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Abstract

In this paper, we study the shift from manual to cognitive work in 10 economies of Central and Eastern Europe. We highlight the growth in the non-routine cognitive component of jobs, but pay particular attention to the increase in routine cognitive tasks, a trend that is pronounced in the CEE economies but absent in the most advanced economies. We show that workforce upgrading and structural change were the main factors behind the increase in all cognitive tasks, but that the growth in routine cognitive tasks is partly attributable to rising shares of routine-intensive occupations. We identify two groups of workers whose jobs depend most on performing routine cognitive tasks: middle-skilled men in the manufacturing sectors and middle-skilled women in the service sectors, who jointly represent 33% of workers in CEE. We find that robust employment and wage growth among routine cognitive workers has so far prevented job polarisation in CEE. However, the relative prices of routine cognitive tasks are already higher than those of other tasks. If the prices of routine cognitive tasks rise further while technological progress continues, routine intensive employment may gradually decline. We conclude with the policy implications of our findings.

Keywords: task content of jobs, routinisation, job polarisation, Central and Eastern Europe

JEL: J21, J23, J24, I25

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Introduction

Since the middle of the 1990s, the economic systems of the CEE countries have undergone substantial structural changes, including macroeconomic convergence and integration with global value chains. These processes have been especially pronounced in the CEE countries that joined the EU in 2004, and that are the focus of this paper.[1] Across the region, the GDP and employment shares of agriculture have declined, the shares of industry have decreased slightly, while the shares of services have increased substantially. A noticeable modernisation has also occurred within sectors. In manufacturing, new leading branches have emerged (e.g., cosmetics and rubber in Poland, machinery and vehicles in the Czech Republic and Slovakia), while traditional branches (e.g., heavy industry and apparel production) have shrunk. In services, the branches that have grown the most (e.g., financial, insurance, and real estate activities; administrative and support activities) barely existed or were undeveloped (e.g., commerce, accommodation and food activities) in the 1990s. Structural changes have led to factor reallocation and have triggered occupational changes, as particular types of activities have come to require different kinds of inputs and the labour demand structure has evolved. These developments posed challenges for workers, firms, and policy-makers.

Structural and occupational changes are linked to technological progress, and the interplay of these developments is a topic that has featured prominently in recent research and policy debates. These discussions often centre on the automation, ICT, and routine-biased technical change (RBTC) hypothesis (Autor et al., 2003; Frey & Osborne, 2013; Goos et al., 2014). Scholars have observed that RBTC increases demand for high-skilled workers who can perform non-routine cognitive work, both analytical and interpersonal, that has so far been non-replaceable by machines, and that complements ICT and automation (e.g., managers, professionals). At the same time, researchers have pointed out that RBTC decreases demand for middle-skilled workers who perform routine work, both manual and cognitive, that can already be done by machines (e.g., clerical support workers; services and sales workers; skilled agricultural, forestry, and fishery workers; craft and related trades workers; plant and machine operators and assemblers); and increases demand for non-routine manual work that is not yet prone to automation, and that can be performed by humans rather cheaply (e.g., janitors, waiters and waitresses, drivers). Changes in occupational structures and in the routine vs. the non-routine composition of jobs the US and Western Europe have been shown to be consistent with RBTC (Autor et al., 2003; Spitz-Oener, 2006), which has raised concerns that the fourth industrial revolution of the digital era will destroy more jobs than it will create (WDR, 2016). However, in CEE routine cognitive work increased between the late 1990s and the mid-2010s.

Labour supply is also a crucial factor in the composition of jobs (Oesch 2013, Salvatori 2015, Hardy et al., 2016). Non-routine and highly skilled work can only grow if the available workers are able to perform these jobs. The decline in routine jobs has more severe consequences if large numbers of workers are unprepared to perform other kind of jobs, and has less severe consequences if these workers are capable of upgrading their skills to perform more non-routine jobs. Learning more about the incidence and the character of routine employment is key to determining which workers are likely to be negatively affected by technological progress. It is especially important in emerging and transition economies, in which the routine work has so far stand firm. This is the aim of our paper, in which we focus on the CEE countries.

[1] Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia. We call this group CEE10. Because of data issues, we omit Bulgaria.

1. How has the task composition of jobs changed?

Occupational change and routine-biased technical progress are often analysed using the task approach (Autor et al. 2003; Acemoglu & Autor, 2011), which we describe in Box 1. Distinguishing between job tasks – i.e., between non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical tasks – allows us to gain a more nuanced picture of labour market evolution than distinguishing between low-, middle-, and high-skilled jobs (see the next section for a more detailed discussion). Following Hardy et al. (2016), we use the EU-LFS data from 1998 to 2013 and the O*NET occupational database to quantify the task structures of jobs in CEE.

We find that a shift away from manual tasks and towards cognitive tasks took place in all CEE10 countries. These countries experienced substantial growth in the average intensity of non-routine cognitive tasks between the late 1990s and the early 2010s (cf. Figure 1).[2] The changes were greatest in Slovenia, Latvia, and Lithuania; and were smallest in Slovakia. Non-routine cognitive personal tasks also grew across the region, but less than analytical tasks. The differences between the growth in analytical tasks and in personal tasks were most pronounced in Romania, the Czech Republic, and Estonia. At the same time, the average intensity of manual tasks, both routine and non-routine, declined in all CEE countries. The changes were again greatest in Slovenia and Latvia, as well as in Romania. The decreases in manual tasks were smallest in Slovakia and Hungary. These shifts are in line with the findings on the most developed countries (Autor et al., 2003; Autor and Price, 2013; Spitz-Oener, 2006), and with the results of other studies on Central and Eastern Europe (Aedo et al., 2013; Arias and Sánchez-Páramo, 2014).

However, the directions of changes in routine tasks were not uniform across the region:

(1) Routine cognitive tasks decreased most noticeably in Slovenia, and to a lesser extent in Hungary.

(2) The average intensity of routine cognitive tasks remained unchanged in the Czech Republic and Slovakia.

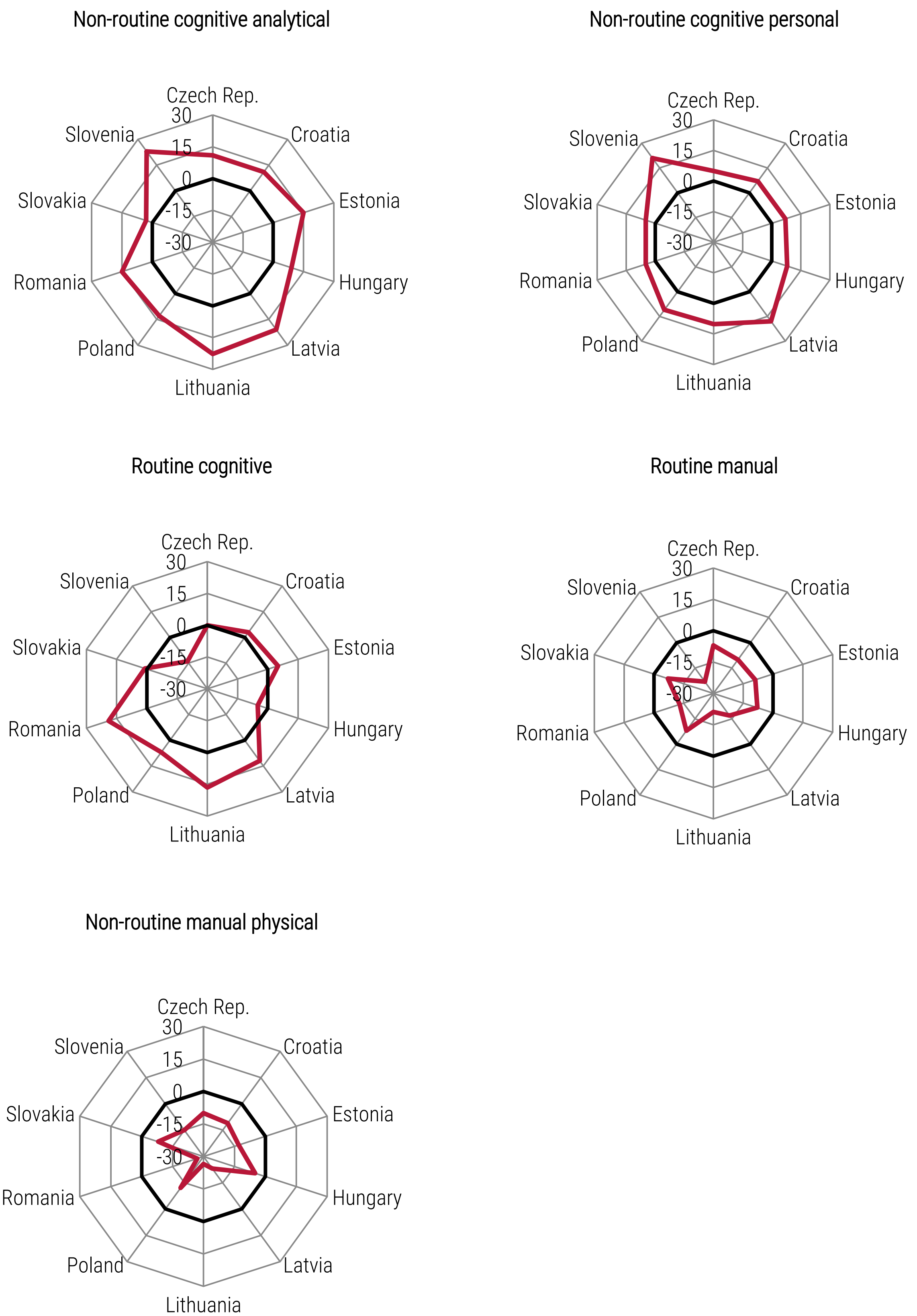
(3) The average intensity of routine cognitive tasks rose especially sharply in Romania and Latvia, and to a lesser extent in Croatia, Estonia, Lithuania, and Poland.

Previous studies also found contrasting evidence for routine cognitive tasks – Autor et al. (2003) showed that these tasks declined in the US, and Spitz-Oener (2006) generated similar findings for Germany; whereas Acemoglu and Autor (2011) and Jaimovich and Siu (2012) found diverse trends for specific periods of time or gender. However, our findings differ, as we show that routine cognitive tasks increased in the CEE countries, while in the US or in the Western European countries they declined to a various degree.

Although previous literature on the most developed countries identified automation and computerisation as factors that contribute directly to changes in the task composition of jobs, we find that in the CEE a large share of these changes can be attributed to structural change and workforce upgrading. To examine this issue in greater detail we calculated the shift-share decomposition of total changes in task intensities (between 1998-2000 and 2011-2013), identifying five separate effects related to (i) structural change, (ii) educational expansion, (iii) between-occupational shifts, (iv) within-occupation changes, and (v) the interaction of all of these factors. The within- and between-occupation effects can be interpreted as measures of the direct and the indirect impact of technology on the character of jobs (Autor et al, 2003).

[2] Relative to country-specific task structures in 1998-2000.

Figure 1. Total change in the task intensity of jobs between 1998-2000 and 2011-2013 in CEE countries.



Source: Own elaboration based on Hardy et al. (2016).

Box 1. Tasks – What are they and how can they be measured?

Tasks are not skills, but they are closely related to skills. A task is a "a unit of work activity that produces output" (Acemoglu and Autor 2011). However, workers need a range of skills to perform various tasks; for instance, an architect needs both high numeracy and math skills to perform highly non-routine cognitive tasks. Skills can be seen as the capability of workers to perform particular tasks. Researchers have distinguished between five major job task types:

Non-routine cognitive tasks are typically performed by high-skilled workers. These tasks, which are often divided into *analytical* and *personal* subcategories, require abstract thinking, creativity, problem-solving, and extraordinary communication skills. Computers complement the performance of non-routine cognitive tasks, as computers have been shown to improve the productivity of high-skilled workers. These tasks are commonly performed by professionals such as managers, designers, engineers, and IT specialists.

Routine cognitive tasks are most often performed by middle-skilled workers. Computers can serve as substitutes for workers who perform routine cognitive tasks. Routine cognitive tasks require the performance of explicit and repeatable sets of activities that can be easily coded into a computer program. Clerks, sales workers, administrative employees, and tellers are among the workers who perform these tasks.

Routine manual tasks are typically performed by middle- and low-skilled workers. Like routine cognitive tasks, these tasks are highly "codifiable" and replaceable by automation. Routine manual tasks are most often carried out by production workers such as assemblers and toolmakers.

Non-routine manual tasks are commonly performed by low-skilled workers. Carrying out these tasks requires situational adaptability, language and visual recognition, and social interactions. Drivers, farmers, mining and construction labourers are examples of workers who perform non-routine manual tasks. These workers are currently not replaceable by machines.

Tasks that belong to all five categories are performed by workers in all occupations. However, the intensities of particular task contents are highly heterogeneous across occupations. For example, car drivers spend most of their working hours performing non-routine manual tasks, but they also perform non-routine cognitive personal and routine cognitive tasks with an above-average intensity. The opposite is the case for analytical and routine manual tasks.

The O*NET database is the most commonly used source of information on the task content of occupations. The O*NET data have been collected in the US since 2003, and currently cover around 1000 occupations. The data include information on the levels and importance of various skills and abilities needed to perform particular jobs, as well as on the work activities associated with each job. The methodology used in constructing the five task content measures is outlined in Acemoglu and Autor (2011).

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

For each country we distinguished 42 education-sector cells. Details of the decomposition are presented in Appendix A1, and the results are shown in Table 1. Lithuania is excluded from the decomposition due to data issues.[3]

[3] Until 2001 "technicum programs" were assigned to ISCED 5, and hence were grouped by Eurostat into tertiary education. Since 2001 they are classified as ISCED 4 and aggregated into secondary education.

Since the late 1990s, there has been a strong increase in tertiary education attainment in the CEE countries.[4] We find that this workforce upskilling was the main factor that contributed to the growth in non-routine cognitive tasks, both analytical and personal. The role of workforce upskilling in the changes in both types of non-routine cognitive tasks was largest in Poland, and smallest in Croatia. In Hungary, the Czech Republic, Slovakia, and Poland, the changes in the intensity of non-routine cognitive tasks attributable to workforce upskilling were even larger than the recorded changes. The greater the increase was in the employment share of tertiary graduates, the greater the impact workforce upskilling had on non-routine tasks (see also Hardy et al., 2016). Structural change mattered mainly for analytical tasks. However, Croatia and Romania were the only countries where structural change was the factor that contributed the most to the increasing intensity of non-routine cognitive tasks. The contributions of between-sector shifts were greatest in the countries that had experienced a substantial reallocation of the labour force out of agriculture; with exception of Slovenia, where it was attributable to shrinking manufacturing employment and rising employment in services (especially financial intermediation, real estate and business activities, and education). The positive contributions of structural and educational shifts to the changes in non-routine cognitive tasks were, however, counterbalanced by between-occupation effects; i.e., the changes in task intensities resulting solely from shifts in the occupational structure. This means that in 2011-2013, workers at a given education level and in a given sector were on average less likely to be employed in non-routine occupations than their counterparts in 1998-2000. In other words, the occupational structure had not fully caught up with the structural change and the educational expansion in the CEE. In the countries where this effect was strongest — i.e., in Poland, Hungary, and Slovakia — it was driven by the manufacturing and education sectors.[5] Within-occupation changes were of marginal importance for the changes in non-routine cognitive tasks.

A slightly different picture emerges for routine cognitive tasks. Structural change contributed positively to the overall changes in these tasks in countries with declining shares of agricultural employment, while it compressed routine tasks in countries with declining manufacturing employment (Slovenia, Estonia). Workforce upskilling was reducing the intensity of routine tasks in all analysed CEE countries, and this effect was strongest in Poland. This negative between-education effect was fuelled by the growing number of university graduates, who usually found jobs with a below-average intensity of routine cognitive tasks. In the majority of countries, the between-occupation effect was also compressing the routine cognitive task intensity, as workers in a given education or sector category became increasingly likely to work in a less cognitively routine occupation. However, in Poland, Latvia, and Romania the opposite pattern can be observed: educational upgrading was counterbalanced by the between-occupation effect (mainly within agriculture and manufacturing sectors). Importantly, the total recorded change in routine cognitive tasks was larger than is implied by the decomposition in all countries except Poland. Although the educational, sectoral, and occupational changes were shaping routine cognitive tasks independently of each other, the education groups, sectors, and occupations that expanded (contracted) between the late 1990s and the early 2010s were mainly those that saw their routine cognitive content increasing (decreasing). As a result, the increase in routine cognitive tasks was greater (or the decrease was smaller) than is suggested by the educational, sectoral, and occupational changes only.

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[4] In 1998, the share of workers with tertiary education in the CEE averaged 17%. By 2013, this share had risen to 28%.

[5] In manufacturing this development was driven by the reallocation of workers with secondary education to jobs poor in non-routine cognitive analytical tasks, such as plant and machine operators, assemblers, and elementary occupations.

Table 1. 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
Between-sector	7	5	5	5	9	6	12	3	10
Between-education	4	11	5	12	11	19	11	11	17
Between-occupation	1	-4	5	-9	-2	-11	-9	-9	0
Within-occupation	-1	-1	-1	2	1	-1	-4	-2	-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
Between-sector	3	3	3	3	5	0	1	1	8
Between-education	2	9	4	10	9	16	9	10	14
Between-occupation	1	-4	2	-4	-2	-8	-13	-3	-2
Within-occupation	-3	-1	-3	1	3	0	-5	-1	0
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
Between-sector	4	1	-1	0	5	8	18	2	-4
Between-education	1	-6	-1	-4	-4	-10	-4	-6	-8
Between-occupation	-1	-2	-1	-6	11	8	2	-4	-8
Within-occupation	0	4	6	2	0	-1	-2	4	1
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
Between-sector	-6	-4	-5	-6	-9	-5	-4	-3	-12
Between-education	-2	-7	-3	-8	-7	-15	-7	-7	-12
Between-occupation	0	4	1	3	1	10	5	1	-2
Within-occupation	0	2	0	4	3	2	3	5	2
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
Between-sector	-6	-5	-4	-5	-9	-5	-22	-4	-8
Between-education	-1	-8	-4	-8	-9	-14	-8	-8	-11
Between-occupation	0	3	-2	8	-1	10	6	4	8
Within-occupation	-1	1	-2	1	-1	-1	-3	1	-1
Interaction	-4	-1	-1	-1	-3	-2	1	-1	-3
Total change	-11	-10	-13	-5	-23	-12	-27	-8	-15

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

The decline in the intensities of routine and non-routine manual tasks across the CEE region was again driven mainly by workforce upskilling, especially in Poland and Slovenia, which experienced the largest increases in tertiary education attainment; and by structural change, particularly in countries that experienced substantial workforce reallocation out of agriculture (Latvia, Romania) or manufacturing (Slovenia). The growth in the number of tertiary educated workers accelerated the decline in manual tasks, especially in sectors such as manufacturing and trade. On the other hand, the decline in manual tasks was somehow mitigated by positive between-occupation changes, especially in Poland, Slovenia, and Romania.

Overall, the shift from manual to cognitive tasks in CEE was mainly driven by educational and structural change. Non-routine cognitive tasks increased primarily as a result of workforce upskilling. Routine cognitive tasks rose in selected countries, especially in those that experienced a net reallocation of labour from agriculture to other sectors, and an increasing incidence of routine-rich occupations within particular sector / education cells.

2. Who are the routine workers in CEE?

The answer to this question is not as straightforward as it may seem. The majority of previous studies on job polarisation or routine-biased technological change showed that routine intensive jobs are held mainly by middle-skilled and/or middle-paid workers (Autor & Acemoglu, 2011). However, the EU-LFS data show that the mapping of education groups onto task contents is ambiguous, at least in the CEE countries. In particular, the data indicate that the middle-educated workers are spread across the distributions of routine manual and routine cognitive tasks (cf. Table 5 in the Appendix).

In the most developed countries, the incidence of routine employment (and the potential rate of replacement of labour by technology) is highest in manufacturing and services, such as administrative and support activities, trade, and repairs (Acemoglu & Autor, 2011, Goos et al., 2014). Frey and Osborne (2013) estimated for a group of OECD countries that manufacturing, transportation and logistics, and services are the sectors in which the highest shares of jobs could be replaced by automation and computerisation over the coming decades. Likewise, Marcolin et al. (2016) showed that manufacturing is highly satiated with routine employment, especially in the post-transition economies. Marcolin et al. (2016) found that Poland, Romania, and Slovakia in particular have high shares of high-routine employment in manufacturing (58%, 47%, and 46%, respectively; compared to the cross-country mean of 41%).[6] Little is known about the gender dimension of routine employment. Autor and Price (2013) showed that in the US between 1960-1990 routine cognitive intensity was higher among women than men, but that this trend reversed in the 2000s. Over the same period, the share of women in the US who were performing non-routine cognitive tasks, especially interpersonal tasks, increased substantially (Autor & Price, 2013). Black and Spitz-Oener (2010) showed that in Germany women were shifting more dynamically than men away from routine cognitive jobs and towards non-routine cognitive jobs. A small number of studies have touched upon the age dimension of these changes. Autor and Dorn (2009) showed that in the US older workers are more likely than younger workers to cluster in routine employment. WDR (2016) argued that in the developing countries, the bulk of “new economy skills”, such as non-routine cognitive skills, are concentrated among younger workers (born after 1974). Similarly, Hardy et al. (2016) found some evidence of an intergenerational divide in task content patterns in the CEE countries.

[6] Marcolin et al. (2016) calculated the routine content of employment based on only one dimension of occupations, which is their routine intensity. Yet not all jobs that involve routine tasks can be done by machines, as these jobs also frequently involve non-routine cognitive tasks that make them harder to automate. We think that the task approach provides more insight into the risk of job automation, as it provides information on non-routine content as well.

In order to create profiles of routine workers, we use latent class analysis (LCA, see Collins & Lanza, 2010).[7] We present our results for three selected CEE countries – Estonia, Poland and Slovenia – in which the evolution of routine cognitive tasks differed. Estimation results for the other countries and for a model expanded with an income decile variable are available upon request.

We have identified the two most pervasive profiles of high-routine workers in the CEE countries. The first profile is of workers employed in jobs that require them to spend large amounts of time performing both routine cognitive and manual tasks, whereas the second profile is of workers employed in jobs that require them to spend most of their time performing highly routine cognitive tasks.

The first group, which is represented by Class 1 in Tables 2-4, accounts for 17% of all workers in the CEE10. The individuals in this group had a high probability of working in a highly routine cognitive job (CEE cross-country average of 73%). We also find that on average in the CEE10, 95% of these workers were in occupations highly satiated with routine manual tasks, and worked in manufacturing (74%). In all of the CEE countries analysed except for the Czech Republic and Estonia, males constituted a majority in this class. Most of these workers had secondary education (82% on average), were aged 35-44, and were in the middle of the income distribution.

The second highly routine group (Class 2 in Tables 2-4) has been found in all countries except for Slovenia and Romania, and accounts for 16% of all workers in the CEE10. A large share of these workers were in highly or medium routine cognitive jobs (75% on average), but a large share of these jobs were poor in routine manual tasks (from 47% in Poland to 100% in Latvia, Slovenia, and Slovakia). Most of the individuals in this group were women (87% on average). In the majority of countries, the individuals in this cluster had secondary education (for instance, 90% in Poland, Table 2). However, in countries such as Estonia or Latvia, a relatively high share of these workers had tertiary education (36% in Estonia, 34% in Latvia). The members of this group also had a high probability of working in market services (dominant in Estonia, Latvia, and Hungary) or in non-market services (dominant in the remaining CEE countries). In addition, the individuals in this cluster were most often situated in the lower tail of the income distribution.

We have also identified the two most common profiles of workers with low routine cognitive task content: the first profile is poor in both routine cognitive and routine manual tasks, while the second profile is poor in routine cognitive tasks only. The first profile (Class 3 in Tables 2-4) represents the largest share of employment of all of the classes (21% on average). Most of these workers had tertiary education (77% on average; the highest share among all identified classes). The vast majority of these workers were in a job with a very low intensity of routine tasks, both cognitive (88% on average) and manual (86% on average). Workers in this cluster were scattered over market services (40%) and non-market services (42%). Women were a majority in this group (57%). Most of these workers performed jobs with high non-routine cognitive content, and were often well paid; for instance, 58% of these workers in Poland and 47% in Hungary were in the top quintile of the wage distribution.

The second group with a low routine cognitive intensity (Class 4 in Tables 2-4) exhibited an above-median intensity of routine manual tasks. In the Czech Republic, Hungary, Slovenia, and Estonia most of the individuals in this cluster were working in manufacturing or construction; whereas in the other countries

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[7] LCA allows us to find patterns of association between multivariate discrete socio-demographic variables. For the specification of models and methodological details, see Appendix A2.

(except in Romania) most of these individuals were working in market services. The vast majority of the workers in these clusters were men (almost 100% on average) and had secondary education (84%).

Finally, a separate profile of workers who were performing very low routine cognitive tasks has been identified in countries in which agriculture accounted for a relatively large share of employment. In Slovenia, Hungary, Estonia, Latvia, and Poland we distinguished a group (Class 5 in Tables 2-4) of individuals who had a high probability of working in agriculture (on average 77%). Most of these workers were men (71%), and were in highly routine manual jobs (90%). Relatively large shares of the workers in this specific cluster had primary education only (from 20% in Poland to 44% in Slovenia). Slovenia stood out, as the share of women (52%) and of workers aged 64+ (15%) in this cluster was higher in Slovenia than in the other countries.

Table 2. LCA estimation for Poland, 2013 (in %)

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
	Factory workers	*Simple services and office workers*	*High-skilled professionals*	*Labourers and builders*	*Farming labourers*	*Officials and medium level office workers*	*Personal services workers*
15-24	10	6	1	8	7	3	13
25-34	27	8	33	25	19	45	34
35-44	27	19	31	26	24	31	26
45-54	23	36	18	22	26	13	18
55-64	13	29	14	18	19	6	9
65 or more	0	1	2	1	4	2	1
Tertiary educated	4	1	78	5	4	71	18
Secondary educated	87	90	22	89	76	29	79
Primary educated	8	9	0	6	20	0	3
Agriculture	0	4	1	2	62	1	0
Manufacturing	83	9	17	21	0	8	2
Construction	6	1	6	22	34	2	0
Services	8	19	40	51	0	35	97
Non-market services	3	66	36	4	3	54	0
Very low routine cognitive	0	26	89	4	1	25	0
Low routine cognitive	4	17	10	65	77	49	1
Medium routine cognitive	46	12	1	29	21	3	81
High routine cognitive	50	45	0	2	1	23	18
Very low routine manual	0	7	96	0	0	0	0
Low routine manual	0	47	3	21	0	98	76
Medium routine manual	2	46	1	74	1	2	21
High routine manual	98	1	0	5	99	0	3
Male	77	13	45	100	74	51	28
Female	23	87	55	0	26	49	72
Relative size of the group	*15*	*12*	*25*	*7*	*19*	*16*	*7*

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

Table 3. LCA estimation for Slovenia, 2013 (in %)

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
	Factory workers	*Simple services and office workers*	*High-skilled professionals*	*Labourers and builders*	*Farming labourers*	*Officials and medium level office workers*	*Personal services workers*
15-24	8	3	1	7	32	8	13
25-34	23	25	26	27	11	34	23
35-44	27	31	36	30	9	28	23
45-54	34	30	24	28	11	23	33
55-64	9	9	12	8	21	7	7
65 or more	0	1	2	0	15	0	1
Tertiary educated	3	54	83	8	7	22	8
Secondary educated	79	45	16	79	50	76	86
Primary educated	18	2	0	12	44	1	6
Agriculture	1	1	0	0	98	1	3
Manufacturing	67	9	11	23	1	10	1
Construction	6	3	2	46	0	0	0
Services	24	32	53	22	1	83	34
Non-market services	2	55	34	9	1	7	62
Very low routine cognitive	0	43	100	0	98	0	0
Low routine cognitive	0	0	0	74	0	62	96
Medium routine cognitive	50	38	0	26	2	33	1
High routine cognitive	50	19	0	0	0	5	3
Very low routine manual	0	0	98	0	0	0	0
Low routine manual	2	100	2	1	0	88	4
Medium routine manual	7	0	0	99	0	12	96
High routine manual	91	0	0	0	100	0	0
Male	77	35	41	97	48	46	18
Female	23	65	59	3	52	54	82
Relative size of the group	*17*	*37*	*19*	*4*	*6*	*9*	*8*

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

Table 4. LCA estimation for Estonia, 2013 (in %)

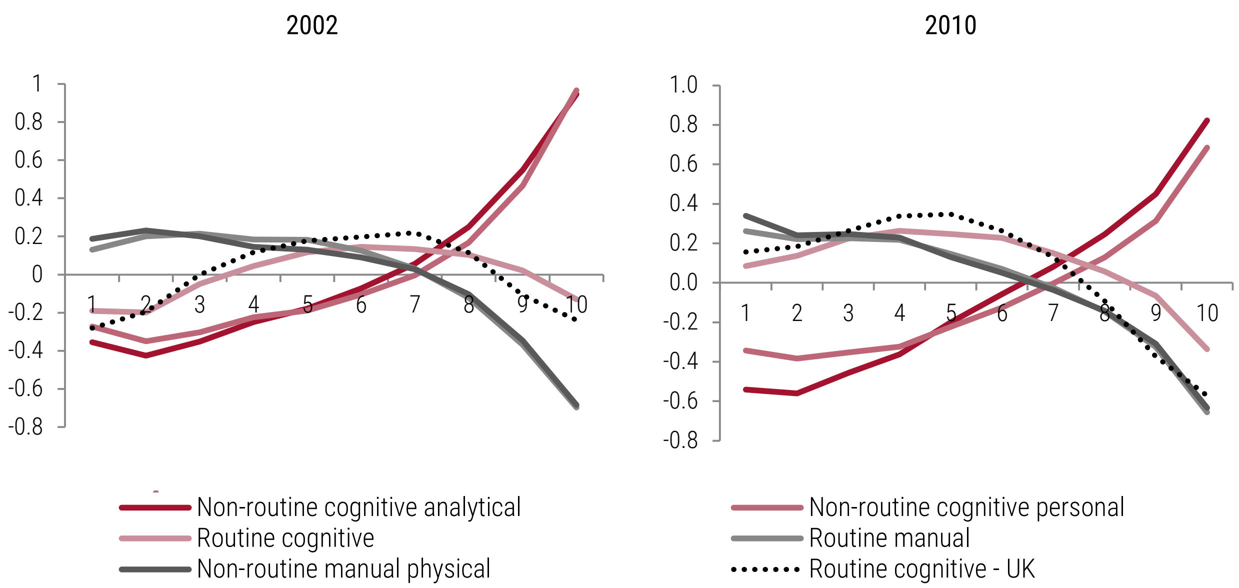
	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
	Factory workers	*Simple services and office workers*	*High-skilled professionals*	*Middle-skilled labourers and builders*	*Farming labourers*	*Officials and medium level office workers*	*Low-skilled builders*
15-24	9	11	5	5	11	14	6
25-34	21	21	24	24	16	26	27
35-44	21	20	28	32	22	20	31
45-54	25	24	22	25	31	22	21
55-64	21	19	17	11	19	16	13
65 or more	4	5	4	2	1	3	2
Tertiary educated	16	36	73	28	12	17	3
Secondary educated	68	59	25	64	61	70	77
Primary educated	16	5	2	8	27	14	20
Agriculture	1	1	2	6	86	0	0
Manufacturing	80	5	7	31	3	11	31
Construction	3	1	1	57	3	6	53
Services	13	61	40	6	5	74	16
Non-market services	3	33	50	0	3	9	0
Very low routine cognitive	0	0	63	45	0	0	0
Low routine cognitive	0	11	33	55	46	34	0
Medium routine cognitive	7	47	4	0	53	60	61
High routine cognitive	93	41	0	0	0	6	39
Very low routine manual	0	0	64	29	0	0	0
Low routine manual	0	50	36	1	0	22	0
Medium routine manual	2	49	0	70	21	78	0
High routine manual	98	1	0	0	79	0	100
Male	50	10	36	95	86	100	99
Female	50	90	64	5	14	0	1
Relative size of the group	*16*	*17*	*27*	*10*	*12*	*6*	*11*

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

3. How much are workers being paid to perform routine tasks?

Jobs that require the worker to perform routine cognitive tasks are still common in the Central and Eastern European labour markets, whereas in the US and the EU15 labour markets the numbers of these jobs have declined. In most advanced economies, routine cognitive jobs tend to be middle-paid (Acemoglu & Autor 2011, Goos et al. 2014). We find that this is also the case in CEE countries. In both 2002 and in 2010,[8] routine cognitive tasks were most abundant in the middle (fifth and sixth deciles) of the wage distribution. In the UK, used here for comparison,[9] routine cognitive tasks were concentrated among middle-paid workers to an even greater extent (see Figure 2). However, among the top 30% of earners, the shares who were performing routine cognitive tasks were higher in the CEE countries than in the UK. This means that in CEE, jobs with high routine cognitive content were spread more evenly across the wage distribution than in the UK (which is one of the countries with a pronounced pattern of job and wage polarisation, cf. Goos et al. 2007). However, in line with patterns observed in other countries, we find that in the CEE countries most of the workers in the top wage deciles were mainly performing non-routine cognitive tasks, while workers at the bottom of wage distribution were mainly performing manual tasks (WDR, 2016).

Figure 2. The mean tasks intensities across hourly wage deciles in 2002 and in 2010 in eight CEE countries and the UK.



Note: Average for Czech Rep., Estonia, Hungary, Lithuania, Latvia, Poland, Romania, and Slovakia.
*Source: Own calculation based on EU-SES and O*NET data.*

Unlike in the Western European countries, in the CEE countries there was solid growth in the hourly wages for jobs rich in routine cognitive tasks and poor in non-routine cognitive tasks. Figure 3 shows the mean real annual growth rate by major ISCO group of occupations between 2002 and 2010, and the initial value of relative routine cognitive intensity (RTI).[10] We can see striking differences between the patterns observed in

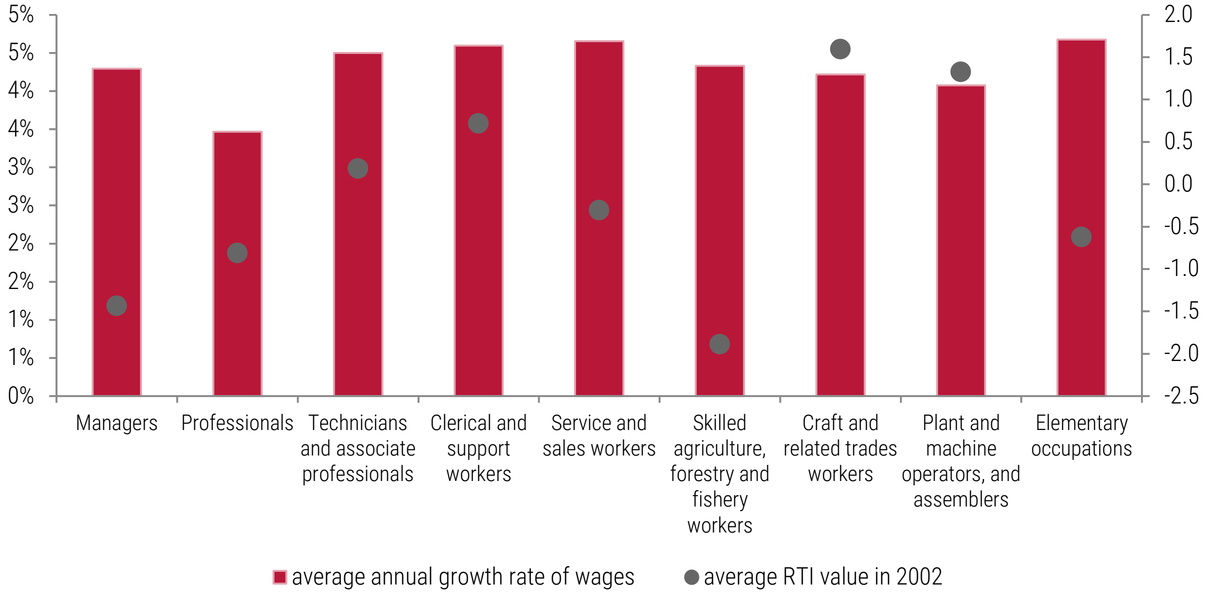
[8] At the time of writing, the most recent EU Structure of Earning Survey (EU-SES) data available were from 2010.

[9] We use the case of the UK as a comparison as it is a well-known example of a European country that has undergone job and wage polarisation (as documented by, for instance, Goos et al. (2007)).

[10] Routine intensity index is defined in more detail in Appendix A2.

the literature for Western European countries (Goos et al. 2007, Goos et al. 2014, Eurofound 2015) and the patterns we have found for the CEE countries. In the highly routine occupations such as clerical support or service and sales, wages were increasing at a faster pace than in the non-routine cognitive jobs, such as manager or professional. This was definitely not the case in the Western European countries (Goos et al. 2007).[11] Moreover, the real wage growth rates for occupations with the highest relative routine cognitive intensity in 2002 (occupation groups 7 and 8 of the ISCO classification) were similar to those of managers, and higher than those of professionals.

Figure 3. Annual real wage growth rates in the period 2002-2010 (left axis) and the relative routine cognitive intensity (RTI) in 2002 (right axis) by major group of ISCO occupations.

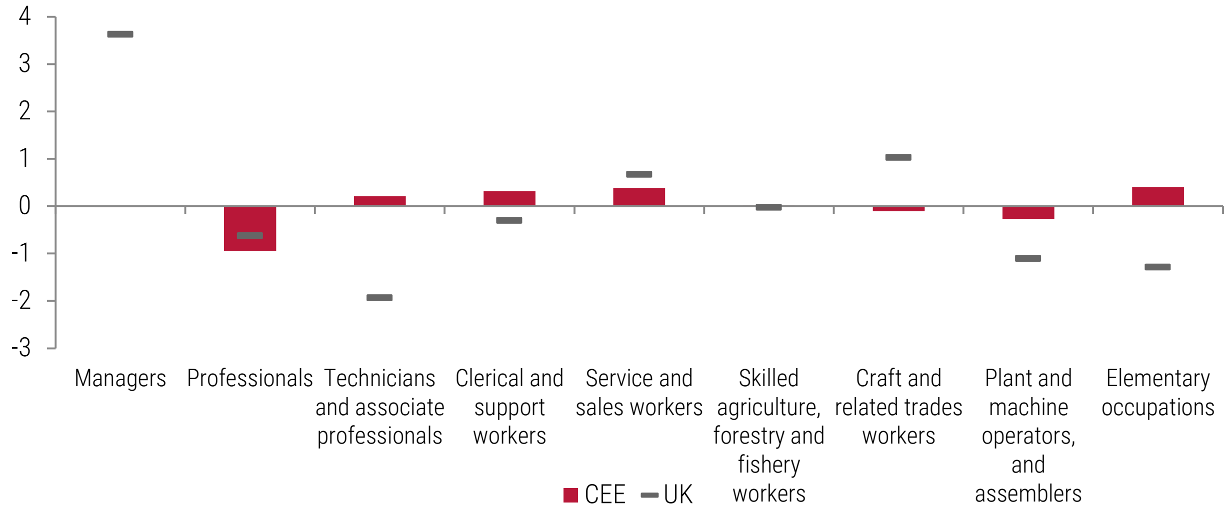


Note: All values are calculated using the weighted average and the relative size of employment of a particular country as weights. Individual EU-SES data for Slovenia are unavailable for research purposes.
Source: Own calculations based on EU-SES data.

Figure 4 confirms that these CEE wage patterns were indeed very different from the patterns identified for the most advanced economies, like the UK. The figure shows the annual wage growth in a given occupation relative to the wage growth in all remaining occupations for the CEE countries jointly, and the UK. We can see that in the UK the wages of managers rose much faster (by 3.6 pp. per year between 2002 and 2010) than the average wages across the other occupations. In the CEE countries, by contrast, the wages of managers increased at virtually the same pace as the wages of all other occupations on average. However, in CEE the highest real wage growth was in service and sales occupations. Moreover, CEE workers in elementary occupations enjoyed real wage growth that was 0.4 pp. per year higher than the average across the other occupations. Finally, the wages of clerical and support workers declined relative to the wages of other occupation groups in the UK, but inched up in CEE. All of these findings suggest that the hypothesis that wage polarisation is driven by the routinisation of the labour force is supported by the data for the UK, but not for the CEE countries.

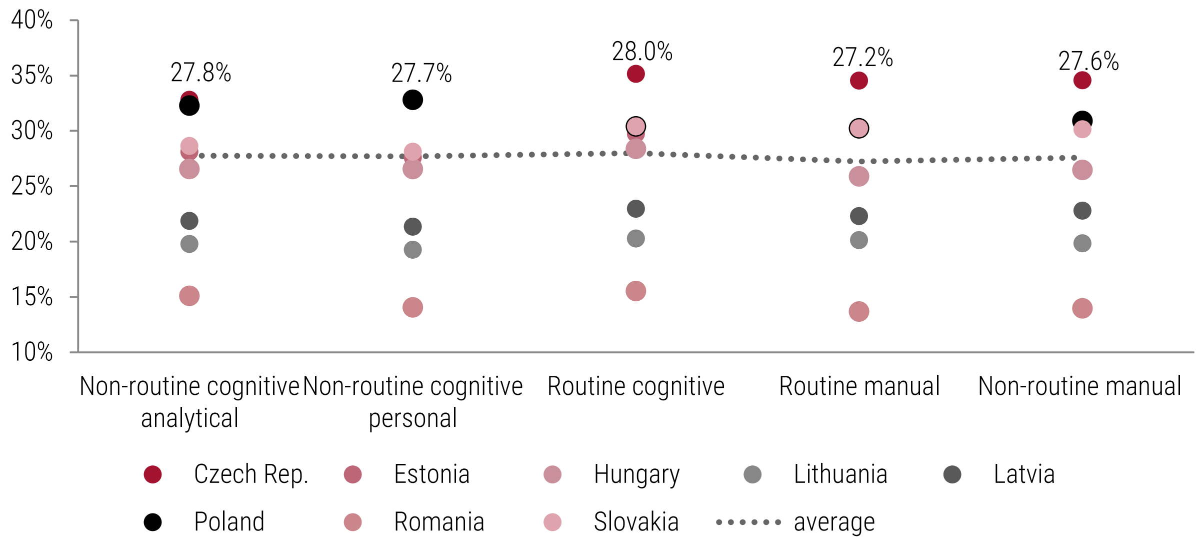
[11] On average in the CEE, the real wages of clerical and support workers and of service and sales workers rose 4.6% per year; while the real wages of managers and professionals increased 4.3% and 3.5%, respectively.

Figure 4. Annual real wage growth rates in given occupation group relative to the mean changes in wages in the remaining occupations, 2002-2010 (in pp.).



Note: The relative wage growth is calculated as a difference between wage growth in a given occupational group, and wage growth in all other occupations. Values for the CEE are calculated using a weighted average and the relative size of employment of a particular country as weights. Individual EU-SES data for Slovenia are unavailable for research purposes.
Source: Own calculations based on EU-SES data.

Figure 5. Prices of tasks in CEE relative to the UK, 2010 (in %).



Note: Individual SES data for Slovenia are unavailable for research purposes.
Source: Own calculations based on EU-SES data.

The robust performance of both the intensity of routine cognitive tasks and the wages in occupations dominated by these tasks may be partly related to the fact that wages in the CEE are lower than wages in the most advanced economies, and especially in the EU15 countries, which are the CEE countries' main partners in production and trade networks. Wages translate into the prices of tasks. The prices of routine cognitive tasks in particular may matter: i.e., as long as the prices of routine cognitive tasks are sufficiently low in comparison to the cost of the technological tools or machines that could also perform these tasks, jobs rich in routine cognitive tasks will not be eliminated (Autor et al., 2003). We have calculated the prices of tasks using the EU-SES data and the formula described in Appendix A3. Figure 5 shows that in 2010, the relative prices of all tasks in the CEE countries were slightly more than one-quarter of the prices of the same tasks in the UK, our reference country. Although the differences between the relative prices of the various tasks were small, routine cognitive tasks had become the most expensive in 2010 – the average price in CEE was 28% of the average price in the UK. Moreover, between 2002 and 2010 the relative price of routine cognitive tasks in the CEE countries increased by 13 pp., more than the prices of other tasks. Thus, if the prices of routine cognitive tasks continue to increase in CEE while they remain stable or decline in Western Europe, and if ICT prices continue to fall, CEE may lose its advantage in routine cognitive work; a job type that was crucial for employment growth between the late 1990s and the mid-2010s.

Policy implications

Between the late 1990s and the mid-2010s, the Central and Eastern European labour markets underwent a substantial shift from manual to cognitive work, which can be largely attributed to structural change and workforce upgrading. As in the US and the EU15 countries, the importance of non-routine cognitive tasks increased substantially in the CEE economies. However, a crucial feature that distinguished CEE from Western labour markets was the resilience of routine cognitive tasks. Among the CEE countries, a decline in routine cognitive jobs similar to that of the most advanced economies occurred only in Hungary and Slovenia; while in Romania, Latvia, Lithuania, and Poland the average intensity of routine cognitive tasks increased substantially. Structural changes are to blame for these different evolutions of routine cognitive tasks. While the Western European countries have experienced severe and deep deindustrialisation, which largely contributed to the hollowing-out of the middle-skilled and middle-paid workers in the 1970s-1980s, the majority of CEE countries have not (Eurofund, 2015). Structural change in CEE mostly encompassed the decline of agriculture, which is a largely manual-intensive sector, whereas the deindustrialisation process was quite shallow. This resulted in decreasing manual content of jobs and increasing cognitive content of jobs, especially routine one. Therefore, these patterns are not a cause for concern, as they have largely been driven by sectoral shifts that are typical for economies converging with the most developed economies. Nevertheless, in several sectors and countries workers started performing more routine cognitive jobs than their (less numerous) peers with the same educational level 15 years earlier. Moreover, the CEE region has not yet experienced wage polarisation, as the wages of middle-skilled, routine intensive jobs have increased substantially across the region. Increases in routine intensity and in wages for routine jobs suggest that the demand for routine cognitive work was probably increasing in the CEE during the period studied.

These patterns can, however, change in the future. As technology becomes more widespread and less expensive, the comparative advantage of routine workers will most likely shrink.Our results show that in 2013 33% of workers in CEE had a highly-routine job which made them susceptible to automation. Arntz et al. (2016)[12] found that in 2012 workers in some CEE countries (the Czech Republic, Poland, Slovakia) were more highly concentrated in occupations at high risk of automation than workers in the US, but that they were performing duties that are relatively hard to automate, which reduced the risk of automation. The opposite was the case in most of the EU15 countries. If the patterns of work in CEE become more similar to those in the EU15, the risk of automation will rise substantially.

[12] 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.

Thus, policies aimed at alleviating the negative employment effects of this shift from routine labour-intensive production to technology-intensive production are of crucial importance. In the area of life-long learning, the CEE countries are still constrained by a mix of low levels of awareness among workers of the need to retrain; undeveloped and/or inefficient adult education systems; and low levels of private spending, in particular by employers. We believe that life-long learning in the CEE countries should be improved, and that the ability to work in a technology-rich environment should be nurtured in every worker. However, we also believe that such initiatives are unlikely to transform all prime-aged routine workers into top non-routine workers, and that some of these workers might need to remain in routine jobs. Thus, countries should seek to keep taxes on workers earning below-median wages as low as their social security systems and fiscal stances allow. A lower tax burden would support the net income of workers who mainly perform routine cognitive work, and could also limit the potential wage pressures that may reduce demand for routine work. In addition, vocational education curricula should take into account forecasts that the numbers of routine intensive jobs will shrink in the future, and that jobs intensive in non-routine manual tasks, especially in high-quality services requiring interpersonal interactions, can provide a middle-paid alternative. Wisely regulated platform economies may also grow into important additional sources of employment and income for workers who are currently performing routine tasks.

However, the CEE countries should avoid trying to stem the tide of technology-complementary, non-routine cognitive work, and should instead support the growth of this type of work with both labour supply and labour demand side policies. A key challenge is to improve and modernise the field of study structure of higher education so that more graduates are equipped to enter occupations intensive in non-routine cognitive tasks. Although the numbers of university graduates have risen in CEE, these countries have struggled to adapt their traditional field of study structures, which could contribute to an over-supply of routine workers in the future. Because cognitive gaps developed at an early age are extremely hard to overcome later in life, it is crucial that all school pupils learn basic skills, and especially numeracy and problem-solving skills. Access to pre-school education and child care should be universal, and participation in pre-school education should be the default option for all children. On the labour demand side, the increasing productivity and digital intensity of firms may be expected to generate higher numbers of non-routine cognitive jobs.[13] Among the policy approaches that would support the further convergence of technology adoption by CEE firms are maintaining a regulatory environment conducive to the further rise of ICT capital stocks and broadband penetration; promoting competition between providers to ensure that businesses have access to high quality, affordably priced digital services; and promoting openness in the trade of goods and services.

[13] According to the Eurostat Enterprises Survey, the shares of enterprises with high digital intensity varied from 10% to 20% in the CEE countries (2015). These levels were similar to those of Greece, Italy, Portugal and France; and were far lower than the shares of 40%-50% observed among the leaders, including the Netherlands and Denmark.

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Appendix

A1. Shift-share decomposition

For each country we distinguish 42 education sector cells. For each task i we decompose the change (between 1998-2000 and 2011-2013) of the average task intensity per worker, TI_i, into contributions of five factors:

(i) changes in the sectoral structure (between-sector effect), BS_i;
(ii) changes in the educational structure (between-education effect), BE_i;
(iii) changes in the occupational structure (between-occupation effect), BO_i;
(iv) changes in the task content intensities within a particular occupation (within-occupation effect), WO_i; and
(v) the interaction between shifts in the employment structure and the associated task intensities, INT_i.[14]

The decomposition is calculated for each country following the formula:

$$\forall_{i\in T}(TI_i^{2013} - TI_i^{1998}) = (\sum_{j\in S}\sum_{k\in E} t_{i,j,k,14}^{13} h_{j,k}^{13} - \sum_{j\in S}\sum_{k\in E} t_{i,j,k,03}^{98} h_{j,k}^{98}) = BS_i + BE_i + BO_i + WO_i + INT_i, (1)$$

$$\forall_{i\in T}\, BS_i = \sum_{j\in S}\left[t_{i,j,03}^{98}\left(h_j^{13} - h_j^{98}\right)\right], (2)$$

$$\forall_{i\in T}\, BE_i = \sum_{j\in S}\left(\sum_{k\in E} t_{i,j,k,03}^{98}\ \left(\frac{h_{j,k}^{13}}{h_j^{13}} - \frac{h_{j,k}^{98}}{h_j^{98}}\right)\right) h_j^{98}, (3)$$

$$\forall_{i\in T}\, BO_i = \sum_{j\in S}\sum_{k\in E}(t_{i,j,k,03}^{13} - t_{i,j,k,03}^{98})\, h_{j,k}^{98}, (4)$$

$$\forall_{i\in T}\, WO_i = \sum_{j\in S}\sum_{k\in E}(t_{i,j,k,14}^{13} - t_{i,j,k,03}^{13})\, h_{j,k}^{98}, (5)$$

$$\forall_{i\in T}\, INT_i = \sum_{j\in S}\sum_{k\in E}\left(t_{i,j,k,14}^{13} - t_{i,j,k,03}^{98}\right)(h_{j,k}^{13} - h_{j,k}^{98}) + \sum_{j\in S}\sum_{k\in E} t_{i,j,k,03}^{98}\left(h_{j,k}^{13}\left(1 - \frac{h_j^{98}}{h_j^{13}}\right) + h_{j,k}^{98}\left(1 - \frac{h_j^{13}}{h_j^{98}}\right)\right), (6)$$

whereby:

- $t_{i,j,k,14}^{y}$ 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;
- $h_{j,k}^{98}$ and $h_{j,k}^{13}$ 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 (see Box 1);

[14] The interaction term is positive (negative) if the task content i increases more (less) than is implied by changes in the sectoral structure, and by changes in the task content of jobs recorded in a given sector in the initial year of the study.

- S is the set of 14 different sectors at the NACE one-digit level;[15] and E is the set of three different educational levels (aggregated based on ISCED levels).

A2. Latent Class Analysis

LCA is a non-parametric method that, using provided covariates, creates a defined number of classes, and estimates the relative size of these classes and the conditional probabilities of having a specific characteristic conditional on being a member of a certain latent class. We estimate two types of LCA models for each country separately.[16] We use EU-LFS and O*NET data (as described in Chapter 2), and all estimations are done for 2013. We estimate seven separate latent classes for each analysed CEE country.[17] In Model 1 we include the set of six categorical variables: age group (six levels), education group (three levels), routine cognitive intensity of job held (four levels), routine manual intensity of job held (four levels), type of economic activity (five levels),[18] and sex (two levels). In Model 2 we also include information on income quintiles; though this variable is, unfortunately, not available for the Czech Republic and Slovenia. The relatively low response rate and the shortage of data on income for farmers are other obstacles to estimating this model. Therefore, in this paper we present estimations for Model 1, and the results obtained using Model 2 are available upon request.

Levels of routine cognitive intensity were estimated using the RTI measure following the approach of Autor and Dorn (2013). For the purposes of this paper, RTI is simply the difference of the natural logarithms of routine cognitive task intensity and non-routine cognitive task intensity (the average of non-routine analytical and personal intensity).[19] Using the RTI index instead of just using routine cognitive intensity provides us with the synthetic measure of the routine content of jobs, as the RTI index also takes into account the non-routine cognitive dimension of occupations. Having calculated the RTI index, we subdivided it into four quartiles and assigned very low routine cognitive jobs to the first quartile, low routine cognitive jobs to the second quartile, medium routine cognitive jobs to the third quartile, and high routine cognitive jobs to the fourth quartile. The levels of routine manual intensity of the occupations were ascribed simply by using routine manual content and dividing it into quartiles; such that the lowest quartile represents very low routine manual jobs, while the highest quartile represents very high routine manual jobs.

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[15] 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 was coupled with sector A). Therefore, the decomposition is performed for 14 economic sectors in accordance with NACE 1.1.

[16] Due to data anonymisation, information on income deciles is not available in the EU-LFS 2013 data for some countries, such as the Czech Republic and Slovenia. Hence, Model 2 is not estimated for these countries.

[17] The number of classes was decided based on the AIC and the BIC values for each model. Bayesian Information Criterion is often cited in the literature as the most reliable indicator of the LCA model goodness of fit. Although the optimal number of classes (based on BIC) differ across countries, we decided to choose the same number of classes for all the countries in the sample.

[18] We aggregate NACE rev. 1.1 economic activities as follows: A, B – agriculture, C, D – manufacturing, F – construction, G-K – market services, L-O – non-market services.

[19] Since our task content measures are standardised and take both negative and positive values, we first rescaled all task content values to be positive using the minimum value of each task content. We also dropped extreme values: i.e., higher than the 99th percentile or lower than first percentile of each task content.

A3. Prices of tasks

The prices of tasks were calculated using EU-SES data. We first excluded from the analysis all individuals with task content intensities lower than the first percentile or higher than the 99th percentile of a given task. Second, we scaled all task content intensities with their minimum values so that they all take positive values only. Then, for each task content $t \in T$, where T is a subset of five tasks and for each individual $i \in I$ we followed the formula below, and calculated the prices of tasks for each country:

$$\forall_{y \in \{2002,2010\}} \forall_{t \in T}\, p_t^y = \frac{\sum_{i \in I} tc_{t,i}^y w_i^y e_i^y}{\sum_{i \in I} tc_{t,i}^y w_i^y},$$

whereby:

- $y \in \{2002, 2010\}$ indicate a year of analysis,
- p_t^y is a price of task $t \in T$in year y,
- $tc_{t,i}^y$ is a value of task content t of individual i in year y,
- w_i^y is a weight ascribed to individual i in year y, and
- e_i^y are hourly earnings of individual i in year y.

A4. Figures & tables

Table 5. Distribution of workers with respect to the task content of jobs in CEE countries, by educational level attained, 1998 (in %)

Below median			
	Tertiary educated	Secondary educated	Primary educated
Non-routine cognitive analytical	4	53	88
Routine cognitive	80	42	65
Routine manual	94	53	43
Above median			
	Tertiary educated	Secondary educated	Primary educated
Non-routine cognitive analytical	96	47	12
Routine cognitive	20	58	35
Routine manual	6	47	57

Note: Average for the Croatia, Czech Republic, Estonia, Hungary, Latvia, Poland, Slovenia, and Slovakia. Data for Croatia are for 2003.
*Source: Own calculations based on O*NET and EU-LFS data.*

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