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Book

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Valuation of Human Capital and the Gender Wage Gap in Europe

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Abstract

This paper investigates the gender wage gap in relation to the multi-dimensional human capital measure across 17 European countries. To date, the role of cognitive and task-specific skills had a limited empirical evidence in the gender wage gap literature. We narrow this research gap by relying on PIAAC (Program of International Assessment of Adult Competencies) data and applying Gelbach's (2016) decomposition methodology. The analysis reveals that occupation-/industry-specific work experience and task-specific cognitive and non-cognitive skills are the most rewarding human capital attainments. Work experience largely decreases the gender wage disparity in all analysed countries. Cognitive numeracy skill is another strong predictor of gender wage disparity. The effect of numeracy is rather homogeneous across countries, namely, controlling for numeracy reduces the wage gap. Unlike studies that stress the decreasing importance of human capital in gender wage gap assessments, we argue that a narrow definition of human capital may undermine the actual effect of the latter. Therefore, we conclude that human capital should be viewed as a combination of multiple characteristics and traits, each having specific valuation on the labour market, and thus, a particular role in explaining the gender wage gap.

Keywords: gender, human capital, cognitive and non-cognitive skills, wage gap

JEL codes: J16, J31, J61

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1. INTRODUCTION

In recent decades, the gender wage gap has remained an open issue, despite ever-increasing scholarly attention. Numerous theories have attempted to explain gender wage disparity, applying advanced empirical methodologies and employing a spectrum of databases. The existing literature addresses multiple factors, from occupation and industry segregation, to gendered preferences and discrimination as core unobserved drivers of the unexplained gender wage disparity. Among these factors, the gender gap in human capital (HC) remains an essential driver of wage disparity, with an extensive theoretical and empirical grounding (Polachek 2006, O'Neill and O'Neill 2006, Bertrand 2011).

Pioneered by Becker's (1964) classical human capital theory, scholars attributed a large part of the gender gap in employment and wages to the gender disparity in human capital. Relying on Becker's theory, various human capital domains were analysed in relation to the gender wage disparity. Formal education, as the most canonical measure of human capital has long been viewed as the main driver of labour market success (Blau and Kahn 2017, Author and Wasserman 2013, Goldin et al. 2006, Schultz 1995). However, the explanatory power of formal education has decreased in recent decades (Cha and Weeden 2014) due to the concave relationship between schooling and earnings (Colclough et al. 2010) and gendered job preferences (Lips 2013).

Gender segregation into college majors and the persistently low share of females in STEM (Science, Technology, Engineering and Mathematics) disciplines is addressed as another important factor behind the male-female wage gap (Black et al. 2008, Angle and Wissman 1981). Self-selection of males into university majors associated with higher earnings eventually transmit into occupation and industry segregation and gender wage disparity (Beede et al. 2011). The labour market experience gap is another widely investigated factor. Since labour market experience is commonly considered a proxy for productivity, on average, the shorter work experience of females is translated into an anticipated lower productivity among women, and consequently, lower wages (Olivetti 2006, Goldin et al. 2006, O'Neill and Polachek 1993).

Cognitive abilities is another commonly accepted driver of male-female gender wage disparity but is sparsely investigated in empirical literature. The predominantly stronger mathematical skills of males have been documented to substantially affect the gender wage gap (Anspal 2015, Hanushek et al. 2015, Altonji and Blank 1999). Verbal abilities, which are on average higher among females, yield no significant association with the gender wage disparity (Niederle and Vesterlund 2010). An increasing share of the unexplained gender pay gap has motivated scholars to look beyond education, experience and cognitive skills and account for soft skills or non-cognitive traits (Fortin 2008, Duncan and Dunifon 1998). Behavioural and personality traits, including leadership, self-esteem, external vs. internal locus of control have been documented to be significantly associated with gender wage disparity (Manning and Swaffield 2008, Waddell 2006, Heckman et al. 2006, Kuhn and Weinberger 2005).

However, the growing importance of occupation- and industry-specific skills, as well as task-specific human capital provides a novel context for the issue of work experience and the gender wage gap (Gathmann and Schönberg 2010, Gibbons and Waldman 2004). Occupation and industry segregations (Blau and Kahn 2017), due to gendered preferences, tastes, competencies or discrimination, lead to males and females possessing different occupation-, or firm-specific abilities (Sullivan 2010, Lazear 2009, Zangelidis 2008). Task-specific human capital directly relates to specific skills and abilities accumulated through carrying out certain job tasks. Therefore, it strongly approximates productive human capital.

However, the common feature of the majority of the aforementioned studies is a relatively narrow empirical measure of human capital. While focusing on the specific domain, other components of the multidimensional human capital were omitted. Despite a number of studies stressing that the key focus should be on a broad definition of human capital (Blau and Kahn 2017, Grove et al. 2011, Goldin et al. 2006), most papers still focus on a human capital measure restricted to a single or several domains. Moreover, general and task-specific cognitive and non-cognitive abilities are commonly not addressed in the literature, due to the scarcity of empirical data.

This paper contributes to the literature by incorporating a multidimensional human capital measure, which includes several empirically novel domains, into the gender wage gap analysis. The study relies on the Program of International Assessment of Adult Competencies (PIAAC) data for 17 European countries. Specifically, we incorporate a set of classical and novel human capital components,[3] including (i) formal education degree and field; (ii) total work experience and work experience related to current employment; (iii) cognitive skills in literacy and numeracy domains; (iv) task-specific cognitive and non-cognitive skills, measured by the on-job use of skills and frequency of performing specific job tasks.

To the best of our knowledge, this is the first paper in gender wage gap analysis to employ a direct measure of on-the-job skill use as a proxy for task-specific human capital. The existing evidence on the role of task-specific human capital in explaining the gender wage gap is limited (Yamaguchi 2018), mostly due to the empirical challenge of measuring task-specific abilities. Therefore, the PIAAC data provides a unique source of on-the-job skill use data, making it possible to shed more light on the abilities accumulated and developed through performing actual job tasks. Furthermore, the study contributes by adding empirical evidence on the role of education major, occupation-/industry-related work experience and cognitive abilities, which were sparsely addressed in previous literature.

This paper conducts a dual empirical exercise. First, we evaluate the total contribution of all human capital domains in explaining the gender wage gap; therefore, we evaluate the total explanatory power of the multidimensional human capital measure. Second, we assess the individual contribution of each specific component in explaining the gender gap. The latter is particularly relevant in light of narrowed or even reversed gender differences in various human capital characteristics. Females do not necessarily possess systematically worse human capital outcomes. However, they may be still worse off than men in particular human capital domains, which are especially valued by the labour market and yield the highest wage returns.[4] Therefore, the relevant question to ask is not who – men or women – have more or have better human capital, but rather, who has an advantage in the specific human capital characteristics valued by the labour market.

To precisely evaluate the actual wage gap contribution of individual human capital domains, we employ Gelbach's (2016) decomposition. The decomposition technique by Gelbach overcomes the limitations of the classical multivariate OLS procedure with the stepwise inclusion of controls. Conditional decomposition by Gelbach allows us to estimate the robust contribution of each variable, independently of the order of their inclusion into the regression, while the classical OLS estimates are subject to a sizable sequence effect. Therefore, we simultaneously incorporate all human capital aspects and derive robust individual contributions

[3] Throughout the paper, the terms human capital domains and components are used interchangeably and denote specific characteristics, which jointly shape the individual human capital.

[4] In this paper, labour market valuation of human capital refers to wage returns to specific human capital components, as compared to wage returns to other human capital domains. Hence, the term "valuation" is applied only in the context of wage returns.

for all domains, as well as a pooled gender pay gap contribution of the collective human capital measure. The study emphasizes cross-country heterogeneity and similarity for unexplained gender wage gaps and individual human capital component contributions. Additionally, we explore the case of Estonia as a country with the highest gender wage gap in Europe. Supplementary analysis includes a number of gender wage gap heterogeneity tests, which provide more detailed evidence on the nature and composition of the gender wage gap in Estonia.

We documented that men and women indeed possess substantially different human capital attainments. However, we do not document that human capital outcomes among females is systematically worse. Instead, we find disparities varying across different human capital domains, with men and women possessing stronger characteristics. The paper shows that human capital largely explains the gender wage gap in all the countries in the study. When controlling for a multi-dimensional human capital measure, the wage gap becomes statistically insignificant in Ireland and economically negligible in the Netherlands and Belgium. In other countries, the gap is substantially reduced. However, the most important evidence is derived from the Gelbach decomposition. We document drastically diverse wage effects from different human capital components. The only dimension that consistently and significantly decreases gender wage disparities in all countries, is work experience related to position currently held. This result is in line with earlier evidence by Sullivan (2010), documenting that occupation and/or industry-specific work experience is an important driver of the gender wage gap.

The wage effects of all other human capital domains vary across countries, with some components (e.g. numeracy, task-specific human capital measured on the basis of cognitive skills, non-cognitive skills and problem solving at work) having a significant effect and reducing the wage gap in several countries. Therefore, the results confirm that the gender gap in human capital should be addressed as made up of numerous components, which altogether shape the human capital profile. However, each component has different value on the labour market and contributes differently to gender wage disparity. Hence, this paper shows that there is still a lot to learn from human capital, especially when its measure incorporates components beyond classical measures, such as formal education degree and total work experience.

The remainder of the paper is organized as follows. Section 2 discusses the data and methodology applied to analyse the gender wage gap. Section 3 presents the major results in four parts – part one discusses the descriptive demographic, employment and human capital profiles of men and women across the countries in the study; part two shows the gender wage gap results based on a cross-country multivariate OLS regression; part three estimates and discusses the results of the Gelbach decomposition; and part four looks at the case of Estonia. Section 4 summarizes and concludes.

2. DATA AND METHODOLOGY

2.1. Data

The analysis relies on the data from the Program of International Assessment of Adult Competencies (PIAAC), collected within a Survey of Adult Skills (OECD 2013). The database includes a range of OECD countries. However, our analysis focuses on the European Union (EU). Due to the data protection policies, a number of EU countries did not disclose income variables. Therefore, our final sample includes only 17 EU countries with the disclosed wage data, namely: Belgium, Czech Republic, Denmark, Estonia, Finland, France, Great Britain, Greece, Ireland, Italy, Lithuania, Netherlands, Norway, Poland, Slovakia, Slovenia and Spain.

The survey was conducted in two rounds. All countries, except Greece, Lithuania and Slovenia were surveyed in 2011–2012, while the latter were surveyed in 2014–2015. We weighted each country-specific sample to the population in the relevant year.

The major advantage of the PIAAC data is availability of test-based measures of cognitive skills in literacy, numeracy and problem solving in technology rich environment domains, as well as self-reported measures of on-the-job skill use in various aspects. Our analysis will focus on literacy and numeracy skill domains, which are disclosed for all countries. The problem solving skill is not reported for France, Italy and Spain. Therefore, to keep the country-specific analysis comparable, we incorporate only literacy and numeracy as cognitive skills controls.[5] Along with cognitive skills, the PIAAC database provides a set of detailed measures of other human capital components of interest.

Appendix A1 discusses all human capital domains incorporated in the analysis, as well their PIAAC-based empirical measures. While the empirical measures for the majority of the domains are straightforward, task-specific skills are not directly inferred from the PIAAC survey, but are self-derived based on a set of questions. Specifically, we rely on the survey questions asking how often respondents apply different skills in performing a number of job tasks. Specifically, all skill use measures are self-reported on a scale from "never" to "every day". Following Allen et al. (2013), we define task-specific skills in a particular domain as an average over a number of components (see Appendix A1).

The first set of task-specific skills – literacy, numeracy and ICT – precisely reflect the use of pure cognitive skills at work. The second set of skill use measures includes the use of organizational, presentation/communication and negotiation skills at work. These to a large extent reflect non-cognitive abilities such as self-confidence, leadership, internal vs. external locus of control, among others (Fortin 2008, Weinberger 2005). The third set of task-specific skills – problem solving – embodies both cognitive and non-cognitive skills. Depending on the specificity of the problem, dealing with it can involve either one type, or both types of skills. Therefore, in the scope of this paper we refer to problem solving at work as a measure of problem solving ability, and therefore a combination of cognitive and non-cognitive skills.

Although PIAAC data has a number of important advantages, several limitations should be acknowledged. Firstly, the PIAAC dataset is cross-sectional data. Since the wage is reported only for currently employed respondents, unemployed respondents are removed from our sample. Employment rates vary from 55% to 80% across countries. Therefore, a rather substantial share of the sample is not included in the analysis due to unemployment or inactivity. However, to check for potential selection, we analysed a descriptive profile of unemployed respondents, finding no systematic differences across employed and unemployed samples in a number of observed characteristics. The second limitation relates to the intensity of skill use at work. These measures are self-reported and the formulation of questions makes arbitrary responses possible. However, we do not expect deviations from the actual frequency to be significant; moreover, individual deviations should not be correlated, and consequently, they balance out in the overall sample.

2.2. Empirical Approach

We start by specifying a Mincer-type earnings equation of the following form:

$$lnW_i = \alpha + \beta \cdot Female_i + \gamma' \cdot X' + \theta' \cdot HC' + \varepsilon_i, \tag{1}$$

[5] As a robustness check, we replicated the analysis adding the problem solving skill for countries where this variable was disclosed. The results are not significantly different from the specification with only two cognitive skill controls.

where, W_i stands for the hourly earnings of salaried worker i, $Female_i$ is a female indicator variable, thus, coefficient β captures the unexplained gender wage gap. X' is a vector of demographic and employment controls with vector γ' comprising respective regression coefficients. Vector HC' incorporates the extensive set of human capital domains, namely (i) formal education level; (ii) field of education; (iii) total work experience; (iv) work experience related to current employment; (v) literacy skill; (vi) numeracy skill; (vii) use of literacy, numeracy and ICT skills at work; (viii) organizing, presenting and negotiating at work; and (ix) solving simple and complex problems at work. The estimated regression coefficients of human capital variables are stored in the vector θ'.[6]
We estimated the regression of form (1) using a multivariate OLS approach with the stepwise inclusion of controls. Coefficient β in a fully specified model represents the gender wage gap explained by neither background factors nor human capital domains. However, the multivariate OLS does not appear to be robust for studying the individual effects of human capital components on the unexplained gap. Following the arguments of Gelbach (2016), estimates of individual effects are influenced by the order that covariates are added to the model. Therefore, the sequential adding of human capital controls provides path-dependent inferences to the gender wage gap effects of these controls.

To elicit path-independent individual effects of human capital domains, unaffected by the sequence of adding the controls, we apply a decomposition methodology developed by Gelbach (2009 and 2016). The estimation procedure relies on the omitted variables bias formula. Unlike the classical Oaxaca-Blinder decomposition, the conditional decomposition procedure by Gelbach derives individual contributions from variables conditional on all covariates. Therefore, the estimates are not affected by the sequencing problem and are robust.[7] The decomposition procedure by Gelbach gives a clear measure of the "effect of adding covariates", unlike the standard and widely used OLS regression with the stepwise inclusion of the controls.

The Gelbach decomposition procedure has previously been applied in the context of gender wage gap assessment (Cardoso et al. 2016, Grove et al. 2011). However, the estimation technique was more widely implemented in settings other than the gender wage gap. For instance, Raposo et al. (2015) used the Gelbach decomposition to analyse the wage losses of displaced workers; Gorsuch (2016) explored the role of behavioural compositional factors and between group change on the time men spent on childcare during the recession; and Buckles and Price (2013) explored the role of marriage on infant health by applying the Gelbach decomposition technique.

Another feature of our estimation procedure relates to the technical characteristics of the PIAAC data. As discussed in the previous sub-section, each skill domain is reported as a set of ten plausible values. Within the descriptive analysis, we account for all ten plausible values and apply a Jackknife replication methodology (OECD 2013). Specifically, the replication procedure benefits the analysis, as it measures standard errors without overestimating them.[8] However, since the multivariate OLS regression and the Gelbach decomposition accounts for

[6] One important limitation of our methodological approach is the potential multicollinearity between human capital components, particularly, between cognitive skills and task-specific human capital. To verify that multicolinearity does not affect our estimates, we additionally estimate VIF measures. The results verified that VIF estimates are below 3, implying stability of coefficients and ensuring that standard errors are not inflated.
[7] For more details see Gelbach (2016).
[8] Technical note on the application of the Jackknife replication methodology. Relying on 80 replication weights and a single population weight, the replication procedure repeatedly selects the sub-samples and estimates the descriptive statistics of interest from these sub-samples. Standard errors are calculated using the variability of the statistics derived from these sub-samples. Since each skill domain incorporated 10 plausible values, 80 replication weights and the population weight, a single skill-based descriptive estimate is a result of 810 replications. For more details see https://www.oecd.org/skills/piaac/_Technical%20Report_17OCT13.pdf

two skill domains simultaneously, it appears computationally complex to use a whole set of plausible values and the Jackknife replication procedure.[9] Therefore, the gender wage gap analysis relies on the first plausible value for literacy and numeracy and incorporates country-specific population weights. A similar approach has been implemented in several PIAAC-based studies (Smith and Fernandez 2017, Anspal 2015, Hanushek et al. 2015)[10].

3. EMPIRICAL RESULTS

3.1. Descriptive profiles of men and women

We start by discussing the average descriptive characteristics of our sample. Appendix A2 presents the average demographic characteristics of men and women across countries. The age of the respondents is relatively homogeneous across countries and varies from 38 to 41 years for both males and females. We document no systematic gender and country differences in the cohabitation rate, which ranges from 68.9% to 84.2% for men and from 66.1% to 85.7% for women. The results reveal systematic cross-country and cross-gender differences in the parenthood rate. Females have children systematically more often than males in our sample. This brings forth the necessity to control for parenthood when estimating the gender wage gap, since motherhood is known to strongly correlate with gender wage disparity (Blau and Kahn 2017, O'Neill 2003).

In terms of ethnicity, we document no significant gender heterogeneity, however, we reveal drastic cross-country variation. The Irish sample comprises an outstanding share of immigrants, namely 24.3% among males and 20.7% among females. The second highest share of foreign-born is documented in Great Britain (14.4% among men and 13.9% among women). The smallest shares of immigrants are found in the Polish (0.2% of men and 0.1% of women) and Slovakian samples (1.9% among men and 2.2% among women). The shares of native speakers are comparable across men and women, while relatively heterogeneous across countries. Generally, a smaller percentage of immigrants results in a greater percentage of native speakers. The only exception is Spain, where with immigrant rates of 12% and 15.2% for men and women, native speaker rates are 94.7% and 94% respectively. This can result from the different characteristics of immigrants in Spain compared to other countries. Specifically, a relatively large share of immigrants in Spain is of Latin American origin with Spanish language as a mother tongue.

Appendix A3 presents the occupational profile of men and women across the analysed countries. Notably, the most pronounced gender gaps are documented in the middle of the occupation classification; that is, in semi-skilled white- and blue-collar positions. Specifically, women occupy semi-skilled white-collar occupations systematically more than men, while the reverse holds for semi-skilled blue-collar occupations. This relates to the composition of occupation categories. White-collar positions include predominantly administrative and clerical work, while blue-collar include various categories of workers, mechanics, and support technical activities. Both categories are relatively gendered due to the nature and physical requirements of the job. Notably, we document no substantial gender gaps in skilled occupations in the

[9] Incorporating two skill domains, will 10 plausible value each, with 80 replication weights and population weight results in 810×810 replications.

[10] However, we additionally verified robustness of our findings on the full set of plausible values in several randomly selected countries. The coefficients are comparable across estimations. The negligible differences across estimates can be explained by relatively big country-specific sample sizes. Accounting for a full set of plausible values is of greater importance when smaller samples are considered (see Tverdostup and Paas 2019).

majority of countries, except Estonia (36.8% men and 50.5% women), Lithuania (33.8% men and 52.1% women), Poland (30% men 50.5% women) and Slovenia (36.4% men and 52.3% women).

Next, we turn to the key human capital variables of interest. First, Figure 1 presents the shares of men and women with low, medium or high levels of education across countries. In line with a large strand of the literature, we document that women hold, on average, higher levels of education compared to men (Author and Wasserman 2013, Becker et al. 2010, Goldin et al. 2006). Notably, we found significant cross-country heterogeneity in the educational profiles of the respondents. The lowest education levels are held by respondents from Italy, Czech Republic and Slovakia; the highest are held by subjects from Poland and Norway.

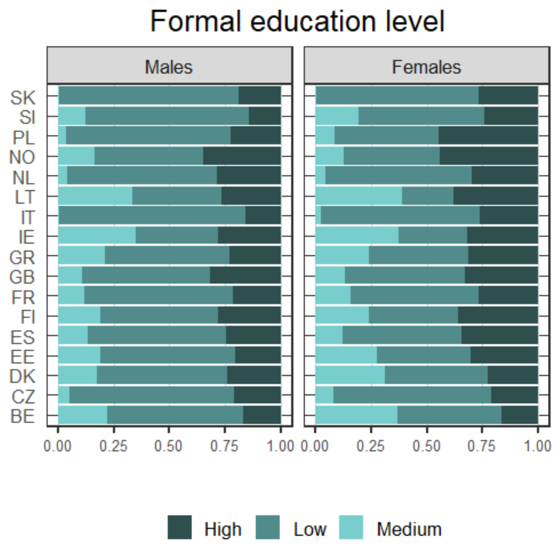


Figure 1. Distribution of low, medium and high levels of education by gender and country

Notes: The estimates account for population weights.

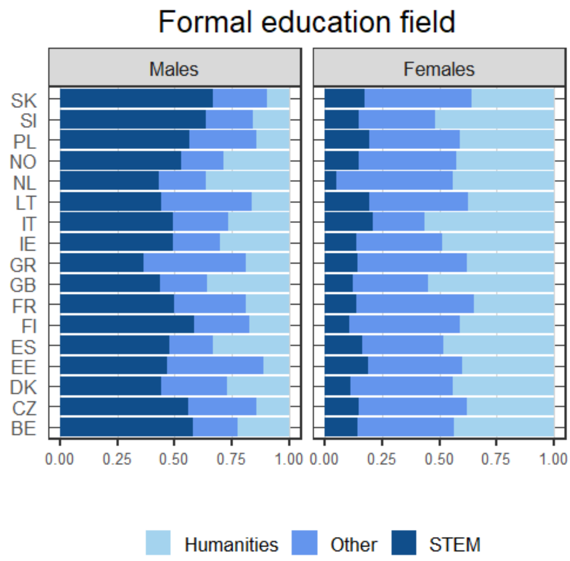


Figure 2. Distribution of education fields by gender and country

Notes: The estimates account for population weights. STEM field includes: science, mathematics and computing; engineering. Humanities incorporate: humanities, languages and arts, social sciences, business and law, teacher training and educational sciences.

The country and gender-specific distribution of education fields is visualized in Figure 2. We classified all educational fields into three broad groups, with STEM incorporating all mathematics and engineering related majors, and broadly defined humanities category capturing the humanities and social sciences, business and educational sciences. The major result is in line with the literature, namely, men significantly outnumber women in STEM fields, while women dominate in the humanities, teaching and social sciences. Similar evidence was provided by Gemici and Wiswall (2013), reporting that college majors remain strongly gendered, and by Ceci et al. (2014) and Blau et al. (2014), documenting that males substantially outnumber females in STEM majors. The substantial gender imbalance in university majors is recognized as one of the factors behind gender wage disparity, as it appears a much more precise predictor of exact abilities and knowledge, compared to mere education level. Therefore, including education field in the compound human capital measure is particularly relevant.

Second, Figure 3 depicts average work experience by gender and country. We document a clear-cut gender gap in work experience, both total and occupation-/industry-related. The descriptive evidence suggests that, on overage, in all countries, except Estonia, Slovakia, Slovenia and Czech Republic, men have more years of total work experience. When it comes to work experience related to currently occupied job, in all countries without exception, women have significantly less experience. Moreover, the average size of the gender gap is substantially bigger in related experience, compared to total experience. Despite the declining gender gap in work experience being widely documented in the literature (Gayle and Golan 2011, Blau and Kahn 2006, Blau and Kahn 1997, O'Neill and Polachek 1993), the disparity still persists. Given the growing literature on the role of occupation and firm-specific experience in explaining the gender wage gap (Sullivan 2010), we expect the systematic gender gap in related experience to significantly affect the gender wage disparity.

Third, we turn to the descriptive analysis of the cognitive skills of men and women. Figure 4 depicts average literacy and numeracy scores on the basis of gender and country. Two stark observations emerge from the figure. The first concerns substantial cross-country heterogeneity of PIAAC-based cognitive test scores, which has already been documented in the literature (Hanushek et al. 2015). The second observation relates to systematically higher literacy scores among women and vice versa for numeracy scores. The greater numeracy proficiency among men has also already been documented in the literature (Hanushek et al. 2015, Niederle and Vesterlund 2010). Our findings, generally, provide further support for this evidence. However, in several countries, the gender gap in the numeracy score is insignificant (Italy, Lithuania, Poland, Slovakia and Slovenia).

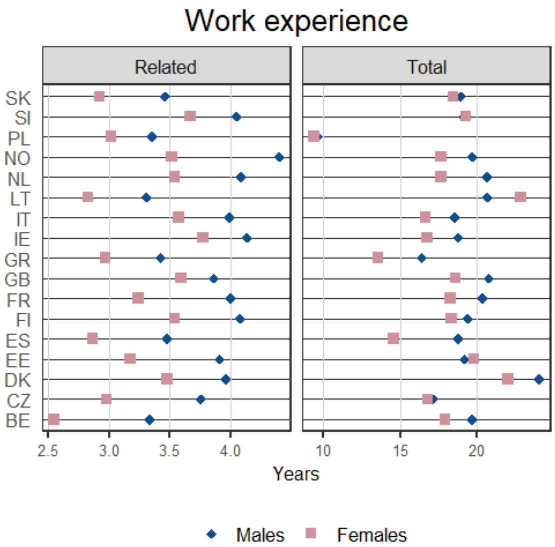


Figure 3. Average total and occupation-/industry-related experience by gender and country

Notes: The estimates account for population weights.

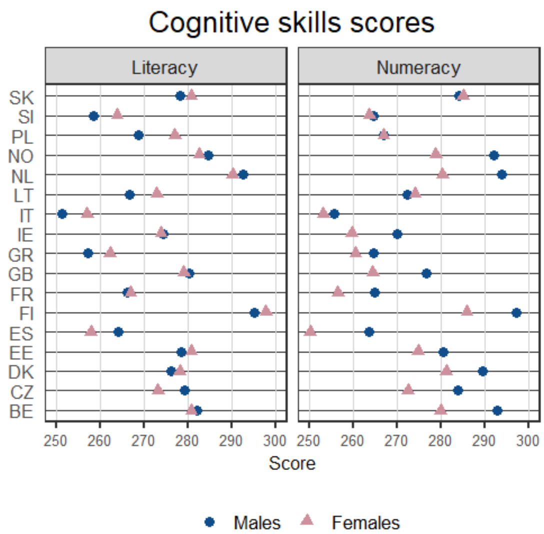


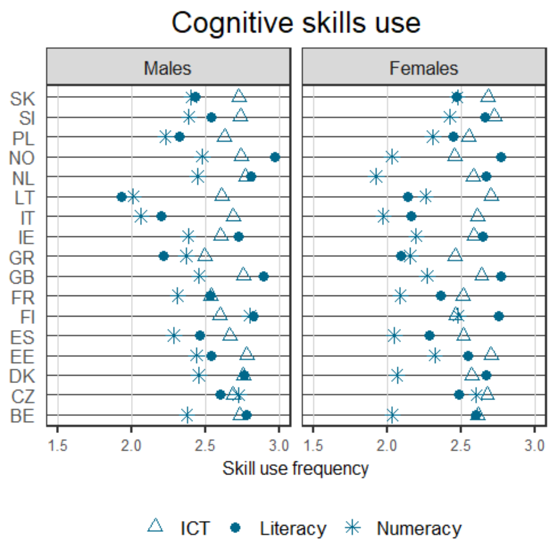
Figure 4. Average cognitive skills by gender and country

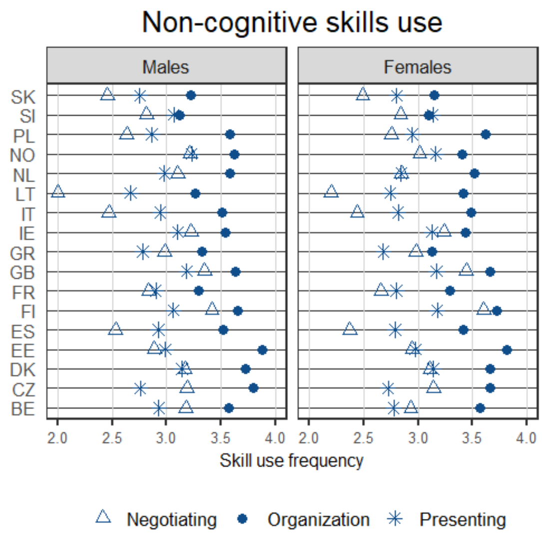
Notes: The estimates rely on a full set of 10 plausible values for both literacy and numeracy skills and account for population weights.

Fourth, we provide descriptive evidence on the intensity of on-the-job skill use as an approximation of task-specific human capital. Figure 5 presents average intensities of on-the-job skill use according to gender and country. Panel (a) depicts the use of cognitive skills. The results reveal that in nearly all countries except Lithuania, Poland, Slovenia and Slovakia, men apply literacy and numeracy abilities systematically more often than women. The use of ICT competencies is even more frequent among males. In all countries, except Lithuania, men more often apply ICT competencies at work. These findings suggest that men may generate more task-specific abilities, compared to women, through on-the-job skill use, facilitating the accumulation and improvement of particular task-specific skills. Another notable result is the very small cross-country dispersion of ICT use intensities, which are concentrated at relatively high rates. While literacy and numeracy skills are relatively widely used across occupations, ICT skill use may be more occupation-specific. As a result, the distribution of ICT use intensity is convex, with either very low or very frequent ICT abilities use.

Panel (b) depicts male and female on-the-job use of non-cognitive abilities. We document much stronger gender equality, compared to panel (a), suggesting that men and women apply organization, presentation and negotiation skills at similar rates. Notably, there is much smaller cross-country dispersion of organization and presentation skills use, while the intensity of negotiation skill use varies drastically across countries. In all countries, both men and women perform organization activities at relatively high rates, while presenting at work is less frequent. This finding can relate to the specificity of the two measures, since organization at work includes both organization of one's own time and that of others. This definition covers rather a broad scope of work activities, while presentation at work is narrowly defined and may relate to a smaller scope of work tasks. Negotiation at work is extremely heterogeneous across countries, with Lithuania having the lowest intensity and Finland the highest. Cross-country heterogeneity can originate from work culture differences across countries. Some countries are more prone to horizontal work structures, implying intense cooperation and negotiations between co-workers, while other countries comply with vertical structures with minimal communication and negotiations between the structural layers.

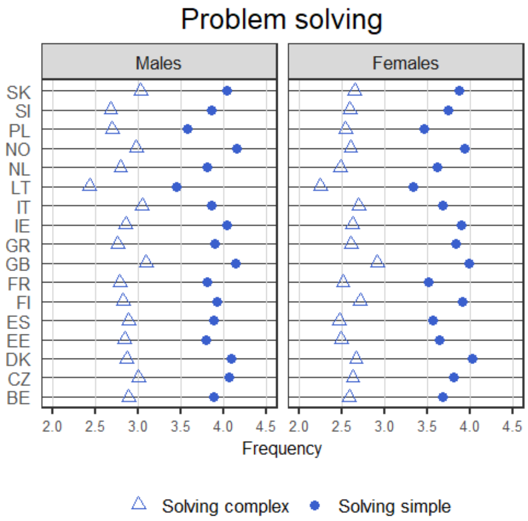
Panel (c) deals with the frequency of solving problems at work. The results yield two important insights. First, men solve both simple and complex problems more frequently, than women, with marginally larger gender gaps for complex problems. Systematic gender gaps can originate from occupation and industry segregation, with women self-selecting into more stable, less stressful jobs, yielding less “trouble-shooting” (Wiswall and Zafar 2018). Second, problem solving frequencies are highly concentrated (i.e. low cross-country heterogeneity), with simple problems solved more frequently than complex problems. The latter result is expected, since simple problems can be faced at all occupational levels, while complex issues are more likely for high level occupations and, on average, are less frequent.





Panel (a). Use of cognitive skills at work.

Panel (b). Use of non-cognitive skills at work.



Panel (c). Problem solving at work.

Figure 5. Average on-the-job use of human capital according to gender and country

Notes: The estimates account for population weights.

Overall, the descriptive results report significant gender differences in nearly all human capital domains. Therefore, the gender wage gap analysis should account for all the aforementioned human capital components for two reasons. The first reason is a straightforward gender disparity in human capital traits, which can reflect on the wage gap. However, the latter holds only if the specific trait is valued on the labour market and generates wage returns. The second reason is differential labour market returns for male and female human capital. As a result, the inclusion of human capital components homogeneous across men and women (in our case, non-cognitive abilities use at work) is also relevant.

3.2. Results from the pooled multivariate OLS

We start with the results from the Mincer-type OLS regression analysis, following equation (1). Relying on the argumentation from section 2.2, we do not interpret the stepwise changes in the estimates, as they are affected by the order in which the controls are added. Instead, we focus on the unexplained gender wage gap, accounting for the compound effect of the controls.

Appendix A4 presents the female coefficients; that is, the unexplained gender wage gap across 17 countries and 13 specifications. The controls are sequentially added to the model, with the base specification controlling for the female dummy, and the remaining specifications adding: age, age squared, living with a spouse/partner, children, immigration status, being a native speaker (specification 2); mother's and father's highest level of education (specification 3); occupation level, industry of employment, type of employment contract (specification 4); own highest education level (specification 5); field of education (specification 6); total work experience (specification 7); work experience related to current employment (specification 8); literacy skill (specification 9); numeracy skill (specification 10); use of literacy, numeracy and ICT skills at work (specification 11); frequency of organizing, presenting and negotiating at work (specification 12); frequency of solving simple and complex problems at work (specification 13).

At first glance, the results from the OLS estimations reveal several important patterns. First, we document substantial cross-country heterogeneity in the relative size of the raw gender wage gap (specification 1), varying from 3.9% in Slovenia and 6.3% in Italy, to 35.5% in Estonia. The latter appears an outlier from the overall pool of countries, since the second largest gender pay gap ranges around 20% in Slovakia, Lithuania and Czech Republic.[11] Second, the total effect of all controls (specification 13 vs. specification 1), including nine sets of human capital measures, varies drastically across the analysed countries. For most of the countries, including all the controls reduced the unexplained gender wage gap. The most drastic overall decrease is documented for Ireland (approx. 87%) and the Netherlands (approx. 57%).

However, in Poland and Slovenia, the effect of the total set of controls is the opposite. For these two countries, the unexplained gender wage gap increased, compared to the raw estimate (specification 1). We found no effect of the total set of controls for Greece and Italy. Hence, the gender wage gap persists even for homogeneous groups of workers with comparable demographic and employment characteristics and a similar range of human capital endowments.

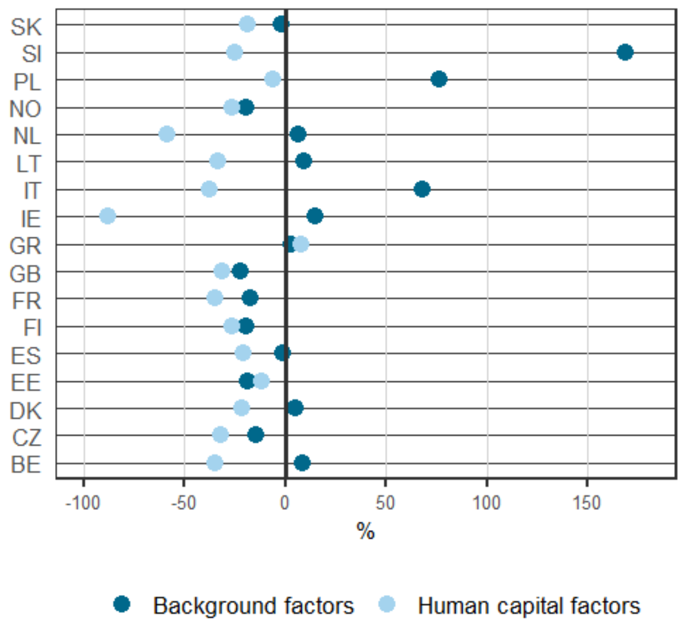


Figure 6. Compound effects of background and human capital controls on the gender wage gap

Note: The estimates are based on regression results reported in Appendix A4. Background factors include factors added in specification 2 to 4. Human capital factors incorporate controls added in specification 5 to 13. A positive contribution implies that the factors widen the gender wage gap, with a negative contribution, the factors narrow the gap.

Next, we split the total effect of all covariates into compound effects of (a) background controls, added sequentially in specification 2 to 4, and (b) human capital controls, included sequentially

[11] Estonia was previously reported as a country with the highest gender wage gap in Europe. For more details see Eurostat https://ec.europa.eu/eurostat/documents/2995521/8718272/3-07032018-BP-EN.pdf/fb402341-e7fd-42b8-a7cc-4e33587d79aa.

on top of the background controls in specifications 5 to 13. Figure 6 depicts the compound effects of these two groups of variables on the unexplained gender wage gap across the analysed countries. The results reveal that, in a half of the countries, background characteristics, incorporating demographic and employment characteristics, as well as parental education level, widen the unexplained gender wage gap. In particular, adding the background controls increases the unexplained wage gap in Slovenia by almost 170%, while in Poland by 76% and in Italy by 68%. However, for another half of the analysed countries, background controls reduce the wage gap. The most drastic reduction of 22% is documented for Great Britain, which is followed by Norway, Finland and Estonia (around 19%). In this sub-section, we will not go into the details of the effects of the individual variables, but rather stay at the group level.[12]

The compound effect of human capital variables is relatively homogeneous in terms of sign, but drastically different in magnitude across countries. We document that the input of human capital controls to narrow the unexplained gap varies from -88.3% in Ireland to -6.4% in Poland, with the only contribution to a gap increase in Greece (7.5%). As with the effect of the background factors, the groups of human capital factors are addressed as a whole in this sub-section, while the individual variable effects are analysed using the Gelbach decomposition and discussed in the following sub-section.

To explore the gender-specific returns on various human capital components we replicated the wage gap analysis (specification 13), adding interaction effects between gender and all human capital domains included in the full specification. The results are provided in Appendix A6. We document no systematic gender-specific returns on human capital domains, except the wage returns on a STEM degree. The latter increases the gender wage gap whenever related statistically significantly (in Belgium, Estonia, France and the Netherlands). Furthermore, the coefficients are economically large, suggesting that men with STEM degrees earn considerably more than women with STEM degrees, provided all other characteristics are fixed. Given that we control for various human capital measures, as well as employment characteristics, negative female-specific returns on STEM degrees may signal potential discrimination. Although, the confounding effects of unobserved non-cognitive traits and job preferences can largely drive the result.

Regarding the female wage returns to task-specific human capital, cognitive skill use domains reveal stronger significance. In particular, the cases of Estonia and Lithuania are rather distinct. These two countries are the only ones with significant female-specific returns on both literacy and numeracy use at work. Furthermore, using literacy skills at work more frequently benefits female wages (9.6% and 10.9% wage gain compared to men), while using numeracy negatively reflects on the wage rate (6.1% and 9.5% wage loss relatively to men). This peculiar result can relate to the specificity of Estonian and Lithuanian labour markets. One possible explanation can be the national language, since both countries have substantial shares of Russian-speaking population. Therefore, proficiency and job use of the Estonian and Lithuanian languages can be correlated with gender selection into particular job characteristics, which yield higher earnings.

3.3. Decomposition analysis

[12] Appendix A5 presents estimations identical to Table 2, but with human capital factors added first, and background factors included on the top of human capital characteristics (i.e. specifications 5–13 are changed into 2–10 and 2–4 into 11–13). As the results reveal, the order in which background and human capital factors groups are added matter even for the group level effect. This provides a strong motivation to abstract from the effects of individual variables within the two groups, as those are subject to an even stronger order effect.

The Gelbach decomposition methodology allows us to elicit the robust effects of individual factors on the unexplained gender wage gap. Unlike the OLS estimates, the results of the Gelbach decomposition are free from the covariate order effect and make it possible to interpret each individual covariate contribution. Table 1 presents the results of the Gelbach decomposition with a base specification controlling for female indicator variables and the full specification including all controls from specification 13 in Appendix 4. Therefore, Table 1 illustrates the contributions from individual variables, grouped into twelve categories,[13] with the first three incorporating the factors included in the background factors group in the previous sub-section, and the remaining categories incorporated into the human capital factors group. The contributions are estimated relying on the coefficients from the full specification.

In the following, we discuss the contributions of all groups of factors and highlight cross-country heterogeneity.

Background characteristics

Demographic characteristics reveal no significant association with the gender wage gap in any of the countries, except Belgium and the Netherlands (7.55% and 14.73% gap reductions respectively). Provided the descriptive evidence in Appendix A2, women in the Belgian sample are 7.6 p.p. more likely to have children and 3.3 p.p. more likely to cohabit, compared to men. In the Dutch sample, women are only 2.9 p.p. more likely to have children. This higher propensity for parenthood may drive the result. Notably, in other countries, females are systematically more likely to have children. However, the wage penalty for motherhood may vary across counties (Molina and Montuenga 2009, Gangl and Ziefle 2009, Anderson et al. 2003). Benelux countries may have either stronger wage penalties for labour market interruptions, or relatively lower monetary incentives for re-entering a labour market, or stronger barriers to return to before-motherhood employment. Notably, the OLS results reveal a different magnitude of the effects of demographic characteristics on the unexplained gender wage gap (Appendix A4, specification 2 vs. 1). This further supports the idea that OLS estimates provide a non-robust measure of the effects of individual covariates.

The contribution of parental background appears insignificant across all analysed counties. The employment controls, including occupation, industry and type of contract, whenever significantly associated with the gander wage gap, decrease the wage disparity. The largest wage reductions are documented for France, Finland, Norway, Estonia and Denmark (37.87%, 29.09%, 27.42%, 24.56% and 24.01% respectively). In other countries, the contribution of employment controls varies between 23% and 14%. Gender occupation and industry segregation can be one of the factors explaining the significant reduction in the gender wage gap after employment characteristics are included (Blau and Kahn 2017). Females may self-select into occupations or sectors other than men, and the selection is largely driven by preferences. Wiswall and Zafar (2018) document that women value work flexibility and job stability, while men have stronger preferences for jobs with earnings growth prospects, which, naturally, affects the occupational choices of men and women and consequently their wages. Moreover, females may face restricted access to certain occupations due to employer discrimination (Bertrand and Hallock 2001).

[13] For convenience, we grouped a full set of controls into twelve distinct groups. Specifically, (i) demographic characteristics (age, marital status, children, immigrant status, native speaker); (ii) parental background (mother's and father's highest level of education); (iii) employment characteristics (occupation, industry, type of employment contract); (iv) education degree; (v) education field; (vi) experience total; (vii) experience related; (viii) literacy skill; (ix) numeracy skill; (x) cognitive skills use at work (using literacy, numeracy, ICT skills); (xi) non-cognitive skills use at work (organizing, presenting, negotiating at work); (xii) problem solving at work (solving simple and complex problems).

Formal education

Next, we focus on the contributions of the human capital controls. Formal education increases the gender wage gap in nine out of seventeen countries. In the remaining countries, it is insignificantly associated with the wage gap. The most drastic wage gap increases are reported for Slovenia (38.56%), Poland (24.24%), Belgium (16%) and Italy (15.85%). Women hold a systematically higher level of education, compared to men in all analysed countries (see Figure 1), which concurs with the literature (Author and Wasserman 2013). However, the explanatory power of education is persistently decreasing (Cha and Weeden 2014). One of the major reasons behind the declining wage returns on formal education is the concave relationship between schooling and earnings (Colclough et al. 2010). Therefore, the relative increase in the wage rate associated with an increase in formal education is diminishing, with the highest wage growth in the lower part of the distribution (for low- and medium-educated individuals). This can be one of the factors explaining the widening gender wage gap with the inclusion of education level in most of the analysed countries.

The field of education increases the gender wage gap in Ireland (by 47.43%), France (by 13.82%) and Estonia (by 10.61%). Despite earlier studies documenting the strong explanatory power of university majors (Black et al. 2008, Daymont and Andrisani 1984), we find supportive evidence only for Denmark (8.75% contribution to explaining the gender wage gap). For the remaining countries, field of education is insignificantly related to gender wage disparity. Notably, the gender distribution of educational majors in three countries with significant associations is comparable to the remaining analysed counties, namely, men significantly outnumber women in STEM disciplines and vice versa in humanities, social sciences and teaching (see Figure 2). Education field largely reflects the actual skills and knowledge accumulated while studying, therefore it is a much stronger predictor of human capital, compared to mere education level. However, since our full specification controls for cognitive abilities and on-the-job skills use, these can mitigate a part of the wage gap effect associated with a university major. Moreover, as we discuss later, work experience may decrease the magnitude of the association between education field and wage level, especially for women, having consistently lower experience durations.

Work experience

Work experience appears to be the strongest factor explaining the gender wage gap. In all analysed countries, either total work experience, or work experience related to current employment, or both experience measures significantly decrease gender wage gaps. Notably, we document even stronger contributions from related experience, as it decreases wage gaps in all counties except Greece, where the association is insignificant. Ireland and Belgium revealed the largest joint contribution of the two work experience variables (approximately 50% and 45%), with the extreme effect of related experience in Ireland (40.53%). In all other countries, gender wage gap reductions associated with related experience are also systematically higher than those associated with total experience. For instance, in France related experience explains 15.51% of the gap, while total only 6.75%; in Estonia 12.13% and 1.47% respectively; in Czech Republic, Denmark, Finland, Great Britain, Italy, Lithuania, the Netherlands, Norway, Poland, Slovakia, Slovenia and Spain total experience is insignificantly associated with the gender wage gap, while related experience significantly decreases the gap.

The economically and statistically strong association between work experience and wage gap results from substantial gender disparities in the total and related experience documented in Figure 3. In line with other literature, we document that these systematic experience gaps are the major driver of wage differentials (Goldin et al. 2006, O'Neill and Polachek 1993, Polachek 1981). Furthermore, Olivetti (2006) shows that the relative returns to experience for women increased more than relative returns for men. This accelerates the gender wage disparity, as employment interruption hurts female wages relatively more than male wages. Therefore, women, while more prone to labour market dropouts, are also suffering more substantial wage penalties upon return compared to men experiencing work interruptions of identical length. The differential nature and reasoning behind the interruptions to employment for men and women, especially at a young age, can be one of the drivers of a higher penalty for females.

Cognitive skills

Our results suggest the relatively weak explanatory power of literacy skill. The only significant contributions are documented for Lithuania (8.02%) and Denmark (1.76%). The overview of gender gaps in relation to cognitive skills (see Figure 4) reveal relatively heterogeneous gender gaps in relation to literacy skills across countries. Lithuania and Denmark reveal gaps that favour females. However, Niederle and Vesterlund (2010) emphasize that, unlike mathematical test scores, verbal test scores are a bad predictor of future earnings. Therefore, literacy and verbal abilities, although an important component of the individual human capital profile, have less effect on wage level. This evidence largely explains the low explanatory power of literacy documented in our analysis. Regarding Lithuania and Denmark, where significant contributions were found, male and female literacy abilities may yield differential wage returns. Moreover, there may be other unobserved specific abilities or traits correlated with literacy in the male sample that positively reflect on their wage rate.

Numeracy, by contrast, contributes to gender wage gap reduction in approximately half of the countries. The stronger explanatory power of numeracy is in line with earlier studies. Hanushek et al. (2015), relying on the same PIAAC database, document that numeracy yields higher wage returns compared to literacy. Similarly, Moll (1998) and Jolliffe (1998) perform analyses of wage returns on cognitive skills and find that when assessing mathematical and reading skills separately, mathematical skills matter more for income. The highest contribution of numeracy skills is documented in Ireland (21.97%), followed by Great Britain (12.76%), Spain (9.83%), Finland (8.01%), France (7.67%), Slovenia (6.56%), Norway (5.93%) and Estonia (3.19%). Lithuania is the only country where numeracy skills widen the gender pay disparity. Descriptive evidence from Figure 4 reveals that Lithuania is one of the few countries where women have marginally higher numeracy skills than men. Coupled with potentially lower returns on the numeracy abilities of females compared to males, the marginally higher skills among women can explain the observed negative effects of numeracy ability on the gender wage gap.

Task-specific skills

The final set of human capital factors incorporates three major categories of task-specific (i.e. productive) skills and competencies. The common feature of all skill use factors is their contribution to gender wage gap reduction. Whenever significantly associated with the wage gap, task-specific skills narrow the disparity in male and female earnings, suggesting that men are using diverse skills more frequently at work, which positively reflects on their human capital profile and wage rate.

The first category includes three domains of on-the-job cognitive skills use, namely literacy, numeracy and ICT skills. These three skill domains largely embody on-the-job applications of cognitive skills and thus task-specific cognitive abilities. The use of cognitive skills has the most pronounced effect on the gender wage gap in Ireland (18.76%), followed by Great Britain (7.62%), Denmark (7.36%) and Norway (5.31%). In the remaining countries, we document no significant effect from on-the-job cognitive skills use in explaining the gender wage gap.

The second set of task-specific abilities includes three domains of on-the-job applications of non-cognitive abilities. Specifically, organizational, presenting and negotiating skills. The use of non-cognitive skills has an economically and statistically lower contribution in explaining the gender wage gap. This is largely explained by the insignificant gender gaps in on-the-job use of non-cognitive skills (see Figure 5, panel (b)). The only three countries with statistically significant contributions from the use of non-cognitive skills are Czech Republic (2.74%), Great Britain (2.01%) and Estonia (1.26%). The third set of productive abilities comprises simple and complex problem solving abilities. Problem solving at work has an economically stronger effect in gender wage gap analysis, as the gender gaps in problem solving are persistent (see Figure 5, panel (c)). This productive human capital measure explains 4.02% of the gap in Denmark, 3.85% in Netherlands and 3.39% in Belgium.

Despite finding statically rather weak associations between gender wage gap and three domains of task-specific human capital, the economic significance of those is non-negligible. The low significance of task-specific human capital domains can be partly explained by the high economic and statistical significance of employment variables, which moderate the pure effect of task-specific human capital. Gibbons and Waldman (2004) suggest that selection into specific occupations implies gender segregation into job tasks, which increases gender gaps in task-specific human capital. Therefore, controlling for the employment profile to a certain extent captures employment segregation and the resulting gender disproportion in accumulated task-specific abilities.

Table 1. Gelbach decomposition of the gender wage gap

	Belgium		Czech Republic		Denmark		Estonia		Finland		France	
	Contr.	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**
Variable (group)												
Demographic characteristics	-0.0057*	7.55	-0.0029	1.57	0.0009	-0.68	-0.004	1.06	0.0039	-2.08	-0.007	5.38
Parental background	0.0001	-0.17	-0.0032	1.72	-0.0003	0.21	-0.0049	1.28	-0.0009	0.50	-0.0009	0.71
Employment characteristics	-0.0011	1.49	-0.038***	20.45	-0.0334***	24.01	-0.0928***	24.56	-0.0544***	29.09	-0.049***	37.87
Education degree	0.0121***	-16.00	-0.0009	0.48	-0.0036	2.59	0.0133**	-3.52	0.0072**	-3.85	0.0167***	-12.79
Education field	0.0100	-13.22	0.0098	-5.24	-0.0121**	8.75	0.0401***	-10.61	-0.0148	7.94	0.018*	-13.82
Experience total	-0.0204***	27.07	-0.0030	1.59	-0.0008	0.58	-0.0055*	1.47	-0.0012	0.65	-0.0088*	6.75
Experience related	-0.0142***	18.76	-0.026***	13.83	-0.0111***	7.98	-0.0458***	12.13	-0.0217***	11.60	-0.020***	15.51
Literacy	-0.0013	1.77	-0.0052	2.79	-0.0024**	1.76	-0.0013	0.35	0.0000	0.00	0	0.02
Numeracy	-0.0046	5.90	0.0036	-1.91	-0.0027	1.95	-0.0121**	3.19	-0.015***	8.01	-0.01**	7.67
Cognitive SUW	0.0006	-0.82	0.0017	-0.90	-0.0102***	7.36	-0.0003	0.09	0.0014	-0.76	0.0044	-3.36
Non-cognitive SUW	0.0024*	-3.20	-0.0051**	2.74	-0.0010	0.72	-0.0048**	1.26	0.002	-1.09	-0.0013	1.03
Problem solving at work	-0.0026**	3.39	-0.0032	1.73	-0.0056***	4.02	-0.0004	0.11	-0.0014	0.75	-0.0017	1.33
Total	**-0.0245****	**32.51**	**-0.072*****	**38.85**	**-0.0823*****	**59.25**	**-0.1186*****	**31.37**	**-0.0948*****	**50.76**	**-0.060*****	**46.29**
N	3418		2700		6038		2084		2081		1686	

Table 1 (continued).

	Great Britain		**Greece**		**Ireland**		**Italy**		**Lithuania**		**Netherlands**	
	Contr.	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**
Variable (group)												
Demographic characteristics	-0.0008	0.43	-0.0253	19.17	-0.0087	11.35	0.0029	-2.97	-0.0147	6.48	-0.0206***	14.73
Parental background	-0.0001	0.06	-0.0036	2.75	-0.0002	0.29	-0.0057	5.88	-0.0063	2.79	0.0015	-1.08
Employment characteristics	-0.0421***	23.16	-0.0068	5.20	-0.0126	16.46	0.0001	-0.08	-0.0370**	16.27	-0.0197*	14.11
Education degree	-0.0038	2.12	0.0190	-14.42	-0.0034	4.40	0.0154**	-15.85	0.0087	-3.84	-0.0055	3.94
Education field	0.0108	-5.97	0.0204	-15.49	0.0364***	-47.43	-0.0025	2.59	-0.0018	0.79	-0.0068	4.84
Experience total	0.0012	-0.65	-0.0222*	16.89	-0.0077 *	10.04	-0.004	4.11	-0.0013	0.59	-0.0002	0.15
Experience related	-0.0241***	13.27	-0.0047	3.54	-0.0311***	40.53	-0.0194***	20.01	-0.0328***	14.42	-0.0283***	20.21
Literacy	0.0020	-1.13	0.0024	-1.83	0.0003	-0.36	-0.0047	4.82	-0.0182**	8.02	-0.0015	1.10
Numeracy	-0.023***	12.76	-0.0008	0.61	-0.0169*	21.97	-0.0062	6.45	0.0221**	-9.72	-0.0051	3.67
Cognitive SUW	-0.0139***	7.62	0.0032	-2.48	-0.0144**	18.76	-0.0048	4.96	0.0018	-0.79	-0.00145	1.03
Non-cognitive SUW	-0.0036*	2.01	0.0015	-1.16	-0.0017	2.26	-0.0038	3.89	0.0031	-1.38	-0.0035	2.49
Problem solving at work	0.0014	-0.79	-0.0013	0.98	0.0044	-5.77	0.0004	-0.44	-0.0030	1.33	-0.0054*	3.85
Total	**-0.0961*****	**52.90**	**-0.0182**	**13.76**	**-0.0556****	**72.51**	**-0.0323**	**33.36**	**-0.0794****	**34.94**	**-0.0966*****	**69.05**
N	2396		537		1246		832		886		1838	

Table 1 (continued).

	Norway		Poland		Slovakia		Slovenia		Spain	
	Contr.	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**	**Contr.**	**% of gap**
Variable (group)										
Demographic characteristics	-0.0012	0.63	0.0051	-4.16	0.0018	-0.61	0.0007	-0.84	-0.0142	8.56
Parental background	-0.0010	0.50	-0.0020	1.60	-0.0055	1.89	-0.0010	1.22	0.0022	-1.35
Employment characteristics	-0.0534***	27.42	-0.0194	15.76	-0.0441***	15.15	-0.0147	17.31	-0.0031	1.90
Education degree	0.0110***	-5.65	0.0299***	-24.24	0.0067	-2.31	0.0328***	-38.56	0.0146**	-8.81
Education field	-0.0094	4.83	0.0132	-10.67	-0.0075	2.59	0.0073	-8.58	-0.0141	8.49
Experience total	-0.0048	2.48	0.0017	-1.39	0.0012	-0.41	-0.0026	3.03	-0.0109	6.56
Experience related	-0.0270***	13.87	-0.016***	13.15	-0.0129**	4.43	-0.0143***	16.81	-0.0118*	7.12
Literacy	-0.0005	0.25	0.0001	-0.05	-0.0000	0.02	0.0013	-1.54	-0.0005	0.28
Numeracy	-0.0116**	5.93	-0.0035	2.86	-0.0054	1.85	-0.0056*	6.56	-0.0163*	9.83
Cognitive SUW	-0.0103*	5.31	0.0007	-0.59	-0.0030	1.03	-0.0029	3.46	-0.0084	5.10
Non-cognitive SUW	-0.0025	1.26	-0.0005	0.38	-0.0024	0.83	-0.0008	0.91	-0.0055	3.34
Problem solving at work	-0.0022	1.12	0.0006	-0.45	-0.0074	2.53	0.0020	-2.36	0.0013	-0.81
Total	**-0.1129*** **	**57.95**	**0.0096**	**-7.80**	**-0.0785*** **	**26.99**	**0.0022**	**-2.58**	**-0.0667** **	**40.20**
N	2089		1866		1279		1339		1070	

Note: Dependent variable is the log of the hourly earnings of salaried workers. Estimations account for country-specific population weights. The variables are grouped as follows: (i) *Demographic characteristics* – age, age squared, living with a spouse/partner, children, immigration status, being a native speaker; (ii) *Parental background* – mother's and father's highest level of education; (iii) *Employment characteristics* – occupation level, industry of employment, type of employment contract; (iv) *Education degree* – own highest education level; (v) *Education field* – field of highest education level attained; (vi) *Experience total* – total work experience; (vii*) Experience related* – work experience related to current employment; (viii) *Literacy* – literacy test score; (ix) *Numeracy* – numeracy test score; (x) *Cognitive SUW* – use of literacy, numeracy and ICT skills at work; (xi) *Non-cognitive SUW* – frequency of organizing, presenting and negotiating at work; (xii) *Problem solving at work* – frequency of solving simple and complex problems at work. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.4. Special case: gender wage gap and human capital in Estonia

In this sub-section we conduct an in-depth investigation of Estonia as a country with the highest gender wage gap in Europe. The results of the OLS regression (Appendix A4) reveal that the gender wage gap unexplained by demographic, employment and multi-dimensional human capital factors is 25.5% in the PIAAC sample. Gelbach decomposition results (Table 1) suggest that all the aforementioned factors reduce the gender wage disparity by only 31.37%. Appendices A7 to A10 disclose several heterogeneity tests aiming to explore the variation in gender wage disparity across several demographic, employment and human capital characteristics. Specifically, we estimate specifications 1 and 13 from Appendix A4 to reveal raw and unexplained gender pay gaps, and therefore elicit how much the considered characteristics reflect on the gender wage gap.

Appendix A7 explore the gender wage gap across age groups, revealing drastic age variations in the gender wage gap. We document a U-shaped relationship between age and unexplained gender wage disparity. Notably, when controlling for demographic, employment and human capital variables, the wage gap becomes statistically insignificant among young respondents aged up to 24 years. In other age groups, the wage disparity reduces drastically, albeit remaining statistically significant. Appendices A8 and A9 depict gender wage gap variation with respect to education and related work experience. The choice of these two human capital domains is motivated by the Gelbach decomposition results (Table 1), suggesting that these two variables significantly associate with the wage disparity. We document a substantial difference between gap estimates in raw and full models; however, in all analysed education and work experience categories, the gender gap remains economically and statistically significant.

Appendix A10 depicts gender wage gaps across four occupation levels: skilled, semi-skilled white-collar, semi-skilled blue-collar and elementary. The results reveal an important pattern. Specifically, the lowest raw gap is found in the lowest occupation group, while the highest in the semi-skilled blue-collar occupation group. Adding a full set of demographic, employment and human capital domains drastically reduces the gap in the lowest employment group, making it statistically insignificant. In three other occupation categories, the gender gaps, although marginally reduced, remain statistically and economically significant.

All in all, heterogeneity analysis suggests that human capital associates with the gender wage gap differently across age, education and related experience groups in Estonia. The effect has a rather homogeneous magnitude across occupation levels and, of particular interest, among low level employees the gap is insignificant. Therefore, while in the total sample the gender wage gap is persistent, it varies in magnitude across different sub-groups. This variation may relate to (i) self-selection of men and women into these sub-groups with respect to education, related experience and occupation; (ii) differential wage returns on various human capital components across age, education, related experience and occupation.[14]

[14] The data in hand does not allow us to explore the first factor. However, to address the second factor we replicated the Gelbach decomposition analysis similar to Table 1 across the age, education, related experience and occupation groups analysed in Appendices A7 to A10. The results do not reveal any systematic variations in the contributions of factors to gender wage disparity. The results are available upon request.

4. Conclusions

This paper makes a twofold contribution to the literature. First, we incorporate a complex multidimensional measure of human capital, instead of focusing on one specific domain. Namely, we empirically investigate (i) several classical and well-established human capital components, such as formal education level and field, total work experience; (ii) a number of acknowledged but empirically under-investigated domains, such as occupation-/ industry-related work experience, literacy and numeracy cognitive skills; and (iii) novel human capital components, including actual on-the-job use of cognitive skills, non-cognitive and problem solving abilities, which jointly reflect task-specific human capital. Second, the paper investigates labour market valuation in the form of wage returns to each specific human capital domain, applying the Gelbach (2016) decomposition methodology. This allows us to investigate the gender wage gap with respect not only to human capital disparities, but rather with respect to disparities in highly-rewarding human capital domains.

Relying on the PIAAC data for 17 European Union countries, we analyse both the joint gender wage gap contribution of all human capital components, and the individual contribution of each human capital domain. The latter is determined in a path-independent manner by applying the Gelbach decomposition. The methodological advantage of the Gelbach decomposition is robust estimation of the wage gap effects of individual controls, unaffected by the order in which each control is added to the model.

The empirical results reveal that the overall contribution of the multidimensional human capital measure to the gender wage gap varies across countries. Accounting for a full set of human capital domains makes the gender wage gap statistically insignificant in Ireland, and economically negligible in the Netherlands and Belgium. However, even in the countries with a persistent wage gap, controlling for multi-dimensional human capital drastically reduces the gap. Unlike demographic and employment characteristics, the effect of human capital measures is homogeneous across countries, namely, accounting for a set of human capital dimensions narrows, or eliminates, the gender wage disparity. This suggests that not only do men possess stronger human capital endowments, but also that human capital domains stronger among males are the ones generating higher wage returns.

The results of the Gelbach decompositions revealed the heterogeneous, yet significant role of a broad range of human capital components in explaining the gender wage gaps in European countries. We found that the strongest effect relates to total and occupation-/industry-specific work experience. Work experience largely decreases the gender wage disparity in all analysed countries. We add to the literature by documenting that work experience related to current employment matters even more for explaining the gender wage gap. Numeracy cognitive skill is another strong predictor of the gender wage disparity. The effect of numeracy is rather homogeneous across countries, namely, controlling for numeracy reduces the wage gap. This finding concurs with the descriptive evidence of lower numerical abilities (on average) among females, coupled with earlier empirical findings of higher wage returns from numeracy skills, as compared to literacy abilities.

We document that task-specific human capital largely explains the gender wage gap. This paper is the first, to the best of our knowledge, to investigate the role of actual on-the-job skill use as a proxy for task-specific human capital. Despite the relatively small economic and statistical significance, three on-the-job skill use sets contribute to narrowing the gender wage gap. Of particular interest, the low significance of task-specific skills can be partly explained by the strong economic and statistical significance of employment-related controls, which capture gendered segregation in occupations and industries. Task-specific skills are largely affected by employment segregation; therefore, employment controls can mitigate the effect of task-specific human capital measures. Moreover, there may be heterogeneity in the wage return on skill use across countries. In countries with an insignificant association between skill use and wages (Greece, Lithuania, Poland, Slovakia, Slovenia, Spain), earnings may be less sensitive to task-specific human capital; therefore, providing lower marginal increases in wages in response to a marginal increase in task-specific human capital.

Out of all human capital components, level of formal education is the sole characteristic widening the gender wage gap systematically across the analysed countries. This result goes in line with earlier findings on the decreasing returns to formal education. Consequently, the higher level of formal education held by women does not yield (on average) a proportional wage gain in the female sample. Formal education increases gender wage disparity, indicating that wage returns on formal education decrease. Similarly, attaining higher literacy skill does not translate into a higher wage rate. This results in disproportional wage returns on male and female human capital profiles, driven not only by human capital gaps, but also by differential labour market valuations of specific human capital domains.

Our results support the initial assumption on the prime role of the labour market valuation of specific human capital components. The analysis revealed that occupation-/industry-specific work experience, total work experience and task-specific cognitive and non-cognitive skills are the most rewarding human capital domains. This result is in line with the literature and indicates that employers value actual abilities, knowledge and experience, and especially those related to the currently occupied job. Unlike studies that stress the decreasing importance of human capital in gender wage gap assessment, we argue that human capital cannot be generalized. Therefore, human capital should be viewed as a combination of multiple characteristics and traits, each having specific valuation properties; that is, wage returns on the labour market, and therefore a particular role in explaining the gender wage gap.

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Appendix A1

Definitions and empirical measures of human capital components

	Human capital characteristic	**Empirical measure**
Classical measures (well-investigated)	*Level of formal education*	Education groups are defined according to the International Standard Classification of Education (ISCED) 2011 as follows: (i) low – early childhood education, primary and lower secondary education; (ii) medium – upper secondary and postsecondary non-tertiary education; (iii) high – short-cycle tertiary education, bachelor's or equivalent level, master's or equivalent level, doctoral or equivalent level.
	Formal education field	Self-reported field of highest education level attained. Includes nine categories: (i) General programmes; (ii) Teacher training and education science; (iii) Humanities, languages and arts; (iv) Social sciences, business and law; (v) Science, mathematics and computing; (vi) Engineering, manufacturing and construction; (vii) Agriculture and veterinary; (viii) Health and welfare; (ix) Services.
	Total work experience	Total years of employment.
Acknowledged measures (under-investigated)	*Related work experience*	Total years of employment in occupation or industry similar to the currently occupied one. Thus, related experience reflects occupation- and industry-specific work experience
	Literacy skill	Test-based cognitive skill measure. Reported as a set of 10 plausible values. Relying on the definition used in the PIAAC dataset, literacy skill is described as "understanding, evaluating, using, and engaging with written text to participate in society, to achieve one's goals, and to develop one's knowledge and potential" (OECD 2013, p.3).
	Numeracy skill	Test-based cognitive skill measure. Reported as a set of 10 plausible values. Numeracy skill is defined as "the ability to access, use, interpret, and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life" (OECD 2013, p.3).
Task-specific human capital	*Cognitive skills use at work:*	
	(i) Literacy use at work	Job tasks requiring literacy ability includes two blocks. 1. Reading components: reading (1) directions or instructions; (2) letters, memos or mails; (3) newspapers or magazines; (4) professional journals or publications; (5) books; (6) manuals or reference materials; (7) financial statements; (8) diagrams, maps or schemes. 2. Writing components: writing (1) letters, memos or mails; (2) articles; (3) reports; (4) filling in forms.
	(ii) Numeracy use at work	Tasks demanding numeracy skill include: (1) calculating costs or budgets; (2) using or calculating fractions or percentages; (3) using a calculator; (4) preparing charts graphs or tables; (5) using simple algebra or formulas; (6) using advanced math or statistics.
	(iii) ICT use at work	Computer-based or internet related tasks include: (1) experience with computer at work; (2) using the internet for mail; (3) using the internet for work related information; (4) using the

	Human capital characteristic	Empirical measure
		internet to conduct transactions;(5) using computer for spreadsheets; (6) using computer for Word; (7) using computer for programming language; (8) use computer for real-time discussions.
	Non-cognitive skills use at work:	
	(i) Organization at work	Compound measure, based on 3 survey questions: (i) organizing own time; (ii) planning own activities; (iii) planning others' activities.
	(ii) Presenting / communication at work	Compound measure, based on 6 survey questions: (i) time cooperating with co-workers; (ii) sharing work-related information; (iii) teaching people; (iv) presentation; (v) selling; (vi) advising people.
	(iii) Negotiating at work	Compound measure, based on 2 survey questions: (i) Influencing people; (ii) Negotiating with people.
	Problem solving at work:	
	(i) Solving simple problems	How often solving simple problems at work.
	(ii) Solving complex problems	How often solving complex problems at work.

Appendix A2.

Demographic profile by gender and country

	Age (years)		**Cohabiting (%)**		**Have children (%)**		**Foreign-born (%)**		**Native speaker (%)**	
	Men	***Women***	***Men***	***Women***	***Men***	***Women***	***Men***	***Women***	***Men***	***Women***
Belgium	41	41	81.7	84.0	68.1	75.7	7.0	7.3	92.0	91.1
Czech Republic	39	41	79.2	68.7	65.2	76.7	4.9	4.1	95.8	96.4
Denmark	40	41	80.3	78.0	63.1	69.6	10.1	10.0	89.4	89.8
Estonia	39	41	81.6	74.2	69.5	76.7	11.2	12.0	98.4	98.7
Finland	41	42	90.2	85.7	63.7	70.0	5.0	5.6	95.5	95.5
France	40	41	81.2	78.2	65.9	72.7	12.8	10.4	88.0	89.8
Great Britain	39	40	69.9	65.8	58.0	65.3	14.4	13.9	86.7	89.8
Greece	40	39	70.4	70.2	54.1	66.2	10.8	14.2	93.3	91.6
Ireland	38	38	71.7	66.1	57.8	59.0	24.3	20.7	83.2	87.3
Italy	40	41	68.9	67.4	53.7	61.5	10.5	12.4	88.2	85.8
Lithuania	42	45	84.2	73.6	79.9	82.4	5.5	2.9	90.1	87.1
Netherlands	39	39	76.9	75.5	56.2	59.1	11.1	10.1	87.1	87.9
Norway	40	40	81.6	76.9	66.0	71.4	14.2	12.0	85.7	87.1
Poland	39	39	73.2	72.3	63.0	69.3	0.2	0.1	98.4	97.7
Slovakia	40	41	69.9	70.9	64.8	75.0	1.9	2.2	95.8	95.7
Slovenia	41	41	76.4	80.9	70.3	81.4	14.2	11.4	83.6	87.3
Spain	40	40	76.0	69.3	61.9	64.9	12.0	15.2	94.7	94.0

Note: Estimates are based on the PIAAC data. Each measure accounts for population in the relevant year.

Appendix A3.

Occupation profile by gender and country

	Occupation (%)							
	Skilled		Semi-skilled white-collar		Semi-skilled blue-collar		Elementary	
	Men	***Women***	***Men***	***Women***	***Men***	***Women***	***Men***	***Women***
Belgium	46.0	48.5	16.8	35.0	31.8	3.7	5.5	12.9
Czech Republic	32.5	36.6	15.0	33.2	48.8	18.0	3.7	12.1
Denmark	44.7	51.1	15.9	35.5	28.4	4.6	11.0	8.8
Estonia	36.8	50.5	9.4	28.5	46.7	10.8	7.2	10.1
Finland	44.0	45.7	14.6	40.3	36.3	5.8	5.1	8.1
France	46.9	41.2	13.7	36.9	31.9	6.2	7.5	15.7
Great Britain	42.1	37.2	21.4	51.7	24.8	2.8	11.7	8.2
Greece	32.0	35.3	31.8	44.5	25.0	4.2	11.2	16.1
Ireland	40.9	39.2	20.1	51.0	26.8	4.1	12.2	5.8
Italy	26.9	34.3	17.1	42.8	44.2	9.4	11.8	13.5
Lithuania	33.8	52.1	9.4	21.9	47.5	13.8	9.3	12.1
Netherlands	51.6	47.8	20.9	42.1	19.3	1.9	8.3	8.2
Norway	48.6	47.5	20.6	45.4	27.5	1.6	3.3	5.6
Poland	30.0	50.5	16.4	31.0	46.5	8.2	7.1	10.3
Slovakia	34.0	46.1	14.5	33.5	43.0	11.1	8.6	9.3
Slovenia	36.4	52.3	15.7	26.1	43.8	11.5	4.1	10.1
Spain	31.2	36.0	25.7	44.8	30.9	3.0	12.2	16.2

Note: Estimates are based on the PIAAC data. Each measure accounts for population in the relevant year

Appendix A4.

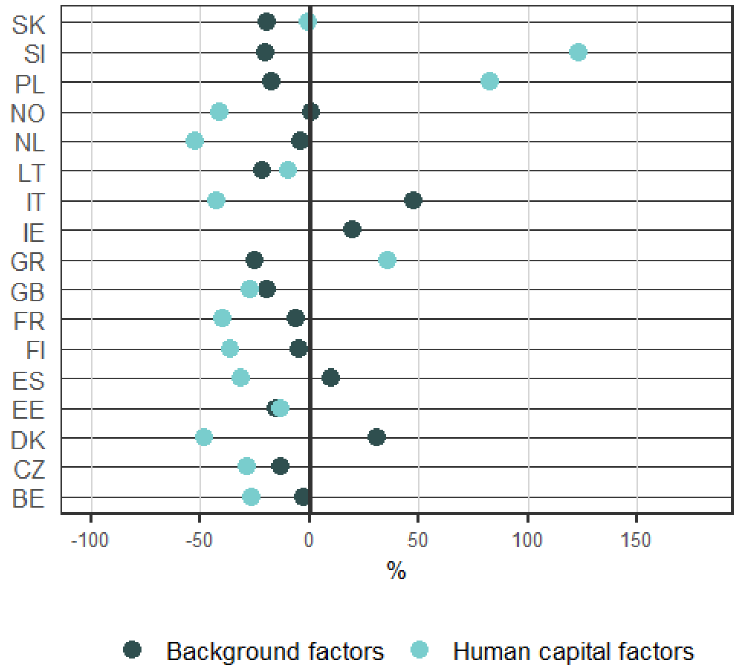
Estimates of the gender gap in hourly earnings across European countries

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Belgium	β	**-0.072**	**-0.084**	**-0.079**	**-0.078**	**-0.084**	**-0.086**	**-0.076**	**-0.06**	**-0.063**	**-0.06**	**-0.049**	**-0.051**	**-0.051**
	s.e.	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	N	5596	5140	4922	4804	4800	4268	4264	4240	4240	4240	3422	3418	3418
Czech Republic	β	**-0.206**	**-0.214**	**-0.198**	**-0.176**	**-0.168**	**-0.178**	**-0.162**	**-0.131**	**-0.133**	**-0.131**	**-0.123**	**-0.117**	**-0.12**
	s.e.	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	N	5310	4434	4300	4254	4254	3984	3978	3930	3930	3930	2726	2704	2700
Denmark	β	**-0.075**	**-0.092**	**-0.095**	**-0.079**	**-0.079**	**-0.086**	**-0.085**	**-0.068**	**-0.07**	**-0.068**	**-0.064**	**-0.064**	**-0.062**
	s.e.	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	N	9386	8234	8166	8102	8098	7016	7014	6984	6984	6984	6074	6042	6038
Estonia	β	**-0.355**	**-0.349**	**-0.353**	**-0.289**	**-0.295**	**-0.308**	**-0.299**	**-0.247**	**-0.256**	**-0.247**	**-0.258**	**-0.257**	**-0.255**
	s.e.	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.03***	0.03***	0.03***
	N	4043	3618	3421	3383	3382	3033	3031	3020	3020	3020	2091	2085	2084
Finland	β	**-0.154**	**-0.166**	**-0.167**	**-0.124**	**-0.132**	**-0.125**	**-0.118**	**-0.098**	**-0.108**	**-0.098**	**-0.096**	**-0.091**	**-0.091**
	s.e.	0.01***	0.01***	0.01***	0.01***	0.01***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	N	3333	2713	2667	2643	2643	2408	2408	2374	2374	2374	2093	2085	2081
France	β	**-0.115**	**-0.14**	**-0.135**	**-0.095**	**-0.108**	**-0.082**	**-0.08**	**-0.059**	**-0.067**	**-0.059**	**-0.061**	**-0.062**	**-0.062**
	s.e.	0.01***	0.01***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	N	3773	3248	2720	2688	2687	2228	2224	2147	2147	2147	1708	1691	1686
Great Britain	β	**-0.154**	**-0.158**	**-0.171**	**-0.12**	**-0.118**	**-0.105**	**-0.104**	**-0.074**	**-0.078**	**-0.074**	**-0.088**	**-0.082**	**-0.082**
	s.e.	0.02***	0.02***	0.02***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
	N	4885	3986	3417	3236	3230	2963	2962	2934	2934	2934	2402	2397	2396
Greece	β	**-0.103**	**-0.099**	**-0.096**	**-0.106**	**-0.112**	**-0.115**	**-0.119**	**-0.111**	**-0.111**	**-0.111**	**-0.087**	**-0.113**	**-0.114**
	s.e.	0.04***	0.04***	0.04***	0.04***	0.03***	0.04***	0.04***	0.04***	0.04***	0.04***	0.05*	0.05**	0.05**
	N	1266	1049	1048	1003	1003	847	846	840	840	840	539	538	537
Ireland	β	**-0.082**	**-0.073**	**-0.083**	**-0.094**	**-0.101**	**-0.078**	**-0.074**	**-0.029**	**-0.047**	**-0.029**	**-0.013**	**-0.011**	**-0.011**
	s.e.	0.02***	0.02***	0.02***	0.02***	0.02***	0.03***	0.03**	0.03	0.03	0.03	0.03	0.03	0.03
	N	2811	2333	2256	2242	2242	1509	1509	1503	1503	1503	1249	1246	1246

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Italy	β	**-0.063**	**-0.082**	**-0.087**	**-0.106**	**-0.114**	**-0.089**	**-0.086**	**-0.062**	**-0.066**	**-0.062**	**-0.061**	**-0.063**	**-0.066**
	s.e.	0.02***	0.03***	0.02***	0.03***	0.02***	0.03***	0.03***	0.03**	0.03**	0.03**	0.03*	0.03**	0.03**
	N	1987	1643	1635	1602	1602	1191	1191	1191	1191	1191	839	833	832
Lithuania	β	**-0.204**	**-0.187**	**-0.189**	**-0.223**	**-0.236**	**-0.238**	**-0.228**	**-0.199**	**-0.201**	**-0.199**	**-0.151**	**-0.151**	**-0.149**
	s.e.	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.05***	0.05***	0.05***
	N	2163	1627	1610	1599	1599	1552	1552	1550	1550	1550	886	886	886
Netherlands	β	**-0.105**	**-0.108**	**-0.113**	**-0.112**	**-0.109**	**-0.075**	**-0.076**	**-0.061**	**-0.063**	**-0.061**	**-0.049**	**-0.047**	**-0.046**
	s.e.	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	N	3209	2851	2814	2801	2800	2075	2075	2060	2060	2060	1849	1841	1838
Norway	β	**-0.142**	**-0.158**	**-0.156**	**-0.114**	**-0.12**	**-0.124**	**-0.124**	**-0.089**	**-0.095**	**-0.089**	**-0.086**	**-0.084**	**-0.084**
	s.e.	0.01***	0.01***	0.01***	0.01***	0.01***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	N	3620	3101	3065	2602	2601	2341	2340	2332	2332	2332	2098	2090	2089
Poland	β	**-0.08**	**-0.098**	**-0.109**	**-0.141**	**-0.142**	**-0.17**	**-0.156**	**-0.139**	**-0.145**	**-0.139**	**-0.133**	**-0.132**	**-0.132**
	s.e.	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
	N	3964	3730	3646	3619	3619	3315	3285	3258	3258	3258	1883	1866	1866
Slovakia	β	**-0.211**	**-0.215**	**-0.216**	**-0.207**	**-0.208**	**-0.205**	**-0.2**	**-0.176**	**-0.179**	**-0.176**	**-0.18**	**-0.173**	**-0.168**
	s.e.	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.03***	0.03***	0.03***
	N	2512	2422	2412	2398	2398	2270	2268	2251	2251	2251	1290	1283	1279
Slovenia	β	**-0.039**	**-0.067**	**-0.069**	**-0.105**	**-0.126**	**-0.124**	**-0.115**	**-0.087**	**-0.095**	**-0.087**	**-0.078**	**-0.079**	**-0.079**
	s.e.	0.02**	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	N	2245	2120	2077	2045	2045	1878	1878	1846	1846	1846	1350	1341	1339
Spain	β	**-0.142**	**-0.114**	**-0.124**	**-0.14**	**-0.147**	**-0.154**	**-0.14**	**-0.115**	**-0.12**	**-0.115**	**-0.111**	**-0.107**	**-0.111**
	s.e.	0.02***	0.02***	0.02***	0.02***	0.02***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
	N	2506	2345	2281	2240	2239	1406	1406	1391	1391	1391	1074	1070	1070

Note: Dependent variable is log of hourly earnings of salaried workers. Estimations account for country-specific population weights. Model (1) includes female dummy. The rest of the models include cumulatively: (2) age, age squared, living with a spouse/partner, children, immigration status, being a native speaker; (3) mother's and father's highest level of education (3 ISCED categories); (4) occupation level (4 ISCO groups), industry of employment (based on NACE Rev. 2 classification), type of employment contract; (5) own highest education level; (6) field of education; (7) total work experience (5-year intervals); (8) work experience related to current employment (6 categories, from "none" to "more than 3 years"); (9) literacy skill (based on the 1st plausible value, 10-points intervals); (10) numeracy skill (based on the 1st plausible value, 10-points intervals); (11) use of literacy, numeracy and ICT skills at work; (12) frequency of organizing, presenting and negotiating at work; (13) frequency of solving simple and complex problems at work. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A5. Contributions to the gender wage gap, based on the OLS regression results



Note: The estimates are derived from OLS regression similar to the one presented in Appendix A4. The graph replicates Figure 6, but with the reverse order of adding the controls. Specifically, human capital factors added first, and background factors included on the top of human capital characteristics (i.e. specifications 5–13 are changed into 2–10 and 2–4 into 11–13). Background factors include factors added in specification 2 to 4 of Appendix A4. Human capital factors incorporate controls added in specification 5 to 13 of Appendix A4. Positive contribution implies that the factors widen the gender wage gap, negative contribution – narrow the gap.

Appendix A6.

Female-specific wage returns to the analysed human capital domains

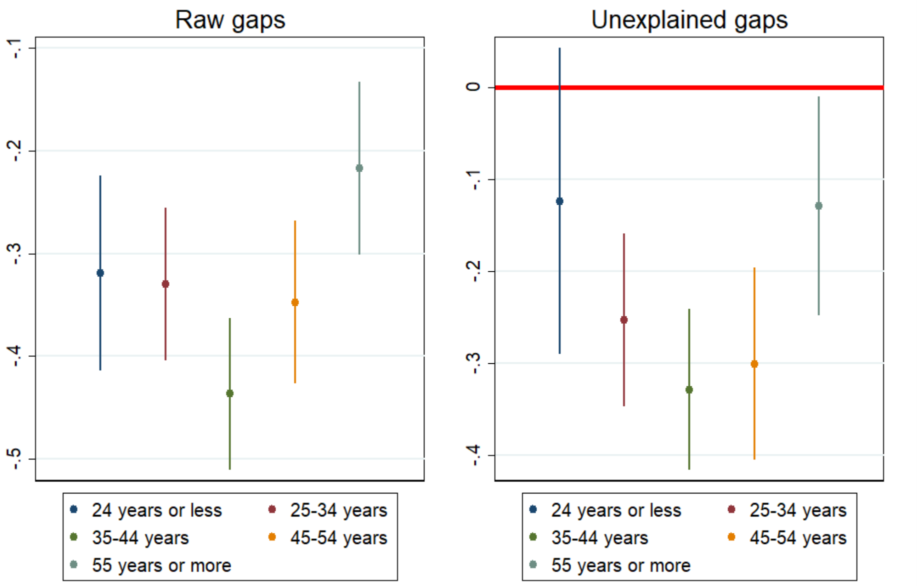
Female #	BE	CZ	DK	EE	FI	FR	GB	GR	IE	IT	LT	NL	NO	PL	SK	SI	ES
	β/s.e.	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e	β/s.e
Medium education	0.100	0.052	-0.025	0.035	-0.052	0.081	0.075	0.105	0.050	-0.198	-0.291	0.025	-0.04	0.069	0.429	0.010	0.116
	0.03***	0.07	0.02	0.06	0.04	0.04*	0.06	0.11	0.06	0.21	0.12**	0.06	0.04	0.10	0.19**	0.05	0.08
Higher education	0.002	-0.045	-0.048	0.137	-0.071	0.023	0.031	-0.019	0.000	-0.101	-0.204	0.032	-0.03	0.046	0.054	0.047	0.161
	0.03	0.05	0.03*	0.06**	0.04*	0.05	0.06	0.13	0.00	0.07	0.14	0.04	0.04	0.07	0.06	0.05	0.07**
Female # STEM field	-0.061	-0.069	0.016	-0.111	0.030	-0.083	-0.016	-0.017	0.004	-0.030	0.124	-0.117	-0.02	-0.01	-0.020	-0.020	0.046
	0.03**	0.05	0.02	0.06*	0.04	0.04*	0.07	0.11	0.08	0.08	0.09	0.05**	0.04	0.07	0.07	0.06	0.08
Humanities field	-0.028	-0.004	0.001	0.012	0.052	-0.070	-0.070	-0.137	-0.006	0.016	-0.051	-0.100	0.011	0.067	0.001	0.033	0.045
	0.03	0.06	0.02	0.06	0.04	0.05	0.06	0.14	0.07	0.07	0.10	0.04***	0.04	0.08	0.07	0.07	0.07
Total work experience	0.004	0.005	-0.001	0.002	-0.004	-0.002	-0.004	-0.014	-0.006	-0.003	0.004	-0.000	0.000	0.000	0.003	-0.000	0.002
	0.00***	0.00***	0.00*	0.00	0.00***	0.00	0.00**	0.00***	0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Related work experience	0.005	0.017	0.004	-0.033	-0.005	0.005	0.001	0.027	0.007	0.003	-0.028	-0.013	-0.01	-0.00	-0.022	-0.008	0.023
	0.01	0.01*	0.00	0.01**	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.01	0.01
Literacy	-0.000	-0.001	-0.001	0.001	-0.000	-0.000	-0.000	0.002	0.001	0.000	-0.001	-0.000	-0.00	0.001	0.001	-0.001	0.000
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Numeracy	0.000	0.003	0.000	-0.001	0.001	0.000	-0.000	-0.002	0.000	-0.002	0.001	-0.000	0.000	-0.00	-0.001	-0.000	-0.002
	0.00	0.00***	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Literacy SUW	0.008	-0.077	-0.001	0.096	-0.015	-0.034	0.021	0.013	0.072	0.028	0.109	-0.021	-0.00	0.014	0.022	0.007	-0.039
	0.02	0.04**	0.02	0.04**	0.02	0.03	0.04	0.07	0.05	0.04	0.06*	0.03	0.03	0.05	0.04	0.03	0.04
Numeracy SUW	-0.001	-0.015	0.012	-0.061	-0.011	-0.035	-0.031	-0.025	-0.056	0.024	-0.095	0.001	-0.00	0.008	-0.018	-0.022	0.009
	0.01	0.02	0.01	0.03**	0.02	0.02**	0.03	0.04	0.03**	0.03	0.04**	0.02	0.02	0.03	0.03	0.02	0.03
ICT SUW	-0.039	0.073	0.027	0.013	0.011	0.053	-0.015	0.054	0.038	0.020	-0.055	0.016	-0.01	-0.00	0.113	0.004	-0.011
	0.02**	0.03**	0.01*	0.03	0.02	0.03**	0.04	0.06	0.03	0.04	0.05	0.03	0.02	0.04	0.04***	0.03	0.04
Organization at work	0.009	-0.034	0.016	-0.006	0.030	-0.028	-0.025	0.004	-0.017	0.000	0.059	-0.011	0.008	-0.00	-0.029	0.010	-0.019
	0.01	0.02*	0.01	0.03	0.02**	0.02*	0.02	0.04	0.02	0.03	0.03*	0.02	0.01	0.03	0.02	0.02	0.03
Presenting at work	0.011	0.001	-0.009	0.063	-0.029	0.053	-0.040	0.075	-0.098	-0.004	-0.033	0.029	-0.04	0.002	-0.009	-0.062	-0.032
	0.02	0.03	0.01	0.03*	0.02	0.03**	0.03	0.06	0.05**	0.04	0.05	0.02	0.02	0.04	0.03	0.03**	0.04

Female #	BE β/s.e.	CZ β/s.e	DK β/s.e	EE β/s.e	FI β/s.e	FR β/s.e	GB β/s.e	GR β/s.e	IE β/s.e	IT β/s.e	LT β/s.e	NL β/s.e	NO β/s.e	PL β/s.e	SK β/s.e	SI β/s.e	ES β/s.e
Negotiation at work	-0.008	0.025	-0.023	-0.008	-0.003	-0.019	0.014	-0.021	0.004	-0.042	0.050	-0.011	-0.01	-0.04	0.013	0.006	0.004
	0.01	0.01*	0.01***	0.02	0.01	0.01	0.02	0.03	0.03	0.02**	0.03*	0.01	0.01	0.02	0.02	0.02	0.02
Solving simple problems	-0.017	0.030	-0.015	0.018	0.004	0.012	-0.013	0.024	0.043	0.045	-0.018	-0.029	-0.01	0.009	-0.024	0.019	0.005
	0.01	0.02*	0.01*	0.02	0.02	0.02	0.02	0.04	0.03	0.03	0.03	0.02*	0.02	0.03	0.03	0.02	0.03
Solving complex problems	-0.000	-0.002	-0.013	-0.001	0.021	-0.000	-0.003	-0.007	-0.031	-0.044	0.016	0.043	0.002	-0.05	-0.017	-0.003	0.003
	0.01	0.02	0.01	0.02	0.01	0.01	0.03	0.03	0.03	0.03	0.03	0.02**	0.01	0.03*	0.03	0.02	0.02
N	3418	2700	6038	2084	2081	1686	2396	537	1246	832	1085	1838	2089	1866	1279	1339	1070
R^2	0.417	0.345	0.398	0.393	0.496	0.453	0.501	0.530	0.471	0.449	0.368	0.535	0.468	0.407	0.358	0.428	0.429

Note: Dependent variable is log of hourly earnings of salaried workers. Estimations account for country-specific population weights. Model additionally includes female dummy, age, age squared, living with a spouse/partner, children, immigration status, being a native speaker, mother's and father's highest level of education, occupation level, industry of employment, type of employment contract, own highest education level, field of education, total work experience, work experience related to current employment, literacy skill, numeracy skill, use of literacy, numeracy and ICT skills at work, frequency of organizing, presenting, negotiating at work, solving simple and complex problems at work. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A7.

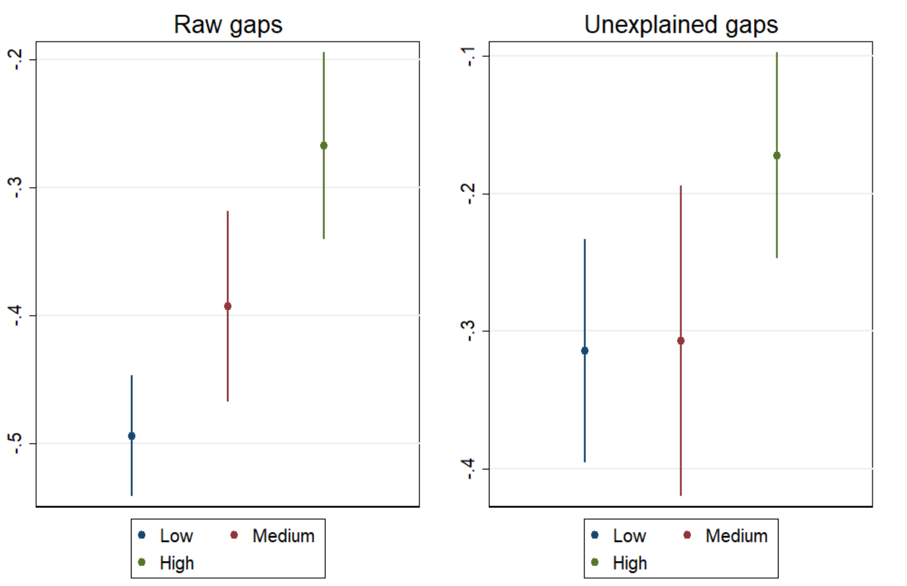
Raw and unexplained gender wage gap in Estonia across age groups



Note: Estimates are based on PIAAC sample for Estonia. Dependent variable is hourly wage of salaried employees. Raw gaps are estimated based on the model controlling for gender only. Unexplained gaps are estimated based on the model identical to specification 13 from Appendix A4, with age variable excluded. Estimates account for population weight.

Appendix A8.

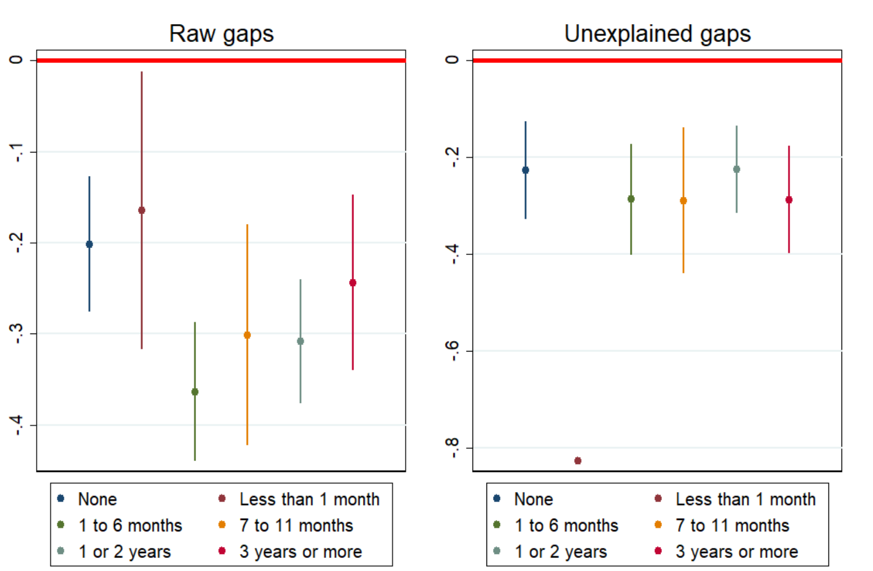
Raw and unexplained gender wage gap in Estonia across education levels



Note: Estimates are based on PIAAC sample for Estonia. Dependent variable is hourly wage of salaried employees. Raw gaps are estimated based on the model controlling for gender only. Unexplained gaps are estimated based on the model identical to specification 13 from Appendix A4, with formal education degree variable excluded. Education levels are defined as follows: Low – early childhood education, primary and lower secondary education; Medium – upper secondary and postsecondary non-tertiary education; High – short-cycle tertiary education, bachelor's or equivalent level, master's or equivalent level, doctoral or equivalent level .Estimates account for population weight.

Appendix A9.

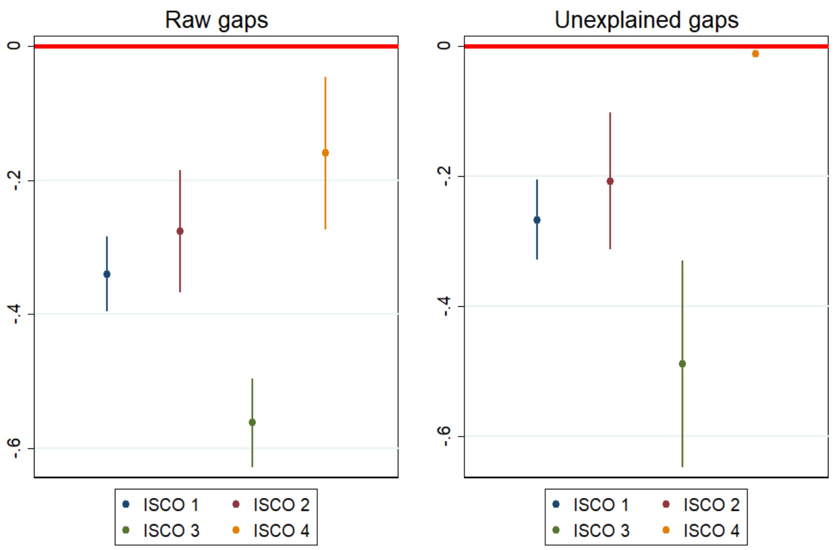
Raw and unexplained gender wage gap in Estonia across occupation-/industry-related experience groups



Note: Estimates are based on PIAAC sample for Estonia. Dependent variable is hourly wage of salaried employees. Raw gaps are estimated based on the model controlling for gender only. Unexplained gaps are estimated based on the model identical to specification 13 from Appendix A4, with related experience variable excluded. Estimates account for population weight.

Appendix A10.

Raw and unexplained gender wage gap in Estonia across occupation levels



Note: Estimates are based on PIAAC sample for Estonia. Dependent variable is hourly wage of salaried employees. Raw gaps are estimated based on the model controlling for gender only. Unexplained gaps are estimated based on the model identical to specification 13 from Appendix A4, with occupation variable excluded. Occupation groups are defined as follows: ISCO 1 – skilled occupations; ISCO 2 – semi-skilled white-collar; ISCO 3 – semi-skilled blue-collar; ISCO 4 – elementary occupations. Estimates account for population weight.

KOKKUVÕTE

Rahvusvahelisele täiskasvanute oskuste uuring (PIAAC - *Program of International Assessment of Adult Competencies*) võimaldab senisest tunduvalt põhjalikumalt analüüsida inimkapitali ja selle seost soolise palgalõhega võttes lisaks nn klassikalistele inimkapitali näitajatele (haridus, töökogemus) arvesse ka töötajate kognitiivseid ja mittekognitiivseid oskusi ning nende kasutamist töökohtadel. Siit tulenevalt on uurimistöö eesmärgiks välja selgitada, kuidas Euroopa riikide tööturgudel väärtustatakse inimkapitali erinevaid osasid tuues välja soolised erinevused nii inimkapitalis kui selle eri osade väärtustamises.

Töös on kasutatud Gelbachi dekompositsiooni analüüsimaks 17 Euroopa riigi näitel, kuidas inimkapitali erinevad osad palga kaudu tööturgudel tunnustust leiavad. Valitud analüüsimeetodi korral on palgavõrrandite hindamistulemused robustsed ning ei sõltu sellest, millises järjekorras selgitavaid muutujaid mudelitesse lülitatakse.

Analüüsi tulemusena leidis kinnitust väide, et inimkapitali ei saa üldistada. Selle osasid tuleb hinnata eraldi, neid väärtustatakse tööturgudel erinevalt ning erinevalt väärtustab tööturg ka meeste ja naiste inimkapitali. Kõige enam hinnatakse tööturgudel erialaspetsiifilist töökogemust ning töötajate kognitiivseid (eelkõige matemaatilist kirjaoskust) ja mittekognitiivseid oskusi ning nende kasutamist. Haridusele ja eriti haridusvaldkonnale pööratakse tööturgudel jätkuvalt tähelepanu, kuid samas on just haridusnäitajad need, mis soolist palgalõhet reeglina suurendavad.

Uurimistöö tulemustest nähtub, et inimkapitali erinevaid komponente väärtustatakse Euroopa riikide tööturgudel erinevalt ning seda ka soolises lõikes. Eesti muster on rohkem sarnane selliste Ida Euroopa riikidega nagu Slovakkia, Sloveenia, Leedu, Tsehhi, ka Poola. Nendes riikides on soolised erinevused naiste tööhõives, tööstaažis, matemaatika oskustes ning kognitiivsete oskuste kasutamises reeglina väiksemad kui Lääne Euroopa riikides. Samas on enamuses Ida Euroopa riikides nagu Eestiski sooline palgalõhe suhteliselt kõrge.

Eestis on soolised palgaerinevused kõige enam selgitatud tööga seotud komponentide (valdkond, eriala, töökoht) poolt (24.6%). Töötamine töökohal, mis vastab varasemale eralasele kompetentsile, selgitab soolisest palgalõhest märkimisväärse osa - 12.1%. Töökoha vahetus, mis naiste puhul on sageli seotud perekondlike põhjustega, võib vähendada palka ning seeläbi suurendab ka palgalõhet. Haridus ja eriti just haridusvaldkond selgitavad Eestis olulise osa soolisest palgalõhest (vastavalt 3.5% ja 10.6%), kuid paraku need inimkapitali komponendid suurendavad palgalõhet. Soolised palgaerinevused varieeruvad vanuse- ja haridusgruppide ning töökohtade lõikes. Näiteks suurim sooline palgalõhe (sh suurima grupisisese varieeruvusega) on ISCO 3 grupis ehk osaliselt kvalifitseeritud sinikraedel.