IBS RESEARCH REPORT 03/2017
MAY 2017

TASKS AND SKILLS IN EUROPEAN LABOUR MARKETS

BACKGROUND PAPER FOR THE WORLD BANK REPORT *GROWING UNITED: UPGRADING EUROPE'S CONVERGENCE MACHINE*

Szymon Górka
Wojciech Hardy
Roma Keister
Piotr Lewandowski

ibs research report 03/2017

may 2017

TASKS AND SKILLS IN EUROPEAN LABOUR MARKETS*

BACKGROUND PAPER FOR THE WORLD BANK REPORT *GROWING UNITED: UPGRADING EUROPE'S CONVERGENCE MACHINE*

Szymon Górka[♥], Wojciech Hardy[♠], Roma Keister[♣], Piotr Lewandowski[♦]

Abstract

Since the 1970s, the reallocation of labour from manual to cognitive jobs, and from routine work to non-routine work, has been one of the key developments on labour markets around the world. In this paper we collect the stylised facts on the evolution of the task content of jobs in European countries between 1998 and 2014. We cover a wider group of countries than covered in the previous research. We match O*NET occupation content data with EU-LFS individual data to construct five task content measures: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical. We find that the non-routine cognitive content of jobs increased in all countries while the manual content decreased in all countries. The routine cognitive content of jobs decreased in the majority of EU15 countries but it increased in the majority of the New Member States of the EU and in Portugal and Greece. We attribute these differences to different patterns of structural change. We also find some convergence in skill levels between the European countries, and a divergence in employment outcomes of workers with different education level within particular European countries.

Keywords: task content of jobs, routinisation, occupational change, skills, O*NET, PIAAC
JEL: J21, J23, J24

---

* This background paper was prepared for the 2018 World Bank Report: *Growing United: Upgrading Europe's Convergence Machine*. The findings, interpretations, and conclusions in the background paper are those of the authors, and do not necessarily represent the views of The World Bank and its affiliated organizations. This paper uses Eurostat data and OECD data. Eurostat and OECD have no responsibility for the results and the conclusions, which are those of the authors.

[♥] Institute for Structural Research (IBS), Warsaw. E-mail: szymon.gorka@ibs.org.pl.

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

[♣] Institute for Structural Research (IBS), Warsaw. E-mail: roma.keister@ibs.org.pl.

[♦] Institute for Structural Research (IBS), Warsaw, and IZA, Bonn. Corresponding author. E-mail: piotr.lewandowski@ibs.org.pl.

Table of contents

1. Introduction

The shift away from manual jobs to cognitive jobs, and from routine work toward non-routine work has been of the crucial medium term developments on labour markets around the world. Autor et al. (2003) showed in a their seminal paper that such changes occur on the US labour market since the 1970s, and attributed them to computerisation and automation of production processes. Goos et al. (2014) argued that similar changes occur in the Western European countries since the 1990s. Spitz-Oener (2006) used a unique German dataset and showed that the higher use of ICT reduced the importance of routine work. These changes have often been related to job polarisation, i.e. the hollowing out of the middle-skilled jobs and meagre wage growth among workers performing them, accompanied by the rising share and wages of high-skilled workers, and increasing shares of low-paid, simple jobs. It is worth noting that studies focused on post-transition, middle-income or developing countries confirm that the importance of non-routine cognitive work (and high-skilled jobs) increases in these countries, but are much more ambiguous regarding the evolution of routine work and middle-skilled jobs which have been rising in several converging countries around the world (Aedo et al, 2013, Gimpelson & Kapeliushnikov 2016, Hardy et al. 2018).

It has been argued that these employment shifts are driven by routine-biased technical change (RBTC) which is supposed to decrease the demand for middle-skilled workers performing routine work, both manual and cognitive, which can be replaced 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). On the other hand, RBTC is supposed to increase the demand for high-skilled workers who can perform non-routine cognitive work, both analytical and interpersonal, so far non-replaceable by machines, and complementary to ICT and automation (e.g. managers, professionals, technicians and associate professionals). Finally, it presumably increases also the demand for non-routine manual work which is not yet prone to automation, and can be provided by humans relatively cheaply (e.g. janitors, waiters and waitresses, drivers), especially if routine jobs are becoming scarce. Offshoring is the other demand-side factor identified in the literature as a potential culprit of deroutinisation and polarisation in the developed world (Goos et al., 2014, , Hummels et al., 2016). However, some authors have stressed the importance of changes in the structure of labour supply by education and labour market institutions as factors behind the composition of jobs (Oesch 2013, Salvatori 2015, Hardy et al., 2018).

The possibilities of testing the RBTC hypothesis are very limited because of data – data which provide information on workers and technology use in the workplace are rare. Therefore, researchers usually analyse whether the changes in the task content of jobs are consistent with the implications of RBTC. The approach of Acemoglu & Autor (2011) is the most detailed one as they distinguished between five task contents: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical.

In this paper we apply the methodology of Acemoglu & Autor (2011) to all European countries with available LFS data between 1998 and 2014. We use O*NET as the source of information on tasks. We aim at collecting the stylised facts on the evolution of task content of jobs and gross reallocation of labour between routine and non-routine work in Europe. We identify the contributions of various groups of workers (by gender, age, education) to the observed changes in the intensity of particular tasks. We also apply a shift-share decomposition to quantify the relative role of the demand-side factors (structural change, occupational change) and supply-side factors (educational change) to these changes. We also calculate trends in the skill levels in particular countries, under the assumption that PIAAC measures can be applied retrospectively. We also present changes in employment and unemployment rates by education in all countries. The paper is accompanied by the data appendix which includes all (and additional) results in Excel files.

2. Data & methodology

2.1 O*NET data sets

We use the Occupational Information Network (O*NET) database as a source of information for the task content of occupations. Since 2003, O*NET data has been collected in the US for approximately 1000 occupations based on the Standard Occupational Classification (SOC), and by July 2014 has been updated fifteen times.[1] In line with the approach of Acemoglu & Autor (2011), we utilise four O*NET datasets: skills, work activities, work context and abilities. Each of them contains descriptors which are measured by scales such as the importance, level or extent of the activity.[2] Since the importance and level scales are highly correlated (0.92 in O*NET 2003 and 0.96 in O*NET 2014), we follow the approach of Acemoglu & Autor (2011) and only apply the importance scale. Table 1 summarises the datasets used. Following Acemoglu & Autor (2011), we focus on five main task content measures: non-routine cognitive analytical, non-routine cognitive personal, routine cognitive, routine manual and non-routine manual physical. Each of these measures was created by adding up the appropriate standardised task items (listed in Table 2) and a subsequent standardisation of each of the resulting (five) task content measures.

Table 1. O*NET datasets used

O*NET dataset	No. of descriptors	No. of scales per descriptor	Types of scales	Data source
Skills	35	2	Importance and level	Analysts
Generalized work activities	41	2	Importance and level	Job incumbents / Experts
Work context	57	1	Importance	Job incumbents / Experts
Abilities	52	2	Importance and level	Analysts

*Source: Own elaboration based on the O*NET website.*

Table 2. Construction of task contents measures

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

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

[1] O*NET is the successor of DOT (the Dictionary of Occupational Titles) which is no longer being updated. O*NET was launched in 1998 on the basis of the BLS Occupational Employment Statistics codes. In 2003 it was changed to SOC, meaning that consistent task content measures can be calculated since 2003.

[2] The scales have different ranges (e.g. the importance scale has values from 1 to 5, the level scale from 0 to 7).

2.2 Data sources on tasks

In order to calculate tasks for the European countries, we merge O*NET datasets with the EU-LFS data for particular countries – in the period 1998-2014.[3] We apply the International Standard Classification of Occupations (ISCO) at the 3-digit level. Because the EU-LFS data for Poland include occupation codes at the 2-digit ISCO level, we instead use the LFS data provided by the Polish statistical office, which include occupations at the 3-digit ISCO level. In order to account for possible changes in the task content within occupations, we use the 2003 and the 2014 editions of O*NET.

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

The ISCO classification underwent a major revision in 2011 when the ISCO-88 was supplanted by the ISCO-08. This resulted in shifts in occupational time-series, since these two classifications are not entirely comparable. In general, we made three adjustments to achieve consistent data for the entire analysed period: a recoding of tasks items for farm workers (see also Aedo et al., 2013), a recoding of tasks for (selected) occupations in wholesale and retail trade, and a general rescaling aimed at removing the break between the 2010 and the 2011 data (discussed in the next subsection). The move from the ISCO-88 (COM) to the ISCO-08 classification led to shifts in the occupational time-series, since the classifications are not entirely comparable. In particular, in the farming occupations the non-routine cognitive task intensities are much higher in the ISCO-88 than in the ISCO-08. However, farming jobs are typically associated with routine and manual tasks (Arias et al., 2014), and involve relatively few non-routine cognitive tasks (Acemoglu & Autor, 2011). We therefore assumed that the ISCO-08 classification is more precise, and replaced the values of task items for some farming occupations in the ISCO-88 data with the task items in the ISCO-88 data. In each country separately, we selected at least three occupations that jointly represented at least 80% of the employment in agriculture (starting from the occupations with the largest shares) in 1998. For those ISCO-88 occupations, we matched the task items from the relevant occupations in the ISCO-08 (an average if more than one was matched).[5] Table A1 in the appendix presents information on which occupations were updated in particular countries in order to ensure the consistency of the task data.

Corrections were also needed in the coding of occupations in the wholesale and retail trade sector. The ISCO-08 distinguishes between salespersons and supervisors within the group 522, whereas the ISCO-88 did not. This occupational group accounts for a large share of employment in wholesale and retail trade, and thus significantly influences the task composition in this sector. Since the EU-LFS occupational data are not coded at a 4-digit level, large shifts emerged in the intensity of routine cognitive tasks between 2010 and 2011 (the time of the transition to the ISCO-08). We therefore excluded occupations 5222 (shop supervisors) and 5221 (shop

---

[3] Previous studies that use O*NET data merged with LFS data for other countries than the US include Arias et al. (2014), Goos et al. (2013), Goos et al. (2014), Dicarlo et al. (2016), and Hardy et al. (2018). Handel (2012) showed that US occupation-based and non-US skill survey-based measures lead to very similar outcomes for European countries. Cedefop (2013) confirmed that it is methodologically valid to use O*NET data to construct occupational measures in European countries.

[4] The complete set of crosswalks that we used is available online: ibs.org.pl/en/resources.

[5] We used the crosswalk available at the ILO website: http://www.ilo.org/public/english/bureau/stat/isco/isco08/

keepers) from our O*NET data; and from 2011 onwards, we assigned the mean task items of occupational group 5223 (shop sales assistants) to the occupational group 522 (shop salesperson). We found no other substantial differences in the ways in which occupations were coded in the ISCO-88 and the ISCO-08, but there are some breaks in the data that may be due to changes in country-specific classifications of occupations that are mapped into the ISCO in the EU-LFS.

2.3 Calculating the task content of jobs

In calculating the task content of occupations, we follow the procedure presented in Acemoglu & Autor (2011). Once the O*NET task items (from both 2003 and 2014 editions) are assigned to the EU-LFS data, we standardise the values of each task item over time, using the survey weights for each country separately. This approach follows the procedures used in the cross-country studies of Arias et al. (2014), Goos et al. (2014), Dicarlo et al. (2016), and Hardy et al. (2018). In the next step, we apply the Acemoglu & Autor (2011) definitions in order to construct five task content measures: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical. In the final step, we standardise the content measures over time using the survey weights for each country separately. As the standardisation of tasks measures is performed within countries, the estimated values of task contents allow for comparisons of task content levels over time within countries, but they do not allow for comparisons of task content levels between countries.

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

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

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

I have only one year before 2003 might not matter a lot

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

Table 3. Data issues (missing data or country-specific coding), by country

Country	Description
Bulgaria	There are important inconsistencies in encoding occupations. Between 2003 and 2006 we observed parallel shifts of similar magnitudes in public administration, where the number of "other associate professionals" curbed by 50 thousand and the number of "personal and protective workers" grew by approx. 40 thousand. We think that these occurring inaccuracies in the methodology of encoding occupations possibly resulted from Eurostat changing the coding guidelines. Moreover, data covers only period 2000-2014
Croatia	Data covers period 2002-2014 only.
Cyprus	Data covers period 1999-2014 only. The data for 1999 does not contain information on the unemployed.
Germany	The data for 1998 do not contain information on the last occupation for the unemployed.
France	Data lacks the information on the last occupation for unemployed individuals (in the period 1998-2011)
Iceland	Data for 1998 lacks information on education.
Italy	Inconsistencies in encoding occupations (shop keepers vs. general managers).
Lithuania	Issues with coding level of education. The data on education in Lithuania evidences a large break between the years 2000 and 2001 with a shift of around 20 pp. from tertiary to secondary education, mainly due to a change in school classification with no later breaks. We therefore did not conduct any education-related analyses for this country.
Netherlands	Data lacks the information on the last occupation for unemployed individuals (in the period 1998-2007)
Poland	We used Polish LFS data instead of the EU-LFS datasets for improved accuracy. Due to national changes in classification, we rescaled the data near the breaks in the Polish classification of occupations (KZiS) in 2003, 2005 and 2011 (see Hardy et al., 2016 for more details on KZiS changes).
Romania	Only 1-digit ISCO available
Slovenia	Only 2-digit ISCO available
Sweden	There is no ISCO-88 information for previous occupations before 2000 or in 2001 or 2002. There is no NACE v1 information for previous industries before 2000 or in 2001, 2002, or 2008. The NACE v2 covers the year 2008.
United Kingdom	Due to national changes in classifications, we rescaled the data near the break in the classification of occupations (the transition to the SOC-00) in 2001. The data for 1998 do not contain information on the last occupation of unemployed individuals.

Source: Own elaboration based on the EU-LFS data, and Eurostat (2014).

2.4 Calculating the skill content of jobs

To analyse skills, we use the Survey of Adult Skills (PIAAC) data which is available for 20 EU countries[6]. We calculate the levels of (i) numeracy skills, (ii) literacy skills and (iii) problem solving in technology-rich environments skills for each person in the microdata sets. Each skill score is constructed as an average of the ten corresponding 'plausible values' reported in the datasets. [7] Then we calculate the country-specific average skill scores in 27 occupation-education cells which are defined as the intersection of three education categories (low, medium, high) with nine 1-digit ISCO occupation groups. The average cell size (in terms of the number of observations in PIAAC) is 141, while the median is 85. The smallest cells pertain to the most uncommon

[6] Austria, Belgium, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Lithuania, Netherlands, Poland, Slovakia, Slovenia, Spain, Sweden, UK, and also Norway. Cyprus, France, Italy and Spain lack information on problem solving skills.

[7] PIAAC reports ten 'plausible values' per each of the three tests (literacy, numeracy and problem solving), that are derived through a combination of IRT scaling of the cognitive items and a latent regression model with information from the background questionnaire. The ten plausible values are highly correlated with each other and each is designed to estimate population parameters. For a detailed report on the construction of the plausible values see: OECD (2013).

combinations (e.g. low-educated professionals), while 90% of unweighted cells have at least 10 observations. However, if the actual workforce structure in the EU is accounted for with the use of PIACC weights, 99% of the entire EU workforce belongs to occupation-education cells that include at least 19 observations each.

In the next step, we assign the occupation-education skill averages (PIAAC) to individuals in the EU-LFS survey between 1998 and 2014, using the relevant information on occupation and education. The occupation information in both PIAAC and EU-LFS is coded with ISCO classification. In PIAAC it is ISCO-08, whereas in EU-LFS it is ISCO-88 between 1998 and 2010, and ISCO-08 from 2011 onwards. It is not possible to match ISCO-88 with ISCO-08 at any level of detail larger than 1-digit, hence we use the 1-digit codes. This allows us to analyse the evolution of skill intensities in the EU between 1998 and 2014, under the assumption that the average skill levels with particular education-occupation cells were constant over time. This assumption is rather strong, but accounting for changes of skills over time within such cells is not possible because there are no internationally comparable surveys of adult skills other than PIAAC.

Importantly, there are several inconsistencies in EU-LFS data (mostly stemming from inconsistencies in the national LFS datasets) that call for caution when analysing the skill trends in specific countries. The inconsistencies are all reported in the EU-LFS documentation data. The most important of them include: the change in educational groups definitions in Lithuania in 2000, the restructuring of the Danish LFS in 2007 (e.g. an increase of the sample size and changes in auxiliary information) that affected education information, and changes in the definitions of selected occupations in Italy (even at a 1-digit level). The changes in occupational classification carry a relatively smaller effect than those in education levels, as the latter are more strongly related to the changes in skill levels.

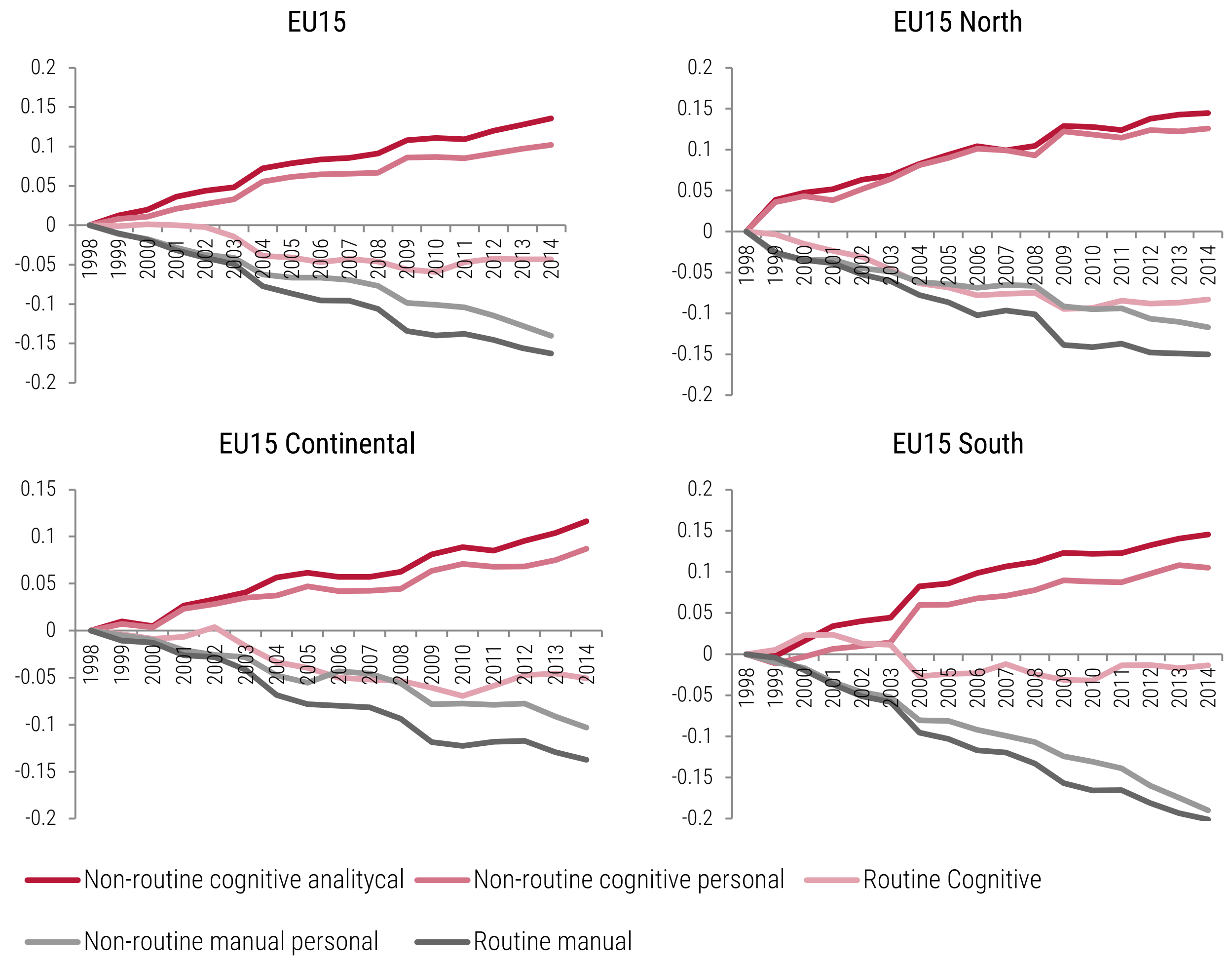
3. The evolution of task content of jobs in Europe

3.1. Overall trends in the task composition of jobs

Employment

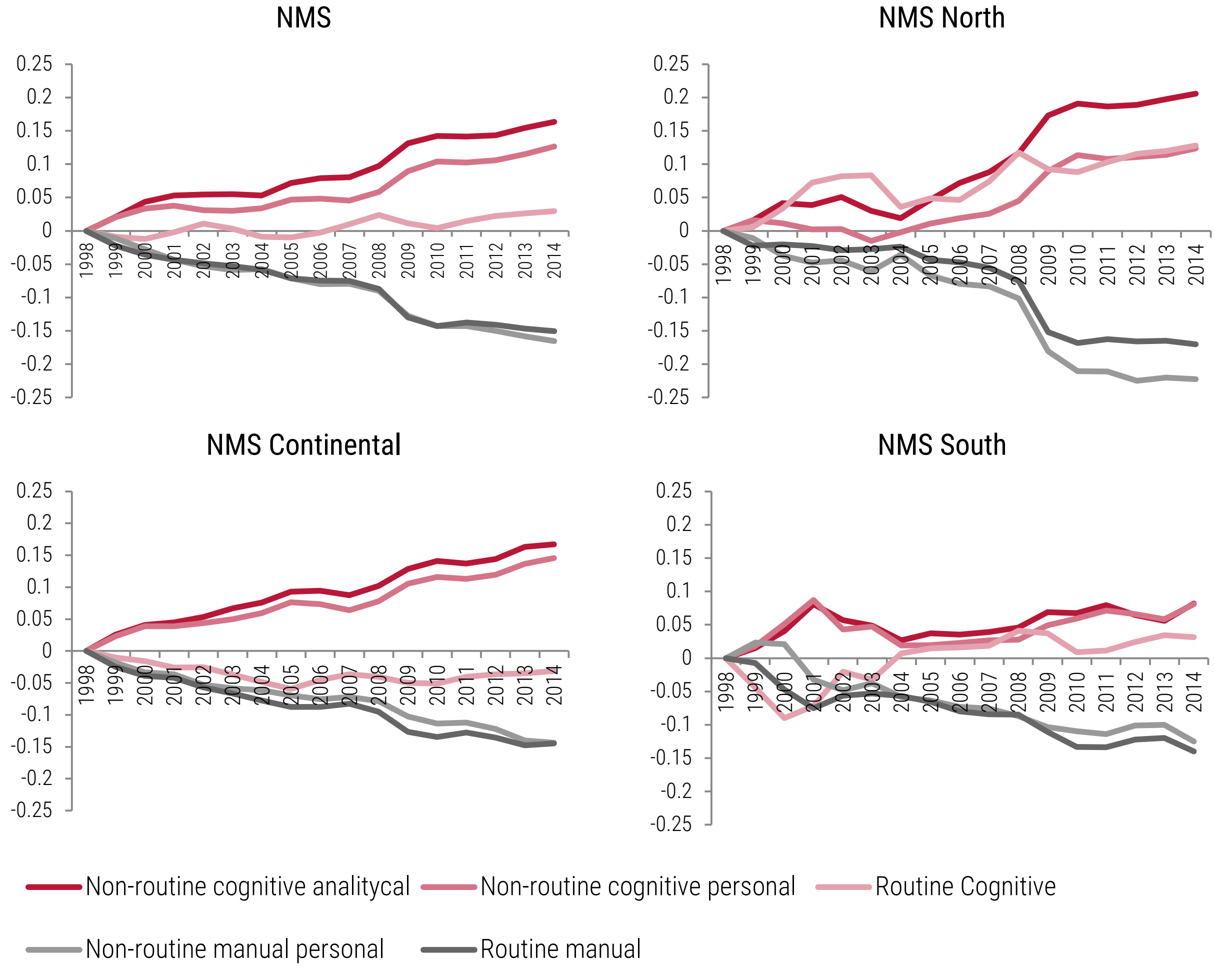
The evolution of task content of jobs was quite similar among European countries. All of them have experienced the growth of non-routine cognitive tasks, and a steep decline of routine manual and non-routine manual tasks. This was true both for the EU15 countries and the New Member States. However, what distinguishes these two regions is the trend observed for routine cognitive tasks. While routine cognitive tasks have decreased (substantially) among the EU15 countries, they have slightly increased in the NMS. There are also significant differences within different regions of the EU15 and the NMS countries. The Continental and the North of EU15 have recorded a larger drop of routine cognitive tasks (comparable to the drop in manual tasks) than the South. The Continental NMS have also recorded a similar decline of (unweighted average of) routine cognitive tasks. However, as already noted, on average, NMS have seen routine cognitive tasks slightly rising. This increase was largely driven by the northern countries of NMS, such as Lithuania, Latvia, Estonia, but also Poland, Slovakia, Romania and Bulgaria. In the southern countries of NMS, the intensity of routine cognitive tasks has barely changed between 1998 and 2014.

Figure 1. The evolution of task content of jobs (among employed) in the EU15 between 1998-2014



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

Figure 2. The evolution of task content of jobs (among employed) in the NMS between 1998-2014*



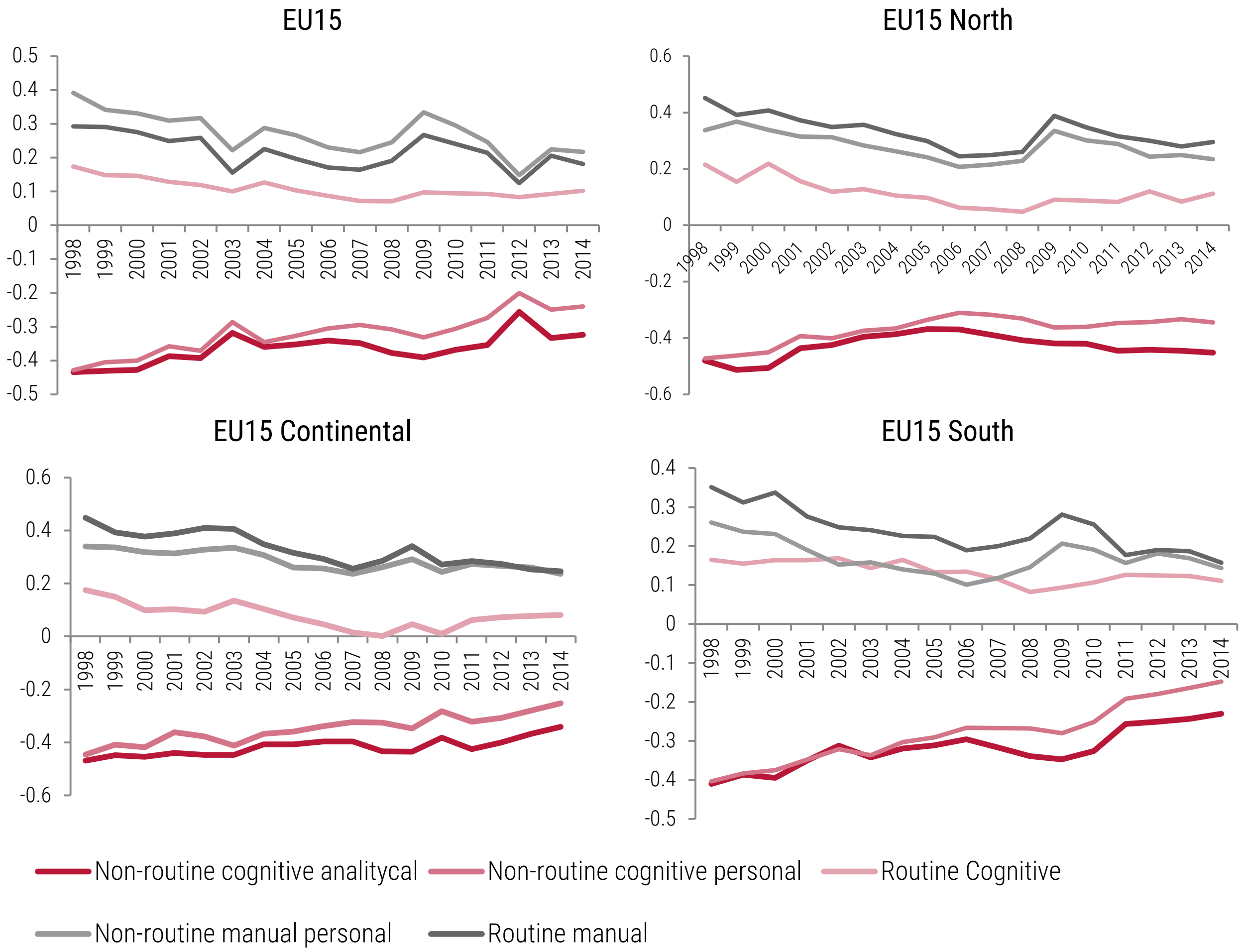
Note: The regions include: EU15 North (IE, DK, FI, SE, UK), EU15 Continental (BE, AT, DE, NL, FR), EU15 South (IT, ES, EL, PT), NMS North(EE, LV, LT), NMS Continental (SI, HU, SK, PL), NMS South (RO, BG, CR, CY).*

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

Unemployment

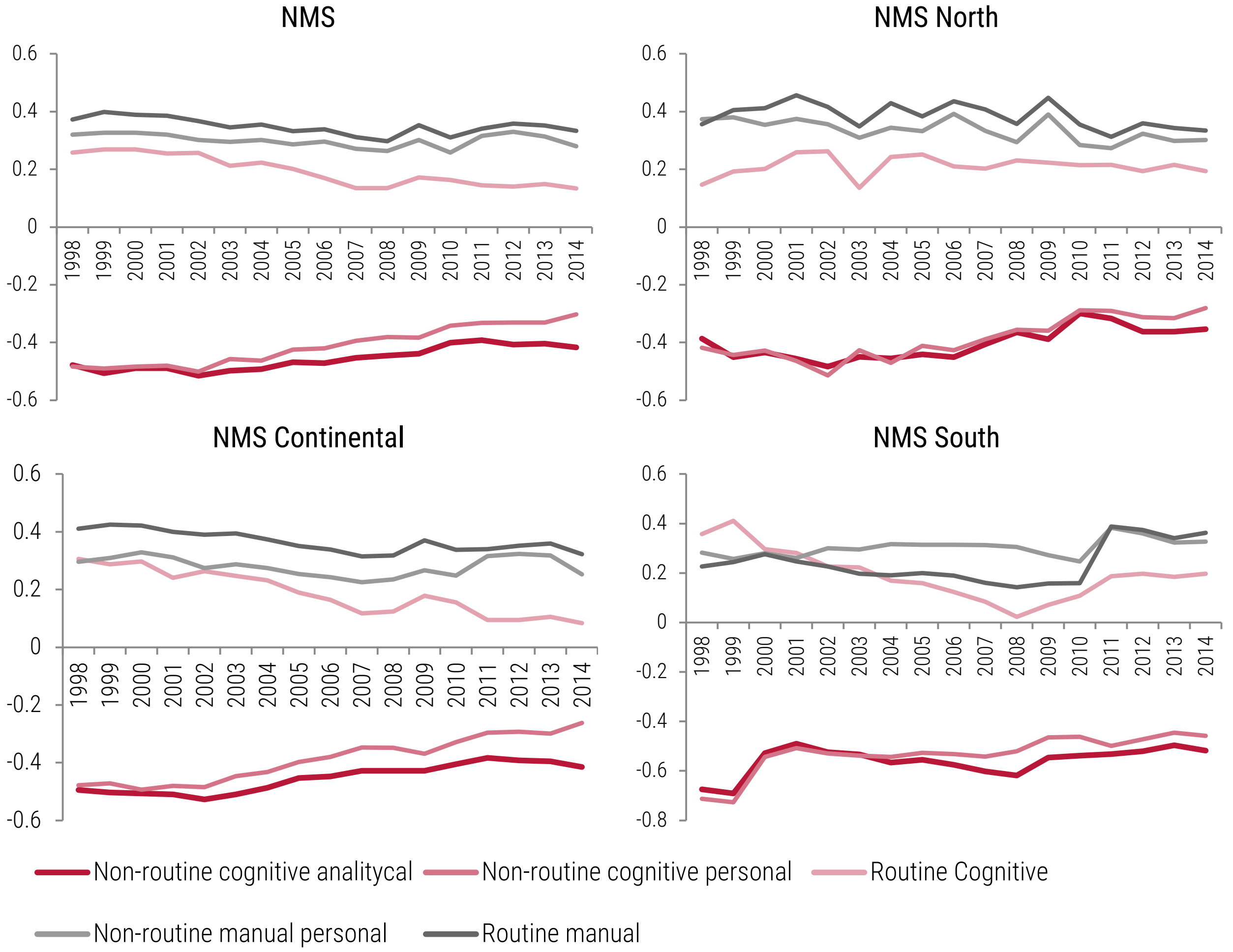
In general, the composition of tasks among unemployed individuals was quite homogenous across countries and regions – manual tasks dominated, followed by routine cognitive tasks. This means that before entering unemployment, the unemployed individuals most often had performed jobs rich in manual tasks (both routine and non-routine ones). Thus, the composition of tasks among unemployed was characterised by high intensity of manual tasks, especially of routine manual tasks. The intensity of routine cognitive tasks among unemployed was likewise high and positive (which means it was above the country-specific, economy-wide average). This was true both for the NMS and the EU15. Moreover, the intensity of routine manual, non-routine manual and routine cognitive tasks among unemployed was slightly decreasing, while the intensity of non-routine cognitive tasks inched up a little during the period studied. Yet, still, the intensity of non-routine cognitive tasks was deep down below 0, and unemployed people had been rarely engaged in these tasks before they entered unemployment. The growth in the intensity of non-routine cognitive tasks was the largest among the South of EU15 and in the South of NMS.

Figure 3. The evolution of task content of jobs (among unemployed) in EU15 between 1998-2014



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

Figure 4. The evolution of task content of jobs (among unemployed) in NMS between 1998-2014*

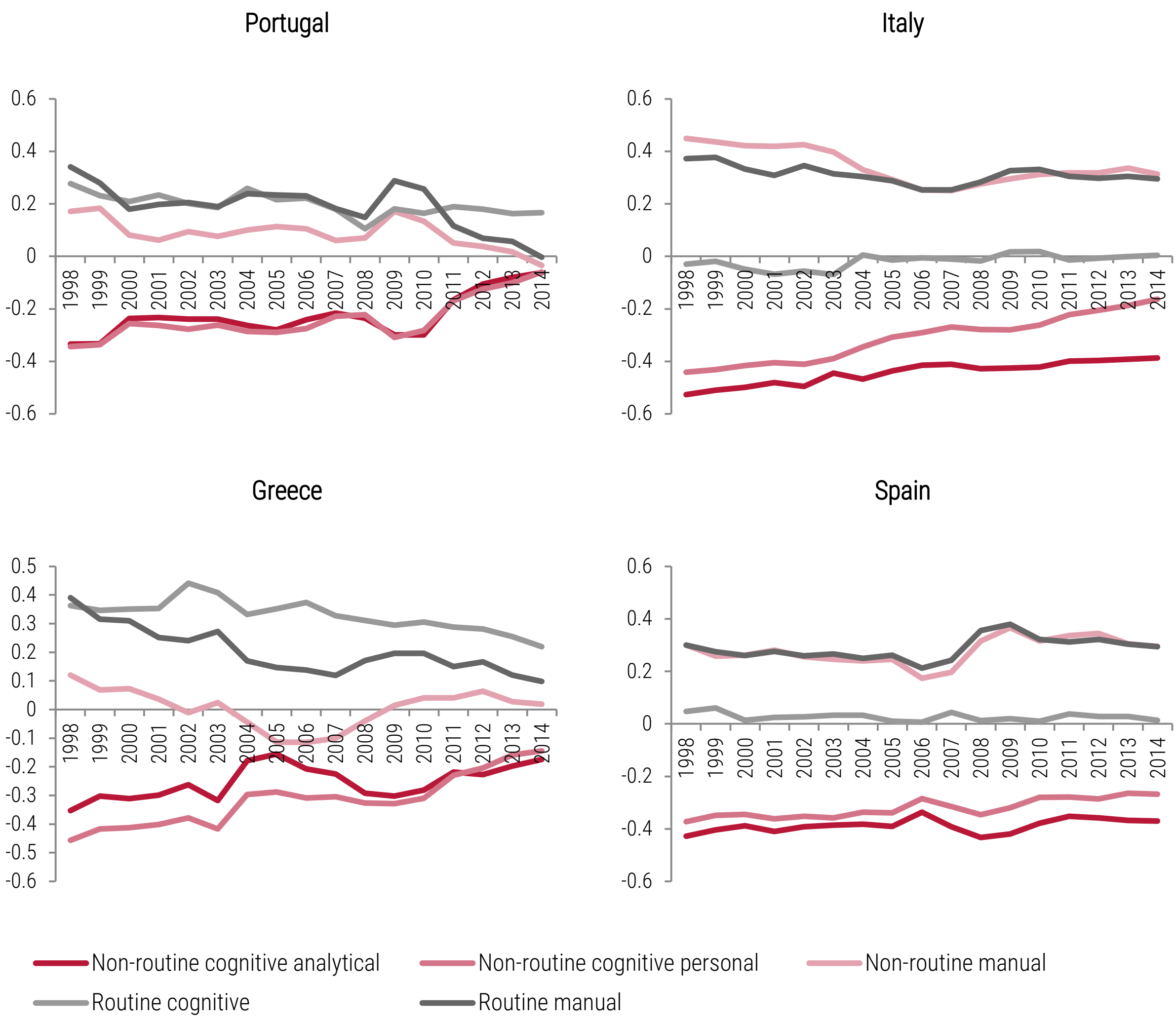


Note: The regions include: EU15 North (IE, DK, FI, SE, UK), EU15 Continental (BE, AT, DE),, EU15 South (IT, ES, EL, PT), NMS North(EE, LV, LT), NMS Continental (SI, HU, SK, PL), NMS South (RO, BG, CR, CY).*

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

At the level of country groups, the effects of Great Recession on the task contents among the unemployed are not clearly visible. This is the country groups are not homogenous in that regard. Let's focus on EU-South countries which were affected by the recession to an exceptionally large extent. However, at the country level we can observe shifts in the crisis. In Portugal and Spain there were noticeable shifts in the intensity of routine manual and non-routine manual physical tasks in 2008/2009. In Italy and Greece, there is a much higher non-response rate regarding the occupation held before unemployment (around 42-55%) in years 1998-2007. The estimated task intensity can therefore be biased due to self-selection. Still, there was a slight increase in the intensity of routine manual tasks among the unemployed in these countries. However, because changes in these countries were not uniform (nor were the relative intensities of particular tasks among the unemployed, cf. much higher routine cognitive in Greece and Portugal than in Italy and Spain), the impact of the crisis is not that visible at the level of EU15 South group, as the unweighted average eliminated some of these country-specific effects.

Figure 5. The evolution of task content of jobs (among unemployed) in the EU-South countries between 1998-2014



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

3.2. Structural, occupational and educational changes behind the evolution of tasks

To delve further into factors driving changes in particular tasks, we use a shift-share decomposition. We decompose total changes in task intensities between 1998-2000 and 2012-2014 into the contributions of: (i) changes in the sectoral structure (structural effect), BS_i; (ii) changes in the educational structure (educational effect), BE_i;(iii) changes in the occupational structure and within-occupational task content (occupational effect), OC_i; and (iv) the interaction between all these effects, INT_i.[8] For each country we distinguish 42 education-sector cells, and for each task i we use the following formula:

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

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

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

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

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

whereby:

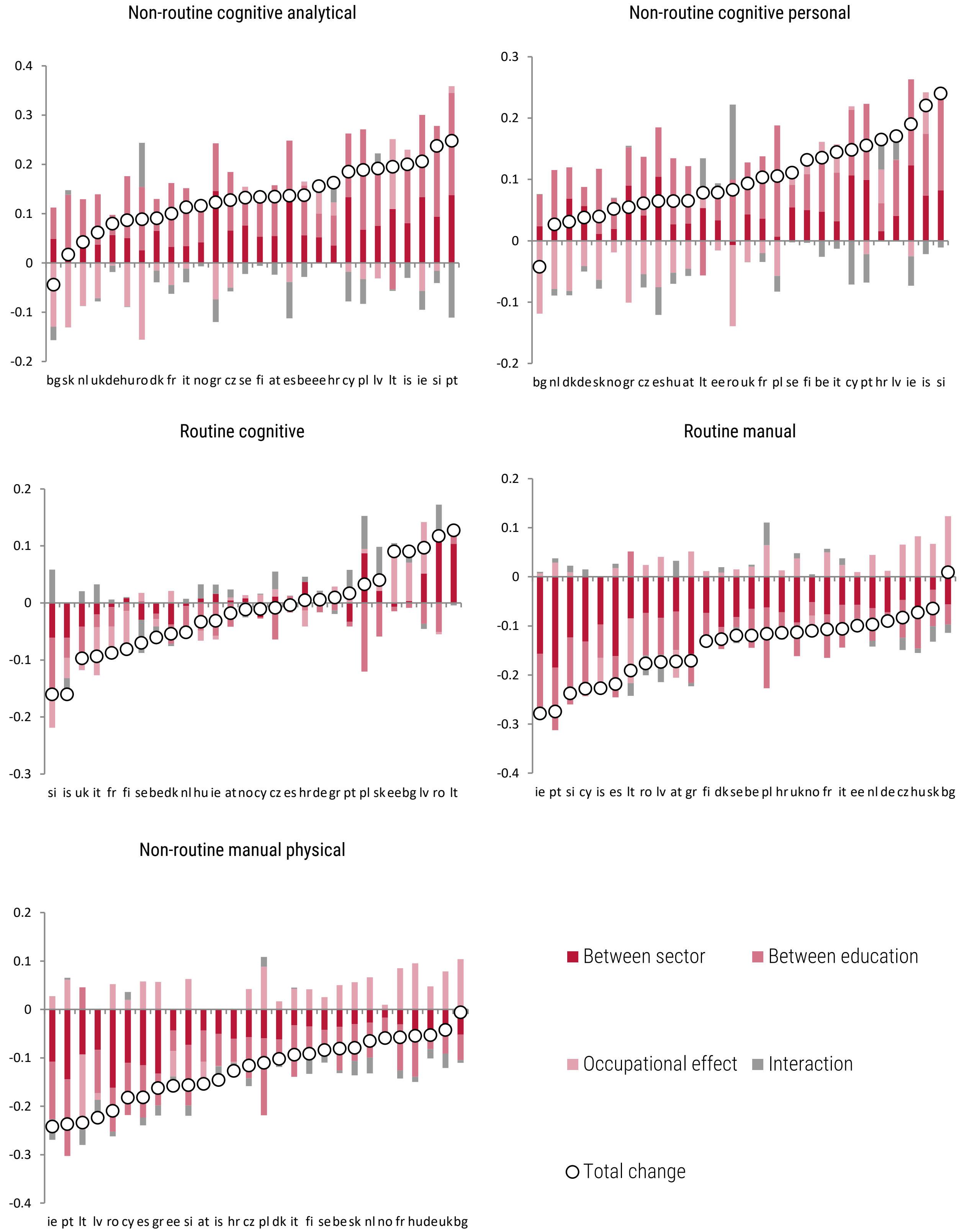
- TI_i^{1998} and TI_i^{2013} are the average intensities of task i in 1998-2000 and 2011-2013, respectively;
- $t_{i,j,k,14}^{y}$ and $t_{i,j,k,03}^{y}$ are the average values of task content i for workers in "sector j, education k" cell in period y, calculated using O*NET 2014 and O*NET 2003, respectively, variables omitting subscript k represent sectoral averages, and $y = \{1998, 2013\}$ represents 1998-2000 and 2011-2013, respectively;
- $h_{j,k}^{98}$ 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;
- S is the set of 14 different sectors at the NACE one-digit level,[9] and E is the set of three different education levels (based on ISCED).

This decomposition was initially proposed by Hardy et al. (2018). Results for all countries covered by the EU-LFS are shown on Figure 6.

[8] 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.

[9] 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.

Figure 6. The shift-share decomposition of changes in task content between 1998-2000 and 2012-2014 in European countries



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

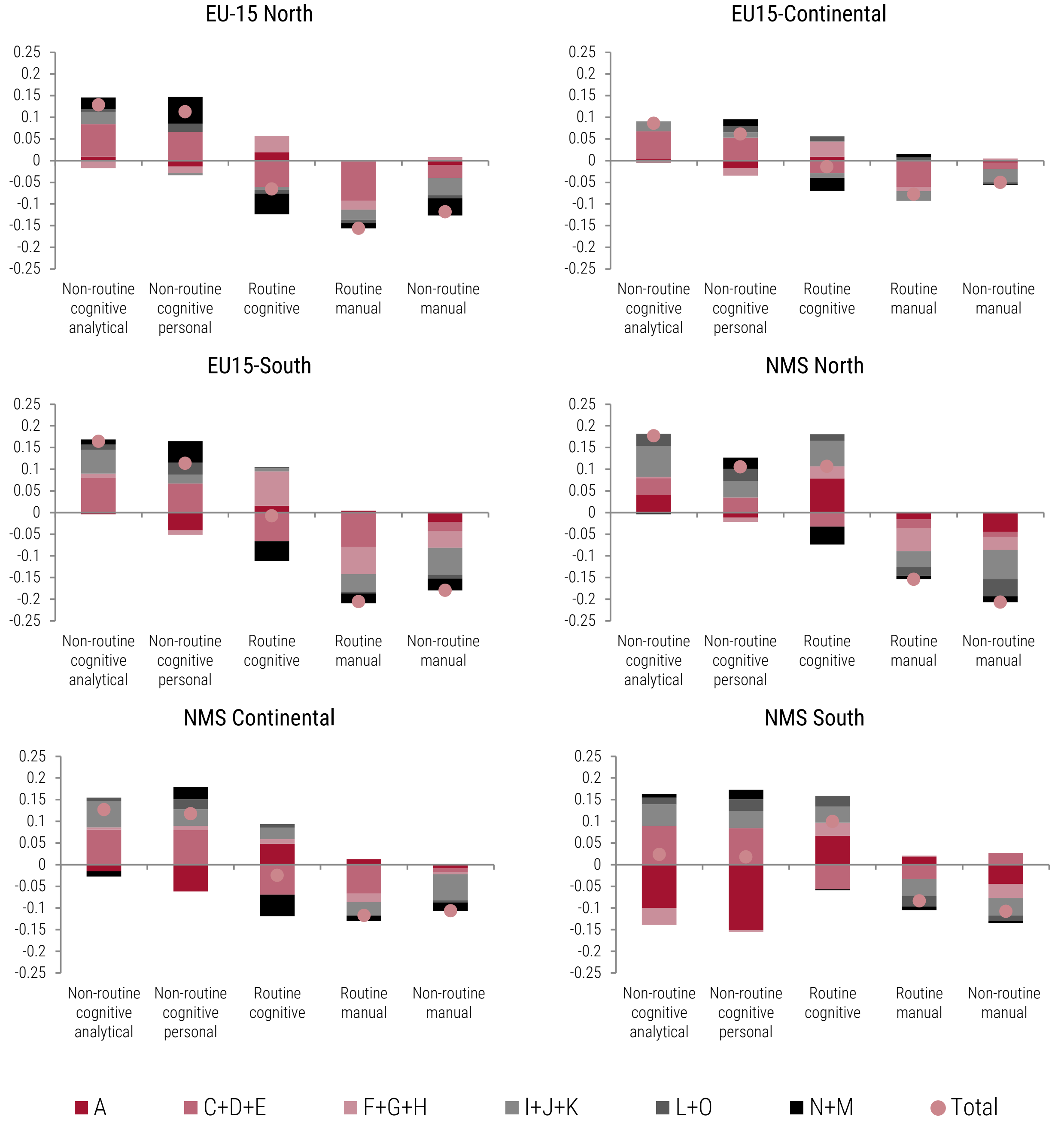
- *Non-routine cognitive tasks rose because of structural change and educational upgrading.*

Non-routine cognitive analytical and non-routine cognitive interpersonal tasks have increased mainly because of between-sector and between-education effects. The positive education effect was largely embodied in the rising workforce shares of tertiary graduates, while the source of positive between-sector effect was twofold. Firstly, decreasing shares of sectors where non-routine cognitive tasks are rarely performed such as manufacturing, and to a lesser extent agriculture, contributed to this positive effect (except for NMS South, which reported the negative contribution of agriculture to non-routine cognitive tasks change largely driven by Romania, see Figure 7). This was further reinforced by the rise of sectors rich in non-routine cognitive tasks such as health care, education, transport, storage and communication, financial intermediation, and real estate and other business activities (see Figure 7). In the vast majority of countries, however, the contribution of the between-education effect was higher than the contribution of the between-sector effect, and it was the strongest in the NMS countries which recorded substantial increases in tertiary attainment. At the same time, the occupational effect was in general negative (except for Lithuania, Estonia, Hungary and Iceland), especially in countries that recorded rather low growth of non-routine cognitive tasks (for instance, Slovakia, Netherlands, UK). This means that as sectors with the high intensity of non-routine tasks have been growing and the education structure of the workforce has been improving, workers with particular education level and in particular sectors have tended to work in less non-routine intensive occupations than their counterparts in the past. In other words, there some occupational downgrading has occurred.

- *The change of routine cognitive tasks was driven by structural and occupational changes.*

Routine cognitive tasks were suppressed by educational changes (workforce upskilling) in all countries except Lithuania and Spain), but these were the structural and occupational changes that determined the direction of changes in the intensity of routine cognitive tasks. In countries where routine cognitive tasks grew (NMS plus Portugal and Greece) it was due to positive structural and occupational changes. The gross reallocation of labour out of agriculture (a sector with jobs where cognitive tasks are rarely performed) was the main facet of structural change in the NMS. In Portugal and Greece this positive structural effect was embodied in the changes that occurred within simple services sectors such as retail and trade, and hotels and restaurant, which saw an ample increase of routine cognitive tasks intensity, and thus contributed positively to the changes of these tasks (cf. Figure 7). In countries where the intensity of routine cognitive tasks declined noticeably (UK, Italy, France, Finland, but also Slovenia and Iceland) the structural and occupational changes aligned with the educational change, but the main structural culprit of these changes was the decline of manufacturing (where jobs are relatively intensive in routine cognitive tasks). EU-15 North countries somehow stood out with the relatively strong negative contribution of education sector to the change of routine cognitive tasks, which resulted in the steepest fall of routine cognitive tasks (compared to other regions). Had the education sector not thrived, the routine cognitive tasks in these countries would have remained flat.

Figure 7. Contributions of sectors (NACE 1.1) to the task content changes between 1998-2000 and 2012-2014



Note: Contribution of a given sector is calculated as a sum of structural, educational, occupational and interaction effect in that sector. Countries are sorted by the country-level task content change. Sectors: A - Agriculture, C - Mining and quarrying, D – Manufacturing, E - Electricity, gas and water supply, F – Construction, G - Wholesale and retail trade, H - Hotels and restaurants, I - Transport, storage and communication, J - Financial intermediation, K - Real estate, L - Public administration and defense, 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. Lithuania is omitted due to data issues.

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

- *Manual tasks shrank due to structural change and educational upgrading.*

The decline of the intensity of manual tasks (both routine and non-routine) was wide-spread. It was the strongest in the Baltic countries, Southern European countries and Ireland. It was mainly driven by the between-sector effect, followed by the between-education effect. In all regions, the decline of manufacturing contributed negatively to the change of manual tasks, fuelling the negative between-sector effect. This effect was, however, larger for routine manual tasks, and lower for non-routine manual tasks. The decline of non-routine manual tasks can be largely attributed to the evolution of transport, storage and communication sector. The negative between-education effect stems from growing number of better educated workers who are less likely to perform manual tasks. The occupational effect was moderately positive in the majority of countries which shows that although the sectors that utilise a lot of manual tasks were declining while workers were getting better educated on average, the manual content of occupations increased slightly which again suggest that some downgrading of jobs happened. However, the contribution of this effect was noticeably smaller than the contribution of between-sector and between-education effect, and manual tasks declined in all countries.

3.3. Labour market outcomes & tasks (absolute approach)

In this subsection we analyse the evolution of labour market outcomes and tasks intensities in Europe from an absolute perspective. This allows us to shed more light on trends behind the shift towards non-routine tasks. We aim to answer the questions whether the shares of workers performing tasks with high routine content were declining, whether the shares of workers performing tasks with low routine content were increasing.

To this aim, we exploit a routine tasks intensity index (RTI). RTI is calculated for each occupation as a relative intensity of routine tasks, following the formula:

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

Our definition follows Lewandowski et al. (2017) and it is consistent with definitions previously used in the literature (Autor & Dorn, 2009, 2013). In line with Goos et al. (2014), we utilise task contents defined using the O*NET data (Acemoglu & Autor, 2011) instead of the DOT (previous occupational classification) values. This updated approach allows us to clearly distinguish between the routine and the non-routine tasks.[10] It also enables us to use two types of routine tasks – cognitive and manual – as indicators of the routine task intensity.[11] The RTI measure increases with the importance of routine tasks, and declines with the importance of non-routine tasks.

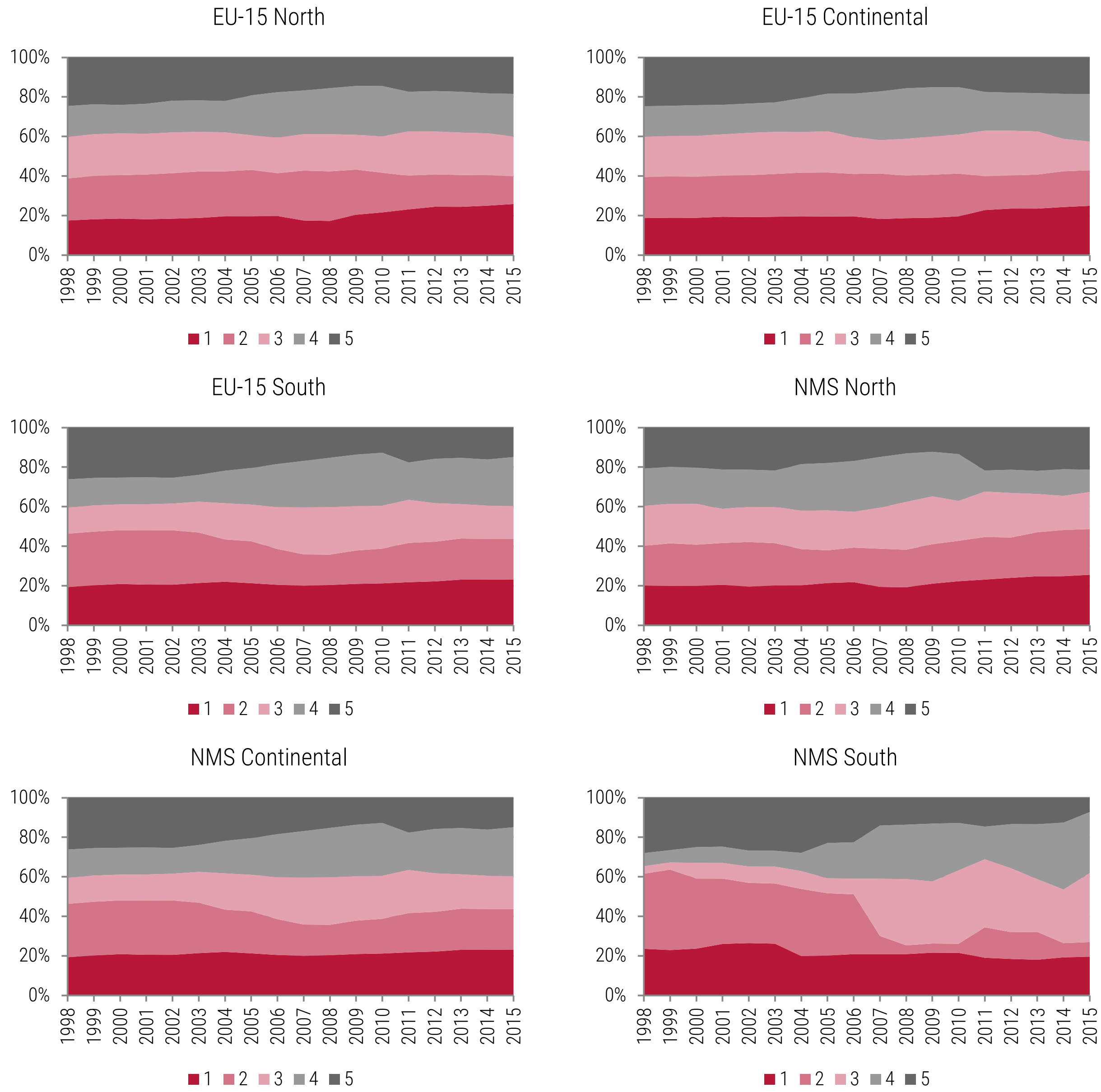
Having calculated the RTI index for each occupation and for all years (1998-2015) in a given country, we assigned a RTI quintiles to each individual in a pooled country-specific sample. RTI deciles were ascribed separately for employed and unemployed individuals, since it is likely that they represent different RTI distributions. In the next step, we calculated the employment and unemployment shares of workers with occupations ranked in particular RTI quintiles over time. The same analysis can be carried out for employment and unemployment numbers, but we think it is more convenient and clear to use employment shares. Results are presented in Figure 8.

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

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

The share of individuals employed in highly routine jobs (5th quintile of the RTI) has been steadily decreasing during the analysed period. The most visible decline was observed for NMS Continental countries, where the share of people employed in occupations in 5th RTI quintile fell from 26.5% to 15.7%. By contrast, in NMS North region the share of high routine employment remained flat (a small increase of 0.6 pp.). At the same time, the share of people employed in jobs with low routine intensity (1st quintile of RTI) grew among all regions, but the extent of this growth was not unanimous across regions. It was the highest in EU15 North countries where the share of people in 20% of least routine jobs increased by 8.3 pp. and the lowest for EU15 South countries where it inched up by 1.6 pp.

Figure 8. Employment shares by RTI quintiles in the period 1998-2015



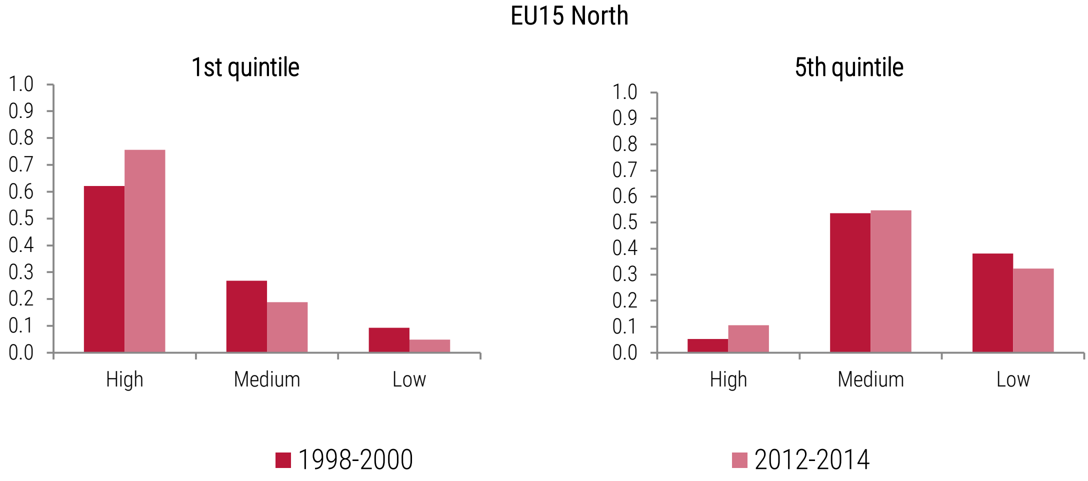
*Source: own calculations based on EU-LFS and O*NET data.*

Jobs with the lowest relative routine intensity were not only growing, but increasingly saturated with high-educated workers. Figure 9 presents the shares of workers with particular education level (low, medium, high) among the 20% of jobs with the lowest relative routine intensity and 20% of jobs with the highest relative routine intensity in particular regions in the late 1990s and the middle 2010s. Quintiles are defined for pooled country-specific samples.

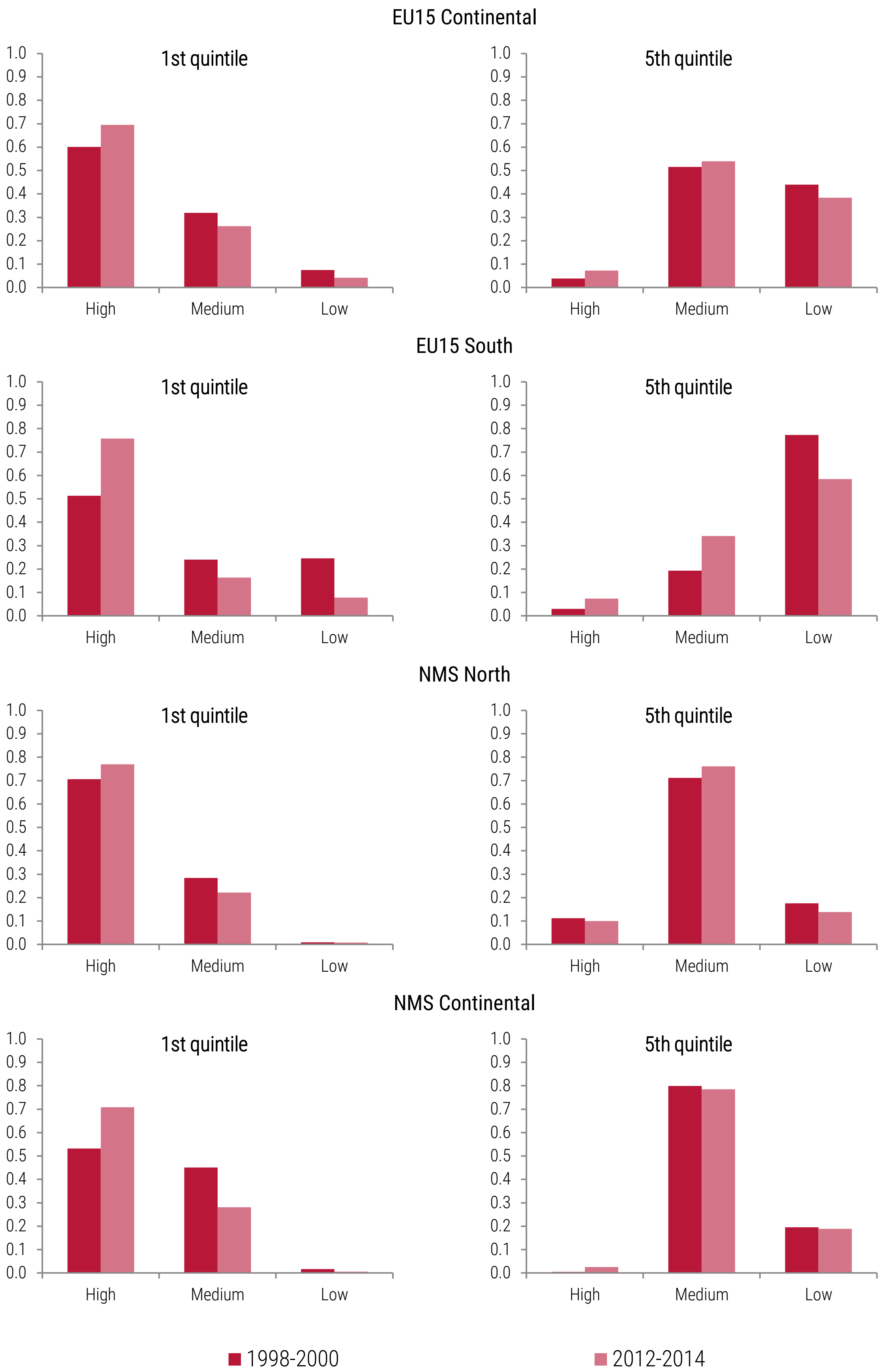
High educated individuals were an increasing majority among the (growing) pool of non-routine workers. Workers with high education (ISCED 5-8) accounted for the largest share of employment in the 1st quintile of RTI (the least routine jobs) already in 1998-2000. This was true for all regions, but the NMS South where these were the medium educated workers (ISCED 3-4) who constituted the majority.[12] By 2012-2014, the share of high skilled workers increased substantially in all regions. In the late 1990s, the medium skilled workers were the second largest group of people working in the 20% least routine jobs (except NMS South), but their share was significantly lower than that of high-skilled workers. Low-educated workers were the smallest group of workers with highly non-routine jobs, especially in the NMS countries. Moreover, the shares of low and medium skilled workers in the 20% least routine jobs declined between 1988-2000 and 2012-2014. Hence, the divide between different educational groups with respect to routine intensity of jobs has widened during the analysed period.

Mirroring the patterns observed for the least routine jobs, the highly routine jobs were dominated by low and medium skilled workers. Among EU-the 15 sub-regions the shares of low and medium skilled workers were almost equal, and did not change much during the last two decades. Among NMS countries, however, these were medium-skilled workers who were the largest group of workers in the 20% of most routine jobs. By 2014 low skilled workers in NMS South increased their share in highly routine employment, whereas the opposite was the case for NMS Continental and NMS North countries.

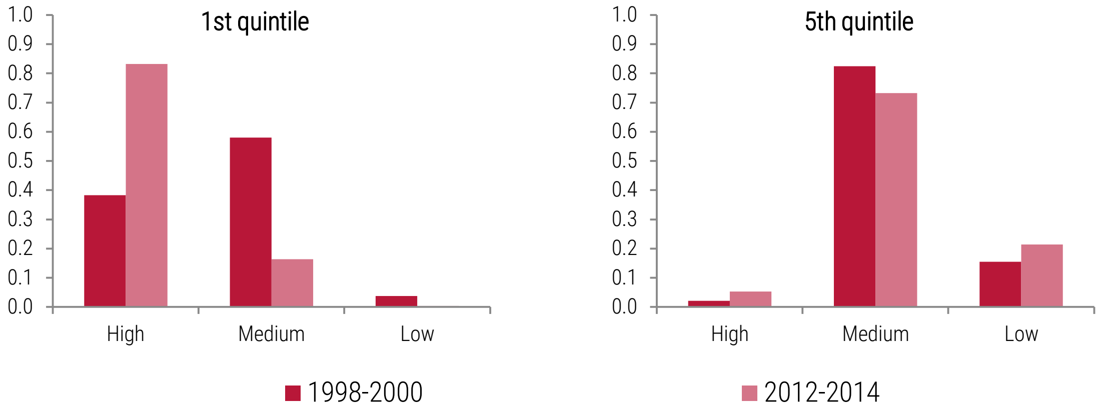
Figure 9. Distribution of employment shares by education levels within 1st and 5th RTI quintiles in 1998-2000 and 2012-2014



[12] NMS South comprises of Bulgaria and Romania. The coding of occupations in Bulgaria in the late 1990s and middle 2010s was rather dubious – the vast majority of workers in public sector were classified as professionals and in turn they have a low relative routine intensity. The coding was later changed – more detailed discussion is presented by Hardy et al. (2018). As a result, the dominant share of medium educated individuals among the least routine workers in the NMS South is an artefact related to an imperfect coding of occupation rather than a secular feature of these labour markets.


EU15 Continental
1st quintile
5th quintile
EU15 South
1st quintile
5th quintile
NMS North
1st quintile
5th quintile
NMS Continental
1st quintile
5th quintile
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
High
Medium
Low
1998-2000
2012-2014

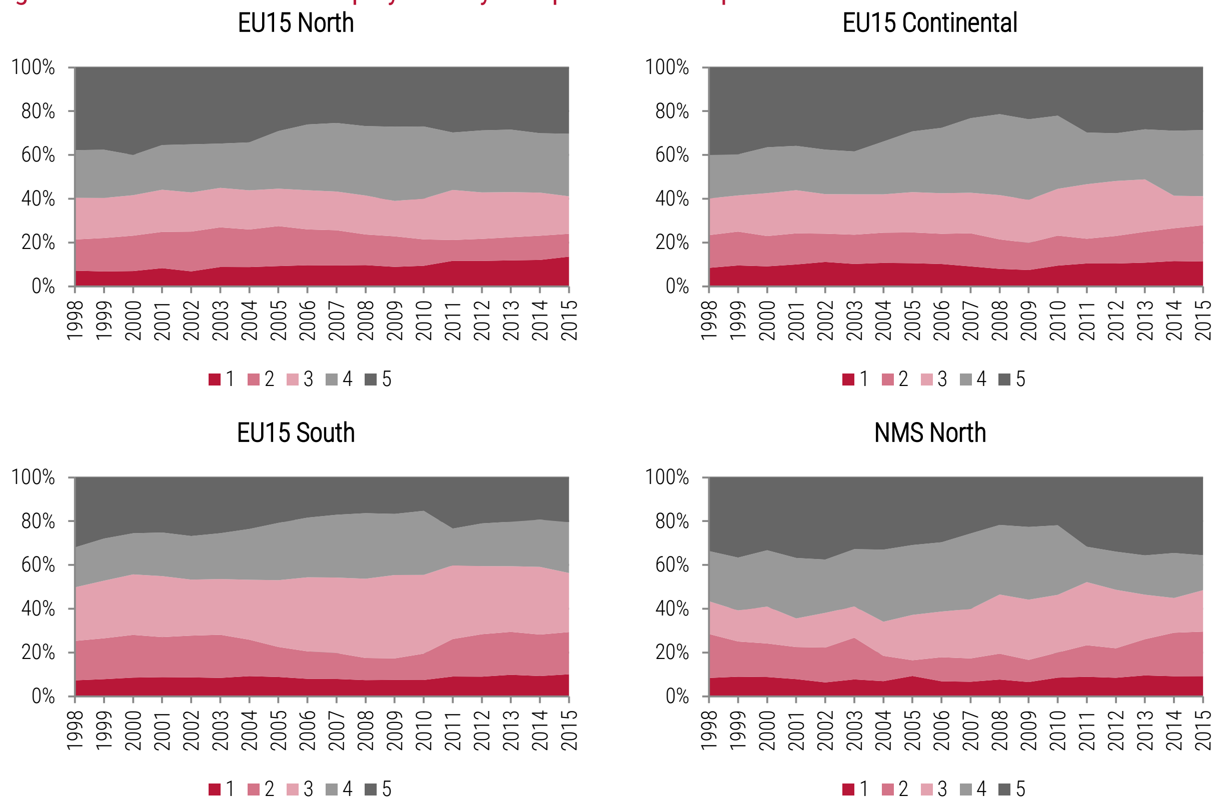
NMS South

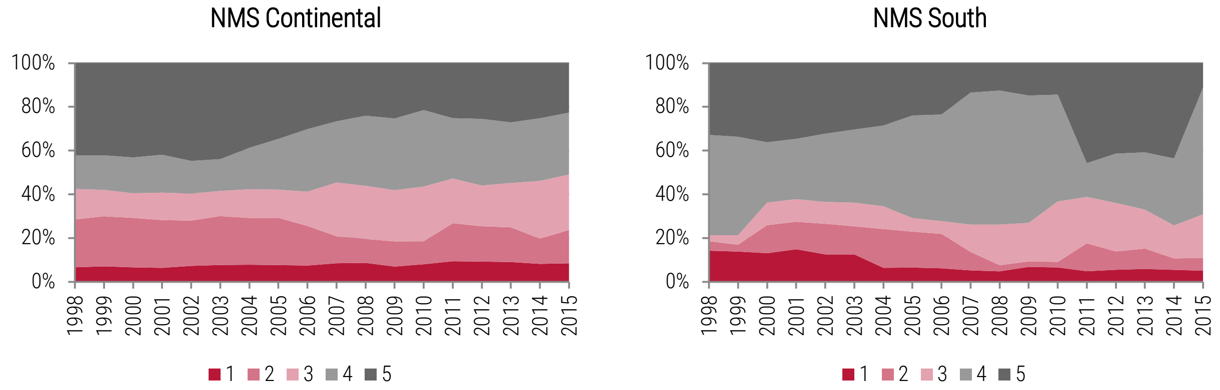


*Source: own calculations based on EU-LFS and O*NET data.*

The share of unemployed individuals who had a highly routine job (the 5th quintile of RTI) before entering unemployment was decreasing in all analysed regions. This decline was the deepest for NMS South countries (with Romania being excluded due to 1-digit ISCO occupations) and amounted to 26.4 pp. The share of unemployed individuals who were previously employed in least routine jobs (1st RTI quintile) inched up in all regions. This growth was rather moderate - in the NMS countries it did not exceed 2pp., whereas it ranged from 2.8 pp. in the EU15 South to 6.4 pp. in EU15 North countries. From the more aggregate perspective, the share of unemployed individuals in jobs with the above median RTI was decreasing in the EU15 North and the EU15 South countries (by 4.5 pp. and 6.2 pp.), while the opposite was the case for other regions. Out of those regions, the EU15 Continental and NMS Continental recorded the highest increase in the share of unemployed who had worked in above median RTI occupations – 5.4 pp. and 3.0 pp., respectively.

Figure 10. Distribution of unemployment by RTI quintiles in the period 1998-2015





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

3.4. Tasks content intensities by the level of skills

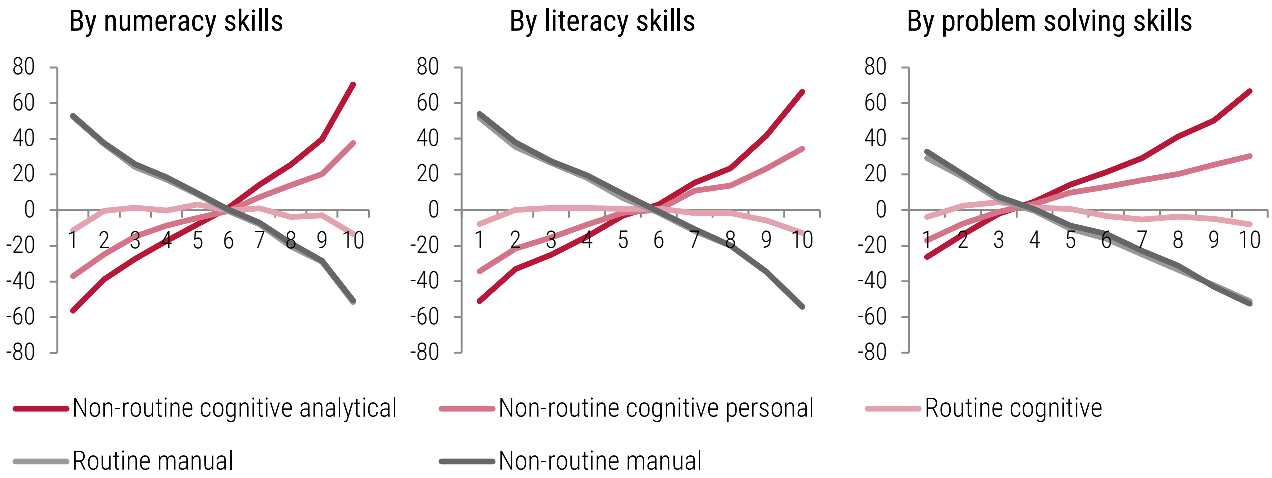
In this section we analyse how the intensities of particular task contents differ by skill level. We use The Programme for the International Assessment of Adult Competencies (PIAAC) data. To calculate tasks, we apply exactly the same procedure of merging O*NET data as the one described in Section 2 with respect to the LFS. The crucial difference lies in the standardisation – as there is only one PIAAC survey per country (conducted between 2012 and 2014, depending on a country), the standardisation is only in the cross-section. Therefore, there is no possibility to analyse tasks over time with PIAAC data. However, the advantage of PIAAC is that it allows analysing the relationship between tasks and skill levels (numeracy, literacy, problem solving). In each country we assigned workers to the deciles of country-specific distribution of a particular skill. In the next step, we calculated average task content intensities by these deciles. Figure 11 presents the averaged results for the EU countries.

The intensities of both non-routine cognitive tasks increase with skill level, whereas the intensities of both manual tasks decrease with skill level. The distribution of task content intensities by skill deciles are similar for different types of skills, especially for numeracy and literacy skills. The workers with below-median skills exhibit above-average manual tasks and below-average non-routine cognitive tasks, while the opposite is true for the workers with above-median skills. [13] However, in the case of problem solving skills, only the 30% of workers with the lowest skills have above-average manual tasks and below-average non-routine cognitive tasks. The median worker in problem-solving skills distribution has above-average non-routine cognitive tasks and below-average manual tasks. As such, it seems that even moderate problem solving skills (4th and 5th decile) are important for the performance of non-routine work, though the general relationship with these skills is flatter than with literacy and numeracy skills.

The relationship between the intensity of routine cognitive tasks and skill level is weak – it is slightly inverse-U shaped for numeracy and literacy skills (negative task intensities among 20% of workers with the lowest and among 20% of workers with the highest skills), and weakly negative for problem solving skills (except for the 20% of workers with the lowest problem solving skills).

[13] Task intensities were standardized for all EU countries jointly. Hence, an average worker in the EU has all task intensities of 0.

Figure 11. Task content intensities by skill deciles. Average across EU countries

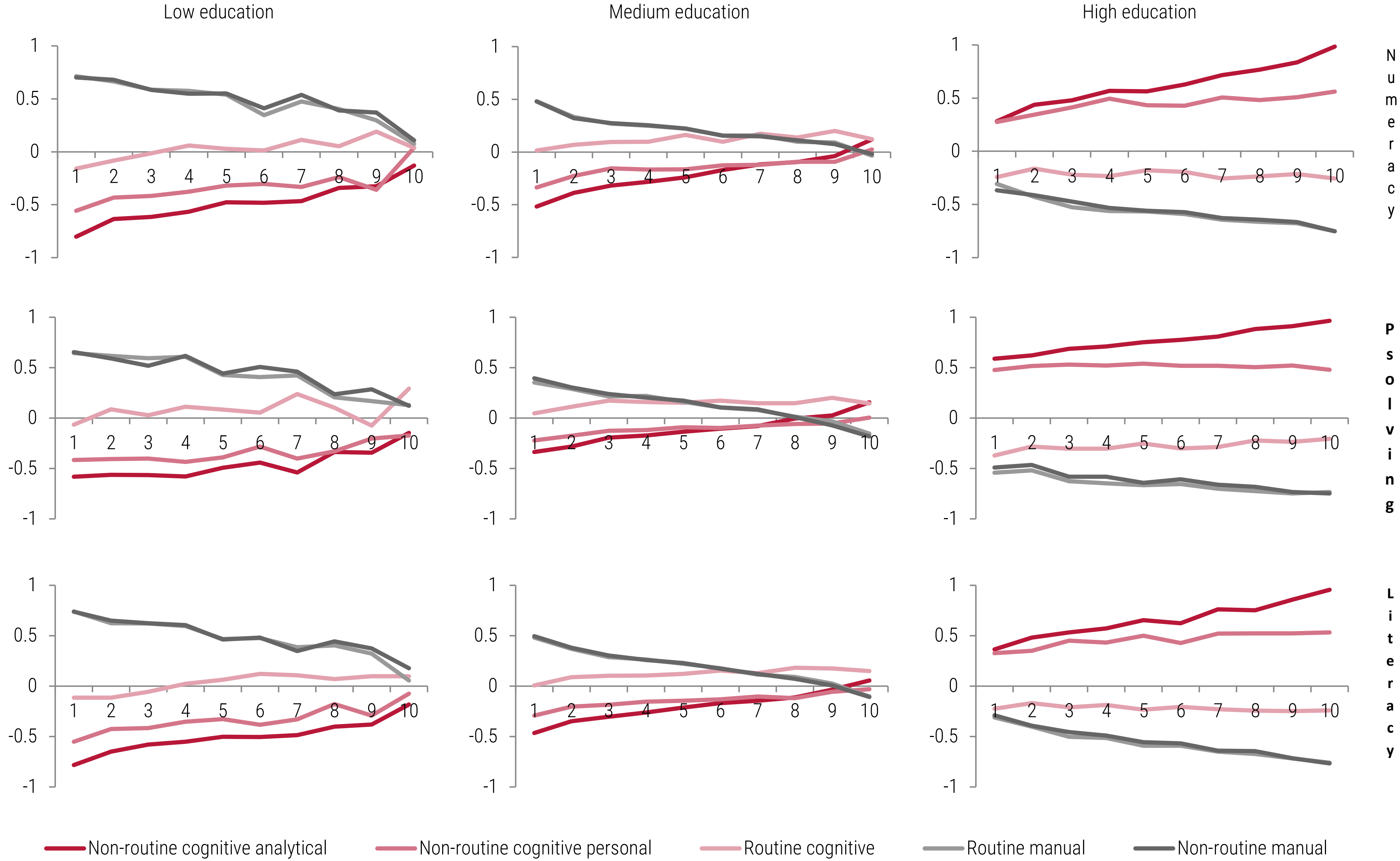


*Source: own calculations based on O*NET and PIAAC.*

The relationships between task intensities and skill level vary between workers with different education levels. At a given level of skills, the higher is the education level of a worker, the higher is the intensity of non-routine cognitive tasks and the lower is the intensity of manual tasks (Figure 12). Workers with high education and very low skill levels (1st decile) exhibit higher intensity of non-routine cognitive and lower intensity of manual tasks than all workers with low or medium education, even those that have the highest levels of skills. These patterns emerge in all types of skills. It seems that high education is a prerequisite for assigning workers to non-routine cognitive work.

The intensity of routine cognitive tasks is the highest among medium educated workers – overall, and at a given level of skills (Figure 12). Among medium educated workers, the intensity of manual tasks is higher than the intensity of routine cognitive tasks among workers with below-median skill levels, while the opposite is true among workers with above-median skill levels. Among 10-20% of medium educated workers with the highest level of skills, the intensity of non-routine cognitive tasks equals the intensity of routine cognitive tasks. It is not the case among the low educated workers who tend to perform manual tasks even if their level of skills is very high. Again, findings are identical for all types of skills.

Figure 12. Task content intensities by deciles of skills, by education levels. Average across EU countries



*Source: own calculations based on O*NET and PIAAC.*

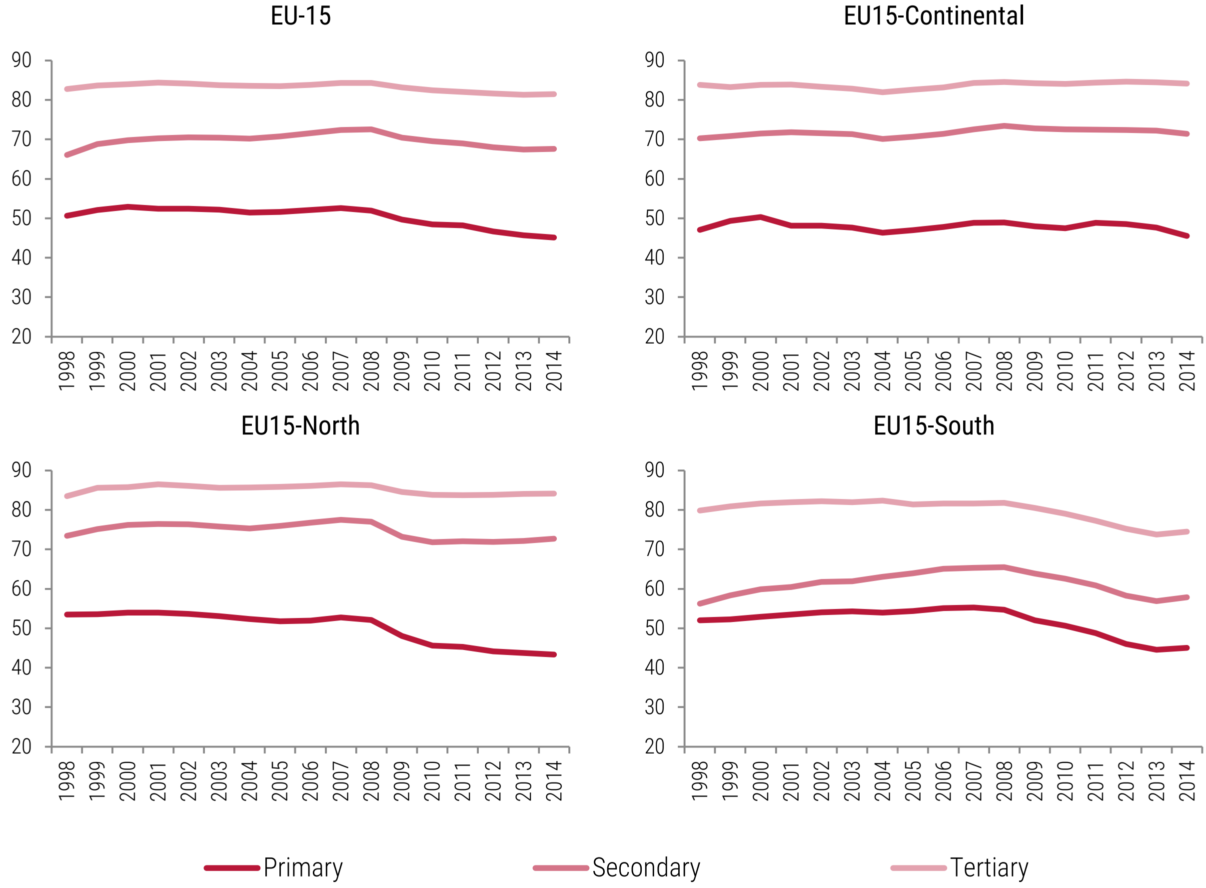
4. Labour market inequalities by education

4.1. Employment rates by education

Education level was a crucial factor behind labour market situation of individuals in all countries and country groups. Except for the Continental NMS countries, differences in employment rates between individuals with various education level attained have increased between the late 1990s and the middle 2010s, mainly because the employment rates among people with primary education have declined the most (by 4.5 pp. in the EU28 on average). Among individuals with secondary and tertiary education level, the decrease of employment rate was on average small decrease (-0.2 pp. and -1.6 pp., respectively).

The strongest declines of employment rates among people with low education level (primary and lower-secondary, ISCED 0-2) were observed in the EU-North countries (-10 pp.), especially in Ireland (-11 pp), and in the NMS-South countries (-8 pp). Lithuania, Romania, Greece, and Czechia also stood out with substantial declines in the employment rates of individuals with primary education. The only countries that recorded an increase in the employment rate of primary educated people were Estonia, Hungary and Netherlands.

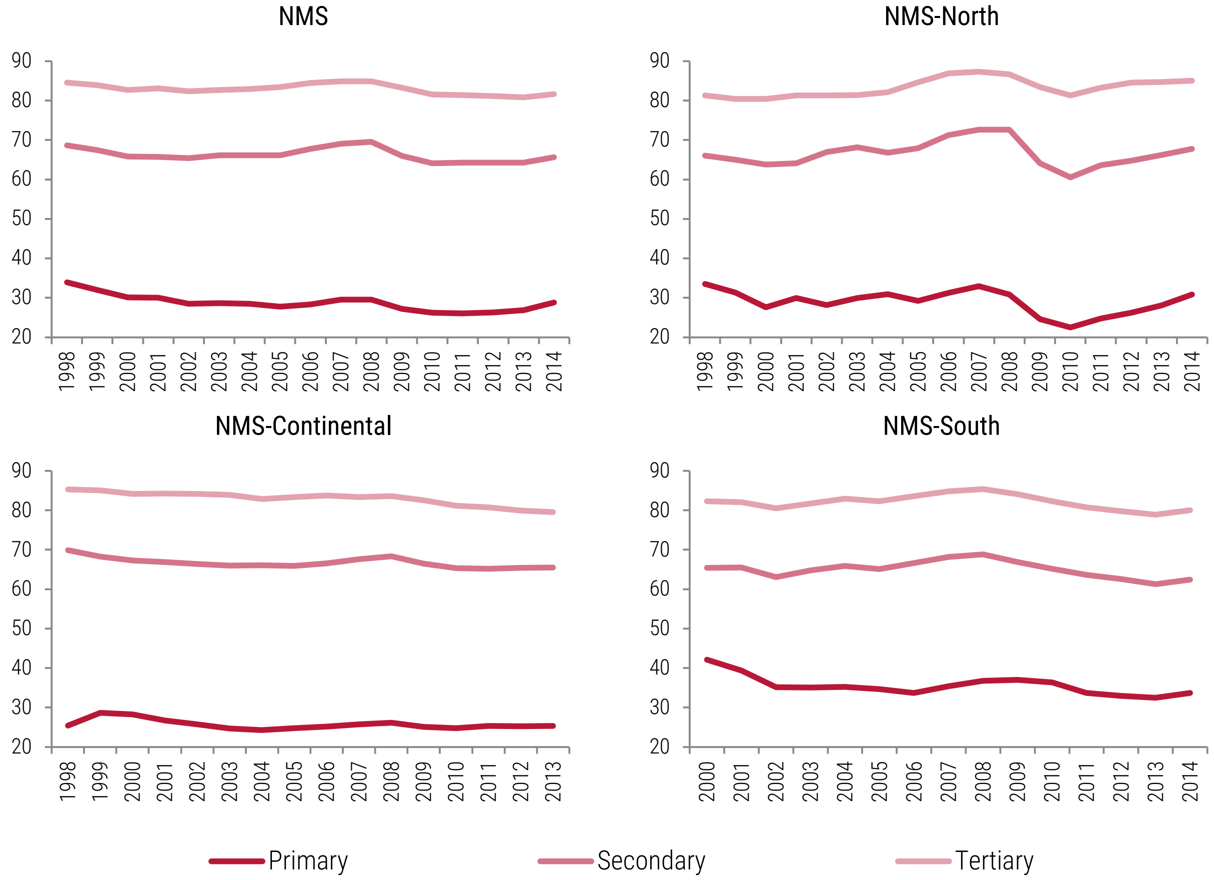
Figure 13. Employment rates by education level in the EU15 countries in 1998-2014.



Source: Own calculations based on Eurostat data.

The developments of the employment rates among people with secondary education (ISCED 3-4) and tertiary education (ISCED 5-6) differed between particular groups of countries. In the EU15, the employment rates among individuals with secondary education increased in all countries except for Ireland and the United Kingdom (on average by 5 pp. between 1998 and 2014), while in the NMS they declined (on average by 2.9 pp.). Similar pattern was observed among people with higher education. Employment rates increased in the EU15 countries (by 3 pp. on average) but they declined in the NMS countries (by 2.8 pp. on average). There were also some heterogeneity within both blocs. In particular, the employment rates of tertiary educated individuals declined in the EU-15 South while they increased in other subgroups of the EU15 countries. Among the NMS, the rates in question rose in the NMS-North while they declined in the other subgroups of the New Member States.

Figure 14. Employment rates by education level in the NMS countries in 1998-2014[x]



Note: [x] Due to data availability, the changes in the 2000-2014 for NMS-South, lack of data for Bulgaria, Croatia and Cyprus.

Source: Own calculations based on Eurostat data.

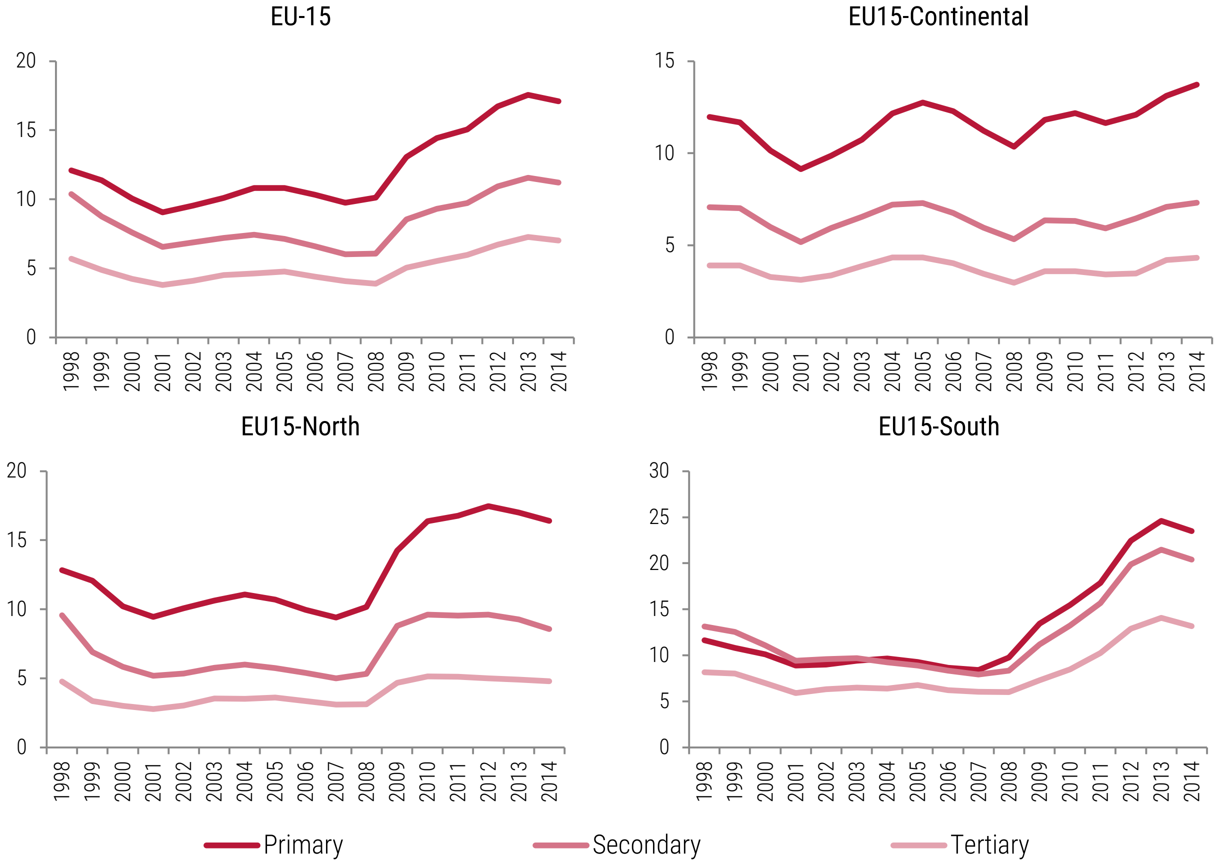
4.2. Unemployment rates by education

The developments of employment rates were reflected in the changes of the unemployment rates by education which increased the most among the individuals with primary education. On average in the EU28, the unemployment of workers with low education by 5.3 pp. between 1998 and 2014, while among the individuals with secondary and tertiary education the increase was much smaller (0.8 pp. and 1.3 pp., respectively). The largest increase in the unemployment rate of people with low education was observed in the EU15-South countries (12 pp. on average, 18 pp. in Greece. On the other hand, the lowest increase of unemployment rates for workers with low education was recorded in the EU15-Continental and NMS–Continental countries.

Among better educated workers the unemployment rates increased less than among the low educated workers. Again, the increases were the strongest in the EU15-South countries (on average 7 pp. among secondary educated workers and 5 pp. among tertiary educated workers), and NMS-South countries (on average 4 pp. for both groups). In the EU15-North and EU15-Continental the unemployment rates of secondary educated workers and tertiary educated workers in 2014 were very close to the values recorded in 1998. In the NMS-North the rates in question were even lower in 2014 than in 1998 (which is related to a severe crisis in the aftermath of the Russian crisis in 1997).

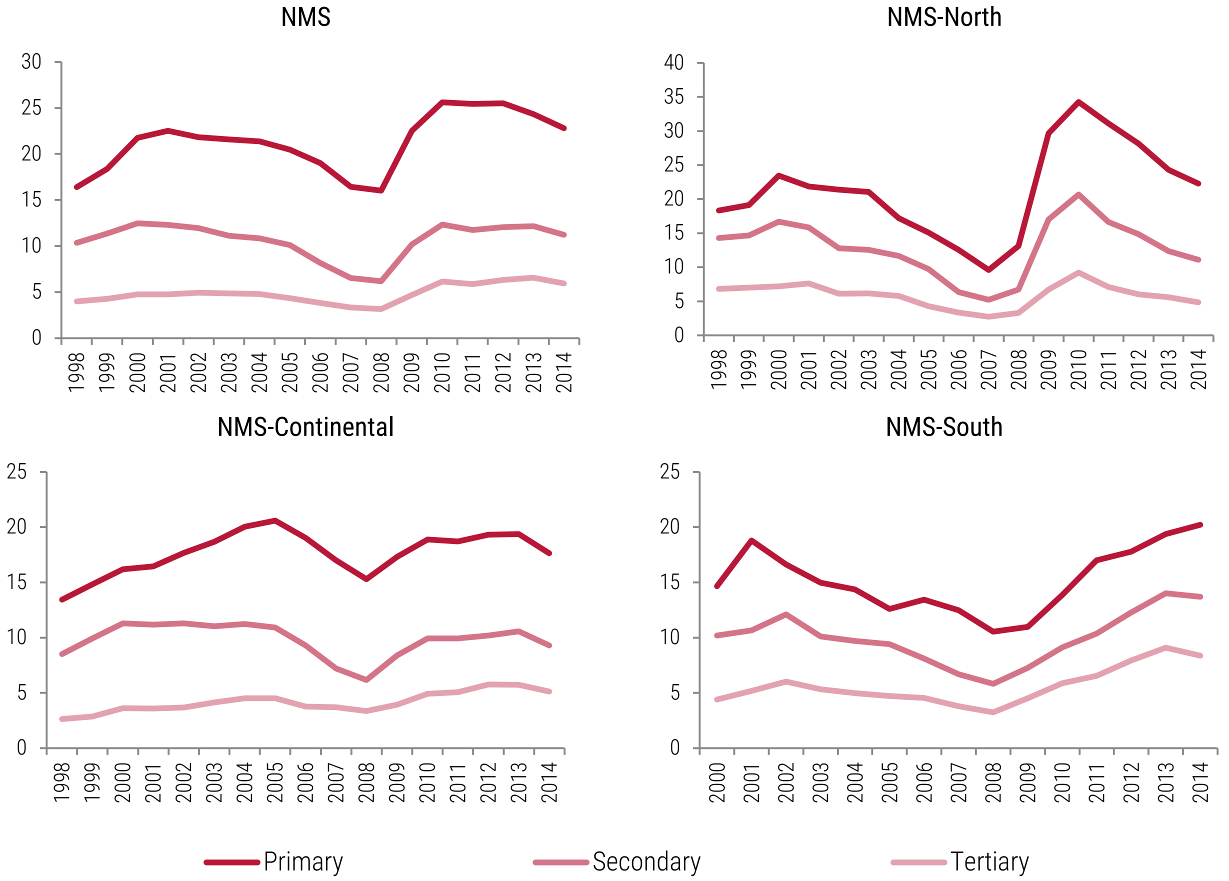
As a result, the gap between the unemployment rates by education increased in the EU mainly because the unemployment rates of individuals with primary and lower-secondary (ISCED 0-2) increased much more than the unemployment rates among secondary and tertiary educated workers.

Figure 15. Unemployment rates by education level in the EU15 countries in 1998-2014



Source: : Own calculations based on Eurostat data.

Figure 16. Unemployment rates by education level in the NMS countries in 1998-2014[x]



Note: [x] Due to data availability, the changes in the 2000-2014 for NMS-South, lack of data for Bulgaria, Croatia and Cyprus

Source: : Own calculations based on Eurostat data.

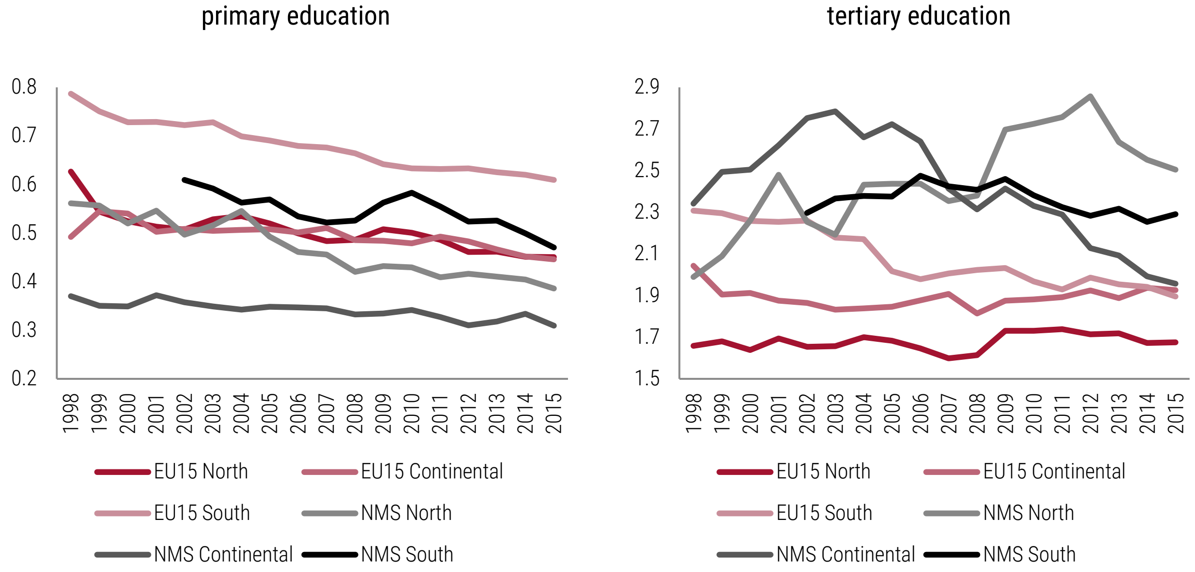
4.3. The impact of education on employment probabilities

The role of education in determining labour market status has evolved over time. Figure 17 shows the average odds ratios associated with education levels estimated in logit regressions with employment as explanatory variable. Besides education, we controlled for age, gender, year and country effects. We used microdata from EU LFS. The secondary education is a reference level for education. We analyse the 15-74 age group.

The results show that primary educated individuals have faced falling chances of employment, relatively to secondary educated individuals. The employment gap between primary and secondary educated individuals has widened, even if we control for other factors that might affect employment probabilities. All country groups recorded a gradual decline in the relative employment chances of primary educated individuals, but it was the strongest in the EU15 South countries.

There was no uniform pattern of change in the case of tertiary educated individuals. In the NMS North countries the chances of employment among the tertiary educated individuals increased (relatively to secondary educated individuals). The opposite was true in the NMS Continental countries and the EU15 South. No clear trend nor significant changes over time were recorded in the EU15 North and EU15 Continental countries.

Figure 17. The education impact on employment probability, odds ratios (secondary education as a reference level)



Source: Own calculations using EU LFS data.

4.4. The evolution of the risk of unemployment by education

In this subsection we assess how the relative risk of unemployment evolved over time for different education groups in European countries. To this aim, we run logit models with unemployment as the dependent variable (0 – employed, 1 – unemployed). Models are estimated separately for each country and for each year.[14] We include the set of standard socio-demographic variables as controls (region, five-year age groups, education, gender). Note that due to the changes in encoding regions some logit models include regions coded at NUTS 1 level, and some regions coded at NUTS 2 level. We use medium educated people as a reference category for high and low educated people. The odds-ratios related to education level for all countries are presented in the data appendix (excel file).

In general, people with low education (ISCED 0-2) were at higher risk of unemployment then people with medium education (ISCED 3–4) during the analysed period. This was true for all countries in the sample apart from Romania, Greece and Portugal. In Romania, individuals with low education were either less likely to be unemployed than individuals with medium education or there were no significant differences between those two groups. The latter was also the case for Greece and Portugal, where in the 1998-2000 period people with low education were as likely to be unemployed as people with medium education attained. Correspondingly, in the majority of analysed countries, highly educated people (ISCED 5-8) were characterised by a lower risk of unemployment then people with medium education. Here Iceland and Norway are exceptions. In these two countries, for most of the studied period, there were no significant differences between individuals with high education and medium education with respect to the risk of unemployment.

[14] Models estimated for country groups would not highlight important differences between countries assigned to particular groups which we discuss here.

In recent decades the relationship between the educational level and the risk of unemployment has changed in Europe. However, these changes were not unanimous across countries. In general, we can distinguish four groups of countries where various patterns emerged:

Czechia, Germany, Latvia, Norway, Italy, Croatia, Greece, France, Spain

- Between 1998-2000 and 2012-2014 people with low education became relatively more exposed to the risk of unemployment, whereas people with higher education attained became relatively less affected by the risk of unemployment.

The "polarisation" of unemployment risk - Austria, Belgium, Denmark, Finland, Hungary, Poland, Portugal, Romania, Slovenia, Slovakia, Sweden

- Both the people with high and low education became relatively more prone to the risk of unemployment relatively to people with medium education. This was most visible in post-transition economies such as Poland, Romania, Slovenia and Slovakia. Yet, still the odds ratios of unemployment for people with high education remained low in these economies (except for Romania, they did not exceed 0.5).

United Kingdom, Iceland, Estonia, Cyprus, Bulgaria

- The relative risk of unemployment rose for people with high education, whereas it decreased for people with low education (relative to people with medium education). In Iceland this decline of the unemployment risk for people with low education was the steepest.

Netherlands, Ireland

- The risk of unemployment decreased for high and low educated people (in relation to medium educated people). Yet, this drop was sharper for people with low education. In Netherlands it was a drop – from odds ratio of 3 to odds ratio of 1.8, in Ireland it was a drop from 2.7 to 1.9.

4.5. Risk of unemployment and skills

In order to analyse the relationship between the skill levels and unemployment risk, we revert to PIAAC data. We estimate three sets of country-specific logistic regressions explaining the probability of being unemployed (relative to working). Each set includes a standardised skill level value of one type (i.e. numeracy, literacy or problem solving) as well as education, gender and age (in 10-year groups) as explanatory variables. Because particular skill measures are highly correlated with each other, we estimate separate regressions which control for a given skill level. Results are presented in Tables 4-6. The skill measures are standardised, so the odds-ratios relate to the effect of a change in the skill level equal to one country-specific standard deviation.

In line with intuition, people with higher skills have lower probabilities of being unemployed, even if education is controlled for. Higher numeracy skills were associated with lower probabilities of being unemployed in all countries except Belgium and Greece. Higher literacy skills were associated with lower probabilities of being unemployed in all countries except Cyprus, Czechia, Finland, Greece and Slovenia. The results for problem solving skills were less consistent, with higher skills unrelated to unemployment in Belgium, Czechia, Finland, Germany, Ireland and Poland and positively related in Denmark, Greece and Slovenia.

Numeracy skills were most strongly related to the risk of unemployment but the relationship varied across countries. In countries like Estonia, Germany, Netherlands, Slovakia, Sweden and the United Kingdom a change of one standard deviation in the level of numeracy skills was associated with the probability of working (instead of unemployment) approx. 1.7 times higher. In countries like Austria, France, Ireland, Poland or Slovenia the change resulted in approx. 1.2 higher chances of work (instead of unemployment).

Having a level of education higher than primary was positively related to unemployment risk. In all countries except Netherlands, having an education level higher than low was associated with lower risk of unemployment. The relationship of achieving at least secondary education and unemployment was larger than the effect of a one standard deviation change in the level of skills.

Women were more likely to be unemployed in several countries. This was true for France, Greece, Italy, Lithuania, Poland and Slovenia. The opposite was true for Ireland. The results were significant despite controlling for education levels and skills.

The youngest were most likely to be unemployed, and the oldest the least. We found that the people aged 15-24 were much more likely to be unemployed (versus working) than people aged 25-34. People aged 55-64 on the other hand were least likely to be unemployed (versus working). These results are likely the effect of relatively few people aged 15-24 working (though many in education) and people aged 55-64 relatively more often becoming inactive than unemployed.

Table 4. Numeracy skills and unemployment risk - odds-ratios estimated in country-specific logit regressions on unemployment

	AT	BE	CY	CZ	DK	EE	FI	FR	DE	GR	IE	IT	LT	NL	PL	ES	SK	SI	SE	UK
Numeracy	0.83*	0.99	0.72***	0.67***	0.71***	0.63***	0.67***	0.81***	0.59***	0.98	0.78***	0.70***	0.66***	0.62***	0.81***	0.69***	0.60***	0.89*	0.57***	0.58***
Education																				
High	0.45**	0.28***	0.43***	0.2***	0.52***	0.42***	0.49***	0.47***	0.42***	0.43***	0.3***	0.51***	0.21***	0.8	0.22***	0.46***	0.21***	0.23***	0.48***	0.58***
Medium	0.51***	0.5***	0.6**	0.26***	0.77*	0.71**	0.71*	0.78	0.57***	0.71**	0.78*	0.86	0.58**	1.03	0.52***	0.62***	0.42***	0.47***	0.61**	0.82
Female	1.13	1.08	1.22	1.19	1.12	1.09	0.83	1.25*	0.87	1.57***	0.69***	1.95***	1.38**	0.83	1.52***	0.91	1.18	1.51***	0.92	0.77*
Age																				
15-24	1.45	3.54***	2.64***	2.15***	1.09	2.32***	2.16***	2.88***	0.95	1.51**	2.36***	1.71**	1.41	1.62**	2.62***	2.38***	2.31***	2.1***	2.14***	2.62***
35-44	0.63*	0.73	0.59**	0.66	0.68*	0.82	0.6**	0.74*	0.95	0.42***	0.81	0.46***	0.51***	0.65	0.61**	0.83	0.91	0.43***	0.55**	0.67*
45-54	0.68	0.29***	0.63**	0.73	0.56***	1	0.45***	0.42***	0.35***	0.46***	0.64***	0.41***	0.55***	0.58**	0.95	0.64***	0.71**	0.31***	0.38***	0.53***
55-64	0.4*	0.26***	0.42***	0.57*	0.42***	1.17	0.29***	0.33***	0.56**	0.46***	0.41***	0.3***	0.49***	0.77	0.73	0.45***	0.41***	0.32***	0.39***	0.52**

Note: Reference group includes working individuals. The reported values are odds ratios. All regressions include robust standard errors.
**** p-value<0.01; ** p-value<0.05; * p-value<0.01.*
Source: own estimations on PIAAC data.

Table 5. Literacy skills and unemployment risk - odds-ratios estimated in country-specific logit regressions on unemployment

	AT	BE	CY	CZ	DK	EE	FI	FR	DE	GR	IE	IT	LT	NL	PL	ES	SK	SI	SE	UK
Literacy	0.75***	0.82*	0.85	0.91	0.82***	0.74***	0.87	0.86**	0.73***	1.11	0.78***	0.8***	0.81**	0.71***	0.89*	0.78***	0.72***	1.04	0.56***	0.64***
Education																				
High	0.51**	0.37***	0.34***	0.13***	0.45***	0.35***	0.37***	0.41***	0.29***	0.38***	0.3***	0.46***	0.16***	0.69	0.2***	0.41***	0.15***	0.19***	0.5**	0.51***
Medium	0.55***	0.56**	0.52***	0.22***	0.7**	0.64***	0.64**	0.73**	0.46***	0.67**	0.79	0.78*	0.53***	0.94	0.49***	0.57***	0.34***	0.42***	0.61**	0.77
Female	1.17	1.08	1.28	1.27	1.2	1.17	0.92	1.31**	0.98	1.55***	0.72***	2.06***	1.42***	0.92	1.56***	0.98	1.19	1.54***	1.04	0.86
Age																				
15-24	1.47	3.61***	2.65***	2.17***	1.07	2.36***	2.18***	2.9***	0.87	1.51**	2.38***	1.9***	1.33	1.62**	2.6***	2.38***	2.22***	2.05***	2.25***	2.5***
35-44	0.61*	0.7	0.58**	0.71	0.65**	0.84	0.66*	0.73*	0.94	0.42***	0.81	0.48***	0.53***	0.66	0.62**	0.83	0.88	0.43***	0.54**	0.63**
45-54	0.65*	0.28***	0.63**	0.78	0.54***	1.03	0.5***	0.42***	0.36***	0.45***	0.63***	0.43***	0.59***	0.57**	0.95	0.66***	0.67**	0.33***	0.37***	0.52***
55-64	0.38**	0.24***	0.42***	0.61	0.41***	1.21	0.33***	0.33***	0.58*	0.46***	0.41***	0.32***	0.53***	0.76	0.74	0.47***	0.39***	0.34***	0.36***	0.48***

Note: Reference group includes working individuals. The reported values are odds ratios. All regressions include robust standard errors.
**** p-value<0.01; ** p-value<0.05; * p-value<0.01.*
Source: own estimations on PIAAC data.

Table 6. Problem solving skills and unemployment risk - odds-ratios estimated in country-specific logit regressions on unemployment

	AT	BE	CZ	DK	EE	FI	DE	GR	IE	LT	NL	PL	SK	SI	SE	UK
Problem solving skills	0.72***	0.88	1.08	1.16*	0.8***	1.1	0.93	1.23***	0.95	0.72***	0.58***	0.92	0.75***	1.17**	0.67***	0.63***
Education																
High	0.33***	0.27***	0.1***	0.32***	0.42***	0.3***	0.18***	0.31***	0.29***	0.3***	1.04	0.29***	0.22***	0.16***	0.48**	0.54***
Medium	0.42***	0.46***	0.16***	0.62***	0.77	0.55***	0.34***	0.53***	0.87	0.74	1.2	0.49***	0.43***	0.41***	0.6**	0.77
Female	1.14	1.12	1.33	1.17	1.3**	0.9	1.05	1.56***	0.76**	1.79***	0.89	1.55***	1.4**	1.73***	1.14	0.85
Age																
15-24	1.33	3.92***	2.43***	0.96	2.78***	2.24***	0.77	1.48**	2.25***	1.59**	1.85**	3.13***	2.54***	1.99***	2.72***	2.83***
35-44	0.44**	0.63	0.55	0.63**	0.77	0.63*	0.82	0.4***	0.78	0.41***	0.55**	0.55**	0.75	0.42***	0.45***	0.57**
45-54	0.64	0.33***	1.07	0.58**	0.71	0.57**	0.32***	0.52***	0.51***	0.3***	0.44***	0.56*	0.51***	0.31***	0.27***	0.4***
55-64	0.28**	0.34**	0.92	0.53***	0.99	0.38***	0.7	0.31**	0.63	0.42***	0.67	0.39	0.26***	0.27***	0.35***	0.47**

*Note: *** p-value<0.01; ** p-value<0.05; * p-value<0.01. The reported values are odds ratios. All regressions include robust standard errors. Problem solving skills assessment is not available for Cyprus, France, Italy and France.*
* *** p-value<0.01; ** p-value<0.05; * p-value<0.01. *

Source: own estimations on PIAAC data.

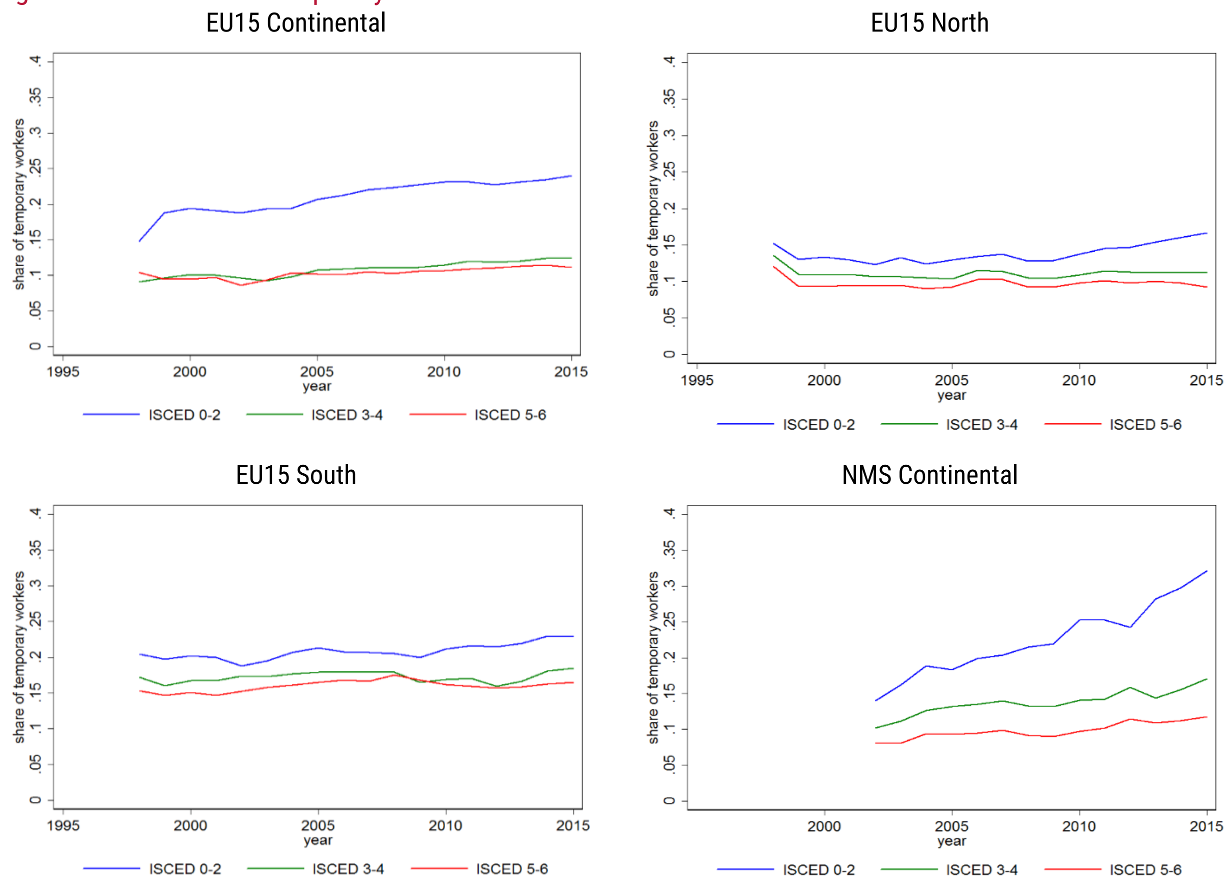
4.6. Temporary employment by education and RTI quintiles

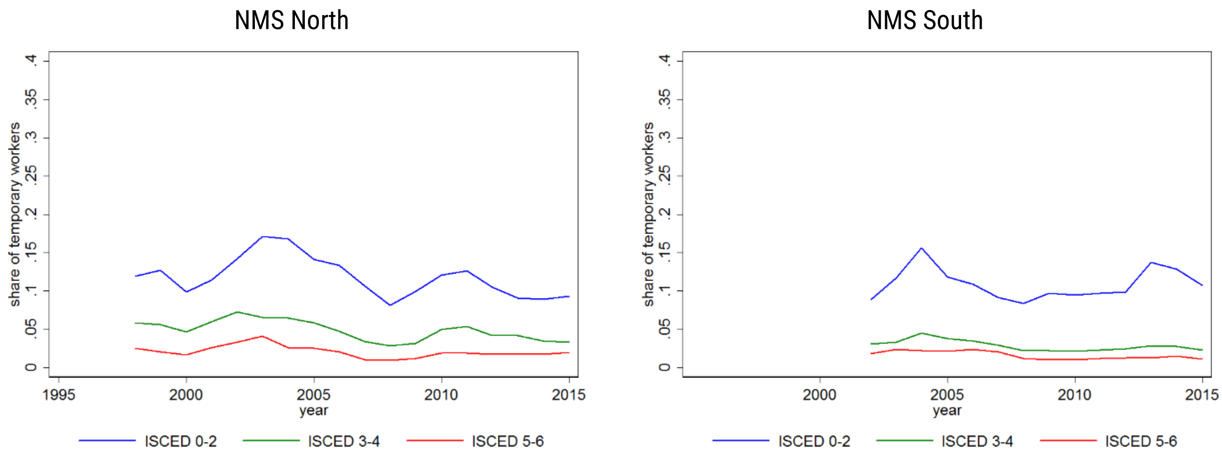
In all country groups primary-educated workers experience a higher risk of temporary employment than workers with other education levels. However, these differences vary across European Union. They are especially evident in the NMS Continental countries and in the EU15 Continental. The EU15 South and the EU15 North countries have experienced relatively small differences in the incidence of temporary employment across education groups. In all countries, the tertiary educated workers have consistently faced the lowest risk of temporary employment.

In the NMS Continental countries, the incidence of temporary employment has increased substantially. This was however largely driven by a rapid growth in temporary jobs in Poland which by 2014 has become the EU country with the highest share of temporary jobs in total employment. However, after 2005 the expansion of temporary employment has somewhat slowed in case of workers with tertiary and secondary education, but has remained fast in case of primary-educated workers. It has made temporary employment risk rates diverge across education groups, putting primary-educated individuals in worse situation.

Other country groups experienced less pronounced changes in temporary employment. The NMS South recorded an increase in the incidence of temporary jobs, but in the remaining country groups there was no evident trend over the last 15 years. The NMS North countries stood out with a clearly anticyclical pattern of temporary employment: its share rose significantly during economic downturns, but shrank when economic situation improved. Primary-educated workers faced the strongest fluctuations which means that they have been at higher risk of falling into temporary employment during recessions than the other groups of workers. No cyclical fluctuations in temporary employment have been observed in other country groups.

Figure 18. The share of temporary workers in EU countries





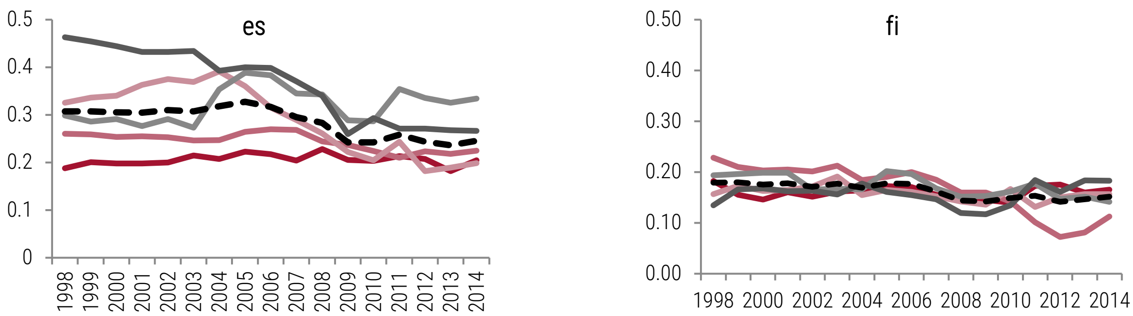
Source: Own calculations using EU LFS data.

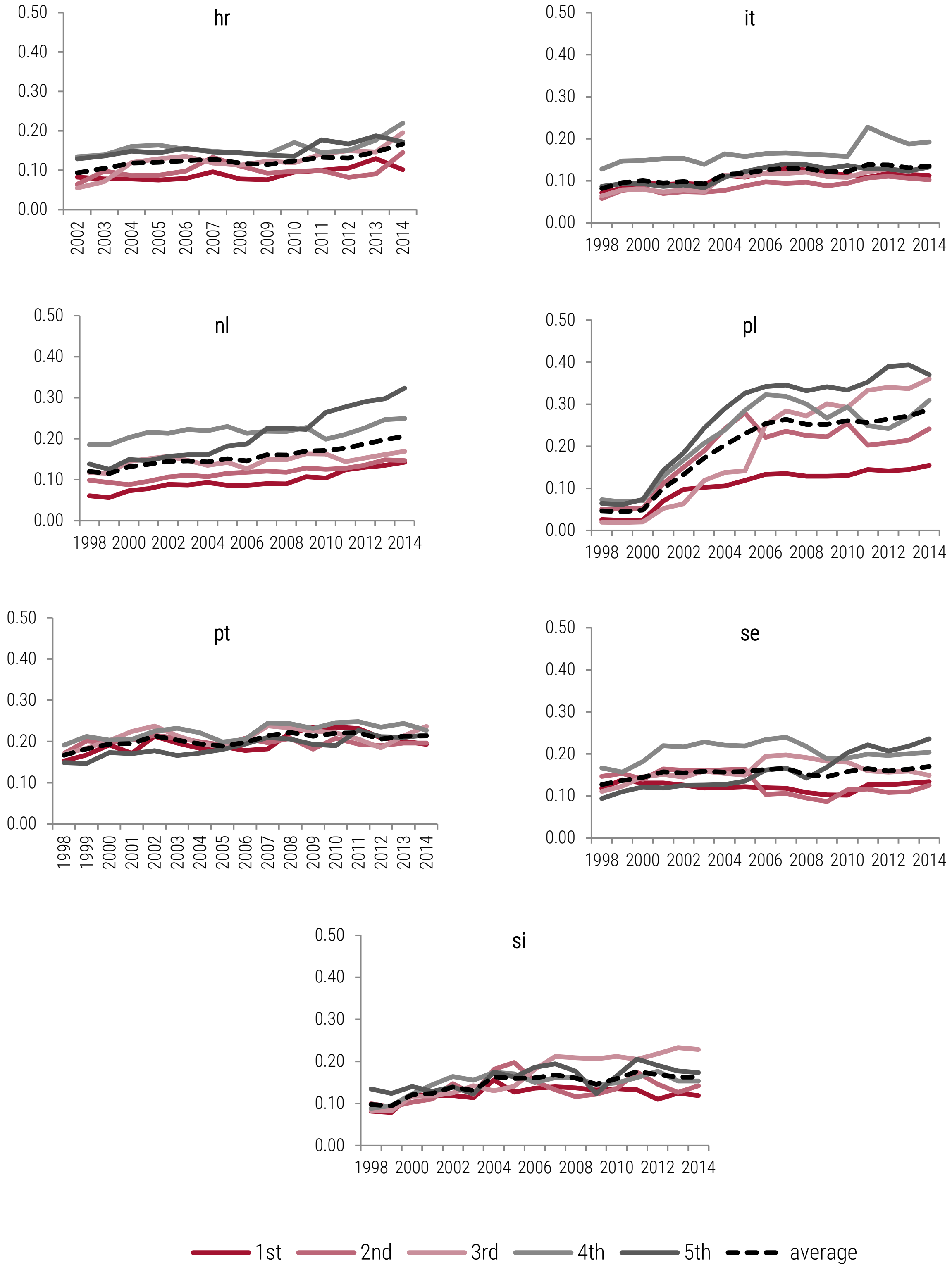
In countries where the temporary employment accounts for a large share of employment we additionally analyse at the evolution of temporary employment shares within RTI quintiles. In general, in all countries we consider in this section, the share of temporary employment was the lowest among the least routine jobs category, namely the jobs in the 1st quintile of RTI. Moreover, the share of temporary employment was rising with the routine intensity of a job.

In Poland and Netherlands temporary employment share was the highest among 5th RTI quintile. In Poland, where in general temporary employment is more pervasive, in 2014 it stood at 37% compared to the economy-wide share of 29% (see Figure 19). In Netherlands among workers with highly routine jobs (5th quintile of RTI) temporary employed individuals in 2014 accounted for 32%, compared to the overall share of 21%. By contrast, in Spain, the highest share of temporary employment was recorded among workers in the 4th quintile of RTI, and in 2014 it was equal to 33%, whereas the overall share of temporary employment stood at 25%. In all these countries the share of temporary employment was developing in line with the economy average.

In other countries that are characterized by the relatively high incidence of temporary employment we do not see much differences between different RTI quintiles. More specifically, the differences between the share of temporary employment in 1st and 5th quintiles in these countries were relatively small – it varied from 2pp. in Finland, Portugal and Italy to 7pp. in Croatia (by comparison it was 22pp. for Poland).

Figure 19. Temporary employment shares by RTI quintiles in the period 1998-2015



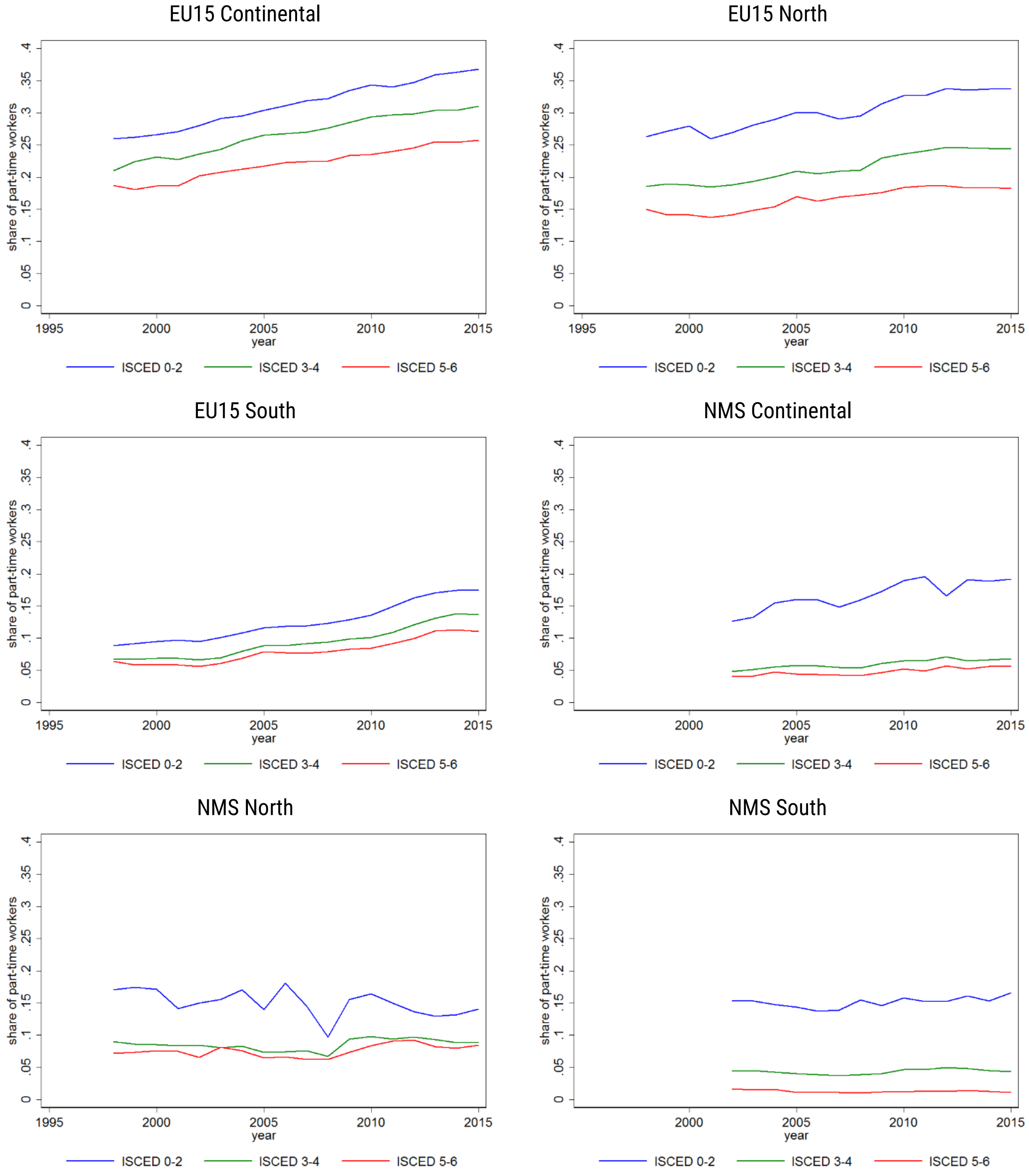


*Source: own calculations based on EU-LFS and O*NET data.*

4.7. Part-time employment and hours worked by education

In all country groups the share of part-time employment was negatively associated with the education level of workers. In the NMS countries the difference in part-time employment share between secondary and primary educated workers was much larger than the corresponding difference between tertiary and secondary educated workers. In the EU15 countries the opposite was true.

Figure 20. The share of part-time workers in European countries



Source: Own calculations using EU LFS data.

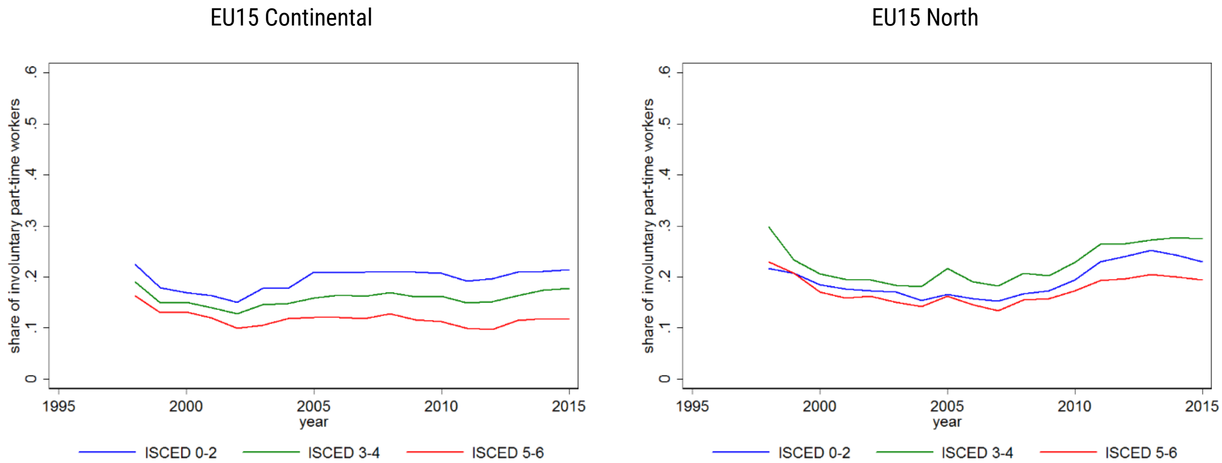
There was a stark difference between the EU15 and the NMS countries in terms of part-time employment evolution in last decades. Part-time employment has been steadily expanding in the EU15 countries among all education groups. In the NMS countries part-time employment has been stable over time. As a result, the incidence of part-time employment diverged between the NMS and the EU15 countries. For instance, in 2015 the share of part-time employment among tertiary-educated workers was four times higher in the EU15 Continental countries than in the NMS countries. The limited access to part-time employment is often mentioned as an important factor preventing further women's employment expansion in the NMS countries (Razzu 2017).

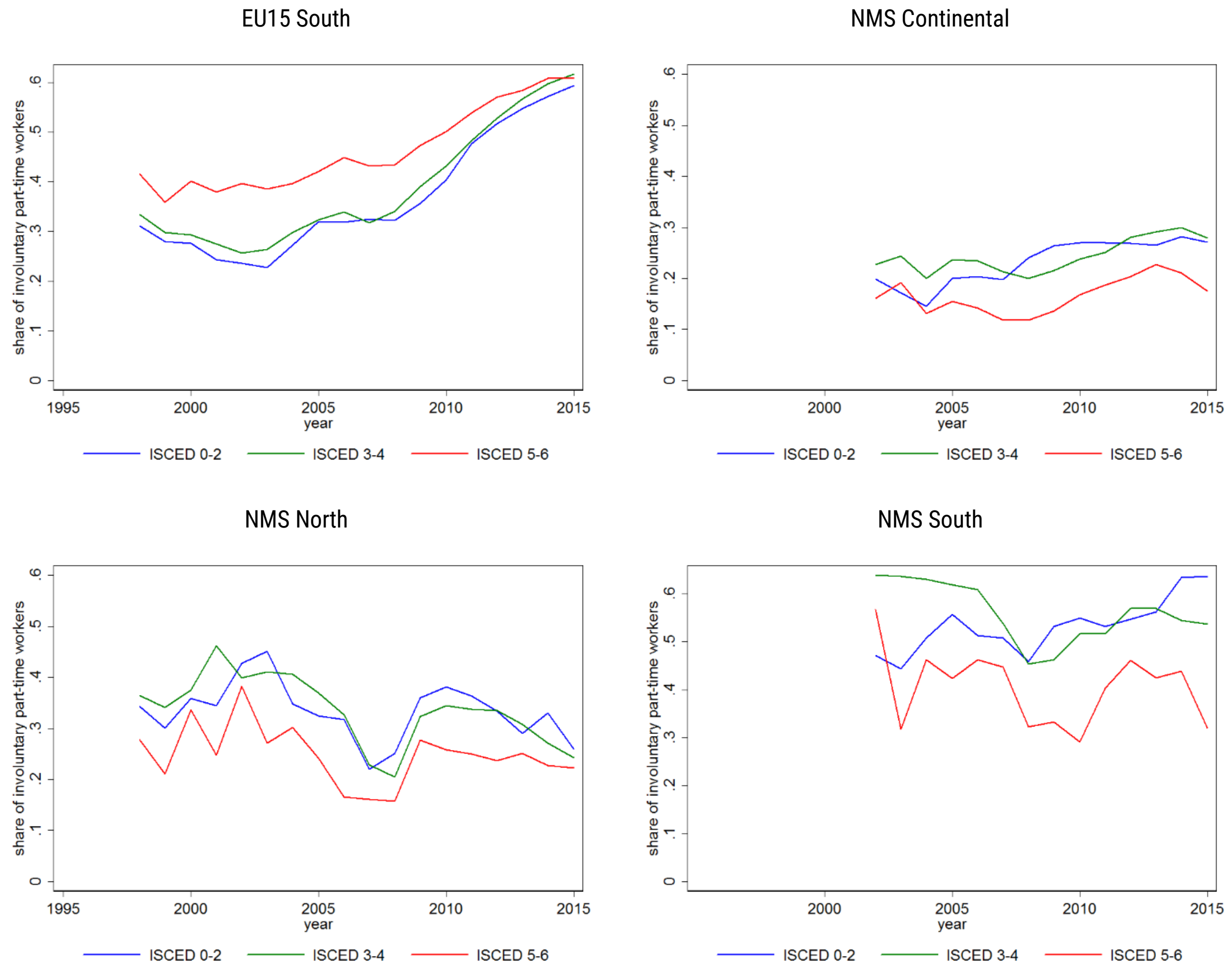
The high incidence of part-time employment is not always involuntary. The EU15 Continental countries, which exhibit the highest shares of part-time workers, have the lowest shares of involuntary part-time employment. The similar applies to the EU15 North countries. However, the EU15 South countries have experienced both the expansion of part-time employment rates and a sharp increase in the shares of part-time workers reporting they would rather prefer working full-time. The growth of involuntary part-time employment was especially sizeable after the onset of the Great Recession. In the NMS countries, the changes in incidence of involuntary part-time have not been uniform, although in case of the NMS Continental countries there was a rising trend.

Education levels are not clearly associated with involuntary part-time employment. In general, the risk of involuntary part-time employment among tertiary-educated workers is usually lower than among primary or secondary-educated workers, but it is not always the case. The EU15 South countries showed a different pattern: until recently, the risk of involuntary part-time employment among tertiary educated workers was above the risk for primary and secondary educated workers.

There was no uniform relationship between the average number of hours worked a week and workers' education levels. In the EU15 Continental and North countries, better educated workers worked longer hours than workers with lower education levels. The difference between tertiary and primary educated workers was prominent and equalled to 4-5 hours a week in 2015. The opposite applies to the EU15 South countries where better educated workers worked shorter hours.

Figure 21. The share of involuntary part-time employment

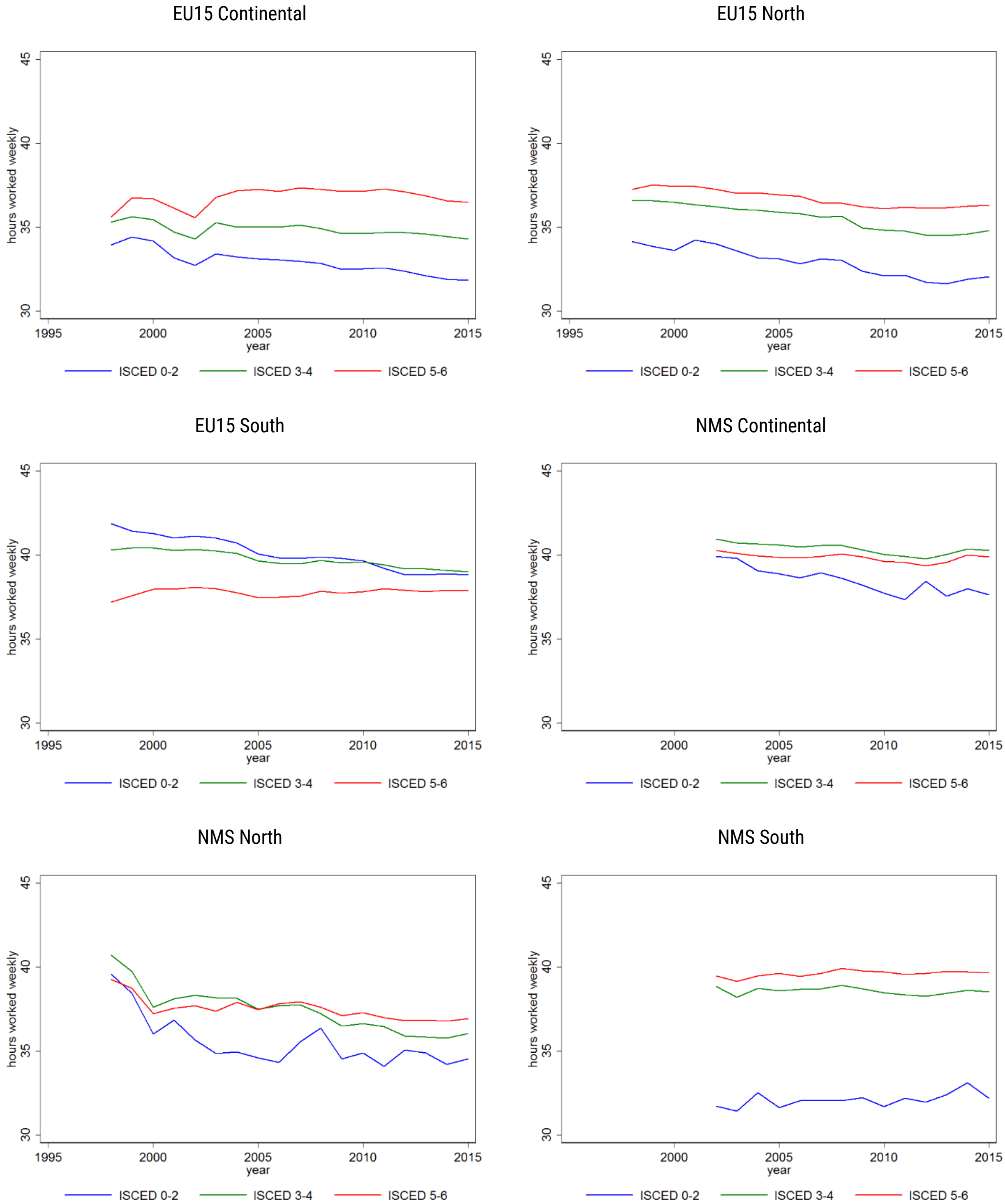




Source: Own calculations using EU LFS data.

The number of hours worked per week has been declining across the EU. This decline was in tur associated to the expansion of part-time employment. In all country groups the average number of hours worked fell more in the case of primary educated workers than in the case of tertiary-educated workers. This widened the education gap in weekly working hours in the EU15 Continental, the EU15 North and the NMS Continental countries, but it reduced the weekly working hours gap in the EU15 South countries.

Figure 22. The average hours worked a week (as usually worked)



Source: Own calculations using EU LFS data.

5. Conclusions

This background paper presents stylised facts on the evolution of the task content of jobs in European countries between the late 1990s and the middle 2010s. We have matched O*NET occupational content data with the EU-LFS data and PIAAC data and distinguished between five tasks: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical. This typology of tasks follows the literature on the subject (Autor et al., 2003, Acemoglu and Autor, 2011, Goos et al., 2104).

We have found that all European countries experienced a shift away from manual work towards non-routine cognitive work. In all countries the intensity of non-routine cognitive tasks, both analytical and interpersonal, increased between 1998 and 2014, while the intensity of manual tasks, both routine and non-routine, decreased. The evolution of routine cognitive tasks was heterogeneous – the intensity of these tasks decreased in the majority of countries, including all EU15 countries with the exception of Greece and Portugal, but it increased in the majority of the New Member States of EU. Nevertheless, a relative de-routinisation of jobs occurred, because even in those countries where the intensity of routine cognitive tasks grew, it grew less than the increase of intensity of non-routine cognitive tasks. We have identified that there were prevailing shifts in the employment structure which were fuelling these changes. The employment share of workers performing the 20% of the least routine-intensive jobs increased, whereas the employment share of workers performing the 20% of the most routine-intensive jobs decreased in all countries. There was not much change in the middle of the distribution of the relative routine intensity of jobs. This shows, although indirectly, that there was no prevalent polarisation of jobs in Europe, in line with a finding based on the analysis of occupational changes presented by Eurofound (2015). At the same time, in all countries the composition of tasks among the unemployed was skewed towards manual tasks and routine cognitive tasks.

Routine cognitive tasks are at the centre of routine biased technological change hypothesis. The decline of the importance of these tasks constitutes a focus of research showing that computerisation and automation reduces demand for human labour that can be performed by machines (Autor et al., 2003, Spitz-Oener, 2006). Although a direct test for the impact of technology is not possible because no data on technology use is available in the LFS, we have shown that labour supply side factors play an important role in the evolution of tasks. In doing so, we follow for instance Oesch (2013), Salvatori (2015) or Hardy et al. (2018) who showed that the educational upgrading of the European workforce is an important driver of occupational structures and task structures.

Using a shift-share decomposition of changes in the intensity of particular tasks, we have shown that substantial shares of these changes can be attributed to changes of educational structure of the workforce (within particular sectors). Even if sectoral structures of economies did not changed since the late 1990s and people with a given education level employed in particular sectors were working in exactly the same occupations as their counterparts in the late 1990s, the shift away from manual tasks and towards non-routine cognitive tasks would have occurred anyway. Educational change was driven by the rising tertiary attainment of the European workforce and decreasing shares of workers with primary or lower secondary education. This workforce upskilling pushed the non-routine cognitive tasks up and compressed the manual tasks, as better educated workers were more likely to perform the former and less likely to perform the latter.

We have also shown that structural changes aligned well with educational changes and strengthened the shift away from the routine work toward the non-routine work. In particular, it was the growth of sectors rich in non-routine cognitive tasks such as health care, education, transport, storage and communication, financial intermediation, and real estate and other business activities, and the reduction of employment shares of manufacturing and agriculture, that contributed to de-routinisation.

The reason why the more developed EU countries recorded a decline in the importance of routine tasks, but the less developed countries (NMS) recorded a growth in the importance of routine tasks, was related to the different patterns of structural change in both regions. In countries where the intensity of routine cognitive tasks grew it was actually due to the contribution of structural change, in the form of the gross reallocation of labour from agriculture or (to a lesser extent) manufacturing to other sectors, in particular services. It is worth noting that these sectoral shifts in the NMS are unlikely to be related to ICT – the reallocation of labour out of agriculture is a secular trend, typical for converging countries. Moreover, the educational change reduced the intensity of routine cognitive tasks across Europe. In other words, if the educational structure of the NMS' workforce didn't improve, the intensity of routine cognitive tasks in these countries would have increased even more (and the intensity of non-routine cognitive tasks would have increased less).

In some of the NMS the occupational changes pushed the routine cognitive tasks up, which suggests that the workers with a given level of education employed in particular sectors in the middle 2010s performed jobs which were more routine-intensive than jobs held by their counterparts in the late 1990s. The opposite was true in the most advanced EU countries that recorded an ample decline in the intensity of routine cognitive tasks. Most of the shift from routine to non-routine work can be attributed to younger and better educated workers.

The importance of education has been confirmed by our analyses based on PIAAC data. We have found that skills clearly matter for tasks performed by workers – the higher is the skill level, the higher is the intensity of both non-routine cognitive tasks and the lower is the intensity of both manual tasks. The intensity of routine cognitive tasks is the lowest among the 20% of the least skilled workers and the 20% of the most skilled workers, but quite similar among the middle 60% of workers in the skill distribution. These patterns have emerged in all types of skills – literacy, numeracy and problem solving. However, when it comes to tasks, education seems to matter even more than skills. We have found that among workers who have the same level of skills (belong to the same decile of the skill distribution), individuals with a higher education level exhibit a higher intensity of non-routine cognitive tasks and a lower intensity of manual tasks. Furthermore, tertiary educated workers who have very low skill levels (1st decile) exhibit a higher intensity of non-routine cognitive and a lower intensity of manual tasks than all workers with low or medium education, even those that have the highest levels of skills. These findings suggest that education level is crucial in sorting workers to occupations and tasks, in particular to non-routine cognitive tasks.

In the light of the above findings, it is not surprising that the inequality in employment rates by education level increased in the EU. It happened mainly because the individuals with primary or low secondary education lost ground with respect to all other workers. These workers tended to perform jobs with high manual and some of them also high routine cognitive content. This pattern was the most pronounced in the Southern European countries. The gaps between secondary and tertiary educated workers have not widened that much. Although the rising supply of tertiary educated workers was instrumental for the growth of non-routine cognitive tasks, we have also found some occupational downgrading of tertiary graduates – in the middle 2010s, in several countries tertiary educated workers in services sectors performed jobs which were more routine-intensive than jobs performed by their (less numerous) counterparts in the late 1990s..

References

Acemoglu, D., Autor, D. H. (2011). *Skills, Tasks and Technologies: Implications for Employment and Earnings*. In: Card, D. and Ashenfelter, O. (eds). Handbook of Labor Economics. Amsterdam: Elsevier, 1043–1171.

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

Arias, O.S., Sánchez-Páramo, C., Dávalos, M.E., Santos, I., Tiongson, E.R., Gruen, C., de Andrade Falcão, N., Saiovici, G., Cancho, C.A. (2014). Back to work: growing with jobs in Eastern Europe and Central Asia, *Europe and Central Asia reports*. Washington, DC.: The World Bank.

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

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

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

European Commission, Eurostat (2016). European Union Labour Force Survey 1998-2014. Brussels: European Commission, Eurostat.

Eurofound, Upgrading or polarisation? Long-term and global shifts in the employment structure: European Jobs Monitor 2015, Publications Office of the European Union, Luxembourg, 2015

Eurostat. (2014). EU Labour Force Survey Database User Guide.

Gimpelson, V., Kapeliushnikov, R. (2016). Polarization or Upgrading? Evolution of Employment in Transitionary Russia. *Russian Journal of Economics* 2 (2), 192–218.

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

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

Hardy, W., Keister, R., Lewandowski, P. (2016). Do entrants take it all? The evolution of task content of jobs in Poland. *Ekonomia. Rynek, gospodarka, społeczeństwo* 47, 23-50.

Hardy, W., Keister, R., Lewandowski, P. (2018). Educational upgrading, structural change and the task composition of jobs in Europe. *Economics of Transition* 26(2), 201-231.

Hummels D., Munch J., Xiang C. (2016). Offshoring and Labor Markets, *NBER Working Papers* No. 22041, National Bureau of Economic Research, Inc.

OECD. (2013). Chapter 17: Scaling PIAAC Cognitive Data. In: Technical Report of the Survey of Adult Skills (PIAAC). By: Yamamoto, K., Khorramdel L. and von Davier M. OECD.

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

Razzu G. (2017). *Gender Inequality in the Eastern European Labour Market Twenty-five years of transition since the fall of communism.* Routledge.

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

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

Appendix

1. Socio-demographic dimensions of changes in tasks

In order to quantify the contribution of various groups of workers, distinguished by gender, education and birth cohort, to the changes in task contents between 1999 and 2014, we apply a shift-share decomposition. For each country we distinguish 60 cohort-education-gender specific cells (means of particular tasks for 1999 and 2014). We then decompose the total changes of five task contents into three effects: (i) between change effect, (ii) within change effect, (iii) interaction effect, using the following formulas:

$$\forall\, i \in T\ (T_i^{2014} - T_i^{1999}) = (\sum_{\substack{j \in H \\ c \in C \\ g \in G}} t_{i,j,c,g}^{14} h_{j,c,g}^{14} - \sum_{\substack{j \in H \\ c \in C \\ g \in G}} t_{i,j,c,g}^{03} h_{j,c,g}^{99}) = BE_i + WE_i + INT_i,$$

$$\forall\, i \in T\ BE_i = \sum_{\substack{j \in H \\ c \in C \\ g \in G}} t_{i,j,c,g}^{03} \left(h_{j,c,g}^{14} - h_{j,c,g}^{99}\right),$$

$$\forall\, i \in T\ WE_i = \sum_{\substack{j \in H \\ c \in C \\ g \in G}} h_{j,c,g}^{99} \left(t_{i,j,c,g}^{14} - t_{i,j,c,g}^{03}\right),$$

$$\forall\, i \in T\ INT_{i,} = \sum_{\substack{j \in H \\ c \in C \\ g \in G}} \left(t_{i,j,c,g}^{14} - t_{i,j,c,g}^{03}\right)\left(h_{j,c,g}^{14} - h_{j,c,g}^{99}\right),$$

whereby:

- $t_{i,j,c,g}^{14}$ and $t_{i,j,c,g}^{03}$ are the average values of task content i for workers with education level j born in cohort c and gender g, calculated using O*NET 2014 and O*NET 2003, respectively,
- $h_{j,c,g}^{14}$ and $h_{j,c,g}^{99}$ are the shares of workers with education level j born in cohort c and gender g in employment in 2014 and 1999 respectively, (except for Bulgaria and Croatia where the period of analysis is 2004 and 2014),
- T is the set of five task content measures,
- H is a set of three different education levels, C is a set of 10 five-year cohorts, and G is a set of two genders.

This decomposition is a revised version of the decomposition presented by Hardy et al. (2016). Results are presented on Figure 1.

- *Non-routine cognitive analytical tasks have thrived everywhere the since late 1990s.*

The source of this growth was threefold, but two factors were especially important. For one, changes of demographic structure largely induced the growth of non-routine cognitive tasks. These changes were most pronounced in Poland and Portugal, slightly smaller but substantial in Cyprus, Latvia, Iceland and Austria. Positive between-change effect is a result of two parallel processes. The first one is due to the increasing employment shares of highly-educated younger cohorts (mostly born after 1970) of both men and women. The second one is related to the decreasing employment shares of older cohorts of low educated men (born before 1950).

In some countries (Norway, Sweden, Croatia, and Estonia) the between-change effect was close to zero. In Norway and Sweden the younger cohorts (1982, medium-educated) contributed negatively to the change of non-routine cognitive analytical tasks, the same was true for the older cohorts of (born before 1951) highly educated men and women who have been exiting the labour market and were characterised by high non-routine cognitive content back in 1999. But, at the same time, some cohorts contributed positively to the change of non-routine cognitive tasks. The highest positive contribution was recorded for low-educated men born before 1951 who have largely left the labour market by 2014, and rarely performed the non-routine cognitive tasks. These two parallel effects cancelled each other out.

The growth of non-routine cognitive tasks was also fuelled by the positive interaction effect, i.e. within and between changes occurring at the same time. This effect is also a product of two phenomena. Younger cohorts, mostly born after 1970, whose employment shares have increased, were at the same time increasingly involved in performing the non-routine cognitive tasks, hence their positive contribution. Likewise, the highly educated individuals in the older cohorts have contributed positively to the change of non-routine cognitive tasks. Back in 1999 they were characterised by high non-routine cognitive content, but by 2014 they have largely left the labour market, and the non-routine cognitive content for this cohort-education group declined. Hence, they recorded a positive interaction effect.

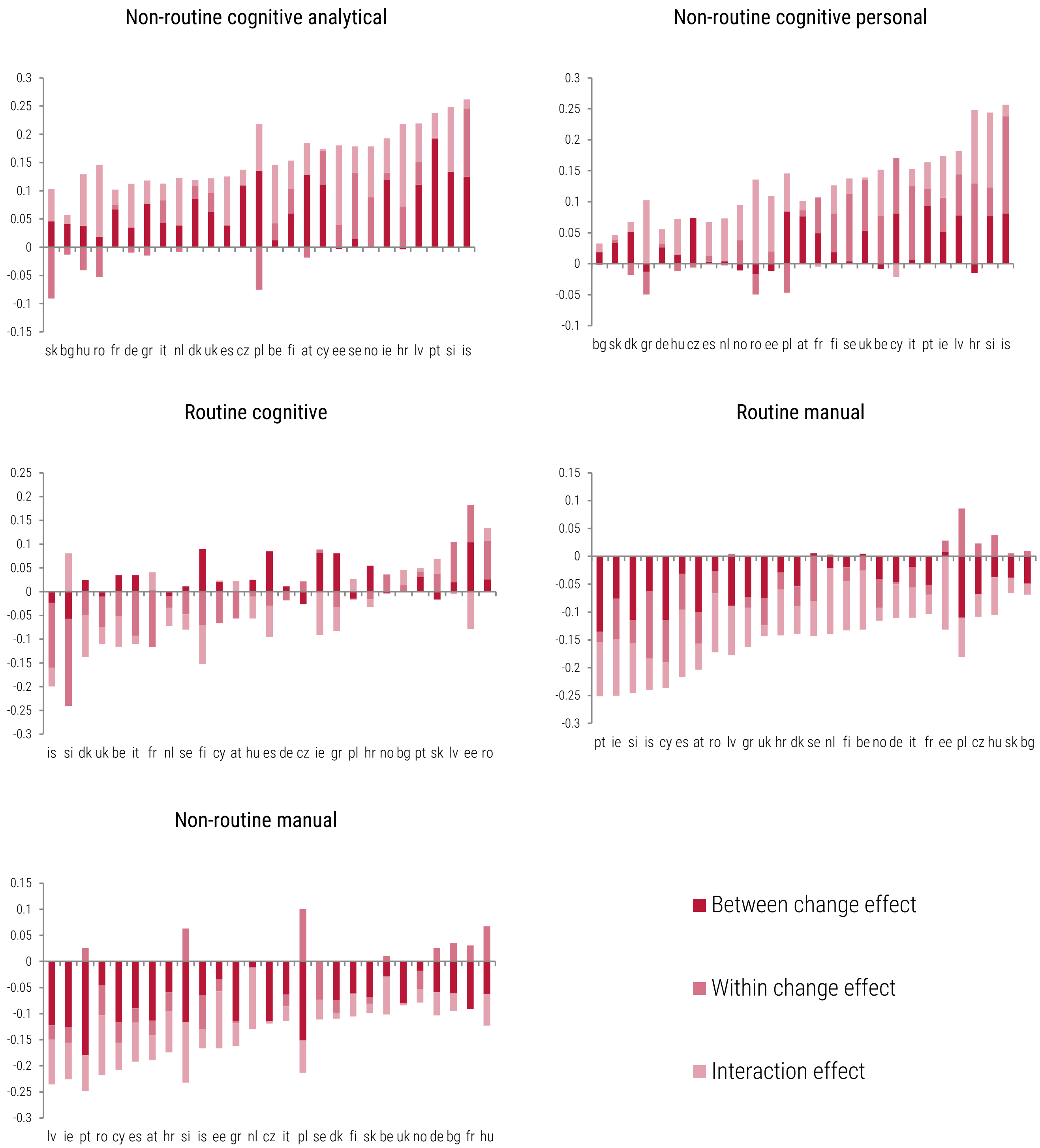
- *Non-routine cognitive personal tasks also thrived, but much of the change was due to changes within particular groups*

Positive within-group change was driven mostly by medium or low-educated older cohorts (born before 1951), which were characterised by a low (negative) non-routine cognitive personal content in 1999. By 2014, their non-routine cognitive personal content shifted towards 0, hence the positive within change effect. At the same time, since these cohorts have largely withdrawn from the labour force, they recorded a negative interaction effect. By contrast, the highly-educated individuals born before 1951 contributed negatively to the within change effect of non-routine cognitive personal tasks and positively to the interaction effect.

The younger cohorts (born after 1967), in particular poeple with at least secondary education, have also played a role in raising the within effect of non-routine personal tasks. Since 1999 they have been increasingly working in jobs rich in non-routine cognitive personal tasks, thus the positive within change. Moreover, as the employment shares of younger cohorts increased between 1999 and 2014, they also contributed positively to the total change of non-routine personal tasks via the interaction effect. This interaction effect driven by younger cohorts was especially evident for Romania, Estonia, Greece and Netherlands.

The between effect (i.e. changes in the demographic structure) outweighed the within or interaction effect in Poland and Portugal. The mechanism behind this positive between change is exactly the same as for non-routine cognitive analytical tasks.

Figure 23. The cohort-education-gender decomposition of changes in task content between 1998-2000 and 2012-2014 in European countries



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

- *The intensity of routine cognitive mostly declined, but grew in some post-transition economies*

In countries where routine cognitive tasks declined, it was mostly due to the negative within change effect, whereas the growth of routine cognitive tasks was induced by the positive within change effect.

The between change was positive in almost all countries (regardless of whether the routine cognitive tasks rose or not). Yet, in some countries (like Greece or Spain) it was driven by older cohorts (born before 1951), especially by those with primary education. Whereas for example in Estonia and Finland the positive between effect stems from high positive contribution of younger cohorts with higher education (born after 1980).

The within change effect proved more ambiguous across countries. It was significantly positive in Romania, Estonia, Latvia, where routine cognitive tasks grew the most. In general it was driven by older cohorts (born in 1950s or early 1960s), who were shifting towards jobs with relatively higher routine cognitive content. It was most evident for secondary and primary educated workers, but it was also the case for tertiary educated ones.

Countries that experienced the steepest fall of routine cognitive tasks (Iceland and Slovenia), recorded large, negative within effect. In Slovenia it was largely embodied in older cohorts (born in 50s) with secondary and primary education. They were characterised by a positive routine cognitive content in 1999 which plummeted and was strongly negative in 2014. We think that this is mostly due to de-industrialisation that took place in Slovenia (see Hardy et al. 2018). The case of Iceland is quite different, since it is hard to find one group of people "responsible" for the negative within effect. For sure, highly educated women born 1952-1972 contributed substantially to this decline. Likewise, women with primary education born in 1982 saw a steep decline of routine cognitive intensity of jobs, hence adding to that negative within effect.

- *All countries have seen manual tasks declining*

In general, the fall of manual tasks was driven by highly negative interaction effect. The negative interaction effect is driven by the decrease in the number of workers who performed a lot manual tasks (in particular, the older cohorts), or, the increase in the share of workers who performed less manual tasks (younger cohorts). The between change effect proved to be important for the evolution of non-routine manual tasks, especially in Portugal and Poland.

2. The evolution of skill content of jobs in Europe (PIAAC merged to LFS)

Skills changes in EU LFS, imputed within ISCO-Education cells

In all countries studied, the skill levels increased between 1998 and 2014, but the skill levels varied noticeably in both periods. This is shown in Figure 3 that presents the levels of skills in European countries in 1998 and 2014 (calculated with PIAAC and LFS data, see subsection 2.4), with the countries ordered by the level of numeracy skills in 2014. Notably, the countries with initially lower skills experienced larger shifts toward skill-intensive occupations and growing shares of tertiary educated workers within occupations. As a result, the between-country variance for each of the three skills dropped, with the largest change among numeracy skills. The literacy skills in EU increased by a similar magnitude on average in EU, but the decrease in variance was smaller than in the case of numeracy skills. These findings suggest that the lower-skilled countries were converging towards the higher-skilled countries, with the fastest convergence occurring in the case of numeracy skills.

Skill levels were highest in the Northern European countries, followed by the Continental European countries, while the Southern European countries exhibited a noticeable skill gap with respect to both those groups (Figure 4). However, the convergence of skill levels is also visible among these groups of countries.

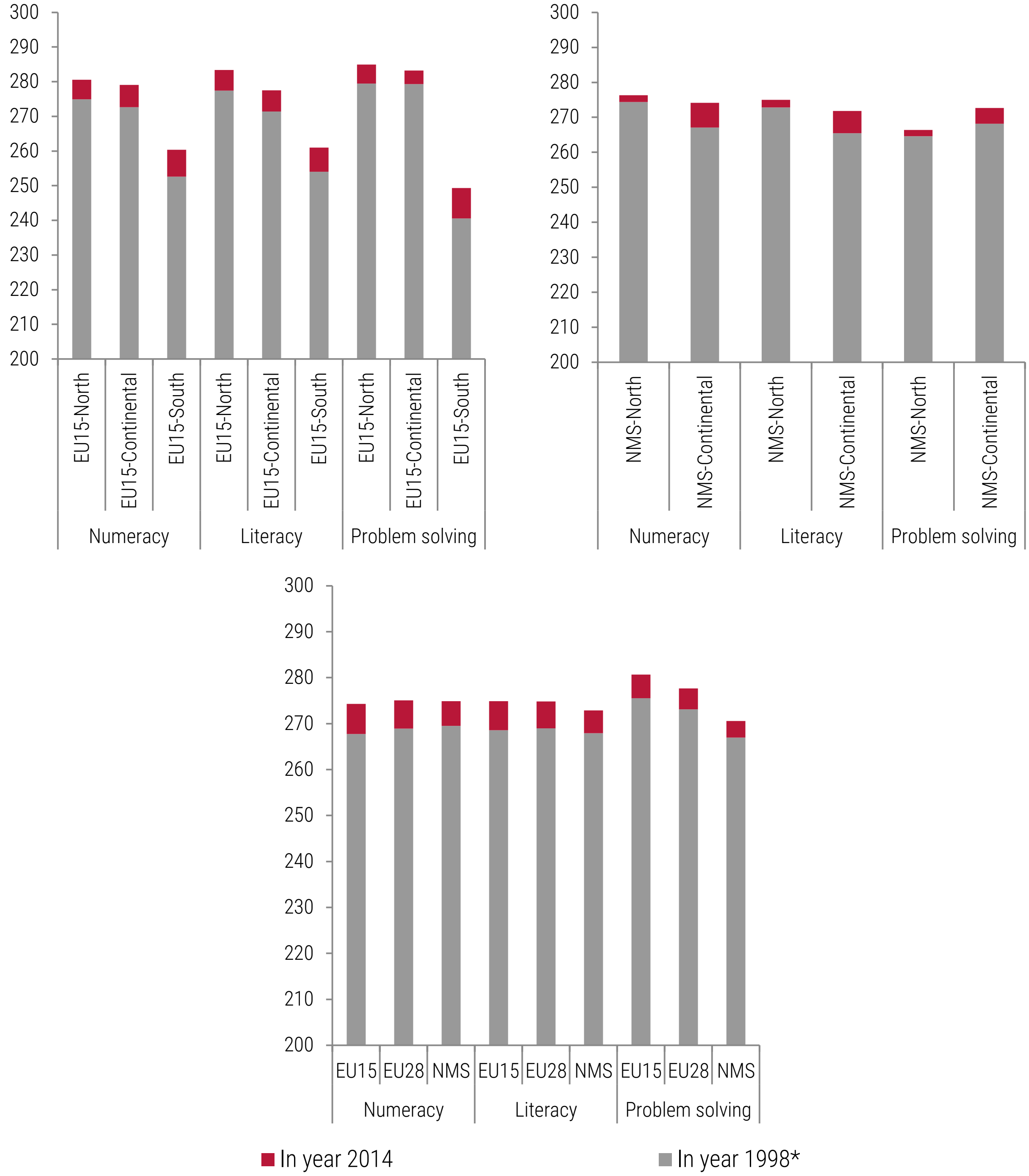
The differences in numeracy and literacy skills between the EU15 and the NMS were very small, but the new member states lagged behind the EU15 in terms of the average level of problem solving in technology-rich environment skills. Neither there was any catching up in the level of problem solving skills. Finally, the differences within the NMS group appear smaller than the differences within the EU15 group.

Figure 24. Numeracy, literacy and problem solving in technology-rich environment skills in European countries, 1998 and 2014

*Note: *1999 instead of 1998 for Cyprus, Germany, Ireland and UK.*

Source: Own calculations using PIAAC and EU-LFS data.

Figure 25. Numeracy, literacy and problem solving in technology-rich environment skills by EU country groups



*Note: *1999 instead of 1998 for Cyprus, Germany, Ireland and UK. Country groups are: EU15-North (Denmark, Finland, Ireland, Sweden and UK), EU15-Continental (Austria, Belgium, Germany, France and Netherlands), EU15-South (Cyprus, Greece, Italy and Spain); new member states (NMS)-Continental (Czechia, Poland, Slovakia and Slovenia), with no Cyprus, France, Italy or Spain in the case of problem solving skills. There is no PIAAC data for the NMS-South country group.*

Source: Own calculations using PIAAC and EU-LFS data.

Skills changes in EU LFS, imputed within ISCO-Education-Age cells

Our initial approach was to use PIAAC to calculate the average skill levels by occupation / education cells. We used 1-digit ISCO occupations (nine groups) and three levels of education. This resulted in 27 cells per country. In the next step, we merged these averages to the EU-LFS data for 1998-2014 and for each country calculated the average skill levels over time. The implicit assumption is that average skill levels in particular cells were constant over time.

The current approach extends this method as we use also five 10-year age groups. The number of cells is substantially higher – on average 132 per country – but the number of observation per cell is much lower – on average 26 observations per country-ISCO-education-age cell (some cells include very few observations).

In comparison to our initial approach, this method leads to a generally lower increase in skill levels over time. It some case it even shows a decline in skills over time (see examples in Figure 1 below). That's because the average skill levels in PIAAC are lower for older people (see Figure 2). In most countries the workforce was ageing so the weight assigned to older workers has been increasing over time.

Moreover, the assumption of constant skill levels within particular cells seems implausible if age is accounted for. Because of cohort effects, it is likely that older workers (e.g. aged 55-64) in the 2010s had better skills than their counterparts in the 1990s (even if education is controlled for). As a result, the assumption of constant skill levels within occupation-education-age groups most likely implies that past skill levels are overestimated. We recommend using the occupation-education cells instead.

Figure 26. Skill levels across time, calculated with ISCO-Education cells and ISCO-Education-Age cells

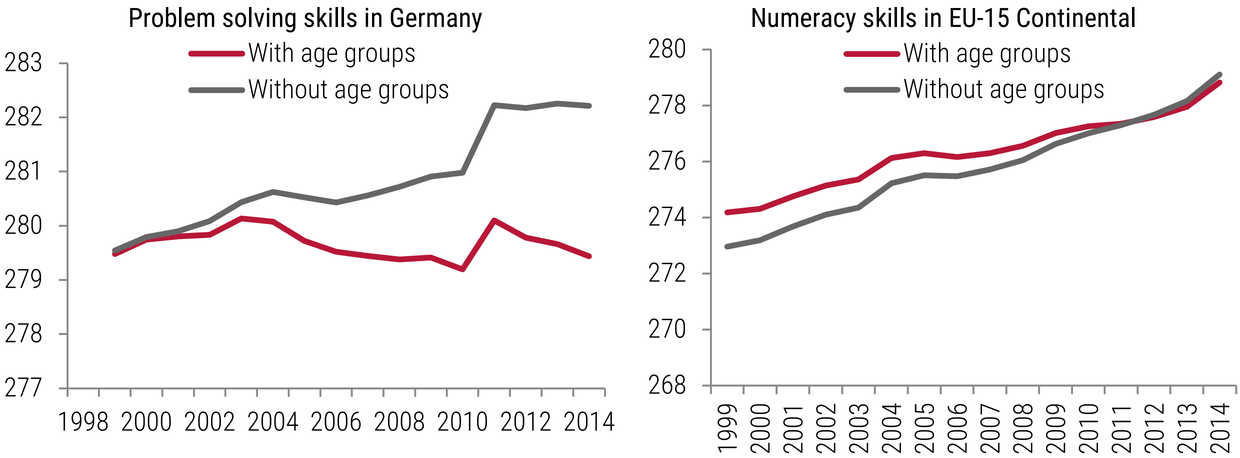
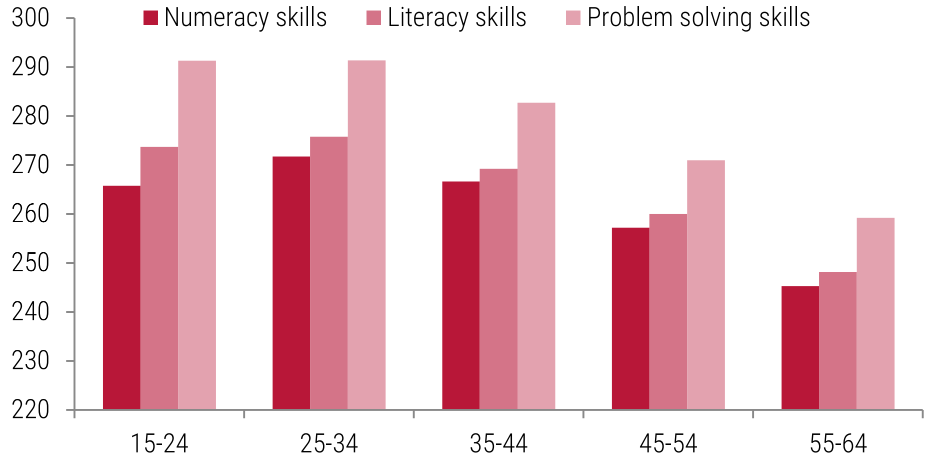


Figure 27. Skill levels across age groups in PIAAC. Average for all EU countries



Changes in employment shares by skill proficiency levels

We categorised the skill levels according to the OECD division of scores into levels from 0 to 5.[15] Due to generally small shares of people scoring at levels 0, 1, 4 and 5, we aggregated the categories into four groups: "0 and 1", "2", "3" and "4 and 5". Then we calculated the shares of every skill group within the occupation education cells (again, 1-digit ISCO occupations and three education levels), for each country separately. Finally, we merged these values to the EU-LFS data and calculated the evolution of employment shares of particular skill level groups over time.

Note: We also tried other approaches which were discussed during the call. First, we tried calculating mean skill scores within occupation-education cells and then grouping the values into categories. However, this approach resulted in almost no variation in skill groups across the cells. Second, we tried aggregating the skill scores into three categories: low ("0 and 1"), medium ("2 and 3") and high ("4 and 5"). However, the medium group constituted a vast majority of employment and changes over time were not informative. Therefore, we distinguish between skill levels "2" and "3" and analyse four groups of workers.

We find that the employment shares of people with higher skills (mostly medium high – i.e. level 3), were slowly increasing over time. These changes were rather small and followed similar patterns across countries and skill types. Figure 3 presents several examples of how the structure of employment by skill level groups evolved.

The changes in structures of employment by skill level were mainly driven by changes in the structure of the workforce by education rather than the occupational changes. The shift share decomposition shows that in all countries most of change in the average levels of numeracy, literacy and problem solving skills between 1998 and 2014 can be attributed to changes in the educational structure of the workforce (see Figure 4).

[15] See: https://www.oecd.org/skills/piaac/Key%20facts%20about%20the%20Survey%20of%20Adult%20Skills.pdf

Figure 28. Employment shares across skill proficiency groups

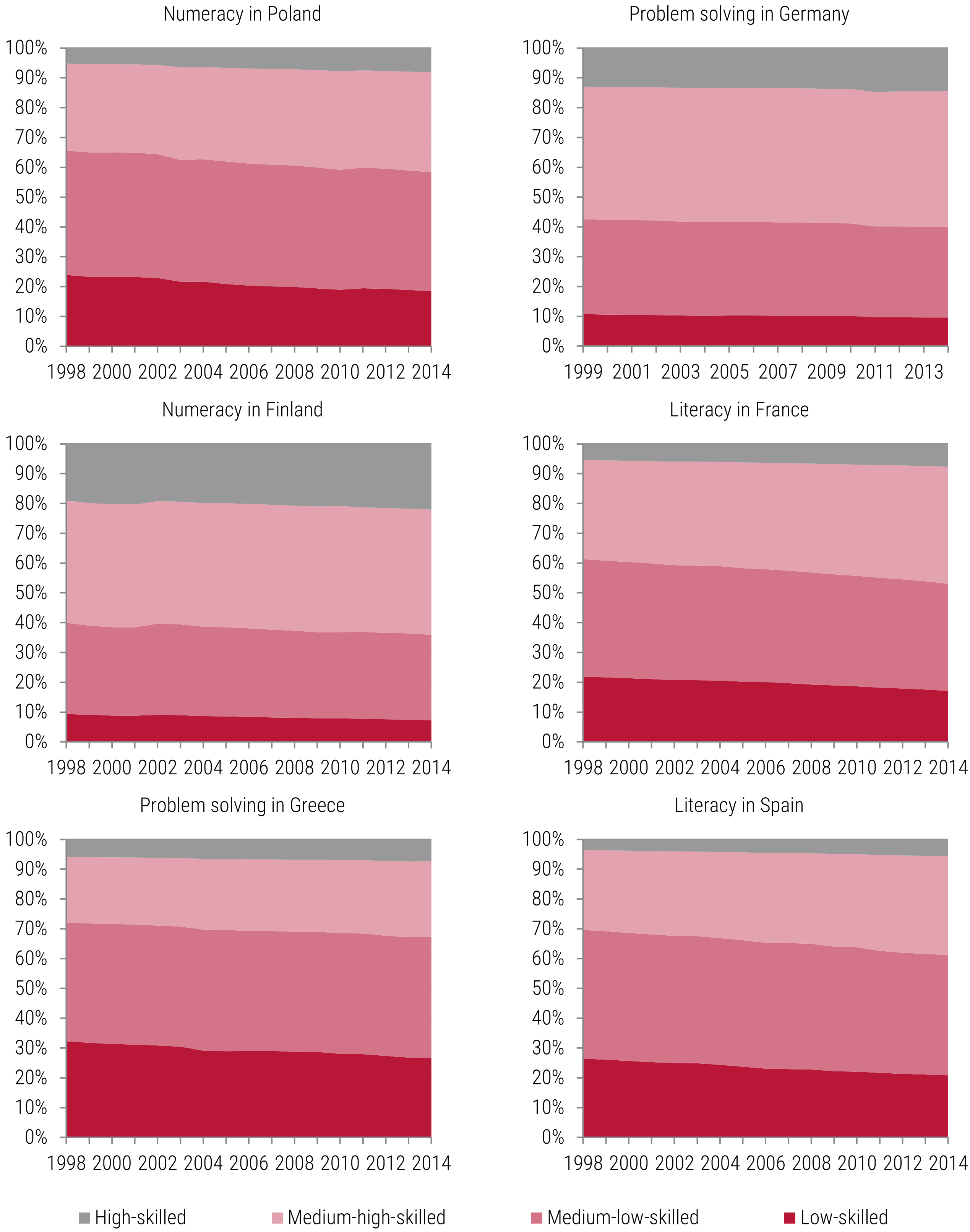
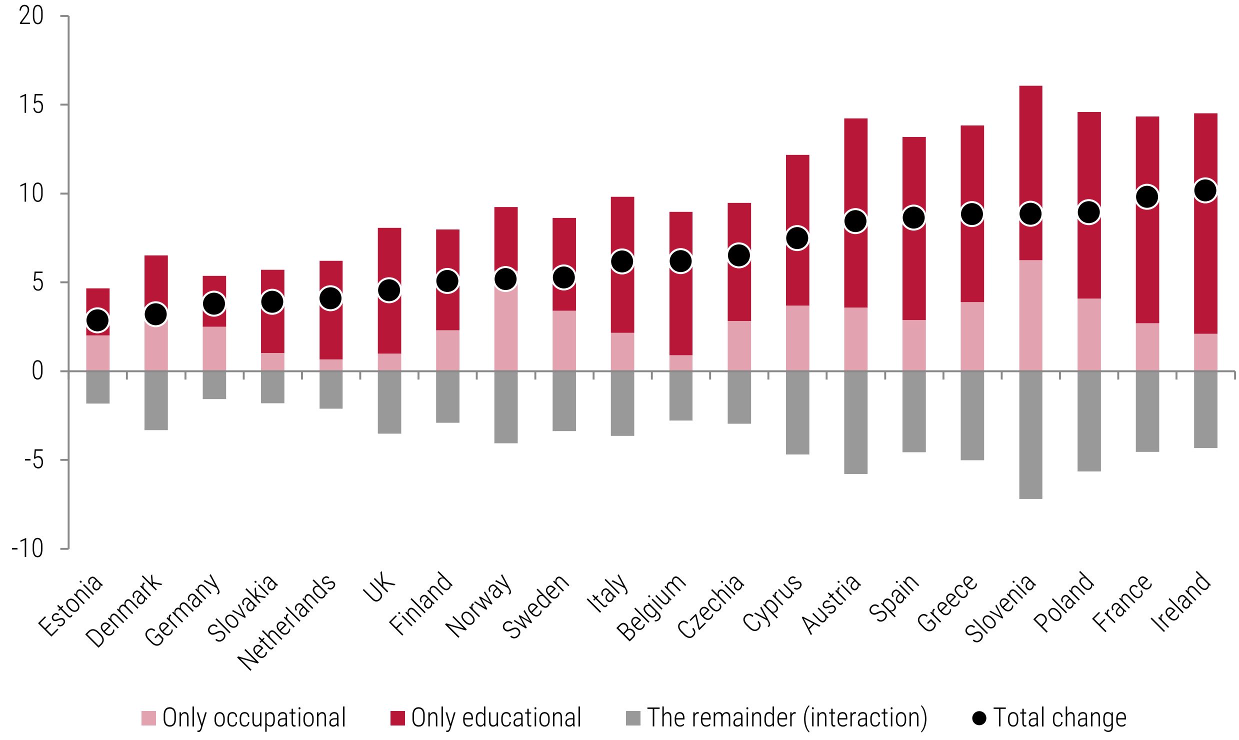


Figure 29. Decomposition of the average numeracy skill scores changes, by education and occupation



instytut
badań
strukturalnych

www.ibs.org.pl