Ref. Ares(2021)8018833 - 31/12/2021

Technequality

Understanding the relation between technological innovations and social inequality

# Technology, class, and inequality: Assessing different consequences for different social classes

## Version 2.0 12-14-2021

Funded by the Horizon 2020 Framework Programme of the European Union

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|---|---|---|
| Deliverable | : | 2.3 |
| Title | : | Technology, class, and inequality: Assessing different consequences for different social classes |
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| Reviewer(s) | : | GIAMPIERO PASSARETTA AND HEIKE SOLGA |
| Document type | : | R |
| Document level | : | PU |
| Date | : | 14 December 2021 |
| Status | : | Complete |

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# Document change log

| Version | Date | Comments |
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# Verification and approval

| Name | Date | Comments |
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## Description of deliverable (100 words)

Technological change may influence the opportunities for workers to utilize their skills, both their formal credentials acquired through education and their actual skills acquired in school and elsewhere. Such mismatch problems may in turn differ across social groups and classes. Deliverable 2.3 explores these issues, first through an analysis of how educational mismatch among lower, middle and upper-middle class occupations is related to occupational automation risks using labor force surveys from around 30 European countries. This is supplemented with an analysis of how the wage effects of educational mismatch depend on problem solving skills, numeracy skills, and active learning in various occupational sectors using data for 26 countries from the Programme for the International Assessment of Adult Competencies (PIAAC).

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## 1. Introduction

Technological change involves the disappearance of some existing occupations and the creation of new ones. It may also encompass extensive alteration of existing occupations, without them vanishing completely. All such changes to the structure and content of occupations will affect the opportunities for workers to make use of their skills, irrespective of whether these skills refer to formal credentials obtained through the educational system or actual skills learnt in school or at work. Moreover, the possibilities for employees to apply their knowledge may vary depending on both the type of skill and the type of work.

There is for instance substantial evidence that the incidence of educational mismatch varies widely, across labour market segments and across countries. Such mismatch can be both vertical and horizontal, the former referring to a mismatch between the level of education attained by the worker and the level of education required by the job and the latter to a mismatch between the type of skills arquired in school and the type of skills required by the job.

Focusing on vertical mismatch, Appendix 1 of Deliverable 2.3 examines the incidence and drivers of educational mismatch among workers belonging to four broad occupational groups as well as how salaries are affected by mismatch and how automation risk modifies this impact. Data of European Union Labour Force Survey for 26 European countries is used and the analyses focus on two specific years: 2009 (during the global financial crisis and economic recession) and 2014 (after the crisis). Educational mismatch is measured using the realized matches approach which compares workers' educational levels with the modal level of schooling of their respective occupational group.

Vertical mismatch includes two different processes: undereducation (upward intragenerational mobility) when workers possess lower qualifications than those required by their job and overeducation (downward mobility) when workers have higher qualifications than necessary to do their job. The results indicate that between 2009 and 2014 the overall rates of undereducation and overeducation remained rather stable, but there are considerable differences between the countries and occupational groups. Overeducation rates are thus

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highest among low-skilled white-collar and undereducation among high-skilled white-collar workers. Overeducated workers in turn experience a wage penalty compared to workers with similar levels of education but who are working in higher positions which match their educational level. In contrast, undereducated workers seem to have a wage premium relative to workers with the same education but who are employed in a job that matches their education.

Regarding automation risk, here too the impact varies across occupational groups. For high-skilled white-collar occupations higher automation risk indicates a clear wage penalty for overeducated and undereducated compared to matched workers and also that the wage gap of under- and overeducated decreases. For low-skilled white-collar employees high automation risk is related to wage premium for the overeducated and increase in automation risk also tends to close the wage gap, but more clearly between matched and undereducated. For high-skilled blue-collar workers we did not find any modifying effect of automation risk on salaries. In case of low-skilled blue-collar workers higher automation risk tends to increase salaries for overeducated and decrease salaries for undereducated.

Appendix 2 of Deliverable 2.3 examines the relationship between (vertical) educational mismatch and wages in further detail, exploring the importance of different types of skills. Particular attention is paid to the relation between (mis-)matches in digital problem-solving skills and wages as well as differential wage returns to skills for different social groups. Digital problem-solving skills are held to be key skills, ensuring that workers remain productive and included in contemporary labour markets and societies. Yet how equipped one is to deal with these changes is likely to depend on social background, and technological innovations may favour certain social groups.

Appendix 2 provides empirical evidence on these issues using objective skills measurements for representative samples of fulltime working employees in 26 industrial countries from the Programme for the International Assessment of Adult Competencies (PIAAC). The results show that skill-to-job matches in digital problem-solving skills matter for wages: shortages are damaging, while a skills surplus is profitable. Digital problem-solving skills re-shape wage

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inequalities, narrowing the divide between social origin groups.

Taken together, these analyses show that techonological change influences workers' opportunites for utilizing their skills, and also of receiving wages commensurate with their skill set. In addition, the results show that the extent of this influence varies substantially across countries - and social classes.

Automation risk thus decreases salaries, yet as noted this impact varies across occupational groups. The relationship between automation risks, skill usage, and salaries differs across high- and low-skilled white-collar employees as well as high- and low-skilled blue-collar workers. Likewise, high levels of digital problem-solving skills pays off more for workers from lower social origin than for the higher social origin group, and for low and medium educated workers more than for graduates. Some of these differences may be related to labour market institutions, and policy differences may also be relevant when it comes to ameliorating the effects of technological change on workers' lives. Opportunities for further training in digital problem-solving skills, the topic of WP3, may for instance be crucial for workers' ability to adapt to the changing labor market, in particular for those from a working class background.

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# Appendix 1

## Education mismatch in European countries during the 2008 financial crisis and after that: determinants by occupational groups and the mismatch on salaries

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## Appendix 1

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## 1. Introduction

The existence of a potential gap between workers' educational attainment and the education actually used at the jobs has been a major concern of social scientists as well as policy makers (Sloane et al., 1999). Vertical mismatch includes two different processes: undereducation (upward intragenerational mobility) – workers possess lower qualifications than those required by their job – and overeducation (downward mobility) – they possess higher qualifications than necessary to do their job[1].

Paper highlights the implications of the gap between the jobs' educational requirements and the workers' actual educational attainment. Undereducation can have a negative impact on the aggregate output because either high-skilled jobs remain vacant, or they are filled with workers with lower educational attainment whose performance in those jobs is lower than optimal. On the individual level undereducation indicate upward social mobility. Overeducation might have very relevant consequences as well. From the macroeconomic perspective overeducation reflects a waste of human capital and national output is potentially lower than it could be if the skills of overeducated workers were fully utilised. Education mismatch can also affect wage inequality (Brunello and Wruuck, 2019). At the level of the organisations, there is some evidence to suggest that overeducation may be associated with lower productivity (Tsang, 1987; Kampelmann et al., 2020) and higher labour turnover (Hersch, 1991; Sicherman, 1991), leading in turn to lost investments in recruitment and training (Tsang et al., 1991; Alba-Ramirez, 1993). At the individual level, overeducated workers have been found to earn less than similarly educated workers whose jobs match their qualifications (Daly et al., 2000; Bauer, 2002; McGuinness and Sloane, 2011). Overeducated workers may also experience lower levels of job satisfaction (Battu et al., 1999; Mateos-Romero and Salinas-Jiménez, 2018) but also downward intragenerational social mobility. Education mismatch can reduce overall work motivation, expressing itself in more frequent absenteeism and higher turnover of the workforce (Tsang

[1] Occupational (labour market) mismatch literature has been placed primarily on formal qualification mismatches (education or formal qualification mismatches) and the mismatches between an individual's set of skills and the skills that are required for a certain job (skills mismatch) (McGuiness et al. 2018a). Because of improved data it has been possible to differentiate these two concepts. Recent empirical studies conclude that education mismatch and skills mismatch are not the same phenomenon (Allen et al. 2013; McGowan and Andrews 2015; Flisi et al. 2017; Choi et al. 2020). Employees can be formally well-matched but mismatched regarding skills (and vice versa).

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and Levin, 1985; Sicherman, 1991; Sloane et al., 1999). Mismatched workers might experience longer unemployment periods during their working life, with negative consequences on their skill endowment and on the probability to find a suitable job (Ordine and Rose, 2015; Berton et al. 2018). On the other hand, educational mismatches reduce job satisfaction thus increasing voluntary unemployment as well as job mobility (Verhaest and Omey, 2006). As a result, less-qualified workers may be displaced and 'bumped down' in the labour market, or into unemployment, by overeducated workers moving into their occupations, particularly in slack labour markets (Battu and Sloane, 2002).

Most of the previous analyses dealing with educational mismatch concentrate on the issue of overeducation (for reviews see McGuinness, 2006; Quintini, 2011; McGuinness et al., 2018b). Human capital deficit, such as undereducation receives relatively little attention in the literature despite that undereducation is assumed to have a direct negative impact on firm-level productivity and determines a large share of the training investments of both employees and firms (McGuinness et al., 2018). In this paper we analyse under- as well as overeducation.

Most of previous research on labour market mismatch has relied on country-specific data sets. The research has focused on identifying the individual- and firm-level determinants of mismatch (Green and McIntosh, 2007; Boll et al., 2016; Muñoz de Bustillo et al., 2018) and the impact of mismatch on individual outcomes, such as salary or job satisfaction. However, there is also substantial evidence that the incidence of mismatch varies widely, not only across individuals, but also across labour market segments and countries. A small but growing body of research has begun to address this question through cross-country comparisons of the incidence of mainly overeducation perspective (see Di Petro, 2002; Poulikas, 2013; Boll et al., 2016; Davia et al., 2017; McGuinness et al., 2018; Delaney et al., 2020). Besides country comparisons many papers have analysed macroeconomic, demographic and institutional forces that drive educational mismatch (supply dynamics: Groot et al., 2000; composition of the labour force: Budria and Moro-Egido, 2018; McGuinness et al., 2018; employment protection legislation: McGowan and Andrews, 2015; Fregin et al., 2020; unemployment benefit systems: Verhaest et al., 2017; collective bargaining coverage: McGuinness, 2006; Verhaest et al., 2017; technological change: Mendes de Oliveira et al., 2000; Di Pietro, 2002; economic cycle: Verhaest and van der Velden, 2013; McGuinness et al., 2018).

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There is a perception that overeducation predominantly affects tertiary graduates and the existing literature tends to be focused on this direction (see e.g., Chevalier and Lindley, 2009; Croce and Ghignoni, 2012; Baert et al., 2013; Carroll and Tani, 2015). The fact that overeducation can also occur at lower levels of educational attainment has been largely overlooked in research. Important shortcoming of most literature is also consideration of mismatched employees as a homogeneous group irrespective of their occupational position. To the best of our knowledge an in-depth examination of the incidence, determinants and effect on salaries by occupational group remains to be performed.

This paper uses data of European Union Labour Force Survey (EU-LFS) from 26 European countries to shed light on a number of previously under-researched issues regarding the incidence and drivers of educational mismatch. Our data and adopted empirical approach allow us to examine these issues within European countries during the financial crisis of 2007–2008 and after the crisis to investigate the relation between economic conditions and education mismatch as well as the impact of different drivers of mismatch during the crisis and after that. We also study the impact of educational mismatch on salaries of different occupational groups. We make three main contributions. Firstly, we trace the incidence of overeducation and undereducation of workers belonging to four broad occupational groups (high-skilled white-collars, low-skilled white-collars, high-skilled blue-collars and low-skilled blue-collars) across European countries in 2009 and 2014. Secondly, we investigate the relationship between educational mismatch rates and the composition of labour supply and demand as well as institutional factors within the European countries. Thirdly, we analyse the impact of educational mismatch on salaries for different occupational groups. Fourth, we study how the automation risk modify the impact of educational mismatch on salaries.

## 2. Theoretical explanations

### *2.1 Educational mismatch*

Several labour market theories have been used to explain educational mismatch. For all these theories workers and employers are central economic agents in the analysis. The focus is on conditions affecting the supply of workers with different educational (skill) level and employers' demand for different type of work. Some theories emphasise supply side. Human capital theory

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suggests that overeducated workers accumulate skills that can be used to switch to higher level positions. Therefore, human capital theory regards educational mismatch as a negligible and temporary phenomenon, which is corrected by the market (Becker, 1964). The career mobility theory assumes that workers enter voluntarily to jobs for which they are overeducated to gain experience and training for career development and therefore overeducation is of limited duration and occurs predominantly at the beginning of individual careers (Sicherman and Galor, 1990).

Other theories emphasise the demand side of the labour market. According to the theory of job competition (Thurow, 1975) workers compete for jobs in certain occupations. They are ranked according to their educational level as a signal of their future job performance and trainability. An increase of supply of graduates on the labour market causes persistent overeducation of graduates whereas lower-educated persons become unemployed. According to signalling (screening) theory (Arrow, 1973; Spence, 1973; Stiglitz, 1975) some skills are acquired by workers to signal their level of productivity to potential employers. If the supply of education (skills) outperforms the demand for this education (skills) the rate of overeducation could increase.

Some theories take into account both the supply and demand sides of the labour market. Theory of job search (Jovanovic, 1979) assumes that in a labour market characterised by uncertainty and costly information, both employers and workers will spend time searching for qualified workers or job positions. Due to the search costs educated workers might be satisfied with finding a position at a level below their education. At the same time, employers are hiring applicants whose education exceeds current job requirements, as this could allow them to save training costs in the future. The theory postulates that overeducation may temporarily arise due to incomplete information on the labour market (Mortensen, 1986). Assignment theory postulates that heterogeneous workers apply for heterogeneous jobs (Sattinger, 1993). As a result, the perfect matching is unlikely, and some individuals end up in jobs for which they are over- or undereducated.

Job competition model and assignment theory predict that the situation of education mismatch will persist until a more efficient allocation of individuals to jobs arises as a result of improved matching processes or governmental policies intended to reduce such inefficiencies.

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## 2.2 Effect of macro level characteristics on education mismatch

A potential source of cross-country differences in educational mismatch is variation in the extent to which there is *an imbalance between the demand for and supply* of skilled workers, either structurally or cyclically (Mendes de Oliveira et al., 2000; Barone and Ortiz, 2010; Croce and Ghignoni, 2012; Verhaest and Van der Velden, 2013). Overeducation can arise if the structure of labour demand by educational level is rigid due to technological reasons and does not respond to the increase of supply of the skilled labour. On the one hand, an oversupply of educated workers may force jobseekers to accept jobs below their level of education. In addition, oversupply allows employers to prefer more highly educated and overeducated job seekers (Thurow, 1975). Therefore, oversupply of educated workers might lead to more overeducation.

Fluctuations in the economy will change the composition in the demand for labour and how workers are utilized within firms. Brunello and Wruuck (2019) mention that the relationship between educational mismatch and the business cycle is driven by several factors. On the one hand, in recession mismatch declines because low level jobs are disappearing and consequently mismatch decreases. On the other hand, mismatch increases because there are less vacancies and jobseekers are willing to accept jobs below their educational level. When the labour market is tight, employers are forced to downward their hiring standards which increases the incidence of undereducation (Healy et al., 2015).

Labour market institutions seem to be of particular theoretical relevance when it comes to optimal education matching as it may explain variations in allocation processes (Estevez-Abe et al., 2001; Hall and Soskice, 2001). The higher the employment protection, the higher the firing costs even with workers who are mismatched and not optimally productive. Strict regulations in firing of permanent employees make it more difficult for firms to adapt the labour force structure to address mismatch between the demand and supply of skills (Di Pietro, 2002). It reduces employers' ability to replace badly matched employees with well-matched jobseekers. The regulation of dismissal process also affects hiring processes. Strong EPL increases hiring risks on the side of employer. Dismissal costs would lower the expected returns and diminish the utility of hiring. The higher the costs for dismissals, the more employers will ensure that

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their workers match their jobs. It makes a positive relation between sticker EPL and optimal education matching more likely than as negative relations (Fregin et al., 2020).

## *2.3 Education mismatch and wages*

Human capital theory suggests that a worker's productivity on-the-job is determined by his/her past investments into human capital through formal education or training. These investments are rewarded by the market, as workers are paid according to their marginal product. Job's requirements would not affect wages. Therefore, overeducated workers would receive similar returns to education as other workers with a similar level of education who are properly matched in their jobs. The theory of job competition and signalling theory emphasise the role of the job's requirements, assuming that job characteristics determine wages whereas education signals unobserved productivity (Spence, 1993) or the rank in the order of jobseekers. As a result, overeducated workers would suffer a wage penalty as compared with adequately educated jobseekers since overeducated workers hold jobs with lower educational requirements, but no wage premium would be observed for the higher educational attainment when compared with their adequately matched colleagues. Similar reasoning could be used for undereducated workers. They have higher wages than adequately placed individuals with the same level of education, but they do not suffer from wage penalty compared to adequately placed workers doing the same job (see also Kracke et al., 2018). Assignment theory assumes that productivity and consequently wages are determined by both individuals' and jobs' characteristics. Not only attained education but also the use of the acquired education in the job determines workers' wage. Overeducated workers would receive a wage premium as compared with their properly matched co-workers as a consequence of their higher levels of education. At the same time, they would not use their skills properly and as a result would earn lower wages compared to workers with the same education but who are adequately placed (see also Mateo-Romero et al., 2018). Undereducated workers would suffer from a wage penalty compared to co-workers who are properly matched. However, they would earn higher wages in comparison with properly matched workers with the same level of education.

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## 3. Previous research

### 3.1 Incidence of education mismatch

Substantial variation has been found in the incidence of overeducation between countries (Di Pietro, 2002; Croce and Ghignoni, 2012; Verhaest and Van der Velden, 2013). However, the results depend on the measurement approach[2] used (see also McGuinness et al., 2018b). An additional factor that can lead the differences between previous results relates to the age group and the number of occupational categories used. There has been found that overeducation rates have remained relatively unchanged over time in many EU countries and are actually declining in others (McGuinness et al., 2018a). McGuinness et al. (2018a) report that the incidence of overeducation in the EU, averaged over all countries and education levels, has remained stable at approximately 18 per cent from 2003 to 2013. But Muñoz de Bustillo et al. (2018) mark different patterns of overeducation across countries over time rather than a common trend. However, convergence in overeducation rates has taken place.

Undereducation has received much less attention. According to meta-analysis presented by McGuinness et al. (2018b), 98 papers were published on overeducation and only 30 papers on undereducation. Additionally, undereducation was not the sole focus of any paper. It was considered in conjunction with overeducation. Previous research indicates that overeducation is generally more common than undereducation, as being overeducated is on average roughly two and a half times more widespread than being undereducated (McGowan and Andrews, 2015).

### 3.2 The impact of individual- and job characteristics

Among the individual level determinants *gender* differences have received a large amount of attention in the recent literature. In many countries the share of overeducated workers among women is higher than among men (Boll et al., 2016; Erdsiek, 2021). But a majority of previous studies have found that the effect of gender on overeducation risk is insignificant in multivariate

[2] Overall, the estimates obtained through the statistical approach tend to be lower than those based on the workers' self-assessment (Leuven and Oosterbeek, 2011).

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models (Büchel and Pollmann-Schult, 2001; Green and McIntosh, 2007; Capsada-Muensch, 2015). Quintini (2011) found that women are more likely undereducated than men.

Another potentially relevant individual characteristic is the worker's *age*. Overeducation could be more common amongst young people since they are more likely to be employed in temporary or entry-level jobs where education demands could be lower. Both country-level and cross-country studies have found that young people are more likely to be overeducated than older workers (Allen et al., 2013; OECD, 2013). The European Commission (2012) also finds a decreasing probability of being overeducated as the age of workers increases. In contrast, Groot and van den Brink (2003) detect no significant impact of age on the incidence of overeducation. Other authors indicate that high-skilled workers from the youngest and the oldest age groups have a particularly high overeducation risks in EU countries (Boll et al., 2016). Muñoz de Bustillo et al. (2018) have detected three different patterns: a U-pattern (with overeducation decreasing with age until mid-age and increasing afterwards) in six countries; a decreasing pattern (decreasing overeducation with age throughout the working career) in 15 countries and L-pattern (with overeducation decreasing with age up to certain point and then remaining relatively stable) in nine countries. Older workers can suffer from skills obsolescence due to technological progress. As a result, incidence of undereducation should be higher for older age groups.

Studies focusing on the impact of *work experience* establish a more clear-cut picture. Most authors indicate a highly significant negative impact of increased experience on the incidence of overeducation (Alba-Ramirez, 1993; Sloane et al., 1999). On the other hand, undereducation is higher for more experienced workers (Quntini, 2011). Undereducated might have acquired further skills during work career, which are not reflected in their educational level but allow them to do more complex jobs than their education suggests.

Most previous studies have concentrated on analysis of overeducation of employees with tertiary education. There are only a few studies comparing educational mismatch of different *educational groups*. For example, Delaney et al. (2020) find that overeducation is highest among young workers educated to tertiary level and lowest for those employees educated to primary or less. Quintini's (2011) analysis indicate no significant impact of educational level on the incidence of undereducation.

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Previous studies demonstrate that the incidence of educational mismatch is strongly related both to *job type and firm characteristics*. Workers in private firms are found to be less likely to be overeducated but more likely to be undereducated than workers in public sector. This result could be explained by the fact that public sector jobs often include education requirements (Quntini, 2011). The evidence on the links between *firm size* and education mismatch are ambiguous. Some cross-country studies have found that overeducation increases with firm size (Allen et al., 2013). There are several arguments in favour of this result. First, large firms are more complex and matching workers to the right jobs is more difficult. Second, larger firms are likely to be less financially constrained and can afford to use a recruitment strategy to ensure a continuous supply of high skills by hoarding overeducated workers (McGowan and Andrews, 2015). Other authors argue that education mismatch should decline with firm size, because larger firms offer more opportunities for highly educated workers compared to small firms (Quintini, 2011) and provide more space for career advancement.

Concerning the job type, the relevant distinction is between *fixed-term* and *permanent contract*. It appears that workers on fixed-term contracts are more likely to be overeducated than those on permanent contract (Green and McIntosh, 2007; Boll et al., 2016). Fixed-term contracts have transitory nature and workers are less concerned about educational levels, as they tend to view these matches as temporary solutions on their career.

Previous studies indicate that *economic sector* has also an impact on the rate of overeducation. Analysing the incidence of overeducation in the EU-15 countries Congregado et al. (2016) find that overeducation is higher in service sector and lower in agricultural sector. In terms of occupations, mismatch is higher in elementary occupations, in services and in technicians (Morrar and Zwick, 2021).

Table 1 summarises results of previous empirical studies presented above.

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*Table 1. Overview of previous empirical results: the impact of individual and job characteristics*

| | Impact on: Overeducation | Undereducation |
|---|---|---|
| *Individual level characteristics* | | |
| Gender | Women > men<br>In multivariate models no gender differences | Women > men |
| Age | Younger > older<br>High skilled younger and older workers > others age groups<br>Different patterns:<br>U-pattern; decreasing pattern; L-pattern | Older > younger |
| Work experience | Higher experience < low experience | Higher experience > low experience |
| Education | Highest among young workers with tertiary level, lowest among young workers with primary education | No impact |
| *Job-related characteristics* | | |
| Private versus public | Workers in private firms > workers in public sector | Workers in private firms < workers in public sector |
| Firm size | Large firms > small firms<br>Decreasing with firm size | Decreasing with firm size |
| Job type | Workers with fixed-term contract > workers with permanent contract | ? |
| Economic sector | Higher in service sector; lower in agricultural sector | Higher in service sector, construction transportation |
| Occupation | Service workers, elementary occupations, technicians | |

### 3.3 Determinants of cross-country differences

Di Pietro (2002) finds that on the supply side, increase in the *educational attainment* of the population is associated with higher overeducation, while on the demand side, increased

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*investment in research and development* is associated with lower overeducation. Figueiredo et al. (2017) as well as Cabus and Somers (2018) show that the recent increase in the average level of education may have had an effect of the intensification of mismatch. In contrary Ordine and Rose (2017) indicate that there is no strong relationship between country level overeducation rates and the share of individuals with tertiary education because supply may create 'its own demand'. However, the relationship between supply and demand seems to be important. Several studies have shown that a structural oversupply of educated workers does result in more overeducation. Davia et al. (2010) consider as a measure of the excess of educated labour supply the ratio of tertiary graduates to employment in professional and managerial positions and show that this measure has a positive effect on the incidence of overeducation.

Croce and Ghignoni, 2012) find that the *business cycle* affects the overall incidence of overeducation. Similarly, Verhaest and van der Velden (2013) find that the business cycle in the year of labour market entry explains cross-country differences in overeducation up to five years after graduation. Poulikas (2013) and Borgna et al. (2018) also demonstrate that during the financial crisis the average rate of overeducation in Europe increased.

Labour market institutions might also explain differences in education mismatch across countries. Previous research has highlighted the effects of flexible *labour market regulations* (Verhaest et al., 2017; Fregin et al., 2020). Verhaest and van der Velden (2013) report that EPL effect was unimportant in explaining cross-country differences in overeducation among a graduate cohort. Other authors have found that countries with a higher level of employment protection have experienced a higher incidence of overeducation (Croce and Ghignoni, 2012; McGowan and Andrews, 2015).

Overview of findings related to the impact of macro-level characteristics on educational mismatch are summarised in Table 2.

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*Table 2. Overview of previous empirical results: the impact of macro-level characteristics*

| | Impact on: Overeducation | Undereducation |
|---|---|---|
| *Rate of workers with tertiary education* | Higher rate is increasing<br>No difference | Not available |
| *Investments in innovation* | Higher investments are decreasing | Higher investments are increasing |
| *Imbalance between demand and supply side* | Oversupply of educated workers is increasing | Not available |
| *Business cycle* | In recession declines<br>In recessions increases | In recession increases |
| *Employment protection legislation* | Higher EPL is increasing | Higher EPL is increasing |

## 3.4 The impact of education mismatch on wages

Previous research consistently points to a wage penalty for overeducated individuals, relative to individuals with the same education in matched employment (McGuinness and Sloane, 2011; Mavromaras et al., 2013; Ordine and Rose, 2015; Kracke et al., 2018). McGuinness et al. (2018b) indicate in their meta-analysis that taking the average of different estimates overeducated individuals earn 13.6% less than matched individuals with similar levels of education. But overeducated workers earn more than adequately educated workers in jobs with requirements that match with their education (Bauer, 2002; Brynin and Longhi 2009; Hartog and Sattinger 2013). Levels et al. (2014) found that having more education than is required for a job is associated with higher wages: specifically, each additional year of education in excess of that required yields a wage premium of 3%. The empirical findings on undereducation are mixed. Verhaest and Omey (2006) find that undereducated receive wage premium relative to workers with the same education in a matched job. However, Sanchez-Sanchez and McGuinness (2015) and Di Pietro and Urwin (2006) find no statistically significant wage effect for undereducated workers. Still, undereducated workers are generally found to earn less than their adequately matched colleagues in jobs with similar requirements.

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There are findings indicating that the estimated overeducation penalty might be overestimated if overeducated workers have lower average ability levels than adequately educated workers with a similar educational background (Verhaest and Omey, 2012). McGuinness (2003), Chevalier and Lindley (2009) and Sohn (2010) included ability related indicators in the earnings equation and still found substantial wage penalties of overeducation.

Some researchers have studied the interaction effect between experience and education mismatch. Cohn and Ng (2000) found evidence for a negative interaction effect between overeducation and experience, whereas the undereducation bonus increased with years of experience. This suggests that overeducated workers experience less skill acquisition or even a depreciation of their skills surplus; undereducated workers seem to compensate their skill deficit with more skill acquisition on-the-job.

***Table 3.*** *Overview of previous empirical results: impact of educational mismatch on salaries*

| | Undereducation | Overeducation |
|---|---|---|
| With the same **educational level** | Increasing | Decreasing |
| With the same **occupational group** | Decreasing | Increasing |

## 4. Data and methods

We are using the EU-LFS data[3], focusing on two specific time periods: 2009 (during the great recession) and 2014 (after the recession). The analysis is based on the pooled data of 26 European countries[4] and the sample for the study is restricted to individuals who are working full-time.

[3] Every year a certain number of changes are applied in the national labour market surveys. These changes can concern the conceptual level (e.g., definitions and concepts used by the labour force survey) or the measurement level (sampling strategy, data collection etc.), which is important because it may produce some discontinuity also in the time series (Eurostat, 2012). More information about comparability over time is available for each survey year in the Quality Report of the European Union Labour Force Survey.

[4] We excluded the following countries from the analysis: Malta because the information about the occupation was only available at the 1-digit level and Luxembourg, Croatia, Iceland, Switzerland because either data was not available for both years or due to small sample sizes.

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First part of the analysis concentrates on educational mismatch. Most commonly used measures for analysing educational mismatch are workers' self-assessment, realized matches and job analysis approach (Flisi et al., 2014). We use the realized matches approach, which compares individual educational level with the modal or mean level of schooling of their respective occupation. We calculated the modal level of education based on four ISCED categories[5] for full-time workers for each ISCO-08 two-digit occupation group in each country separately. Accordingly, individuals are classified as being overeducated if their level of attained schooling is one level above the mode of their occupation, they are defined as matched if their educational level is equal to the modal level of schooling and undereducated if their acquired education is below the mode of their occupation.

We selected realized matches approach because it is indicated to adjust to skills upgrading due to technological change or new formal qualification requirements, what might ease the comparisons across cohorts, time points and countries (Capsada-Munsech, 2019). Still, the critics point out that the overall increase in educational attainment in a country without structural employment change might lead to a supply driven increase in the modal educational level of many jobs. In such cases, the use of the realized matches approach will interpret such increase as an increase in terms of the requirements, even if the jobs actually have not changed and have roughly the same requirements than before and will therefore potentially underestimate the level of overeducation (Muñoz de Bustillo et al., 2018).

The aim of the report is to analyse the variation in both the levels and trends in over- and undereducation and the factors explaining the country-level variance. In the first part of the analysis, we are using descriptive statistics to show how educational mismatch differs between different time periods, by countries and occupational groups. Secondly, we use multilevel logistic regression to analyse the overall incidence of being overeducated (ref matched) and undereducated (ref matched). We include to the analysis different individual (e.g. gender, age

[5] ISCED 0–2 primary education and less; 2 upper-secondary; 3 post-secondary non-tertiary; 4 short-cycle tertiary education and higher.

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group, job tenure, occupational group[6], automation risk of the occupation[7]), workplace (industry, size of the firm, type of contract) and macro-level characteristics (percentage of tertiary educated among working-age[8] population, unemployment rate, ratio of workers employed in managerial or professional occupations to people who have higher education[9], summary innovation index[10], strictness of employment protection legislation[11]) that reflect the potential demand- and supply-side as well as institutional and other structural characteristics which may have an effect on the incidence of over- and undereducation.

EU-LFS provides individual data on salary deciles. The vast literature traditionally uses the logarithm of salaries as an outcome. However, absolute amounts of salaries are not available in EU-LFS. Recent economic literature argues that categorical salary data with some thresholds are appropriate to relax the assumption of linearity (Bloome at al., 2018; Araki, 2020). This means, although linear models utilising continuous salary measures are preferable when analysing the link between education and salary, linear models with categorical outcomes may provide robust findings.

In the third part we analyse the impact of educational mismatch on salaries. First, we use linear regression models, controlling for educational level (Appendix 1A, Table 8A) and occupational group (Appendix 1A, Table 9A) in separate analyses. In the following step, we analyse the impact of educational mismatch in four broad occupational groups using multilevel linear regression, controlling also for educational level (Appendix 1A, Tables 10A-13A) and occupational group (Appendix 1A, Tables 14A-17A). We include to the salary analysis same individual and workplace characteristics which we are using in the multilevel logistic regression models. In addition, we add to the multilevel linear regression analysis a model with the

[6] High-skilled white-collar (ISCO 100-300), low-skilled white-collar (ISCO 400-500), high-skilled blue-collar (ISCO 600-700) and low-skilled blue-collar (ISCO 800-900).
[7] We are using the indicator of occupational automation risk from the TECHNEQUALITY project. The indicator measures the percentage of tasks on which less time will be spent, and it is coded for 2-digit ISCO-08 occupations.
[8] 25–64-year-olds.
[9] ISCED 5–8.
[10] It is a composite indicator obtained by taking an unweighted average of the indicators. Due to data revisions, summary innovation index results are not comparable across different time periods. 2009 data extracted from European Innovation scoreboard 2016 report and 2014 data from European Innovation scoreboard 2020 database.
[11] Individual and collective dismissals (regular contacts) version 1, which is extracted from OECD database (https://stats.oecd.org/Index.aspx?DataSetCode=EPL_OV)

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interaction of automation risk with educational mismatch variables to examine how the automation risk of the occupational group modify the effect of educational mismatch on salaries.

## 5. Results

Descriptive results show (Figure 1) that across all European countries observed in this paper, undereducation and overeducation rate has remained rather stable between 2009 and 2014, i.e., during and after the 2008 financial crisis. Undereducation rate is somewhat higher than overeducation, in 2014 respectively 18.1% and 15.6%. However, there are considerable country differences (see Appendix 1A, Table 1A). Undereducation decreased the most in Belgium, France, Lithuania and the UK, while increase is most notable in Hungary, Italy, Spain, Romania, Slovenia, Cyprus and Poland (percentage change from 2009 to 2014 ≥ 20%). Overeducation dropped considerably in Denmark, Ireland, Cyprus, Poland, Spain and Italy, and expanded in the UK, Portugal, Norway, Belgium and Slovakia. One way to explain the differences in educational mismatch is that there is an imbalance between the demand for and supply of skilled workers which is caused by structural or cyclical changes in the economy. Pouliakas (2013) and Borgna et al. 2018 have indicated that during the financial crisis the average rate of overeducation in Europe increased. Our analysis does not confirm this for all the countries. Overall, the results show that the recession affected countries differently concerning the educational mismatch.

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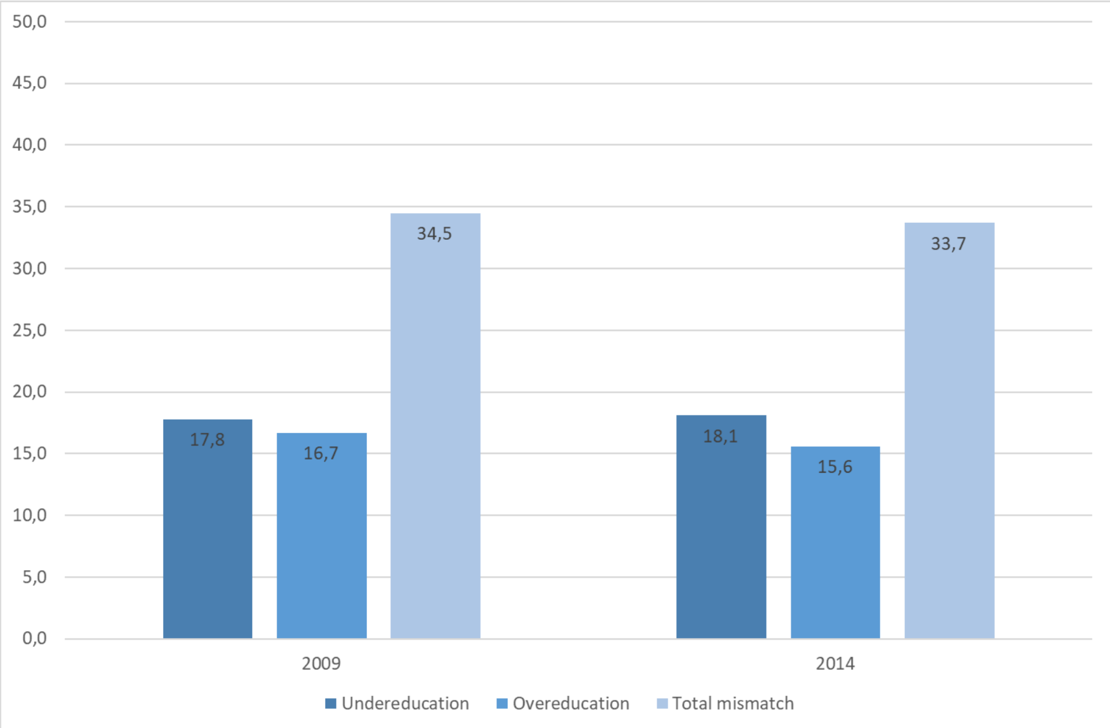


*Figure 1. Under- and overeducation rate in 2009 and 2014, pooled data (%)*

*Source:* Authors' calculations based on EU-LFS 2009, 2014; realized matches approach, sample restricted to full-time workers.

In the following, we focus on the pooled data to examine individual, job-related and macro-level characteristics on over- and undereducation by four major occupational groups. According to Figure 2 the share of undereducated workers is highest in high-skilled white-collar (ISCO 1–3) occupational groups in 2014 and 2009 and overeducation is the highest for both years specifically in the low-skilled white-collar (ISCO 4–5) occupational groups. Among low-skilled blue-collar (ISCO 8–9) workers over- and undereducation rate is distributed rather evenly, while for high-skilled blue-collar group (ISCO 6–7) overeducation is somewhat higher than undereducation. Results by occupational groups by countries are presented in the Appendix 1A (see Tables 2A to 5A).

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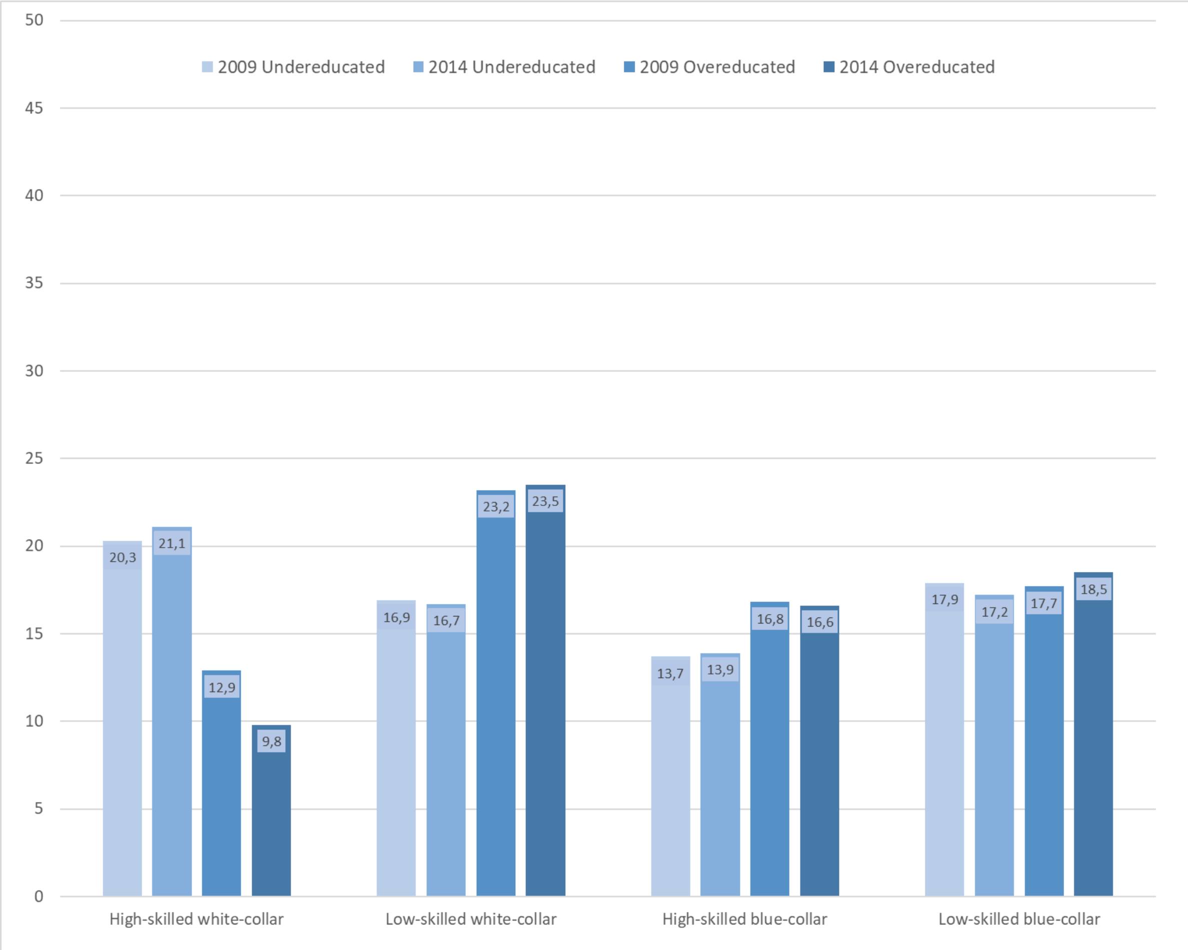


*Figure 2*. Under- and overeducation rates by occupational groups in 2009 and 2014 *(%)*

*Source:* Authors' calculations based on EU-LFS 2009, 2014; realized matches approach, sample restricted to full-time workers.

## *5.1 The impact of individual and job-related characteristics on educational mismatch*

Beginning with individual characteristics, results from multilevel logistic regressions summarised in Table 3 show that contrary to some previous findings regarding *gender* differences, men are more likely than women to be over- and undereducated in both time periods, with the exception of overeducation in 2014, where there is no statistically significant gender impact. The latter finding on overeducation in 2014 confirms majority of studies applying multivariate analysis.

In accordance with several previous findings, we observe that *age* of a worker tends to decrease the probability of being overeducated (ref the youngest, i.e., 20–29-year-olds) and this holds for both 2009 and 2014. For undereducation we find that it increases with age and in 2014 in

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particular, probability of being undereducated is lowest among 30–39-year-olds and highest among 50+ age group, which could be expected as technological innovation is associated with skills obsolescence in older age groups. Overall, economic crisis of 2008 does not seem to have change the impact of age on educational mismatch.

Research on educational mismatch (mostly concerning overeducation) has not focused on variations between different occupational classes, however, our results indicate significant *occupational group* differences. It appears that overeducation in both time periods is highest among low-skilled white-collars (ref high-skilled white-collars) but is rather high also among low-skilled blue-collars. In 2009, undereducation is highest among low-skilled white-collars as well, while undereducation is lowest among high-skilled blue-collars in both 2009 and 2014. So mostly educational mismatch seems to affect middle class occupational groups particularly.

We are also interested in the impact of automation risk of occupations on educational mismatch. Higher automation risk is associated with increasing overeducation. However, in both years automation risk tends to decrease the probability of being undereducated compared to those who are matched in their jobs.

*Work experience* or job tenure is clearly reducing the probability of being overeducated both during and after the economic recession. Results are in line with previous findings also regarding undereducation, as we observe that higher tenure is increasing undereducation, suggesting that with time undereducated workers may obtained further skills to perform more complex tasks than assumed by their level of education.

Regarding job-related characteristics, it appears that results considering *contract type* impact on overeducation in both years contradict previous findings as workers with permanent contract are more likely to be overeducated than those with temporary contract (although in 2014 the association is weaker). However, results indicate that workers on permanent contract are less mismatched in terms of undereducation because they have lower probability to be employed in jobs where higher level of education is expected.

According to *firm size*, previous findings for educational mismatch are rather mixed. Our results show that overeducation probability is lower in middle sized firms with 11–19 and 20–49 employees (ref up to 10). However, lending support to some of the previous findings,

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overeducation is highest in large firms (50+ employees), suggesting that these firms have more resources to employ high-skilled workers. Additionally, we find that undereducation decreases with firm size in both time periods. Thus, results imply that larger firms might offer more opportunities for career advancement.

***Table 4***. *Impact of individual and job-related characteristics on over- and undereducation in 2009 and 2014*

| | Overeducation | | Undereducation | |
|---|---|---|---|---|
| | 2009 | 2014 | 2009 | 2014 |
| *Gender* (ref women) | Men > women | No impact | Men > women | |
| *Age* (ref 20–29) | Decreasing with age | | Increasing with age | Decreasing for 30–39 and highest for 50+ |
| *Occupational group* (ref high-skilled white-collars) | Highest for low-skilled white-collars and low-skilled blue-collars | | Highest for low-skilled white-collars; lowest for high-skilled blue-collars | Lowest for high-skilled blue-collars |
| *Job tenure* (months) | Higher tenure is decreasing | | Higher tenure is increasing | |
| *Contract type* (temp.) | Higher with permanent contract | | Lower with permanent contract | |
| *Firm size* (ref up to 10) | Lower in middle-sized firms; highest in large firms | | Decreasing with firm size | |
| *Economic sector* (ref construction, mining, etc.) | Decreasing/lowest in retail, accommodation and catering; highest in administration and services | Highest in administration and services | Highest in retail, accommodation and catering; lowest in administration and services | Highest in retail, accommodation and catering; lowest in administration and services |
| *Automation risk* | Increasing with higher automation risk | | Decreasing with higher automation risk | |

*Note:* Summary of results presented in Appendix 1A, Table 6A–Table 7A.

Previous studies on the impact of *economic sector* suggest higher overeducation in service sector, which our results confirm, as overeducation is highest in both years among those working in administration and services (ref construction, mining, etc.). However, contrary to

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previous findings, in 2009 overeducation is lowest in retail, accommodation and catering sector compared to construction, mining, etc. In both years we find highest probability of undereducation in retail, accommodation and catering (the effect is clearer in 2009). Yet undereducation appears to be lowest in administration and services, also in both 2009 and 2014.

## 5.2 The impact of macro-level characteristics on educational mismatch

Results of the multilevel analysis summarised in Table 5 indicate that in case of overeducation only *unemployment rate*, as one indicator of the fluctuations in the economy, has significant impact. Expectedly, higher unemployment rate is increasing overeducation in both 2009 and 2014. Regarding undereducation, unemployment rate shows no significant impact in both years.

The rate of working-age population with *tertiary education* is increasing undereducation in both time periods. However, the impact of *investment in innovation* on undereducation is in the expected direction – higher investments tend to increase undereducation. Combining supply and demand of knowledge and skills, *imbalance between demand and supply*, i.e., structural oversupply of workers with higher education indicates decreasing impact on undereducation. Results regarding the impact of the *employment protection legislation* contradict previous findings, as stronger regulations are associated with decreasing undereducation.

*Table 5. Impact of macro-level characteristics on over- and undereducation in 2009 and 2014*

| | Overeducation | | Undereducation | |
|---|---|---|---|---|
| | 2009 | 2014 | 2009 | 2014 |
| *Rate of population with tertiary education* | No impact | | Increasing | |
| *Investments in innovation* | No impact | | Increasing | |
| *Imbalance between demand and supply side* | No impact | | Decreasing | No impact |
| *Unemployment rate* | Increasing | | No impact | |
| *Employment protection legislation* | No impact | | Decreasing | |

*Notes:* Summary of results presented in Appendix 1A, Table 6A–Table 7A.

## *5.3 The impact of educational mismatch on salaries*

In Table 6 we summarise results from the linear regression examining impact of over- and undereducation (ref matched workers) on *salaries*, first by controlling for highest educational level completed, and second by controlling for occupational group (for more detail see Appendix 1A Table 8A and 9A). When controlling for educational level, overeducation tends to decrease salary, while undereducation tends to increase salary. The impact is similar for both 2009 and 2014. This lends support to previous research indicating wage penalty for overeducated (McGuinness, 2003; Chevalier and Lindley, 2009; Sohn, 2010; McGuinness and Sloane, 2011; Mavromaras et al., 2013; Ordine and Rose, 2015; Kracke et al., 2018) and wage premium for undereducated (Verhaest and Omey, 2006) relative to those with same education in matched jobs. Our findings show that the existence of a wage penalty due to overeducation and a wage premium due to undereducation are not symmetric. Overeducation has stronger effect on wages than undereducation.

When controlling for occupational group, the impact of educational mismatch has a reversed effect. Namely, in this model overeducation is associated with higher salary and undereducation with lower salary. These results regarding overeducation also support some of previous findings (Levels et al., 2014) that overeducation increases wages, and in general, undereducated workers compared to matched workers are found to have lower salary. The negative effect of undereducation is stronger than a positive effect of overeducation.

*Table 6. Impact of over- and undereducation on salaries in 2009 and 2014*

| | 2009 | 2014 |
|---|---|---|
| *Educational level*[1] | | |
| Overeducation | Decreasing | Decreasing |
| Undereducation | Increasing | Increasing |
| *Occupational group*[2] | | |
| Overeducation | Increasing | Increasing |
| Undereducation | Decreasing | Decreasing |

*Notes:* [1]Summary of results presented in Appendix 1A Table 8A (model 3).

[2]Results are presented in Appendix 1A Table 9A (model 3).

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The analysis by occupational groups indicates the patterns of the impact of over-and undereducation on salaries, again first by controlling for the effect of educational level, second excluding the effect of educational level (see Table 7). Previous studies have not investigated the impact of mismatch on salaries by occupational groups, however, our analysis shows some significant differences. While controlling for educational level, results show that for several occupational groups the effect of mismatch on salaries is in line with results presented above on a pooled dataset (see Table 6). Yet in some instances we find no significant mismatch impact, particularly during the economic crisis in 2009. Most notably, there is no significant impact of mismatch on salaries for high-skilled blue-collars in 2009 and 2014. It could be that these jobs have concrete tasks which require relatively standardised skills and perhaps educational level is not directly associated with performance of such tasks. In 2009, we find no significant mismatch effect in terms of both over- and undereducation for low-skilled white-collars and only undereducation for low-skilled blue-collars. Finally, for low-skilled blue-collars, there appears to be no significant effect on salaries of undereducation in 2009 and overeducation in 2014. Some previous studies also do not observe statistically significant effect on salaries for undereducated workers (Sanchez-Sanchez and McGuinness, 2015; Di Pietro and Urwin, 2006).

When not controlling for educational level, the effect of mismatch is rather homogenous across all occupational groups, namely overeducation tends to increase salaries, while undereducation tends to decrease salaries compared to matched workers. But with one exception, because for high-skilled white-collars overeducation in both years is associated with wage penalty, therefore matched workers appear to be most advantaged. For high-skilled white-collars the undereducation penalty is highest. Our previous analysis indicated that the rate of undereducation is higher for this occupational group compared to other groups. There has been some criticism about expansion of higher education. Our results seem to indicate that this expansion is not quick enough to fill the demand for highly educated workers. At the same time, overeducation has quite strong positive impact on salaries of low-skilled white-collars. As our analysis shows, the rate of overeducation is highest among this occupational group. Perhaps some highly skilled workers prefer to work in jobs demanding lower educational level due to higher salaries. Alternatively, structural factors could explain this result. There are not enough jobs demanding higher education. However, we suppose there is much variation across countries in this regard.

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*Table 7. Impact of over- and undereducation on salaries of different occupational groups in 2009 and 2014*

| | Overeducation | | Undereducation | |
|---|---|---|---|---|
| | 2009 | 2014 | 2009 | 2014 |
| **Model with educational level**[1] | | | | |
| High-skilled white-collar | decreasing | decreasing | increasing | increasing |
| Low-skilled white-collar | no impact | decreasing | no impact | increasing |
| High-skilled blue-collar | no impact | no impact | no impact | no impact |
| Low-skilled blue-collar | decreasing | no impact | no impact | increasing |
| **Model excluding educational level**[2] | | | | |
| High-skilled white-collar | decreasing | decreasing | decreasing | decreasing |
| Low-skilled white-collar | increasing | increasing | decreasing | decreasing |
| High-skilled blue-collar | increasing | increasing | decreasing | decreasing |
| Low-skilled blue-collar | increasing | increasing | decreasing | decreasing |

*Note:* [1]Summary of results presented in Appendix 1A, Table 10A–Table 13A (model 1).

[2]Summary of results presented in Appendix 1A, Table 14A-17A (model 1).

## 5.4 The modifying impact of automation risk on educational mismatch on salaries

As a final step, we investigate whether and how automation risk is associated with the effect of educational mismatch on salaries, while controlling for the educational level. It appears that in 2009 and 2014, automation risk is decreasing salaries (Table 8, model 2). Furthermore, automation risk tends to amplify the negative impact of overeducation on salaries but reduce the positive impact of undereducation on salaries (interaction effect not significant in 2014) (Table 8, model 3 interaction effects).

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Moreover, the analysis reveals some differences by occupational groups (while not controlling for the educational level, see Appendix 1A Table 14A-17A)[12]. Overall, among the *high-skilled white-collars* wage penalty for undereducation is higher than for overeducation (compare also with Table 7 above). For this occupational group in case of lower automation risk there are no significant differences in salaries between matched and overeducated workers. Yet increase in automation risk is associated with clear wage penalty for overeducated compared to matched and the penalty for under- and overeducation equalises. Among *low-skilled white-collars* low automation risk is related to clear wage advantage for overeducated compared to both matched and undereducated workers. However, higher automation risk closes the wage gap between matched and undereducated, but in 2014 also for overeducated. We find no modifying effect of automation risk for *high-skilled blue-collars*. Finally, in case of *low-skilled blue-collars*, low automation risk yields in no differences between matched, over- and undereducated workers. While higher automation risk gives advantage to overeducated and results in wage penalty for undereducated.

Overall, we observe a somewhat surprising trend, as during the economic crisis high automation risk seems to have positive impact on salaries of low-skilled white- and blue-collars. We might assume that during the crisis there was an urgency to fill these jobs and hence to pay higher salaries. Additionally, these results could reflect the measurement of automation risk variable, because data on automation of occupations was gathered in 2019 and therefore some jobs that were considered at a high risk of automation in 2019, might have not been at the risk in 2009. So for instance in the group of low-skilled white-collars general clerk tasks (e.g., classifying and filing information, input and process text and data, proofreading and correcting, preparing invoices) or among low-skilled blue-collars assemblers work (assembling the components or parts of electrical, electronic or mechanical machinery equipment) in 2009 probably was less automated by machines and computers compared to 10 years later. Accordingly, we could expect that in 2009 the effect of automation and digitalisation on the salary of these occupational groups is positive.

[12] In this analysis we do not control for two variables, i.e., occupational group is fixed, but the models do not control for the highest educational level completed.

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*Table 8. Impact of automation risk on over- and undereducation on salaries in 2009 and 2014*

| | 2009, pooled sample | | | 2014, pooled sample | | |
|---|---|---|---|---|---|---|
| Male (ref female) | .973*** | .958*** | .958*** | .969*** | .943*** | .941*** |
| Age group (ref 20-29) | | | | | | |
| 30-39 | .784*** | .781*** | .778*** | .797*** | .784*** | .783*** |
| 40-49 | .996*** | .997*** | .994*** | 1.053*** | 1.036*** | 1.035*** |
| 50+ | .833*** | .831*** | .828*** | .879*** | .867*** | .866*** |
| Job tenure (months) | .003*** | .003*** | .003*** | .004*** | .004*** | .004*** |
| Educational mismatch (ref matched) | | | | | | |
| Undereducation | 1.108*** | .995*** | 1.340*** | 1.408*** | 1.290*** | 1.413*** |
| Overeducation | -1.201*** | -1.120*** | -.715*** | -1.630*** | -1.516*** | -1.166*** |
| Educational level (ref tertiary education) | | | | | | |
| Primary or less | -3.669*** | -3.459*** | -3.452*** | -4.294*** | -4.044*** | -4.059*** |
| Secondary | -2.133*** | -2.037*** | -2.081*** | -2.526*** | -2.405*** | -2.420*** |
| Postsecondary | -.455*** | -.425*** | -.441*** | -1.471*** | -1.395*** | -1.383*** |
| Industry (Ref construction, mining etc) | | | | | | |
| Retail, accommodation, catering | -.347*** | -.364*** | -.364*** | -.881*** | -.893*** | -.893*** |
| Administration and services | -.120*** | -.140*** | -.139*** | -.424*** | -.486*** | -.484*** |
| Firm size (ref less than 11) | | | | | | |
| 11-19 | .156*** | .164*** | .162*** | .310*** | .315*** | .315*** |
| 20-49 | .290*** | .298*** | .295*** | .250*** | .251*** | .251*** |
| 50+ | .673*** | .687*** | .685*** | .558*** | .583*** | .582*** |
| Don't know, but more than 10 | .306*** | .302*** | .299*** | .589*** | .605*** | .606*** |
| Permanent (ref temporary) | 1.435*** | 1.443*** | 1.442*** | 1.011*** | .996*** | .993*** |
| Automation risk | | -1.083*** | -.584*** | | -2.330*** | -2.045*** |
| Undereducation*automation risk | | | -1.001*** | | | -.317 |
| Overeducation* automation risk | | | -1.127*** | | | -.940** |
| Constant | 4.593*** | 4.941*** | 4.794*** | 5.495*** | 6.349*** | 6.262*** |

Multilevel linear regression*** p ≤ .001; **p ≤ .01; * p ≤ .05
Source: Own calculations based on EU-LFS 2009 and 2014.
Notes: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

## 6. Conclusions

Using data of European Union Labour Force Survey (EU-LFS) from 26 European countries the report shed light on a number of previously under-researched issues regarding the incidence and drivers of educational mismatch as well as the impact of educational mismatch on salaries. We examine these issues within European countries during the financial crisis of 2007–2008 and after the crisis (in 2014) to investigate the relation between economic conditions and education mismatch, the impact of different drivers of mismatch during the crisis and after that

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as well as the impact of educational mismatch on salaries. We pay special attention on the modifying role of automation risk on the incidence of educational mismatch and its effect on salaries.

Our results show that undereducation and overeducation rate has remained rather stable between 2009 and 2014, but the recession affected countries differently concerning the educational mismatch. Results about the impact of most socio-demographic measures as well as of job-related characteristics on the incidence of educational mismatch are in line with the previous findings.

Previous research on educational mismatch (mostly concerning overeducation) has not focused on variations between different occupational groups. Our analysis indicates substantial differences between occupational groups. Overeducation is highest among low-skilled white-collars. Overeducation is rather high also among low-skilled blue-collars. There are some differences between 2009 and 2014: in 2009 undereducation was highest among low-skilled white-collars but in 2014 among high-skilled white-collars. Our analysis shows that educational mismatch seems to affect middle class occupational groups in particular.

Higher automation risk is associated with increasing overeducation and therefore with increasing intragenerational downward mobility. However, in both years automation risk tends to decrease the probability of being undereducated (and also intergenerational upward social mobility) compared to those who are matched in their jobs. We do not have previous studies to rely on for explanations, but it seems rather logical that higher automation risk would increase overeducation (certain jobs [will] disappear and one must accept jobs below acquired educational level); and decrease undereducation. However, we should mention the imprecise measurement of the probability that a job is automated. We have used a measure developed in the TECHNEQUALITY project. The measure is based on human resources professionals' expert assessments of the time spent on certain job tasks in the next five years. It may well be that these trends do not apply to the workers in our sample, especially since our window of observation starts already in 2009, when these occupations might not have been under the risk of automation. Nevertheless, it is possible that this measure picks up long term trends already visible 10 years earlier.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

From macro level characteristics *unemployment rate*, as one indicator of the fluctuations in the economy, has significant impact on overeducation as expected. Therefore, it seems that fewer available jobs mean more willingness to accept jobs requiring lower educational credentials than attained. Therefore, higher unemployment is also increasing downward mobility. On the supply side, increase in the *educational attainment* of the population is associated with higher undereducation and hence facilitating upward mobility. It appears that higher supply of highly educated workers might increase educational level of certain occupations (even when actual educational level or skill requirements have not increased) and those who were employed in these occupations before, find themselves undereducated. On the demand side, increased investment in research and development is also associated with higher undereducation (and higher upward mobility) as expected. But supply and demand have no effect on overeducation. Our result seems to support the previous conclusion that supply may create 'its own demand' (see Ordine and Rose, 2017). A structural oversupply of educated workers does result in less undereducation. Previous research has indicated the effects of flexible labour market regulations. Our results show that employment protection legislation has no impact on incidence of overeducation, but stronger regulations are associated with decreasing undereducation. The explanation could be that countries with stricter regulations are rather avoiding hiring workers with lower education than is required by their job position, because it will be difficult to replace them afterwards.

It is generally found that overeducated workers earn less than adequately educated workers with a similar educational background. Similarly, undereducated workers seem to earn more than adequately educated workers with a similar educational background. Our results support these previous findings and job assignment theory indicating that not only attained education but also the use of the acquired education in the job determines workers' wage. A wage penalty due to overeducation seems to be stronger than a wage premium due to undereducation. However, there seems to be some differences between occupational groups. Overeducation is indeed decreasing and undereducation increasing salaries for high-skilled white-collars in 2009 and 2014. Nevertheless, there are no differences in salaries of matched, under- and overeducated among high-skilled blue-collars. For low-skilled white-collars we found expected effects in 2014. During the crisis the impact of educational mismatch was insignificant. Perhaps high rate of overeducated among this group could explain this result.

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Previous research consistently suggests that overeducated workers earn more than adequately educated workers in jobs with requirements that match their education and undereducated earn less. Once again, our result supports these conclusions for all workers irrespective of occupational group as well as low-skilled white-collars and both groups of blue-collars. But for high-skilled white-collars over- and undereducation have negative effect on salaries. This result could be explained by country variations. Assumingly, in countries with fast educational expansion, but relatively slow technological innovation, overeducation indeed could result in wage penalty because there are not enough jobs for highly educated workers. While in countries where the process of educational expansion and technological innovation are more in balance, overeducation might not have significant impact on salaries.

Overall, our results indicate that automation risk decreases salaries; more specifically increases the negative impact (wage penalty) of overeducation and decreases the positive impact (wage premium) of undereducation. However, this impact varies across occupational groups. Higher automation risk in the group of high-skilled white-collars leads to wage penalty in case of overeducated relative to matched workers, but the wage gap between over- and undereducated decreases. For low-skilled white-collars, increase in automation risk also tends to close the wage gap, but more clearly between matched and undereducated. Analysis does not reveal significant modifying effect of automation risk on salaries among high-skilled blue-collars. In case of low-skilled blue-collars higher automation risk tends to increase salaries for overeducated and decrease salaries for undereducated. Interestingly, during the economic crisis higher automation risk is positively associated with salary for both low-skilled occupational groups. Partly the explanation could be that there was rather high demand for such jobs and therefore salaries were higher. Additionally, these results could point to the fact that in 2009 low-skilled occupational groups (e.g., clerks, sales workers, assemblers, plant and machine operators) were not in such high risk of automation as they are about 10 years later, because the baseline for the measure we use for automation risk is 2019.

We suppose that the contribution of different theories as well as the most appropriate policy recommendations will vary across countries and more research is needed in this respect. Our results seem to indicate that overeducation among low-skilled white-collars is less common in lower wage economies. Therefore, structural factors are a key determinant of mismatch.

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Previous research states that the relative demand for intermediate labour declines as economies grow due to skill-biased technological change. But country level differences could also be driven by variations in the strength of labour market institutions across countries. The relative role of structural demand and labour market institutions in explaining country differences in terms of the effect of educational mismatch on salaries is a matter for future research.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

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*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

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*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

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*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

## Appendix 1A

### *Table 1A. Over-and undereducation rates in 2009 and 2014 (%), country differences*

| | Overeducation | | Undereducation | |
|---|---|---|---|---|
| | 2009 | 2014 | 2009 | 2014 |
| AT | 19.8 | 18.2 | 17.1 | 17.4 |
| BE | 11.5 | 13.8 | 27.9 | 21.5 |
| BG | 12.6 | 11.3 | 13.6 | 13 |
| CY | 24 | 16.1 | 15.6 | 19.2 |
| CZ | 10.2 | 8.2 | 7.9 | 8.3 |
| DE | 19.6 | 17.1 | 17.6 | 20.5 |
| DK | 15.8 | 10 | 22.1 | 20.7 |
| EE | 15.8 | 18.3 | 20.3 | 18.2 |
| ES | 26.6 | 20.7 | 9.9 | 14 |
| FI | 6.2 | 5.7 | 25.4 | 21.9 |
| FR | 11.8 | 12.7 | 28.6 | 22.8 |
| GR | 24.4 | 26.8 | 13.7 | 12.6 |
| HU | 16.9 | 16 | 7.7 | 14.3 |
| IE | 22.1 | 14.7 | 23.5 | 27.2 |
| IT | 25.3 | 20.1 | 10.9 | 17.2 |
| LT | 22.8 | 20.7 | 17.4 | 13.9 |
| LV | 17.1 | 14.1 | 16.7 | 17.1 |
| NL | 15.4 | 12.8 | 25.2 | 24.4 |
| NO | 5.7 | 6.9 | 28.7 | 26 |
| PL | 12.4 | 9.2 | 11.1 | 13.4 |
| PT | 18.1 | 23.3 | 4.9 | 5.2 |
| RO | 16.2 | 15.5 | 8.4 | 11.2 |
| SE | 14.8 | 14.5 | 21.9 | 21.9 |
| SI | 9.7 | 9.5 | 11.2 | 14.5 |
| SK | 9.8 | 11.8 | 6.2 | 6.9 |
| UK | 8.7 | 15.9 | 32 | 23.9 |

*Source:* Authors' calculations based on EU-LFS 2009, 2014; realized matches approach, sample restricted to full-time workers.

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*Table 2A*. Overeducation rates by occupational groups in 2009 and 2014 *(%), country differences*

| | Overeducation High-skilled white-collar | | Overeducation Low-skilled white-collar | |
|---|---|---|---|---|
| | 2009 | 2014 | 2009 | 2014 |
| AT | 29 | 19 | 19.1 | 19.9 |
| BE | 7.7 | 4.9 | 7.3 | 31.7 |
| BG | 15.7 | 6.3 | 15.8 | 17.1 |
| CY | 0 | 0 | 33.3 | 27.6 |
| CZ | 19.2 | 13.5 | 5.9 | 10.1 |
| DE | 21.3 | 14.8 | 25.1 | 27.7 |
| DK | 13.8 | 10.7 | 12.8 | 11.9 |
| EE | 4 | 7.1 | 38.5 | 40 |
| ES | 8.6 | 0 | 39.5 | 30.7 |
| FI | 1.9 | 0 | 13.8 | 13.8 |
| FR | 7.1 | 5.9 | 19.4 | 25.1 |
| GR | 9.4 | 2.9 | 29.5 | 34.2 |
| HU | 22 | 12.1 | 12 | 27.3 |
| IE | 10.9 | 0 | 29.5 | 16.4 |
| IT | 16.6 | 11 | 24.2 | 11.5 |
| LT | 0 | 2.1 | 45.9 | 42.2 |
| LV | 19.1 | 5.5 | 24.6 | 31.4 |
| NL | 10.3 | 5.8 | 20.5 | 22.7 |
| NO | 0.7 | 1.3 | 14.2 | 16.9 |
| PL | 17.6 | 6.4 | 22.1 | 21.4 |
| PT | 13.5 | 20.6 | 37.5 | 34.8 |
| RO | 17.8 | 12.9 | 13 | 18 |
| SE | 17.6 | 11.2 | 16.7 | 23.8 |
| SI | 11.9 | 11.5 | 6.3 | 12.1 |
| SK | 22.2 | 20.8 | 5.6 | 13 |
| UK | 2.2 | 12 | 21.8 | 27.1 |

*Source:* Authors' calculations based on EU-LFS 2009, 2014; realized matches approach, sample restricted to full-time workers.

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*Table 3A*. Overeducation rates by occupational groups in 2009 and 2014 *(%), country differences*

| | Overeducation High-skilled blue-collar | | Overeducation Low-skilled blue-collar | |
|---|---|---|---|---|
| | 2009 | 2014 | 2009 | 2014 |
| AT | 13.1 | 16.5 | 6.3 | 15.2 |
| BE | 11.1 | 13.1 | 30 | 19.1 |
| BG | 12.7 | 16.9 | 5.2 | 7.1 |
| CY | 36.8 | 15.4 | 38.6 | 29.7 |
| CZ | 1.2 | 1.5 | 1.6 | 1.1 |
| DE | 17.1 | 13.1 | 6.1 | 11.6 |
| DK | 8.7 | 3.9 | 35.4 | 10.9 |
| EE | 18.4 | 20 | 18 | 19.8 |
| ES | 35.6 | 33 | 34.2 | 34.8 |
| FI | 8.3 | 9.2 | 7.1 | 7.7 |
| FR | 7.8 | 10.4 | 18.6 | 17.2 |
| GR | 30.8 | 36.6 | 42.6 | 51.9 |
| HU | 5 | 12.7 | 27.3 | 14 |
| IE | 23.2 | 30.4 | 46.4 | 42.7 |
| IT | 35.6 | 34.7 | 35 | 39.1 |
| LT | 38 | 33.8 | 33.8 | 30 |
| LV | 13.2 | 17 | 8.8 | 11.2 |
| NL | 11 | 7.4 | 36.5 | 41 |
| NO | 9.5 | 11.9 | 8.8 | 14 |
| PL | 3.8 | 5.9 | 4.3 | 5.9 |
| PT | 8 | 16.4 | 11.7 | 20.8 |
| RO | 20.8 | 20.2 | 7.4 | 7.5 |
| SE | 8 | 10.6 | 9.2 | 18.3 |
| SI | 2.1 | 4.4 | 13.6 | 7.8 |
| SK | 1.4 | 3.5 | 0.9 | 3.2 |
| UK | 10.5 | 14 | 7.7 | 13.9 |

*Source:* Authors' calculations based on EU-LFS 2009, 2014; realized matches approach, sample restricted to full-time workers.

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*Table 4A*. Undereducation rates by occupational groups in 2009 and 2014 *(%), country differences*

| | Undereducation High-skilled white-collar | | Undereducation Low-skilled white-collar | |
|---|---|---|---|---|
| | 2009 | 2014 | 2009 | 2014 |
| AT | 9.2 | 17.4 | 16.7 | 16 |
| BE | 20.8 | 19.2 | 43.2 | 16.3 |
| BG | 7.5 | 14.4 | 7.8 | 7.6 |
| CY | 23 | 17.1 | 14.7 | 21.8 |
| CZ | 8.4 | 12.8 | 5.6 | 3.4 |
| DE | 16.2 | 24.7 | 15.5 | 12.8 |
| DK | 21 | 14.2 | 27.7 | 22.8 |
| EE | 28.8 | 24.5 | 7.3 | 9.1 |
| ES | 16.3 | 18.7 | 16.1 | 20 |
| FI | 26.5 | 23.9 | 23 | 21.4 |
| FR | 30.1 | 23.8 | 24.5 | 16.7 |
| GR | 22.3 | 17.8 | 21.4 | 19.2 |
| HU | 4.8 | 16.4 | 7.6 | 6.6 |
| IE | 18.9 | 24.2 | 31.8 | 39.2 |
| IT | 17.7 | 22.8 | 17.2 | 29.3 |
| LT | 26.5 | 17.6 | 13.4 | 12.7 |
| LV | 17.8 | 23.9 | 7.2 | 5.3 |
| NL | 26.9 | 26.6 | 25.3 | 19.1 |
| NO | 29.7 | 27.9 | 26.6 | 23.1 |
| PL | 11.8 | 18.6 | 3.3 | 8.5 |
| PT | 17.9 | 9.4 | 0 | 6.7 |
| RO | 5.6 | 12.2 | 8 | 8.7 |
| SE | 18.6 | 23.5 | 21 | 17.4 |
| SI | 6.5 | 12.4 | 5.1 | 5.1 |
| SK | 7.9 | 11.5 | 2.5 | 2.6 |
| UK | 34.2 | 22.1 | 23.5 | 21.7 |

*Source:* Authors' calculations based on EU-LFS 2009, 2014; realized matches approach, sample restricted to full-time workers.

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*Table 5A.* Undereducation rates by occupational groups in 2009 and 2014 *(%), country differences*

| | Undereducation High-skilled blue-collar | | Undereducation Low-skilled blue-collar | |
|---|---|---|---|---|
| | 2009 | 2014 | 2009 | 2014 |
| AT | 21.2 | 16.5 | 32.7 | 21.6 |
| BE | 35.5 | 29.1 | 21 | 29.7 |
| BG | 17.3 | 10.4 | 23.5 | 19.9 |
| CY | 8.8 | 25.6 | 10 | 15.6 |
| CZ | 4.6 | 3.9 | 14.1 | 10.2 |
| DE | 16.9 | 16 | 29 | 25.2 |
| DK | 26.8 | 23.6 | 12.6 | 39.1 |
| EE | 16.1 | 14.7 | 18 | 17.2 |
| ES | 0 | 7.8 | 0 | 0 |
| FI | 21.1 | 16.5 | 31.1 | 21.4 |
| FR | 30.9 | 24.8 | 28.2 | 26.8 |
| GR | 0.6 | 2.7 | 0 | 0.5 |
| HU | 11.5 | 8 | 10 | 23.1 |
| IE | 41.1 | 27.4 | 6.2 | 16.2 |
| IT | 0 | 3.5 | 0 | 0 |
| LT | 9.2 | 11.1 | 10.8 | 9.4 |
| LV | 18.4 | 14.1 | 22 | 17.9 |
| NL | 37.3 | 33.9 | 3.4 | 6.6 |
| NO | 26 | 19.3 | 33.6 | 30.1 |
| PL | 13.7 | 10.9 | 14.3 | 11.8 |
| PT | 0 | 0 | 0 | 0 |
| RO | 5.3 | 7.2 | 19.6 | 20.1 |
| SE | 23.9 | 20.7 | 32.2 | 23.6 |
| SI | 23.2 | 19.4 | 18.1 | 25.6 |
| SK | 2.5 | 4 | 9.7 | 8.2 |
| UK | 25.3 | 24.3 | 42.9 | 34.8 |

*Source:* Authors' calculations based on EU-LFS 2009, 2014; realized matches approach, sample restricted to full-time workers.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

*Table 6A. Impact of individual, job and macro-level characteristics on overeducation in 2009 and 2014*

| | Overeducation 2009, pooled sample | | | | | | | Overeducation 2014, pooled sample | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Male (ref female) | .002 | .050*** | .050*** | .058*** | .050*** | .050*** | .050*** | -.007 | -.011 | -.011 | -.027*** | -.011 | -.011 | -.012* |
| Age group (ref 20-29) | | | | | | | | | | | | | | |
| 30-39 | -.109*** | -.099*** | -.099*** | -.099*** | -.099** | -.099*** | -.100*** | -.123*** | -.100*** | -.100*** | -.087*** | -.100*** | -.100*** | -.101*** |
| 40-49 | -.312*** | -.322*** | -.322*** | -.347*** | -.322*** | -.322*** | -.323*** | -.364*** | -.368*** | -.368*** | -.347*** | -.368*** | -.368*** | -.368*** |
| 50+ | -.405*** | -.417*** | -.418*** | -.477*** | -.418*** | -.417*** | -.419*** | -.497*** | -.523*** | -.523*** | -.511*** | -.523*** | -.523*** | -.522*** |
| Job tenure (months) | -.002*** | -.001*** | -.001*** | -.001*** | -.001*** | -.001*** | -.001*** | -.001*** | -.001*** | -.001*** | -.001*** | -.001*** | -.001*** | -.001*** |
| Industry (Ref construction, mining etc) | | | | | | | | | | | | | | |
| Retail, accommodation, catering | .043*** | -.093*** | -.093*** | -.084*** | -.093*** | -.093*** | -.093*** | .198*** | .030*** | .030*** | .026** | .030*** | .030*** | .030*** |
| Administration and services | .130*** | .134*** | .134*** | .148*** | .134*** | .134*** | .135*** | .144*** | .111*** | .111*** | .105*** | .111*** | .111*** | .112*** |
| Firm size (ref less than 11) | | | | | | | | | | | | | | |
| 11-19 | -.084*** | -.072*** | -.072*** | -.085*** | -.072*** | -.072*** | -.072*** | -.062*** | -.038*** | -.038*** | -.039*** | -.0380*** | -.038*** | -.037*** |
| 20-49 | -.054*** | -.037*** | -.037*** | -.038*** | -.037*** | -.037*** | -.038*** | -.063*** | -.025** | -.025** | -.027** | -.020** | -.025** | -.025** |
| 50+ | .100*** | .120*** | .120*** | .128*** | .120*** | .120*** | .120*** | .065*** | .127*** | .127*** | .130*** | .127*** | .127*** | .128*** |
| Don't know, but more than 10 | -.053*** | -.060*** | -.060*** | -.062*** | -.060*** | -.060*** | -.061*** | .003 | .008 | .008 | .011 | .008 | .008 | .008 |

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| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Permanent contract (ref temporary)** | .039*** | .061*** | .061*** | .066*** | .061*** | .061*** | .061*** | -.010 | .021* | .021* | .026** | .021* | .021* | .021* |
| **Occupational group (ref high-skilled white-collar)** | | | | | | | | | | | . | .914*** | | |
| Low-skilled white-collar | | .580***<br>. | .580*** | .554*** | .580*** | .580*** | .574*** | | .914*** | .914*** | 920*** | .327***<br>.713*** | .914*** | .907*** |
| High-skilled blue-collar | | 040*** | .040*** | .018 | .040*** | .040*** | .034*** | | .327*** | .327*** | .374*** | | .327*** | .321*** |
| Low-skilled blue-collar | | .474*** | .474*** | .497*** | .474*** | .474*** | .470*** | | .713*** | .713*** | .768*** | | .713*** | .708*** |
| **Automation risk** | .966*** | | | | | | | 3.80*** | | | | | | |
| **Macro-level variables** | | | | | | | | | | | | | | |
| Unemployment rate | | | .055* | | | | | | | .034* | | | | |
| EPL | | | | .056 | | | | | | | .025 | | | |
| Isco1-2/Isced 5-8 ratio | | | | | -.258 | | | | | | | -.295 | | |
| Inno | | | | | | .047 | | | | | | | .272 | |
| Tertiary | | | | | | | .007 | | | | | | | .005 |
| Constant | -1.679*** | -<br>1.618*** | -<br>2.092*** | -<br>1.771*** | -1.442* | -1.639*** | -<br>1.773*** | -<br>2.811*** | -<br>1.833*** | -<br>2.174*** | -<br>1.854*** | -<br>1.649*** | -<br>1.950*** | -1.964*** |
| Number of groups | 26 | 26 | 26 | 21 | 26 | 26 | 25 | | 26 | 26 | 23 | 26 | 26 | 25 |

*** p ≤ .001; **p ≤ .01; * p ≤ .05

**Source**: Own calculations based on EU-LFS 2009 and 2014

Notes: Multilevel logistic regression. Coefficients are calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

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*Table 7A. Impact of individual, job and macro-level characteristics on undereducation in 2009 and 2014*

| | Undereducation 2009, pooled sample | | | | | | | Undereducation 2014, pooled sample | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Male (ref female) | -.011 | .064*** | .064*** | .085*** | .064*** | .064*** | .063*** | -.023*** | .042*** | .042*** | .060*** | .042*** | .042*** | .039*** |
| Age group (ref 20-29) | | | | | | | | | | | | | | |
| 30-39 | .022* | .020* | .020* | .045*** | .020* | .020* | .026** | -.080*** | -.104*** | -.104*** | -.125*** | -.104*** | -.104*** | -.102*** |
| 40-49 | .324*** | .320*** | .320*** | .380*** | .320*** | .321*** | .322*** | .188*** | .171*** | .171*** | .179*** | .171*** | .171*** | .174*** |
| 50+ | .601*** | .597*** | .597*** | .640*** | .597*** | .597*** | .604*** | .437*** | .424*** | .424*** | .435*** | .424*** | .424*** | .426*** |
| Job tenure (months) | .001*** | .001*** | .001*** | .001*** | .001*** | .001*** | .001*** | .001*** | .001*** | .001*** | .001*** | .001*** | .001*** | .001*** |
| Industry (Ref construction, mining etc) | | | | | | | | | | | | | | |
| Retail, accommodation, catering | .259*** | .141*** | .141*** | .159*** | .141*** | .141*** | .142*** | .082*** | .020* | .020* | .035*** | .020* | .020* | .019* |
| Administration and services | -.282*** | -.361*** | -.361*** | -.381*** | -.361*** | -.361*** | -.355*** | -.224*** | -.322*** | -.322*** | -.349*** | -.322*** | -.322*** | -.317*** |
| Firm size (ref less than 11) | | | | | | | | | | | | | | |
| 11-19 | -.084*** | -.088*** | -.088*** | -.093*** | -.088*** | -.088*** | -.091*** | -.089*** | -.112*** | -.112*** | -.106*** | -.112*** | -.112*** | -.112*** |
| 20-49 | -.136*** | -.150*** | -.150*** | -.141*** | -.150*** | -.150*** | -.150*** | -.182*** | -.225*** | -.225*** | -.219*** | -.226*** | -.225*** | -.225*** |
| 50+ | -.223*** | -.254*** | -.254*** | -.236*** | -.254*** | -.254*** | -.253*** | -.245*** | -.321*** | -.321*** | -.312*** | -.321*** | -.321*** | -.319*** |
| Don't know, but more than 10 | -.037** | -.052*** | -.052*** | -.064*** | -.052*** | -.052*** | -.052*** | -.077*** | -.116*** | -.116*** | -.127*** | -.116*** | -.116*** | -.116*** |
| Permanent contract (ref temporary) | -.187*** | -.188*** | -.188*** | -.192*** | -.188*** | -.188*** | -.189*** | -.318*** | -.339*** | -.339*** | -.346*** | -.339*** | -.339*** | -.340*** |
| Occupational group (ref high-skilled white-collar) | | | | | | | | | | | | | | |
| Low-skilled white-collar | | | | | | | | | | | | | | |

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| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| High-skilled blue-collar | | .076*** | .076*** | .111*** | .076*** | .076*** | .080*** | | -.244*** | -.244*** | -.239*** | -.244*** | -.244*** | -.243*** |
| Low-skilled blue-collar | | -.420*** | -.420*** | -.444*** | -.420*** | -.420*** | -.414*** | | -.670*** | -.670*** | -.725*** | -.670*** | -.670*** | -.665*** |
| | | -.039*** | -.039*** | -.102*** | -.039*** | -.039*** | -.035*** | | -.146*** | -.146*** | -.210*** | -.146*** | -.146*** | -.144*** |
| **Automation risk** | -.705*** | | | | | | | -1.198*** | | | | | | |
| **Macro-level variables** | | | | | | | | | | | | | | |
| Unemployment rate | | | -.025 | | | | | | | -.020 | | | | |
| EPL | | | | -.592*** | | | | | | | -.391** | | | |
| ISCO1-2/ISCED 5-8 ratio | | | | | -2.636** | | | | | | | -.703 | | |
| Innovation | | | | | | 2.298*** | | | | | | | 1.614*** | |
| Tertiary | | | | | | | .071*** | | | | | | | .042*** |
| Constant | -1.265*** | -1.436*** | -1.223*** | .005 | .367 | -2.472*** | -3.312*** | -.795*** | -.976*** | -.771*** | -.051 | -.538 | -1.667*** | -2.311*** |
| Number of groups | 26 | 26 | 26 | 21 | 26 | 26 | 25 | 26 | 26 | 26 | 23 | 26 | 26 | 25 |

*** p ≤ .001; **p ≤ .01; * p ≤ .05

Source: Own calculations based on EU-LFS 2009 and 2014

Notes: Multilevel logistic regression. Coefficients are calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

*Table 8A. Impact of individual and job-related characteristics and educational mismatch on salaries, controlling for educational level in 2009 and 2014*

| | Salary 2009, pooled sample | | | Salary 2014, pooled sample | | |
|---|---|---|---|---|---|---|
| **Educational mismatch (ref matched)** | | | | | | |
| Undereducation | -.836*** | .209*** | .233*** | -.495*** | .854*** | .794*** |
| Overeducation | .007 | -.828*** | -.692*** | -.242*** | -1.087*** | -.920*** |
| **Educational level (ref higher education)** | | | | | | |
| Primary and less | | -2.764*** | -2.939*** | | -3.416*** | -3.479*** |
| Secondary | | -1.756*** | -1.844*** | | -2.172*** | -2.205*** |
| Postsecondary | | -.456*** | -.389*** | | -1.123*** | -1.024*** |
| **Gender (ref female)** | | | 1.097*** | | | 1.139*** |
| **Age group (ref 20-29)** | | | | | | |
| 30-39 | | | .781*** | | | .786*** |
| 40-49 | | | .845*** | | | .996*** |
| 50+ | | | .560*** | | | .764*** |
| **Firm size (ref less than 11)** | | | | | | |
| 11-19 | | | .329*** | | | .268*** |
| 20-49 | | | .277*** | | | .399*** |
| 50+ | | | .603*** | | | .832*** |
| Don't know but more than 10 | | | .712*** | | | .103*** |
| **Industry (ref construction, mining)** | | | | | | |
| Retail, accommodation, catering | | | -.390*** | | | -.466*** |
| Administration and services | | | -.259*** | | | -.193*** |
| **Permanent contract (ref fixed)** | | | .474*** | | | 1.026*** |
| **Job tenure (months)** | | | .005*** | | | .004*** |
| Constant | 6.149*** | 7.457*** | 4.969*** | 6.398*** | 7.866*** | 4.726*** |
| R Square | .015 | .117 | .286 | .006 | .175 | .372 |

**Linear regression**, unstandardized coefficients. *** p ≤ .001; **p ≤ .01; * p ≤ .05
**Source**: Own calculations based on EU-LFS 2009 and 2014.
**Notes**: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

***Table 9A**. Impact of individual and job-related characteristics and educational mismatch on salaries, controlling for occupational group in 2009 and 2014*

| | Salary 2009, pooled sample | | | | | Salary 2014, pooled sample | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Educational mismatch (ref matched)** | | | | | | | | | | |
| Undereducation | -.825*** | -.883*** | -.938*** | -1.095*** | -1.059*** | -.494*** | -.623*** | -.691*** | -.933*** | -.924*** |
| Overeducation | .000 | .200*** | .318*** | .117*** | .199*** | -.241*** | .106*** | .226*** | -.378*** | -.382*** |
| **Occupational group (high-skilled white-collar)** | | | | | | | | | | |
| Low-skilled white-collar | | -2.195*** | -1.734*** | -1.899*** | -2.399*** | | -2.361*** | -1.884*** | -2.173*** | -2.321*** |
| High-skilled blue-collar | | -1.556*** | -2.023*** | -2.109*** | -2.274*** | | -1.880*** | -2.222*** | -2.412*** | -2.470*** |
| Low-skilled blue-collar | | -2.100*** | -2.395*** | -2.433*** | -2.723*** | | -2.467*** | -2.681*** | -2.849*** | -2.990*** |
| **Gender (ref female)** | | | 1.127*** | 1.125*** | 1.116*** | | | 1.141*** | 1.140*** | 1.152*** |
| **Age group (ref 20-29)** | | | | | | | | | | |
| 30-39 | | | .770*** | .770*** | .766*** | | | .806*** | .800*** | .801*** |
| 40-49 | | | .861*** | .864*** | .866*** | | | .997*** | 1.000*** | 1.005*** |
| 50+ | | | .617*** | .616*** | .617*** | | | .809*** | .812*** | .820*** |
| **Firm size (ref less than 11)** | | | | | | | | | | |
| 11-19 | | | .349*** | .348*** | .333*** | | | .308*** | .306*** | .305*** |
| 20-49 | | | .356*** | .350*** | .331*** | | | .495*** | .484*** | .482*** |
| 50+ | | | .699*** | .689*** | .660*** | | | .959*** | .946*** | .937*** |
| Don't know, 10+ | | | .708*** | .700*** | .692*** | | | .236*** | .230*** | .230*** |
| **Industry (ref construction, mining)** | | | | | | | | | | |
| Retail, accommodation, catering | | | -.533*** | -.523*** | -.444*** | | | -.565*** | -.549*** | -.529*** |
| Administration and services | | | -.437*** | -.447*** | -.408*** | | | -.328*** | -.347*** | -.312*** |
| **Permanent contract (ref fixed)** | | | .502*** | .502*** | .503*** | | | 1.036*** | 1.036*** | 1.037*** |

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| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Job tenure (months)** | | | .004*** | .004*** | .004*** | | | .003*** | .003*** | .003*** |
| **Educational mismatch* occgroup** | | | | .317*** | .267*** | | | | .460*** | .455*** |
| Undereducation*lowwhite | | | | .336*** | .293*** | | | | .426*** | .412*** |
| Undereducation*highblue | | | | .209*** | .167*** | | | | .501*** | .489*** |
| Undereducation*lowblue | | | | .547*** | .440*** | | | | 1.159*** | 1.139*** |
| Overeducation*low white | | | | .210*** | .111 | | | | .866*** | .867*** |
| Overeducation*high blue | | | | -.026 | -.118* | | | | .565*** | .566*** |
| Overeducation*low blue | | | | | | | | | | |
| **Automation risk** | | | | | 2.413*** | | | | | 1.462*** |
| Constant | 6.146*** | 7.286*** | 4.858*** | 4.918*** | 4.205*** | 6.398*** | 7.624*** | 4.503*** | 4.635*** | 4.123*** |
| R Square | .014 | .159 | .311 | .313 | .317 | .006 | .203 | .384 | .389 | .391 |

Linear regression, unstandardized coefficients. *** p ≤ .001; **p ≤ .01; * p ≤ .05

Source: Own calculations based on EU-LFS 2009 and 2014.

Notes: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

***Table 10A**. Impact of individual and job-related characteristics and educational mismatch on salaries, high-skilled white-collars 2009 and 2014*

| | 2009, high-skilled white-collar, pooled sample | | | 2014, high-skilled white-collar, pooled sample | | |
|---|---|---|---|---|---|---|
| **Male (ref female)** | .992*** | .979*** | .982*** | .825*** | .791*** | .792*** |
| **Age group (ref 20-29)** | | | | | | |
| 30-39 | 1.038*** | 1.031*** | 1.022*** | 1.102*** | 1.094*** | 1.093*** |
| 40-49 | 1.426*** | 1.419*** | 1.412*** | 1.445*** | 1.446*** | 1.446*** |
| 50+ | 1.377*** | 1.368*** | 1.358*** | 1.386*** | 1.388*** | 1.387*** |
| **Job tenure (months)** | .002*** | .001*** | .001*** | .002*** | .002*** | .002*** |
| **Educational mismatch (ref matched)** | .611*** | .569*** | .591*** | .592*** | .567*** | .192 |
| Undereducation | -.738*** | -.696*** | .250* | -.877*** | -.840*** | -.179 |
| Overeducation | | | | | | |
| **Educational level (ref tertiary)** | -2.296*** | -2.209*** | -2.176*** | -2.389*** | -2.348*** | -2.346*** |
| Primary and less | -1.600*** | -1.528*** | -1.494*** | -1.680*** | -1.649*** | -1.648*** |
| Secondary | -.682*** | -.639*** | -.718*** | -2.092 | -1.859 | -1.810 |
| Postsecondary | | | | | | |
| **Industry (Ref construction, mining etc)** | | | | | | |
| Retail, accommodation, catering | -.281*** | -.250*** | -.251*** | -.592*** | -.534*** | -.532*** |
| Administration and services | -.231*** | -.220*** | -.228*** | -.344*** | -.305*** | -.307*** |
| **Firm size (ref less than 11)** | | | | | | |
| 11-19 | .128** | .129** | .115* | .283*** | .289*** | .291*** |
| 20-49 | .353*** | .358*** | .349*** | .395*** | .410*** | .414*** |
| 50+ | .741*** | .745*** | .735*** | .682*** | .673*** | .676*** |
| Don't know, but more than | .124 | .110 | .100 | .464*** | .508*** | .511*** |
| 10 | 1.542*** | 1.546*** | 1.545*** | 1.384*** | 1.351*** | 1.348*** |
| **Permanent (ref temporary)** | | 1.084*** | 1.766*** | | 4.371*** | 4.352*** |
| **Automation risk** | | | -.122 | | | 1.153 |
| **Undereducation*aut risk** | | | -3.377*** | | | -2.063* |
| **Overeducation* aut risk** | | | | | | |
| Constant | 4.308*** | 3.959*** | 3.761*** | 4.785*** | 3.381*** | 3.388*** |

Multilevel linear regression*** p ≤ .001; **p ≤ .01; * p ≤ .05

Source: Own calculations based on EU-LFS 2009 and 2014.

Notes: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

***Table 11A**. Impact of individual and job-related characteristics and educational mismatch on salaries, low-skilled white-collars 2009 and 2014*

| | 2009, low-skilled white-collar, pooled sample | | | 2014, low-skilled white-collar, pooled sample | | |
|---|---|---|---|---|---|---|
| **Male (ref female)** | .927*** | .943*** | .943*** | .970*** | .973*** | .975*** |
| **Age group (ref 20-29)** | | | | | | |
| 30-39 | .471*** | .469*** | .469*** | .424*** | .426*** | .425*** |
| 40-49 | .655*** | .659*** | .659*** | .562*** | .564*** | .567*** |
| 50+ | .428*** | .419*** | .418*** | .262*** | .264*** | .266*** |
| **Job tenure (months)** | .004*** | .004*** | .004*** | .005*** | .005*** | .005*** |
| **Educational mismatch (ref matched)** | 1.090 | .890 | .567 | .749*** | .728*** | -.076 |
| Undereducation | -.300 | -.085 | -.400 | -.445* | -.427* | -.660* |
| Overeducation | | | | | | |
| **Educational level (ref tertiary)** | | | | | | |
| Primary and less | -2.448* | -1.999* | -1.983* | -2.197*** | -2.157*** | -2.048*** |
| Secondary | -.887 | -.641 | -.585 | -1.107*** | -1.085*** | -1.148*** |
| Postsecondary | .137 | .105 | .085 | -.384 | -.381 | -.382 |
| **Industry (Ref construction, mining etc)** | | | | | | |
| Retail, accommodation, catering | -.491*** | -.390*** | -.389*** | -.938*** | -.934*** | -.926*** |
| Administration and services | -.033 | .079 | .076 | -.403*** | -.393*** | -.388*** |
| **Firm size (ref less than 11)** | | | | | | |
| 11-19 | .137* | .125* | .124* | .398*** | .397*** | .396*** |
| 20-49 | .282*** | .266*** | .268*** | .206*** | .206*** | .205*** |
| 50+ | .607*** | .565*** | .566*** | .671*** | .669*** | .666*** |
| Don't know, but more than 10 | .436*** | .379** | .375** | .915*** | .913*** | .910*** |
| **Permanent (ref temporary)** | 1.332*** | 1.328*** | 1.325*** | .582*** | .583*** | .583*** |
| **Automation risk** | | 1.408*** | 1.096*** | | .114 | -.247 |
| **Undereducation*aut risk** | | | .775* | | | 1.516** |
| **Overeducation* aut risk** | | | .772* | | | .416 |
| Constant | 3.483*** | 2.509** | 2.597*** | 4.526*** | 4.450*** | 4.659*** |

Multilevel linear regression*** p ≤ .001; **p ≤ .01; * p ≤ .05

Source: Own calculations based on EU LFS 2009 and 2014.

Notes: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

***Table 12A**. Impact of individual and job-related characteristics and educational mismatch on salaries, high-skilled blue-collars 2009 and 2014*

| | 2009, high-skilled blue-collar, pooled sample | | | 2014, high-skilled blue-collar, pooled sample | | |
|---|---|---|---|---|---|---|
| **Male (ref female)** | 1.505*** | 1.478*** | 1.484*** | 1.370*** | 1.315*** | 1.308*** |
| **Age group (ref 20-29)** | | | | | | |
| 30-39 | .972*** | .975*** | .974*** | .768*** | .778*** | .779*** |
| 40-49 | 1.000*** | .999*** | .998*** | .899*** | .906*** | .907*** |
| 50+ | .747*** | .742*** | .741*** | .805*** | .819*** | .818*** |
| **Job tenure (months)** | .002*** | .002*** | .002*** | .002*** | .002*** | .002*** |
| **Educational mismatch (ref matched)** | | | | | | |
| Undereducation | .161 | .177 | 1.154 | -.929 | -.838 | -1.775 |
| Overeducation | -.698 | -.703 | -.712 | .437 | .026 | .984 |
| **Educational level (ref tertiary)** | | | | | | |
| Primary and less | -2.350 | -2.347 | -2.346 | -.090 | -.543 | -.472 |
| Secondary | -1.579 | -1.578 | -1.578 | -.324 | -.706 | -.634 |
| Postsecondary | -.412** | -.412** | -.411** | X | X | X |
| **Industry (Ref construction, mining etc)** | | | | | | |
| Retail, accommodation, catering | -.322*** | -.311*** | -.313*** | -.858*** | -.856*** | -.850*** |
| Administration and services | -.497*** | -.469*** | -.471*** | -.800*** | -.816*** | -.818*** |
| **Firm size (ref less than 11)** | | | | | | |
| 11-19 | .345*** | .350*** | .350*** | .221 | .235 | .244 |
| 20-49 | .308*** | .315*** | .315*** | .285** | .296** | .301** |
| 50+ | .799*** | .810*** | .812*** | .513*** | .519*** | .518*** |
| Don't know, but more than 10 | .808*** | .764*** | .765*** | .967*** | .967*** | .966*** |
| **Permanent (ref temporary)** | 1.610*** | 1.621*** | 1.628*** | .590*** | .579*** | .577*** |
| **Automation risk** | | 1.945*** | 2.381*** | | -2.482** | -2.430* |
| **Undereducation*aut risk** | | | -2.569 | | | 2.415 |
| **Overeducation* aut risk** | | | .019 | | | -2.409 |
| Constant | 3.798 | 3.080 | 2.906 | 3.663*** | 5.048*** | 4.964*** |

Multilevel linear regression*** p ≤ .001; **p ≤ .01; * p ≤ .05

Source: Own calculations based on EU LFS 2009 and 2014.

Notes: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

***Table 13A**. Impact of individual and job-related characteristics and educational mismatch on salaries, low-skilled blue-collars 2009 and 2014*

| | 2009, low-skilled blue-collar, pooled sample | | | 2014, low-skilled blue-collar, pooled sample | | |
|---|---|---|---|---|---|---|
| **Male (ref female)** | 1.140*** | 1.135*** | 1.123*** | 1.148*** | 1.111*** | 1.110*** |
| **Age group (ref 20-29)** | | | | | | |
| 30-39 | .488*** | .470*** | .464*** | .311*** | .283*** | .285*** |
| 40-49 | .515*** | .506*** | .500*** | .658*** | .615*** | .613*** |
| 50+ | .245*** | .227*** | .228*** | .455*** | .403*** | .403*** |
| **Job tenure (months)** | .003*** | .003*** | .003*** | .003*** | .003*** | .003*** |
| **Educational mismatch (ref matched)** | .173 | .217* | 2.88*** | .257* | .357*** | .552 |
| Undereducation | -.291** | -.321*** | -1.929 | -.185 | -.287** | -2.282*** |
| Overeducation | | | | | | |
| **Educational level (ref tertiary)** | | | | | | |
| Primary and less | -1.075*** | -1.147*** | - | -1.035*** | -1.228*** | -1.170*** |
| Secondary | -.505*** | -.547*** | 1.094*** | -.493*** | -.587*** | -.527*** |
| Postsecondary | .056 | .070 | -.503*** | -1.840 | -1.926 | -1.877 |
| | | | .039 | | | |
| **Industry (Ref construction, mining etc)** | | | | | | |
| Retail, accommodation, catering | -.456*** | -.458*** | -.458*** | -1.175*** | -1.238*** | -1.238*** |
| Administration and services | -.615*** | -.610*** | -.605*** | -1.020*** | -1.000*** | -1.001*** |
| **Firm size (ref less than 11)** | | | | | | |
| 11-19 | .204** | .186* | .185* | .142 | .143 | .140 |
| 20-49 | .174** | .170** | .168** | -.062 | -.060 | -.068 |
| 50+ | .425*** | .429*** | .424*** | .224*** | .253*** | .247*** |
| Don't know, but more than 10 | .227 | .237 | .224 | .295 | .325* | .321 |
| **Permanent (ref temporary)** | .860*** | .892*** | .891*** | .710*** | .698*** | .698*** |
| **Automation risk** | | -1.424* | .281 | | -3.660*** | -3.934*** |
| **Undereducation*aut risk** | | | - | | | -.448 |
| **Overeducation* aut risk** | | | 6.314*** | | | 4.774** |
| | | | 3.871 | | | |
| Constant | 3.149*** | | 3.020*** | 3.961*** | 5.748*** | 5.789*** |

Multilevel linear regression*** p ≤ .001; **p ≤ .01; * p ≤ .05

Source: Own calculations based on EU LFS 2009 and 2014.

Notes: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

***Table 14A**. Impact of individual and job-related characteristics and educational mismatch on salaries, high-skilled white-collars 2009 and 2014*

| | 2009, high-skilled white-collar, pooled sample | | | 2014, high-skilled white-collar, pooled sample | | |
|---|---|---|---|---|---|---|
| **Male (ref female)** | 1.043*** | .997*** | 1.001*** | .782*** | .744*** | .745*** |
| **Age group (ref 20-29)** | | | | | | |
| 30-39 | 1.147*** | 1.116*** | 1.097*** | 1.144*** | 1.133*** | 1.133*** |
| 40-49 | 1.526*** | 1.495*** | 1.480*** | 1.440*** | 1.441*** | 1.441*** |
| 50+ | 1.472*** | 1.439*** | 1.419*** | 1.340*** | 1.344*** | 1.343*** |
| **Job tenure (months)** | .001*** | .001*** | .001*** | .002*** | .002*** | .002*** |
| **Educational mismatch (ref** | | | | | | |
| **matched)** | -.781*** | -.732*** | -.134 | -.908*** | -.905*** | -1.129*** |
| Undereducation | -.414*** | -.327*** | 1.257*** | -.524*** | -.488*** | .331 |
| Overeducation | | | | | | |
| **Industry (Ref construction, mining etc)** | | | | | | |
| Retail, accommodation, catering | -.414*** | -.305*** | -.303*** | -.658*** | -.591*** | -.590*** |
| Administration and services | -.093*** | -.077** | -.099*** | -.040 | -.002 | -.004 |
| **Firm size (ref less than 11)** | | | | | | |
| 11-19 | .297*** | .281*** | .254*** | .275*** | .282*** | .284*** |
| 20-49 | .507*** | .501*** | .480*** | .428*** | .445*** | .449*** |
| 50+ | .926*** | .914*** | .890*** | .785*** | .772*** | .776*** |
| Don't know, but more than | .225 | .194 | .172 | .567*** | .612*** | .617*** |
| 10 | 1.589*** | 1.596*** | 1.592*** | 1.379*** | 1.343*** | 1.341*** |
| **Permanent (ref temporary)** | | 3.225*** | 4.821*** | | 4.924*** | 5.098*** |
| **Automation risk** | | | -2.063*** | | | .689 |
| **Undereducation*aut risk** | | | -5.803*** | | | -2.557** |
| **Overeducation* aut risk** | | | | | | |
| Constant | 3.489*** | 2.550*** | 2.118** | 4.271*** | 2.700*** | 2.645*** |

Multilevel linear regression*** p ≤ .001; **p ≤ .01; * p ≤ .05
Source: Own calculations based on EU LFS 2009 and 2014.
Notes: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

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***Table 15A**. Impact of individual and job-related characteristics and educational mismatch on salaries, low-skilled white-collars 2009 and 2014*

| | 2009, low-skilled white-collar, pooled sample | | | 2014, low-skilled white-collar, pooled sample | | |
|---|---|---|---|---|---|---|
| **Male (ref female)** | .926*** | .943*** | .943*** | .963*** | .975*** | .978*** |
| **Age group (ref 20-29)** | | | | | | |
| 30-39 | .469*** | .467*** | .467*** | .422*** | .431*** | .429*** |
| 40-49 | .651*** | .656*** | .657*** | .552*** | .563*** | .566*** |
| 50+ | .423*** | .414*** | .415*** | .248*** | .255*** | .259*** |
| **Job tenure (months)** | .004*** | .004*** | .004*** | .005*** | .005*** | .005*** |
| **Educational mismatch (ref matched)** | | | | | | |
| Undereducation | -.466*** | -.464*** | -.826*** | -.311*** | -.317*** | -1.059*** |
| Overeducation | .618*** | .579*** | .175 | .634*** | .622*** | .577** |
| **Industry (Ref construction, mining etc)** | | | | | | |
| Retail, accommodation, catering | -.492*** | -.389*** | -.389*** | -.949*** | -.931*** | -.921*** |
| Administration and services | -.036 | .079 | .076 | -.388*** | -.346*** | -.340*** |
| **Firm size (ref less than 11)** | | | | | | |
| 11-19 | .139* | .126* | .125* | .403*** | .396*** | .393*** |
| 20-49 | .283*** | .266*** | .269*** | .209*** | .210*** | .207*** |
| 50+ | .608*** | .565*** | .566*** | .679*** | .670*** | .665*** |
| Don't know, but more than 10 | .433*** | .376** | .373** | .918*** | .909*** | .904*** |
| **Permanent (ref temporary)** | 1.334*** | 1.330*** | 1.327*** | .568*** | .574*** | .573*** |
| **Automation risk** | | 1.434*** | 1.106*** | | .479* | .138 |
| **Undereducation*aut risk** | | | .772* | | | 1.751*** |
| **Overeducation* aut risk** | | | .831* | | | .123 |
| Constant | 2.688** | 1.934* | 2.090* | 3.456*** | 3.224*** | 3.369*** |

Multilevel linear regression*** p ≤ .001; **p ≤ .01; * p ≤ .05

Source: Own calculations based on EU LFS 2009 and 2014.

Notes: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

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***Table 16A**. Impact of individual and job-related characteristics and educational mismatch on salaries, high-skilled blue-collars 2009 and 2014*

| | 2009, high-skilled blue-collars, pooled sample | | | 2014, high-skilled blue-collar pooled sample | | |
|---|---|---|---|---|---|---|
| **Male (ref female)** | 1.505*** | 1.478*** | 1.484*** | 1.370*** | 1.313*** | 1.306*** |
| **Age group (ref 20-29)** | | | | | | |
| 30-39 | .973*** | .976*** | .975*** | .769*** | .779*** | .780*** |
| 40-49 | 1.004*** | 1.003*** | 1.002*** | .899*** | .907*** | .907*** |
| 50+ | .751*** | .746*** | .745*** | .806*** | .821*** | .820*** |
| **Job tenure (months)** | .002*** | .002*** | .002*** | .002*** | .002*** | .002*** |
| **Educational mismatch (ref matched)** | | | | | | |
| Undereducation | -.616*** | -.597*** | .379 | -.697*** | -.676*** | -1.615 |
| Overeducation | .786*** | .778*** | .733 | .753*** | .719*** | 1.649 |
| **Industry (Ref construction, mining etc)** | | | | | | |
| Retail, accommodation, catering | -.322*** | -.311*** | -.313*** | -.857*** | -.854*** | -.849*** |
| Administration and services | -.495*** | -.467*** | -.469*** | -.799*** | -.814*** | -.817*** |
| **Firm size (ref less than 11)** | | | | | | |
| 11-19 | .345*** | .349*** | .349*** | .217 | .228 | .238 |
| 20-49 | .309*** | .317*** | .316*** | .285** | .294** | .300** |
| 50+ | .802*** | .813*** | .815*** | .513*** | .519*** | .519*** |
| Don't know, but more than 10 | .806*** | .762*** | .764*** | .966*** | .966*** | .965*** |
| **Permanent (ref temporary)** | 1.610*** | 1.621*** | 1.627*** | .589*** | .577*** | .574*** |
| **Automation risk** | | 1.935*** | 2.357*** | | -2.510** | -2.434* |
| **Undereducation*aut risk** | | | -2.562 | | | 2.418 |
| **Overeducation* aut risk** | | | .117 | | | -2.525 |
| Constant | 2.016 | 1.302 | 1.134 | 3.334*** | 4.329*** | 4.312*** |

Multilevel linear regression*** p ≤ .001; **p ≤ .01; * p ≤ .05

Source: Own calculations based on EU LFS 2009 and 2014.

Notes: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

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***Table 17A**. Impact of individual and job-related characteristics and educational mismatch on salaries, low-skilled blue-collars 2009 and 2014*

| | 2009, low-skilled blue-collar, pooled sample | | | 2014, low-skilled blue-collar, pooled sample | | |
|---|---|---|---|---|---|---|
| **Male (ref female)** | 1.179*** | 1.180*** | 1.166*** | 1.218*** | 1.197*** | 1.193*** |
| **Age group (ref 20-29)** | | | | | | |
| 30-39 | .482*** | .467*** | .460*** | .312*** | .288*** | .289*** |
| 40-49 | .497*** | .489*** | .484*** | .636*** | .595*** | .593*** |
| 50+ | .226*** | .212*** | .213*** | .418*** | .366*** | .368*** |
| **Job tenure (months)** | .003*** | .003*** | .003*** | .003*** | .003*** | .003*** |
| **Educational mismatch (ref matched)** | | | | | | |
| Undereducation | -.352*** | -.337*** | 2.405*** | -.228*** | -.220*** | .171 |
| Overeducation | .147* | .152* | -1.813 | .212** | .192** | -2.003** |
| **Industry (Ref construction, mining etc)** | | | | | | |
| Retail, accommodation, catering | -.474*** | -.474*** | -.474*** | -1.193*** | -1.251*** | -1.251*** |
| Administration and services | -.724*** | -.723*** | -.713*** | -1.209*** | -1.223*** | -1.216*** |
| **Firm size (ref less than 11)** | | | | | | |
| 11-19 | .200** | .182* | .180* | .150 | .155 | .149 |
| 20-49 | .176** | .171** | .168** | -.067 | -.067 | -.073 |
| 50+ | .431*** | .431*** | .426*** | .216** | .240*** | .233*** |
| Don't know, but more than 10 | .190 | .198 | .186 | .275 | .302 | .297 |
| **Permanent (ref temporary)** | .854*** | .889*** | .888*** | .700*** | .686*** | .688*** |
| **Automation risk** | | -1.109 | .574 | | -3.172*** | -3.347*** |
| **Undereducation*aut risk** | | | -6.479*** | | | -.904 |
| **Overeducation* aut risk** | | | 4.636* | | | 5.168** |
| Constant | 2.537*** | 2.987*** | 2.274 | 3.249*** | 4.656*** | 4.733*** |

Multilevel linear regression*** p ≤ .001; **p ≤ .01; * p ≤ .05

Source: Own calculations based on EU LFS 2009 and 2014.

Notes: Calculated based on full-time workers. CH, MT, IS, LU, HR excluded from the analysis.

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## Appendix 2

# The future is now
# Cross-country evidence on mismatches in digital problem-solving skills and wage inequalities[13]

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Abstract

In all industrialised countries, digitalisation and automation lead to a profound transformation of work and skill requirements of jobs. Thereby, digital problem-solving skills are becoming increasingly important for workers' productivity and performance. However, not much is known yet about individual skill-to-job matches, and particularly shortages, in these skills and their relation with wages and social inequalities. As technological innovations may favour certain social groups, a thorough assessment of social inequalities is the main gap in the literature. Systematically assessing the value of skills and skill-to-job matches for intragenerational social mobility, our article sets out to narrow that gap. Drawing on micro data from the Programme for the International Assessment of Adult Competencies (PIAAC), our research is based on objective skills measurements for representative samples of employees in 26 industrial countries. We build a skill matching model to show that skill-to-job matches in digital problem-solving skills matter for wages: shortages are damaging, while a skills surplus is profitable. Digital problem-solving skills re-shape wage inequalities, narrowing the divide between social origin groups. These key skills may also help to reduce the gender wage gap, as high levels of digital-problem solving skills appear to pay off more for women than for men.

*Keywords: PIAAC, digital skills, skill mismatch, wages, social inequality, gender*

[13] The authors thank Jan Koucky for the provision of indices for the importance of digital skills based on O*NET data, and Ineke Bijlsma for support with the analyses.

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## 1. Introduction

Automation is not only changing the way we work, but also affects social inequalities. In industrial countries, labour automation only had a moderate impact on the *quantitative* demand for labour so far. Nevertheless, it is pervasively and irreversibly transforming work in a *qualitative* way (Frank et al., 2019; Pew Research Center, 2018; Frey and Osborne, 2017; Brynjolfsson and McAfee, 2014; Autor and Dorn, 2013; Acemoglu and Autor, 2011). This is not new. The adaptation of digital technologies has led to fundamental changes in the demand for skills since the mid-1990s (e.g., Elliot, 2017; Green, 2013; Levy, 2010; Acemoglu, 2002). However, the ubiquitous availability of information and communication technology (ICT) induces specific forms of tasks that demand information-processing and digital problem-solving (Brynjolfsson and McAfee, 2014; Acemoglu and Autor, 2011; Levy, 2010; Autor, Levy, and Murnane, 2002). This leads to a situation, in which digital skills are thought to be *key skills* for everybody (OECD, 2016d; 2016f; 2016e). As automation not only infuses into work but also everyday life, digital skills are not only key to ensure that workers remain productive and employable in labour markets but also included in societies (OECD, 2013b). Artificial Intelligence (AI) and Robotic Process Automation (RPA) are thought to further exacerbate that trend in the future (Nazareno und Schiff, 2021; WEF, 2021; Moore, 2019; Pew Research Center, 2018). However, social groups are unequally equipped to deal with these changes and technological innovations may favour certain social origin groups (e.g., European Commission, 2018a; Goldin and Katz, 2010).

The increasing impact of computer-based technologies implies a measurable change in the composition of job tasks both at work and in everyday life (e.g., Autor, Salomons und Seegmiller, 2021; Acemoglu and Restrepo, 2020; Autor and Dorn, 2013). The key to understanding this is the assumption that Digital problem-solving is considered a *key skill*, capturing the general capability of adults to generate appropriate performance in all kinds of technology-rich environments (OECD, 2016a: 96). Key skills are highly transferrable and can be used as a measure of cognitive competencies needed for the 21st century and "general" information-processing skills that allow adults to fully participate in labour markets and multiple situations in social and civic life (OECD, 2016a: 16). As they allow adults to adapt to and perform adequately in changing environments, digital problem-solving skills capture the fluid ability that is assumed to become ever more important in the increasingly digitised labour markets of the near future (OECD, 2016g; 2016f; 2016e). However, these skills are already important for a successful participation in present labour markets. About 85% of all jobs currently available in the EU require at least a basic level in digital skills (Cedefop, 2018: 5), and ICT skills are substantially rewarded at the labour market (Falck, Heimisch and Wiederhold, 2016; Lane and Conlon, 2016; Hanushek, Schwerdt, Wiederhold, and Woessmann, 2015b). In the more automated labour markets of the future these skills will most likely become even more important to ensure employability as well as social inclusion. However, social groups are unequally equipped with those skills and the knowledge needed to deal with the profound and irreversible changes.

Can labour markets adjust to changing skill demands? And how do these changing skill demands affect social inequalities? Previous research on the topic suggests that the rapid developments are increasing the incidence of mismatches between the skills that workers possess and what is required by the workplace (Felstead, Gallie, and Green, 2017; Holmes and Mayhew, 2015; Green, 2013; Verhaest and van der Velden, 2013). In a 2013 survey, no less than 40% of all EU employers said that they have difficulty finding workers with the right skills when recruiting (Cedefop, 2018: 5). The concern is that mismatches, and particularly shortages, in what we think of as "future skills" are exacerbating existing and generating new social inequalities (e.g., De La Rica and Gortazar, 2017; Goldin and Katz, 2010). Mismatches in digital skills may have a broad impact on outcomes both in work and daily life.

A large body of literature suggests that income inequalities are to a large extent related to skills differences (e.g. Bol, Ciocca Eller, van de Werfhorst, and DiPrete, 2019; van der Velden and Bijlsma, 2018; Cedefop, 2018; Holmes, 2017; OECD, 2017; 2013b; Hanushek and Woessmann, 2015a; Hanushek et al., 2015b; Levels, van der Velden, and Allen, 2014b; Perry, Wiederhold, and Ackermann-Piek, 2014; Quintini, 2014; Leuven, Oosterbeek and van Ophem, 2004; Allen and van der Velden, 2001; Groot and Maassen van den Brink, 2000; Hartog, 2000). Most studies merely focus on general cognitive skills such as literacy and numeracy. The few available empirical studies on returns to computer skills have important limitations. For example, most rely on subjective measures of computer use (e.g., Borghans and ter Weel, 2004). Worker self-assessment bears several problems for analyses, the most pressing one being the lack of an

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objective anchor (Allen and van der Velden, 2005) and the risk of social bias ("talking up the job"). Objective measures give a better and more valid picture of the 'real' skills and their relation with outcomes, but only very few studies use such measures. The most important findings are that, first, ICT skills are substantially rewarded at the labour market, with the highest returns in occupations that heavily rely on the use of these skills (Falck, Heimisch, and Wiederhold, 2016). Second, the use of computers is a key driver of wage inequalities (De La Rica and Gortazar, 2017). And third, significantly higher returns to increasing levels of ICT skills can compensate for lower levels of other marketable qualifications (Lane and Conlon, 2016). However, a skilled population is not enough to achieve growth and inclusive digital societies: skills need to be put into productive use (*cf.* Quintini, 2014; see also van der Velden and Bijlsma, 2018).

Many studies ignore the importance of the match between worker's digital problem-solving skills and the level of skills that is required at the workplace. This leads to a lack of information about the (productive) use of skills and talent and related social inequalities in labour market outcomes. There is a digital skill divide between social groups, e.g., between age groups, workers with different educational attainment, social origin groups, migrants and immigrants and gender (European Commission, 2018a; 2018b; 2015; OECD, 2016c; 2016f; Nanos and Schluter, 2014). However, not much is known about how this digital skill divide translates into group-specific returns to skills and whether wage inequalities will be exacerbated or reduced if digital problem-solving skills get ever more important in the future. When it comes, for example, to gender, it is a longstanding finding that women are consistently underpaid relative to men, even when they are equally skilled and educated (Lauder, Brown and Ashton, 2017: 418; see also Amado, Santos and São José 2018; Holmes, 2017; Becker, 1957). Moreover, the relation between skill and wage is stronger for men than for women (e.g., Hanushek et al., 2015b). However, only few studies examine digital skills and the gender pay gap (European Commission, 2018b; Kupfer, 2014). Another study investigates returns to digital skills and mismatches by focussing on immigrants (Perry, 2017). Overall, however, the research on social inequalities and skill mismatches is scarce. In fact, a systematic and thorough assessment of inequalities between social origin groups is the main gap in the literature.

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This hiatus in knowledge is important to fill. Skill shortages are increasingly driven not solely by the widespread adoption of ICT but also by structural changes in the economy and a lack of synchronization with developments of educational systems and opportunities for lifelong learning (Samek et al., 2021; Xie et al., 2021; Acemoglu and Autor, 2011). Access to workplace training and related wage premia may also differ between social groups, e.g., men and women (Holmes, 2017: 367). At the same time, organisational changes in production and service delivery processes lead to a technology-induced and job specific skill obsolescence that is different from obsolescence stemming from actual ageing of skills and knowledge (Allen and van der Velden, 2002: 28). The need for reskilling makes continuous learning a necessity for employees of all educational levels and in all fields. Against the background of recent breakthroughs in ever more advanced technologies, the incidence of mismatch is likely to increase (McKee-Ryan and Harvey, 2011: 963 *cf.* Livingstone, 2017: 295, see also Xie et al., 2021; Samek et al., 2021). Skill-to-job matching has become a matter of analytical concern as well as a persistent problem for advanced market economies (Buchanan, Finegold, Mayhew and Warhurst, 2017: 11). Incongruencies between changing demands for, and supply of, digital skills also provide a challenge when it comes to preventing increasing levels of inequality in societies more generally (Green, 2013: 69; also see Goldin and Katz, 2010; Bills, 2003; 2004). Against this background, policy makers and the scientific community seek to better understand which social groups will be affected most and how. Therefore, we address the following research questions:

*(1) To what extent do mismatches in digital problem-solving skills matter for wages?*

*(2) Do mismatches in digital problem-solving skills affect all workers in the same way – or are there (new) inequalities between social groups?*

Addressing our research questions demands comprehensive and high-quality information on requirements of jobs concerning ICT skills as well as digital problem-solving skills. There is only one dataset that provides objective, valid and internationally harmonised assessments of these skills: The Adult Skill Survey from the OECD's Programme for the International Assessment of Adult Competencies (PIAAC). This survey provides micro data for representative samples of workers in more than 30 countries. We use these data to measure digital skill levels of workers and the match with the skill requirements of their respective jobs (skill-to-job matches). To

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identify technology-driven occupations, we enrich PIAAC micro data with information on occupational skills profiles. We use measurements of skills requirements of jobs in terms of ICT and problem-solving skills that are based on O*NET data and provided by Cedefop (2015). Our results show that skill-to-job matching in digital problem-solving skills matters for wages: shortages are damaging, while a skills surplus is profitable. We furthermore provide empirical evidence that the digital divide translates into groups-specific wage inequalities. At the same time, however, our analyses show that digital problem-solving could serve as emancipatory skill, with the potential to narrow the divide between socio origin groups. These types of skills may also help to tackle the gender pay gap as high levels of digital-problem solving skills seem to pay off more for women than for men.

## 2. Theory: mismatches in digital problem-solving skills and wages

Starting in the 1960s with Gary S. Becker and Jacob Mincer, researchers have analysed the relation between schooling and productivity based on human capital theory (Mincer, 1974; Becker, 1962). The central idea is that skills and knowledge have economic value, which can be realised if skills are put to (productive) use on the labour market (Cedefop, 2018; van der Velden and Bijlsma, 2018; OECD, 2017, 2013b; Hanushek and Woessmann, 2015a; Hanushek et al., 2015b; Levels, van der Velden and Allen, 2014b; Quintini, 2014; Leuven et al., 2004; Groot and Maassen van den Brink, 2000; Hartog, 2000; Duncan and Hoffman, 1981). However, one downside of the human capital theory is the fixation on the supply side, largely ignoring the importance of the demand side of labour. Concerning the (productive) use of human capital, the match between skills possessed by a worker and the skills requirements of his or her job is crucial for a productive use of talent (e.g., Quintini, 2014). As the combination of supply and demand determines outcomes, evidence suggests that returns to education and skill (mis-)matches are best explained by matching models (Groot and Maassen van den Brink, 2000; Hartog, 2000). To examine the relation between over- and underskilling and wages, we therefore build on the logic of the classical Overeducation–Required education–Undereducation (ORU) model by Duncan and Hoffman (1981). The ORU model breaks down the individual educational attainment into three components (years of education required for the job, years of overeducation, and years of undereducation). The model assumes positive returns to required years of schooling, a wage premium for overeducation, and a wage penalty for undereducation. These results have been replicated numerous times, and for many different countries (e.g., van der Velden and Bijlsma, 2018; Levels et al., 2014b; Allen, Levels, and van der Velden, 2013; Groot and Maassen van den Brink, 2000; Hartog, 2000).

We make use of the ORU-logic to develop a matching model for *skill-to-job matches* with which we assess economic outcomes related to surpluses and shortages in digital problem-solving skills. These skills are key information-processing skills that allow workers to be productive and to generate adequate performance in contemporary labour markets. We make use of measures of digital problem-solving skills, as it is exactly these types of key skills that become more important because work is increasingly digitised while the required skills are still not fully taught in education systems (OECD, 2016a; 2016g). Against the background of technology-induced changes in the task composition of workplaces, digital problem-solving is increasingly important for productivity in most occupations (Cedefop, 2018). These key skills should, therefore, also relate to wages. However, digitalisation at the workplace is nothing new. With our analyses we seek to capture the current situation, asking: Is the relation with future skills already evident for present wages? Is the future now?

Using the logic of the Duncan and Hoffman (1981) ORU-model, we address the mechanism that relates mismatches in digital problem-solving skills to differential wage effects. The underlying idea of the ORU-model is that more skills generally lead to higher wages. Based on the ORU-logic, we assume that every occupation has a typically required level of skills. However, depending on skill requirements of their job, workers can have significantly too much or too little skills. In its vertical dimension, the concept of skill mismatch refers to a working situation in which the skills possessed by workers do not meet or exceed the skill requirements of their jobs. We consider workers that possess significantly more skills than needed at the workplace overskilled, whereas we regard workers with significant shortages to be underskilled. This over- or underskilling is related to wages (e.g., van der Velden and Bijlsma, 2018). In the case of underskilling, workers lack required skills, which entails wage penalties. By contrast, overskilled workers make more money than well-matched co-workers in the same job, but not as much as they could earn in a job that requires their own (higher) level of skills. Studies on numeracy and literacy skill mismatches show that economic returns to required skills are positive and bigger than returns to excess skills, which, in turn, are bigger than the (absolute value of) the penalties that are related to skills shortages (e.g., van der Velden and Bijlsma, 2018; Levels et al., 2014b). We expect to find that (mis-)matches in digital problem-solving skills are generally related to economic outcomes in the same way in which numeracy and literacy skills are associated with wages (e.g., Perry, 2017; Hanushek et al., 2015b). Under the assumptions that digital problem-solving skills are key to generating productivity in all kinds of occupations, and that returns to digital problem-solving skills are variable and dependent on the match with what is required at the workplace, we expect to find support for the following hypotheses:

*H1a.* *The higher the required level of digital-problem solving skills in an occupation, the higher the returns.*

*H1b.* *Underskilling in digital problem-solving entails wage penalties, while overskilling in digital problem-solving is positively related to wages as surplus skills pay off.*

Looking at skill-to-job matches of the *employed* workforce we cannot assume that a wage penalty is entirely driven by the fact that workers lack the skills required by their job. Because why then would they (still) be employed in their job? There are two possible explanations: (1) underskilled workers will soon leave their jobs, or (2) they compensate shortages in one skill domain with a higher proficiency in other skills that we do not observe, for example management skills. It is known from the literature that this holds for certain groups of workers more than for others. However, wage inequalities can only partly be explained by the individual differences in skill proficiency.

Human capital theory assumes that employers reward employees for their productivity, i.e. for skills used at work (Becker, 1962). The underlying assumption is that a higher productivity leads to higher wages. Educational attainment and age (displaying experience), for example, are thought to serve as valuable market signals to proxy acquired human capital. Accordingly, highly educated and older workers are expected to be more productive than low educated or young entrants to the labour markets (Bills, 2004; Becker, 1962). However, human capital theory cannot explain differential wage effects for equally productive workers. Therefore, the economic theory of discrimination is of particular importance here (e.g., Sesselmeier et al., 2010; Becker, 1971) next to job market signalling theory (Bills, 2004; 2003; Spence, 1971). The argument is that the market value of productivity is not exclusively based on the actual productivity but also (1) driven by the performance as perceived by the wage-setter, and (2) by

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potentially differential value judgments about the extent to which performance should be rewarded. This subjective evaluation of performance implies that the rewards for productivity may be systematically affected by value judgements about perceived personal indices and characteristics of the worker – such as gender, migration background or social origin. When it comes to digital problem-solving skills and labour market outcomes, personal characteristics could even be more important than for numeracy or literacy skills as digital problem-solving is often not taught and certificated at schools, especially for adults and older generations. We therefore expect differential returns to skills and skills mismatches for different social groups.

Concerning the market value of personal characteristics, the gender pay gap is long standing finding. Women are consistently found to be underpaid relative to men, even when they are equally skilled and educated (Lauder, Brown and Ashton, 2017: 418; Holmes 2017; Kupfer, 2014; OECD, 2012; Blau and Kahn, 2003; Goldin, 1986; Becker, 1971). Although the actual gender differences in digital problem-solving skills are rather small (OECD, 2016c), the relation between skill and wage is known to be stronger for men than for women (e.g., Hanushek et al., 2015b).[17] Prejudice can lead to affirmative action and effective discrimination (Becker, 1971)[18]. Gender stereotypes, such as the one that women are less capable than men when it comes to maths or handling ICT and solving problems in technology-rich environments (see e.g. PISA 2015 results as provided by OECD, 2016h) can lead to unequal labour market outcomes. This holds irrespective of the fact that actual gender differences in skill proficiency are small, which is evident for digital problem-solving skills of adults across countries (OECD, 2016c: 83). As the salary of women is partly driven by discrimination and the relation between skill and wages is stronger for men, we expect to find:

*H2. While a small part of the wage gap between male and female employees is explained by differences in digital problem-solving skill proficiency, the wage penalty for a*

[17] Results based on PISA 2015 show that this does not start at labour market entry but is evident also for pre-market situations at young ages: "Gender-related differences in science engagement and career expectations appear more related to disparities in what boys and girls think they are good at and is good for them, than to differences in what they actually can do" (OECD, 2016h: 18).

[18] Another study finds that normative contexts in which individuals are raised can explain gender differences in educational attainment, both over time and across countries (van Hek, Kraaykam, and Wolbers, 2016).

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*shortage in digital problem-solving skills is higher for **females**, and the wage premium for overskilling is higher for **male employees**.*

Previous studies also find that returns to cognitive skills such as numeracy are higher for non-immigrants than for migrants (e.g., Hanushek et al., 2015b). Non-immigrants also tend to be more often wellskilled for their jobs, with lower levels of skill mismatches than migrants (Perry, 2017; OECD 2016c)[19]. As digital problem-solving skills are often merely trained on the job, the type of technology used in the home country could affect proficiency, particularly for first-generation migrants (Sanromá, Ramos, and Simón, 2015; Chiswick and Miller, 2008; 2009). Besides, differential wage returns could go back to the above outlined discriminatory mechanism: Migrants could be perceived less capable as they might have language difficulties or lack cultural codes. Ethnicity as personal characteristic can modify the market value of (excess) skills, leading to lower returns and aggravated penalties for immigrants as compared to non-immigrants (Hanushek et al., 2015b; Oreopoulos, 2009; Seibert and Solga, 2005). Measuring returns to skill-to-job mismatches, we expect to find:

*H3. While part of the wage gap between non-immigrants and migrants is explained by differences in skill proficiency, the wage penalty for a shortage in digital problem-solving skills is higher for **migrants**, and the wage premium for overskilling is higher for **non-immigrant** employees.*

While technological developments of the past mainly affected routine jobs, recent breakthroughs in AI and business process automation also affect high skilled jobs and human experts (Xie et al., 2021; WEF, 2021; Schwab, 2017; Susskind and Susskind, 2017). Accordingly, a lack of digital skills should be detrimental for workers throughout the labour market. However, we would expect that certain social groups, such as higher social origin, have more means to compensate skill shortages in one domain with higher levels of other skills[20]. Social origin forms a classic predictor for wage inequalities, and e.g. Hanushek et al. (2015b) show

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[19] Reasons for higher shares of skill mismatch among immigrants may be an imperfect transferability and signalling of skills (Chiswick and Miller, 2009), a lower language proficiency and citizenship issues could also be important (Dustmann and van Soest, 2002).

[20] In our analyses, we focus on background characteristics such as social origin, taking into account social background characteristics that cannot be changed by individuals. We do not focus on, e.g., worker´s current social class, as this is conflated with labour market success.

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that returns to numeracy skills are higher for workers with high parental education. Besides, non-cognitive skills, better means to express oneself, higher negotiating skills, or more cultural capital could all lead to a positive discrimination for higher social origin groups as compared to lower social origin groups. Against this background, we expect to find:

H4. *While part of the wage gap between workers with higher and lower social origin is explained by differences in skill proficiency, the wage penalty for a shortage in digital problem-solving skills is higher for workers with* ***lower social origin****, and the wage premium for overskilling is higher for* ***workers from higher social origin****.*

Educational attainment serves as proxy for acquired human capital, having a strong and independent effect on labour market outcomes (Bills, 2004; 2003; Spence, 1973; Becker, 1962). Even returns to skills depend on formal qualifications (Heisig and Solga, 2017). Even if no certificate exists that covers digital problem-solving skills, we would expect that the signalling effect of formal qualifications serves as such powerful screening device when assessing productivity that the effect of 'real' digital problem-solving skills is played off. Accordingly, for lower educated workers, the effect of surplus skills should be superimposed by the signal of lower education. We phrase the following hypothesis:

H5. *While part of the wage gap between higher and lower educated employees is explained by differences in skill proficiency, the wage penalty for a shortage in digital problem-solving skills is higher for* ***workers with medium or low education****, and the wage premium for overskilling is higher for* ***high educated workers****.*

Next to educational credentials, age also serves as proxy for acquired human capital, generating higher wage premia e.g., for more experienced (and therefore older) employees as compared to younger workers. Older workers are paid more on the basis of skills, less on credentials (van der Velden and Bijlsma, 2018; Altonji and Pierret, 2001). As skills matter more for older than for younger workers, we would expect to find that mismatches also matter more. As employers tend to valuate particularly long-lasting and high-trust relations to experienced employees, we would expect that high levels of skills and overskilling pay off more for older than for younger workers, while shortages are more penalised (e.g., van der Velden and Bijlsma, 2018; Hanushek et al., 2015b). Comparing age groups, we would expect to find:

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H6. *While part of the wage gap between older and younger workers is explained by differences in skill proficiency, the wage penalty for a shortage in digital problem-solving skills is higher for* ***older workers****, and the wage premium for overskilling is also higher for* ***older workers****.*

## 3. Data and Methods

We test our hypotheses using micro data from the OECD Programme of the International Assessment of Adult Competencies (PIAAC; see OECD, 2016a; 2016b). For PIAAC, representative samples of the working age population (ages 16-65) in more than 30 countries were tested in key skills related to information processing at work and in daily life[21]. The survey conducted assessments in three different skill domains: literacy, numeracy and problem solving in technology-rich environments. The survey addressed key demographic and socioeconomic characteristics, also gathering information about the workplace. In most cases, the assessment was computer-based. Adaptive testing and item response techniques were implemented to derive 10 plausible values (PVs) of the competency level of each respondent. Taken together, these PVs provide unbiased estimates of the 'real' competency scores (OECD, 2016b). Providing internationally comparable skills measurements for many countries, the objective and high-quality PIAAC micro data are a unique opportunity to investigate digital skills and related outcomes across countries. For the study at hand, we make use of the problem solving in technology-rich environments (PS-TRE) skill domain in PIAAC, which we here refer to as "digital problem-solving skills". This shorthand contains the two components of the PS-TRE framework: Technology-rich environments and problem-solving skills.

### *3.1 What are "digital problem-solving skills"?*

In PIAAC, digital problem-solving skills are defined as "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks" (PIAAC Expert Group, 2009: 9). The problem solving in technology-rich

[21] In the majority of participating countries, the PIAAC survey was conducted in the years 2011/12, while some countries tested in 2014/15 (OECD, 2016a).

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environments domain is a scenario-based assessment, entailing nine response items that cover specific problems that people encounter when using computer-based artefacts at the workplace or in daily life. The core feature of problem-solving is that the tasks are designed in a way that prevents the respondents to reach the goal using simple routine actions (PIAAC Expert Group, 2009: 7). Therefore, digital problem-solving is more than basic or routine computer skills. By contrast, it involves active strategies to set goals and the workers' endowment of capabilities to use strategies (and develop the mindset) needed to interact with databases. It also involves the capabilities to navigate online and through digital interfaces, tools and folders as well as documents as well as the use of networks to acquire or process information and perform practical tasks and digital communication (Acemoglu and Autor, 2011: 1045; PIAAC Expert Group, 2009). Completing the PIAAC-tasks requires skills from basic digital navigation to advanced knowledge to conduct and interpret searches, interact within databases, and make decisions about competing information in order to solve so-called information-rich problems. The problem-solving scale has a range from zero to 500, with an OECD international average of 278 (OECD, 2016b).

## *3.2 Measurement and operationalisation of theoretical concepts*

### *3.2.1 Measuring mismatches in digital problem-solving skills*

The concept of skill mismatch requires measures of both skills possessed (available in PIAAC) and skills required at the workplace. As the survey covers all jobs in many countries, information on the latter is not available in PIAAC. Addressing the vertical dimension of mismatches (i.e., mismatch by level of skills/ skill proficiency), we use a Realised Matches Approach (RMA). This commonly used statistical measure captures the deviation of the individual skill proficiency from the mean skill level in each occupation in each country (e.g. van der Velden and Bijlsma, 2018; Perry, Wiederhold, and Ackermann-Piek, 2014). Generally, the RMA assumes that every occupation has a typically required skill level that differs between countries. The RMA defines a worker as overskilled or underskilled if the worker has a skill proficiency level of—usually—one standard deviation above or below that occupation-specific level (e.g., Perry et al., 2014). The cut-off point of one standard deviation is chosen as it captures approximately the distance between two proficiency levels in PIAAC (OECD, 2016a; 2016b). We follow this approach, defining a corridor between one standard deviation above and below the robust required skill

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level of each occupation-country-cell to identify well-matched workers. If the skill level of a worker lies outside that corridor, we classify the respective worker as mismatched, i.e., misallocated by level of skill[22]. We exclude observations from ISCO 2-digit-country-cells that contain less than 25 observations. For all cells with the necessary number of observations, we estimate robust required skill levels, making use of calculations performed by Allen and Bijlsma (forthcoming)[23].

We use data for those 26 countries that participated in PIAAC and took part in the assessment of digital problem-solving skills[24]. We exclude Russia and Australia due to data quality issues and administrative restrictions. As the Canadian sample is much bigger than the other countries' samples, we select a random sample of Canada's respondents to avoid overrepresentation in our dataset. For our main analyses, we restrict the sample to fulltime working employees. This was done to avoid that different wage-setting regimes for part-time workers affect our analyses. We exclude self-employed workers as the relation between skills and earnings for such workers is quite different from that of employees. We also exclude members of the armed forces, (unpaid) family workers and students/interns as for these workers wage setting is different from other employees. Our dependent variable is log hourly wages that we trimmed per country, omitting the first and 99th percentile of the respondents in each country. Our main analyses rely on a working sample of 58,761 male and female fulltime working employees from 26 countries. The additional analyses, in which we include part-time workers, rely on micro level data for 72,004 employees.

### 3.2.2 How do we treat respondents who did not take the problem-solving test?

PIAAC used computer-based testing. However, about 18% of the fulltime workers did not take the test (OECD, 2016c: 54). Test scores are missing for three groups of adults: (1) adults lacking computer experience, (2) respondents who failed the "ICT core" test implemented in PIAAC and thus lack the computer skills needed for computer-based competency testing, and (3)

[22] We compute the standard deviation of the 10 PVs of the individual PS-TRE scores in PIAAC, pooling over ISCO 2-digit categories. We use the repest-command in Stata 15 to properly take into account the PIAAC replicate weights.
[23] Van der Velden and Bijlsma (2018) show that the total explained variance does not change if they use 3-digit instead of 2-digit ISCO categories.
[24] Cyprus, France, Italy, Indonesia (Jakarta), and Spain did not offer the PS-TRE tests. A list of all countries under study is provided in Table A1 (Appendix 2A).

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people who would have had the required skills but refused to use a computer for testing (OECD 2016c: 54 et seq.). While gender differences are rather small, non-respondents are a selective group that contains more migrants than non-immigrants, and that is, on average, older than the respondents who took the computer-based assessment, has lower levels of education and more often belongs to middle or lower social origin as compared to workers from higher social origin (Table 1 and Figure A1 in Appendix 2A; also see OECD, 2016c: 56). Although it is valid to assume that these respondents should be at the lower end of the proficiency scale, not all of them can per se be classified as underskilled. If they are in a job that requires very little or no digital problem-solving skills, they could also be wellskilled. We deal with this by using a special imputation procedure to assign match/mismatch for the respondents with missing test scores in digital problem-solving skills. For each ISCO 2-digit-country-cell, we compare the posterior mean with the empirically observed proficiency levels for the problem-solving scale in PIAAC (OECD, 2016b: p. 13; also see Additional Material 1, Appendix 2A).

### *3.2.3 Operationalisation: social groups and importance of skills*

For each social group under study, we compute a dummy variable. First, we compare male vs. female fulltime working employees, whereby 45% of our sample are women and 55% men. Second, we compare migrants and non-immigrant workers, whereby migration background equals 1 for first and second-generation migrants. In our sample, we have 13% migrants and 87% non-immigrants (that is workers who were born in the country in which they now reside, and this holds also for their parents). Third, we identify workers with high vs. lowersocial origin. Social origin is operationalised using information on the educational background of parents as provided in PIAAC (at least one parent with tertiary education vs. no parent with tertiary education). Our sample consists of 25% workers of high social backgrounds and 71% workers of lower social backgrounds (information is missing for 4% of the full sample). Fourth, we compare tertiary educated vs. low and medium educated workers. Educational level is assessed on the basis of the highest educational attainment, with 30% tertiary educated workers and 70% with medium or low education. Last, we compare younger (aged<45) vs. older workers (aged>=45). The age of 45 is used as a cut-off for younger vs. older workers as this age marks the half of what is usually captured as “prime age” in terms of careers. Workers of 45 are clearly older than entry ages while still clearly younger than exit ages. In our sample, we have 39% older and 61% younger workers (for a detailed description of the social groups see Table 1a).

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To control for the occupation-specific importance of digital problem-solving skills, we resort to detailed information on occupational skills profiles (OSPs) as provided by Cedefop (2015). These data summarise essential characteristics required for each job at ISCO 2-digit level (Cedefop, 2015: 7). We make use of six OSP scales that – together – capture something qualitatively very close to the digital problem-solving domain in PIAAC, covering the relevant aspects of both ICT skills and problem-solving skills. We perform orthogonal factor analyses to obtain the first unrotated factor that we use to identify scores on the importance of digital problem-solving skills for each occupation. We introduce these scores in our statistical models as micro level control, explaining wage returns (for details see Additional Material 2 in Appendix 2A).

### *3.3 Analytical strategy*

First, we provide sample statistics, describing the prevalence of the mismatch phenomenon among social groups and countries. We then estimate wage returns to mismatches in digital problem-solving skills using multilevel mixed-effects models. In our main model, we compute the individual-level wage regression with trimmed log hourly wages as dependent variable. The model is based on the following Equation [1]:

$$W_{ic} = \alpha_c + \beta_1 RS_c + \beta_2 US_{ic} + \beta_3 OS_{ic} + \beta_4 I_c + \beta_5 C_{ic} + \upsilon_{ic} + \omega_c \qquad [1]$$

where, for each individual i in country c; $W_{ic}$ is the natural logarithm of the hourly wages; $\alpha_c$ captures the country-specific constant; and $RS_c$ is the robust estimate of the required skill level in each ISCO 2-digit occupation-country-cell. $US_{ic}$ and $OS_{ic}$ are dummies that indicate individual under- or overskilling. $I_c$ is the factor that measures importance of ICT and problem-solving skills in the occupation. $C_{ic}$ is a vector of control variables, including a dummy for missing test scores in digital problem-solving skills, age and age squared. Last, $\upsilon_{ic}$ and $\omega_c$ are error terms at the individual and country levels, respectively.

As outlined in the theoretical section, the main focus of this paper is to examine inequalities between social groups in returns to mismatches in digital problem-solving skills. For each social group that we outlined in the theoretical section, we compute a series of nested models, answering the question: to what extent is the wage gap between social groups (Model 1) explained by the individual skill proficiency (Model 2) and skill matching (Model 3), and how

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can mismatches in problem-solving skills explain wage inequalities between social groups (Model 4)?

The analyses are based on following Equations [2-5]:

$$W_{ic} = \alpha_c + \beta_1 SG_{ic} + \beta_2 I_c + \beta_3 C_{ic} + \upsilon_{ic} + \omega_c \quad [2]$$

$$W_{ic} = \alpha_c + \beta_1 SG_{ic} + \beta_2 I_c + \beta_3 SP_{ic} + \beta_4 C_{ic} + \upsilon_{ic} + \omega_c \quad [3]$$

$$W_{ic} = \alpha_c + \beta_1 SG_{ic} + \beta_2 I_c + \beta_3 RS_c + \beta_4 US_{ic} + \beta_5 OS_{ic} + \beta_6 C_{ic} + \upsilon_{ic} + \omega_c \quad [4]$$

$$W_{ic} = \alpha_c + \beta_1 SG_{ic} + \beta_2 I_c + \beta_3 RS_c + \beta_4 US_{ic} + \beta_5 OS_{ic}$$

$$+ \beta_6 SG_{ic}{*}RS_c + \beta_7 SG_{ic}{*}US_{ic} + \beta_8 SG_{ic}{*}OS_{ic} + \beta_9 C_{ic} + \upsilon_{ic} + \omega_c \quad [5]$$

In addition to the legend above, $SG_{ic}$ is a binary variable capturing social group index, $SP_{ic}$ is the individual proficiency in digital problem-solving skills, and the two multiplicative terms in [5] capture interactions between social group and the skill (mis-)match indicators. Note that we control for age and age squared in all analyses, except the comparison of age groups.

We run a series of robustness checks and additional analyses. We repeat our main model based on Equation [1] four times: First, excluding the respondents with missing test scores; second, only for the countries with less than 20% missing test scores in digital problem-solving skills; third, to assess whether our results change if we include micro level characteristics other than age and age squared, we repeat our main model, controlling for worker- and job-related characteristics; and fourth, we leave out one country at a time to assess whether single countries drive our main results. To furthermore assess differences between new and old skills, we repeat the series of nested models based on Equations [2] to [5] for social origin using literacy skills instead of digital problem-solving skills. Our dataset contains individuals nested in sampling clusters (characterised by a specific weighting procedure) nested in countries. To properly take into account macro level errors, we estimate multilevel mixed-effects regression models (using the 'mixed' command in Stata 15)[25]. Computing multilevel models, we cannot

[25] Our multilevel logit models have 26 observations on the level 2-variable. The main interest of the analyses that we provide here lies in the robust estimation of the fixed parameters on individual-level predictors. According to

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use the replicate weights implemented in PIAAC. All analyses are weighted using a 'rescaling to cluster size' approach with which we adjust the overall sample weight to account for different sizes of the country samples (for detailed information about the dataset and technical issues, see OECD 2016a; 2016b). To assess the goodness of fit of our models, we calculate the amount of explained variance (Snijders and Bosker, 2012).

## 4. Results

[Table 1 about here]

### *4.1 Descriptive results*

Table 1b gives descriptive statistics for all groups of individuals under study. We find that, over all 26 countries, 78% of the fulltime working employees are wellmatched in terms of digital problem-solving skills. By contrast, 10% are classified as overskilled, whereas 12% have shortages in these skills. While gender differences are comparably small, we still find that overskilling is more prevalent among male employees and non-immigrant workers. Besides, overskilling is clearly more prevalent for workers with a high social origin, workers with tertiary education, and younger workers. Underskilling, by contrast, is more widespread among female fulltime working employees, migrants, workers with lower social origin, workers with secondary or compulsory education and older employees. Table 1b also provides an overview of the percentages of respondents that could or would not take the computer-based problem solving-test (i.e., missing test scores). Here, too, we find large differences between social groups. The percentage of non-respondents in our analytical sample is more than twice as big among older workers compared to younger workers (27% vs. 13%). The share of non-respondents is also bigger among migrants (24% vs. 17% for non-immigrants), lower social origin (21% vs. 8% for the higher SES), middle or low educated workers (23% vs. 6% for tertiary graduates), while, again, gender differences are rather small (22% men vs. 17% females)[26]. The percentage of wellskilled employees ranges from 70% in Japan to 86% in Slovakia. In most countries,

Bryan and Jenkins (2015: 18), these estimates are unaffected by a small number of countries and calculated without bias and with the correct SEs with multilevel models.

[26] In addition to Table 1b, Figure A1 (Appendix 2A) gives an overview of missings over ISCO 2-digit categories and importance levels. Across countries, we find considerable differences in the amount of skill mismatch (Figure 1, also see Table A1 in Appendix 2A).

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underskilling is more prevalent than overskilling, although the differences between the two mismatch categories are rather small.

## *4.2 Multilevel analyses*

We now move on to our regression analyses, referring to our main model for fulltime working employees (Table 2).

[Table 2 about here]

Our first finding is that digital problem-solving skills matter for wages: the higher the required skill level in digital problem-solving in an occupation, the higher the returns. An increase of one standard deviation in required digital problem-solving skills is associated with a wage return of around 8%, which supports Hypothesis 1a. The coefficient capturing the occupation-specific importance of digital problem-solving also displays a positive and statistically highly significant association with wages. Both mismatch indicators are statistically highly significant and supporting Hypothesis 1b. Surplus skills pay off with a considerable wage premium of 12%. The premium for overskilling is thereby bigger than the (absolute value) of the penalty for underskilling, with around -10%, which is in line with other analyses on returns to mismatches in numeracy skills using the same data (e.g., van der Velden and Bijlsma, 2018). As in all following analyses, we find that the wage premium increases with the importance of digital problem-solving skills in the respective job. Our main model can explain 31% of the total variance.

[Table 3 about here]

Moving on to the social group analyses, we explore the extent to which returns to skill mismatches are different for different groups of workers. We compute the above outlined series of nested models, starting with an examination of digital problem-solving skills and the gender wage gap (Table 3). Are returns to digital problem-solving skills different for men and women? Model 1 shows that returns to skills are around 17% lower for women than for men,

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even controlled for the occupation-specific importance of digital problem-solving skills[27]. Model 2 shows that only a small part of around 2 percentage points of the gender pay gap can be explained by differences in skill proficiency, controlled for the importance of digital problem-solving in the job. The skill matching Model 3 shows that a higher level of required skills pays off with around 10% higher earnings, while shortages are penalised, and surplus skills are additionally rewarded. Concerning differential wage returns, Model 4 shows that an investment in digital problem-solving skills pays off for women, as they receive higher wages than men if they make it into jobs that require a higher level of these skills. Surprisingly, Model 4 counteracts our theoretical considerations and leads to a rejection of Hypothesis H2: Overskilling pays more off for women than for men, although the coefficient is rather small (4%). The average marginal effect of underskilling, by contrast, is no longer significant. We find that Model 4 can explain 36% of the total variance.

[Table 4 about here]

We move on to the analyses of migrants as compared to non-immigrants, displayed in Table 4. Based on the academic discourse on discrimination, we expected to find that (excess) skills pay off less for immigrants, which could be explained by the discriminatory context in which a migration background depreciates the market signal provided by a productive use of skills in the job (Spence, 1973; Becker, 1971; also see Seibert and Solga, 2005; Perry, 2017). However, we find that the relatively small wage gap that we see in Model 1 can be fully explained by a lack of skills when we include skill proficiency and the skill matching model in Models 2 and 3. Model 4 shows that migrants in our sample get even higher wage premia than non-immigrants if they work in occupations that require a higher level of digital problem-solving skills (this could be, e.g., IT specialists from abroad, who are really paid based on their required skills). Returns to skill mismatches do not differ between non-immigrants and migrants, which does not support Hypothesis H3.

[Table 5 about here]

[27] Note that we restrict our analyses to fulltime working employees to avoid different wage setting regimes for part-time employees. We include part-time workers as additional analysis, finding that the gender gap stays the same while part-time work correlates with slightly higher earnings (Table A4 in Appendix 2A).

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Table 5 shows a wage premium of around 8% related to a higher social origin, controlling for importance of digital problem-solving in the job (Model 1). The premium is reduced to 5% but persistent, even when we control for skills proficiency as well as the importance of digital problem-solving skills in the job (Model 2). Model 3 give the expected results for the skill matching model: overskilling pays off, while underskilling entails penalties. Model 4, however, bears surprising results. First, the wage penalty related to both required skills and underskilling is the same for workers from upper and lower social origin: there is no additional social origin or status premium when working in a job that requires a higher level of digital problem-solving. Second, there is a general wage premium for the social origin, but the interaction between overskilling and social origin is negative and significant at the 5% level. An investment in high levels of digital problem-solving skills pays off specifically for workers with a low social origin, but not for workers with a high social origin – which leads us to a rejection of Hypothesis H4. This finding is unexpected and potentially highly important: it suggests that digital problem-solving skills could potentially work as social emancipation lever, narrowing the divide between social origin groups when it comes to wage inequalities. We will further assess this with robustness checks in the next section. The following Table 6 shows similar findings for social group differences defined on educational credentials.

[Table 6 about here]

Table 6 shows a substantial wage premium of 20% for tertiary education (Model 1), only part of which is explained by individual skill proficiency (Model 2). The wage premium for graduates is not just for digital problem-solving skills. Model 3 shows that mismatches do explanatory value when it comes to differences in wage returns. Model 4, however, shows that there is no additional bonus for tertiary educated workers in jobs that requires a high level of digital problem-solving skills, while underskilling even relates to positive returns. The most important finding, however, is the interaction between tertiary education and overskilling, which is – as in the case of social origin – negative while statistically highly significant. Surprisingly, we find that an investment in high levels of digital problem-solving skills pays off specifically for workers with lower educational levels. Similar to workers from high social origin, workers with tertiary education seem to get their premium not for digital problem-solving skills but for other skills,

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be it job specific skills or other cognitive or non-cognitive key skills. These findings do not support Hypothesis H5.

[Table 7 about here]

Based on theoretical reasoning, we argued that, next to educational credentials, age can serve as proxy for acquired human capital. Model 1 in Table 7 shows that workers aged 45 or older earn around 11% more than younger workers, while this wage gap is larger than can be expected on the basis of skills proficiency (Model 2). In the other social group analyses, the wage gaps that we found were narrowed or even closed when we control for skill proficiency. But this is not the case for age. Older workers really receive a higher wage premium which is not based on their proficiency in digital problem-solving skills. There is a large digital (skill) divide between older and younger workers and skill shortages are clearly more widespread among older workers (see Table 1). However, younger workers do not get an extra premium for surplus expertise while older workers do. Age might indeed serve as proxy for acquired skills. But the premium for older workers is clearly not defined on proficiency in digital problem-solving. Other analyses show that this holds for numeracy and literacy skills as well (see e.g., van der Velden and Bijlsma, 2018). While we find that skills are more important for older workers, there is no additional penalty related to underskilling for older workers. These finding partly support Hypothesis H6.

### *4.3 Robustness, sensitivity, and additional analyses*

We run a series of checks to assess the robustness of our findings. Given the special imputation procedure that we used to assign skill match/mismatch values for the respondents who did not take the problem-solving test, we repeat our main model (see Table 2), excluding respondents with missing test scores. We obtain results that point in the same direction, although effect sizes are different (Table A3, Model 1 in Appendix 2A). It seems like we underestimate the penalty related to underskilling by assigning values to those workers who did not take the test. By contrast, for overskilling we seem to overestimate the average marginal effect. What, then, is the most appropriate model? We know from the literature that the group of adults who did not take the test is selective, and generally at the lower end of the proficiency scale (see Table 1 or OECD, 2016c). If we would leave out the respondents with missing test scores, we would

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generally overestimate the effect of underskilling because we selectively leave out people who have lower skills. However, we can also not generally assume that these respondents are underskilled because many of them work in jobs that require (very) low proficiency levels in digital problem-solving skills. Against this background, we should use the model in which we impute the scores and be aware that the size of the coefficients is underestimated in the case of underskilling and overestimated in the case of overskilling.

Given the large differences in the amount of missings across countries, we repeat our main model again, using only the data for those countries with less than 20% missing test scores (Table A3, Model 2 in Appendix 2a). Although the effect sizes are somewhat different (which is what we would have expected based on the reduced sample), the results point in the same direction. This means that our main findings are not driven by countries with extremely high percentages of missing test scores. To assess whether our results change if we include micro confounders, we run an additional model in which we control for individual and job-related characteristics, finding that our main results are robust (Table A3, Model 3). We furthermore repeat our main model, leaving out one country at a time. We do so to check whether our results are driven by single countries, which is not the case (Table A3a).

In the results section, we reported unexpected findings for social origin. The wage premium that employees with higher social origin receive is *not* based on additional returns to higher levels of required skills or excess digital skills, but must be based on other criteria. Theoretical reasoning suggested a positive discrimination related to a general expectation of higher productivity for workers with a high social origin. Against this background, the finding that high digital problem-solving skills pay off for low social origin workers but not for high social origin workers is unexpected. Based on theoretical reasoning, we argued that the interaction between overskilling and social origin should be positive instead of negative. Based on the negative interaction, we suggested that digital problem-solving skills could serve as some kind of emancipatory skill that helps to narrow the divide between social origin or status groups. This finding is unexpected and further research should focus on additional analyses.

Digital problem-solving skills are generally less related to social origin. By contrast, literacy is typically more related to social origin. To provide further evidence that helps us to assess the potential of digital problem-solving skills as emancipatory lever, we repeat our series of nested

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models using literacy skills instead of digital problem-solving skills (Table A2 in Appendix 2A). We run these additional analyses with the exact same sample selection to ensure comparability. For literacy skills, we find that none of the interactions between literacy skills and social origin is significant, while the general social origin premium is persistent.

## 5. Conclusion and discussion

In all industrialised countries, the increasing adaptation of digital technologies at workplaces leads to a profound and persistent transformation of work and skill requirements of jobs (Frank et al., 2019; Pew Research Center, 2018; Frey and Osborne, 2017; OECD, 2016e; 2016f; Brynjolfsson and McAfee, 2014; Autor and Dorn, 2013; Acemoglu and Autor, 2011). The ubiquitous availability of IC technology induces specific forms of tasks that demand information-processing and digital problem-solving (Acemoglu and Restrepo, 2020; Brynjolfsson and McAfee, 2014; Acemoglu and Autor, 2011; Levy, 2010; Autor, Levy, and Murnane, 2002). This leads to a situation, in which digital problem-solving skills are thought to be *key skills* for everybody (OECD, 2016d), as these skills allow workers throughout the occupational spectrum to be productive and to generate adequate performance in 21$^{st}$ century labour markets. Recent breakthroughs in ever more advanced technologies and increasing automation are thought to further exacerbate that trend (e.g., Xie et al., 2021; WEF, 2021; Autor et al., 2021; Samek et al., 2021; Frank et al., 2019; Brynjolfsson and McAfee, 2014). We may, therefore, think of digital problem-solving as "future skills", as it is exactly these types of key skills that will become more important in the near future while the required skills are still not fully taught in education systems (OECD, 2016a; 2016g). Throughout societies, however, social groups are unequally equipped with skills and knowledge needed to deal with profound and irreversible technology-induced changes (see e.g. Goldin and Katz, 2010.

Not much is known yet about individual skill-to-job matches, and particularly shortages, in digital problem-solving skills and their relation with wages and inequalities. How does the digital skills divide – e.g., younger and older workers or between high and low educated employees – translate into group-specific returns to skills? And will wage inequalities (e.g. between workers from different social origins, gender or age groups) be exacerbated or reduced? When it comes to future skills and present wages, a systematic and thorough assessment of social inequalities is the main gap in the literature. In our paper, we investigate mismatches, and particularly shortages, in digital problem-solving skills. We look at wage gaps to see how digital problem-solving skills explain wage inequalities between social groups, controlling for individual differences in skill proficiency. Our research is based on objective skills measurements for representative samples of adult employees in 26 industrial countries, as provided by the Programme for the International Assessment of Adult Competencies (PIAAC). We develop a skill matching model to show that when it comes to digital problem-solving skills and wages, the future is now: surplus skills pay off, while shortages in digital skills entail wage penalties. Our analyses show that wage inequalities − e.g., between men and women, the upper and lower SES groups, educational attainment and age groups − can only partly be explained by differences in skill proficiency: generally, wage inequalities are more related to a *social group premium* rather than a *skill premium.*

However, our most important finding is that digital problem-solving skills seem to be (re-)shaping group-specific wage inequalities – with the potential to narrow, e.g., the divide between social origin groups. We find that an investment in high levels of digital problem-solving skills pays off more for workers from lower social origin than for the higher social origin group, and for low and medium educated workers more than for graduates. This leads us to the – tentative − conclusion that digital problem-solving skills could serve as potential emancipatory lever, narrowing wage gaps between groups from higher vs. lower social origin. Based on the economic theory of discrimination, we argued that high social origin workers are positively discriminated when it comes to wages due to generally higher expectations concerning their proficiency. However, we find that when workers from higher social origin work in occupations that require high levels of digital problem-solving skills, their wage premium is even smaller than for low social origin workers, while they still get compensated despite that. One might argue that the higher social origin worker generally has higher skill, but the premium that they get is not based on high levels of digital problem-solving skills but most likely based on other skills or, e.g., cultural capital. Additional analyses using literacy skills provide further support for this explanatory mechanism. Compared to literacy, which is known to be highly related to parental education and i.e., social origin (see e.g., PISA 2015 results; OECD, 2016h), digital problem-solving skills is generally more open and accessible for all social origin groups. Further research is necessary to assess the potential of problem-solving skills as social emancipation lever. But based on our findings, we conclude that digital problem-solving

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skills may have the potential to re-shape wage inequalities and to to narrow the divide between social origin groups.

Our analyses on differential wage returns for male vs. female workers also show that digital problem-solving skills could potentially be a lever to reduce the gender pay gap: If women work in jobs that require a high level of digital problem-solving skills and/or have excess skills, they get higher wage returns than men. High levels of digital problem-solving skills pay off more for women than for men. This could be explained by a positive discrimination of women that make it into jobs that require a high level of digital problem-solving or that have surplus skills. By contrast, differential wage effects between migrants and immigrants can be explained by differences in skill proficiency, which is also in line with the literature (Nanos and Schluter, 2014: 5). However, against the background of the increasing importance of digital problem-solving skills for employability as well as inclusion in digital societies, we are inclined to further investigate the potential of digital problem-solving skills to serve as social emancipatory lever. While our analyses merely explain variance, further research should, for example, try to link variables causally, further more trying to assess the caveat about missing data for digital problem-solving skills as well as using a broader assessment of cognitive and non-cognitive skills (e.g., ideation skills) that will be increasingly important when the future becomes now.

*This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330*

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# Tables

## Table 1a: Descriptive analyses: Social groups

| Group variable | Dummy coding | | Obs. | Missings | Percentage Dummy==1 | Percentage Dummy==0 |
|---|---|---|---|---|---|---|
| Gender | D=1, female | D=0, male | 58,761 | 0 | 44.99 | 55.01 |
| Migration background | D=1, migback (1st and 2nd gen) | D=0, no migback | 58,528 | 233 | 13.21 | 86.39 |
| SES[1] | D=1, high SES | D=0, lower SES | 56,374 | 2,387 | 24.93 | 71.01 |
| Education | D=1, tertiary education | D=0, medium/low edu | 58,740 | 21 | 29.66 | 70.31 |
| Age | D=1, age>=45 | D=0, age<45 | 58,761 | 0 | 39.04 | 60.96 |

[1] SES is operationalised using information on parental education (High SES = at least one parent with tertiary education; Lower SES = no parent with parental education)

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## Table 1b: Descriptive analyses: skill mismatch over micro level groups

| | FULLTIME WORKERS | Male fulltime workers | Female fulltime workers | Non-immigrants[1] | Migrants (1st + 2nd generation)[1] | Higher SES[2] | Lower SES[2] | Tertiary Education[3] | Second. or compulsory Education[3] | Younger (16-44 y/o) | Older (45-65 y/o) | Whole sample[4] | Part-time workers |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Underskilled | 7,291 (12.41%) | 3,794 (11.74%) | 3,497 (13.23%) | 5,858 (11.54%) | 1,396 (17.98%) | 1,285 (8.77%) | 5,612 (13.45%) | 1,692 (9.71%) | 5,593 (13.54%) | 3,053 (8.52%) | 4,238 (18.48%) | 9,186 (12.76%) | 1,895 (14.31%) |
| Wellskilled | 45,645 (77.68%) | 25,016 (77.40%) | 20,629 (78.02%) | 39,647 (78.10%) | 5,818 (74.93%) | 10,865 (74.16%) | 32,939 (78.94%) | 12,929 (74.19%) | 32,703 (79.16%) | 27,782 (77.55%) | 17,863 (77.88%) | 55,920 (77.66%) | 10,275 (77.59%) |
| Overskilled | 5,825 (9.91%) | 3,512 (10.87%) | 2,313 (8.75%) | 5,258 (10.36%) | 551 (7.10%) | 2,500 (17.06%) | 3,173 (7.60%) | 2,806 (16.10%) | 3,017 (7.30%) | 4,988 (13.92%) | 837 (3.65%) | 6,898 (9.58%) | 1,073 (8.10%) |
| *Missing PS-TRE test score* | *10,745 (18.29%)* | *6,347 (19.64%)* | *4,398 (16.63%)* | *8,846 (17.43%)* | *1,829 (23.55%)* | *1,163 (7.94%)* | *8,957 (21.47%)* | *1,098 (6.30%)* | *9,639 (23.33%)* | *4,483 (12.51%)* | *6,262 (27.30%)* | *13,466 (18.70%)* | *2,721 (20.55%)* |
| Total | 58,761 | 32,322 | 26,439 | 50,763 | 7,765 | *14,650* | *41,724* | 17,427 | 41,313 | 35,823 | 22,938 | 72,004 | 13,243 |

Notes: [1] For 233 respondents the information on migration status is missing; [2] Information on parental education is used to operationalise social origin. Thereby, higher SES = at least one parent with tertiary education; lower SES = no parent with tertiary education), information on SES is missing for 2,387 respondents; [3] Information on highest education is missing for 21 respondents; [4] "Whole sample" = male and female, fulltime and part-time workers (see additional analyses in supplementary Appendix 2A)

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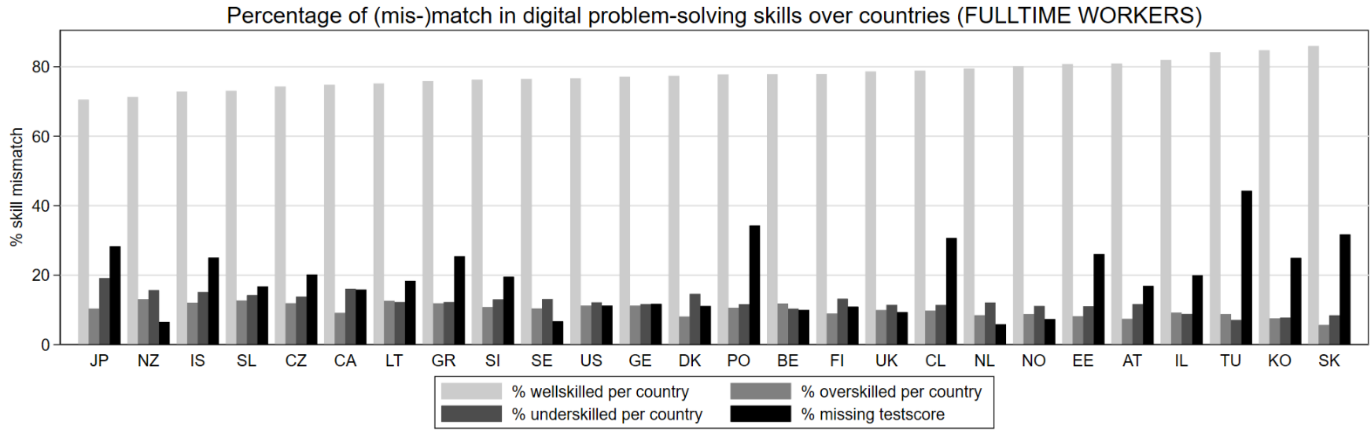
## Figure 1: Percentage in (mis-)match in digital problem-solving skills and missing test scores over countries

Sample: Fulltime working employees



## Table 2: MAIN MODEL – Fulltime working employees

Mixed model; DV: Trimmed ln hourly wage

| VARIABLES | | Model 1<br>Fulltime |
|---|---|---|
| Required skill level (standardised) | | 0.076*** |
| | | (0.026) |
| Underskilled in digital PS-skills (Dummy) | | -0.096*** |
| | | (0.009) |
| Overskilled in digital PS-skills (Dummy) | | 0.121*** |
| | | (0.011) |
| Importance of digital skills (std.)[1] | | 0.148*** |
| | | (0.015) |
| Observations | 58,761 | 58,761 |
| Number of groups | 26 | 26 |
| BIC | 74441 | 57208.3 |

| VARIANCE COMPONENTS | Int. Model | Model 1 |
|---|---|---|
| Between Variance | 0.182 | 0.127 |
| Within Variance | 0.0107 | 0.00586 |
| Total Variance | 0.1927 | 0.13286 |
| **% EXPLAINED VARIANCE** | | **Model 1** |
| % Explained Between Variance | | 30.22 |
| % Explained Within Variance | | 45.23 |
| % Explained Total Variance | | 31.05 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1;
std. = standardised; D. = Dummy; MODELS ARE WEIGHTED; Controls include age, age2, and a dummy for missing test scores
[1] Note that this variable displays the first unrotated factor of a PCA, which is standardised by definition.

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## Table 3: Female vs. male fulltime working employees

Sample: Fulltime working employees; Mixed model; DV: Trimmed ln hourly wage

| VARIABLES | Model 1<br>Fulltime | Model 2<br>Fulltime | Model 3<br>Fulltime | Model 4<br>Fulltime |
|---|---|---|---|---|
| Gender Dummy (D.=1, female) | -0.167*** | -0.156*** | -0.173*** | -0.176*** |
| | (0.020) | (0.020) | (0.020) | (0.019) |
| Importance of dig. skills (std.) | 0.202*** | 0.161*** | 0.132*** | 0.130*** |
| | (0.012) | (0.009) | (0.014) | (0.014) |
| Proficiency dig. PS-skills (std.) | | 0.096*** | | |
| | | (0.007) | | |
| Required skill level (std.) | | | 0.098*** | 0.084*** |
| | | | (0.025) | (0.025) |
| Underskilled in dig. P-S (D.) | | | -0.093*** | -0.083*** |
| | | | (0.010) | (0.015) |
| Overskilled in dig. P-S (D.) | | | 0.109*** | 0.096*** |
| | | | (0.011) | (0.013) |
| Req. skills*Female (D.=1) | | | | 0.047*** |
| | | | | (0.011) |
| Underskilled*Female (D.=1) | | | | -0.024 |
| | | | | (0.019) |
| Overskilled*Female (D.=1) | | | | 0.038*** |
| | | | | (0.014) |
| Constant | 1.653*** | 1.564*** | 1.633*** | 1.622*** |
| | (0.074) | (0.076) | (0.068) | (0.070) |
| Observations | 58,761 | 48,016 | 58,761 | 58,761 |
| Number of groups | 26 | 26 | 26 | 26 |
| BIC | 55867.1 | 41613.5 | 54401 | 54205.7 |

| VARIANCE COMPONENTS | Int. | Model 1 | Int. | Model 2 | Int. | Model 3 | Int. | Model 4 |
|---|---|---|---|---|---|---|---|---|
| Between Variance | 0.185 | 0.147 | 0.169 | 0.128 | 0.185 | 0.12 | 0.185 | 0.119 |
| Within Variance | 0.0109 | 0.00613 | 0.0108 | 0.00606 | 0.0109 | 0.0058 | 0.0109 | 0.00586 |
| Total Variance | 0.1959 | 0.15313 | 0.1798 | 0.13406 | 0.1959 | 0.1258 | 0.1959 | 0.12486 |
| **% EXPLAINED VARIANCE** | **Int.** | **Model 1** | **Int.** | **Model 2** | **Int.** | **Model 3** | **Int.** | **Model 4** |
| % Exp. Between Var. | | 20.54 | | 24.26 | | 35.14 | | 35.68 |
| % Exp. Within Var. | | 43.76 | | 43.89 | | 46.79 | | 46.24 |
| % Exp. Total Var. | | 21.83 | | 25.44 | | 35.78 | | 36.26 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; std. = standardised; D. = Dummy
ALL MODELS ARE WEIGHTED; Controls include age, age2, and a dummy for missing test scores

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## Table 4: Migrants vs. non-immigrant employees

Sample: Fulltime working employees; Mixed model; DV: Trimmed ln hourly wage

| VARIABLES | Model 1<br>Fulltime | Model 2<br>Fulltime | Model 3<br>Fulltime | Model 4<br>Fulltime |
|---|---|---|---|---|
| Migr. background (D.=1, migback) | -0.038* | -0.009 | -0.026 | -0.024 |
| | (0.020) | (0.022) | (0.020) | (0.019) |
| Importance dig. skills (std.) | 0.202*** | 0.160*** | 0.148*** | 0.149*** |
| | (0.012) | (0.009) | (0.015) | (0.015) |
| Proficiency dig. PS-skills (std.) | | 0.099*** | | |
| | | (0.007) | | |
| Required skill level (std.) | | | 0.076*** | 0.069*** |
| | | | (0.027) | (0.024) |
| Underskilled in dig. P-S (D.) | | | -0.094*** | -0.092*** |
| | | | (0.009) | (0.011) |
| Overskilled in dig. P-S (D.) | | | 0.120*** | 0.120*** |
| | | | (0.011) | (0.011) |
| Req. skills * Migback (D.=1) | | | | 0.035** |
| | | | | (0.016) |
| Underskilled * Migback (D.=1) | | | | -0.014 |
| | | | | (0.015) |
| Overskilled * Migback (D.=1) | | | | 0.002 |
| | | | | (0.029) |
| Constant | 1.594*** | 1.498*** | 1.570*** | 1.557*** |
| | (0.077) | (0.080) | (0.074) | (0.076) |
| Observations | 58,528 | 47,853 | 58,528 | 58,528 |
| Number of groups | 26 | 26 | 26 | 26 |
| BIC | 58146.3 | 43422.6 | 56917 | 56891.2 |

| VARIANCE COMPONENTS | Int. | Model 1 | Int. | Model 2 | Int. | Model 3 | Int. | Model 4 |
|---|---|---|---|---|---|---|---|---|
| Between Variance | 0.185 | 0.15 | 0.169 | 0.129 | 0.185 | 0.128 | 0.185 | 0.129 |
| Within Variance | 0.010<br>9 | 0.00617 | 0.0108 | 0.00623 | 0.010<br>9 | 0.00588 | 0.0109 | 0.00596 |
| Total Variance | 0.195<br>9 | 0.15617 | 0.1798 | 0.13523 | 0.195<br>9 | 0.13388 | 0.1959 | 0.13496 |
| **% EXPLAINED VARIANCE** | **Int.** | **Model 1** | **Int.** | **Model 2** | **Int.** | **Model 3** | **Int.** | **Model 4** |
| % Exp. Between Var. | | 18.92 | | 23.67 | | 30.81 | | 30.27 |
| % Exp. Within Var. | | 43.39 | | 42.31 | | 46.06 | | 45.32 |
| % Exp. Total Var. | | 20.28 | | 24.79 | | 31.66 | | 31.11 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; std. = standardised; D. = Dummy
MODELS ARE WEIGHTED; Controls include age, age2, and a dummy for missing test scores

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## Table 5: Higher vs. lower social origin

Sample: Fulltime working employees; Mixed model; DV: Trimmed ln hourly wage

| VARIABLES | Model 1 Fulltime | Model 2 Fulltime | Model 3 Fulltime | Model 4 Fulltime |
|---|---|---|---|---|
| Social origin (D.=1, high social origin) | 0.075*** | 0.049*** | 0.058*** | 0.066*** |
| | (0.009) | (0.007) | (0.008) | (0.008) |
| Importance of digital skills (std.) | 0.196*** | 0.156*** | 0.145*** | 0.146*** |
| | (0.012) | (0.009) | (0.015) | (0.015) |
| Proficiency dig. PS-skills (std.) | | 0.095*** | | |
| | | (0.007) | | |
| Required skill level (std.) | | | 0.073*** | 0.077*** |
| | | | (0.028) | (0.028) |
| Underskilled in dig. P-S (D.) | | | -0.089*** | -0.093*** |
| | | | (0.009) | (0.008) |
| Overskilled in dig. P-S (D.) | | | 0.115*** | 0.131*** |
| | | | (0.010) | (0.010) |
| Req. skills * social origin (D.=1) | | | | -0.017 |
| | | | | (0.012) |
| Underskilled * social origin (D.=1) | | | | 0.016 |
| | | | | (0.022) |
| Overskilled * social origin (D.=1) | | | | -0.036** |
| | | | | (0.015) |
| Constant | 1.546*** | 1.468*** | 1.533*** | 1.529*** |
| | (0.079) | (0.081) | (0.075) | (0.075) |
| Observations | 56,374 | 46,254 | 56,374 | 56,374 |
| Number of groups | 26 | 26 | 26 | 26 |
| BIC | 55905.8 | 41953.2 | 54845.6 | 54847.8 |

| VARIANCE COMPONENTS | Int. | Model 1 | Int. | Model 2 | Int. | Model 3 | Int. | Model 4 |
|---|---|---|---|---|---|---|---|---|
| Between Variance | 0.186 | 0.147 | 0.171 | 0.129 | 0.186 | 0.127 | 0.186 | 0.127 |
| Within Variance | 0.0112 | 0.00621 | 0.0112 | 0.00638 | 0.0112 | 0.006 | 0.0112 | 0.00599 |
| Total Variance | 0.1972 | 0.15321 | 0.1822 | 0.13538 | 0.1972 | 0.133 | 0.1972 | 0.13299 |
| **% EXPLAINED VARIANCE** | **Int.** | **Model 1** | **Int.** | **Model 2** | **Int.** | **Model 3** | **Int.** | **Model 4** |
| % Exp. Between Var. | | 20.97 | | 24.56 | | 31.72 | | 31.72 |
| % Exp. Within Var. | | 44.55 | | 43.04 | | 46.43 | | 46.52 |
| % Exp. Total Var. | | 22.31 | | 25.70 | | 32.56 | | 32.56 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; std. = standardised; D. = Dummy
MODELS ARE WEIGHTED; Controls include age, age2, and a dummy for missing test scores

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## Table 6: Tertiary education vs. secondary/ compulsory education

Sample: Fulltime working employees; Mixed model; DV: Trimmed ln hourly wage

| VARIABLES | Model 1<br>Fulltime | Model 2<br>Fulltime | Model 3<br>Fulltime | Model 4<br>Fulltime |
|---|---|---|---|---|
| Tertiary education (D.=1, tert. edu) | 0.199*** | 0.163*** | 0.177*** | 0.175*** |
| | (0.020) | (0.018) | (0.017) | (0.022) |
| Importance of digital skills (std.) | 0.165*** | 0.133*** | 0.131*** | 0.131*** |
| | (0.009) | (0.007) | (0.015) | (0.015) |
| Proficiency dig. PS-skills (std.) | | 0.082*** | | |
| | | (0.006) | | |
| Required skill level (std.) | | | 0.053** | 0.052** |
| | | | (0.025) | (0.026) |
| Underskilled in dig. P-S (D.) | | | -0.080*** | -0.089*** |
| | | | (0.009) | (0.008) |
| Overskilled in dig. P-S (D.) | | | 0.094*** | 0.113*** |
| | | | (0.010) | (0.011) |
| Req. skills * Tertiary edu (D.=1) | | | | 0.005 |
| | | | | (0.023) |
| Underskilled * Tertiary edu (D.=1) | | | | 0.043** |
| | | | | (0.020) |
| Overskilled * Tertiary edu (D.=1) | | | | -0.039*** |
| | | | | (0.011) |
| Constant | 1.568*** | 1.488*** | 1.552*** | 1.549*** |
| | (0.079) | (0.081) | (0.077) | (0.077) |
| Observations | 58,740 | 48,003 | 58,740 | 58,740 |
| Number of groups | 26 | 26 | 26 | 26 |
| BIC | 56089.5 | 42104.1 | 55351 | 55351.1 |

| VARIANCE COMPONENTS | Int. | Model 1 | Int. | Model 2 | Int. | Model 3 | Int. | Model 4 |
|---|---|---|---|---|---|---|---|---|
| Between Variance | 0.185 | 0.148 | 0.169 | 0.131 | 0.185 | 0.133 | 0.185 | 0.133 |
| Within Variance | 0.0109 | 0.00571 | 0.0108 | 0.00581 | 0.0109 | 0.00554 | 0.0109 | 0.00553 |
| Total Variance | 0.1959 | 0.15371 | 0.1798 | 0.13681 | 0.1959 | 0.13854 | 0.1959 | 0.13853 |
| **% EXPLAINED VARIANCE** | **Int.** | **Model 1** | **Int.** | **Model 2** | **Int.** | **Model 3** | **Int.** | **Model 4** |
| % Exp. Between Var. | | 20.00 | | 22.49 | | 28.11 | | 28.11 |
| % Exp. Within Var. | | 47.61 | | 46.20 | | 49.17 | | 49.27 |
| % Exp. Total Var. | | 21.54 | | 23.91 | | 29.28 | | 29.29 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; std. = standardised; D. = Dummy
MODELS ARE WEIGHTED; Controls include age, age2, and a dummy for missing test scores

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## Table 7: Younger vs. older employees (age>=45 vs. age<45)

Sample: Fulltime working employees; Mixed model; DV: Trimmed ln hourly wage

| VARIABLES | Model 1<br>Fulltime | Model 2<br>Fulltime | Model 3<br>Fulltime | Model 4<br>Fulltime |
|---|---|---|---|---|
| Age Dummy (D.=1, age >=45) | 0.106*** | 0.175*** | 0.128*** | 0.121*** |
| | (0.019) | (0.020) | (0.019) | (0.018) |
| Importance of dig. skills (std.) | 0.215*** | 0.182*** | 0.165*** | 0.166*** |
| | (0.013) | (0.010) | (0.015) | (0.015) |
| Proficiency dig. PS-skills (std.) | | 0.083*** | | |
| | | (0.006) | | |
| Required skill level (std.) | | | 0.070*** | 0.054** |
| | | | (0.027) | (0.026) |
| Underskilled in dig. P-S (D.) | | | -0.089*** | -0.091*** |
| | | | (0.009) | (0.013) |
| Overskilled in dig. P-S (D.) | | | 0.096*** | 0.083*** |
| | | | (0.011) | (0.012) |
| Req. skills*Age>=45 (D.=1) | | | | 0.040*** |
| | | | | (0.011) |
| Underskilled*Age>=45 (D.=1) | | | | -0.003 |
| | | | | (0.015) |
| Overskilled * Age>=45 (D.=1) | | | | 0.093*** |
| | | | | (0.025) |
| Constant | 2.546*** | 2.531*** | 2.543*** | 2.544*** |
| | (0.074) | (0.072) | (0.070) | (0.071) |
| Observations | 58,761 | 48,016 | 58,761 | 58,761 |
| Number of groups | 26 | 26 | 26 | 26 |
| BIC | 61326.8 | 47226 | 60405.2 | 60260.6 |

| VARIANCE COMPONENTS | Int. | Model 1 | Int. | Model 2 | Int. | Model 3 | Int. | Model 4 |
|---|---|---|---|---|---|---|---|---|
| Between Variance | 0.185 | 0.15 | 0.169 | 0.134 | 0.185 | 0.13 | 0.185 | 0.131 |
| Within Variance | 0.0109 | 0.00606 | 0.0108 | 0.00623 | 0.0109 | 0.0058 | 0.0109 | 0.00584 |
| Total Variance | 0.1959 | 0.15606 | 0.1798 | 0.14023 | 0.1959 | 0.1358 | 0.1959 | 0.13684 |
| **% EXPLAINED VARIANCE** | **Int.** | **Model 1** | **Int.** | **Model 2** | **Int.** | **Model 3** | **Int.** | **Model 4** |
| % Exp. Between Var. | | 18.92 | | 20.71 | | 29.73 | | 29.19 |
| % Exp. Within Var. | | 44.40 | | 42.31 | | 46.79 | | 46.42 |
| % Exp. Total Var. | | 20.34 | | 22.01 | | 30.68 | | 30.15 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; std. = standardised; D. = Dummy
MODELS ARE WEIGHTED; Controls include a dummy for missing test scores

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# Appendix 2A - Supplementary material

## Additional Material 1: Background information on how we treat respondents who did not take the problem-solving test

Around 19% of our working sample – the fulltime working employees – did not take the computer-based problem-solving test in PIAAC[28]. There are various reasons for the refusal, a lack of computer-skills being one of them. Respondents who did not want to take the test at the computer also have a missing test score; not only those with insufficient computer skills. The assessment of the skill (mis-)match value is based on a comparison between skills possessed by workers and skills required by the workplace. If they are in a job that does not require digital problem-solving skills, even workers that completely lack those skills must be considered as well-matched. Following the logic of the Realised Matches Approach (RMA) to measure skill mismatch, we decided to use a special procedure to impute adequate skill mismatch values for respondents with missing test scores in the skill domain of digital problem-solving skills (PS-TRE domain in PIAAC).

For those respondents, we make use of the PS-TRE proficiency levels in PIAAC to define the individual match/mismatch. The problem-solving scale has a range from zero to 500 (OECD, 2016b). The score boundaries for item classification for the PS-TRE domain are defined as follows: an individual score of 0-240 points is classified as "below level 1", 241-290 is defined as level 1, 291-340 is level 2, and scores between 341 and 500 are classified as level 3. Our imputation routine is as follows: We compare the posterior mean for each ISCO 2-digit-country-cell with these PS-TRE proficiency levels. People who did not take the PS-TRE test are included in the following way: If the posterior mean in a certain occupation in a certain country is below the PS-TRE proficiency level 1 or level 1, we define respondents that did not take the test as wellskilled. This gives a share of 12% underskilled over all 26 countries. Based on what we know

[28] In the assessment of digital problem-solving, Japan´s respondents performed best with an average score of 294, followed by Finland (289) and Australia (289). Greece (257), Turkey (253), and Chile (252) have the lowest average scores (OECD, 2016b: 17). Digital problem-solving skills correlate highly with the other skill domains measured in PIAAC (correlation with literacy = 0.77; with numeracy = 0.73), which is less strong than the correlation between literacy and numeracy (0.82). All three PIAAC skill domains measure different dimensions of the respondent´s skills set (OECD, 2016b).

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about the prevalence of the mismatch phenomenon in the other PIAAC skill domains, this is a realistic value (e.g., OECD, 2016a). If the posterior mean of an occupation-country-cell equals level 2 (or if it would be level 3, but this does not exist), we define respondents with missing test scores as underskilled. By having a missing test score dummy in all our statistical models, we effectively control for the imputation.

## Additional Material 2: Background information on how we assess the importance of digital problem-solving skills on the level of occupations

Cedefop used scales from the O*NET which they collapsed into 13 dimensions that, together, form the so-called Occupational Skill Profiles (OSP). We make use of average values of the original O*NET scales for each ISCO 2-digit category for each country. Particularly, we use data of the following six scales:

1. Complex problem solving
2. Processing information
3. Analysing data or information
4. Programming skills
5. Knowledge of computers and electronics
6. Practical skills in interacting with computers

The first three scales thereby capture problem-solving whereas scales 4 to 6 capture ICT skills. We assess the *importance* of each skill based on a scale from 1 to 5 (available upon request).

We use orthogonal factor analysis, which aims at explaining the outcome of p variables in the data matrix X using fewer variables, the so-called factors. These factors are interpreted as latent (unobserved) common characteristics, in our case of the underlying scales that capture digital problem-solving. The first unrotated factor (a normalised variable) thereby binds most of the common variation of the underlying scales. Using this factor, we extract 89.8% of the common information of the six OSP scales that we use. We find that factor 1 covers 89.8% of the information available (= explained variance of the six underlying scales). The eigenvalue of factor 1 is very high (4.78), also compared to factor 2 (0.34) that only captures 6% more of the total variance. We use factor 1 to obtain a score for each occupation, which we then introduce in our statistical models as micro-level control variable.

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## Table A1: Descriptive analyses: skill mismatch and missing test scores over countries

Sample: Fulltime working employees

| Country | Country sample size (Freq.) | Missing test score PS-TRE (%) | Underskilled % | Wellskilled % | Overskilled % |
|---|---|---|---|---|---|
| Austria | 2,064 | 349 (16.91%) | 241 (11.68%) | 1,670 (80.91%) | 153 (7.41%) |
| Belgium | 1,986 | 198 (9.97%) | 205 (10.32%) | 1,546 (77.84%) | 235 (11.83%) |
| Canada | 2,403 | 380 (15.81%) | 387 (6.01%) | 1,797 (47.78%) | 219 (9.11%) |
| Chile | 1,815 | 557 (30.69%) | 207 (11.40%) | 1,431 (78.84%) | 177 (9.75%) |
| Czech Republic | 2,144 | 433 (20.20%) | 296 (13.84%) | 1,593 (74.30%) | 255 (11.89%) |
| Denmark | 3,353 | 372 (11.09%) | 489 (14.58%) | 2,594 (77.36%) | 270 (8.05%) |
| Estonia | 3,414 | 890 (26.07%) | 377 (11.04%) | 2,758 (80.79%) | 279 (8.17%) |
| Finland | 2,621 | 286 (10.91%) | 345 (13.16%) | 2,042 (77.91%) | 234 (8.93%) |
| Germany | 2,142 | 251 (11.72%) | 250 (11.67%) | 1,652 (77.12%) | 240 (11.20%) |
| Greece | 833 | 212 (25.45%) | 102 (12.24%) | 632 (75.87%) | 99 (11.88%) |
| Ireland | 1,790 | 357 (19.94%) | 158 (8.83%) | 1,467 (81.96%) | 165 (9.22%) |
| Israel | 1,829 | 458 (20.04%) | 277 (15.14%) | 1,332 (72.83%) | 220 (12.03%) |
| Japan | 2,416 | 684 (28.31%) | 463 (19.16%) | 1,703 (70.49%) | 250 (10.35%) |
| Korea | 2,518 | 628 (24.94%) | 195 (7.74%) | 2,133 (84.71%) | 190 (7.55%) |
| Lithuania | 2,286 | 420 (18.37%) | 280 (12.25%) | 1,718 (75.15%) | 288 (12.60%) |
| Netherlands | 1,787 | 104 (5.82%) | 216 (12.09%) | 1,420 (79.46%) | 151 (8.45%) |
| New Zealand | 2,379 | 156 (6.56%) | 373 (15.68%) | 1,696 (71.29%) | 310 (13.03%) |
| Norway | 2,208 | 162 (7.34%) | 245 (11.10%) | 1,769 (80.12%) | 194 (8.79%) |
| Poland | 3,109 | 1,066 (34.29%) | 362 (11.64%) | 2,418 (77.77%) | 329 (10.58%) |
| Singapore | 2,736 | 534 (19.52%) | 355 (12.98%) | 2,086 (76.24%) | 295 (10.78%) |
| Slovakia | 2,148 | 682 (31.75%) | 181 (8.43%) | 1,846 (85.94%) | 121 (5.63%) |
| Slovenia | 1,983 | 332 (16.74%) | 282 (14.22%) | 1,449 (73.07%) | 252 (12.71%) |
| Sweden | 2,237 | 150 (6.71%) | 293 (13.10%) | 1,711 (76.49%) | 233 (10.42%) |

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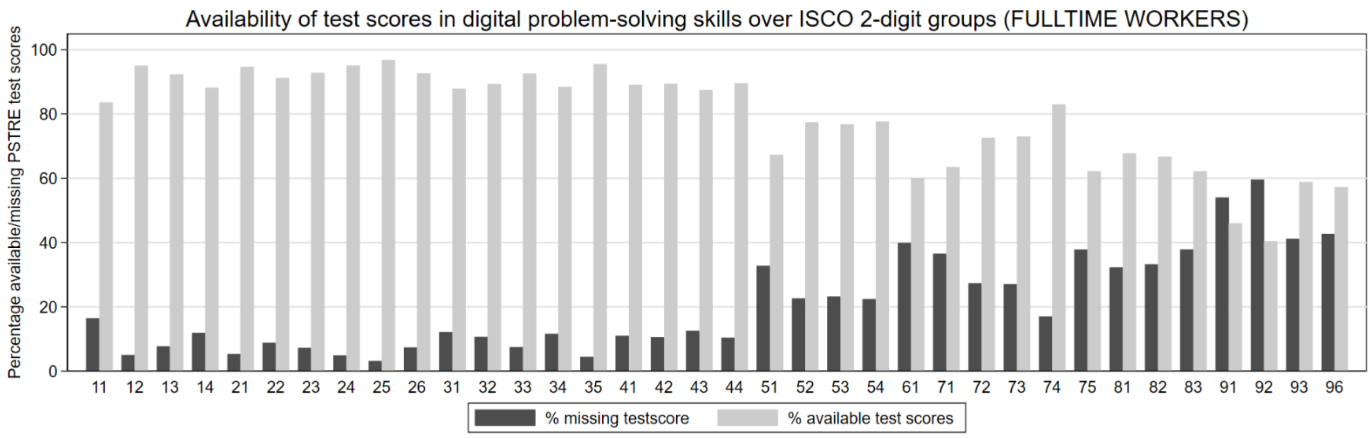
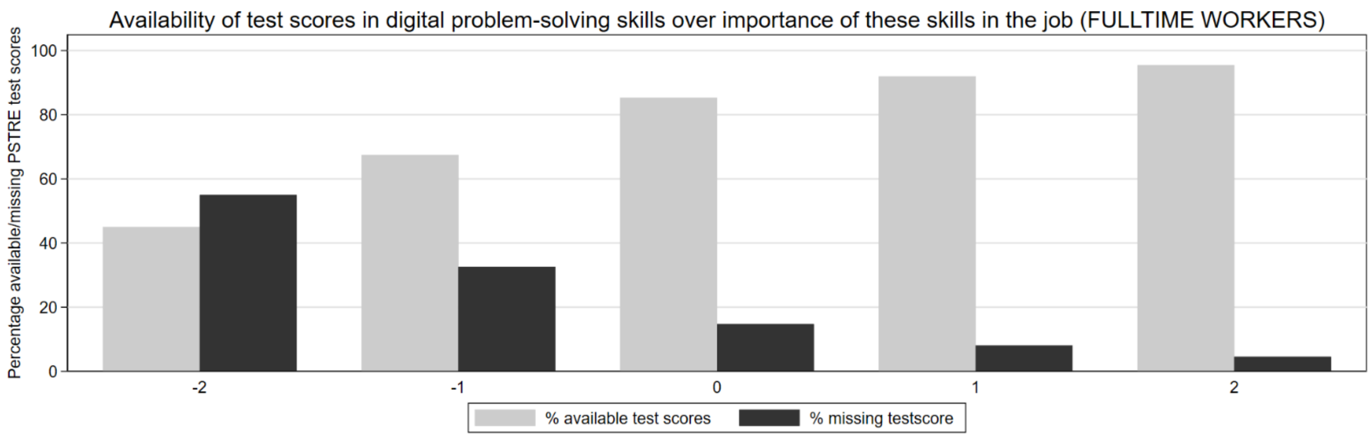
| | | | | | |
|---|---|---|---|---|---|
| Turkey | 1,231 | 545 (44.27%) | 87 (7.07%) | 1,036 (84.16%) | 108 (8.77%) |
| United Kingdom | 3,151 | 294 (9.33%) | 361 (11.46%) | 2,477 (78.61%) | 313 (9.93%) |
| United States | 2,178 | 245 (11.25%) | 264 (12.12%) | 1,669 (76.63%) | 245 (11.25%) |
| Total | 58,761 | 10,745 (18.29%) | 7,291 (12.41%) | 45,645 (77.68%) | 5,825 (9.91%) |

NOTE: [1] Numbers in parentheses display percentage of (mis-)matched employees in the respective country, excluding PIAAC-respondents who did not take the problem-solving test.

## Figure A1: Missing PSTRE-test scores over ISCO 2-digit categories and level of importance

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## Table A2: Additional analyses using *LITERACY SKILLS* – Social origin analysis

Sample: Fulltime working employees; Mixed model; DV: Trimmed ln hourly wage

| VARIABLES | Model 1<br>Fulltime | Model 2<br>Fulltime | Model 3<br>Fulltime | Model 4<br>Fulltime |
|---|---|---|---|---|
| Social origin (D.=1,) | 0.075*** | 0.046*** | 0.062*** | 0.063*** |
| | (0.009) | (0.008) | (0.010) | (0.011) |
| Importance of digital skills (std.) | 0.196*** | 0.156*** | 0.217*** | 0.216*** |
| | (0.012) | (0.009) | (0.020) | (0.020) |
| Proficiency LITERACY (std.) | | 0.107*** | | |
| | | (0.009) | | |
| Required LITERACY skill level (std.) | | | -0.022 | -0.024 |
| | | | (0.022) | (0.022) |
| Underskilled in LITERACY (D.) | | | -0.154*** | -0.151*** |
| | | | (0.020) | (0.023) |
| Overskilled in LITERACY (D.) | | | 0.104*** | 0.110*** |
| | | | (0.012) | (0.011) |
| Req. LITERACY skills * social origin (D.=1) | | | | 0.011 |
| | | | | (0.009) |
| Underskilled LITERACY * social origin (D.=1) | | | | -0.016 |
| | | | | (0.029) |
| Overskilled LITERACY * social origin (D.=1) | | | | -0.017 |
| | | | | (0.012) |
| Constant | 1.546*** | 1.511*** | 1.560*** | 1.561*** |
| | (0.079) | (0.082) | (0.076) | (0.077) |
| Observations | 56,374 | 46,254 | 56,374 | 56,374 |
| Number of groups | 26 | 26 | 26 | 26 |
| BIC | 55905.8 | 41792 | 54480.9 | 54502.8 |

| VARIANCE COMPONENTS | Int. | Model 1 | Int. | Model 2 | Int. | Model 3 | Int. | Model 4 |
|---|---|---|---|---|---|---|---|---|
| Between Variance | 0.186 | 0.147 | 0.171 | 0.13 | 0.186 | 0.141 | 0.186 | 0.141 |
| Within Variance | 0.0112 | 0.00621 | 0.0112 | 0.00633 | 0.0112 | 0.00592 | 0.0112 | 0.00592 |
| Total Variance | 0.1972 | 0.15321 | 0.1822 | 0.13633 | 0.1972 | 0.14692 | 0.1972 | 0.14692 |
| **% EXPLAINED VARIANCE** | **Int.** | **Model 1** | **Int.** | **Model 2** | **Int.** | **Model 3** | **Int.** | **Model 4** |
| % Exp. Between Var. | | 20.97 | | 23.98 | | 24.19 | | 24.19 |
| % Exp. Within Var. | | 44.55 | | 43.48 | | 47.14 | | 47.14 |
| % Exp. Total Var. | | 22.31 | | 25.18 | | 25.50 | | 25.50 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; std. = standardised; D. = Dummy
ALL MODELS ARE WEIGHTED; Controls include age, age2, and a dummy for missing test scores

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## Table A3: Robustness checks MAIN MODEL

Sample: Fulltime working employees; Mixed model; DV: Trimmed ln hourly wage

***Legend:*** *Model 1: Main model, excluding respondents with missing PS-TRE test scores*

*Model 2: Main model, excluding countries with more than 20% missing test scores*

*Model 3: Main model, including additional micro controls*

| VARIABLES | | Model 1† | | Model 2† | | Model 3†† |
|---|---|---|---|---|---|---|
| Required skill level (std.) | | 0.081*** | | 0.106*** | | 0.081*** |
| | | (0.025) | | (0.041) | | (0.021) |
| Underskilled in digital PS-skills (D.) | | -0.139*** | | -0.100*** | | -0.054*** |
| | | (0.010) | | (0.006) | | (0.009) |
| Overskilled in digital PS-skills (D.) | | 0.123*** | | 0.120*** | | 0.071*** |
| | | (0.011) | | (0.017) | | (0.008) |
| Importance of digital skills (std.) | | 0.137*** | | 0.129*** | | 0.018 |
| | | (0.015) | | (0.021) | | (0.013) |
| Observations | ***48,016*** | ***48,016*** | 35,514 | 35,514 | 52,737 | 52,737 |
| Number of groups | 26 | 26 | ***15*** | ***15*** | 26 | 26 |
| BIC | 55793.4 | 44268.9 | 37782.6 | 26247.9 | 64718.6 | 41273.1 |
| | | | | | | |
| VARIANCE COMPONENTS | Int. Model | Model 1 | Int. Model | Model 2 | Int. Model | Model 3 |
| Between Variance | 0.159 | 0.121 | 0.121 | 0.0844 | 0.172 | 0.114 |
| Within Variance | 0.0102 | 0.00636 | 0.00618 | 0.00387 | 0.011 | 0.00526 |
| Total Variance | 0.1692 | 0.12736 | 0.12718 | 0.08827 | 0.183 | 0.11926 |
| % EXPLAINED VARIANCE | | Model 1 | | Model 2 | | Model 3 |
| % Explained Between Variance | | 23.90 | | 30.25 | | 33.72 |
| % Explained Within Variance | | 37.65 | | 37.38 | | 52.18 |
| % Explained Total Variance | | 24.73 | | 30.59 | | 34.83 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; std. = standardised; D. = Dummy

MODELS ARE WEIGHTED

† Controls include age, age2

†† Controls include age, age2, highest education, migration background, ISCO 1-dig, sector dummies (ISIC 1-digit), firm size, temporary contract (dummy), use of influence skills at work, and worker autonomy (task discretion), and a dummy for missing test scores.

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## Table A3a: Robustness check MAIN MODEL, repetition with n-1 countries

Sample: Fulltime working employees; Mixed model; DV: Trimmed ln hourly wage

| *without…* | Austria<br>no_40 | Belgium<br>no_56 | Canada<br>no_124 | Chile<br>no_152 | Czech Rep.<br>no_203 | Denmark<br>no_208 | Estonia<br>no_233 | Finland<br>no_246 | Germany<br>no_276 | Greece<br>no_300 | Ireland<br>no_372 | Israel<br>no_376 | Japan<br>no_392 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Required skill level (std.) | 0.075*** | 0.079*** | 0.079*** | 0.069** | 0.078*** | 0.075*** | 0.085*** | 0.077*** | 0.076*** | 0.076*** | 0.077*** | 0.075*** | 0.080*** |
| | (0.027) | (0.027) | (0.027) | (0.028) | (0.028) | (0.027) | (0.026) | (0.027) | (0.028) | (0.027) | (0.027) | (0.029) | (0.027) |
| Underskilled (D.) | -0.096*** | -0.096*** | -0.094*** | -0.098*** | -0.098*** | -0.098*** | -0.094*** | -0.098*** | -0.096*** | -0.097*** | -0.095*** | -0.094*** | -0.102*** |
| | (0.010) | (0.010) | (0.010) | (0.009) | (0.010) | (0.010) | (0.009) | (0.010) | (0.010) | (0.010) | (0.009) | (0.010) | (0.008) |
| Overskilled (D.) | 0.120*** | 0.124*** | 0.124*** | 0.118*** | 0.121*** | 0.122*** | 0.119*** | 0.125*** | 0.122*** | 0.121*** | 0.119*** | 0.120*** | 0.122*** |
| | (0.011) | (0.010) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.010) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Importance dig. skills (std.) | 0.149*** | 0.149*** | 0.147*** | 0.150*** | 0.148*** | 0.154*** | 0.143*** | 0.149*** | 0.148*** | 0.149*** | 0.147*** | 0.147*** | 0.145*** |
| | (0.015) | (0.015) | (0.015) | (0.016) | (0.015) | (0.014) | (0.014) | (0.015) | (0.015) | (0.015) | (0.015) | (0.016) | (0.015) |
| Observations | 56,697 | 56,775 | 56,358 | 56,946 | 56,617 | 55,408 | 55,347 | 56,140 | 56,619 | 57,928 | 56,971 | 56,932 | 56,345 |
| Number of groups | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 |

*Robustness check with n-1 countries (continued)*

| *without…* | Korea<br>no_410 | Lithuania<br>no_440 | Netherlands<br>no_528 | New Zealand<br>no_554 | Norway<br>no_578 | Poland<br>no_616 | Singapore<br>no_702 | Slovak R.<br>no_703 | Slovenia<br>no_705 | Sweden<br>no_752 | Turkey<br>no_792 | UK<br>no_826 | USA<br>no_840 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Required skill level (std.) | 0.081*** | 0.080*** | 0.076*** | 0.079*** | 0.075*** | 0.073*** | 0.051*** | 0.077*** | 0.077*** | 0.079*** | 0.076*** | 0.076*** | 0.076*** |
| | (0.027) | (0.027) | (0.027) | (0.027) | (0.027) | (0.028) | (0.016) | (0.027) | (0.028) | (0.027) | (0.027) | (0.028) | (0.027) |
| Underskilled (D.) | -0.096*** | -0.094*** | -0.096*** | -0.096*** | -0.098*** | -0.097*** | -0.094*** | -0.094*** | -0.095*** | -0.099*** | -0.095*** | -0.094*** | -0.094*** |
| | (0.010) | (0.009) | (0.010) | (0.010) | (0.010) | (0.010) | (0.009) | (0.009) | (0.010) | (0.010) | (0.009) | (0.010) | (0.010) |
| Overskilled (D.) | 0.120*** | 0.116*** | 0.121*** | 0.123*** | 0.122*** | 0.119*** | 0.119*** | 0.119*** | 0.121*** | 0.123*** | 0.119*** | 0.118*** | 0.119*** |
| | (0.011) | (0.010) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Importance dig. skills (std.) | 0.143*** | 0.146*** | 0.149*** | 0.147*** | 0.151*** | 0.150*** | 0.159*** | 0.147*** | 0.149*** | 0.151*** | 0.148*** | 0.147*** | 0.146*** |
| | (0.014) | (0.015) | (0.015) | (0.015) | (0.015) | (0.016) | (0.012) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) |
| Observations | 56,243 | 56,475 | 56,974 | 56,382 | 56,553 | 55,652 | 56,025 | 56,613 | 56,778 | 56,524 | 57,530 | 55,610 | 56,583 |
| Number of groups | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; ALL MODELS ARE WEIGHTED; Controls include age, age2, and a dummy for missing test scores

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## Table A4: Additional analysis – Whole sample, including part-time working employees

Sample: *WHOLE SAMPLE;* Mixed model; DV: Trimmed ln hourly wage

| VARIABLES | Model 1<br>*Whole sample* |
|---|---|
| Required skill level (std.) | 0.087*** |
| | (0.022) |
| Underskilled in digital PS-skills (D.) | -0.083*** |
| | (0.010) |
| Overskilled in digital PS-skills (D.) | 0.096*** |
| | (0.010) |
| Importance of digital skills (std.) | 0.143*** |
| | (0.013) |
| Gender Dummy = 1, female | -0.171*** |
| | (0.020) |
| Part-time employment Dummy = 1 | 0.091** |
| | (0.041) |
| Observations | 72,004 |
| Number of groups | 26 |
| BIC | 74121.7 |

| VARIANCE COMPONENTS | Int. Model | Model 1 |
|---|---|---|
| Between Variance | 0.163 | 0.115 |
| Within Variance | 0.00965 | 0.00526 |
| Total Variance | 0.17265 | 0.12026 |
| **% EXPLAINED VARIANCE** | | **Model 1** |
| % Exp. Between Var. | | 29.45 |
| % Exp. Within Var. | | 45.49 |
| % Exp. Total Var. | | 30.34 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; std. = standardised; D. = Dummy
MODELS ARE WEIGHTED; Controls include age, age2, and a dummy for missing test scores