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REVISITING THE GENDER WAGE GAP IN EUROPE: HOW MUCH CAN IT BE EXPLAINED BY THE GENDER SEGREGATION INTO JOB TASKS?

Master's thesis

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I have written this Master's Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

Abstract

The persistent gender wage gap continues to impact economic development, and despite progress in gender equality, the gap remains even within similar occupations. The gender wage gap within occupations may be influenced by factors such as task segregation, which, in turn, can be shaped by differences in the skills required to perform a job. However, the literature on this matter is very limited, and no studies have explored the broad range of skills and their reflection on the gender wage gap. This thesis aims to investigate the extent of within-occupation/within-industry gender segregation into job tasks and its role in explaining the gender wage gap across EU-27 countries using data from the European Skills and Jobs Survey (ESJS) data from 2014. Results suggested a clear pattern of gender segregation into job tasks – men tend to choose advanced numeracy, ICT, and technical tasks, while women prioritize softer skills such as learning, teamwork, and communication. Regional analysis reveals that Northern Europe – despite its high Gender Equality Index – exhibits the highest degree of gender task segregation. However, gender segregation into job tasks has a minimal impact on the gender wage gap in the region. The gender wage gap is largely shaped by occupational, industrial, and job-related characteristics, such as hours worked and firm type. The results also suggest the persistence of a sizeable unexplained gender wage gap in all regions. The findings of this thesis hold important implications for policy development and offer insights for future research.

Keywords: gender gap; gender equality; skills; segregation; tasks; labour market outcomes; European countries

CERCS codes: S180, S196, S212

1. Introduction

The gender wage gap is a social and economic issue that negatively affects the economic development of countries. According to the Economic Policy, in 2023, women in the EU-27 earned, on average, 13% less than men (Directorate-General for Communication, 2023). However, tackling wage differences could significantly benefit economic development. According to the McKinsey Global Institute, closing the gender wage gap could add $12 trillion to the global GDP by 2025 (Woetzel, 2015).

Existing literature explores the gender wage gap mostly by examining occupational and industrial segregation (e.g Bergmann, 1971; Blau & Kahn, 2017), meaning that women and men choose different occupations and industries, and women tend to choose lower-paying ones, resulting in lower wages for women compared to men. For example, women may tend to choose lower-paid occupations such as teaching, while men may pursue roles as directors. In terms of industries, women may be more likely to work in healthcare or education, whereas men may be more likely to work in STEM-related industries. However, despite the decline in occupational and industrial segregation (Blau et al., 2013), the gender wage gap still exists. Trends in the wage gap have largely stagnated since 1990, and only a minimal decrease was observed (Gould, 2024). Therefore, occupational segregation alone does not explain the wage gap since even within the same narrowly defined occupations, the gender wage gap still exists (Strawinski et al., 2018; Tomaskovic-Devey, 2018). A possible explanation for the gender wage gap within occupations and industries is the difference in tasks that men and women engage in within the same jobs due to gender differences in skills and competencies. This results in within-occupation/within-industry gender segregation into job tasks, which is referred to as gender segregation into job tasks throughout this paper.

While research on gender differences in skills is extensive (e.g. Borgonovi et al., 2021; Hyde et al., 2008; Stoet & Geary, 2018), there is limited research on within-occupation/within-industry gender segregation into job tasks explained by skills and their impact on the gender wage gap.

The primary reason behind limited empirical evidence on within-occupation/within-industry gender segregation into job tasks is the lack of data that provides information about skill usage at work and includes descriptive data about respondents, such as their demographic profile, occupation, industry, etc. So far, the main dataset used for exploring gender segregation into job tasks is the International Assessment of Adult Competencies (PIAAC) data (Pető & Reizer, 2021). However, PIAAC data is limited because it provides information on only three categories of skills: literacy, numeracy, and ICT skills. It does not account for other skills, particularly soft skills, such as social and communication skills.

The most comprehensive dataset providing information on the skills of women and men and their use at work is the European Skills and Jobs Survey (ESJS) data. Even though it is empirically challenging to understand which skills women and men use in their jobs, this dataset reports how important women and men consider thirteen types of skills in their jobs: basic numeracy, advanced numeracy, basic literacy, advanced literacy, basic ICT, average ICT, advanced ICT, technical skills, teamwork, problem-solving, learning, foreign language, and communication skills. By examining the importance that women and men place on these skills in their jobs, it is possible to gain a better understanding of skill selections and usage.

While being a valuable data source, the ESJS survey has largely been overlooked by researchers when exploring gender segregation into job tasks and its reflection on the gender wage gap across the EU. The aim of this thesis is to evaluate the extent of within-occupation/within-industry gender segregation into tasks[1] and to quantify to what extent it explains the gender wage gap in EU-27. In doing so, the paper addresses the following questions:

- Do men and women select into different job tasks, and how does this segregation differ by occupations, industries, and the EU-27 regions (Northern Europe, Eastern Europe, Southern Europe, Western and Central Europe)?
- How does the within-occupation of men and women into job tasks reflect on the gender wage gap?

To address the first research question, we explored gender segregation into job tasks within jobs, controlling for industries, occupations, types of firms, and working hours. We used an ordered logistic regression model, first for the pooled country sample and later disaggregated by occupations, industries, and regions, to understand whether gender segregation into job tasks exists and to what extent it varies across occupations and industries, as well as EU-27 macro-regions.

Our results suggested that even within the same occupation and industry, there is a noticeable pattern in task selection, with men choosing advanced numeracy, ICT, and technical tasks, while women tend to choose softer skills such as learning, teamwork, and communication skills. The thesis contributes to the literature by providing robust empirical

[1] This research employs the term "gender segregation into job tasks" extensively. However, in the context of ESJS data gender segregation into job tasks is approximated using the difference between average importance of skills reported by women and men.

insights into within-occupation and within-industry gender selection in thirteen different job skills. Moreover, the thesis makes an additional contribution by examining within-occupation and within-industry segregation into job tasks by EU-27 regions. While Northern Europe was known for having higher occupational segregation, we demonstrated that this also holds true within occupations, with differences being the strongest within occupations.

Afterward, we examined how this gender segregation reflects on the gender wage gap, both in the pooled country sample and when disaggregated by occupations, industries, and EU-27 regions. The results suggested that job-related characteristics, such as occupation, industry, and hours worked, play a more significant role in explaining the gender wage gap than skill usage. Occupations, industry, and regional specifics were observed, including a higher unexplained gender wage gap in Eastern Europe and in male-dominated industries. By examining these aspects, we contributed to a deeper and broader understanding of the factors behind the gender wage gap and provided a detailed analysis of these factors.

The analysis relies on the data from the first and only publicly available wave of the ESJfS[2], conducted in 2014. The rest of the thesis is organized as follows. Section 2 presents a literature review, focusing on studies explaining the gender wage gap and identifying the gaps in existing research. Section 3 provides an overview of the ESJS data and explains the research methodology. Section 4 presents the main results on gender segregation into job tasks in a pooled sample by occupational and industrial categories and by regions, further exploring how this segregation reflects on the gender wage gap. Finally, Section 5 provides conclusions on the key findings.

2. Literature review

An extensive strand of research has been dedicated to understanding the gender wage gap and its causes. One explanation of the gender wage gap lies within human capital theory. It explains the gender wage gap through differences in human capital - knowledge and skills that women and men get through education and experience. According to human capital theory, individuals with higher human capital tend to earn higher wages because the higher education, skills, and experience the person has, the higher their productivity will be, and since women have more domestic responsibilities, they participate in the labor force less and invest less in education. Therefore, their wages turn out to be lower than men's (Becker, 1964). However, in recent decades, women have surpassed men in formal educational attainments, and the

[2] The second wave of ESJS was carried out in 2021; however, it is not publicly accessible. The first wave is only available data currently.

experience gap has been vastly diminishing. Although this contributed to reduce the gender wage gap in the past, there are more factors to be analyzed in order to reduce gender wage gap further (Blau & Kahn, 2017). Eveline and Todd argue that human capital theory may oversimplify the issue by explaining the wage gap only by differences in education and work experience (Eveline & Todd, 2009)

One of the most contributive factors to the gender wage gap was seen in occupational and industry segregation (Blau & Kahn, 2017). Occupational segregation means that women and men tend to be involved in different occupations, with women often being in occupations with lower salaries and fewer opportunities for career growth. Industrial segregation refers to the imbalanced representation of men and women in various industries, and women are overrepresented in industries with lower wages, including public services and support activities. Bergmann (1971) introduced the Crowding Hypothesis explaining occupational segregation, suggesting that women are disproportionately focused on a limited number of occupations and men have access to a wider variety of occupations. It leads to an oversupply of labor in fields where women are mainly employed. As a result, wages in these occupations tend to be lower than in others.

The literature on occupational and industry gender segregation remains divided, albeit extensive (Borrowman & Klasen, 2020; Preston, 1999; Scarborough, 2020). While an assumption that women's empowerment can lead to a decrease in gender segregation is plausible, research has shown that the correlation is negative, implying that higher level of women's empowerment is associated with higher gender segregation into occupations and skills (Blackburn & Jarman, 2006).

Claudia Goldin, in her Nobel Prize-winning research, found that the income of women with children is lower than those of non-mothers due to reduced hours, career interruptions, and types of tasks performed at work, which can be influenced by factors such as societal expectations (Goldin, 2023). Polachek (1987) revealed that the impact of occupational segregation is less significant in explaining the gender wage gap than other factors, and differences in human capital between women and men contribute more to the gender wage gap. Occupational segregation alone does not explain the gender wage gap, especially given the variations in wages for similar roles across firms. In their research, Strawinski et al. (2018) revealed that even within the same occupations, gender wage gaps persist. Tomaskovic-Devey (1993) found that the gender wage gap is higher within occupations than between occupations. The research by Cobb-Clark & Tan (2011) also confirmed that the gender wage gap is significant within specific occupations. In recent years, more literature pointing out that gender segregation even within occupations, specifically about tasks performed at work, has emerged (Babcock et al., 2017; Fana et al., 2021; Pérez et al., 2019).

One explanation behind the gender wage gap within jobs with similar characteristics is differences in tasks performed by women and men. Gender differences in skills can be a reason why women and men take different job tasks, which contributes to the gender wage gap. For example, men usually demonstrate stronger numeracy skills, while women tend to excel in literacy skills, and numeracy skills are more highly rewarded in the labor market than literacy skills (Lindemann, 2015). This may lead women to specialize in tasks that are less well-compensated, even though they may have similar levels of human capital. Therefore, understanding gender segregation into job tasks requires an understanding the skills required in jobs dominated by women and men.

However, there is no consensus about skill differences. Data from the 2015 Programme for International Student Assessment (PISA) has found that girls outperform boys in collaborative problem-solving (Borgonovi et al., 2021). Hyde et al. (2008) revealed only a minimal gender gap in mathematical skills. Research by Stoet & Geary (2018) showed that the gender gap in mathematics varies greatly depending on cultural and educational context. For example, in gender-equal societies, there may be lower female representation in STEM fields compared to more conservative ones. Women may outperform men in verbal skills, such as reading comprehension, vocabulary acquisition, and verbal fluency (Hedges & Nowell, 1995; Voyer & Voyer, 2014). According to Lindemann (2015), men generally use numeracy skills more, whereas women tend to outperform men in literacy. This pattern exists even when women and men have the same age, work experience, and education - despite equal education levels, women tend to be involved in fewer analytical tasks and more routine and social tasks than men. Research by Fana et al. (2021) has found that men are less involved in repetitive and routine tasks than women, and despite the idea that women handle mainly social aspects of jobs, it has not found such significant differences.

Another aspect to consider is how women and men perceive their skills, regardless of the actual skills they possess. Since some studies rely on self-assessed perceptions of skills, it is important to consider whether self-reported skills differ from the actual skills that women and men have. For example, the paper by Mejía-Rodríguez et al. (2021) documented that even though girls performed equally well or even better than boys in schools, they still reported lower confidence in mathematics. Moreover, women tend to rely more on external assessment to make conclusions about their performance than men, while men tend to disregard negative feedback and rely more on positive feedback to shape their self-evaluations about specific skills (Roberts, 1991). Men are more likely to overestimate their performance and show higher levels of confidence in their self-assessments (Beyer, 1998). This confidence gap can lead to lower wage bargaining power for women. This is supported by Bowles' findings, which show that women tend to feel more anxious than men during salary negotiations (Bowles et al., 2005). Moreover, women also perceive negotiation as socially disapproved behavior (Greig, 2010).

While research on gender differences in skills is extensive, there is limited research on gender differences in actual on-the-job use of skills, as even while possessing comparable skills, men and women can engage in job tasks differently. Research by Pető & Reizer (2021) found using the PIAAC data that even within the same occupation, women use cognitive skills, such as literacy, numeracy, and ICT skills, less than men do, and this difference exists even despite the similar skill levels of women and men, measured by cognitive test scores, and therefore cannot be explained by human capital. Examining non-cognitive skills, such as planning and influencing, the study finds out that women also report lower usage of these skills than men. There are differences in skill use across countries – in Japan and some Scandinavian countries (Denmark, Norway), the gender gap in skill use is higher, while post-communist countries (Slovakia, Russia, Poland) show a smaller gap.

Another point to consider is how gender segregation into job tasks reflects in the gender wage gap. The PIAAC-based study by Christl and Köppl-Turyna (2020) explores how cognitive skills, tasks, skills matching, and flexibility of work contribute to the gender wage gap in Austria. The results suggest that cognitive skills and task assignments decrease the unexplained part of the gender wage gap by about 6 to 9 percentage points. Moreover, the study reveals that women are slightly more likely to be overqualified than men and have skill mismatches.

Limited empirical evidence on job tasks and skills of women and men largely stems from limited data, with the PIAAC and ESJS survey being rare exceptions. The objective of the latter survey was to research the skill level of employees across 27 countries of the European Union and the UK. The survey reports data on the importance of thirteen different skill domains in their jobs, as well as other key demographic and employment characteristics of respondents. A paper by Moro-Egido (2020) utilizes ESJS data and reports that previous experiences of skill mismatches are more strongly related to current over-skilling in men, while qualification mismatches are more significant for women. Additionally, labor market characteristics influence men and women differently, and country-specific factors play a more critical role for women. However, no paper was found exploring gender segregation into job tasks within the same occupation and industry and its reflection on the gender wage gap using the ESJS survey.

The literature review indicates that there is a gap within the same job-related characteristics, such as within-occupation and industry differences, and it is worth exploring. While there is extensive research on the skills of women and men and the jobs they are involved in, no study has been found on the association between gender segregation into job tasks and its reflection on the gender wage gap. We consider it important to explore this topic since addressing it can bring valuable policy insights into decreasing the gender wage gap. Therefore, this research aims to fill this gap and closely examine whether there are any differences in how women and men use skills in their jobs and how this can contribute to the gender wage gap.

3. Data and methodology

To understand the extent of gender segregation into job tasks, we utilized data from the European Skills and Jobs Survey (ESJS). The initial ESJS was conducted in 2014 across all EU-27 Member States and the UK, surveying approximately 49,000 adult employees. Currently, the first wave of ESJS is the only wave publicly available. The survey was financed and developed by the European Centre for the Development of Vocational Training (Cedefop) in collaboration with a network of skills experts, the OECD, and Eurofound (Cedefop, 2015). The majority of the data was collected through online panels, chosen for their time and cost-effectiveness. Additionally, telephone interviews were conducted in several markets to ensure representativeness, particularly for older people or in regions where internet penetration was low. A quota sampling approach was applied during data collection.

The survey captured various demographic and family characteristics of respondents (e.g., age, immigration status, living with a partner and children), job-related characteristics (e.g., occupation, industry, firm type, hours worked, wages in local currency), the importance of various skills needed to perform their job, and their perceptions of their qualifications (e.g., whether they feel overqualified or underqualified).

The data we used to understand gender segregation into job tasks is based on the self-reported variables on the importance of thirteen different skills in performing job tasks. We acknowledge that self-reported importance of skills does not guarantee entirely accurate information about how these skills are used in the job. However, due to the empirical difficulties in measuring the degree of skill usage, the importance that respondents assign to tasks can provide valuable insights and patterns related to skill usage. The importance of skills was assessed in the ESJS survey using the question: “On a scale from 0 to 10, where 0 means not at all important, 5 means moderately important, and 10 means essential, how important are the following for doing your job?” As a result, information about thirteen skill domains was obtained.

The skills explored included:

- basic and advanced literacy skills;
- basic and advanced numeracy skills;
- basic, average, and advanced ICT skills;
- technical skills (e.g., specialist knowledge for job duties, knowledge of specific products or services, ability to operate specialized technical equipment);
- communication skills (e.g., sharing information with coworkers or clients, teaching, making presentations);
- teamwork skills (e.g., cooperating with coworkers, negotiating);
- foreign language skills (e.g., using a language other than one’s mother tongue for job duties);
- problem-solving skills (e.g., identifying and solving problems, finding root causes);
- learning skills (e.g., adapting to new methods, engaging in self-learning).

The ESJS allows for cross-country comparability as it provides data for all EU-27 member states and the UK. However, for this research, we focused solely on EU-27 members, excluding the UK. Observations with missing or invalid responses for key variables were also excluded. This resulted in a total of 42,788 observations across the following countries: Germany (3,887), France (3,819), Sweden (942), Italy (2,899), Greece (1,958), Czech Republic (1,427), Poland (3,771), Netherlands (1,446), Denmark (957), Hungary (1,456), Spain (3,807), Austria (967), Belgium (1,417), Ireland (972), Slovakia (961), Finland (1,922), Portugal (1,457), Estonia (955), Romania (1,456), Lithuania (971), Cyprus (494), Slovenia (982), Bulgaria (955), Latvia (953), Luxembourg (485), Malta (497), and Croatia (975).

The data also includes population weights that account for the population's educational structure. Thus, all calculations in our analysis were weighed using these population weights. We began by employing descriptive statistics to gain an initial understanding of the data and then proceeded to apply econometric models.

To address our first research question and analyze whether women and men engage in different job tasks, we employed an ordered logistic regression model with the following specification on the pooled country sample:

$$Logit\big(P(Y_{ic}' \leq k)\big) = \alpha + \beta \cdot Female_{ic} + \boldsymbol{\delta} \cdot IC_{\boldsymbol{ic}}' + \theta \cdot JC_{ic}' + \gamma_c \quad (1)$$

Here, the vector of dependent variables ($\boldsymbol{Y_{ic}}$) considers the importance of different job skills (e.g., basic numeracy, advanced literacy) for individual i in country c. $Female_{ic}$ is a binary female identifier. The vector of individual-level control variables (IC_{ic}') includes demographic and family characteristics such as age, immigration status, education level, and whether the individual lives with a partner or children. The job-level control variables (JC_{ic}') include occupation, industry, firm type, and hours worked per week.

Afterward, we ran this model disaggregating by broad occupational and industrial categories. We categorized occupations into four categories:

- White-collar high-skilled: managers, professionals, technicians, and associate professionals
- White-collar low-skilled: clerical support workers
- Blue-collar high-skilled: skilled agricultural, forestry, and fishery workers, craft and related trades workers, plant and machine operators, and assemblers
- Blue-collar low-skilled: service and sales workers, elementary occupations

Industries were categorized into five groups:

- Primary and utility industries: agriculture, horticulture, forestry or fishing; supply of gas or electricity; mining or quarrying; and supply, management, or treatment of water or steam
- Manufacturing, construction, and infrastructure: manufacturing or engineering; construction or building
- Trade, transportation, and accommodation: retail, sales, shop work or wholesale; accommodation, catering or food services; and transportation or storage
- Professional and financial services: information technology or communication services; financial, insurance, or real estate services; professional, scientific, or technical services
- Public, cultural, and personal services: administration and support services, including public administration and defense; services related to education or health; cultural industries (arts, entertainment, recreation); social and personal services; something else.

To analyze gender segregation into job tasks across regions, we grouped the countries into four regions and ran the same model separately for each:

- Eastern Europe: Czech Republic, Poland, Hungary, Slovakia, Estonia, Romania, Lithuania, Bulgaria, Latvia.
- Western and Central Europe: Germany, France, Netherlands, Austria, Belgium, Ireland, Slovenia, Luxembourg.
- Northern Europe: Sweden, Denmark, Finland.
- Southern Europe: Italy, Greece, Spain, Portugal, Cyprus, Malta, Croatia.

Afterward, we moved to the analysis of the association between gender segregation into job tasks and the gender wage gap. We ran four models with stepwise inclusion of controls. The first model (2) included only gender and country fixed effects, capturing the raw gender wage gap:

$$\ln\_wage_{gross} = \alpha + \beta \cdot Female_{ic} + \gamma_c + \varepsilon. \quad (2)$$

Here, the dependent variable ($\ln\_wage_{gross}$) represents the logarithm of gross wage, $Female_{ic}$ is a binary female identifier, γ_c represents country fixed effects, and ε - error term. In the second model (3), we added demographic controls:

$$ln\_wage_{gross} = \alpha + \beta \cdot Female_{ic} + \boldsymbol{\delta} \cdot IC'_{\boldsymbol{ic}} + \gamma_c + \varepsilon, \quad (3)$$

where vectors of individual-level control variables (IC'_{ic}) include a set of demographic and family characteristics, including age, immigration status, education level, living with a partner, living with kids, and age squared used to account for non-linear age effects.

In the third model (4), we included job-related controls such as occupation, industry, firm type, and hours worked per week:

$$\ln\_wage_{gross} = \alpha + \beta \cdot Female_{ic} + \boldsymbol{\delta} \cdot IC'_{ic} + \boldsymbol{\theta} \cdot JC'_{ic} + \gamma_c + \varepsilon, \quad (4)$$

where vector of job-level control variables ($JC_{ic}{}'$) includes a set of job-related characteristics such as occupation, industry, firm type, and hours worked per week.

Finally, the fourth model (5) incorporated skill importance variables to assess their impact:

$$\ln\_wage_{gross} = \alpha + \beta \cdot Female_{ic} + \boldsymbol{\delta} \cdot IC'_{ic} + \boldsymbol{\theta} \cdot JC'_{ic} + \boldsymbol{\mu} \cdot Y'_{ic} + \gamma_c + \varepsilon \quad (5)$$

where (Y'_{ic}) represents the importance of different job skills (e.g., basic numeracy, advanced numeracy), which will represent skill usage.

Afterward, we also ran these regression models separately for each occupation, industry category, and EU-27 region to examine the situation better.

We acknowledged that the simultaneous inclusion of all thirteen skill use domains could cause sizeable multicollinearity issues. Therefore, by running VIF tests, we identified strongly collinear variables and, as a result, excluded basic numeracy, basic literacy, basic and average ICT, analyzing only advanced numeracy, literacy, and ICT skills. Other skills did not have multicollinearity issues and were therefore included.

Although we have presented the results through tables and figures in the Results section and the Appendix, additional data is available upon request if needed.

We anticipate that the chosen methods will allow us to examine gender segregation into job tasks and its impact on the gender wage gap. However, it should also be mentioned that the scores of respondents are self-assessed, and therefore, this research can have its limitations since the actual skills that respondents use in their jobs can differ from those reported.

4. Result and discussion

4.1. Gender segregation into job tasks and its variation across the EU-27 regions

4.1.1. Descriptive analysis

Our aim in this section was to understand the overall structure of our data and the gender differences across variables, including the importance of skills considered in this analysis via descriptive analysis. Table A in the Appendix represents the percentages of women and men across various dimensions in our sample, such as age, occupation, industry, education, skills, promotions, etc.

A clear pattern is observed in occupations and industries where women and men are employed. Women are more unevenly distributed across occupations and industries than men. The highest concentration of women is in clerical support, which also shows the most significant gender gap – about 34% of women work in this field, compared to only 15% of men. The second most frequent industry of employment for women is social and personal services. The other occupations with significant gender differences are plant and machine operator and assembly, as well as building, crafts, or related tradesperson, with significantly more men employed in these occupations.

This distribution reflects common perceptions about distinct patterns in how women and men are spread across different sectors – women are more likely to work in social fields such as healthcare and education, while men are more often in engineering-related fields. Since women are unevenly distributed across occupations and industries, the Crowding Hypothesis introduced by Bergmann (1971), appears relevant, as it explains women's lower pay by their concentration in a limited number of occupations.

Women tend to achieve higher levels of formal education than men, with 39% of women holding a higher education degree compared to 33% of men. The proportion of men and women with a medium level of education is almost identical. However, despite having the same level of education, men were more likely than women to perceive themselves as overqualified and less likely to see themselves as underqualified, and more likely to be promoted within their company and to have a permanent contract. One potential reason could be, on average, shorter employment tenure of women within the same company. However, in our sample, this factor does not apply, as mobility between companies was almost the same for both genders, with women averaging 10 years in the same job and men 11 years. Therefore, differences in job tenure cannot explain the difference in career advancement. Women, despite having the same or even higher education and higher educations, achieve lower career advancement.

Men and women tend to work nearly the same amount of time with their employers, yet women experience lower career advancement. This phenomenon may be related to different factors, such as the organizational environment's role in empowering women to advance their careers and individual factors specific to women. Women were also more likely to work part-time than men – 26% of women worked fewer than 30 hours per week, compared to only 9% of men, which may also help explain the lower career advancement observed among women. Differences in family structures might contribute to these disparities, as more women than men have children in our sample, which could impact their working hours and career advancement possibilities.

Next, we analyzed how women and men perceive the importance of cognitive, social, and communication skills.

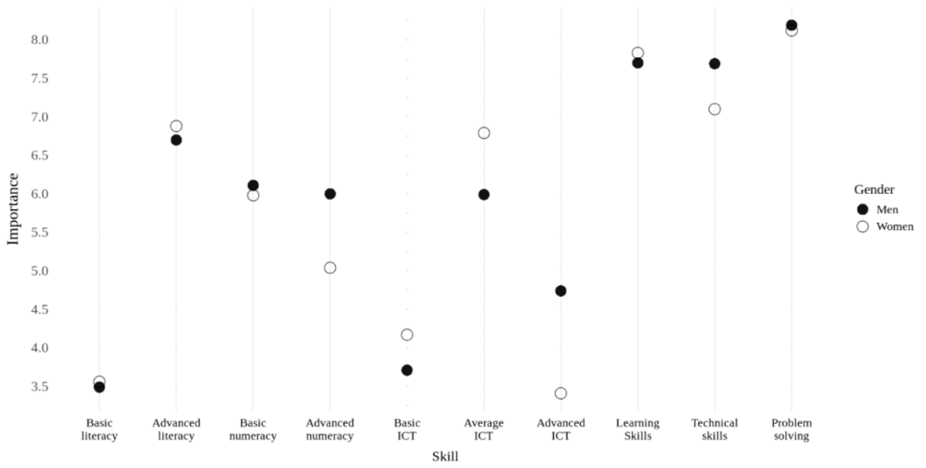

Figure 1. The importance of self-assessed cognitive skills by women and men

Note: Population weights apply.

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations.

Among cognitive skills (Figure 1), women tend to perceive literacy skills as more important than men, while men place a higher emphasis on numeracy skills. For ICT skills, although women view basic and intermediate ICT skills as more important, men tend to perceive advanced ICT skills as more crucial. There is no major gender difference in the importance placed on learning and problem-solving skills, while technical skills are generally assessed as more important by men. These perceptions may contribute to the gender allocation of tasks in jobs, which in turn contributes to the gender wage gap. These results align with traditional assumptions and results from literature review (e.g., Hyde et al., 2008; Lindemann, 2015).

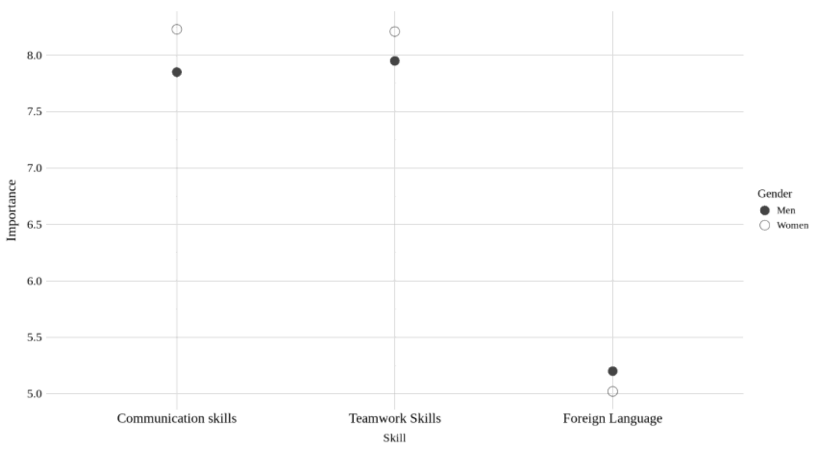

Figure 2. The importance of self-assessed communication and social skills by women and men

Note: Population weights apply.

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations.

Among communication and social skills (Figure 2), women place greater importance on social and communication skills, rating the importance of communication and teamwork skills higher than men, while scores for foreign language skills are nearly identical between men and women. These findings align with the literature analysis where women tend to outperform men in verbal skills, such as reading comprehension, vocabulary acquisition, and verbal fluency (e.g., Hedges & Nowell, 1995; Voyer Voyer, 2014).

4.1.2. Selection into different job tasks within the same occupation and industry in a pooled sample

The descriptive results showcased a sizable gender gap in the assessment of the importance of different skills in performing job tasks. However, the descriptive results do not account for gender segregation into occupations and industries, which is widely documented in earlier literature and, expectedly, results in significant gender disparity in job skills (Borrowman & Klasen, 2020; Preston, 1999; Scarborough, 2020). Hence, we next turn to the empirical assessment of within-occupation/within-industry gender segregation into job skills, with the latter evaluated using self-reported importance of specific skill domain in performing everyday job tasks to answer the question of whether men and women select different job tasks and how this segregation differs by regions. We first conducted the pooled sample analysis and later analyzed gender segregation into job tasks by region.

Table 1

Skills importance in performing job tasks - ordered logistic model estimation

Dependent variable	Basic numeracy	Advanced numeracy	Basic literacy	Advanced literacy	Basic ICT	Average ICT	Advanced ICT	Technical	Teamwork	Problem Solving	Learning	Foreign Language	Communi cation
Female	**1.266*****	**1.247*****	**1.616*****	**1.483*****	**1.396*****	**1.651*****	**1.072**	**0.889*****	**1.473*****	**1.129*****	**1.311*****	**0.907*****	**1.449*****
	(0.0308)	(0.0430)	(0.0485)	(0.0389)	(0.0619)	(0.0421)	(0.0542)	(0.0167)	(0.0279)	(0.0214)	(0.0246)	(0.0178)	(0.0276)
Age	1.009***	1.011***	1.009***	1.013***	1.009***	1.007***	1.005**	1.002**	1.004***	1.004***	1.003***	0.989***	1.004***
Immigrant	0.931*	0.919	0.847***	0.995	1.181**	0.849***	0.970	1.061*	0.939**	1.057*	1.041	1.619***	0.944*
Education:													
Medium Education	0.990	1.250***	0.960	1.417***	1.094*	1.072	1.946***	1.122***	1.170***	1.083***	1.128***	1.245***	1.174***
High education	0.959	1.418***	0.970	1.811***	1.191***	1.025	1.753***	1.046	1.083**	1.145***	1.118***	1.634***	1.283***
Living with partner	1.047*	1.127***	1.112***	1.006	1.030	0.999	0.970	1.147***	1.139***	1.128***	1.109***	0.984	1.116***
Living with kids	1.052**	1.049	1.042	1.043*	1.065	1.002	1.084*	1.031*	1.101***	1.019	1.016	0.985	1.062***
Occupations:													
2= Professionals	1.364***	0.970	1.161**	1.175	1.063	0.997	0.754	1.658***	1.294***	1.848***	1.547***	1.130**	1.084*
3 = Technicians and Associate Professionals	1.013	0.320***	0.732*	0.872	1.192	1.037	1.126	0.835	1.420***	1.582***	1.257*	1.007	0.944
4 = Clerical Support Workers	1.265***	0.862	1.175***	1.096	1.342***	1.021	0.614**	0.826***	1.527***	1.773***	1.111**	1.873***	1.956***
5 = Service and Sales Workers	2.085***	1.190	1.748***	1.576***	2.279***	2.203***	0.752*	0.699***	0.990	1.503***	1.156***	2.157***	1.511***
6 = Skilled Agricultural, Forestry, and Fishery Workers	1.944***	1.199*	1.629***	1.543***	1.594***	1.856***	1.417**	1.725***	1.426***	2.609***	1.700***	2.384***	1.817***
7 = Craft and Related Trades Workers	2.108***	1.301**	1.662***	2.102***	1.392***	1.879***	1.419**	1.407***	1.424***	2.936***	2.187***	2.828***	2.263***
8 = Plant and Machine Operators and Assemblers	2.431***	1.299**	1.786***	2.366***	1.843***	1.869***	1.041	1.102**	1.984***	3.316***	1.758***	2.832***	3.204***
9 = Elementary Occupations	0.793***	0.463***	0.756***	0.607***	0.981	0.785*	0.117***	0.481***	0.758***	0.611***	0.521***	0.925	0.661***
Private firm	1.193***	0.959	1.033	0.894***	0.975	0.967	0.998	1.061***	0.898***	1.083***	0.949**	1.208***	0.964*

Dependent variable	Basic numeracy	Advanced numeracy	Basic literacy	Advanced literacy	Basic ICT	Average ICT	Advanced ICT	Technical	Teamwork	Problem Solving	Learning	Foreign Language	Communi cation
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Working hours	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	27.378	13.283	19.335	22.858	8.803	24.559	7.124	44.768	45.382	45.373	45.469	39.597	45.217

Notes: The table reports odds ratios from ordered logistic regressions. Population weights apply. *,**,*** correspond to the results significant at 1%, 5%, and 10% respectively.

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations.

Table 1 presents ordered logistic regression results following specification (1). The results suggest that within the same occupations and industries, men and women across the EU-27 approach and assign importance to tasks differently. Most skills, except technical and foreign language skills, are rated as more important by women. While men place greater importance on technical and foreign language skills, the difference is not large. On average, women's scores for these skills were approximately 90% of men's scores.

For technical skills, men rate their importance higher in both descriptive and econometric analyses. This may suggest that men are more likely to work in occupations and industries where technical skills are highly valued and to use these skills more within the same occupation. For foreign language skills, however, there was no major difference in the descriptive analysis across all occupations and industries, and no evidence indicated that men placed significantly greater importance on foreign language skills across occupations. The difference in the assessment of foreign language skills within occupations and industries may be linked to the slightly higher proportion of men in the immigrant population.

Several interesting observations emerged regarding differences in skill ratings within and across occupations and industries. Descriptive results across occupations showed that men assessed advanced numeracy skills as more important. However, within the same occupations, the pattern was reversed, and women rated these skills as 24.7% more important than men. This may be because women are less often employed in occupations where advanced numeracy skills are critical. However, when they do work in such occupations, they may perceive these skills as more important due to lower self-confidence, as advanced numeracy skills are often perceived as “male” qualities. The literature indicates that women tend to assess their skills as lower than men, which can undermine their confidence in their abilities (Mejía-Rodríguez et al., 2020; Roberts, 1991). This lack of confidence may lead women to emphasize the importance of skills more strongly because they may feel a greater need to meet or exceed expected competencies. This information aligns with the trend observed in this analysis, where women rated the importance of almost all skills higher than men did.

One more skill assessed as more important by men across occupations and industries was advanced ICT skills; however, the coefficients for it were not significant, and therefore, we can not draw any conclusions from it.

Running models in the pooled sample without disaggregating by occupations and industries showed that women place more importance on most tasks, except technical and foreign language skills, while descriptive analysis across occupations and industries suggested that men place more importance on advanced numeracy, advanced ICT, and technical skills. To explore this topic further, in the next subchapter, we will disaggregate the results by occupation and industry categories.

4.1.3. Selection into different job tasks within the same occupation and industry – occupational and industrial disaggregation

To explore the topic further, we decided to disaggregate the results by occupation and industry categories and run models for each of them separately.

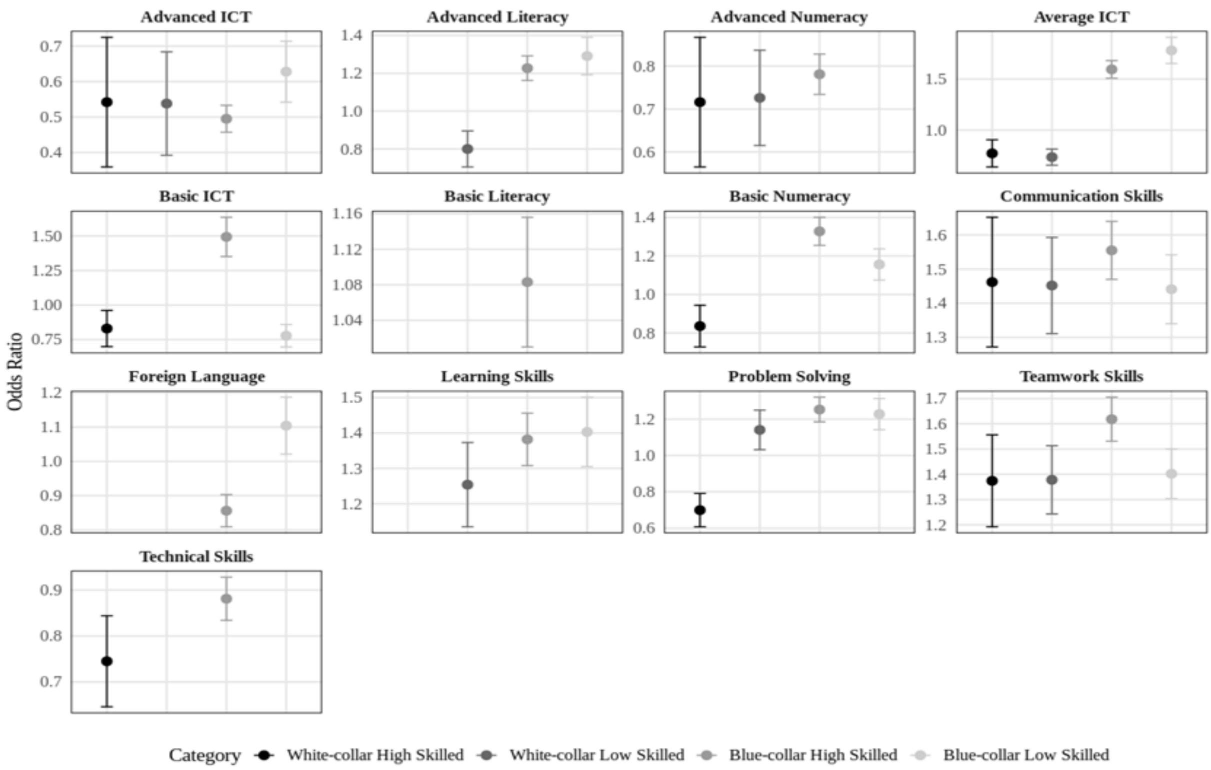

Figure 3. Skills importance in performing job tasks – gender coefficient derived from ordered logistic model estimation by occupation categories

Notes: The table reports odds ratios from ordered logistic regressions. Population weights apply. Only coefficients significant at the 1% level are included.

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations.

Figure 3 presents results for occupation categories. By examining occupational categories, a clear pattern of gender segregation into job tasks emerges. Men place greater importance on advanced ICT skills, advanced numeracy skills, technical skills, and foreign language skills. The largest gender segregation into job tasks is observed for advanced ICT skills. In contrast, women assign greater importance to softer skills, such as learning, teamwork, and communication skills.

Several interesting observations arise. The highest gender segregation in job tasks is observed in Advanced ICT skills within blue-collar high-skilled occupations – for skilled agricultural, forestry, and fishery workers; craft and related trades workers; plant and machine operators and assemblers. Women use these skills only 50% as much as men.

For Problem-Solving skills, an unusual pattern emerges. Women use problem-solving skills more than men across most occupational categories, except in the white-collar high-skilled category, which includes managers, professionals, technicians, and associate professionals, where men use them more. This observation can relate to the over-representation of men in white-collar, high-skilled occupations and the potential selection of men into more challenging and demanding job tasks within the occupation group. Furthermore, generally, higher confidence in men may play an even greater role on the top of the career ladder, as men holding white-collar, high-skilled jobs may see their job tasks requiring problem-solving skills of more paramount importance than women.

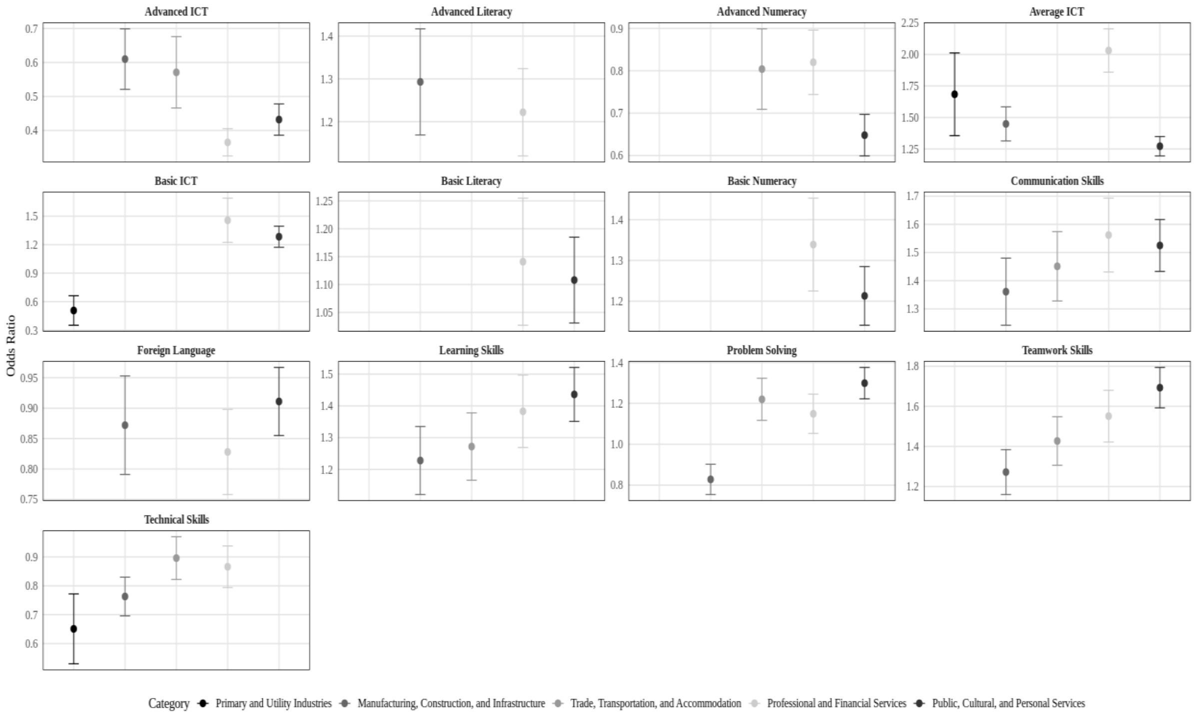

Figure 4. Skills importance in performing job tasks – gender coefficient derived from ordered logistic model estimation by industry categories

Notes: The table reports odds ratios from ordered logistic regressions. Population weights apply. Only coefficients significant at the 1% level are included.

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations.

A similar pattern of gender segregation into job tasks is observed when disaggregating by industry categories (Figure 4). Men assign higher importance to advanced ICT skills, advanced numeracy skills, technical skills, and foreign language skills, while women emphasize communication, learning, and teamwork skills. Similar to occupation categories, the highest gender segregation in job tasks is observed in advanced ICT skills, particularly in professional and financial services - women's usage of these skills is only 37% of that of men.

Similarly, not all industries follow the same pattern for problem-solving skills. Men use problem-solving skills more than women across most industries, but in manufacturing, construction, and infrastructure industries, women place more importance on these skills than men.

This analysis supports the assumption that clear gender segregation exists in job tasks within industries and occupations. These findings align with our descriptive analysis across occupations and industries – men tend to emphasize technical and analytical skills, while women prioritize communication and literacy-related skills. This pattern holds true for the same occupations and industries.

Moreover, the results disaggregated by occupational and industrial categories align with previous research on PIACC data, which also found that women use numeracy and computer skills less than men within the same occupations (Pető & Reizer, 2021). These findings also align with Lindemann's (2015) research, which analyzed occupational and industrial categories and reported that men typically engage more in numeracy tasks while women excel in literacy tasks. Our contribution highlights that these patterns are also evident within individual occupations.

4.1.4. Gender segregation into job tasks by EU-27 regions

After analyzing the importance of skills in all EU, we conducted a regression by region to understand how gender segregation differs by region.

Our initial assumption was that in countries with higher gender equality index (European Institute for Gender Equality, 2023), gender segregation into job tasks within the same occupations would be lower – women and men would choose approximately the same importance of tasks within occupations and industry. Average indexes for each region according to Gender Equality Index 2023 (*Gender Equality Index 2023 | European Institute for Gender Equality*, 2024) are the following: for Northern Europe 78.1%, Western and Central Europe 73.6%, Southern Europe – 65.6%, and Eastern Europe – 60.4%. Therefore, Northern Europe was expected to exhibit lower gender segregation within occupations and industries in job tasks, while Eastern Europe and Southern Europe were expected to show the highest.

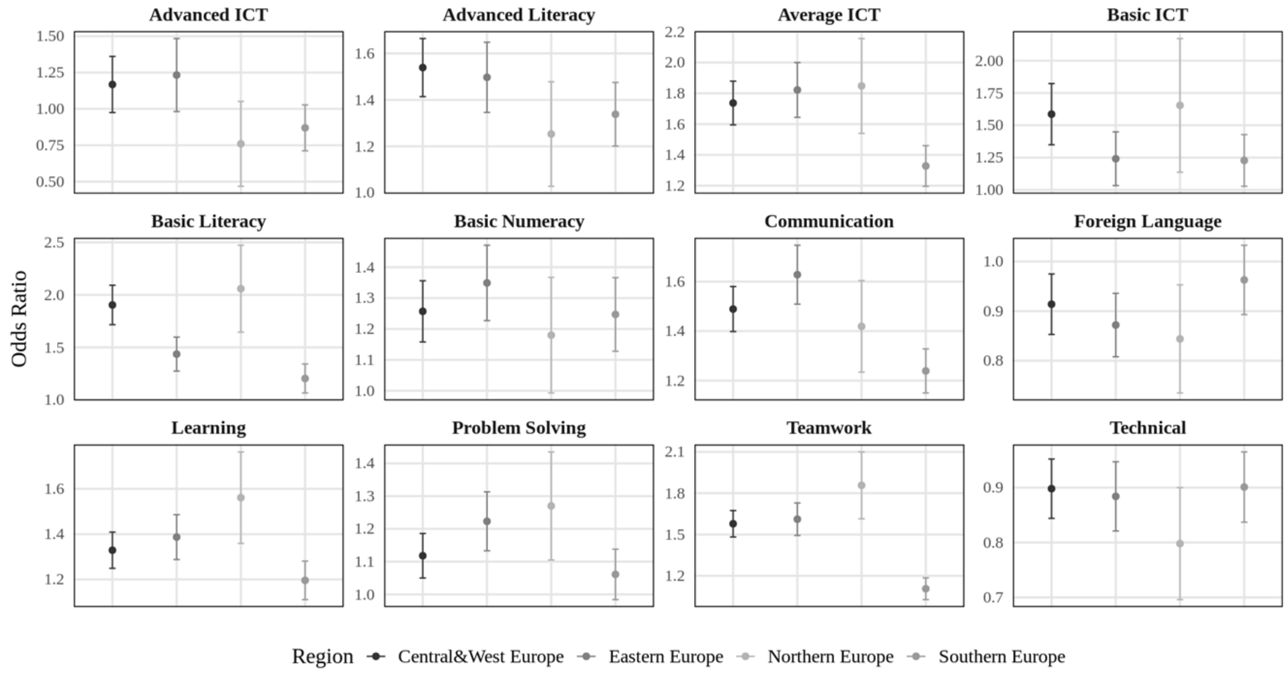

Figure 5. Skills importance in performing job tasks - ordered logistic model estimation by regions

Notes: The table reports odds ratios from ordinal logistic regressions. Population weights apply. Advanced numeracy and ICT skills are excluded due to low significance

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations

Gender differences in basic numeracy and advanced literacy skills were indeed less pronounced in Northern Europe (Figure 5). However, despite smaller gender differences in this skill use domains, Northern Europe exhibited the highest gender differences in the perceived importance of many other skills, such as basic literacy, basic and average ICT, problem-solving, learning, and teamwork skills, with women rating these skills as more important than men within the same occupation.

Gender differences were also higher in Northern Europe for skills that men assessed as more important. This region showed the greatest gender segregation in technical and foreign language skills, with men placing significantly more importance on these skills than women. The importance placed on technical skills by women was 80% of that placed by men. A similar pattern was observed for foreign language skills, where the average importance score for women was 84% of that for men.

For advanced ICT skills, while women in Central & Western and Eastern Europe placed more importance on these skills, men prioritized them more in Northern and Southern Europe. Gender segregation into job tasks in Northern Europe is also the highest in Northern Europe.

While Northern Europe mostly exhibited higher gender differences, Southern Europe emerged as the region with the lowest gender differences in perceived skill importance. Compared to other regions, Southern Europe demonstrated the smallest differences in basic ICT, basic literacy, communication, foreign language, learning, problem-solving, teamwork, and technical skills. Consequently, gender segregation was lower in Southern Europe.

Initially, we assumed that in more developed regions, such as Northern Europe, gender differences in skill importance would be lower. However, the results did not support this hypothesis. Despite Northern Europe's reputation for relatively lower gender inequality, gender segregation in tasks persisted, even within the same occupations. Southern Europe, having a relatively lower Gender Equality Index, exhibited lower gender segregation in job tasks. Therefore, while it may be tempting to assume that countries with lower gender equality would have higher gender segregation in job tasks within the same occupation, the findings contradicted this assumption.

Upon closer examination, confidence intervals revealed a higher gender gap ratio in Northern Europe compared to other regions, which suggests greater variability in the data. This indicates that gender differences in task importance are less uniform across skills, as respondents within the same occupation and industry in Northern Europe may have highly diverse views on task importance. This diversity among respondents in Northern Europe could contribute to the larger observed gender differences.

The literature review revealed that gender segregation across occupations could be higher in more developed countries (Blackburn & Jarman, 2006). Moreover, in countries with higher gender equality – such as the Nordic countries (e.g., Norway, Finland, and Sweden) – women are less likely to choose STEM fields compared to women in countries with lower gender equality (e.g., Turkey or Algeria) (Pető & Reizer, 2021). Our contribution in this part is that we found similar patterns occurring within the same occupations with similar job characteristics. Even when choosing the same occupation, women and men tend to assign different levels of importance to tasks in more developed countries such as the Nordic countries.

We looked more closely at the situation in less developed regions, such as Southern Europe, to understand whether lower gender segregation in job tasks occurs due to lower skill usage by both women and men and lower human capital, such as education; however, this did not hold true, and respondents exhibited higher human capital.[3] One explanation of why more

[3] Data is available upon the request.

developed regions may have higher gender segregation into job tasks is that in societies with higher gender equality, individuals are freer to choose careers and tasks based on their personal interests, while in less developed countries, women may be more motivated to choose analytical skills because these skills offer greater bargaining power. This may also suggest that gender segregation into job tasks contributes less to the gender wage gap in more developed countries than in less developed ones. From this perspective, if women in developed countries do not feel the economic pressure to enter higher-paying STEM industries, they may be more satisfied with their salaries, even in industries generally considered lower-paid across most countries.

4.2. The impact of gender segregation into job tasks on the gender wage gap

4.2.1. Econometric analysis of the role of segregation into tasks in a pooled sample

Next, we turn to the analysis of the association between within-occupation/within-industry segregation of men and women into job tasks and the gender wage gap. We wanted to understand how gender segregation into job tasks within occupation and industry reflects into gender wage gap.

Table 3

Regression results of determinants of wages

Variables	Model 1	Model 2	Model 3	Model 4
Female	-0.262***	-0.258***	-0.114***	-0.118***
	-0.0202	-0.0205	-0.0224	-0.0221
Age		0.0573***	0.0457***	0.0469***
Age squared		-0.000564***	-0.000434***	-0.000447***
Immigrant		-0.0239	-0.00505	-0.013
Medium Education		0.218***	0.111**	0.100**
High education		0.526***	0.268***	0.240***
Living with partner		0.0960***	0.0824***	0.0803***
Living with kids		0.0167	0.0203	0.0139
Country	Yes	Yes	Yes	Yes
2= Professionals			-0.156**	-0.168**
3 = Technicians and Associate Professionals			-0.218*	-0.219**
4 = Clerical Support Workers			-0.145*	-0.176**
5 = Service and Sales Workers			0.0316	-0.00214
6 = Skilled Agricultural, Forestry, and Fishery Workers			0.119	0.0645

Variables	Model 1	Model 2	Model 3	Model 4
7 = Craft and Related Trades Workers			0.252***	0.177**
8 = Plant and Machine Operators and Assemblers			0.458***	0.388***
9 = Elementary Occupations			-0.189*	-0.199**
Agriculture, horticulture, forestry or fishing			-0.0889	-0.0917
Supply of gas or electricity, mining or quarrying			0.179***	0.177***
Supply, management or treatment of water or steam			0.0112	0.0161
Manufacturing or engineering			0.152***	0.137***
Construction or building			-0.0313	-0.0179
Retail, sales, shop work or whole sale			-0.0343	-0.0303
Accommodation, catering or food services			-0.0568	-0.0621
Transportation or storage			0.0298	0.0204
Information technology or communication services			0.164***	0.127***
Financial, insurance or real estate services			0.163***	0.162***
Professional, scientific or technical services			0.0448	0.0256
Services relating to education or health			-0.0707**	-0.0634*
Cultural industries (arts, entertainment or recreation)			-0.196***	-0.201***
Social and personal services			-0.179***	-0.170***
Something else			-0.184	-0.183
Private firm			-0.0387	-0.0398
Working hours between 10 and 20 hours per week			-0.139	-0.137
Working hours between 20 and 30 hours per week			0.324***	0.326***
Working hours between 30 and 40 hours per week			0.659***	0.645***
Working hours more than 40 hours			0.771***	0.743***
Importance of advanced literacy skills				Yes
Importance of advanced numeracy skills				Yes
Importance of advanced ICT skills				Yes
Importance of technical skills				Yes
Importance of communication skills				Yes
Importance of teamwork skills				Yes
Importance of foreign language skills				Yes
Importance of problem-solving skills				Yes
Importance of learning skills				Yes
Number of observations	21,339	21,339	21,339	21,339

Notes: The table reports coefficients from an ordered linear model. Population weights are applied. *, **, and *** correspond to results significant at 1%, 5%, and 10%, respectively.

For numeracy, literacy, and ICT skills, only advanced skills are included due to high multicollinearity.

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations

Table 3 presents gender wage gap regression estimations. The raw gender wage gap between women and men is approximately 26.2%, indicating that, on average, women earn 26.2% less than men. When additional factors such as age, immigration status, education, and family structure are accounted for in Model 2, the wage gap slightly decreases to 25.8%. This suggests that demographic factors have limited power in explaining the gender wage gap.

When industry, occupation, hours worked, and firm type are included in Model 3, the gender wage gap decreases by 14.4 p.p. This suggests that these factors explain a large portion of the gender wage gap, as men are more likely to work in higher-paying occupations and industries and to work longer hours than women.

Table 3 reveals that, even though the coefficients for some occupations and industries were not significant, higher wages were associated with craft and related trades workers and plant and machine operators – occupations employing more men than women – and lower wages were associated with cultural industries and social and personal services, which are dominated by women. Therefore, occupations with higher male representation tend to have a stronger positive association with salaries, while those with higher female representation exhibit the opposite trend.

The type of firm might also play an important role in shaping the gender wage gap. However, the coefficients were not significant enough to support this claim. Expectedly, longer workhours are positively associated with wages. As observed in the descriptive analysis, women are more likely than men to work part-time, which could be related to the fact that our sample systematically includes more women with children than men with children. Motherhood yields a significant wage and career penalty, as documented, among others, by Goldin (2022). Shorter work time, slower career growth, and selection into less challenging yet less rewarding jobs are among the key disadvantages experienced by women during child-rearing years. Other factors may include societal expectations for women to perform traditional roles, which can lead them to spend less time on their careers.

To understand whether gender segregation into job tasks contributed to the gender wage gap, in Model 4, we controlled for skill importance while also accounting for other variables, such as firm type, occupation, and industry. Including skill importance variables widened the gender wage gap by 0.4 p.p. These results suggest that differences in task involvement cannot explain the wage gap in the pooled sample. When comparing the impact on the gender wage gap, occupational factors, industry, and hours worked have a much stronger association than the importance of skills.

Even after controlling for the mentioned factors, the analysis indicates that women still earn approximately 11.8% less than men. Even when women and men work in the same industry, occupation, and firm type, have similar family status and age, and use the same skills, the unexplained gender wage gap persists. This represents the unexplained portion of the gender wage gap, which can stem from many factors. One of the factors addressed in the literature is negotiating abilities. Women are more likely than men to feel anxious during salary negotiations (Bowles et al., 2005) and perceive negotiation as socially disapproved behavior (Greig, 2010). This can prevent women from asking for higher salaries during recruitment or their work experience, making them less likely to be promoted, as was also shown in our descriptive analysis.

4.2.2. Econometric analysis of the role of segregation into tasks – occupational and industrial disaggregation

The analysis in the previous subchapter suggested that skill usage/importance does not significantly contribute to explaining the gender wage gap, whereas job-related characteristics such as industry, occupation, and hours worked were identified as the main contributing factors. In this subchapter, we investigate whether the results hold when disaggregating by occupations and industries.

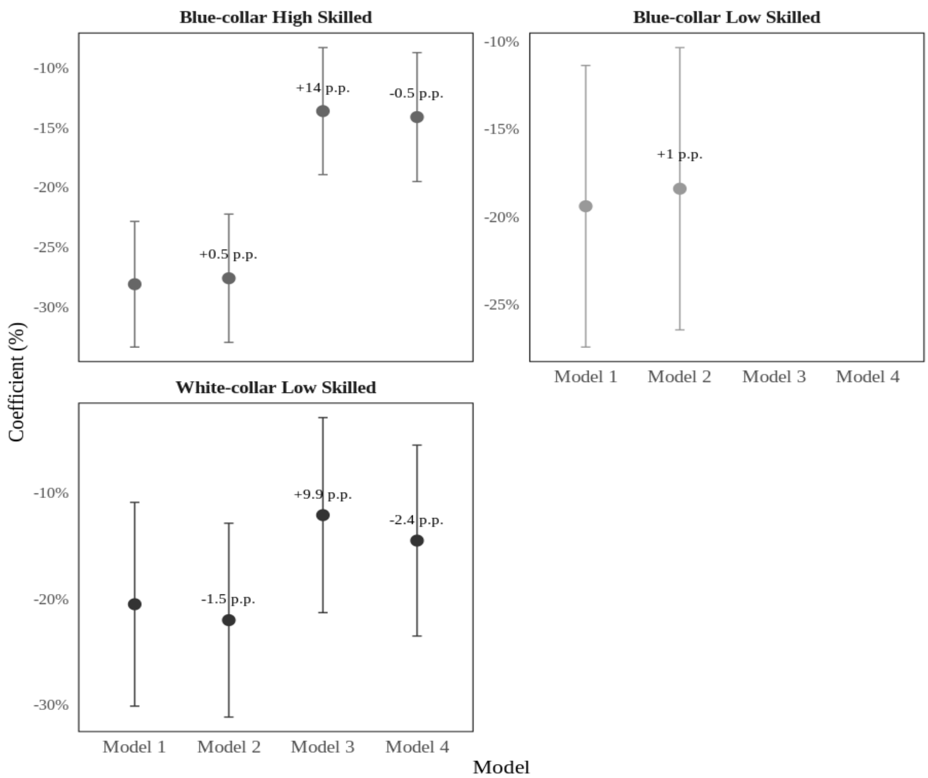

Figure 6. Comparison of models' female dummy coefficients across occupational categories

Notes: The table reports coefficients from ordered linear model. Only significant at 1% were included. Population weights apply. For numeracy, literacy, and ICT skills, only advanced skills are included due to high multicollinearity.

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations

Figure 6 shows a comparison of model coefficients across occupational categories. Most coefficients were found to be non-significant; however, for the significant ones related to high-skilled blue-collar and low-skilled white-collar occupations, we observe that occupational and industrial segregation, along with hours worked, explain the gender wage gap much more than skill usage does. Adding skills even widens the gender wage gap, especially for the white-collar, low-skilled category (clerical support workers). This could indicate that even when women and men perform the same tasks as clerical support workers, women may still be rewarded less for performing tasks that are stereotypically perceived as male jobs.

Occupational categories, industries, and hours worked explain the gender wage gap for high-skilled blue-collar occupations (skilled agricultural, forestry, and fishery workers, craft and related trades workers, plant and machine operators, and assemblers) more than for low-skilled white-collar occupations (clerical support), which could be due to the requirements of high-skilled blue-collar jobs, such as technical expertise, longer hours worked, and rigid schedules for higher salaries, which may result in women being more involved in lower-paid industries and occupations.

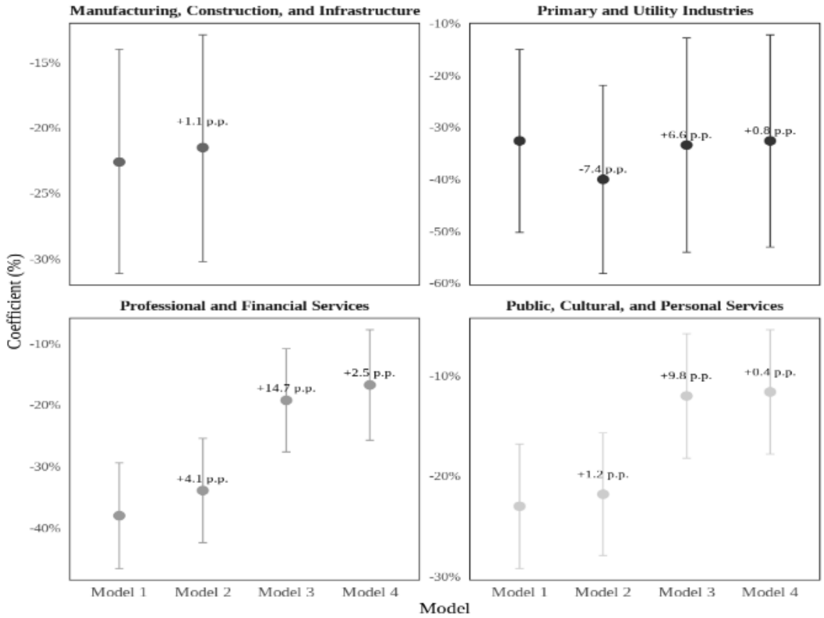

Figure 7. Comparison of models' female dummy coefficients across industrial categories

Notes: The table reports coefficients from the ordered linear model. Only significant at 1% were included. Population weights apply. For numeracy, literacy, and ICT skills, only advanced skills are included due to high multicollinearity.

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations

After disaggregating by occupational categories, we also look at industrial disaggregation (Figure 7). Out of five industrial categories, the significance of only three categories allowed us to examine all models and make comparisons: primary and utility industries, professional and financial services, and public, cultural, and personal services.

Several interesting observations emerge for primary and utility industries. While controlling for factors such as age, immigration status, education level, living with a partner, and living with children contributes to a decrease in the gender wage gap in other industries, it actually widens the gap in primary and utility industries, such as agriculture, horticulture, forestry or fishing, supply of gas or electricity, mining or quarrying, and the supply, management, or treatment of water or steam. Possible reasons for this include the physical demands of these industries: older men may be more likely to remain in physically demanding roles and accumulate wage premiums, and men with higher education levels may enter more technical roles, while women, despite having similar qualifications, may remain in support positions.

Controlling for occupation, industry, and hours worked also reduces the gender wage gap – if women and men work the same hours and hold the same roles within the same industry, the gap decreases. However, the unexplained gender wage gap remains significantly higher in primary and utility industries than in other industries – 33%. On the other hand, the industry category with the lowest unexplained gender wage gap is public, cultural, and personal services – 12%. This suggests that discrimination, biases, and other unanalyzed factors may be more prevalent in male-dominated sectors, such as primary and utility industries, than in female-dominated sectors.

Professional and financial services, which include information technology or communication services, financial, insurance, or real estate services, and professional, scientific, or technical services, is the industry category with the highest contribution of factors to the gender wage gap. Despite the high raw gender wage gap, controlling for factors significantly decreases it. This reduction is first visible with demographic and family characteristics, then with job-level control variables, and even when skill usage is added as a factor. Therefore, professional and financial services could be the industry requiring more advanced cognitive skills, such as advanced numeracy and advanced ICT skills, and having more formalized evaluations - such as fixed higher salaries for higher occupations and compensation for longer working hours.

4.2.3. Econometric analysis of the role of segregation into tasks by EU-27 regions

After examining whether gender segregation into job tasks significantly contributes to explaining the gender wage gap and what constitutes the unexplained gender wage gap, we turn to the analysis of regional variation.

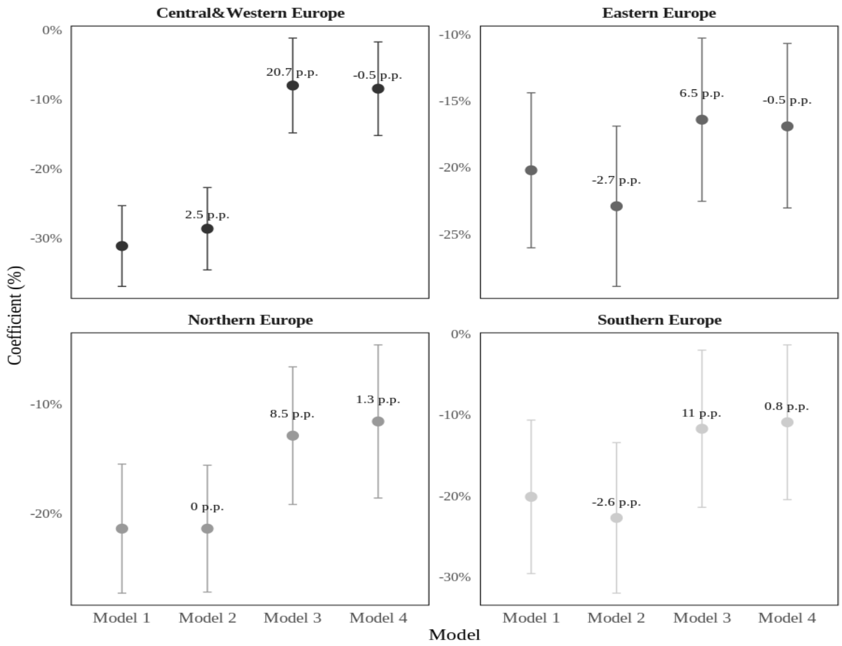

Figure 8. Comparison of models' female dummy coefficients across regions

Notes: The table reports coefficients from the ordered linear model. Population weights apply. For numeracy, literacy, and ICT skills, only advanced skills are included due to high multicollinearity.

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations

Figure 8 presents a regional variation in the gender wage gap. Occupation, industry, firm type, and work hours explain the gender wage gap more in Central & Western Europe than in other regions. These factors account for 20.7 p.p. of the gap in this region. In contrast, in Eastern Europe, the gender wage gap is the least explained by these factors, with only 6.5 p.p. accounted for. In Northern Europe, job-related characteristics explain the gender wage gap slightly better than in Eastern Europe, though still less than in Central & Western Europe and Southern Europe.

When considering skill importance, the addition of skill importance has a greater impact on explaining the gender wage gap in Northern Europe than in other regions, contributing a change of 1.3 p.p. Among all regions, Eastern Europe shows the highest unexplained gender wage gap at 16.9%. Eastern Europe also has the lowest Gender Equality Index (Table 4), which may associate to its higher unexplained wage gap. This could potentially be connected to factors such as negotiating skills, biases, or discrimination. Central & Western Europe, on the other hand, has the lowest unexplained gender wage gap of 8.4%.

Overall, while factors such as occupation, industry, and work hours explain a portion of the gender wage gap, a substantial unexplained gap persists across all regions. Addressing this is especially important for Eastern Europe, as it has the highest unexplained gender wage gap. It is also important to focus on addressing occupational and industrial segregation and differences in hours worked in all regions, especially in Central & Western Europe, where these factors explain a larger portion of the gender wage gap.

5. Conclusions

In this thesis, we analyzed the differences in the perceived importance of skills in similar jobs between women and men – referred to as gender segregation into job tasks – and its impact on the gender wage gap, using data from the European Skills and Jobs Survey (ESJS), first wave. First, we examined the gender gap in skill usage across the EU-27 as a pooled sample, as well as by occupational and industrial categories. Additionally, we conducted a regional analysis to better understand variations across different EU-27 regions. Finally, we explored how this gender segregation impacts the gender wage gap, analyzing the pooled sample, occupation, industry categories, and regional levels.

Our findings suggest that gender segregation in job tasks persists. Even when working in jobs with similar characteristics, such as the same industry, occupation, number of hours, and firm type, women and men tend to choose jobs that require different skills. Men generally place greater emphasis on advanced ICT skills, advanced numeracy skills, technical skills, and foreign language skills, while women prioritize softer skills, such as learning, teamwork, and communication skills. Our contribution on this point is that, even though there has been some research on analyzing literacy, numeracy, and ICT skill usage within occupations, no research has focused on gender segregation into job tasks while analyzing such a broad range of cognitive and non-cognitive skills.

Exploring how gender segregation into job tasks reflects on the gender wage gap, we found that differences in task involvement, in general, cannot explain the wage gap. When comparing the impact on the gender wage gap, occupational factors, industry, and hours worked have the greatest influence among all factors. However, even after controlling for various factors, such as demographics, job-related characteristics, and skill importance, women still earn approximately 11.8% less than men. This is an unexplained gender wage gap, which can include negotiation abilities, discrimination, biases, and other factors that should be explored further.

Turning to regional variations, we expected that relatively developed regions with higher Gender Equality Indexes, such as Northern Europe, would exhibit lower gender segregation into job tasks. However, Northern Europe demonstrated higher gender segregation into job tasks. These results aligned with the literature on occupational gender segregation, which found that in more developed countries, such as the Nordic countries (e.g., Norway, Finland, and Sweden), women were less likely to choose STEM fields compared to women in countries with lower gender equality (e.g., Turkey or Algeria) (Pető & Reizer, 2021).

Therefore, one of our main contributions was understanding that these unusual patterns within occupations and industries are similar to those observed across them. Moreover, the addition of skill importance has a relatively greater impact on explaining the gender wage gap in Northern Europe than in other regions, contributing to a change of 1.3 p.p. Even though results show that Northern Europe could benefit the most from decreasing gender segregation into job tasks, this topic is worth exploring further, given that the gender equality index in this region is higher than in other regions.

Apart from answering the main question about gender segregation and its reflection on the gender wage gap, this thesis has contributed by identifying occupation, industry, and region-specific findings that can be used for policy implications as well as future research.

First of all, the gender wage gap in the professional and financial services industry can be explained the most by the factors considered in our analysis, despite the high raw gender wage gap and the highest gender segregation in job skills, particularly advanced ICT skills. This reduction becomes evident first with demographic and family characteristics, then with job-level control variables, and even when skill usage is added as a factor – unlike in other industries with significant coefficients. Therefore, policy implementation and future research can focus on ways to decrease gender differences, as these can contribute to closing the gender wage gap.

Secondly, the unexplained gender wage gap is much higher in male-dominated sectors, such as primary and utility industries, than in female-dominated sectors, such as public, cultural, and personal services. This observation requires further analysis because if the gap is not due to occupation, industry, hours worked, individual characteristics, or skill usage, subjective factors such as biases, negotiation abilities, and discrimination in wage assessments may play a role, and additional factors should be investigated.

Thirdly, Eastern Europe has the highest unexplained gender wage gap, alongside the lowest gender equality index. More efforts should be made to research and address this issue. Finally, while occupation, industry, firm type, and hours worked explain the largest fraction of the gender wage gap across all regions, this contribution is higher for Central and Western Europe than in other regions, which is worth further examination.

Appendix

Table A

Variables	Women (%)	Men (%)
Age (mean)	42	43
Occupation (distribution of women and men across occupations in %)		
Plant and Machine Operator and Assembler	2.23	10.9
Building, Crafts or a Related Trade Person	1.97	11.2
A Skilled Agricultural, Forestry and Fishery Worker	0.302	1.08
A Sales, Customer or Personal Service Worker	16.7	11.4
Clerical Support	33.8	15.1
A Technician or Associate Professional	15	20
A Professional	19.9	16.5
A Manager	5.26	9.47
Elementary occupations	4.74	4.42
Industry (distribution of women and men across industries in %)		
Administration and support services, including public administration and defence	14.4	11.8
Agriculture, horticulture, forestry or fishing	1.29	1.78
Supply of gas or electricity, mining or quarrying	1.3	2.5
Supply, management or treatment of water or steam	0.826	1.17
Manufacturing or engineering	12.7	19.3
Construction or building	4.76	8.43
Retail, sales, shop work or whole sale	11.5	9.62
Accommodation, catering or food services	3.07	2.98
Transportation or storage	2.65	8.6
Information technology or communication services	4.03	8.05
Financial, insurance or real estate services	4.99	4.74
Professional, scientific or technical services	6.05	5.85
Services relating to education or health	21.5	8.72
Cultural industries (arts, entertainment or recreation)	1.95	1.53
Social and personal services	7.74	3.69
Something else	1.14	1.25
Education (% of women and men at each level of education)		
Low education	11.5	16.2
Medium education	49.9	50.8
High education	38.7	32.9
Education (% of total at each level of education)		
Low education	39.7	60.3
Medium education	47.8	52.2
High education	52.3	47.7
Immigrants (% among immigrants)	8	7.9
Immigrants (% among women and men)	48.5	51.5
Cognitive skills importance (index)		
Basic literacy importance	3.56	3.49
Advanced literacy Importance	6.88	6.7
Basic numeracy Importance	5.98	6.11
Advanced numeracy importance	5.04	6
Basic ICT Importance	4.17	3.71
Average ICT Importance	6.79	5.99
Advanced ICT Importance	3.41	4.74
Problem solving Importance	8.12	8.19
Learning Skills Importance	7.83	7.7
Technical skills Importance	7.1	7.69
Non-cognitive skills importance (index)		
Communication skills Importance	8.23	7.85

Teamwork Skills Importance	8.21	7.95
Foreign Language Importance	5.02	5.2
Promotion (% among promoted employees)	41.2	58.8
Promotion (% among women and men)	25.3	33.7
Permanent Contracts (% among those with permanent contracts)	47.3	52.7
Permanent Contracts (% among women and men)	83.2	86.5
Overqualification (% among overqualified workers)	46.3	53.7
Overqualified (% among women and men)	38.3	41.5
Underqualified (% among underqualified workers	50.7	49.3
Underqualified (% among women and men)	5.62	5.11
Living with Partners (% among women and men)	65.7	71.9
Living with Kids (% among women and men)	40.5	37.1
Immigration (% among women and men)	8.02	7.93
Working Hours (% among women and men)		
between 0_10 hours in a week	3.97	2.33
between 10_20 hours in a week	8.98	2.46
between 20_30 hours in a week	13.3	3.84
between 30_40 hours in a week	58.1	62.1
more than 40 hours in a week	15.6	29.3
Working Hours (% of women and men among those working certain hours per week)		
between 0_10 hours in a week	61.4	38.6
between 10_20 hours in a week	77.3	22.7
between 20_30 hours in a week	76.4	23.6
between 30_40 hours in a week	46.6	53.4
more than 40 hours in a week	33.2	66.8
Years in current job	10.1	11.2

Notes: Population weights apply.

Source: European Skills and Jobs Survey (ESJS), wave 2014, own calculations

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Resümee

SOOLISE PALGALÕHE ÜLEVAATAMINE EUROOPAS: MIL MÄÄRAL SAAB SEDA SELGITADA SOOLISE SEGREGATSIOONIGA TÖÖÜLESANNETE JÄRGI

Püsiv sooline palgalõhe mõjutab endiselt majandusarengut ning vaatamata edusammudele soolise võrdõiguslikkuse saavutamisel püsib lõhe isegi sarnastes ametites. Ametisisene sooline palgalõhe võib olla mõjutatud ülesannete segregatsioonist, mida omakorda võivad kujundada erinevused tööülesannete täitmiseks vajalikes oskustes. Selle teema kohta on teaduskirjandus siiski väga piiratud ja puuduvad uuringud, mis käsitleksid laia oskuste valikut ja nende seost soolise palgalõhega. Käesoleva töö eesmärk on uurida, mil määral esineb ametisisest ja tööstusharusisest soolist segregatsiooni tööülesannete järgi ning millist rolli see mängib soolise palgalõhe selgitamisel EL-27 riikides. Uuring põhineb European Skills and Jobs Survey (ESJS) 2014 aasta andmetel. Tulemused näitavad selget mustrit soolisest segregatsioonist tööülesannete järgi – mehed eelistavad sageli edasijõudnud arvutus-, IKT- ja tehnilisi ülesandeid, samas kui naised keskenduvad rohkem pehmetele oskustele, nagu õppimine, meeskonnatöö ja suhtlemine. Regionaalne analüüs näitab, et Põhja-Euroopa, hoolimata oma kõrgest soolise võrdõiguslikkuse indeksist, paistab silma suurima soolise tööülesannete segregatsiooniga. Siiski on sooline segregatsioon tööülesannete järgi piirkonnas soolise palgalõhe kujunemisel minimaalne. Soolise palgalõhe kujunemist mõjutavad enamasti ametialased, tööstusharulised ja tööga seotud tegurid, nagu töötundide arv ja ettevõtte tüüp. Tulemused viitavad ka märkimisväärse selgitamata soolise palgalõhe püsimisele kõigis regioonides.Selle töö tulemused omavad olulist mõju poliitikakujundamisele ning pakuvad väärtuslikke suuniseid tulevastele uurimustele.

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