Upskilling, deskilling or polarisation? Evidence on change in skills in Europe

Abstract

What are the directions of change in the complexity of work and the required levels of skills of the labour force in Europe? Three prominent strands of literature suggest conflicting expectations – upskilling, deskilling and polarisation. This question is answered by employing a novel work complexity indicator that measures how tasks are performed at work according to three dimensions: routinisation of tasks, autonomy at work and continuous skill building. The measurements rely on the European Working Conditions Surveys carried out in 2005, 2010 and 2015. The results show that the European labour markets witness upskilling with some polarisation, although there are significant cross-national differences. They also show that individually neither shifts in work complexity within occupations (deskilling hypothesis), nor changes in employment structure (focus of upskilling and polarisation hypotheses) can provide an adequate view of trends in the European labour markets. Instead, both vectors of change should be analysed collectively.

Keywords: composite indicators, job requirements approach, labour force, skills

1. Introduction

What are the directions of change in the complexity of work and the required levels of skills of the labour force in Europe? Three strands of literature provide conflicting hypotheses. First, the deskilling hypothesis originally proposed by Braverman (1974, 1998) suggests that division of work into simple standardised tasks, codification and embeddedness of knowledge in work organisation processes and technology have deskilled work in most occupations. While this view has been criticised as outdated, applicable only to craftwork (Heisig, 2009) and exaggerating the impact of Taylorism on the workplace (Meiksins, 1994; Huws, 2003), it remains highly influential. A literature review by McNally (2010) found that Braverman's argument remains relevant in explaining deskilling in traditionally high skill occupations, such as nursing, librarianship, journalism and law (p.359). Similarly, Haakestad and Friberg (2017) argue that deskilling in the Norway's construction sector can be explained by the adoption of Taylorism and the related shift in power from workers to managers (p.18-19).

The second strand of the literature advances the skill-biased technological change (SBTC) argument (Katz and Murphy, 1992; Acemoglu 2002 among others): technological progress since the mid-20th century has resulted in a higher demand for skills. This is suggested by persistently high education premiums in the face of increasing supply of skilled workers. Berman et al. (1998: 1273) found that at least 70% of the displacement of unskilled workers in the U.S. can be explained by the SBTC. They also found that similar trends were observed in many developed countries. Similarly, Esposito and Stehrer (2008) found that SBTC can explain the shifts in labour that happened in Central and Eastern European countries during the transition from planned to market economy during the 90s. Recent studies also identified similar trends in Germany (Hutter and Weber, 2017) as well as in Organisation for Economic Co-operation and Development (OECD) countries (Neto et al, 2019).

The past decade has also witnessed a rise of the third view – the polarisation hypothesis. Acemoglu and Autor (2010) and Goos et al. (2014) argue that routine tasks performed mostly by mid-skilled occupations are increasingly carried out by machines. As a result, technological change has brought a decline in employment in mid-skilled occupations and growth in low- and high-skilled ones. This is contrary to a more monotone relationship between technology and skills that the SBTC stipulates. The polarisation hypothesis is increasingly supported in recent studies (e.g. see Breemersch et al., 2017; Keister and Lewandowski, 2017; Fonseca et al., 2018).

The conflicting results of the three strands of the literature can be (at least partially) explained by the different approaches to estimating changes in skills. The proponents of the deskilling hypothesis focus on changes within occupations. The advocates of upskilling and the polarisation hypothesis focus on the changing structure of the employment, i.e. changes between the occupations. Furthermore, while some employ proxies for measuring the skills of individuals (e.g. education levels or wages), others focus on occupations and tasks that comprise them. To mitigate this issue, some (e.g. Autor and Handel, 2013; Molina-Domene, 2018; Stinebrickner et al., 2019) try to merge the two views by using surveys to measure what tasks individuals perform on the job.

This article aims to shed light on the above debates by developing and empirically testing a new work complexity indicator that merges the personal and occupational view of skills. Just like many newer skill measures, it is based on tasks. However, in contrast to other similar efforts (e.g. Autor and Handel, 2013) the indicator does not assess, what tasks individuals perform, because it is problematic to compare the level of skills needed for performance of different tasks. Instead, the indicator measures how the tasks are performed according to three dimensions: (i) level of non-routine tasks, (ii) autonomy of work and (iii) continuous skill building. The indicator builds on the methodology proposed by Autor A and relies on data from the European Working Conditions Surveys (EWCS) carried out by Eurofound in 2005, 2010 and 2015 in 35 European countries. The main value added of this work is that it allows for comparative and longitudinal analysis of changes within and across occupations.

Since there is no publicly available micro-level data on introduction of new technology, it is difficult to test the causal relationships proposed by the deskilling, upskilling and polarisation hypotheses. However, the proposed indicator allows observing the empirical implications of the hypotheses, i.e. whether work complexity within occupations has decreased (deskilling hypothesis) and whether the shares of employment in occupations characterised by high (upskilling hypothesis) or high and low complexity (polarisation hypothesis) have changed. The results show that shifts in work complexity within occupations and across occupations, while provide interesting insights, do not reveal a clear pattern of change. However, when combining the two factors we find that European labour markets witness upskilling with some polarisation, i.e. the proportion of employed in deciles characterised by very high complexity has significantly increased and the share of employment in the deciles characterising the lowest complexity slightly increase in 2005 – 2015. The aggregated results for all European countries under analysis, however, conceal significant cross-national differences. While majority of countries demonstrate polarisation or upskilling, a significant share of countries in the sample also witnessed deskilling. Since both groups include countries that were severely hit by the global financial crisis in 2008, this finding merit further research.

The rest of the article is structured as follows: section two discusses the relative merits and drawbacks of existing approaches to measuring skills of the labour force. Sections three and four outline the proposed methodology for measuring complexity of work and the results of the validity test, respectively. Section five discusses changes in work complexity in Europe in 2005 – 2015 within occupations as well as shifts in structure of employment. The last section concludes the article.

2. Literature review: measuring skills

There are two broad strategies for measuring skills of the labour force. The human capital approach (Mincer, 1958; Becker, 1964) views education and training as an investment in acquisition of skills, which subsequently provides returns in the form of higher wages. Accordingly, years of schooling provide a proxy for measurement of skill levels and increasing supply of university graduates could indicate up-skilling of labour force. While education proxies are widely used due to availability of data, they have also been heavily criticised.

First, education proxies implicitly assume that skills are static (i.e. do not depreciate due to not being used or increase with work experience) and that the quality of education and training is the same for all individuals (Hanushek and Kimko, 2000). Second, many higher education programmes that offer the same qualifications and would be treated as equals by the education proxy, differ substantially in terms of content and quality (Esposto, 2008). Third, they measure only individuals' potential to carry out tasks rather than how the abilities, knowledge, past experience and so on are actually used in the workplace (Autor A). As a result, the trend of increasing years of schooling does not necessarily indicate upskilling of the labour force, if the acquired skills are not used or further developed on the job (Autor and Handel, 2013; Firpo et al., 2010).

Some of these issues could be mitigated by other proxies (e.g. wage) or more sophisticated skill measures. For example, Hanushek et al. (2015) and Quintini (2014) suggested using the results of the Programme for the International Assessment of Adult Competencies (PIAAC) survey, which provides information on the level of literacy, numeracy and problem-solving skills of individuals.

However, this approach remains silent on how and what skills are used on the job. Hence, the literature proposed an alternative approach that focuses on the contents of work rather than characteristics of an individual (Autor et al., 2003; Felstead et al., 2007).

The job requirements approach argues that the level of skills depends on the nature and contents of tasks that a work entails (e.g. see Mane and Miravet, 2016). It is based on a premise that skills refer to interactions between the individual's potential to carry out work (due to past education and experience) and the characteristics of work domain (types of tasks, technology, work organisation, etc.). Accordingly, the types of tasks an individual carries out should reflect his/her level of skills. The literature uses several strategies to estimate the levels of skills according to the job requirements approach.

The first strategy relies on the descriptions of occupations as provided in the administrative databases. For example, Kremer and Maskin (1996) and Esposto (2008) estimated skills by broadly defining the level of skills required for each occupation (e.g. managers and professionals are highly skilled while labourers, machine operators and drivers, etc. are lower) (Esposto, 2008). Accordingly, an increase in employment in high-skilled occupations implies upskilling, while a relative decline in employment in mid-skilled occupations would point towards polarisation. Others (e.g. Autor et al., 2003; Goos et al., 2014), used the Dictionary of Occupations (DOT) or its successor the Occupational Information Network (O*NET) databases, to assess what tasks does an occupation entail and what skills and knowledge is required to perform work. However, the major drawback of using administrative databases to gauge skill requirements is that this strategy ignores empirically observed differences within occupations in terms of range of tasks carried out and how they are performed (Autor and Hendel, 2013).

To mitigate this issue, the second strategy relies on employees' surveys, which focus on tasks performed in each occupation as well as related skill requirements. Accordingly, literature has focused on abilities and knowledge used to perform tasks (Payne et al, 1992; Marshall and Byrd, 1998), the ways in which tasks are carried out (Segal, 1982; Bonner, 1994; Brown and Miller, 2000), level of uncertainty in carrying out tasks (Wood, 1988; Bell and Ruthven, 2004), perceived difficulty of carrying out the tasks (Hendy et al., 1997). These studies are increasingly gaining traction due to availability of large-scale datasets, such as the Princeton Data Improvement Initiative (PDII) survey that covers the U.S. (see Autor and Hendel, 2013) and longitudinal Linked-Employer-Employee Data covering Germany (see Molina-Domene, 2018). While survey-based strategies aim to directly capture tasks performed and skills used at work, it has two limitations. First, it is not possible to adopt this approach for comparative longitudinal study due to lack of the necessary data. Second, focus on tasks performed and skills used at work poses an analytical challenge – how can we compare the skill requirements of jobs that encompass completely different tasks? To address these issues and shed light on the upskilling, deskilling and polarisation debate the article uses an alternative approach to measuring skills.

3. Methodology

The proposed work complexity indicator (so entitled to avoid terminological confusion with other skills indicators) focuses on how tasks are performed rather than what tasks are carried out and what skills they do require. Such strategy is motivated by the fact that occupations entail multiple combinations of tasks that require varying depths of skills, which implies that it is inherently difficult to establish unambiguous points of reference for the assessment of relative difficulty or routinisation of tasks and the levels of skills required. For example, the widely used routinisation index proposed by Autor et al. (2003) suggests that performance of mathematical operations measures nonroutine analytical tasks. However, this does not tell us, whether this is more / less complex than, for instance, managerial or emotional support tasks. Furthermore, one can easily find a number of examples, where machines perform advanced mathematical tasks, which would imply that this is a routine analytical task. To give another example, Autor et al. (2003) argue that finger dexterity is a measure of routine manual tasks. However, a number of occupations (e.g. musicians, surgeons, jewellers, etc.) rely on finger dexterity to perform non-routine complex work. Hence, it is difficult to interpret information on task contents of a job as well as to compare the relative difficulty or routinisation of different tasks. This problem is addressed by comparing how different tasks are performed according to a set of common criteria.

Spenner (1983, 1990) and others (Vallas, 1990; Witte and Steijn, 2000) argued that the level of skills required to perform work should be measured on two dimensions. According to the first one, high skills are required, if work encompasses variety and non-repetitive tasks, work includes a great deal of uncertainty and cannot be carried out according to codified procedures and cannot be easily monitored. Spenner (1983) called this dimension substantive complexity, while the more recent literature (Autor et al., 2003; Goos et al., 2014, Autor, 2015) refers to this as non-routine tasks. To avoid terminological confusion the later term is used. The second dimension refers to the level of autonomy, which is understood as the level and scope of responsibility and decision making on contents, sequence and manner of execution of tasks (Spenner, 1983). As previous research suggests (Witte and Steijn, 2000) both dimensions should be used, since introduction of new technology can lead to higher share of non-routine tasks, but also reduce the scope for autonomy. The two dimensions, however, do not account for capacity to deal with disequilibria, i.e. learn and adapt in the face of organisational, economic or technological changes (Schultz, 1975). As numerous studies have shown (e.g. see Russo, 2016), continuous learning is associated with upskilling as well as development and absorption of workplace innovations. Therefore, a third dimension is added – continuous skill building.

In line with above discussion, we define complex work as the one that relies on non-routine tasks, provides significant level of autonomy, as well as opportunities for learning. Accordingly, the level of work complexity is measured on three dimensions: non-routine tasks, autonomy and continuous skill building. The measurements are based on the questionnaires and data of European Working conditions surveys carried out in 2005, 2010 and 2015 in 35 European countries. Below we discuss operationalisation and measurement of each dimension.

Insert Table 1 about here

Non-routine tasks

The first dimension – non-routine tasks – is defined as the extent to which work relies on variety of non-repetitive tasks that do not follow explicitly codified procedures and therefore cannot be easily monitored. This is largely equivalent to the conceptualisation of (non)routine tasks as provided by Autor et al. (2003), Acemoglu and Autor (2010), Autor and Dorn (2013), Goos et al. (2014). They argue that routine work is distinguished by its repetitive nature as well as following well understood explicit rules.

Empirically, performance of non-routine of tasks is captured by five EWCS 2015 questions (see Table 1). The extent to which work relies on variety of non-repetitive tasks is measured by two questions: does the work involve short repetitive tasks of less than 10 minutes (Q48b) and does the job involve monotonous tasks (Q53d). The extent to which performance of work relies on codified procedures and therefore can be easily monitored is measured by three questions whether pace of work is dependent on: numerical production targets or performance targets (Q50c), on automatic speed of a machine or movement of a product (Q50d) and on the direct control of a boss (Q50e).

To check if these questions are related and measure the same concept, we estimated their Cronbach's[1] alpha, which obtained the value of 0.51. This suggests that there is some internal consistency between the questions, although it is not very high. Further analysis of separate questions suggests that the relatively low interconnectivity is not because the questions measure unrelated concepts, but rather they measure different aspects. This is further reinforced by rather expected results, suggesting that stationary plant and machine operators, assemblers and laborers in mining, construction, etc. perform routine tasks, while non-routine tasks are carried out by professionals (for details see Appendix 2).

Autonomy of work

Autonomy of work refers to the extent to which workers can decide on content, manner and speed of performing tasks. Higher levels of autonomy require holistic understanding of value creation as well as skills and knowledge in managing working environment. Workers with high level of autonomy have the opportunities to continuously improve their own work and that of others.

The level of autonomy is calculated by using eight questions that are related to how many things an employee can change in his/her job (e.g. rate or methods of work), as well as how much influence a worker has on work organisation (e.g. ability to apply own ideas). The overall Cronbach's alpha of these variables is 0.83, which implies a high level of interconnectivity of the variables. The average Spearman's correlation between the variables that belong to this dimension is 0.342. This implies that the variables selected measure the same concept (because of high Cronbach's alpha), but also that each variable captures a bit different aspect of this dimension (because of the relatively low, but statistically significant, correlation level).

Continuous skill-building

The third dimension – continuous skill-building – refers to opportunities of workers to learn new skills. Workers with such opportunities should be able to perform more complex work as well as have higher capacities to adapt to workplace innovations. This dimension complements the other two as it adds dynamics to otherwise static conception of work complexity (Autor A).

Continuous skill building is measured by the questions regarding learning new things at work (Q53f) as well as different types of training over the past 12 months (Q65 a, c, d). Some argue that training opportunities is a poor measure of skills as it can be affected by age, type of employment and sectors. To check whether this is the case the assessment of validity of the work complexity indicator includes control for gender, age, tenure and workhours of each individual surveyed in the EWCS (see next section). The Cronbach's alpha for the selected questions is 0.59, which implies weak interconnectivity. Average accuracy of the four questions, which is a measure of how many times individuals provided the same answer to the questions comprising this dimension (see Table 1 for the questions), was around 60%, which further supports the interconnectivity conclusion.

Construction of aggregate work complexity indicator

The measurements on each dimension are scaled from zero to one. The correlation between autonomy and other dimensions is relatively weak, but statistically significant. The correlation between non-routine tasks with continuous skill building is very low (see Table 2). This is probably because performance of even the most routine tasks still requires training. However, this could also imply that the two dimensions measure different empirical phenomena. Therefore we ran an optimisation algorithm, which assessed if different (smaller) weights for one of the dimensions of the indicator would produce better correlation with wage.[2] This test rests on an assumption that higher work complexity should be rewarded with higher wage premium (see Elias, 2001; Mcintosh, 2001; Blundell et al., 2005; and others). If one of three dimensions was not relevant or poorly constructed, the assessment would propose giving it lower weight. However, the results of the analysis suggest that no combination of weights improved the Spearman's correlation (this type of correlation was used as the variables are non-normal) between work complexity and wage by more than 0.01. This implies that the dimensions measure the same concept and an exclusion of any of them would decrease the explanatory power of the work complexity indicator. Hence, equal weights are used.

Insert Table 2 about here

4. Validity tests

To ensure that the proposed indicator is of high quality we follow Adcock and Collier (2001) and carry out two tests – convergence and nomological validity.[3] The assessment of convergence validity aims to establish whether the indicator correlates with other measurements of the same concept. Convergent validity is assessed by comparing the proposed indicator with the level of education of the respondents of the EWCS, 2015. Additionally, the indicator is also compared with literacy, numeracy and problem-solving skills as measured by the PIAAC[4]. For the purposes of comparison all measures were transformed to a zero to one scale. The comparison includes only countries present in both the EWCS (2015) and the Adult Literacy Survey (2013).[5]

The results suggest that overall all three measures correlate (see Figure 1 below), although some differences exist. On the one hand, education tends to overlap with the work complexity the worst (see Figure 1 below). For example, the results suggest that skilled agricultural workers (sixth International Standard Classification of Occupations (ISCO) group) have the lowest educational attainment although our measure does not suggest the lowest work complexity. On the other hand, the PIAAC adult literacy survey provides very similar results to our work complexity measure. The results are consistent with all three PIAAC adult skill level measures (i.e. literacy, numeracy and problem solving) as well as the aggregate PIAAC measure. The only substantial difference is that professionals demonstrated the highest scores in the PIAAC tests, whereas the work complexity index assigns the highest score to managers. Despite these nuances, the work complexity index is overall convergent with the other measures of skills of the labour force.

Insert Figure 1 about here

Assessment of nomological validity assumes that a well-established hypothesis is correct and tests the indicator. The research assumes that the following hypothesis is correct: the higher the work complexity, the higher the wage premiums. This assumption is tested using a Mincerian earnings equations:

$$\ln(W_i) = \alpha + \beta_1 WorkComplexity_i + \beta_2 ISCED_i + \beta_x\ controls_i$$

Where i is an individual surveyed in the EWCS 2015, $\ln(Wi)$ is the natural logarithm of their wage[6], α is the intersect, $WorkComplexity_i$ is the proposed index, $ISCED_i$ is the education level and $controls_i$ is the list of controls per each respondent, including gender, age, tenure, workhours, gross domestic product (GDP) per capita of a country and self-employment status. Regression coefficients are estimated using ordinary least squared method. The empirical analysis relies on data from the EWCS (2015).

According to the results (see table 3), the work complexity index is a strong predictor for wage. A one unit increase in our index leads to an around 92% increase in wage. Since work complexity measure ranges from zero to one, this means that keeping everything constant, a person working at a job with a complexity level of 0.1 higher than another individual earns 9.2% more. Considering that these results were obtained while controlling for education, tenure, type of employment (i.e. self-employed or not) and a number of other factors, the work complexity index is nomologically valid as well as provides additional insights about the labour market in Europe.

Insert Table 3 about here

Additionally, to check consistency of the work complexity indicators its distribution was checked. The results suggest that work complexity, assessed at the ISCO-08 level 2 occupations, follows a relatively normal distribution (see Appendix 3). However, it also has a relatively high standard deviation, which does not change much by occupation (see Appendix 2). This implies that there is quite a large variation inside occupations in terms of work complexity. This is consistent with the findings of Autor and Handel (2013), who found that the performance of tasks varies substantially within occupations.

5. Discussion and implications

This section uses the work complexity indicator to answer two questions. First, what explains cross-country differences in terms of work complexity: is it the structure of employment or the differences within occupations? Second, what are the observable implications of the proposed measure for the deskilling, upskilling and polarisation debate?

Differences between countries

The countries covered by the EWCS significantly differ in terms of mean work complexity (see Appendix 4). It is the highest and equals to or exceeds 0.62 in all the Nordic countries and the Netherlands, while it is the lowest in Greece (mean score of 0.37) and a number of other Southern European countries (Malta being an interesting exception). To what extent is this due to differences in work complexity within the same occupations or structure of employment?

On the one hand, variation in work complexity in different countries within the same occupations is rather small and equals 0.075.[7] The smallest average difference in work complexity is for other clerical support workers (0.024), while the largest is for information and communications technicians (0.148). Though for the majority of occupations the difference is on the smaller side. This is surprising, given that the sample of countries includes global innovation leaders (e.g. the Nordic countries) and followers (e.g. non-European Union (EU) Members in the Balkan Peninsula).

On the other hand, the top five countries with the highest mean work complexity employ 16.4% of the labour force in the top five occupations by work complexity.[8] In comparison the five countries characterised by the lowest mean work complexity employ only 7.8% of labour force in the respective occupations. Hence, cross-national variation in average work complexity is well explained by the differences in the structure of employment

Deskilling hypothesis: change within occupations?

The proponents of deskilling hypothesis argue that changes in work organisation processes and technology have resulted in deskilling in most occupations (Braverman, 1974, 1998). We cannot directly test this hypothesis due to lack of data on the independent variable. However, we can test its observable implications: if the deskilling hypothesis is correct, we should observe a decline in work complexity over time. The analysis covers the countries that participated in all three waves of the EWCS[9] and occupations per country that had at least 25 observations in each time period.

The data suggests that on average work complexity in 2005 – 2015 increased by 0.01 points. Looking at specific occupations we do not find a clearly pronounced trend. Work complexity increased for stationary plant and related operators and physical, mathematical and engineering science professionals, but declined for customer service clerks and other craft and related trade workers. At the aggregate level work complexity in more than half of the countries in our sample slightly increased[10], while it declined[11] in the rest in 2005 – 2015 (see Appendix 5). Countries that witnessed the largest growth in work complexity include United Kingdom, (0.075), Germany (0.073) and the Netherlands (0.066), while Switzerland (-0.071), Greece (-0.051) and Cyprus (-0.049) had the largest decline. The changes, however, are relatively small as they are smaller than the standard deviation of work complexity for the countries, even though the differences are statistically significant. In addition, the differences between the groups of countries cannot be readily explained by the GDP per capita, levels of unemployment, impact of financial crisis and other characteristics. The results suggest that while overall work complexity within occupations has slightly increased, these changes alone cannot provide a compelling story.

Upskilling and polarisation: change in the structure of employment?

The proponents of the upskilling (Katz and Murphy, 1992, Acemoglu, 2002) and polarisation (Acemoglu and Autor, 2010; Goos et al., 2014) hypotheses argue that changing technology and trade patterns have resulted in shifts in the occupational structure. The proposed indicator allows testing the observable implications of these hypotheses, i.e. whether the structure of employment shifted towards occupations relying on more complex work (upskilling) as well as the highest and the lowest complexity of work (polarisation). This is done by, first, dividing all occupations (ISCO-88 level 2) into ten deciles according to the level of work complexity in 2005, and second, estimating the changed share of employment in each decile from 2005 and 2015.

The results (see Figure 2) suggest that while the structure of occupations has changed, there is no clear trend pointing to upskilling or polarisation. More specifically, the substantial increase in employment middle complexity occupations goes against the polarisation hypothesis as well as against upskilling as there is also a decline in the higher complexity occupations (seventh and tenth deciles). One possible reason for the lack of pronounced direction of change at the European level is that the EWCS includes a variety of countries, which might have been subject to divergent trends. However, estimates of changes in the share of employment in the ISCO-88 level 2 occupations at the country level also provided mixed results. More specifically, there appears to be upskilling in 10, deskilling in 2, polarisation in 1 and no clear trend in the remaining 18 countries.[12] The mixed results suggest that changes in the structure of employment do not provide a compelling support for upskilling or polarisation hypotheses.

Insert Figure 2 about here

Combined effects of changes within and across occupations

The combined effect of the changing structure of employment and within occupations is analysed by estimating how the share of employees changes in each decile characterised by the level of work complexity. More specifically, first, individuals surveyed in the EWCS 2005 are divided into ten deciles according to work complexity. Second, the share of employment in each decile is estimated. Third, each individual surveyed in the EWCS 2015 is assigned to the appropriate previously estimated decile. Forth, using the previous results the share of employment in each decile in 2015 is estimated. Finally, the difference between the share of employees in the EWCS 2005 and 2015 is calculated.

The results (see Figure 3) show a relative decline in employment in mid-complexity deciles and an increase in the two deciles of occupations characterised by the highest work complexity (2.1% and 1.5% respectably). There was also a minor increase in the share of employed people in the lowest decile (0.2%). This suggests that European labour markets witness upskilling with some polarisation.

Insert Figure 3 about here

The aggregated results for all European countries under analysis, however, conceal significant cross-national differences. While the majority of countries demonstrate polarisation or upskilling, a significant share of countries in our sample also witnessed deskilling (see Appendix 6), which cannot be readily explained by the impact of financial crisis of 2008. The Netherlands, Estonia and France witnessed the largest growth of employed people in deciles characterised by the highest work complexity. This is surprising, given that Estonia was significantly hit by the global financial crisis and the burst of domestic real-estate bubble in 2008. Furthermore, Switzerland, Greece and Sweden had the largest increase in the share of workers in the lowest complexity deciles. While this result (due to the financial crisis) is expected for Greece, it is rather surprising to find Switzerland and Sweden in the same group.

6. Conclusions

The article makes two contributions. First, it proposes an approach for measuring change in complexity of work within and across individuals, occupations and countries. The measuring strategy of the work complexity index builds on a task-based approach; however, unlike many other similar approaches it does not look at tasks *per se*, but rather how they are performed. By focusing on how tasks are performed the indicator does not fall into pitfalls that many others do, including the difficulty of comparing individuals that perform widely different tasks. In addition, it is also superior to conventional measures (i.e. education, wages, Routine Task Intensity index), because it directly captures how tasks are performed, does not treat skill level of individuals as static and allows for analysis of change across countries and over time. The proposed approach, however, suffers from the traditional limitations of using survey data. This challenge is addressed by focusing on factual questions as well as carrying out a number of validity tests.

The proposed indicator allows comparison of European countries as well as changes over time. First, the results indicate that there are significant differences across countries in the level of work complexity, which correlate rather well with GDP per capita. The differences can be explained by the structure of employment rather than differences at the level of work complexity within occupations. Second, the European labour markets in 2005 – 2015 witnessed upskilling with some polarisation. The results conceal important within country differences that cannot be easily explained by changes in GDP per capita or the impact of the global financial crisis of 2008 and its aftermath.

These findings have important implications for the deskilling, upskilling and polarisation debate. The hypotheses proposed in the literature focus on changes within occupations (deskilling) or shifts in the structure of economy (upskilling and polarisation hypotheses). However, the results indicate that countries in the sample experienced shifts in both, while some even experienced changes in opposite directions. For example, Germany witnessed a large increase in work complexity within occupations, although the changes in the structure of employment moved in the opposite direction – the relative share of employment in high work complexity occupations has slightly decreased. Hence, focussing only on the shifts within or across occupations can lead to biased results.

The findings leave ample of open questions for further research. First, how to explain variety of change trajectories across European countries? A preliminary assessment of the most likely factors, such as economic crisis, has not provided a satisfactory answer. Second, how to explain seemingly contradictory changes in work complexity within and across occupations? To answer this question, a better micro-level data and measurements of changes in technology and work organisation processes are needed.

Notes

1. A statistical test that is often used with surveys to measure how well the questions estimate the same phenomenon. The measure ranges from 0 to 1, where a value of less than 0.5 implies weak internal consistency, while values above represent from medium (0.5-0.6) to excellent (more than 0.9) internal consistency. Here it used to assess if the selected questions measure the same skill level dimension.
2. The optimisation algorithm tries out all possible weight combinations and finds which combination produced the best result.
3. We ignore context validity at this stage as we already indirectly covered it in the literature review section of the article.
4. The analysis relies on the results of the last PIAAC adult literacy survey, conducted in 2013. This survey provides information about literacy, numeracy and problem-solving skills of many individuals through the world. In the comparison, all of the three dimensions are used as well as their means.
5. Austria, Belgium, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom, Greece, Ireland, Lithuania, Netherlands, Norway, Poland, Slovakia, Slovenia, Sweden and Turkey.
6. The wage for all individuals was expressed in euros to allow for cross country comparison.
7. Only occupations that had at least 25 employees in more than five countries were analysed to prevent bias. Because of this requirement, on average only information about 17 occupations per country was included in the analysis. In addition, the difference between the same occupation in difference countries was estimated using the average work complexity of said occupation in each country.
8. To prevent the larger countries from skewing the results, the percentage was estimated by averaging the share of employment from each country.
9. EWCS 2005 does not provide any information about Albania, FYROM, Montenegro, or Serbia, hence, they were excluded from the analysis.
10. Countries that observed an increase in work complexity within occupations (in descending order from largest increase to smallest) – Germany, Netherlands, Estonia, France, Slovenia, Malta, Poland, Belgium, Turkey, Portugal, Ireland, Spain, Czech Republic, Finland, Italy, Luxembourg, Austria
11. Countries that observed a decrease in work complexity within occupations (in descending order from largest decrease to smallest) – Switzerland, Greece, Cyprus, Sweden, Romania, Lithuania, Croatia, Hungary, Bulgaria, Norway, Latvia, Denmark, Slovakia.
12. Considering change in the structure of employment the results are as follows: upskilling – Austria, Croatia, Cyprus, Czech Republic, France, Italy, Lithuania, Malta, Norway and United Kingdom; deskilling – Bulgaria and Germany; polarisation – Slovenia; no-trend clearly pronounced trend – Belgium, Denmark, Estonia, Finland, Hungary, Greece,

Ireland, Latvia, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovakia, Spain, Sweden, Switzerland, Turkey.

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Tables

Table 1. Skill level dimensions and their operationalisation

Dimensions	Questions in the EWCS (2015)	Answers (Recoding)
Non-routine tasks	Q48b. Please tell me, does your job involve short repetitive tasks of less than 10 minutes?	Yes (0) No (1)
	Q50c. On the whole, is your pace of work dependent on numerical production targets or performance targets?	
	Q50d. On the whole, is your pace of work dependent on automatic speed of a machine or movement of a product?	
	Q50e. On the whole, is your pace of work dependent on the direct control of your boss?	
	Q53d. Generally, does your main paid job involves monotonous tasks?	
Level of autonomy	Q54a. Are you able to choose or change your order of tasks?	Yes (1) No (0)
	Q54b. Are you able to choose or change your methods of work?	
	Q54c. Are you able to choose or change your speed or rate of work?	
	Q61c. You are consulted before objectives are set for your work?	Always (1) Most of time (0.75) Sometimes (0.5) Rarely (0.25) Never (0)
	Q61d. You are involved in improving the work organisation or work processes of your department or organisation?	
	Q61e. You have a say in the choice of your work colleagues?	
	Q61i. You are able to apply your own ideas in your work?	
	Q61n. You can influence decisions that are important for your work?	
Continuous skill-building	Q53f. Generally, does your main paid job involve learning new things?	Yes (1) No (0)
	Q65a. Over the past 12 months, have you undergone any training paid for or provided by your employer?	
	Q65c. Over the past 12 months, have you undergone any on-the-job training (co-workers, supervisors)?	
	Q65d. Over the past 12 months, have you undergone any other training?	

Source: Own compilations based on the questionnaire from the European Working Conditions Survey (2015).

Table 2. Spearman's correlation between the dimensions

	Autonomy	Non-standardisation	Skill building
Autonomy	1	-	-
Non-standardisation	0.177*	1	-

Skill-building	0.296*	0.027*	1

* Correlation is significant at 0.01 level (two tailed)

Source: Own estimates based on the European Working Conditions Survey (2015).

Table 3. Results of the Mincerian earnings equation

	β	$e^{\beta} - 1$	t-ratio	p-value
Constant	3.77340	42.5278	33.76	<0.01***
Work Complexity	0.652253	0.91986	28.25	<0.01***
ISCED	0.038574	0.03933	23.70	<0.01***
Gender (Male)	0.216138	0.24127	25.18	<0.01***
Age	0.000517	0.00052	1.13	0.2586
Tenure	0.010648	0.01070	21.12	<0.01***
Work hours	0.018896	0.01908	33.26	<0.01***
GDP per capita	0.000031	0.000031	111.4	<0.01***
Self-employed	0.477696	0.612355	4.481	<0.01***

N = 19160

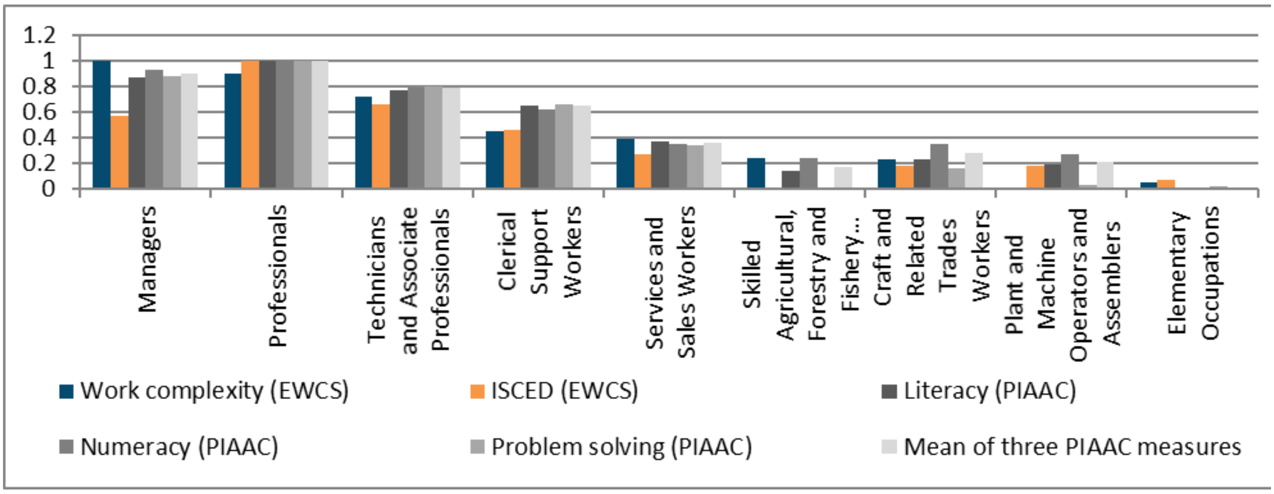
Note: Heteroskedasticity-robust standard error was applied to the model to improve its quality, though without it the results are virtually the same; No strong collinearity was observed between the variables; omission of the Age variable, which is not statistically significant, only marginally changes the results.

Adjusted R-squared equals to 0.600443

*** - significant at 0.01

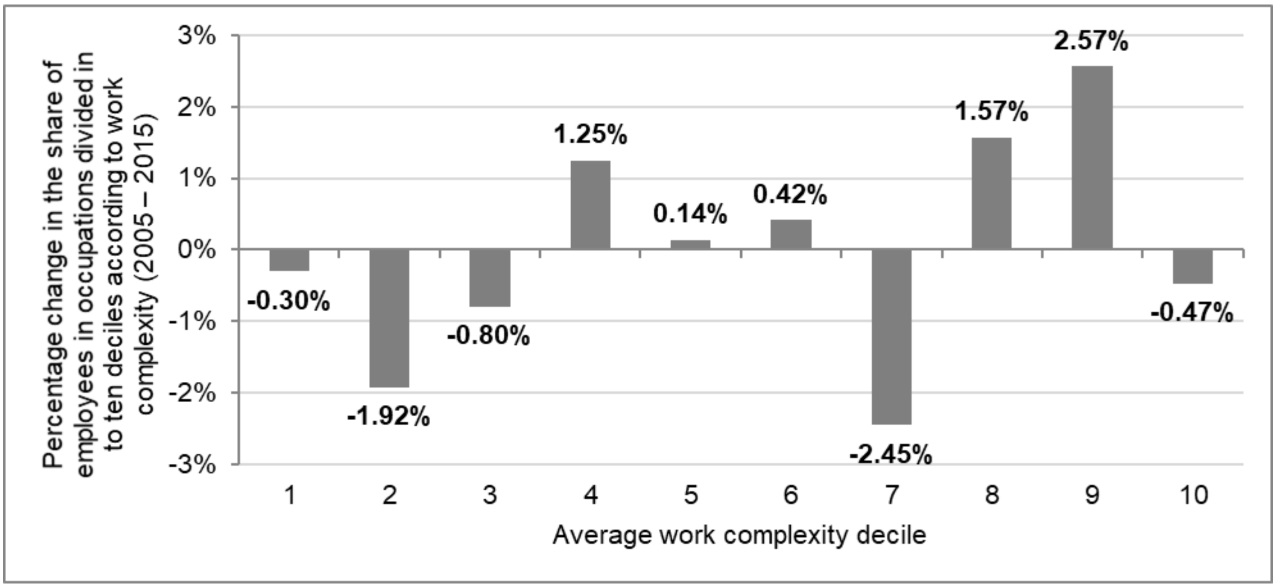
Figures

Figure 1. Work complexity, occupational groups and other measurements of levels of skills.



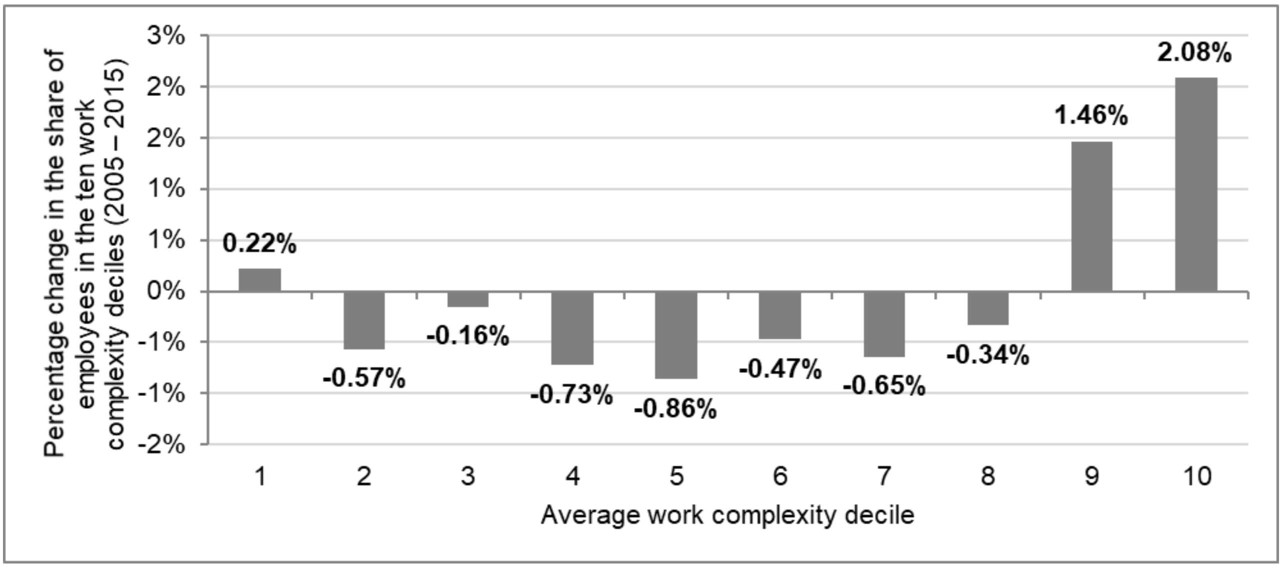
Source: Own estimates based on the European Working Conditions Survey (2015) and PIAAC Adult Literacy Survey (2013).

Figure 2. Percentage change in the share of employees in occupations in each decile (highest work complexity in decile 10) between 2005 and 2015



Source: Own estimates based on the EWCS 2005 and 2015.

Figure 3. Percentage change in the share of employees in each decile (highest work complexity in decile 10) between 2005 and 2015



Source: Own estimates based on the EWCS 2005 and 2015.

Appendix 1

Abbreviations

DOT	Dictionary of Occupations
EU	European Union
EWCS	European Working Conditions Surveys
GDP	Gross domestic product
ISCO	International Standard Classification of Occupations
O*NET	Occupational Information Network
OECD	Organisation for Economic Co-operation and Development
PDII	Princeton Data Improvement Initiative
PIAAC	Programme for the International Assessment of Adult Competencies
SBTC	Skill-biased technological change

Appendix 2

Table 4. Work complexity level by ISCO-08 level two occupational group

ISCO-08 code	ISCO-08 name	Work complexity		Non-routine tasks		Autonomy		Skill-building	
		Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
01	Commissioned armed forces officers	0.61	0.17	0.61	0.24	0.62	0.25	0.61	0.17
02	Non-commissioned armed forces officers	0.57	0.13	0.59	0.23	0.58	0.25	0.57	0.13
03	Armed forces occupations, other ranks	0.55	0.17	0.63	0.27	0.50	0.28	0.55	0.17
11	Chief executives, senior officials and legislators	0.67	0.15	0.74	0.23	0.85	0.19	0.67	0.15
12	Administrative and commercial managers	0.67	0.15	0.70	0.23	0.79	0.18	0.67	0.15
13	Production and specialised services managers	0.68	0.15	0.69	0.25	0.81	0.18	0.68	0.15
14	Hospitality, retail and other services managers	0.62	0.14	0.71	0.23	0.80	0.21	0.62	0.14
21	Science and engineering professionals	0.62	0.16	0.68	0.26	0.71	0.21	0.62	0.16
22	Health professionals	0.62	0.15	0.71	0.24	0.61	0.23	0.62	0.15
23	Teaching professionals	0.66	0.13	0.77	0.22	0.68	0.19	0.66	0.13
24	Business and administration professionals	0.62	0.16	0.68	0.25	0.69	0.22	0.62	0.16
25	Information and communications technology professionals	0.66	0.14	0.72	0.24	0.71	0.19	0.66	0.14
26	Legal, social and cultural professionals	0.62	0.15	0.74	0.23	0.68	0.22	0.62	0.15
31	Science and engineering associate professionals	0.57	0.18	0.60	0.28	0.63	0.24	0.57	0.18
32	Health associate professionals	0.57	0.16	0.67	0.26	0.54	0.24	0.57	0.16
33	Business and administration associate professionals	0.59	0.16	0.68	0.25	0.64	0.23	0.59	0.16
34	Legal, social, cultural and related associate professionals	0.63	0.16	0.73	0.23	0.69	0.23	0.63	0.16
35	Information and communications technicians	0.62	0.15	0.66	0.27	0.69	0.21	0.62	0.15
41	General and keyboard clerks	0.53	0.16	0.63	0.26	0.58	0.23	0.53	0.16
42	Customer services clerks	0.49	0.16	0.59	0.27	0.47	0.25	0.49	0.16
43	Numerical and material recording clerks	0.52	0.17	0.62	0.26	0.58	0.25	0.52	0.17
44	Other clerical support workers	0.50	0.17	0.62	0.25	0.53	0.26	0.50	0.17
51	Personal service workers	0.48	0.16	0.65	0.26	0.56	0.27	0.48	0.16
52	Sales workers	0.47	0.17	0.65	0.26	0.52	0.28	0.47	0.17
53	Personal care workers	0.59	0.15	0.76	0.22	0.57	0.24	0.59	0.15
54	Protective services workers	0.52	0.16	0.70	0.24	0.45	0.25	0.52	0.16
61	Market-oriented skilled agricultural workers	0.46	0.16	0.67	0.25	0.69	0.26	0.46	0.16
62	Market-oriented skilled forestry, fishery and hunting workers	0.52	0.17	0.65	0.27	0.64	0.25	0.52	0.17
63	Subsistence farmers, fishers, hunters and gatherers	0.39	0.19	0.70	0.25	0.63	0.32	0.39	0.19
71	Building and related trades workers, excluding electricians	0.46	0.16	0.56	0.28	0.60	0.26	0.46	0.16
72	Metal, machinery and related trades workers	0.48	0.18	0.54	0.30	0.56	0.26	0.48	0.18
73	Handicraft and printing workers	0.42	0.18	0.53	0.29	0.52	0.29	0.42	0.18
74	Electrical and electronic trades workers	0.55	0.18	0.63	0.28	0.62	0.26	0.55	0.18
75	Food processing, wood working, garment and other craft and related trades workers	0.37	0.19	0.47	0.31	0.49	0.30	0.37	0.19
81	Stationary plant and machine operators	0.34	0.17	0.34	0.27	0.39	0.28	0.34	0.17
82	Assemblers	0.38	0.18	0.38	0.31	0.42	0.28	0.38	0.18
83	Drivers and mobile plant operators	0.43	0.16	0.60	0.28	0.44	0.27	0.43	0.16
91	Cleaners and helpers	0.43	0.15	0.63	0.24	0.49	0.25	0.43	0.15
92	Agricultural, forestry and fishery labourers	0.40	0.19	0.55	0.27	0.51	0.31	0.40	0.19
93	Labourers in mining, construction, manufacturing and transport	0.37	0.18	0.45	0.29	0.40	0.27	0.37	0.18
94	Food preparation assistants	0.41	0.15	0.55	0.28	0.45	0.28	0.41	0.15
95	Street and Related Sales and Services Workers	0.38	0.16	0.63	0.24	0.48	0.29	0.38	0.16
96	Refuse workers and other elementary workers	0.41	0.17	0.60	0.28	0.47	0.28	0.41	0.17

Appendix 3

Figure 4. Examples of the work complexity index density in selected ISCO-08 level 2 occupations (general cases)

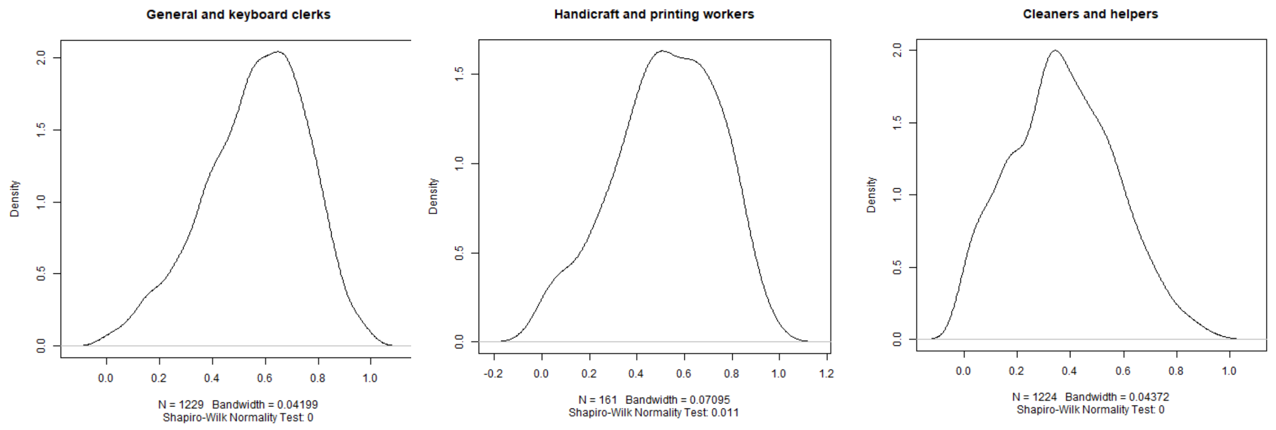
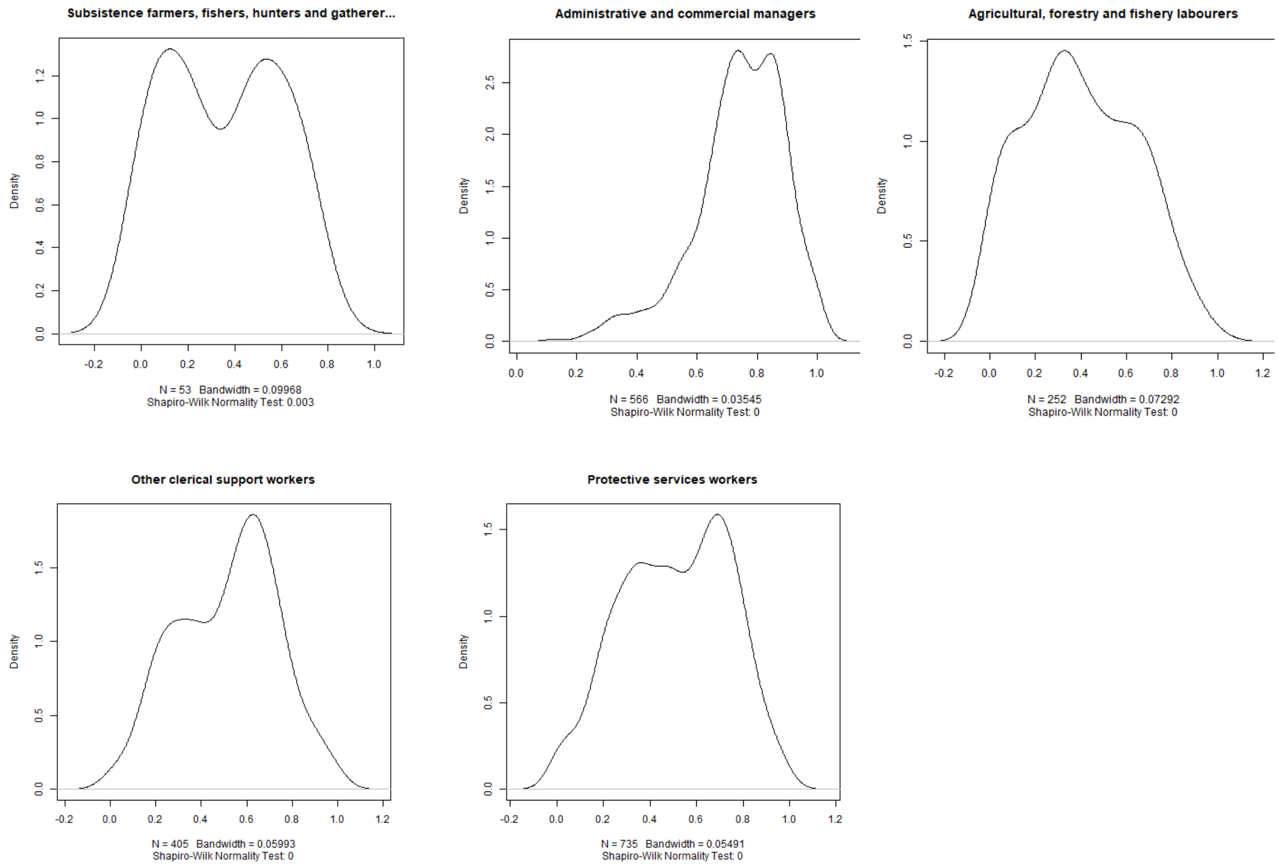


Figure 5. Examples of the work complexity index density in selected ISCO-08 level 2 occupations (exceptional cases)



Appendix 4

Table 5. Work complexity level by country

	Work complexity			Non-routine tasks			Autonomy			Skill-building		
Country	**Mean**	**Standard deviation**	**N**	**Mean**	**Standard Deviation**	**N**	**Mean**	**Standard Deviation**	**N**	**Mean**	**Standard deviation**	**N**
Albania	0.43	0.15	385	0.58	0.27	808	0.56	0.24	526	0.25	0.26	555
Austria	0.54	0.18	725	0.68	0.27	894	0.58	0.27	840	0.39	0.30	860
Belgium	0.56	0.18	1889	0.67	0.27	2310	0.61	0.26	2139	0.44	0.29	2188
Bulgaria	0.43	0.18	759	0.58	0.29	945	0.50	0.32	892	0.26	0.24	883
Switzerland	0.51	0.19	788	0.63	0.28	952	0.58	0.26	911	0.35	0.29	853
Cyprus	0.43	0.15	724	0.53	0.25	902	0.49	0.29	835	0.33	0.27	819
Czech Republic	0.52	0.17	730	0.64	0.28	915	0.55	0.25	842	0.39	0.29	845
Germany	0.52	0.19	1558	0.70	0.26	1934	0.51	0.27	1757	0.37	0.31	1826
Denmark	0.62	0.15	839	0.68	0.25	946	0.70	0.20	917	0.49	0.24	938
Estonia	0.61	0.17	759	0.64	0.26	920	0.67	0.23	870	0.51	0.31	895
Spain	0.46	0.18	2149	0.54	0.28	3008	0.56	0.29	2531	0.34	0.27	2763
Finland	0.63	0.16	710	0.66	0.26	916	0.70	0.20	884	0.54	0.28	794
France	0.53	0.17	1206	0.60	0.27	1415	0.58	0.25	1309	0.42	0.26	1395
Greece	0.37	0.16	496	0.57	0.26	820	0.49	0.30	690	0.19	0.23	645
Croatia	0.48	0.19	728	0.62	0.25	904	0.52	0.29	838	0.33	0.28	841
Hungary	0.47	0.19	769	0.65	0.26	940	0.55	0.29	886	0.24	0.28	859
Ireland	0.58	0.17	747	0.66	0.27	982	0.63	0.27	858	0.50	0.29	828
Italy	0.47	0.18	693	0.66	0.27	1127	0.55	0.29	992	0.27	0.26	965
Lithuania	0.49	0.19	730	0.59	0.29	926	0.55	0.26	818	0.35	0.32	864
Luxembourg	0.56	0.18	749	0.62	0.27	897	0.61	0.26	863	0.48	0.30	890
Latvia	0.51	0.18	563	0.69	0.27	778	0.57	0.27	761	0.31	0.29	827
Montenegro	0.45	0.16	551	0.66	0.26	794	0.54	0.28	769	0.21	0.22	696
FYROM	0.48	0.18	668	0.64	0.27	893	0.56	0.28	855	0.31	0.27	728
Malta	0.61	0.16	723	0.71	0.25	879	0.69	0.19	820	0.45	0.28	876
Netherlands	0.62	0.18	732	0.74	0.24	907	0.66	0.23	847	0.47	0.30	870
Norway	0.64	0.15	850	0.70	0.26	960	0.69	0.20	935	0.53	0.27	939
Poland	0.52	0.18	777	0.65	0.28	1048	0.57	0.26	961	0.37	0.30	1009
Portugal	0.46	0.17	581	0.66	0.26	902	0.50	0.28	668	0.27	0.25	727
Romania	0.45	0.15	631	0.53	0.29	872	0.56	0.26	802	0.30	0.27	860
Serbia	0.50	0.17	602	0.71	0.25	896	0.55	0.28	783	0.28	0.26	705
Sweden	0.62	0.17	828	0.74	0.23	937	0.62	0.22	918	0.51	0.26	922
Slovenia	0.59	0.19	1233	0.71	0.26	1521	0.60	0.26	1386	0.46	0.28	1369
Slovakia	0.51	0.19	745	0.65	0.29	903	0.50	0.26	863	0.42	0.30	861
Turkey	0.47	0.15	1098	0.60	0.27	1682	0.60	0.27	1592	0.26	0.23	1341
UK	0.59	0.17	1208	0.63	0.27	1490	0.62	0.25	1403	0.55	0.30	1365

Source: Own estimates based on the European Working Conditions Survey (2015).

Appendix 5

Table 6

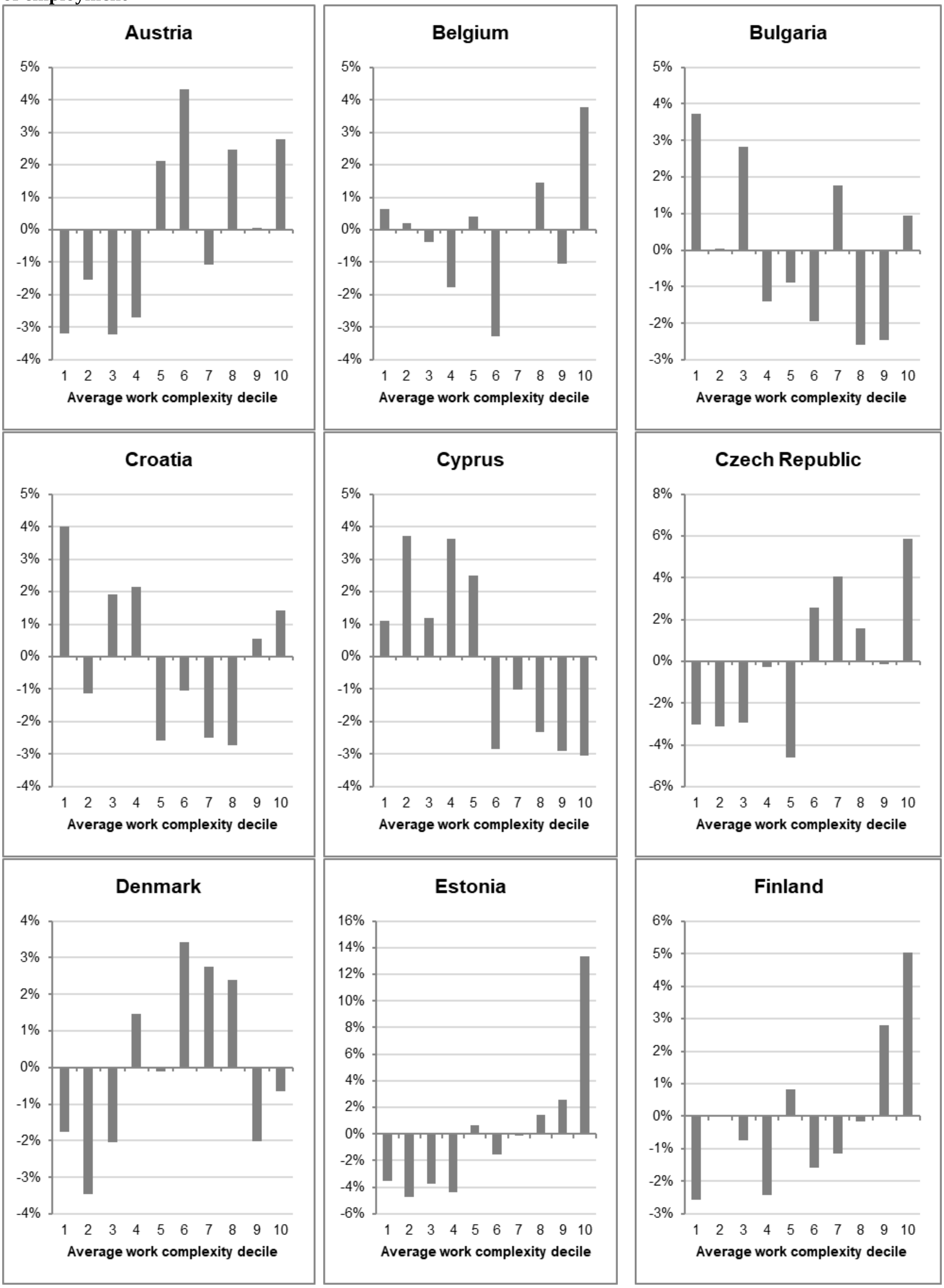
The average change in work complexity for occupations in each country*

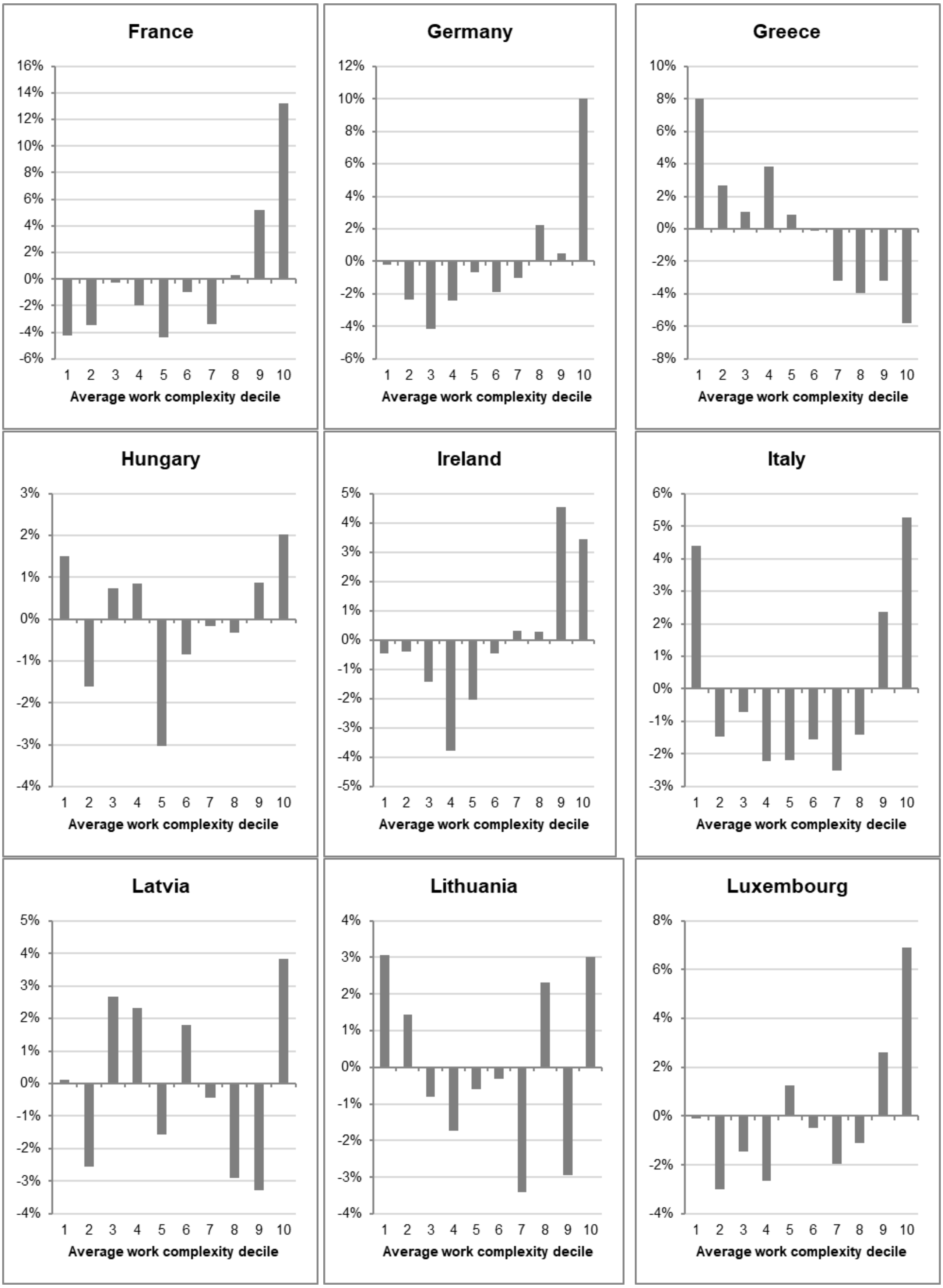
	Change in work complexity from 2005 to 2015	Change in work complexity from 2005 to 2010	Change in work complexity from 2010 to 2015
Austria	0.012	-0.062	0.074
Belgium	0.034	0.009	0.025
Bulgaria	-0.008	-0.043	0.035
Croatia	-0.010	-0.012	0.002
Cyprus	-0.049	-0.114	0.065
Czech Republic	0.030	-0.050	0.080
Denmark	-0.004	-0.073	0.068
Estonia	0.053	0.005	0.048
Finland	0.027	-0.027	0.054
France	0.045	0.040	0.004
Germany	0.073	-0.001	0.074
Greece	-0.051	-0.037	-0.014
Hungary	-0.008	-0.034	0.026
Ireland	0.031	0.012	0.019
Italy	0.026	-0.038	0.064
Latvia	-0.005	-0.074	0.069
Lithuania	-0.017	-0.042	0.025
Luxembourg	0.024	0.018	0.006
Malta	0.042	-0.025	0.067
Netherlands	0.066	-0.024	0.089
Norway	-0.007	-0.062	0.056
Poland	0.042	-0.020	0.062
Portugal	0.032	-0.087	0.119
Romania	-0.026	-0.054	0.028
Slovakia	0.000	-0.038	0.038
Slovenia	0.044	-0.023	0.068
Spain	0.030	-0.046	0.076
Sweden	-0.037	-0.040	0.003
Switzerland	-0.072	-	-
United Kingdom	0.075	0.013	0.062
Turkey	0.033	0.001	0.032

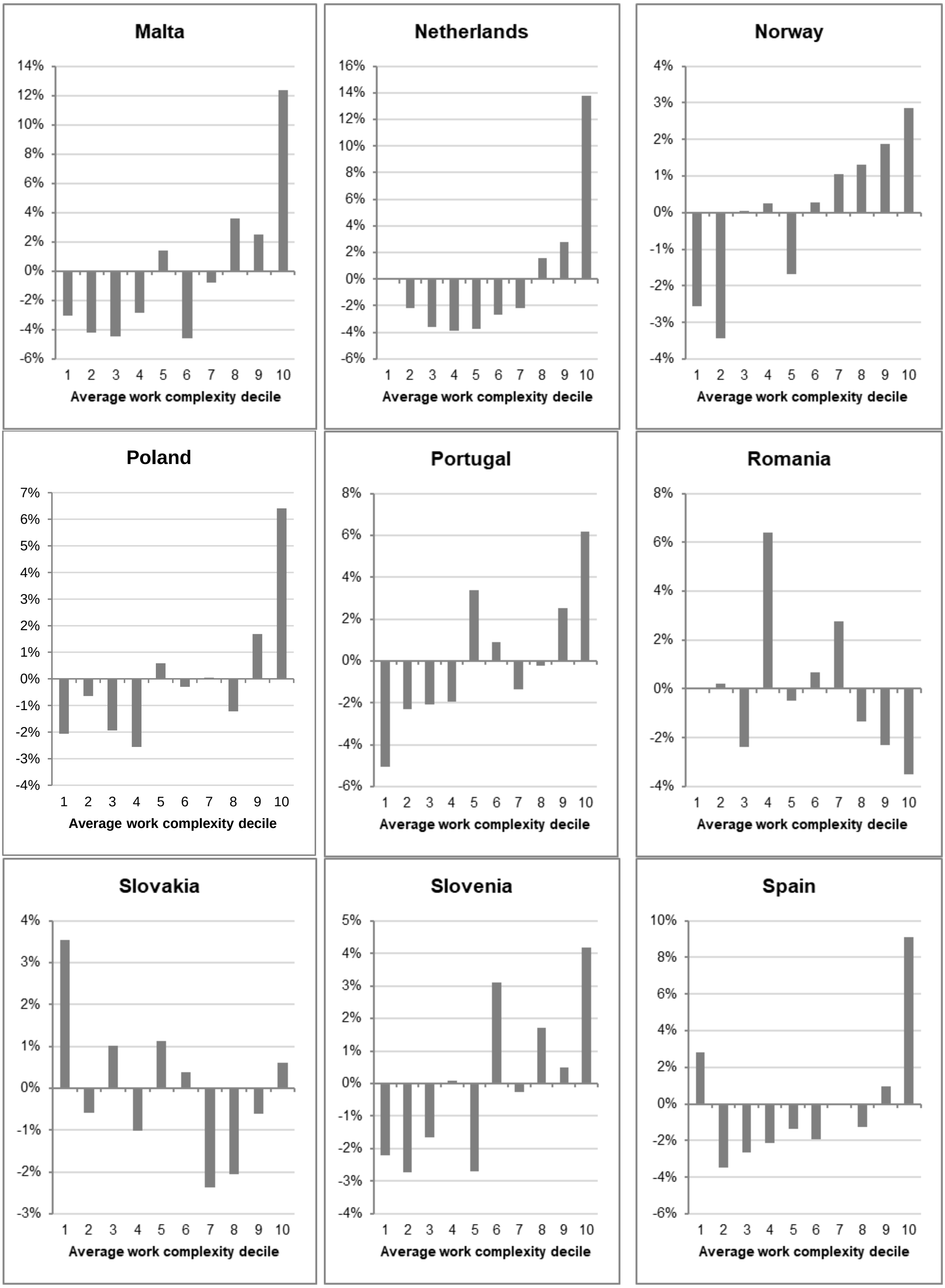
* Occupation was included in estimating the average work complexity of a country only if it had more than 25 observations.

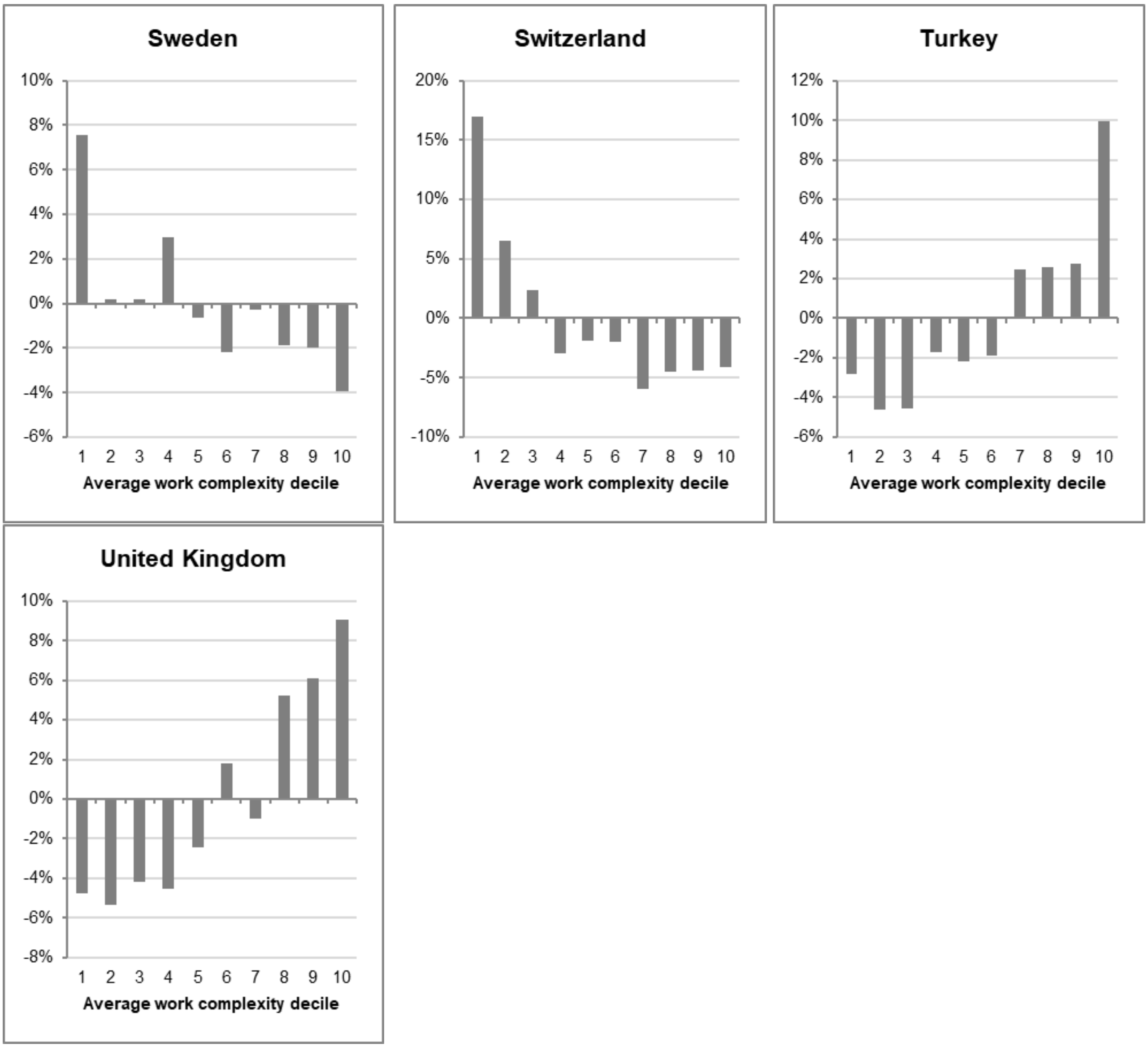
Appendix 6

Figure 6. Percentage change in work complexity, including shifts within occupations and changes in structure of employment




France
16%
14%
12%
10%
8%
6%
4%
2%
0%
-2%
-4%
-6%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Germany
12%
10%
8%
6%
4%
2%
0%
-2%
-4%
-6%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Greece
10%
8%
6%
4%
2%
0%
-2%
-4%
-6%
-8%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Hungary
3%
2%
1%
0%
-1%
-2%
-3%
-4%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Ireland
5%
4%
3%
2%
1%
0%
-1%
-2%
-3%
-4%
-5%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Italy
6%
5%
4%
3%
2%
1%
0%
-1%
-2%
-3%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Latvia
5%
4%
3%
2%
1%
0%
-1%
-2%
-3%
-4%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Lithuania
4%
3%
2%
1%
0%
-1%
-2%
-3%
-4%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Luxembourg
8%
6%
4%
2%
0%
-2%
-4%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile


Malta
14%
12%
10%
8%
6%
4%
2%
0%
-2%
-4%
-6%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Netherlands
16%
14%
12%
10%
8%
6%
4%
2%
0%
-2%
-4%
-6%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Norway
4%
3%
2%
1%
0%
-1%
-2%
-3%
-4%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Poland
7%
6%
5%
4%
3%
2%
1%
0%
-1%
-2%
-3%
-4%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Portugal
8%
6%
4%
2%
0%
-2%
-4%
-6%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Romania
8%
6%
4%
2%
0%
-2%
-4%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Slovakia
4%
3%
2%
1%
0%
-1%
-2%
-3%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Slovenia
5%
4%
3%
2%
1%
0%
-1%
-2%
-3%
-4%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile
Spain
10%
8%
6%
4%
2%
0%
-2%
-4%
-6%
1 2 3 4 5 6 7 8 9 10
Average work complexity decile



Source: Own estimates based on the EWCS 2005 and 2015.