Gender disparities in wage returns to human capital components: how different are European labour markets?

Tverdostup, Maryna; Paas, Tiiu

Baltic Journal of Economics

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rbec20

Gender disparities in wage returns to human capital components: how different are European labour markets?

Maryna Tverdostup & Tiiu Paas

To cite this article: Maryna Tverdostup & Tiiu Paas (2022) Gender disparities in wage returns to human capital components: how different are European labour markets?, Baltic Journal of Economics, 22:1, 28-48, DOI: 10.1080/1406099X.2022.2033418

To link to this article: https://doi.org/10.1080/1406099X.2022.2033418

BALTIC JOURNAL OF ECONOMICS
2022, VOL. 22, NO. 1, 28–48
https://doi.org/10.1080/1406099X.2022.2033418

Gender disparities in wage returns to human capital components: how different are European labour markets?

Maryna Tverdostup [a,b] and Tiiu Paas[b]

[a]The Vienna Institute for International Economic Studies (wiiw), Vienna, Austria; [b]School of Economics and Business Administration, University of Tartu, Tartu, Estonia

ABSTRACT
The paper investigates the gender wage gap in relation to the multi-dimensional human capital measure, asking which human capital components are most valued in the European labour markets. Relying on the Programme of International Assessment of Adult Competencies (PIAAC) data for seventeen European countries and applying Gelbach (2016) decomposition, we document remarkable cross-country disparities in the returns to different human capital components. The only dimension that consistently and significantly decreases gender wage disparities in all countries is work experience related to a currently occupied position. Numeracy cognitive ability is another strong predictors of the gender wage disparity, while job-specific cognitive and non-cognitive skills reveal weaker than expected association with the gender wage gap. Unlike the studies stressing the decreasing importance of human capital in the gender wage gap assessment, we argue that a narrow definition of human capital may undermine the actual effect of the latter.

ARTICLE HISTORY
Received 1 June 2021
Accepted 20 January 2022

KEYWORDS
Decomposition; European labour markets; gender wage gap; human capital

JEL
J16; J31; J61

1. Introduction

In recent decades, the gender wage gap has remained an open issue, despite ever-increasing scholarly attention. 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 remains an essential driver of wage disparity, with an extensive theoretical and empirical grounding (Polachek, 2008).

This paper contributes to the literature by incorporating the multidimensional human capital measure, which includes several empirically novel domains, into the gender wage gap analysis. The study relies on the Programme of International Assessment of Adult Competencies (PIAAC) data for seventeen European countries. Specifically, we incorporate a set of classical and novel human capital components,[1] including (i) formal education

CONTACT Maryna Tverdostup tverdostup@wiiw.ac.at The Vienna Institute for International Economic Studies (wiiw), Rahlgasse 3, Vienna 1060, Austria
Supplemental data for this article can be accessed at https://doi.org/10.1080/1406099X.2022.2033418.

degree and field; (ii) overall work experience and work experience related to the current job, hereinafter total and job-specific experience; (iii) cognitive abilities in literacy and numeracy domains; (iv) job-specific cognitive, non-cognitive and problem-solving skills, measured by the frequency of performing job tasks related to specific skill domain.

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. Formal education as the most canonical measure of human capital has long been viewed as the main driver of labour market success (Blau & Kahn, 2017; Goldin et al., 2006; Schultz, 1995). However, the explanatory power of formal education has decreased in recent decades (Cha & 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 persistently low share of females in STEM (Science, Technology, Engineering and Mathematics) disciplines is addressed as another important factor behind male-female wage gap (Angle & Wissman, 1981; Black et al., 2008). 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 marker 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 anticipated lower productivity of women and, consequently, lower wages (Goldin et al., 2006; Kimhi & Hanuka-Taflia, 2019; Olivetti, 2006; O'Neill & Polachek, 1993).

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

However, the growing importance of occupation- and industry-specific skills, as well as task-specific human capital provides a novel context to the issue of work experience and gender wage gap (Gathmann & Schönberg, 2010; Gibbons & Waldman, 2004). Occupation and industry segregations (Blau & Kahn, 2017; Shatnawi et al., 2014; Vieira et al., 2005), due to gendered preferences, tastes, competencies or discrimination, lead to males and females possessing different occupation-, or firm-specific abilities (Lazear, 2009; Sullivan, 2010; Zangelidis, 2008).

The common feature of most 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 are omitted. Despite several studies stressing that the key focus should be on a broad definition of the human capital (Blau & Kahn, 2017; Goldin et al., 2006; Grove et al., 2011), most papers still focus on the human capital measure restricted to a single or several domains. Moreover, general and job-task-specific cognitive and non-cognitive abilities are commonly not addressed in the literature, due to the scarcity of empirical data. These are precisely the research gaps this paper aims to contribute to.

To the best of our knowledge, this is the first paper in gender wage gap analysis to employ a direct measure of job-specific skills as a proxy for occupation-/industry-specific abilities. The existing evidence on the role of job-specific skills in explaining the gender wage gap is limited (Yamaguchi, 2018), mostly due to the empirical challenge of measuring the skills related to a currently occupied job. Therefore, the PIAAC data provide a unique source of job-specific skill measures, allowing 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, job-specific 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. Second, we assess the individual contribution of each specific component in explaining the gender pay gap, applying path-independent conditional decomposition by Gelbach (2016). The latter empirical exercise 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.[2] 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.

We document that men and women indeed possess substantially different human capital attainments. However, we do not find systematically worse human capital outcomes among females. Instead, we find disparities varying across different human capital domains, which are stronger either among men or women. The paper shows that human capital largely explains the gender wage gap in all analysed countries. Most importantly, we document the drastically diverse wage effects of different human capital components across countries. The only analysed dimension, which is consistently and significantly associated with gender wage disparities in all counties, is job-specific experience, i.e. tenure on the current job. Women's shorter job-specific work experience may stem from family reasons indicating that women adjust their labour market behaviour to the current conditions and family-level factors more often than men do. There may be other factors behind females' shorter job-specific tenure, such as employer's attitudes and unequal treatment, causing women to change jobs more frequently. Furthermore, unobserved abilities may play a role in explaining the positive association between the gender wage gap and longer job-specific experience, as employers may keep high-ability women employed and pay them a competitive wage, resulting in longer job-specific experience and lower gender wage gap. However, we cannot disentangle the underlying factors with the data our research relies on.

The wage effects of all other human capital domains vary across countries, with some components (numeracy ability, job-specific skills, measured by the frequency of on-the-job use of cognitive, non-cognitive, and problem-solving skills at work) significantly associated with the gender wage gap reduction in several countries. Yet, the role of non-canonical factors, such as job-specific skills appeared lower than expected, which may arise from (i) role of unobserved factors, such as unobserved abilities or job characteristics; (ii) relatively small variation of non-canonical human capital components across respondents in some countries; (iii) relatively small sample size in case of several countries, e.g. Greece, Italy, Lithuania, and Spain.

Our results confirm that the gender human capital gap should be addressed as a multiple of numerous components, which altogether shape the human capital profile. However, each component has different valuation on the labour market and contributes differently to the gender wage disparity. Hence, this paper shows that there is still a lot to learn from human capital, especially when it incorporates components beyond formal education degree and total work experience. Studying the diversity of human capital components and returns to specific skills has special importance in times of economic recessions, such as the one caused by the COVID-19 pandemic. The new strand of literature addresses the question of whether adjustment to turbulent conditions differs by gender, with a special focus on the role of different human capital components in these adjustment processes (Doorley et al., 2021). This suggests the rising importance of human capital research in the context of employment and wage disruption and recovery in post-pandemic times.

The rest of the paper is organized as follows. Section 2 discusses data and methodology. Section 3 presents major results in two parts. Part one discusses descriptive human capital profiles of men and women across analysed counties. Part two estimates and discusses the results of Gelbach decomposition. Section 4 summarizes and concludes.

2. Data and methodology

2.1. Data

The analysis relies on the data from the Programme of International Assessment of Adult Competencies (PIAAC), collected within a Survey of Adult Skills (OECD, 2013). 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. Due to the data protection policies, several EU countries did not disclose income variables. Therefore, our final sample includes only seventeen European countries – Belgium, Czech Republic, Denmark, Estonia, Finland, France, Greece, Ireland, Italy, Lithuania, Netherlands, Norway, Poland, Slovakia, Slovenia, Spain, and Great Britain. We weighted each country-specific sample to the population in the relevant year. The PIAAC samples for each country rely on a target population, which is mainly drawn on population registers and is comparable across countries. Complex sampling procedures ensure high representativeness of the sample and cross-country comparability (OECD, 2019).[3]

Appendix A1 discusses all human capital domains incorporated in the analysis, as well as explanations of their PIAAC-based empirical measures. While the empirical measures for the majority of the domains are straightforward, job-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.[4] Following Allen et al. (2013), we define job-specific skills in a particular domain as an average over a number of components.[5]

Although PIAAC data have strong advantages when it comes to test-based cognitive skill measures, several limitations should be acknowledged. The PIAAC dataset provides only cross-sectional data and it does not allow for causal identification, therefore, all reported effects should be addressed as associations. Following Hanushek et al. (2017) we expect that estimated relationships hold in presence of plausible alternative explanations of wage returns to human capital, such as unobserved cognitive and non-cognitive abilities or behavioural factors. Another limitation refers to omission of unemployed respondents. Since the wage is reported only for currently employed respondents, unemployed respondents are excluded from our sample. However, to check for potential selection we analysed a descriptive profile of unemployed respondents finding no systematic differences across employed and unemployed samples in several observed characteristics.[6]

Finally, the intensity of skill use at work measures need to be address with cautiousness. Firstly, these measures are self-reported and the formulation of questions makes arbitrary responses possible. However, individual deviations should not be correlated and, consequently, they balance out in the overall sample. Secondly, the skill use at work measure is a proxy of human capital, not a direct measure, but it is expected to precisely reflect extents of specific skill use domains. Yet, skill use measures should not be treated as human capital per se, rather as mediators suggesting how intensely certain ability is applied at work, thus serving as a good measure of productive human capital. Thirdly, intensity of skill use may relate to characteristics other than human capital, as men and women may self-select into jobs requiring application of specific skills based on unobserved ability or preference toward specific job characteristics. To partly address this issue, we control for an extensive set of detailed employment characteristics to largely rule out a role of self-selection into jobs. Individual motivation is likely affecting skill use intensity. However, we do not expect motivation to differ systematically for men and women and as we control for a large set of background characteristics the role of potential motivation bias is expected to be small, yet it has to be acknowledged.

2.2. Empirical approach

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

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

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 (background characteristics) with vector γ comprising respective regression coefficients. Vector HC' incorporates an extensive set of human capital characteristics, namely (i) formal education level; (ii) field of education; (iii) total work experience; (iv) job-specific experience; (v) literacy ability; (vi) numeracy ability; (vii) use of literacy, numeracy, and ICT skills at work – job-specific cognitive skills; (viii) organizing, presenting, and negotiating at work – job-specific non-cognitive skills; and (ix) solving simple and complex problems at work – job-specific problem-solving skills. The estimated regression coefficients of human capital variables are stored in the vector θ.[7]

To elicit path-independent individual effects of human capital components, unaffected by the sequence of adding the controls, we apply a decomposition methodology developed by Gelbach (2016) to estimate the earnings Equation (1). The estimation procedure relies on the omitted variables bias formula and the decomposition procedure derives individual contributions from variables conditional on all covariates. Therefore, the estimates are not affected by the sequencing problem and are robust.[8] This decomposition procedure gives a clear measure of the 'effect of adding covariates', unlike the widely used OLS regression with a stepwise inclusion of controls.

Gelbach decomposition procedure was previously used to analyse the gender wage gap (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 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; Buckles and Price (2013) explored the role of marriage on infants' health applying 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 test-based cognitive ability domain is reported as a set of ten plausible values. Within the descriptive analysis, we account for all ten plausible values and apply Jackknife replication methodology (OECD, 2013). Specifically, the replication procedure benefits the analysis as it measures standard errors without overestimating them.[9] However, Gelbach decomposition accounts for two skill domains simultaneously and using a whole set of plausible values and Jackknife replication procedure requires an immense computational power.[10] Therefore, the gender wage gap analysis relies on the first plausible value for literacy and numeracy and incorporates country-specific population weights. Similar approach was implemented in several PIAAC-based studies (Anspal, 2015; De La Rica et al., 2020; Hanushek et al., 2015; Hanushek et al., 2017; Smith & Fernandez, 2017).

3. Empirical results and discussion

3.1. Disparities in gender profiles across countries

We start by discussing average human capital characteristics of our sample.[11] Figure 1 depicts education profiles of men and women across countries. In line with a large strand of literature, we document that women hold, on average, higher levels of education compared to men (Author & Wasserman 2013; Becker et al., 2010; Goldin et al., 2006). Notably, we find significant cross-country heterogeneity in the educational profiles of the respondents. The country and gender-specific distributions of education fields are visualized in Figure 2. We document that males substantially outnumber females in STEM majors in line with the previous literature (Blau et al., 2014). The substantial gender imbalance in university majors is recognized as one of the factors behind gender wage disparity, as it appears as a more precise predictor of exact abilities and knowledge, compared to mere education level.

We document a clear-cut gender gap in work experience (Figure 3). The descriptive evidence suggests that in all countries, except Estonia, Slovakia, Slovenia and Czech

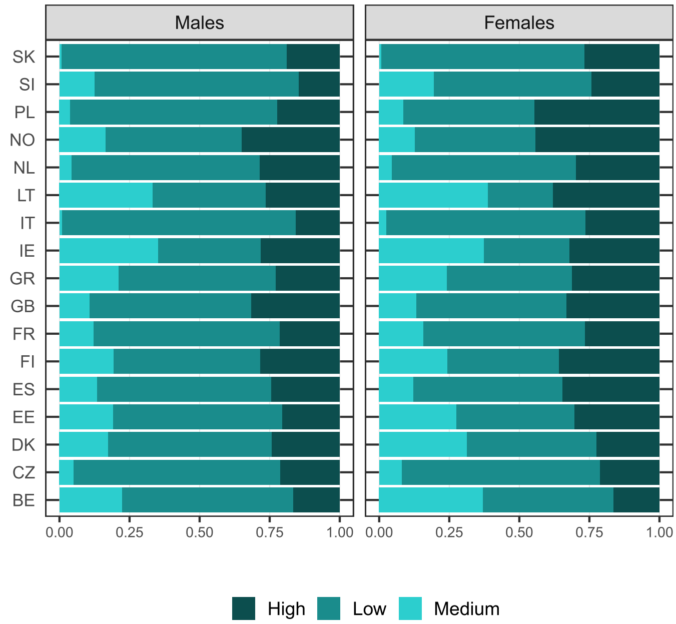

Figure 1. Distribution of education levels by gender and country.

Note: The estimates are based on Programme of International Assessment of Adult Competencies data and account for population weights.

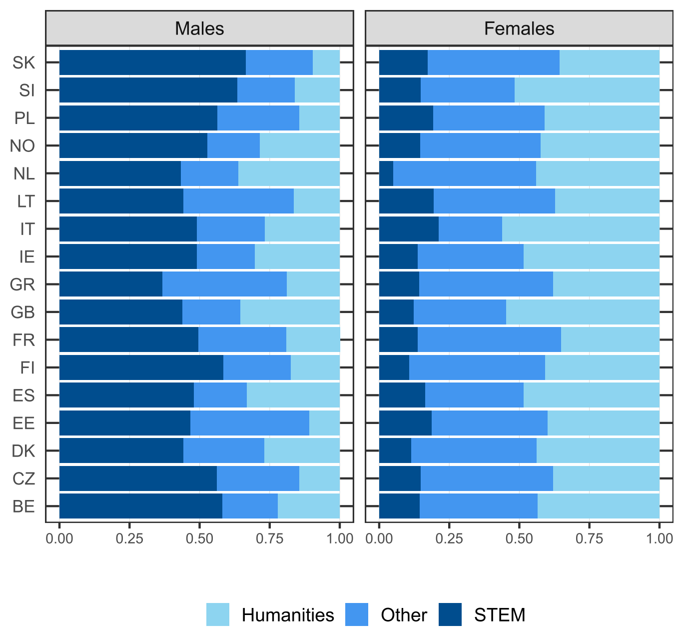

Figure 2. Distribution of education fields by gender and country.

Note: The estimates are based on Programme of International Assessment of Adult Competencies data and account for population weights. STEM field includes science, mathematics, and computing, engineering. Humanities incorporate languages and arts, social sciences, business and law, teacher training, and educational sciences.

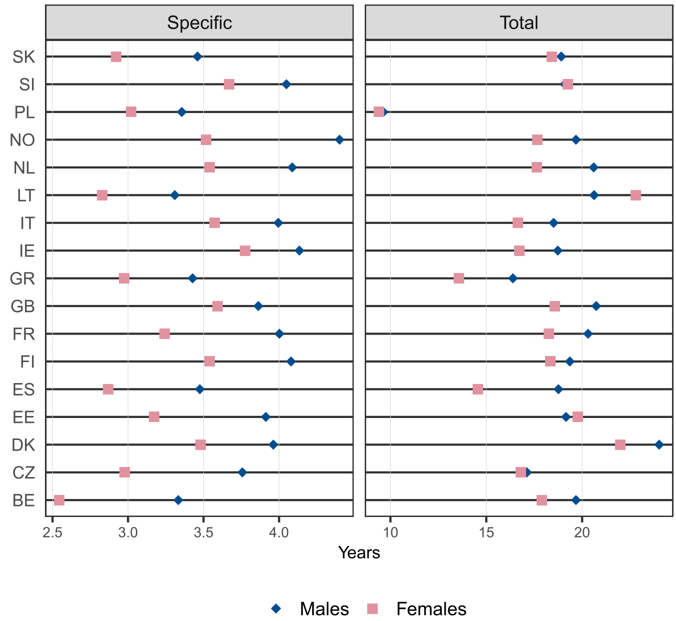

Figure 3. Average total and job-specific experience by gender and country.

Note: The estimates are based on Programme of International Assessment of Adult Competencies data and account for population weights.

Republic, men have, on average, more years of total work experience. When it comes to job-specific experience, in all countries without exception women have significantly lower job-specific tenure levels.

Two stark observations emerge from the descriptive evidence on the cognitive skill levels across men and women (Figure 4). 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 been already documented in the literature (Hanushek et al., 2015; Niederle & Vesterlund, 2010). Our findings, generally, provide further support to this evidence. However, in several countries (Italy, Lithuania, Poland, Slovakia, and Slovenia) the gender gap in the numeracy score is insignificant.

The results of job-specific skills as an approximation of occupation-/industry-specific human capital show that in nearly all countries except some post-socialist countries (Lithuania, Poland, Slovenia, and Slovakia), men apply literacy and numeracy abilities systematically more often than women (Appendix A4). We also document much stronger gender equality in job-specific non-cognitive skills compared to job-specific cognitive skills, suggesting that men and women apply organization, presentation, and negotiation skills at similar rates. We suppose that cross-country variability in using non-cognitive abilities can somewhat originate from differences in work culture, as well as from prevalence of gender norms. Some countries, i.e. Scandinavian states, are more prone to horizontal work structures implying intense cooperation and negotiations between co-workers, while other countries, i.e. the ones with more conservative norms, comply with vertical

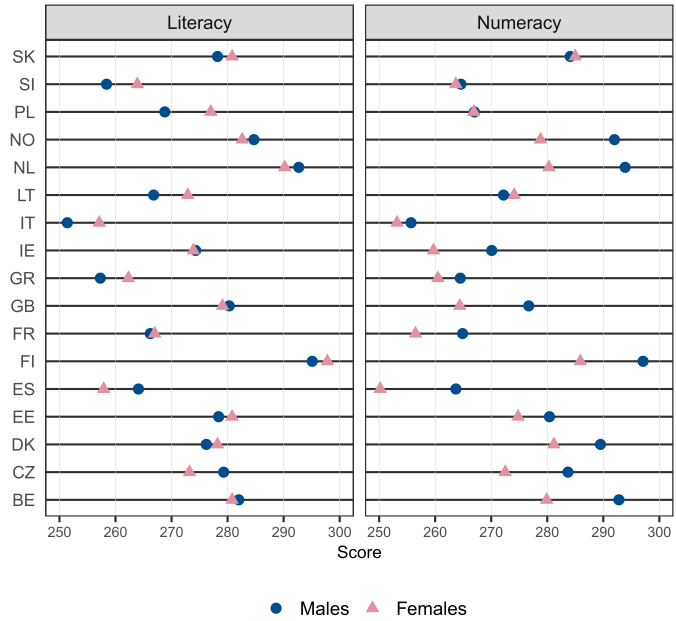

Figure 4. Average cognitive skills by gender and country.

Note: The estimates are based on Programme of International Assessment of Adult Competencies data. Average values are derived relying on a full set of 10 plausible values for both literacy and numeracy skills and account for population weights.

structures with minimal communication and negotiations between the hierarchical layers.[12]

Our descriptive estimates suggest that men solve both simple and complex problems more frequently than women with marginally larger gender gaps for complex problems (Appendix A4). Systematic gender gaps can originate from occupation and industry segregation with women self-selecting into more stable and less stressful jobs, which yield less 'trouble-shooting' (Wiswall & Zafar, 2018).

Overall, the descriptive results report significant gender differences in nearly all human capital components. Therefore, the gender wage gap analysis should account for multi-dimensional human capital characteristics at least 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. Decomposition analysis

Country-level factors are likely related to observed heterogeneities in gender gaps in human capital. Appendix A5 presents three major labour market indicators relevant for given research – total and female employment rates and gender wage gap. We cannot attribute observed differences in job-specific skills (Borck, 2014).

Table 1 presents the results of the Gelbach decomposition with a model specification following (1), where all controls are grouped into twelve categories, with the first three incorporating the background factors and the remaining categories incorporating the human capital factors.

3.2.1. Background characteristics

Demographic characteristics reveal no significant association with the gender wage gap in majority of the countries, except Belgium and the Netherlands (7.55% and 14.73% gap reductions, respectively). The employment controls, including occupation, industry, and type of contract, whenever significantly associated with the gender wage gap, decrease the wage disparity. The latter suggests that men are employed in occupations, industries and under types of contracts yielding higher wage rates systematically more than women in analysed countries. 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%. This result appears consistent with the literature and imply that gender occupation and industry segregation is one of the factors largely associated with the gender wage gap in majority of the sample countries (Blau & Kahn, 2017). Women may self-select into occupations or sectors other than men, and the selection may be largely driven by their 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 & Hallock, 2001). The latter is particularly true in countries with stringent gender norms.

Insignificant association between employment controls and gender wage gap in Greece, Ireland, Italy, Poland, Slovenia, and Spain may stem from low female employment (see Appendix A5). In countries with higher labour market commitment women remain on a labour market throughout a lifecycle, even upon childbirth. Yet interrupted and resumed careers of mothers reflect on their labour market trajectories, driving a divergence of male and female employment profiles and explaining the negative selection of women. In countries with low female employment rate, labour market drop-out rates are strikingly high, particularly for mothers. Hence, females who remained on labour market are positively selected in terms of their positions, experience, skills and wage rates, explaining a convergence in male and female employment profiles and resulting in insignificant contribution of employment segregation in explaining the gender wage gap.

3.2.2. Formal education

Formal education positively associates with the gender wage gap in nine out of the seventeen analysed countries. Women hold a systematically higher level of education compared to men in all analysed countries (see Figure 1), which concurs with the literature (Author & Wasserman, 2013). However, the explanatory power of education is persistently decreasing (Cha & Weeden, 2014). One of the major reasons behind the declining marginal wage returns to formal education is the concave relationship between schooling and earnings (Colclough et al., 2010). Therefore, the relative increase in the wage rate

Table 1. Gelbach decomposition of the gender wage gaps across sample countries.

	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
Raw wage gap	−0.0754***		−0.1864***		−0.1389***		−0.3781***		−0.1868***		−0.1305***	
Background factors:												
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
Human capital factors:												
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
Total experience	−0.0204***	27.07	−0.0030	1.59	−0.0008	0.58	−0.0055*	1.47	−0.0012	0.65	−0.0088*	6.75
Job-specific experience	−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
Job-specific cognitive skills	0.0006	−0.82	0.0017	−0.90	−0.0102***	7.36	−0.0003	0.09	0.0014	−0.76	0.0044	−3.36
Job-specific non-cognitive skills	0.0024*	−3.20	−0.0051**	2.74	−0.0010	0.72	−0.0048**	1.26	0.002	−1.09	−0.0013	1.03
Job-specific problem-solving skills	−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 contribution	−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	

	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
Raw wage gap	−0.1817***		−0.1323***		−0.0767***		−0.0968***		−0.2272***		−0.1399***	
Background factors:												
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
Human capital factors:												
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
Total experience	0.0012	−0.65	−0.0222*	16.89	−0.0077 *	10.04	−0.004	4.11	−0.0013	0.59	−0.0002	0.15
Job-specific experience	−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
Job-specific cognitive skills	−0.0139***	7.62	0.0032	−2.48	−0.0144**	18.76	−0.0048	4.96	0.0018	−0.79	−0.00145	1.03
Job-specific non-cognitive skills	−0.0036*	2.01	0.0015	−1.16	−0.0017	2.26	−0.0038	3.89	0.0031	−1.38	−0.0035	2.49
Job-specific problem-solving skills	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 contribution	−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	

	Norway		Poland		Slovakia		Slovenia		Spain	
	Contr.	% of gap	Contr.	% of gap	Contr.	% of gap	Contr.	% of gap	Contr.	% of gap
Raw wage gap	−0.1948***		−0.1231***		−0.2908***		−0.0853**		−0.1659***	
Background factors:										
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
Human capital factors:										
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
Total experience	−0.0048	2.48	0.0017	−1.39	0.0012	−0.41	−0.0026	3.03	−0.0109	6.56
Job-specific experience	−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
Job-specific cognitive skills	−0.0103*	5.31	0.0007	−0.59	−0.0030	1.03	−0.0029	3.46	−0.0084	5.10
Job-specific non-cognitive skills	−0.0025	1.26	−0.0005	0.38	−0.0024	0.83	−0.0008	0.91	−0.0055	3.34
Job-specific problem-solving skills	−0.0022	1.12	0.0006	−0.45	−0.0074	2.53	0.0020	−2.36	0.0013	−0.81
Total contribution	−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	

Notes: Dependent variable is the log of the hourly earnings of salaried workers. Estimations account for country-specific population weights. Raw wage gap stands for an unadjusted gender wage gap. Total contribution stands for an overall contribution of all background and all human capital factors to explaining the gender wage gap. Individual contribution with minus sign (and positive percent) implies that this factor narrows the gap, while contribution with plus sign (and negative percent) means that factor widens the gap. 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) *Total experience*– total work experience; (vii*) Job-specific experience* – work experience related to current employment; (viii) *Literacy* – literacy cognitive ability (test score); (ix) *Numeracy* – numeracy cognitive ability (test score); (x) *Job-specific cognitive skills* – self-reported use of literacy, numeracy, and ICT skills at work; (xi) *Job-specific non-cognitive skills* – self-reported frequency of organizing, presenting and negotiating at work; (xii) *Job-specific problem-solving skills* – self-reported frequency of solving simple and complex problems at work. Statistical significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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).

3.2.3. Field of education

Despite earlier studies documenting the strong explanatory power of university majors (Black et al., 2008; Daymont & Andrisani, 1984), we find supportive evidence only for Denmark (8.75% contribution to explaining the gender wage gap), reflecting a substantial gender gap in STEM degrees (see Figure 2). The field of education positively associates with the gender wage gap in Ireland (by 47.43%), France (by 13.82%), and Estonia (by 10.61%), indicating disproportional wage returns to men and women with the same degree. The latter is likely related to higher wage rates of men holding STEM degrees, as compared to women.[13] For the remaining countries, field of education is insignificantly related to gender pay gap. 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 a mere education level. However, since our full specification controls for cognitive abilities and job-specific skills, 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 shorter labour market activity.

3.2.4. Work experience

In all analysed countries, either total, or job-specific experience, or both experience measures significantly associate with gender wage gaps and decrease it, suggesting that persistently shorter employment experience and tenure in current job distort female earnings, resulting in larger gender wage gap. Notably, we document even stronger contributions from job-specific experience, as it decreases wage gaps in all counties except Greece, where the association is insignificant. Greece may appear as an outlier due to an outstandingly low employment rates, both in total population and for women specifically, which may associate with very low wage returns to work experience (see Appendix A5). Ireland and Belgium reveal the largest joint contribution of the two work experience variables (approximately 50% and 45%) with an extreme effect of job-specific experience in Ireland (40.53%). In all other countries, gender wage gap reductions associated with job-specific experience are also systematically higher than those associated with total experience. For instance, in France, job-specific experience explains 15.51% of the gap, while total only 6.75%; in Estonia 12.13% and 1.47%, respectively.

Thus, our empirical results are in line with other literature documenting that work experience gaps are the major driver of wage differentials (Goldin et al., 2006; O'Neill & Polachek, 1993). 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. Women's shorter job-specific experience often stem from family reasons indicating that women adjust their labour market behaviour and skills' developments with current conditions more often than men do.

3.2.5. Test-based cognitive abilities

Numeracy has a much stronger explanatory power comparing to literacy and it contributes to the gender wage gap reduction in approximately half of the countries. The highest contribution of numeracy is documented in Ireland (21.97%), followed by Great Britain (12.76%), Spain (9.83%), Finland (8.01%), and France (7.67%). Lithuania is the only country where numeracy associates with widening the gender pay disparity. Lithuania is one of the few countries where women have marginally higher numeracy ability than men (see Figure 4) and employment rates of men and women are largely comparable (see Appendix A5 for total and female employment rates). Yet, having stronger numeracy skills does not associate with higher wages for women. Literacy and verbal abilities, although an important characteristic of an individual human capital profile, have less effect on the wage level. We document a significant association between literacy abilities and wage only in two countries: Lithuania, where the contribution of literacy in explaining gender wage gap is 8.02%, and Denmark with 1.76% contribution. Positive association of gender wage gap with literacy skill may stem from the country-specific sample characteristics. Substantial Polish and Russian minorities in Lithuania could make a national language command even more valuable on the labour market, as demand for it persists and per cent of foreign-speaking population is high. Since women in Lithuania have on average higher literacy skills they tend to benefit from it relatively more than their peers benefit from their home language command in other countries.[14]

3.2.6. Self-reported job-specific skills

The final set of human capital characteristics incorporates three major groups of job-specific skills. The first group includes three domains of job-specific cognitive skills, namely literacy, numeracy, and ICT skills. These three skill domains largely embody on-the-job applications of cognitive skills and thus occupation-/industry-specific cognitive abilities. The use of cognitive skills has the most pronounced association with the gender wage gap in Ireland (18.76%), followed by Great Britain (7.62%), Denmark (7.36%), and Norway (5.31%), suggesting that women tend to apply cognitive abilities at work relatively less than men, inflating the wage disparity. Substantial gender gaps in on-the-job use of numeracy and ICT skills (see Appendix A4) in aforementioned countries may drive the observed significant association, as these job-specific skills require particular knowledge and training, which may be tailored to specific position and relatively rare on the labour market. We do not document statistically significant association between job-specific cognitive skills and the gender wage gap in remaining countries.

The second group includes three domains of job-specific non-cognitive skills – organizational, presenting, and negotiating skills. An association between job-specific non-cognitive skills and gender wage gap is economically and statistically lower compared to job-specific cognitive skills. There are only three countries with statistically significant, yet economically limited, contributions of the job-specific non-cognitive skills: Czech Republic

(2.74%), Great Britain (2.01%), and Estonia (1.26%). Appendix A4 suggests that, on average, more intensive use of organizational skills by men in Czech Republic and Estonia, and presentation skills in Great Britain, may contribute to observed positive association between job-specific non-cognitive skills and gender wage gap in three sample countries.

The third group incorporated two domains of job-specific problem-solving skills, namely solving simple and complex problems. This measure explains 4.02% of the gender wage gap in Denmark, 3.85% in Netherlands and 3.39% in Belgium. These associations may stem from, on average, more intense application of problem-solving skills in dealing with complex problems among men in all three countries. The latter may relate to an unobserved effect of managerial duties and/or challenging and highly rewarding job obligations carried out by men systematically more often than by women, In the remaining countries the relationship is statistically insignificant. Despite finding statically weak associations between gender wage gap and abovementioned three groups of job-specific skills, the economic significance of those is non-negligible. Whereas we document a statistically insignificant and/or economically weak associations between literacy, job-specific cognitive, non-cognitive, problem-solving skills, and gender wage gap in many countries in our sample, one has to acknowledge potential effect of small variation in human capital controls and/or relatively small sample sizes (particularly in Greece, Italy, Lithuania, and Spain), which can cause false negative estimates. Furthermore, controlling for a wide range of employment and human capital characteristics can mitigate the association between job-specific skills and wage gap. We agree with Gibbons and Waldman (2004), who suggest that selection into specific occupations implies gender segregation into job tasks, which increases gender gaps in job-specific skills. Therefore, controlling for the employment profile to a certain extent captures employment segregation and the resulting gender disproportion in accumulated job-specific skills.

4. Conclusions

This paper makes a twofold contribution to the literature. Firstly, we incorporate a complex multidimensional measure of human capital, instead of focusing on several narrow domains. 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 job-specific work experience, literacy, and numeracy cognitive abilities; (iii) novel human capital components, including actual job-specific cognitive, non-cognitive, and problem-solving skills, which jointly reflect the occupation-/industry-specific human capital. Secondly, the paper investigates path-independent wage returns to each specific human capital domain, applying Gelbach (2016) decomposition methodology and relying on the PIAAC data for seventeen European countries. 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. Having different human capital does not necessarily translate into wage disparity, as the labour market valuation of specific human capital components matters.

The results of Gelbach decompositions reveal the heterogeneous, yet significant association between of a broad range of human capital components and the gender wage gaps in sample countries. We find that the strongest association relates to the total and job-specific experience. Work experience contributes to a decrease in the gender wage disparity in all analysed countries. We add to the literature by documenting that job-specific experience matters even more for explaining the gender wage gap, as women possess, on average, shorter job-specific experience due to greater flexibility of their career paths and ability to adjust to external demands and challenges, such as child-care for mothers. Numeracy ability is another factor having strong association with the gender wage disparity. The role of numeracy is rather homogeneous across countries, namely, controlling for numeracy associates with the wage gap decline. 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, as compared to literacy.

We document that task-specific human capital, approximated by the job-specific skills, is associated with the gender wage gap in several sample countries. This paper is the first, to the best of our knowledge, to investigate the role of actual job-specific skills as a proxy of occupation-/industry-specific human capital. Despite the relatively small economic and statistical significance, three sets of job-specific skills contribute to narrowing the gender wage gap. Of particular interest, the low significance of job-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. Job-specific skills are largely affected by employment segregation; therefore employment controls can mitigate the effect of job-specific skill measures. Moreover, there may be heterogeneity in the wage return on skill use across countries. In countries with insignificant association between skill use and wage (Greece, Lithuania, Poland, Slovakia, Slovenia, Spain), earnings can be less sensitive to the job-specific abilities; therefore, providing lower marginal increase in wage as a response to a marginal increase in the job-specific skills. Furthermore, a potential role of unobserved job-related factors, as well as relatively small sample sizes across several countries in mitigating significance of job-specific skills estimates should be acknowledged.

Out of all human capital components, formal education degree is the sole characteristic contributing to systematically wider gender wage gaps across all the analysed countries. This result goes in line with the earlier findings on the decreasing marginal 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. Similarly, attainting higher literacy 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 mere 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 labour market valuation of specific human capital components. The analysis reveals that job-specific work experience, total work experience, and job-specific cognitive and non-cognitive skills are the most rewarding human capital domains. This result supports earlier findings 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.

Notes

1. Throughout the paper, terms human capital 'domains' and 'components' are used interchangeably and denote specific characteristics, which jointly shape the individual human capital.
2. 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.
3. The oversampling in several countries need to be accounted for. Namely, in Czechia population aged 16–29 years, in Denmark population aged 55–65 years and immigrants aged 16–65 years, in Poland population aged 19–26 were overrepresented. For more details, please, refer to OECD (2019).
4. All on-the-job skill use measures are self-reported on a scale from 'never' to 'every day'.
5. Given a broad range of human capital measures included in the analysis, potential multicollinearity issue should be acknowledged. To check for it, VIF estimates were produced for all human capital variables both in pooled cross-country sample and for individual country samples. In the pooled sample, field of education and related work experience VIF estimates range between 5.4 and 7.8, whereas for all other human capital covariates VIF estimates are between 1.4 and 4.8. These results suggest that multicollinearity has, if anything, very weak effect on robustness of our estimates. Similar patterns are observed in country-specific samples, with minor differences in magnitude of VIF estimates and specific human capital components with estimates below/above 5. The VIF estimates are available upon request.
6. Results are available upon request. Unfortunately, the cross-section data does not allow to study gender differences in job separation and employment stability.
7. One limitation of our methodological approach is the potential multicollinearity between human capital components, particularly, between test-based cognitive abilities and self-reported job-specific skills. To verify that multicollinearity 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. Estimates are available upon request. Reverse causality issue has to be acknowledged, as an association between gender wage gap and job-specific experience, as well as use of literacy, numeracy, and ICT skills at work may go both ways. It may be the case that lower gender wage gap causes longer job-specific tenure or more intense use of skills at work. We cannot address this issue empirically, therefore, all empirical estimates are addressed as mere associations, with no causal inference.
8. For more details see Gelbach (2016).
9. Technical note on Jackknife replication methodology. When 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 cognitive ability domain incorporated 10 plausible values, 80 replication weights and population weight, a single estimate is a product of 810 replications. For more details see https://www.oecd.org/skills/piaac/_Technical%20Report_17OCT13.pdf.
10. Incorporating two cognitive ability domains, with 10 plausible value each, with 80 replication weights and a single population weight results in 810 $\times$ 810 replications.
11. Appendix A2 presents the average demographic characteristics and Appendix A3 the occupational profile of men and women in the analysed countries.
12. The role of work culture in shaping gender wage gap is an important research questsion by itsef and has been addressed in the earlier literature (please, see Van der Lippe et al., 2019). Furthermore, a work-family culture prevailing in the country may reflect on gender wage gap and gender discrepancies in skill use at work, as employers supportive towards maternal

employment may facilitate equal pay and equal employment opportunities for both men and women.

13. Since we control for a broad STEM field, we cannot differentiate between gender gaps wage returns to specific disciplines – science, technology, engineering, and mathematics. Therefore, one has to admit potential heterogeneities in wage returns to the degrees in aforementioned sub-fields we cannot control for.
14. The similar conclusion should hold for Estonia, given a substantial Russian minority. However, Estonia was one of the few countries where the survey was conducted in two languages – Estonian and Russian. Thus, the analysis does not differentiate between literacy skills of those who took the test in Estonian and in Russian languages, diminishing potentially strong association between Estonian literacy skill and gender wage gap.

Acknowledgements

The authors are very thankful to Jaanika Meriküll, Jaan Masso, and Mihails Hazans for their feedback and valuable suggestions. The authors are grateful to the participants of the 11th Estonian Social Science Conference (Tartu) for insightful discussions, as well as to all members of 'The economic integration of the Nordic-Baltic region through labour, innovation, and trade' (LIFT) and 'Income Wealth and Gender' (InWeGe) projects for valuable feedback during project meetings. The authors want to thank two anonymous reviewers for their insightful comments, which helped to improve the paper a lot. The content of this publication represents the views of the authors only and is their sole responsibility. The European Commission does not accept any responsibility for use that may be made of the information it contains.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This research was funded by the EEA and Norway Grants Programme (2014–2021) project 'The economic integration of the Nordic-Baltic region through labour, innovation, and trade' (LIFT; LT08-2-LMT-K.01-070) and by the European Union's Rights, Equality and Citizenship Programme (2014–2020) project InWeGe ("Income, Wealth and Gender"), No. 820778.

Data availability statement

The data and Stata codes used for the analysis are available upon request.

Notes on contributors

Maryna Tverdostup is an economist at Vienna Institute of International Economic Studies and a research fellow at the University of Tartu, School of Economics and Business Administration. She holds a PhD in Economics from the University of Tartu. Her research interests cover diverse labour market issues, including gender inequalities and immigrants' integration, as well as experimental analysis and game-theoretic modelling of markets with asymmetric information.

Tiiu Paas is a Professor of Economics at the University of Tartu, School of Economics and Business Administration. She holds a PhD in Economics from the University of Tartu. Her research topics are related to the use of quantitative methods in the analysis of economic processes and forecasting of economic development. Tiiu Paas has conducted an empirical research covering various labor market issues, including migration, gender pay gap, and new forms of work.

ORCID

Maryna Tverdostup http://orcid.org/0000-0003-1286-9814

References

Allen, J., Levels, M., & Van der Velden, R. (2013). *Skill mismatch and skill use in developed countries: Evidence from the PIAAC study* (pp. 1–49). Research Centre for Education and the Labour Market, Maastricht University. https://doi.org/10.26481/umaror.2013017

Altonji, J. G., & Blank, R. (1999). Race and gender in the labor market. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Vol. 3c, pp. 3144–3259). Elsevier Science.

Angle, J., & Wissman, D. (1981). Gender, college major, and earnings. *Sociology of Education*, *54*(1), 25–33. https://doi.org/10.2307/2112510

Anspal, S. (2015). Non-parametric decomposition and the choice of reference group: A study of the gender wage gap in 15 OECD countries. *International Journal of Manpower*, *36*(8), 1266–1280. https://doi.org/10.1108/IJM-03-2015-0047

Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. National Bureau of Economic Research. The University of Chicago Press.

Becker, G. S., Hubbard, W. H., & Murphy, K. M. (2010). Explaining the worldwide boom in higher education of women. *Journal of Human Capital*, *4*(3), 203–241. https://doi.org/10.1086/657914

Beede, D. N., Julian, T. A., Langdon, D., McKittrick, G., Khan, B., & Doms, M. E. (2011). *Women in STEM: A gender gap to innovation*. Economics and Statistics Administration Issue Brief. 04-11.

Bertrand, M., & Hallock, K. F. (2001). The gender gap in top corporate jobs. *ILR Review*, *55*(1), 3–21. https://doi.org/10.1177/001979390105500101

Black, D. A., Haviland, A. M., Sanders, S. G., & Taylor, L. J. (2008). Gender wage disparities among the highly educated. *Journal of Human Resources*, *43*(3), 630–659. https://doi.org/10.3368/jhr.43.3.630

Blau, F. D., Ferber, M. A., & Winkler, A. E. (2014). *The economics of women, men, and work* (7th ed.). Pearson.

Blau, F. D., & Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, *55*(3), 789–865. https://doi.org/10.1257/jel.20160995

Borck, R. (2014). Adieu rabenmutter – culture, fertility, female labour supply, the gender wage gap and childcare. *Journal of Population Economics*, *27*(3), 739–765. https://doi.org/10.1007/s00148-013-0499-z

Buckles, K. S., & Price, J. (2013). Selection and the marriage premium for infant health. *Demography*, *50*(4), 1315–1339. https://doi.org/10.1007/s13524-013-0211-7

Cardoso, A. R., Guimarães, P., & Portugal, P. (2016). What drives the gender wage gap? A look at the role of firm and job-title heterogeneity. *Oxford Economic Papers*, *68*(2), 506–524. https://doi.org/10.1093/oep/gpv069

Cha, Y., & Weeden, K. A. (2014). Overwork and the slow convergence in the gender gap in wages. *American Sociological Review*, *79*(3), 457–484. https://doi.org/10.1177/0003122414528936

Colclough, C., Kingdon, G., & Patrinos, H. (2010). The changing pattern of wage returns to education and its implications. *Development Policy Review*, *28*(6), 733–747. https://doi.org/10.1111/j.1467-7679.2010.00507.x

Daymont, T. N., & Andrisani, P. J. (1984). Job preferences, college major, and the gender gap in earnings. *Journal of Human Resources*, *19*(3), 408–428. https://doi.org/10.2307/145880

De La Rica, S., Gortazar, L., & Lewandowski, P. (2020). Job tasks and wages in developed countries: Evidence from piaac. *Labour Economics*, *65*, Article 101845. https://doi.org/10.1016/j.labeco.2020.101845

Doorley, K., O'Donoghue, C., & Sologon, D. M. (2021). *The gender gap in income and the COVID-19 pandemic* (IZA Discussion Paper 14360).

Duncan, G. J., & Dunifon, R. (1998). "Soft-skills" and long-run labor market success. *Research in Labor Economics*, *17*, 123–149. Available at SSRN 112431.

Fortin, N. M. (2008). The gender wage gap among young adults in the United States the importance of money versus people. *Journal of Human Resources*, *43*(4), 884–918. https://doi.org/10.3368/jhr.43.4.884

Gathmann, C., & Schönberg, U. (2010). How general is human capital? A task-based approach. *Journal of Labor Economics*, *28*(1), 1–49. https://doi.org/10.1086/649786

Gelbach, J. B. (2016). When do covariates matter? And which ones, and how much? *Journal of Labor Economics*, *34*(2), 509–543. https://doi.org/10.1086/683668

Gibbons, R., & Waldman, M. (2004). Task-specific human capital. *American Economic Review*, *94*(2), 203–207. https://doi.org/10.1257/0002828041301579

Goldin, C., Katz, L. F., & Kuziemko, I. (2006). The homecoming of American college women: The reversal of the college gender gap. *Journal of Economic Perspectives*, *20*(4), 133–156. https://doi.org/10.1257/jep.20.4.133

Gorsuch, M. M. (2016). Decomposing the increase in men's time on childcare during the great recession. *Review of Economics of the Household*, *14*(1), 53–82. https://doi.org/10.1007/s11150-014-9263-8

Grove, W. A., Hussey, A., & Jetter, M. (2011). The gender pay gap beyond human capital heterogeneity in noncognitive skills and in labor market tastes. *Journal of Human Resources*, *46*(4), 827–874. https://doi.org/10.3368/jhr.46.4.827

Hanushek, E. A., Schwerd, G., Wiederhold, S., & Woessmann, L. (2017). Coping with change: International differences in the returns to skills. *Economics Letters*, *153*, 15–19. https://doi.org/10.1016/j.econlet.2017.01.007

Hanushek, E. A., Schwerdt, G., Wiederhold, S., & Woessmann, L. (2015). Returns to skills around the world: Evidence from PIAAC. *European Economic Review*, *73*, 103–130. https://doi.org/10.1016/j.euroecorev.2014.10.006

Heckman, J. J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, *24*(3), 411–482. https://doi.org/10.3386/w12006

Kimhi, A., & Hanuka-Taflia, N. (2019). What drives the convergence in male and female wage distributions in Israel? A shapley decomposition approach. *The Journal of Economic Inequality*, *17*(3), 379–399. https://doi.org/10.1007/s10888-019-9406-5

Kuhn, P., & Weinberger, C. (2005). Leadership skills and wages. *Journal of Labor Economics*, *23*(3), 395–436. https://doi.org/10.1086/430282

Lazear, E. P. (2009). Firm-specific human capital: A skill-weights approach. *Journal of Political Economy*, *117*(5), 914–940. https://doi.org/10.1086/648671

Lips, H. M. (2013). The gender pay gap challenging the rationalizations. Perceived equity, discrimination, and the limits of human capital models. *Sex Roles*, *68*(3–4), 169–185. https://doi.org/10.1007/s11199-012-0165-z

Manning, A., & Swaffield, J. (2008). The gender gap in early-career wage growth. *The Economic Journal*, *118*(530), 983–1024. https://doi.org/10.1111/j.1468-0297.2008.02158.x

Niederle, M., & Vesterlund, L. (2010). Explaining the gender gap in math test scores: The role of competition. *Journal of Economic Perspectives*, *24*(2), 129–144. https://doi.org/10.1257/jep.24.2.129

OECD. (2013). *Technical report on the survey of adult skills (PIAAC)*. OECD Publishing.

OECD. (2019). *Technical report on the survey of adult skills (PIAAC)* (3rd ed.). OECD Publishing.

Olivetti, C. (2006). Changes in women's hours of market work: The role of returns to experience. *Review of Economic Dynamics*, *9*(4), 557–587. https://doi.org/10.1016/j.red.2006.06.001

O'Neill, J., & Polachek, S. (1993). Why the gender gap in wages narrowed in the 1980s. *Journal of Labor Economics*, *11*(1, Part 1), 205–228. https://doi.org/10.1086/298323

Polachek, S. (2008). How the human capital model explains why the gender wage gap narrowed. In F. D. Blau, M. C. Brinton, & D. B. Grusky (Eds.), *The declining significance of gender?* (pp. 102–124). Russell Sage Foundation.

Raposo, P., Portugal, P., & Carneiro, A. (2015). *Decomposing the wage losses of displaced workers: The role of the reallocation of workers into firms and job titles* (IZA Discussion Paper 9220).

Schultz, T. P. (1995). *Investment in women's human capital*. University of Chicago Press.

Shatnawi, D., Oaxaca, R., & Ransom, M. (2014). Movin'on up: Hierarchical occupational segmentation and gender wage gaps. *The Journal of Economic Inequality*, *12*(3), 315–338. https://doi.org/10.1007/s10888-013-9257-4

Smith, W. C., & Fernandez, F. (2017). Education, skills, and wage gaps in Canada and the United States. *International Migration*, *55*(3), 57–73. https://doi.org/10.1111/imig.12328

Sullivan, P. (2010). Empirical evidence on occupation and industry specific human capital. *Labour Economics*, *17*(3), 567–580. https://doi.org/10.1016/j.labeco.2009.11.003

Van der Lippe, T., Van Breeschoten, L., & Van Hek, M. (2019). Organizational work–life policies and the gender wage gap in European workplaces. *Work and Occupations*, *46*(2), 111–148. https://doi.org/10.1177/0730888418791652

Vieira, J. A. C., Cardoso, A. R., & Portela, M. (2005). Gender segregation and the wage gap in Portugal: An analysis at the establishment level. *The Journal of Economic Inequality*, *3*(2), 145–168. https://doi.org/10.1007/s10888-005-4495-8

Waddell, G. R. (2006). Labor-market consequences of poor attitude and low self-esteem in youth. *Economic Inquiry*, *44*(1), 69–97. https://doi.org/10.1093/ei/cbj005

Wiswall, M., & Zafar, B. (2018). Preference for the workplace, investment in human capital, and gender. *The Quarterly Journal of Economics*, *133*(1), 457–507. https://doi.org/10.1093/qje/qjx035

Yamaguchi, S. (2018). Changes in returns to task-specific skills and gender wage gap. *Journal of Human Resources*, *53*(1), 32–70. https://doi.org/10.3368/jhr.53.1.1214-6813R2

Zangelidis, A. (2008). Occupational and industry specificity of human capital in the British labour market. *Scottish Journal of Political Economy*, *4*(55), 420–443. https://doi.org/10.1111/j.1467-9485.2008.00460.x