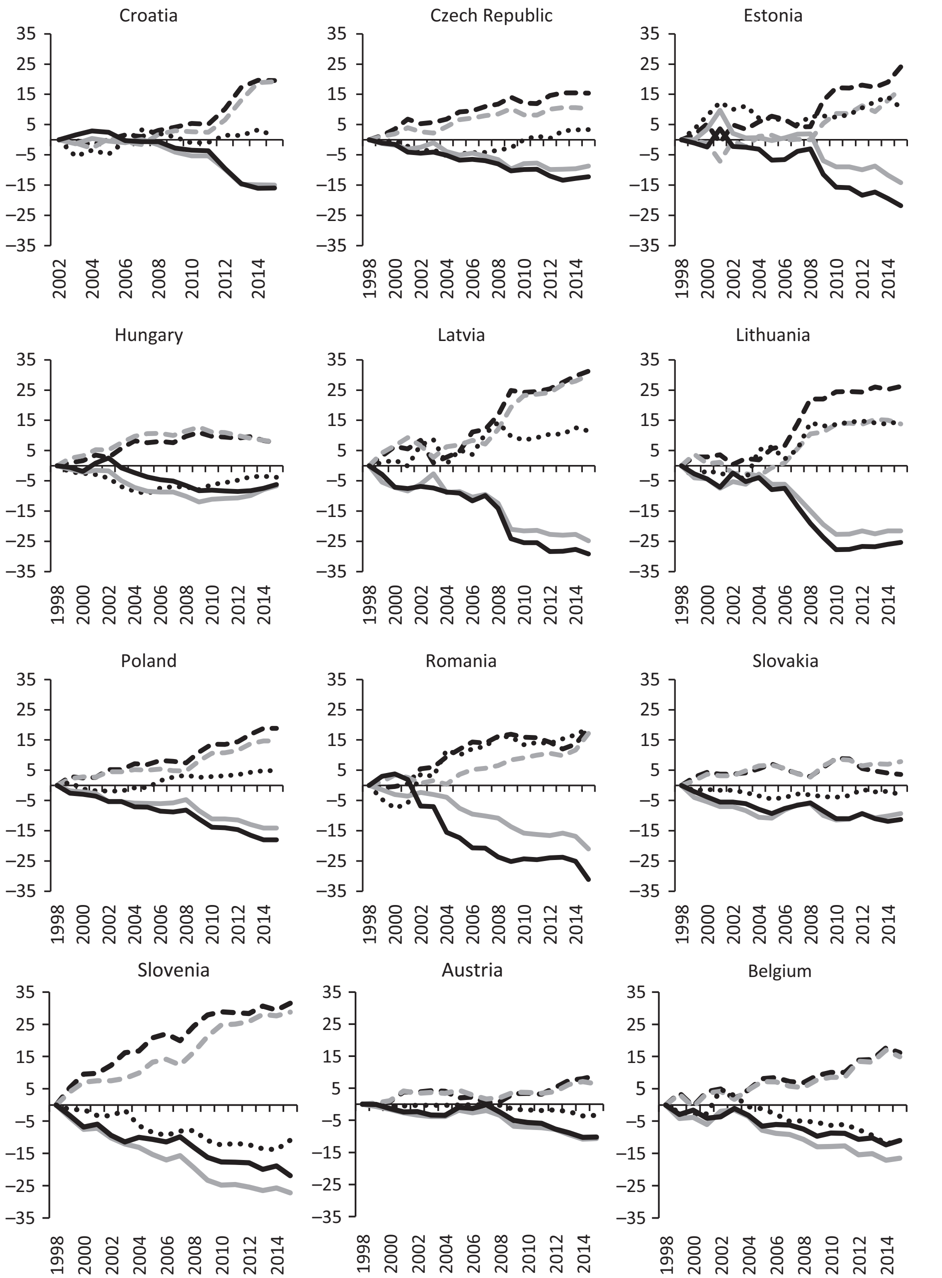
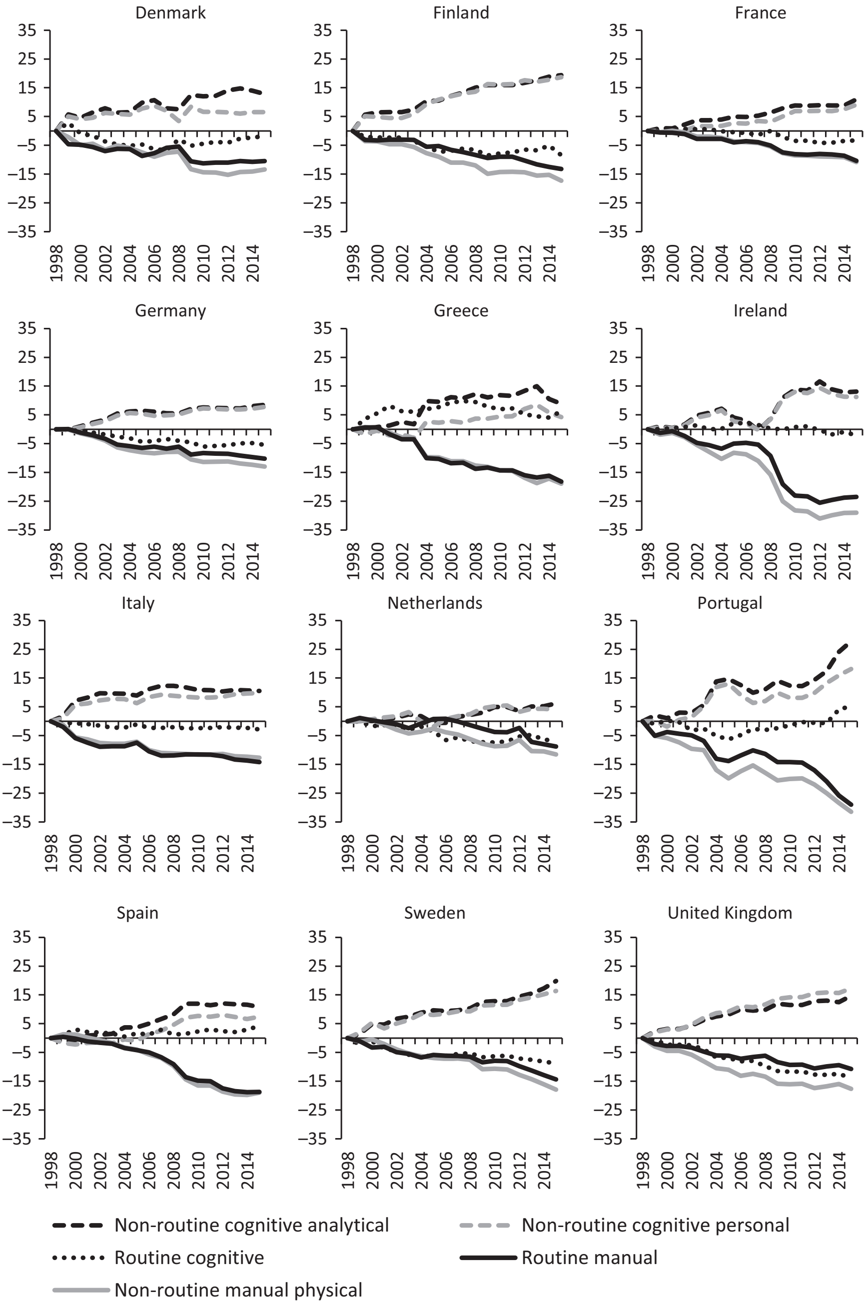


Figure 1. (Continued)



Note: A weighted average was used to combine the derived mean task content measures from the 2003 and 2014 O*NET datasets. To make the results comparable the task indices were rescaled so that the initial value of all of them was 0. The values represent percentages of initial (1998-2000) standard deviation of a given task in each country.
Source: Own calculations based on EU-LFS and O*NET data.

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. While 11 of the EU14 countries in our sample recorded a drop in the intensity of routine cognitive tasks during the period studied (Spain, Greece and Portugal recorded increases), 7 out of 10 CEE countries saw a growth in these tasks. This growth was most pronounced in Latvia, Lithuania and Romania, where it exceeded 10. Estonia was next in line with an increase in eight, followed by Croatia and Poland (5). Among the CEE countries which recorded the growth of routine cognitive tasks intensity, Czech Republic experienced the smallest increase (by 3.5) but it was still larger than in any of the EU14 countries. Slovenia, Hungary and Slovakia were the only CEE countries to have recorded drops in routine cognitive tasks, with the one in Slovenia (by 12) much larger than in any the other two countries (two in Hungary and one in Slovakia). Overall, our results show that CEE countries recorded a potent and substantial shift from manual to cognitive tasks, which in most CEE countries involved an increase in the intensity of routine cognitive tasks. This last feature distinguished the CEE countries from the EU14 countries.

3.2 The decomposition of changes in the task content of jobs

The task content of jobs differed substantially between workers with different education level and between sectors. In all countries the higher the education level attained, the higher the average intensity of non-routine cognitive tasks and the lower the intensity of manual tasks (see Figure A5). The tertiary educated workers stood out in this regard, while the difference between the secondary and primary educated workers was less pronounced. At the same time, the secondary educated workers had the highest intensity of routine cognitive tasks, in line with previous findings that the routine-intensive jobs are being performed by the medium-skilled workers (Goos *et al.*, 2014). These patterns did not change much between 1998 and 2015. In all countries there were also persistent differences between sectors. Workers in agriculture, mining, manufacturing, and electricity, gas and water supply had high intensity of manual tasks and low intensity of non-routine cognitive tasks (see Figure A6 in the Appendix). The opposite was true for workers in transport, storage and communication, financial intermediation, real estate, public administration and defence, education, health and social work. The intensity of routine cognitive tasks was high in industry and most of market services, but low in agriculture and education, health and social work.

In all countries studied, both the educational structure and the sectoral structure of employment changed noticeably between 1998 and 2015 (Tables A1–A3). In order to quantify the relationship between these changes and the evolution of task content of jobs in particular countries, we use a shift-share decomposition. We decompose total changes in task intensities between 1998 and 2000 and 2013 and 2015 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, BO_i, (iv) within-occupational task content (occupational effect), WO_i; and (v) the interaction between all these effects, INT_i.[13] For each country we distinguish 42 education-sector cells, and for each task i we use the following formulae:

$$\forall_{i\in T}(TI_i^{2015} - TI_i^{1998}) = (\sum_{j\in S}\sum_{k\in E} t_{i,j,k,14}^{15} h_{j,k}^{15} - \sum_{j\in S}\sum_{k\in E} t_{i,j,k,03}^{98} h_{j,k}^{98}) = BS_i + BE_i + BO_i + WO_i + INT_i, \tag{1}$$

$$\forall_{i\in T} BS_i = \sum_{j\in S} t_{i,j,03}^{98}\left(h_j^{15} - h_j^{98}\right), \tag{2}$$

$$\forall_{i\in T} BE_i = \sum_{j\in S}\left[\sum_{k\in E} t_{i,j,k,03}^{98}\left(\frac{h_{j,k}^{15}}{h_j^{15}} - \frac{h_{j,k}^{98}}{h_j^{98}}\right)\right] h_j^{98}, \tag{3}$$

$$\forall_{i\in T} BO_i = \sum_{j\in S}\sum_{k\in E}(t_{i,j,k,03}^{15} - t_{i,j,k,03}^{15}) h_{j,k}^{98}, \tag{4}$$

$$\forall_{i\in T} WO_i = \sum_{j\in S}\sum_{k\in E}(t_{i,j,k,14}^{15} - t_{i,j,k,03}^{15}) h_{j,k}^{98}, \tag{5}$$

$$\forall_{i\in T} INT_i = \sum_{j\in S}\sum_{k\in E}\left(t_{i,j,k,14}^{15} - t_{i,j,k,03}^{98}\right)(h_{j,k}^{15} - h_{j,k}^{98}) + \sum_{j\in S}\sum_{k\in E} t_{i,j,k,03}^{98}\left(h_{j,k}^{15}\left(1 - \frac{h_j^{98}}{h_j^{15}}\right) + h_{j,k}^{98}\left(1 - \frac{h_j^{15}}{h_j^{98}}\right)\right) \tag{6}$$

whereby:

[13] 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.

- TI_i^{1998} and TI_i^{2015} are the average intensities of task i in 1998–2000 and 2013–2015, 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, 2015} represents 1998–2000 and 2013–2015, respectively;
- $h_{j,k}^{98}$ and $h_{j,k}^{15}$ are the employment shares of workers in 'sector j, education k' cell in 1998–2000 and 2013–2015, respectively, and variables omitting subscript k represent sectoral employment shares;
- S is the set of 14 different sectors at the NACE one-digit level[14] ;
  and E is the set of three different educational levels (based on ISCED).

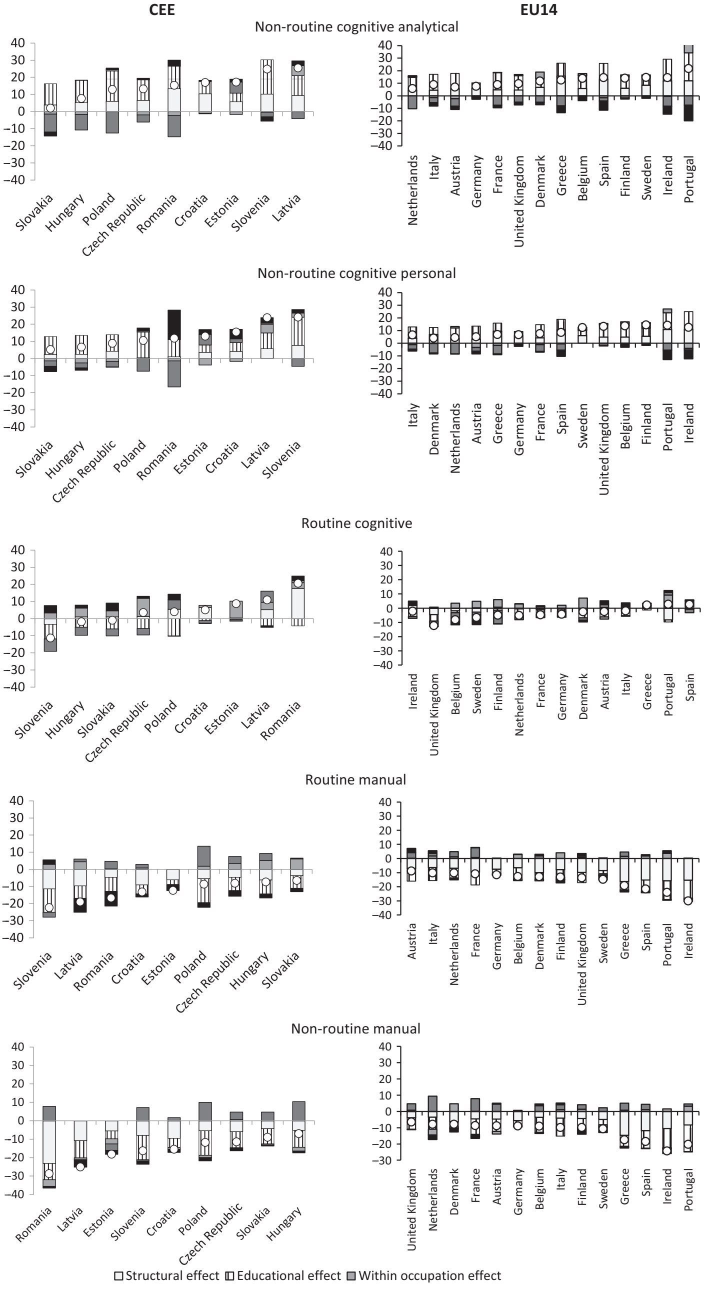
The structural effect quantifies changes in task content intensities which would happen if only the sectoral composition of employment changed, but educational and occupational structures within sectors, and task content of occupations remained constant. The educational effect quantifies changes in task content intensities which would happen if only the educational composition of employment in particular sectors changed, but sectoral structure, occupational structure within sectors and task content of occupations remained constant. The between-occupation effect quantifies changes in task content intensities which would happen if the occupational structure of workers at a given education level in particular sectors changed, but sectoral structure, educational structure within sectors and task content of occupations remained constant. The within-occupation effect quantifies changes in task content intensities which would happen if only the within-occupational task content of workers changed (as measured by O*NET) but sectoral, educational and occupational structures remained constant.[15] Figure 2 presents the decomposition results.

Changes in the educational structure played a central role in the changes of task content structure. Most of the increase in non-routine cognitive tasks intensity between 1998–2000 and 2013–2015, both in CEE and EU14 countries, can be attributed to the educational effect. Its contribution to the growth of non-routine cognitive tasks' was, however, the highest among CEE countries which experienced a rapid increase in the share of tertiary graduates. Among CEE countries, these were Poland and Slovenia that recorded the highest contribution of educational effect to the increase in non-routine cognitive tasks. Moreover, in Hungary, Poland and Slovakia, the changes in non-routine cognitive tasks implied by the educational upgrading were larger than the total observed change in these tasks. The educational effect had a vital contribution to the growth of non-routine cognitive tasks also among EU14

[14] 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.

[15] 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 do not allow us to identify and separate these different effects.

Figure 2. Shift-share decomposition of task content changes between 1998–2000 and 2013–2015 in CEE and EU14 countries.



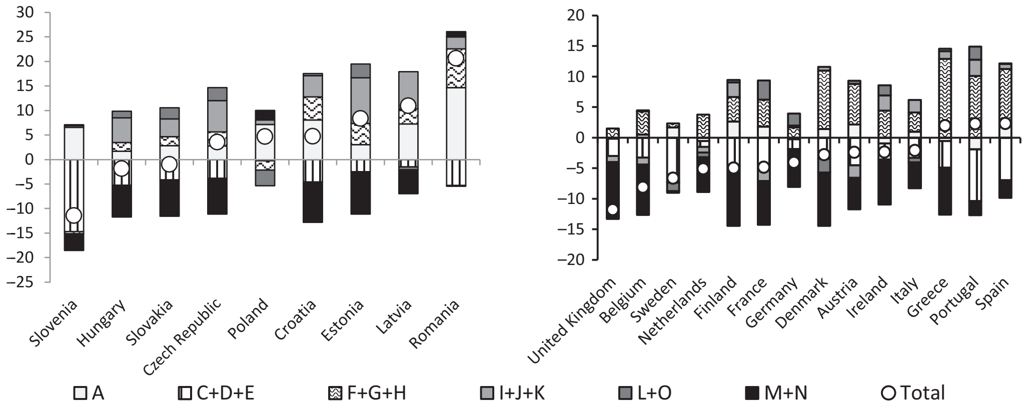
Note: Lithuania is omitted due to education data coding issues (see Appendix A1). Data for Croatia are for 2002 and 2015. Data for Germany, Ireland and the UK are for 1999 and 2015. The values represent percentages of initial (1998-2000) standard deviation of a given task in each country.
Source: Own calculations based on EU-LFS and O*NET data.

countries, especially in Ireland and Portugal. Correspondingly, improvements in educational structures contributed to the drop of manual tasks intensity. Among CEE countries, contrary to other effects considered, educational effect largely suppressed the growth of routine cognitive tasks, especially in Poland and Slovenia. Similarly, its contribution was negative for the EU14 countries, where it added to the drop of routine cognitive tasks in all countries but Sweden and Spain (where its contribution was close to null).

Structural effect was a factor with the second most potent contribution to the task content changes. In CEE countries, it contributed positively to the change in all cognitive tasks, including the routine ones (with the exception of Slovenia), and negatively to the change in manual tasks. Importantly, in all countries where routine cognitive tasks grew, the contribution of structural effect was positive (in Estonia it was negligible and close to null). On the other hand, its contribution to routine cognitive tasks was either negative or negligible among the EU14 countries. Different sectoral shifts are responsible for these different structural contributions to the evolution of routine cognitive tasks in both groups of countries. In CEE countries much of the structural effect may be attributed to the gradually declining agriculture sector (Figure 3).[16] The contribution of agriculture to the change in routine cognitive tasks was also positive in several EU14 countries but it was much smaller than in the CEE countries. It was also much smaller in absolute terms than the negative contribution of other sectors. The second important difference between the CEE and the EU14 lies in the contribution of financial, insurance and real estate services, as well as transport, storage and communication. In all CEE countries these services sectors contributed positively to the change in routine cognitive tasks, and in all countries except for Poland and Slovenia this contribution was substantial. Among the EU14 countries, only Finland, Ireland, Italy and Portugal recorded a visibly positive contribution of these sectors. In the remaining EU14 countries it was either tiny or negative (in five countries). In all countries, manufacturing contributed negatively to the change in routine cognitive tasks, but the size of this contribution varied. Among the CEE, it was Slovenia, and to a lesser extent Hungary and Slovakia, that saw a large negative contribution of this sector, stronger than the total change in routine cognitive tasks. Likewise, the decreasing share of manufacturing in employment resulted in the negative contribution to the change in routine cognitive tasks in the EU14. This was further reinforced by the large negative contribution of education and healthcare sectors in EU14 countries (also present in CEE). In Greece, Portugal

[16] Results of structural, educational and occupational effect by sectors are available upon request. Contributions of sectors to changes in other tasks are presented in Figures A1–A4 in Appendix A2.

Figure 3. Contributions of sectors to changes of routine cognitive tasks between 1998–2000 and 2013–2015 in CEE9 and EU14.



Note: Contribution of a given sector is calculated as a sum of structural, educational, occupational and interaction effects 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 are for 2002 and 2015. Lithuania is omitted due to data issues (see Appendix A1). Data for Germany, Ireland and the UK are for 1999 and 2015. The values represent percentages of initial (1998–2000) standard deviation of a given task in each country.
Source: Own calculations based on EU-LFS and ONET data.

and Spain, where routine cognitive tasks inched up, this can be mostly attributed to the positive contribution of the wholesale and retail trade sector. In the CEE countries this sector also contributed positively to the change in intensity of routine cognitive tasks, albeit only to a much smaller extent.

The contributions of structural and educational effects to the change in non-routine cognitive tasks were to some extent offset by the between-occupation changes within particular sector-education cells (negative between-occupation effect, Figure 2; except in Estonia). The pattern occurred both in the CEE and the EU14 countries, but was more marked in the former. Changes in the occupational structure likewise contributed negatively to the change in routine cognitive tasks, both in the CEE and in the EU14, but it was larger in the latter. However, changes that occurred within occupations were of greater importance for the evolution of routine cognitive tasks. The within-occupation effect contributed positively to the change of these tasks in all CEE and EU14 countries but Poland, Austria and Italy. It was also positive for the change in routine manual tasks.

Overall, the decomposition shows that educational upgrading contributed most to the shift from routine and manual to non-routine cognitive jobs in the CEE and EU14 countries. Structural shifts also contributed to these changes, mostly through the outflow from agriculture to other sectors, and were of greater importance for the CEE. Differences in the evolution of routine cognitive tasks in both groups of countries can be attributed to different patterns of sectoral changes. In countries where routine cognitive tasks rose most (the majority of CEE), it can be largely attributed to gross reallocation of the workforce from agriculture to services. In countries where routine cognitive tasks fell most (the majority of the EU14 plus Slovenia), it can be largely attributed to the deindustrialization embodied in the declining share of manufacturing in employment.

4. Conclusions

In this paper, we study the evolution of 10 Central and Eastern European and 14 ‘old’ EU Member States, labour markets in the period 1998–2015 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 to cover the CEE region. We use O*NET data from 2003 and 2014 and combine it with EU-LFS data, using mostly a three-digit occupation classification. We analyze the economy-wide changes in the task content of jobs, and their educational and structural components.

We find that all CEE countries witnessed an increase in non-routine cognitive tasks and a decrease in manual tasks, similar to the EU14 countries. This finding is in line with the previous literature on the most developed economies (Acemoglu and Autor, 2011; Autor *et al.*, 2003; Spitz-Oener (2006)). However, routine cognitive tasks increased in seven CEE countries and declined in three (in two only marginally), contrary to the EU14 countries and the patterns found in the previous literature on the US and Western European countries, and at odds with routine-replacing technological change hypothesis. 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 Lithuania which in the 1990s had higher agriculture shares of employment and which saw these shares decline more substantially, experienced higher increases 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.

Several implications stem from our findings. Workforce upskilling played a major role in the evolving task structure of jobs in CEE countries. In previous studies, workforce upskilling was often perceived as inferior to routine-biased technology progress. However, we find that educational change remains a major factor in 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 the CEE educational boom as it had the largest contribution to the changes in task content structure. We also find that structural changes, which in CEE countries followed a standard pattern of declining agriculture and rising share of services, can largely explain why several CEE countries have 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 deroutinization 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 deroutinization and increase the risk of hollowing out of routine-intensive jobs. Arntz *et al.* (2016)[17] show that workers in CEE countries (Czech Republic, Poland, Slovakia) were to a larger extent concentrated in occupations at high risk of automation than workers in the US (in 2012), but they were more often performing duties which are relatively difficult to automate, which reduced the risk of automation. The opposite was the case in most of the EU14 countries, so if work organization in CEE countries were to become more like the EU14, the risk of automation would rise.

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

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Appendix

A1. Data

We encountered two major problems with exploited data. The first problem stems from changes of the ISCO classification, while the second 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. It 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 tasks seems implausible as agriculture is typically associated with routine and manual tasks (Arias *et al.*, 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 years 1998–2010 and in each country identified at least three that jointly constituted at least 80 percent of agricultural employment (starting with the occupations with the largest shares). In most cases the identified three-digit occupations either belonged to the 61 ISCO-88 category (*market-oriented skilled agricultural and fishery workers*), or were occupations 832 and 833 (*motor-vehicle drivers* and *agricultural and other mobile-plant operators*) or occupation 921 (*agricultural, fishery and related labourers*). 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). 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).

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. Since the EU-LFS occupational data are not coded at a four-digit level, it is not possible to construct a precise crosswalk for these occupations. As this occupational group accounted for a large share of employment in wholesale and retail trade in all countries, the classification change resulted 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 percentage points 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 an OLS regression of the share of tertiary

Figure A1. Contributions of sectors to changes of non-routine cognitive analytical tasks between 1998–2000 and 2013–2015 in CEE countries.

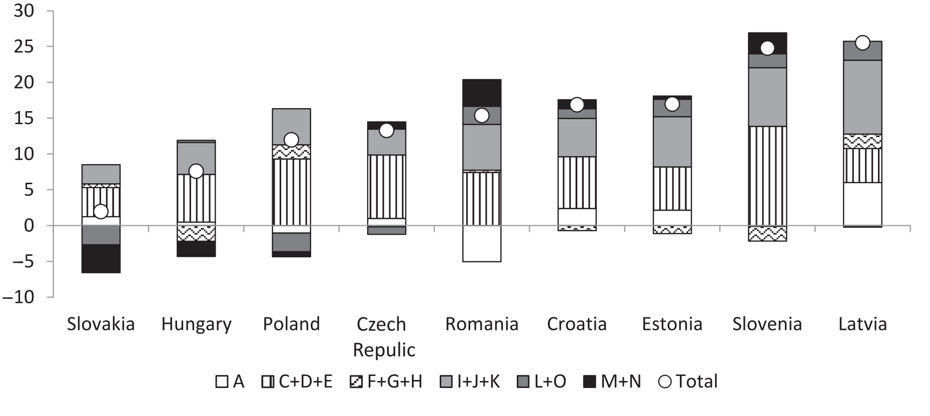
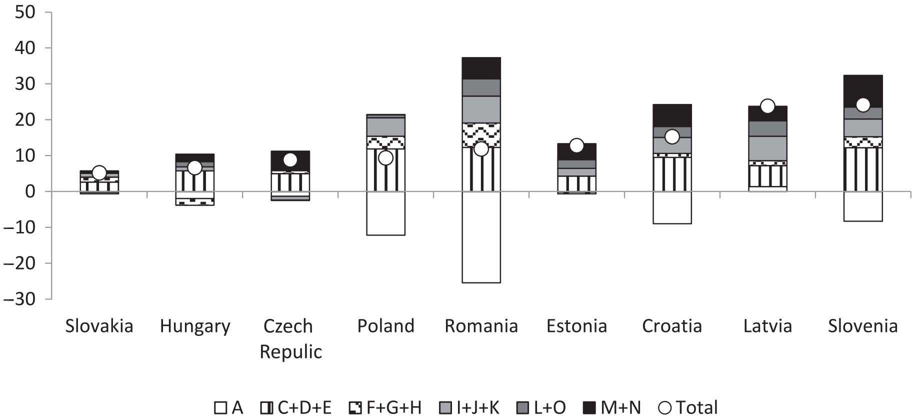


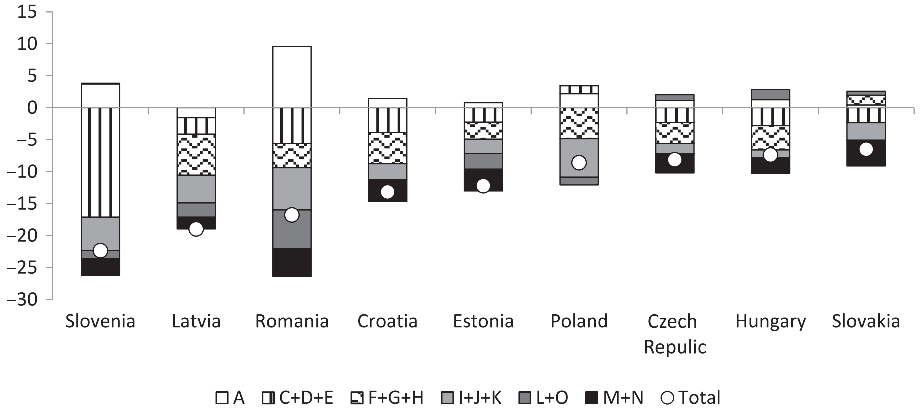
Figure A2. Contributions of sectors to changes of non-routine cognitive personal tasks between 1998 and 2000 and 2013–2015 in CEE countries.



Note: Contribution of a given sector is calculated as the sum of structural, educational, occupational and interaction effects 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. The values represent percentages of initial (1998-2000) standard deviation of a given task in each country.
*Data for Croatia are for 2002 and 2015. Lithuania is omitted due to data issues (see Appendix A1).
Source: Own calculations based on EU-LFS and O*NET data.

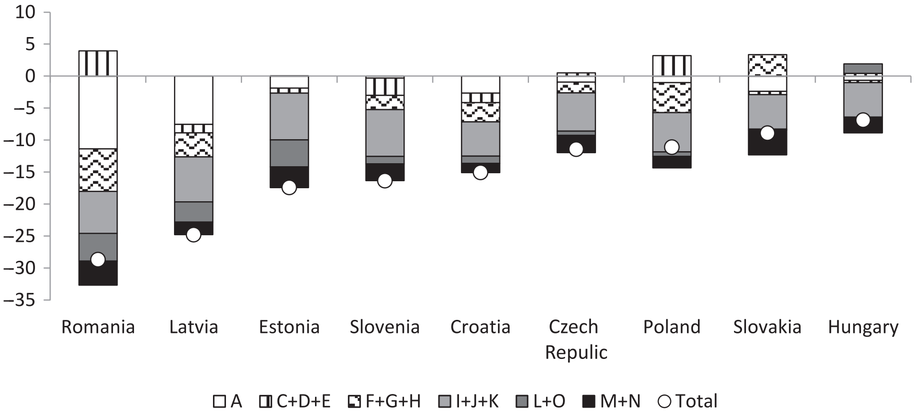
education on years and a dummy indicating the years before the shift. We then deducted the coefficient attached to the dummy from the shares of tertiary educated and added it to the shares of secondary educated before 2001. We report the corrected values in Table A3 and use them for the analyses in further sections (apart from the decomposition in the Section 3.2).

Figure A3. Contributions of sectors to changes of routine manual tasks between 1998–2000 and 2013–2015 in CEE countries.



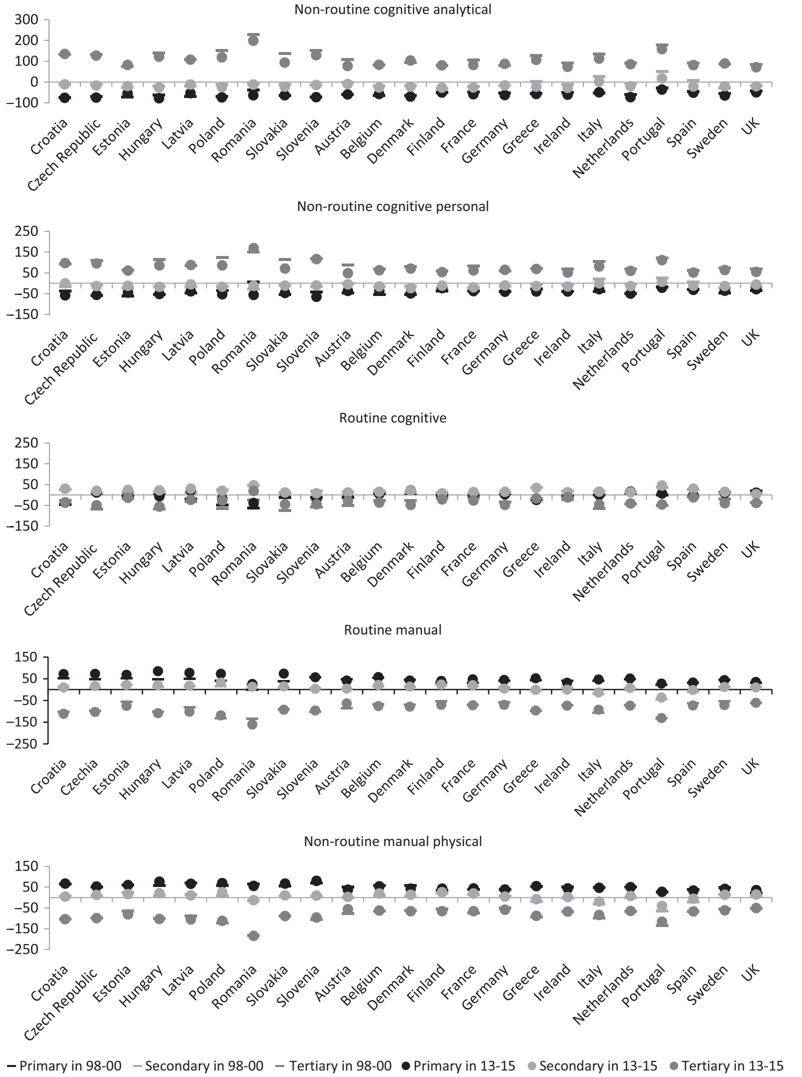
***Note*:** Contribution of a given sector is calculated as the sum of structural, educational, occupational and interaction effects in that sector. Countries are sorted by the country-level task content change. Sectors: A – Agriculture, C – Mining and quarrying, D – Manufacturing, E – Electricity, gas 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. The values represent percentages of initial (1998-2000) standard deviation of a given task in each country.
*Data for Croatia are for 2002 and 2015. Lithuania is omitted due to data issues (see Appendix A1).
Source: Own calculations based on EU-LFS and O*NET data.

Figure A4. Contributions of sectors to changes of non-routine manual physical tasks between 1998–2000 and 2013–2015 in CEE countries.



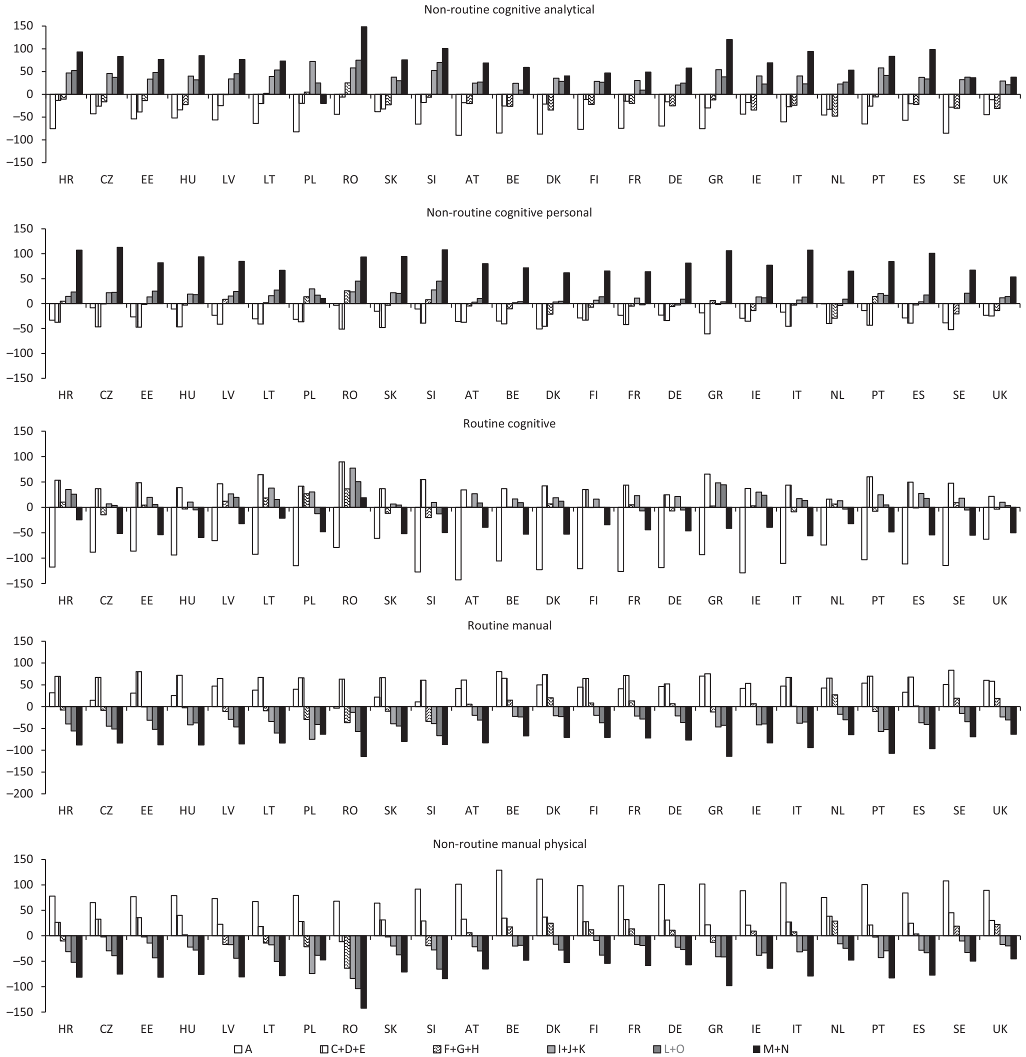
Note: Contribution of a given sector is calculated as the sum of structural, educational, occupational and interaction effects in that sector. Countries are sorted by the country-level task content change. Sectors: A – Agriculture, C – Mining and quarrying, D – Manufacturing, E – Electricity, gas and 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. The values represent percentages of initial (1998-2000) standard deviation of a given task in each country.
*Data for Croatia are for 2002 and 2015. Lithuania is omitted due to data issues (see Appendix A1).
Source: Own calculations based on EU-LFS and O*NET data.

Figure A5. Mean task content of jobs by education levels in 1998–2000 and 2013–2015.



***Note*:** Data for Croatia are for 2002 and 2015. Data for Germany, UK and Ireland are for 1999 and 2015. Lithuania is omitted due to data issues (see Appendix A1). The values represent percentages of initial (1998-2000) standard deviation of a given task in each country.
***Source*:** Own calculations based on EU-LFS and O*NET data.

Figure A6. Mean task content of jobs by sectors in 1998–2015



***Note*:** Data for Croatia are since 2002. Data for Germany, UK and Ireland are since 1999. 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. The values represent percentages of initial (1998-2000) standard deviation of a given task in each country.
***Source*:** Own calculations based on EU-LFS and O*NET data.

Table A1. Employment shares by NACE 1.1 in 1998 (in %)

	A	C+D+E	F+G+H	I+J+K	L+O	M+N
CEE10						
Croatia*	16	23	27	13	9	11
Czech Republic	6	32	27	15	9	11
Estonia	8	26	25	17	9	15
Hungary	7	29	23	15	10	15
Latvia	19	22	22	13	11	14
Lithuania	19	23	22	11	9	16
Poland	17	26	28	7	8	13
Romania	42	25	14	7	5	7
Slovakia	7	31	25	13	10	14
Slovenia	12	34	22	13	8	11
EU14						
Austria	7	22	30	17	10	14
Belgium	2	21	25	19	12	20
Denmark	4	20	24	19	9	24
Finland	7	23	20	20	9	22
France	5	21	24	19	10	19
Germany	3	26	27	16	12	16
Greece	18	16	31	13	9	11
Ireland	9	21	30	18	8	14
Italy	6	26	27	15	12	13
Netherlands	4	17	26	22	10	21
Portugal	9	26	32	10	9	11
Spain	7	21	33	15	9	11
Sweden	3	21	21	19	9	27
United Kingdom	1	20	27	22	10	19

Note: 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 are for 2002.
Source: Own calculation based on EU-LFS data.

Table A2. Employment shares by NACE 1.1 in 2015 (in %)

	A	C+D+E	F+G+H	I+J+K	L+O	M+N
CEE10						
Croatia*	9	20	27	19	10	14
Czech Republic	3	31	23	19	10	13
Estonia	4	21	26	22	11	16
Hungary	5	24	23	19	14	14
Latvia	8	16	26	24	11	16
Lithuania	9	17	27	20	10	17
Poland	11	23	30	12	10	13
Romania	26	21	23	14	7	9
Slovakia	3	28	25	17	11	15
Slovenia	7	26	23	18	9	16
EU14						
Austria	5	17	29	21	11	17
Belgium	1	14	24	24	12	24
Denmark	3	13	25	22	10	27
Finland	4	15	22	25	10	24
France	3	14	23	23	13	23
Germany	1	21	25	22	11	19
Greece	13	11	31	18	11	14
Ireland	6	13	27	24	9	21
Italy	4	20	27	22	9	15
Netherlands	2	11	26	26	11	24
Portugal	8	19	26	17	10	18
Spain	4	14	30	21	12	15
Sweden	2	12	22	26	11	27
United Kingdom	1	11	25	27	11	24

Note: 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 are for 2002.
Source: Own calculation based on EU-LFS data.

Table A3. Employment shares of workers by educational attainment, 1998 and 2015 (in %)

	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	**2015**	**Δ**	**1998**	**2015**	**Δ**	**1998**	**2015**	**Δ**
CEE10									
Croatia*	23	11	−12	58	62	4	19	28	9
Czech Republic	9	4	−5	79	73	−6	11	23	12
Estonia	12	8	−4	56	52	−4	32	40	8
Hungary	19	12	−7	65	61	−4	16	27	11
Latvia	14	8	−6	67	57	−10	19	35	16
Lithuania	13	4	−9	66	52	−14	21	44	23
Poland	18	6	−12	70	61	−9	12	33	21
Romania	36	23	−13	55	57	2	8	20	12
Slovakia	10	4	−6	78	73	−5	12	23	11
Slovenia	23	10	−13	62	56	−6	15	33	18
EU14									
Austria	21	13	−8	69	54	−16	9	33	24
Belgium	31	17	−14	37	40	3	32	43	11
Denmark	23	20	−2	53	44	−9	25	36	11
Finland	25	11	−13	44	46	2	31	43	12
France	32	16	−16	44	45	0	24	39	15
Germany	18	13	−6	58	59	1	24	29	4
Greece	47	26	−21	34	41	7	19	34	14
Ireland	35	15	−19	41	38	−4	24	47	23
Italy	50	32	−18	39	47	8	11	21	10
Netherlands	30	21	−8	46	42	−4	24	36	13
Portugal	80	50	−30	11	25	14	9	25	16
Spain	57	33	−24	18	24	6	25	43	18
Sweden	21	13	−8	50	47	−3	29	39	10
UK	30	18	−13	41	40	−1	29	42	14

Note: *Data for Croatia are for 2002 and 2015. Data for Lithuania are adjusted as described in the Appendix A1. Data for Germany, UK and Ireland are for 1999 and 2015.
Source: Own elaboration based on EU-LFS data.

Table A4. Sample sizes of the data in the first and last year of the period under study

	1998	2015
Final sample size – CEE		
Croatia*	7,825	13,273
Czech Republic	31,622	18,392
Estonia	7,006	11,478
Hungary	28,902	94,828
Latvia	7,444	17,291
Lithuania	3,905	27,079
Poland	105,497	128,067
Romania	24,378	102,365
Slovakia	12,151	37,888
Slovenia	8,404	26,290
Final sample size – EU14		
Austria	26,813	84,915
Belgium	28,840	28,840
Denmark	8,074	55,960
Finland	7,100	11,798
France	63,358	194,876
Germany	138,124	236,273
Greece	31,824	71,162
Ireland	43,486	77,813
Italy	66,703	199,634
Netherlands	25,396	41,268
Portugal	21,420	68,611
Spain	63,280	37,705
Sweden	10,004	151,526
United Kingdom	63,838	36,609

***Note*:** *Data for Croatia are for 2002 and 2015.
Source: Own elaboration based on EU-LFS data.