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The Gender Gap in Digital Skills at Work

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Abstract

We analyse the gender gap in digital skills use at work across Europe. We find a substantial gap, with women significantly less likely to perform advanced digital tasks. A raw gender gap of around 16 percentage points is observed, of which only 30 per cent is attributable to observable factors. Oaxaca-Blinder decompositions using unconditional decile regressions reveal that the gap is most pronounced at the upper end of the digital intensity distribution, where women are substantially underrepresented. The explained component of the gender digital skills gap increases with digital task intensity, suggesting that access to highly digital jobs is shaped by gendered educational and occupational sorting. However, persistent unexplained gaps from intermediate levels indicate potential structural, cultural, or other organisational barriers at play. Furthermore, we find that younger women already face larger gaps in advanced digital skill use than older workers, suggesting that it is not a legacy issue.

JEL classification

J16, J24, O33, I25

Keywords

digitalisation, digital skills gap, gender inequality, labour markets, technological change, task-based analysis, decomposition analysis, inclusive growth

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1. Introduction

Persistent gender gaps in digital skill usage are of policy concern, as they imply that women may benefit less from ongoing technological progress in the workplace and that firms and economies may experience productivity losses due to underutilised human capital. While many studies have documented gender gaps in ICT education and in STEM occupations (Card and Payne, 2021; Cimpian et al., 2020; Beede et al., 2020; Tandrayen-Ragoobur and Gokulsing, 2022), less is known about gender differences in the digital task content of jobs. For example, do female employees use advanced digital tools and perform high-tech tasks at the same rate as male employees with similar backgrounds? If not, what explains the gap? How much of the gap is due to women's concentrated presence in certain fields of study and/or occupational roles, or does the gap persist even among comparable workers suggesting other barriers? An understanding of such issues is crucial for designing policies that ensure women are not left behind in an advancing digital economy.

Digital competencies have become increasingly important in modern labour markets and knowledge economies. Possessing digital skills has transitioned from being a distinct advantage to being a pre-requisite for effective economic and social participation (Reddy, Sharma, and Chaudhary, 2020; Fraillon et al., 2020; Falck et al., 2021). Research shows that employers seek a workforce that is highly adept in a broad range of digital tools, and lacking these skills is associated with negative consequences in terms of wages and career prospects (OECD, 2024; Reddy, Sharma, and Chaudhary, 2020; Garcia-Lazaro et al., 2025). On a broader scale, digital skill gaps pose barriers to economic development and reinforce existing inequalities, with the exclusion of women from this digital revolution estimated to have cost developing countries a cumulative $1 trillion over the last decade alone (A4AI, 2021). As the digital transformation accelerates, there is a fear that this may deepen the already present digital divide between men and women (see Martínez-Cantos, 2017; Reddy, Sharma, and Chaudhary, 2020).

Digital skill gaps not only hinder individual career outcomes but also pose barriers to broader economic development by constraining the talent pool. As digital transformation accelerates, there is a risk that existing skill divides could widen further, highlighting the urgency of proactive measures to build an inclusive and digitally proficient workforce. Policymakers across Europe and globally recognise the critical importance of digital skills for future development. The European Commission has launched several initiatives to address the gender digital divide, such as the Digital Education Action Plan, EU Gender Equality Strategy 2020-2025, and the Digital Skills and Jobs Coalition.

Despite a growing literature, there is limited evidence on gender gaps in workplace digital task use using harmonised cross-country data limited evidence on gender gaps in workplace digital task use using harmonised cross-country data. This study contributes by shifting the focus from education and occupational proxies to the digital tasks workers report performing on the job. It also documents how gender gaps vary not only on average but across the distribution of digital intensity. To address this gap, we use the 2nd wave of Cedefop's European Skills and Jobs survey (ESJS), which contains detailed data on European employees' education, occupation, and the tasks they perform as part of their jobs. Our findings show that, despite near parity in basic digital task usage at work, women remain significantly less likely than men, by 14 percentage points (p.p.), to engage in advanced digital tasks (comprising activities like software programming, machine learning and AI tools, and managing IT infrastructure). Probit regression estimates reveal robust gender differences in digital task use that persist even after controlling for education, occupation, and sector. We construct a Job Digital Intensity Index (JDII) that summarises the digital task content of jobs on a 0–100 scale. According to this index, women's mean score is almost five points below that of men, conditional on occupation and education characteristics. Oaxaca-Blinder decompositions indicate that only about 30 per cent of this gap can be attributed to observable factors such as educational field, industry and occupation. Many of women's barriers appear to arise from underrepresentation in ICT and engineering studies and in digital-intensive sectors while their overall higher educational attainment helps to offset the gap slightly.

When the analysis is extended beyond the mean to different points of the distribution of digital intensity, using Recentered Influence Function (RIF) decompositions, women's lower engagement with digital tasks becomes even more pronounced. The gender differential widens as women remain underrepresented at higher levels of the JDII, consistent with a 'glass ceiling' in access to the most digitally intensive jobs. At both the mean and the 70th percentile, most of the digital gender gap remains unexplained, indicating that differences in measured characteristics account for only a minority of the gap at these points of the distribution. However, at the very top decile, approximately 77 per cent of the gender gap is explained, with results indicating that entry into the top digitally intense jobs is tightly linked to gendered educational and occupational pathways. Overall, our results show the importance of addressing gender sorting in education and work, and furthermore, the level of unexplained inequalities that constrain women's participation in high-digital roles. The unexplained component suggests that unmeasured factors such as within-occupation task assignment, unequal returns to similar qualifications, unobserved training opportunities, structural rigidities and institutional norms, or potentially discrimination play an important role in sustaining the gender gap in digital skill use.

The remainder of the paper is structured as follows. In Section 2, we discuss the previous relevant literature. Section 3 describes the data in more detail and how our variables are constructed (including the JDII). In Section 4, we outline our empirical methodology. In Section 5, we present our findings. Section 6 concludes with our summary and some reflections on the policy implications.

2. Literature Review

This section reviews the main strands of research relevant to our analysis. We begin with literature on (i) task-based approaches to understanding technological change and inequality, followed by, (ii) occupational sorting and gender gaps in digital task use. Finally, we review relevant literature on the gender digital divide in education and attitudes.

A growing body of research highlights how technological change affects the task content of jobs rather than simply transforming entire occupations. The task-based approach introduced by Autor, Levy and Murnane (2003) and broadened by Acemoglu and Autor (2011) analyses the bundle of tasks that workers perform (rather than entire occupations) in order to understand how technology reshapes inequality, this lens has seldom been applied to gender gaps in workplace digital task use. To our knowledge, no cross-country study directly examines gender differences in the application of digital competencies at work, despite strong evidence of their wage-enhancing effects (Falck et al., 2021). A noteworthy single-country exception is Black and Spitz-Oener (2010), who find that women's increased supply of non-routine analytical tasks explained a large share of the declining gender wage gap in Germany. McGuinness et al. (2023), for the EU, find that women are less prone to technology-driven skill obsolescence than men. Building on these insights and using a task-based approach, we examine whether comparable gender differences exist in the digital task content of jobs across Europe.

Another relevant strand of research concerns how gender-based occupational sorting interacts with technological change to shape labour market outcomes. Acemoglu (1999) and Acemoglu and Autor (2011) demonstrate how technological change interacts with worker sorting across occupations, contributing to wage dispersion and inequality. More recent studies (Card et al., 2013; Song et al., 2019) highlight how high-wage workers are increasingly concentrated in high-wage firms and tend to work alongside others with similar profiles. While this literature has primarily focused on skill-based sorting, there is growing recognition that

gender-based sorting may play a crucial role in explaining disparities in digital skill use. For example, Blau and Kahn (2017) highlight how persistent occupational segregation channels women away from STEM and other technical fields, which are some of the most digitally intensive sectors of the economy. This suggests that men and women may sort into different occupations with varying degrees of digital intensity, whether due to differences in educational choices, social norms and stereotypes about "appropriate" fields for women, or structural barriers that limit access to more digitally intensive roles (Reuben et al., 2014; Bordalo et al., 2019; Ceci et al., 2014). Our analysis builds on this literature by examining whether gender-based sorting into less digitally intensive roles contributes to the gender digital gap, and whether this sorting more fully explains the disparities observed in digital task use.

While our focus is on digital tasks in the workplace, earlier life-stage factors such as education, confidence, and digital exposure may shape the subsequent occupational pathways that become apparent in the workplace. Several studies have explored the gender digital divide in education, often finding a complex pattern. When computers were first introduced to schools, they were often viewed as *"boy's toys"* (Master, Meltzoff, and Cheryan, 2021), with an assumption that male students would adapt more quickly to digital technology. However, an expanding body of research challenges this stereotype. For example, Siddiq and Scherer (2019) find a small but significant performance advantage for girls in ICT-based assessments. Similarly, results from the 2013 International Computer and Information Literacy Study (ICILS) show that eighth-grade girls outperform boys in Computer and Information Literacy (Gebhardt et al., 2019). Digging deeper, this advantage appears domain-specific. While girls excel in Computer Information Literacy (CIL), using computers to investigate, create, and communicate, the gender differences are reversed when looking at Computational Thinking (CT), which involves algorithmic problem-solving, where boys tend to demonstrate higher achievement (Kaarakainen et al., 2017; Fraillon et al., 2020). This distinction matters in a labour market context, as CT-related skills are more strongly linked to wage premiums (OECD, 2024a; 2024b).

Gender also has an interesting interaction with age. Literature has shown that while boys and girls have comparable levels of digital competency at school-going age, the gender gap evolves as individuals get older.[1] Bachmann and Hertweck (2025), using German data, find almost no gap at age 14, but a substantial and growing one by the end of secondary school, with males outperforming females in digital skill tests. This finding is also corroborated by Gnambs (2021). Notably, both studies control for important confounding factors such as field of study, subject specialisation, and the intensity of digital tool usage in school, indicating that other mechanisms may be driving the divergence. At the European level, too, men and women aged 16 to 24 report similar digital skill levels, but among older adults, men are more likely to report advanced digital competencies (OECD, 2024b). These early-stage dynamics, differences in confidence, subject choice, and self-perception, may also influence later occupational and task-based sorting, reinforcing gender gaps in digital skill use at work.

In summary, the literature highlights several mechanisms through which gender disparities in digital task use can emerge and persist. Task-based frameworks show how technological change reshapes jobs at the task level, often to the disadvantage of those not allocated to high-skill digital functions. Occupational sorting literature explains how gender differences in education, job roles, and workplace assignment may concentrate women in less digitally intensive positions. Yet, even after accounting for such factors, other social and psychological influences may remain important. Experimental and theoretical studies reveal that gender stereotypes and belief distortions can limit women's participation in technical domains, not due to ability, but due to biased perceptions and institutional practices. For instance, Risse (2018) provides evidence that personality traits and confidence gaps contribute to gender wage differentials, reinforcing the view that unexplained components may partly reflect attitudinal mechanisms**.** These findings suggest that observable differences in characteristics tell only part of the story, and that a complex interplay of sorting, beliefs, and opportunity

[1] Similar findings have been shown for achievements in mathematics. See for example, Fryer and Levitt (2010), who find that gender gaps in math performance emerge early and differ significantly across countries, and Niederle and Vesterlund (2010), who argue that differences in competitiveness and preferences partly explain gender differences in math outcomes. Card and Payne (2021) extend this to STEM, showing that even among high-achieving women, structural and social factors continue to deter participation in math-intensive fields. These parallels suggest that observed gaps in digital task use may similarly reflect a combination of educational, occupational, and behavioural dynamics.

structures may underpins the digital gender gap. Our study builds on this literature by providing cross-country evidence of gender disparities in actual workplace digital task use at work across Europe.

3. Data and Descriptive Statistics

In our analyses, we utilise data from the latest wave of Cedefop's European Skills and Jobs Survey (ESJS), conducted in 2021. The ESJS is a comprehensive European-wide survey designed to capture information on skills requirements, competencies, and initial and ongoing learning among adult employees (aged 24-65) across European labour markets (Cedefop, 2021). This dataset is particularly relevant for our study as it collects detailed information regarding the digital technologies that European employees use in their day-to-day work, alongside extensive background data such as employment characteristics, industry sector, education level, field of education, gender, age, and other job-related attributes. We restrict our focus to employees.

3.1 Measuring Digital Task Use

A unique feature of the ESJS data is that they contain information on practical exposure to digital technologies for workers in their current job across 27 European[2] countries. The following question is asked: *"Did you perform any of the following activities as part of your main job in the last month?"*

[2] EU-27 less Cyprus and Malta, plus Iceland and Norway

Respondents indicated yes or no to the following tasks:

1. “Use the internet for browsing, sending emails or using social media for your work”
2. “Write or edit text, for instance using Word or similar software”
3. “Prepare presentations of your work, for instance using PowerPoint or similar software”
4. “Use spreadsheets, for instance using Excel or similar software”
5. “Use more advanced functions of spreadsheets, for instance macros or complex formulas”
6. “Work with specialised sector- or occupation-specific software, for instance for accounting, legal analysis, inventory control, web design, graphic design, customer relationship management, etc.”
7. “Manage and merge databases, for instance using Access, Oracle or similar software, and related query techniques (e.g., SQL)”
8. “Write programs or code using a computer language, for instance C++, Python, Java, Visual Basic, etc.”
9. “Write programs using artificial intelligence methods, for instance machine-learning or deep-learning algorithms”
10. “Develop or maintain IT systems, hardware or software”

For empirical clarity, we group these tasks into three categories based on their complexity and the level of digital proficiency required. Following Cedefop’s own categorisation (Cedefop, 2022), we define:

- **Basic Technology Use**: internet browsing, word processing, presentation preparation, and simple spreadsheet work;
- **Intermediate Technology Use**: more complex spreadsheet operations (e.g., using macros), working with specialised occupation-specific software, and managing databases;
- **Advanced Technology Use**: programming, use of artificial intelligence or machine learning methods, and IT system development or maintenance.

3.2 Characteristics of Women and Men

At a descriptive level, there are gender differences in the digital task usage reported by individuals in their current jobs. Responses to these questions vary notably by country and gender. Table 1 provides descriptive statistics on the prevalence of each of the ten digital tasks and three task categories for workers, disaggregated by gender. A full list of the other key variables and controls used in our analyses can be seen in Appendix Table A1.

Table 1: Descriptive Statistics by Gender

			Prevalence		
Variable	***Classification***	**Obs.**	**Overall**	**Male**	**Female**
Internet Browsing	*Basic (I)*	39,867	0.85	0.83	0.86
Word Processors	*Basic (I)*	39,859	0.76	0.74	0.79
Presentation Software	*Basic (I)*	39,862	0.44	0.45	0.44
Spreadsheet Software	*Basic (I)*	39,853	0.69	0.69	0.68
Advanced Spreadsheet Formulae/Macros	*Inter. (II)*	39,819	0.31	0.36	0.26
Occupation-Specific Technology	*Inter. (II)*	39,836	0.57	0.58	0.55
Database Management	*Inter. (II)*	39,804	0.27	0.31	0.22
Programming Languages	*Advanced (III)*	39,839	0.16	0.21	0.11
AI/Machine Learning	*Advanced (III)*	39,832	0.08	0.10	0.06
ICT System Maintenance	*Advanced (III)*	39,833	0.19	0.25	0.13
(I) Basic Technology		39,864	0.92	0.91	0.92
(II) Intermediate Technology		39,820	0.67	0.69	0.64
(III) Advanced Technology		39,823	0.25	0.32	0.18

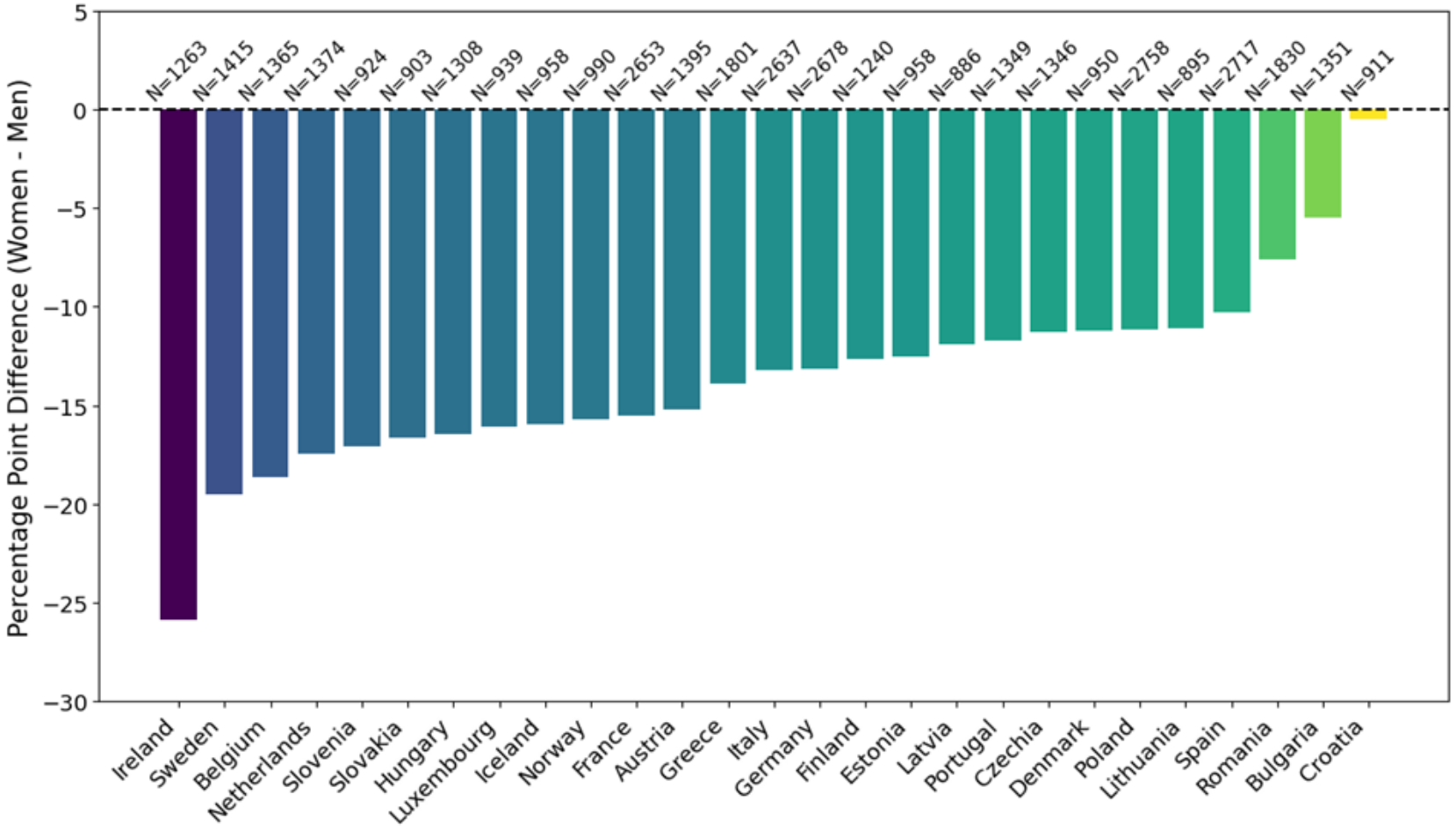
Notes: Prevalence of each digital task, and task intensity classification by gender; Weighted.

The data shows that basic digital activities such as internet browsing, and word processing are widely used across both genders. Gender differences become more pronounced as task complexity increases. Specifically, men are more likely to report engagement with advanced digital tasks, including the use of programming (21% compared to 11%), AI or machine learning (10% vs. 6%), and ICT system maintenance (25% vs. 13%). These disparities contribute to the observed gender gap in the advanced technology task grouping. On average, 32% of men report using advanced digital skills at work, compared to only 18% of women, yielding a gap of approximately 14 percentage points. In contrast, intermediate tasks such as

spreadsheet and presentation software show more balanced usage, though still skewed slightly toward men (64% vs. 69%). Overall, while both genders participate broadly in digital work, a clear and persistent gender gap emerges in the use of higher-level digital technologies. Furthermore, this is consistent with patterns explored in our subsequent empirical analysis.

Figure 1 illustrates the raw gender gaps in the proportion of male and female workers across European countries who report using advanced digital skills in their jobs. The data shows a consistent and substantial gender gap across nearly all countries reflecting a widespread structural pattern across the European labour market. While the absolute levels vary across countries, the direction of the gap is universally negative for women, indicating a systemic underrepresentation of women in highly intensive digital roles. The disparity persists even in countries with relatively high female labour force participation and strong digital infrastructure (for example, Belgium, Ireland, Netherlands, and Sweden). The gender gap in advanced digital skills varies from 26 percentage points in Ireland to less than 1 percentage point in Croatia.

Figure 1: Gender Gap in Advanced Digital Skills Usage at Work



Notes: Bars show the difference in weighted proportions (women minus men) reporting any advanced digital task (programming, AI/ML, or IT systems), computed within each country.

3.3 Job Digital Intensity Index (JDII)

It is important to acknowledge that employees rarely possess skills exclusively in one singular category. Their digital skill profiles typically exhibit a combination of basic, intermediate, and/or advanced digital competencies. Therefore, we construct a Job Digital Intensity Index (JDII) to capture a continuous measure of digital competency, reflecting the diversity and intensity of digital tasks performed in the workplace. This index facilitates a more detailed analysis of digital skills across different demographic groups. The JDII is constructed as follows:

$$\mathbf{JobDigitalIntensityIndex}_{\boldsymbol{i}} = 1 \cdot \sum_{j \in \mathbf{B}} x_{ij} + 2 \cdot \sum_{j \in \mathbf{I}} x_{ij} + 3 \cdot \sum_{j \in \mathbf{A}} x_{ij} \quad (1)$$

Where $x \in \{0,1\}$ is a dummy variable indicating whether employee i engages in task j, B is the set of basic tasks, I is the set of intermediate tasks, and A is the set of advanced tasks (as defined in Table 1). This index assigns weights of 1, 2, and 3 to basic, intermediate, and advanced tasks, respectively, reflecting the increasing level of digital skill required. The specific choice of these numbers is arbitrary; however, they represent the feasible relationship between tasks of different difficulty levels.[3] The potential value of the index for each employee runs from 0 to 19.

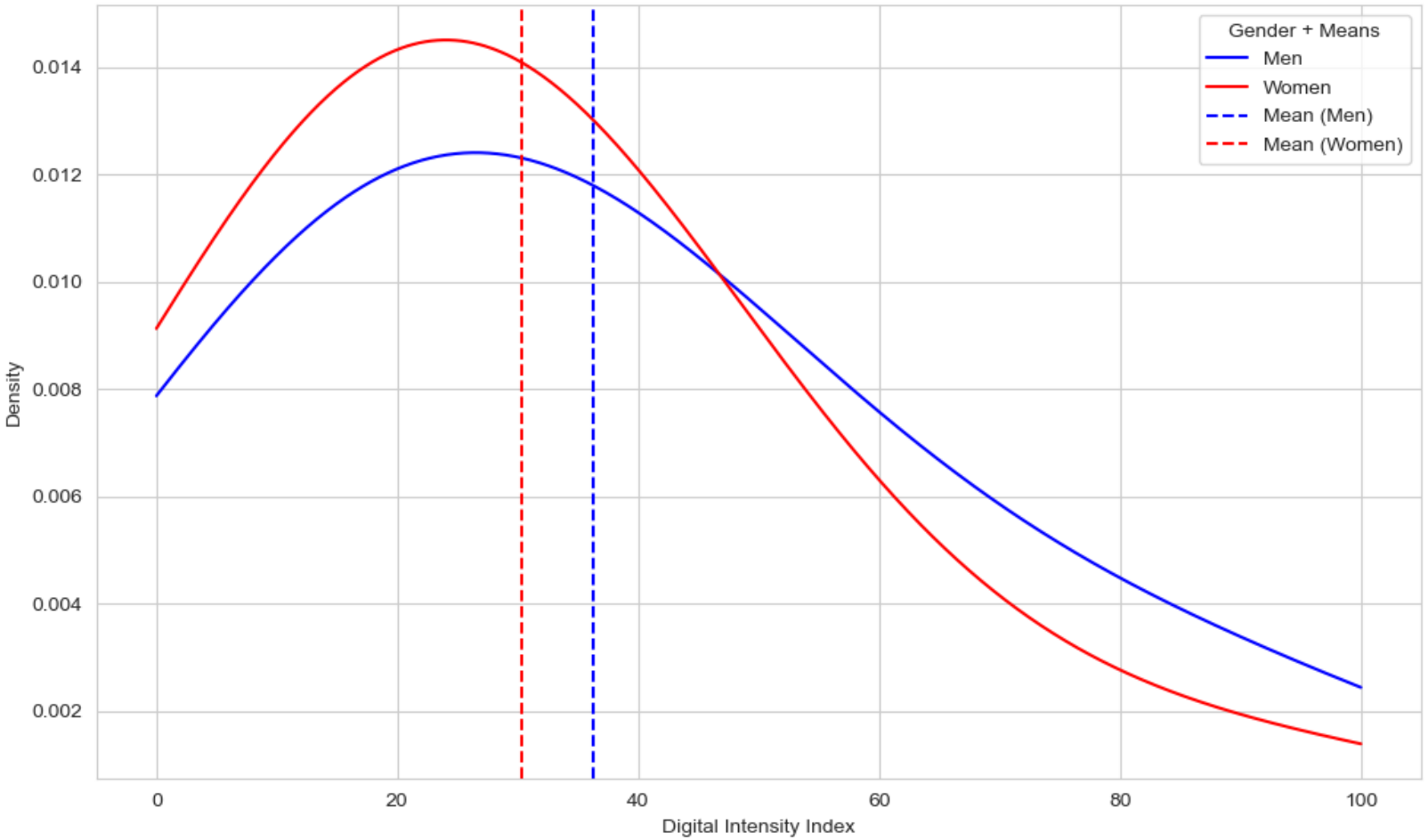
To facilitate interpretation and comparability, we have rescaled the JDII from its original range of 0 to 19 onto a 0 to 100 scale. This linear transformation enhances readability and enables easier communication of results, particularly when visualising the distribution of digital task intensity across groups.[4] The distribution of the JDII by gender is shown in Figure 2. The overall distribution of the variable is skewed left, indicating that lower levels of digital intensity are

[3] Advanced tasks contribute more to an employee's digital intensity score than intermediate tasks, and intermediate tasks contribute more than basic digital tasks. Even when we construct a more complex index based on task rarity and association with technological-underskilling, the correlation between the two indices is very high (R≈0.975). As such, we have chosen to use the above index in our analyses as it is more intuitive and easier to comprehend.

[4] For Figure 2, we apply kernel density smoothing to the JDII to provide a clearer visual representation of the gender-specific distributions, especially in the upper tail of the index. This approach reduces noise and improves interpretability while preserving the underlying distributional patterns.

common, and the density of the distribution decreases as the value of the JDII increases (employees with very high scores are rarer). The raw, unsmoothed version of the JDII distribution, using the original 0–19 scale, is presented in the Appendix (Figure A2) for reference showing that men were more concentrated in the upper JDII raw values (12–19), whereas the distribution for women is more concentrated in the lower-to-mid range (5–12). Men are overrepresented at higher intensity levels, while distributions converge in the lower deciles.

Figure 2: Distribution of Job Digital Intensity Index (JDII) by Gender



Notes: We have rescaled and smoothed the JDII from its original range of 0 to 19 onto a 0 to 100 scale. Distributions are shown using a Gaussian kernel density estimate (KDE). For observations $x_1, \ldots, x_n$, the estimated density at x is $\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} \phi(\frac{x-x_i}{h})$, where $\phi(\cdot)$ is the standard normal pdf and h is the bandwidth. In implementation, the bandwidth is set to 20 in rescaled JDII units weighted. The raw, unsmoothed version of the JDII distribution is presented in the Appendix

4. Empirical Strategy and Methodology

Our empirical approach to quantify and understand the gender gap in digital skills at work uses three complementary tools: (i) probit and OLS regression models to estimate the conditional likelihood of digital skill use; (ii) Blinder-Oaxaca decomposition to partition observed gender gaps into explained and unexplained components; and (iii) distributional analysis based on the unconditional decile methods, implemented via the recentred influence function (RIF) approach (Firpo et al., 2009), which allows us to assess whether gaps are larger in high digital-intensity jobs than in the middle or lower parts of the distribution. This triangular approach aims to provide a comprehensive view of both the magnitude and sources of digital task inequalities.

Our analysis is based on the following regression:

$$\text{DigitalUsage}_{i,j} = \alpha + \beta_h * H_{i,j} + \beta_p * P_{i,j} + \epsilon_{i,j} \quad (2)$$

The dependant variable takes a number of forms depending on the model being estimated ranging from a dummy variable for the use of intermediate or above or the use of advanced digital skills, to the constructed continuous index, JDII, for individual i in country j. Our dependent variables are regressed on a vector of human capital, personal, and job characteristics. These include gender, age, education level, field of study, sector (public, private or not-for-profit), contract type (permanent, temporary or none), part-time status, firm size, occupation, and industry. The coefficient on gender from our Probit or OLS regression for Equation (2) gives an estimate of the gender digital skills gap at work, controlling for other personal, job and human capital characteristics. We sequentially introduce three model specifications to control for a range of independent variables: specification one includes basic controls (country fixed effects, age, area of residence); specification two adds detailed job and demographic controls (tenure, part-time status, education level, contract type, occupation type, firm size, sector); and, specification three further includes field of education and limits the sample to those with at least upper secondary education. Standard

errors are clustered at the country level, and all models are weighted using survey weights. Results are reported as marginal effects (see Table 2).

Based on our digital usage regression, we carry out two decomposition methods that are explained in the section below. The first is the classic decomposition by Oaxaca (1973) and Blinder (1973), which decomposes the mean digital usage. Second, is a method by Firpo et al. (2009) which decomposes the digital usage in the spirit of Oaxaca and Blinder but can be applied at different deciles of the digital intensity distribution. By focusing only on the mean digital usage, standard OLS and Oaxaca decomposition techniques are limited in their ability to provide insights for other parts of the JDII distribution. Therefore, employing unconditional quantile regression techniques enable us to examine the JDII across the entire distribution.

4.1 Oaxaca-Blinder Decomposition

To distinguish between the share of the digital skill gap that can be attributed to observable differences in characteristics (e.g. age, education, occupation) versus unexplained components, we employ the Oaxaca–Blinder (1973) decomposition technique. For the binary outcomes: (i) use of intermediate-or-above digital tasks and (ii) use of advanced tasks, we use the Fairlie (2005) nonlinear decomposition, which is appropriate for probit models. For the continuous outcome: (iii) the Job Digital Intensity Index (JDII), we use the standard Oaxaca-Blinder (Oaxaca 1973; Blinder, 1973) decomposition. Together, these methods decompose the average gender gap into an explained component due to differences in observed characteristics and an unexplained component due to differences in coefficients and unobserved factors.

For ease of exposition, let X_i be a vector which includes both personal, job and human capital outcome of individual i. Then let $\bar{X}_M$ and $\bar{X}_F$ represent the mean endowments for men and women and denote the corresponding estimated coefficient vectors by $\hat{\beta}_M$ and $\hat{\beta}_F$. The Oaxaca-Blinder decomposition expresses the mean gender gap in outcome as,

$$Y_M - Y_F = (\bar{X}_M - \bar{X}_F) * \beta^* + \left[\bar{X}_F * \left(\hat{\beta}_M - \beta^*\right) + \bar{X}_F\left(\beta^* - \hat{\beta}_F\right)\right], \quad (4)$$

where the choice of the non-discriminatory coefficient vector β^* determines the reference structure. Following Neumark (1988) and Oaxaca & Ransom (1994), we use the pooled coefficients approach, in which β^* is estimated from a regression on the pooled sample of men and women. The pooled method avoids privileging one group's task structure as the normative benchmark and produces decomposition results that are less sensitive to the choice of reference group.

We decompose the gap using the entire pooled sample of employees across 28 countries, before proceeding to decompose the gap for European regions separately. This allows us to rank regions by the magnitude of the gap as well as the degree of gender convergence in digital skills-enhancing characteristics. Table 3 presents the decomposition results across all outcomes, and Figure 4 shows the decomposition by country region.

4.2 Unconditional Decile Decomposition

While the Oaxaca technique allows us to decompose the Digital Intensity Gap at the mean, it does not allow us to assess the degree to which the gap, or the factors that determine it, vary across the digital intensity distribution. To further understand heterogeneity in the gender digital gap across the digital skills distribution, we implement decile regression analysis on the Job Digital Intensity Index (JDII). We employ a technique proposed by Firpo *et al.* (2009) to extend the methodology of Oaxaca and Blinder to decompose the digital intensity across the entire distribution. For more detailed information on decomposition methods, focusing particularly on such decompositions beyond the mean, please see Fortin *et al.* (2011).

We estimate conditional quantile regressions at various deciles of the JDII, using the same control set as in the earlier probit regressions. This allows us to explore whether the gender

gap in digital task intensity is larger at the top end of the distribution, as might be expected if men dominate highly digital-intensive roles (e.g., software engineering, AI development).

In a standard OLS regression, the β coefficient can be interpreted as the effect of a change in X on the unconditional mean of Y. As such, OLS regressions can be used in the Oaxaca decomposition to examine the unconditional mean difference in gender digital usage. However, the β coefficient from a quantile regression of Y on X gives the effect of a change in X on the conditional quantile, thereby making the unconditional quantile decomposition less straightforward than a standard Oaxaca decomposition. The method proposed by Firpo *et al.* (2009) overcomes this difficulty.

The Firpo *et al.* (2009) technique can be outlined in three stages. In the first stage, the re-centred influence function (RIF) of the unconditional quantile of the dependent variable is calculated. Denoting q_τ as the τ^{th} quantile of interest, the RIF is derived by first calculating the influence function (IF) as follows:

$$IF = (\tau - 1\{Y \leq q_\tau\})/f_y(q_\tau) \quad (6)$$

where Y denotes the dependent variable (JDII), $f_y(q_\tau)$ is the density at point q_τ, and $1\{Y \leq q_\tau\}$ is a dummy variable that equals one for observations in which Y is less than or equal to q_τ. To get the RIF, one adds back the quantile to the IF, such that $RIF = q_\tau + IF$.

In the second stage, the RIF is used as a dependent variable in an OLS regression. The resulting β from the RIF regression captures the marginal effect of a change in X on the unconditional quantile of Y. Finally, in the third stage, a standard Oaxaca decomposition is carried out on the RIF regression, which yields the unconditional quantile decomposition. Unlike earlier decomposition approaches (for example, Mata and Machado, 2005), the Firpo *et al.* (2009) method not only allows for the estimation of the 'explained' and

'unexplained' gap but also allows us to break these down further to identify the contributions of the individual explanatory variables in a more straightforward way.

5. Results

5.1 Probit and OLS Regression Estimates

Table 2 presents the marginal effects from probit regressions estimating the probability that individuals use either *intermediate-or-above* digital tasks (Columns 1-3) or *advanced* digital tasks in their job (Columns 4-6). Furthermore, Table 2 (Columns 7-9) presents the marginal effects from OLS regressions estimating the continuous digital intensity *JDII* variable on a scale from 0-100. Across all specifications, the gender coefficient is negative and statistically significant, confirming that women are less likely than men to engage in digital work tasks requiring intermediate to advanced skill levels.

In the baseline model (Specification 1), being female is associated with a 6.4 percentage point lower probability of using intermediate-or-above digital tasks and a 13.4 percentage point lower probability of performing advanced tasks. Adding detailed individual and job controls (Specification 2) reduces these gaps slightly to 6 and 10.1 percentage points, respectively. After additionally controlling for field of education and restricting the sample to those with at least upper secondary education (Specification 3), the gaps remain large and statistically significant i.e. 4.3 percentage point lower for intermediate tasks and 9.3 percentage point lower for advanced tasks. For the continuous digital intensity JDII variable, women on average score significantly lower (4.6 points) than men, even after controlling for job and worker characteristics. The gap persists even after controlling for age, education, occupation, industry, and firm characteristics. Controls explain part of the gap, but a large unexplained component remains. These results suggest that differences in observed characteristics such as education, job type, and sector only partially account for the gender gap, especially at higher levels of

digital skill complexity. Notably, women remain significantly underrepresented in digital work even when they have comparable education and work in similar sectors as men.

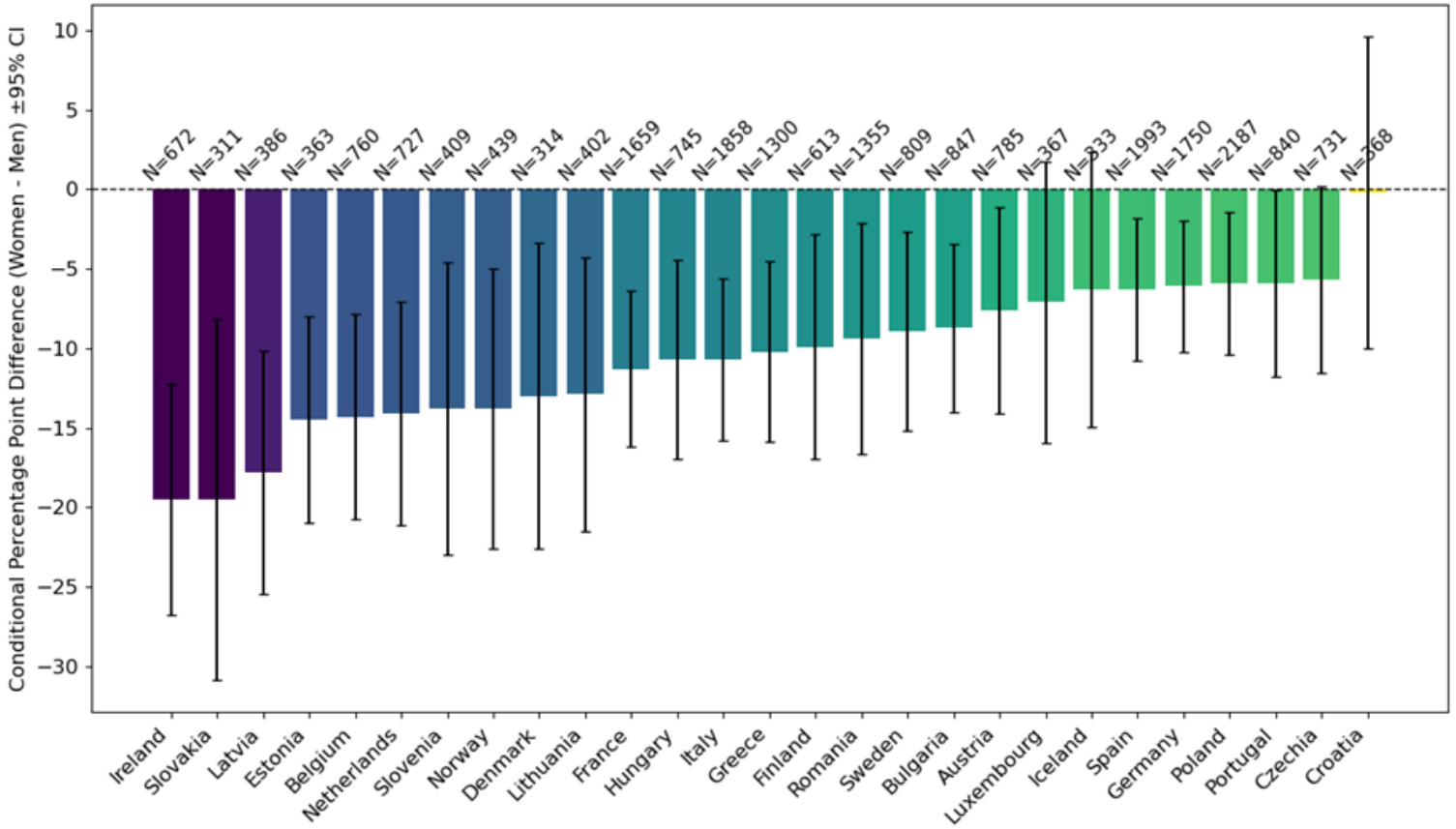
Figure 3 illustrates the conditional advanced digital task gap by country, based on the fully controlled specification (Table 2, Column 6). The figure plots the gender difference in the probability of performing advanced digital tasks for each country, after accounting for individual and job characteristics including field of study. The results show substantial cross-country variation in the magnitude of the gap, but nevertheless a consistent pattern. In all countries (except Croatia), men are more likely than women to use advanced digital tools at work. The largest gender gaps are observed in countries such as Ireland, Slovakia, and Latvia, where the difference exceeds 15 p.p. smaller gaps (though still present) appear in countries like Czechia, Poland, and Portugal. These findings suggest that while national labour market structures and education systems influence digital participation on-the-job, gender-based barriers may exist in high-skill digital employment across Europe.

Table 2: Regression Results for Digital Skills Use for (Pooled): Intermediate+, Advanced Tasks, and JDII (Marginal Effects)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Intermediate or above tasks (Probit ME)			Advanced tasks (Probit ME)			JDII (OLS)		
Female	-0.064***	-0.060***	-0.043***	-0.134***	-0.101***	-0.093***	-5.66***	-5.64***	-4.56***
	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)	(0.007)	(0.30)	(0.32)	(0.40)
Detailed controls	NO	**YES**	**YES**	NO	**YES**	**YES**	NO	**YES**	**YES**
Education Field controls	NO	NO	**YES**	NO	NO	**YES**	NO	NO	**YES**
Observations	39,756	38,139	24,354	39,769	38,151	24,349	39,598	38,007	24,320

Note: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1. Detailed controls include ISCO-2 occupation, NACE-1 industry, Area of residence, firm size, Sector (public, private etc.), Education level, contract type, part-time status, age and country FE. Non-detailed controls include Age, area of residence and country FE. Weighted. Field of education is only recorded for a limited sample, thus these specifications only include individuals with High-school education or above.

Figure 3: Conditional Advanced Digital Task Gap by Country (including Field of Study)



Notes: Coefficients reported are from separate country level probit regressions on advanced task usage. It is the marginal effect of the female variable. Whiskers represent 95% confidence interval. Weighted.

5.2 Decomposing the Gender Digital Skills Gap

To quantify how much of the observed gender gap can be explained by differences in characteristics versus returns to those characteristics, we conduct a Blinder-Oaxaca decomposition. Table 3 presents a decomposition of the average gender gaps in digital task use across Europe, distinguishing the portion attributable to differences in observable characteristics (explained) from the portion due to differential returns to those characteristics or unobserved factors (unexplained). For advanced digital tasks, the raw gender gap is 15.7 percentage points. Approximately 40% of this gap can be explained by observable factors, with the remaining 60% unexplained. For the Job Digital Intensity Index (JDII), the gender gap is 6.9 p.p., of which 34% is explained and 66% remains unexplained. The largest contributing factors to the explained component include field of education (particularly the underrepresentation of women in ICT), occupation and industry which each account for around 15-20% of the gap in advanced tasks. This reflects persistent gender segregation in educational pathways and occupation employment patterns. Furthermore, age, contract type, area of residence and firm size also contribute modestly. However, variables such as, sector, education level and part-time status contribute negatively or minimally to the explained share, reinforcing that sector, formal qualifications and part-time status do not fully account for the disparity.

The detailed breakdowns of the decomposition results (see Tables A3, A4 and A5) point to the fact that, in Europe, a higher proportion of men are employed in roles like ICT specialists, engineers, or technical managers i.e. jobs which naturally involve advanced digital tasks, whereas women are overrepresented in roles such as personal services, education, or administrative support, which on average have lower digital intensity (Table A5). Educational attainment and experience differences between male and female workers play a smaller role (in part because, in our sample, women on average have equal or higher formal education than men, which works to narrow the gap). However, one educational factor that does matter is the field of study: women are much less likely to have degrees in ICT or STEM fields (Table A4). With respect to industry, the lower intensity of females in ICT intensive occupations represented the biggest component of the explained effect (Table A3). In sum, the results

suggest that if women had the same distribution across industries, occupations, and fields of study as men, the gender gap in digital task engagement would shrink, however, not disappear, due to the remaining unexplained component. The unexplained component should be interpreted as capturing differences not measured in the survey and may be consistent with mechanisms such as within-occupation task assignment, differential access to training, workplace practices and norms, or potentially discrimination, but it does not identify the underlying causes. Accordingly, the decomposition results motivate attention both to sorting (education and jobs) and to within-job processes that shape access to advanced digital tasks.

Table 3: Blinder-Oaxaca Decomposition for the Gender Digital Gap for (pooled)

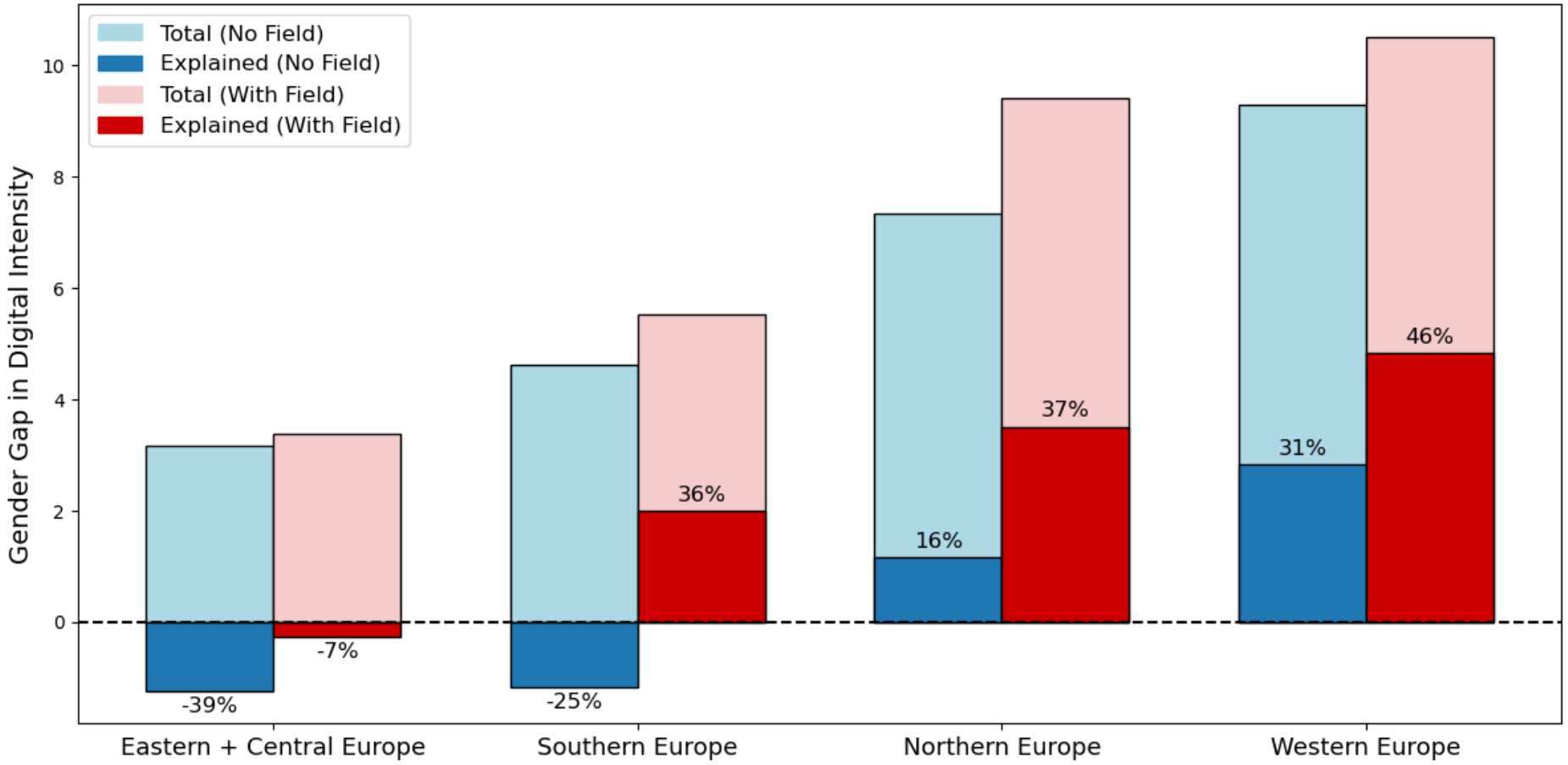
VARIABLES	1	2	3	4	5	6
	Intermediate or above tasks (Probit)		Advanced tasks (Probit)		JDII (OLS)	
Men	75.2%		36.4%		39.0	
Women	67.3%		20.7%		32.1	
Difference	7.9p.p.		15.7p.p.		6.9	
	EXPLAINED	*UNEXPLAINED*	*EXPLAINED*	*UNEXPLAINED*	*EXPLAINED*	*UNEXPLAINED*
Total	43.0%	57.0%	41.0%	59.0%	34.0%	66.0%
Age	1.3%	-49.4%	0.6%	-27.4%	0.9%	-46.4%
Part-Time	2.5%	5.1%	-3.2%	6.4%	-1.1%	7.7%
Education field	21.5%	6.3%	19.1%	1.3%	22.9%	4.6%
Contract type	2.5%	0.0%	1.3%	6.4%	2.3%	15.0%
Education level	-8.9%	-3.8%	-3.2%	-3.8%	-9.8%	-6.0%
Area of residence	0.0%	3.8%	0.6%	-1.9%	0.7%	0.2%
Firm size	2.5%	5.1%	0.6%	0.0%	2.8%	2.1%
Sector	-2.5%	-12.7%	-7.0%	-1.3%	-6.6%	-3.4%
Occupation	1.3%	-65.8%	17.8%	-89.2%	2.1%	-15.0%
Country	0.0%	-11.4%	0.0%	-3.8%	1.1%	-3.2%
Industry	22.8%	26.6%	14.6%	-1.3%	18.7%	-5.8%
Shift component		155.7%		173.9%		116.2%
Observations	24,631	24,631	24,628	24,628	24,605	24,605

Notes: Oaxaca-Blinder decomposition of three outcome variable. Percentages show the percent a variable contributes to the gender gap in the outcome variable. Intermediate and above, and advanced specifications show the difference in gender mean %, JDII specification shows the gap in mean JDII value. Weighted.

We next explore how the gender digital gap differs across countries groupings using similar mean decomposition techniques. Figure 4 summarises the Blinder–Oaxaca decomposition of the JDII gender gap by country. Given that we are dealing with many countries, for the purposes of our analysis, we group these into four categories based on geographical proximity, economic development, and integration within the single market. *'Western'* includes Austria, Belgium, France, Germany, Ireland, Luxembourg, and the Netherlands. *'Eastern & Central'* includes Bulgaria, Croatia, Czechia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia. *'Northern'* includes Denmark, Estonia, Finland, Iceland, Norway, and Sweden. *'Southern'* includes Greece, Italy, Portugal, and Spain.

For each grouping, Figure 4 shows the total gender gap in the JDII and the share explained by gender differences in observable characteristics. Generally, we find the gap is lowest in the Eastern and Central, and Southern groups, and highest in the Western and Northern groups. There are also variations in terms of the shares of the gap explained ranging from -7% to 46% with the inclusion of field of study. In countries where the explained share is high, targeted policies to encourage women into specific fields or roles may substantially reduce the gap. In contrast, where the unexplained share is more dominant, factors not captured by observed characteristics may play a larger role. In all groupings, however, the unexplained portion constitutes more than half of the gap, consistent with the European-wide results.

Figure 4: Blinder-Oaxaca Decomposition for the Gender Gap in Job Digital Intensity Index by Country



Notes: Bar fill represents the % explained of the overall gender gap in JDII for that specific country, according to Oaxaca-Blinder decomposition. Weighted.

5.2 Distributional Patterns in Digital Tasks Usage

In the next step, we examine the distributional nature of the gender digital usage gap for Europe (Figure 5). Our analysis finds that the gap is not uniform across the distribution of job digital intensity. Women's underrepresentation is especially pronounced in the most digitally intensive jobs. For example, in our data the top decile of jobs ranked by digital intensity (the 10% of workers with the highest JDII scores) shows a gender gap nearly three times larger than the gap at the median of the distribution. The raw JDII distributions by gender (Appendix Figure A2) shows that relatively few women occupy jobs with the very highest digital intensity levels i.e. the upper tail of the women's distribution is visibly thinner than that for men.

The decile decomposition (Table 4) indicates that at the 90th percentile of JDII, 77% of the gender gap can be explained by differences in characteristics (particularly industry, occupation, and field of study), whereas around the middle of the distribution the explained share is much lower (often under 30%). In fact, at the extreme low end (10th percentile), we observe a reversed gap where women are marginally ahead of men in some cases. This is likely to be because certain lower-skilled office jobs held by women still require basic digital tasks. Overall, these patterns reiterate the fact that gender differences are most acute in the high-tech, high-skill segment of the labour market. This pattern remains even after controlling for field of study and job characteristics (Figure A3). For example, at the 90th percentile of the JDII distribution, the estimated conditional gender gap is approximately 10 points indicating that women are systematically underrepresented in the most digitally intensive jobs.

Figure 6 presents a detailed decile decomposition of the explained component of the gender gap in the Job Digital Intensity Index (JDII) focusing on the specific components of field of education, occupation (ISCO), and industry (NACE). The results show that the explanatory power of these observable characteristics increases at higher deciles, indicating that compositional factors matter more in highly digital-intensive jobs. These findings suggest that gender differences in job type and educational background account for a growing share of the

gap as digital task complexity increases, although there remain substantial unexplained disparities remain even at the top of the distribution.

To further examine where in the digital task distribution gender disparities are most pronounced, we also examine the unexplained components of the JDII gap across deciles using a detailed decomposition approach. Table 5 presents the unexplained components of the gender gap in the Job Digital Intensity Index (JDII) across the distribution. The results show that the unexplained share is highest in the lower deciles, peaking at 170% in Decile 2, and steadily declining to 23% in the top decile.[5] The main contributors to the explained component (shown in Figure A5) are differences in field of education, and industry (NACE) with occupation (ISCO) playing a more significant role in the 75th percentile, compared to at the mean. Disaggregated analysis (see Tables A3–A5) shows that specific industries such as health and education (both employing a high share of women but characterised by lower levels of digital task intensity) explain a large portion of the gap at the mean. However, technical fields of study like ICT and engineering, also less gender-balanced, contribute more to the explained component at the 75th percentile due to their higher digital intensity. The same is true for industry and occupation, where the most important industries/occupations are characterised by being either low-tech-female-concentrated or high-tech-male-concentrated.

Generally, unobservable factors play a disproportionate role in driving gender disparities in lower and mid-range digital intensity jobs, whereas observable characteristics explain more of the gap at higher levels of digital engagement. Among the individual drivers, large negative unexplained effects are observed again for age, sector, and education level, especially in the lower deciles, indicating significant differences in how these characteristics translate into digital task use between men and women. The occupation (ISCO) and industry (NACE) variables are shown to contribute positively to the unexplained gap in the upper deciles, implying differential returns or task assignments within similar occupational or sectoral categories. A large and persistent residual (constant) term across the distribution further

[5] Figure A5 compares the explained components at both the mean and upper tail (75th percentile) of the JDII distribution, illustrating that while approximately 34% of the overall gender gap in digital intensity is explained at the mean, approx. 40% is explained at the 75th percentile.

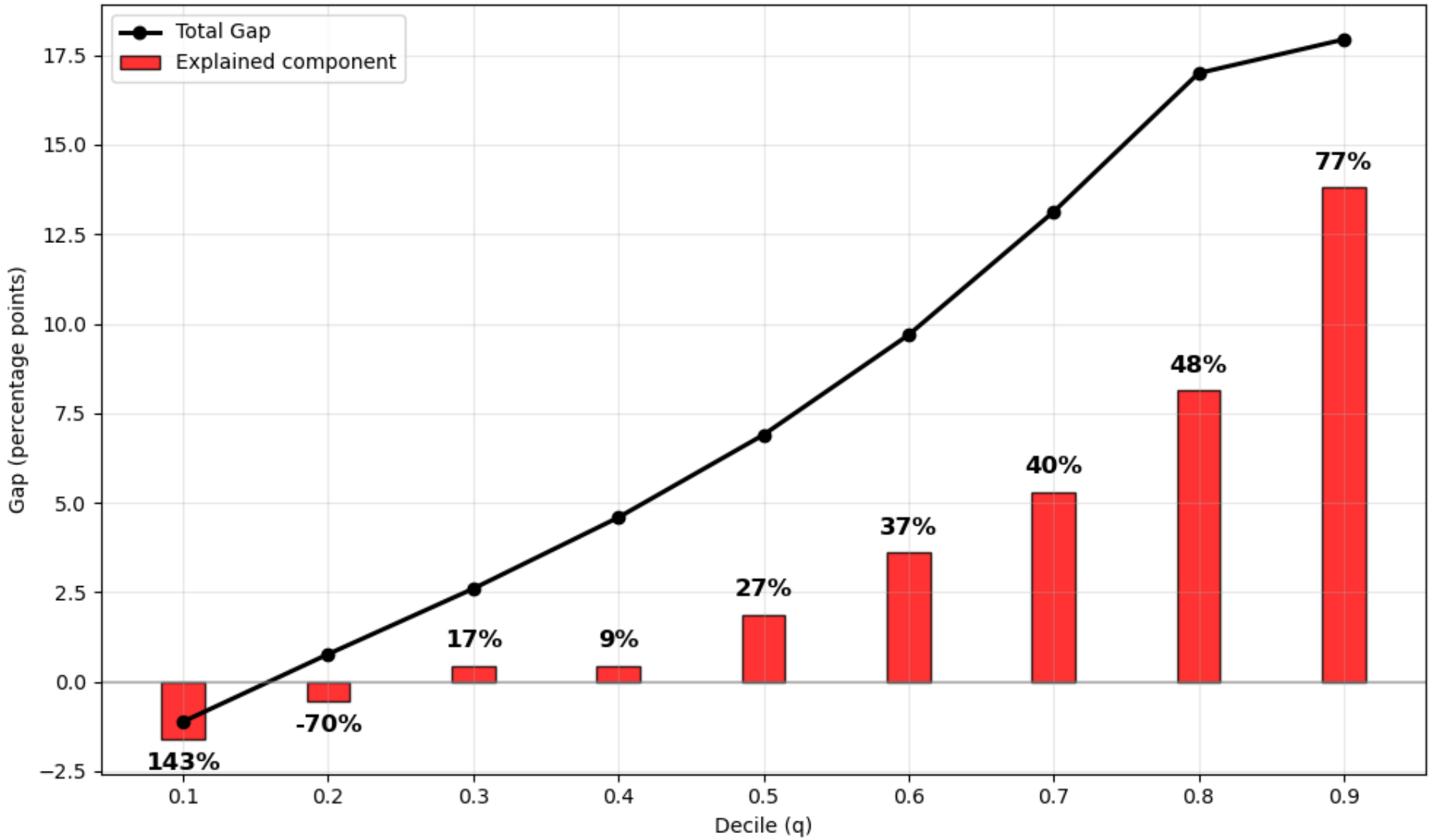
highlights the role of unmeasured structural or institutional factors, such as within-role task allocation, informal training access, or potentially discrimination, in sustaining gender differences in digital skill use.

Cross-country and regional variations (Figure A4) suggest that while baseline differences between country groups are relatively small, the shape and trajectory of the gender gap are strikingly consistent across regions. In all groupings, the gender gap in digital task use is narrow at the lower end of the distribution (low-intensity jobs) but widens progressively at higher quantiles. This pattern suggests that women are similarly underrepresented in the most digitally intensive roles across all parts of Europe, regardless of country-specific factors such as digital infrastructure or labour market institutions. The cross-regional similarity implies that structural barriers to women's participation in advanced digital work are broadly shared across European countries, even where overall levels of digitalisation differ.

Age consistently emerges as an important dimension of the digital gender gap. Across specifications, older workers perform fewer digitally intensive tasks, but Oaxaca-Blinder decompositions reveal that age contributes a sizable negative unexplained component, suggesting cohort-specific dynamics or differing age penalties by gender. When the sample is split by age, the conditional gender gap in advanced digital task use is substantially larger among workers under 35, even after controlling for education and occupation. For younger cohorts, much of this gap remains unexplained, whereas for older workers a greater share is accounted for by observable characteristics. Unconditional decompositions similarly show that the gap is wider among younger workers across the digital intensity distribution, and that a smaller proportion of this gap is explained by observable factors (see Figure A6).[6]

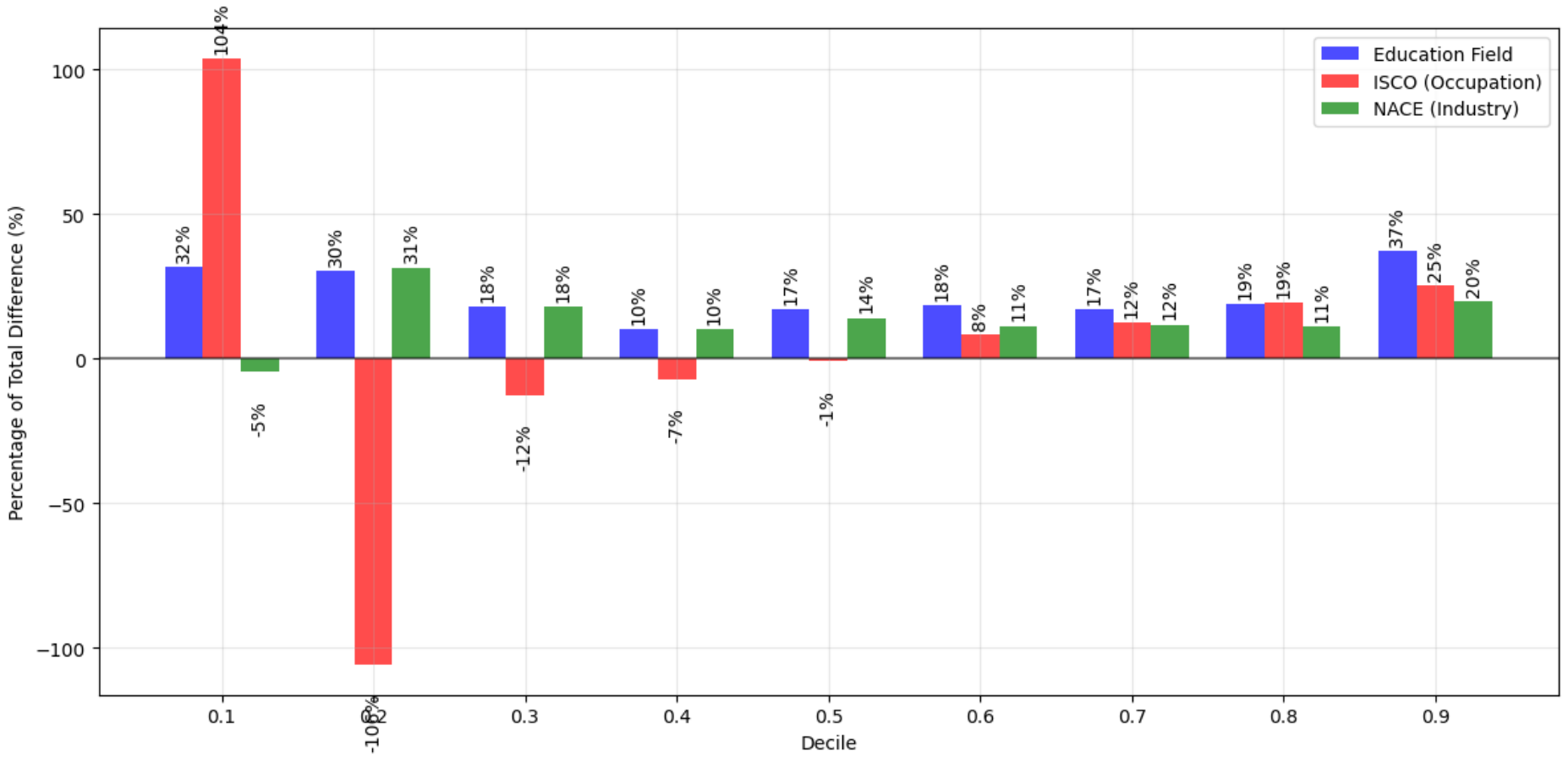
[6] Detailed results on the age effects are available from authors upon request.

Figure 5: Decile Decomposition of JDII by Gender, Gap and % Explained



Notes: Total Gender Gap (Men – Women) and % explained from RIF-Oaxaca at deciles of JDII. Weighted.

Figure 6: Decile Decomposition: Explained Component by Driver



Notes: Percentage of total Gender Gap (Men – Women) in JDII explained by Education Field, Occupation and Industry at each decile, obtained from RIF-Oaxaca at deciles of JDII. Weighted

Table 4: Decile Decomposition of JDII Detailed Results (Explained Components)

	D1	D2	D3	D4	D5	D6	D7	D8	D9
Group 1 (Men)	9.8%	17.4%	23.7%	29.9%	36.2%	43.9%	53.0%	64.6%	87.0%
Group 2 (Women)	10.9%	16.6%	21.1%	25.4%	29.3%	34.2%	39.9%	47.6%	69.0%
Difference	-1.1 p.p.	0.8 p.p.	2.6 p.p.	4.6 p.p.	6.9 p.p.	9.7 p.p.	13.1 p.p.	17.0 p.p.	17.9 p.p.
Total Explained	143.2%	-69.7%	16.7%	9.4%	27.1%	37.1%	40.4%	47.8%	77.0%
Education Field	31.9%	30.2%	17.8%	10.1%	17.2%	18.4%	17.2%	19.1%	37.4%
ISCO Occupation	103.9%	-105.8%	-12.5%	-7.1%	-0.9%	8.3%	12.4%	19.4%	25.4%
NACE Industry	-4.6%	31.5%	18.0%	10.2%	14.1%	11.4%	11.8%	10.9%	19.9%
Education Level	37.4%	-64.1%	-21.9%	-12.4%	-8.3%	-6.6%	-4.5%	-3.3%	-2.0%
Contract Type	-8.0%	14.5%	4.6%	2.6%	2.5%	1.2%	1.0%	0.7%	1.5%
Area Residence	-0.0%	1.6%	0.2%	0.1%	0.0%	0.3%	0.4%	0.5%	0.7%
Sector	19.8%	-29.1%	-6.1%	-3.4%	-3.5%	-3.2%	-2.2%	-1.5%	-5.4%
Age	-1.3%	2.7%	1.0%	0.5%	0.5%	0.5%	0.4%	0.5%	0.9%
Part Time	-29.3%	38.2%	11.0%	6.3%	3.8%	4.4%	2.3%	-0.6%	-6.0%
Company Size	1.3%	2.7%	1.5%	0.9%	1.0%	1.9%	1.6%	2.1%	3.5%

Notes: Detailed explained components from Decile Decomposition of gender gap in JDII. Weighted.

Table 5: Decile Decomposition of JDII Detailed Results (Unexplained Components)

	D1	D2	D3	D4	D5	D6	D7	D8	D9
Group 1 (Men)	9.8%	17.4%	23.7%	29.9%	36.2%	43.9%	53.0%	64.6%	87.0%
Group 2 (Women)	10.9%	16.6%	21.1%	25.4%	29.3%	34.2%	39.9%	47.6%	69.0%
Difference	-1.1 p.p.	0.8 p.p.	2.6 p.p.	4.6 p.p.	6.9 p.p.	9.7 p.p.	13.1 p.p.	17.0 p.p.	17.9 p.p.
Total Unexplained	-43.2%	169.7%	83.3%	90.6%	72.9%	62.9%	59.6%	52.2%	23.0%
Education Field	-8.3%	27.5%	14.0%	14.5%	13.1%	14.2%	10.9%	8.2%	-6.7%
ISCO Occupation	68.9%	-27.3%	-8.1%	5.6%	18.3%	21.7%	29.9%	33.0%	-19.9%
NACE Industry	-30.7%	75.1%	22.3%	26.4%	19.8%	18.5%	16.5%	24.0%	-5.0%
Education Level	-22.4%	-40.8%	-15.5%	-10.9%	-11.8%	-8.9%	-9.7%	-5.5%	-3.5%
Contract Type	130.3%	82.6%	56.1%	39.5%	15.6%	18.7%	16.9%	16.7%	2.6%
Area Residence	-7.8%	4.7%	4.1%	1.6%	2.1%	-2.0%	1.5%	-0.4%	-0.2%
Sector	41.7%	-171.2%	-21.7%	-8.1%	-18.4%	-9.1%	-5.6%	-4.6%	8.2%
Age	-11.8%	-305.1%	-155.5%	-150.5%	-100.5%	-80.3%	-88.1%	-87.1%	69.8%
Part Time	-6.7%	-5.4%	4.4%	5.9%	5.5%	8.8%	8.6%	6.8%	-1.3%
Company Size	-4.3%	75.3%	29.2%	16.8%	5.8%	2.4%	1.7%	1.7%	-2.2%
Constant	-119.8%	375.0%	208.4%	212.6%	186.0%	159.2%	152.9%	139.2%	17.9%

Notes: Detailed unexplained components from Decile Decomposition of gender gap in JDII. Weighted.

6. Conclusions

This paper examines the gender gap in the use of digital skills at work across Europe. Using the European Skills and Jobs Survey (ESJS), we quantify gender disparities not only in the incidence of digital tasks but also in the complexity and intensity of digital engagement on the job. Using a combination of descriptive analysis, regression modelling, Blinder–Oaxaca decomposition, and distributional techniques, we assess the extent to which these gaps can be explained by differences in observable characteristics such as education and occupation, and where they remain unexplained.[7] We construct a novel, task-based Job Digital Intensity Index (JDII), scaled from 0 to 100 for interpretability. The index captures the level of digital complexity embedded in the job tasks performed by each individual and enables a more nuanced distributional analysis of digital skill use.

Our findings show a significant gender gap in advanced digital skill use. On average about one-third of male employees' report engaging in advanced digital tasks at work, compared to only about one-fifth of female employees. This yields a raw difference of approximately 14 percentage points in favour of men. For intermediate level digital tasks, the gap is smaller at approximately 5 percentage points, whereas for basic tasks there is virtually no gap. Thus, the gender digital divide is most pronounced at the higher level of the digital skills spectrum. These gaps persist even among younger workers. Although younger generations of women have similar levels of basic digital skills, we find a considerable gender gap in advanced task use among youth cohorts. This suggests that cohort differences alone are unlikely to account for the pattern, including the allocation of women and men to different tasks among jobs or specialisations. These patterns imply that generational change alone may not resolve digital

[7] Our approach to analysing gender gaps is also enriched by applying both mean-based decomposition and decile-based distributional techniques (Firpo et al., 2007), which allow us to observe how disparities evolve across the digital task spectrum.

inequalities without targeted interventions focused on the early stages of career development.

To investigate the determinants of the gap, we estimate probit models for the likelihood of performing intermediate and advanced digital tasks. We find that being female is associated with a significantly lower probability (10 percentage points) of using advanced digital skills, even after controlling for a wide range of individual, job and location characteristics. These results imply that observable characteristics (such as women being on average younger, having higher levels of educational attainment, or sorting into certain occupations) explain only part of the raw gap. Subsequently, we use Blinder-Oaxaca decompositions to quantify the share of the gender gap that can be attributed to differences in characteristics (explained) versus difference in coefficients (unexplained factors). This decomposition when applied to intermediate, advanced and the JDII confirms that most of the gap is unexplained. In the case of advanced task usage and the JDII, roughly 40 per cent of the gap is accounted for, while 60 per cent remains unexplained. These findings suggest that even if women had the same measured characteristics as men, in terms of education, occupation etc., the large gap in advanced digital skill use would persist. In summary, the 'coefficients' effect dominates the 'characteristics' effects.

To investigate the distributional patterns, we employ unconditional quantile regression on the continuous JDII, i.e. the index summarising the level of complexity of digital tasks performed by each worker. Results show that the gender gap is small to negligible at the lower end of the digital intensity distribution but widens substantially at higher quantiles. Therefore, this confirms that for jobs with relatively light digital requirements (e.g. basic computer use), women and men are equally likely to be involved. However, at the higher end, jobs that involve several advanced digital tasks, a significant gender gap emerges, where women are underrepresented. This finding aligns with prior research noting that the gender digital divide is most acute in advanced technological domains, often referred to as the "glass ceiling" in digital skill use appearing at the highest levels of digital intensity. It also complements evidence from task-based analyses of gender gaps. For example, Brussevich et al. (2019) show

that women tend to perform more routine, automatable tasks than men which implies that men more often engage in non-routine analytical tasks that likely involve advanced digital skills. Our decile decomposition results provide direct support for this where women are observed less in the roles that heavily utilise complex digital competencies.

We also explore how the gender gap varies across countries and regions within Europe. We find substantial cross-country heterogeneity. In some Northern European countries, the conditional gender gap in advanced digital task use is relatively small, whereas in several Southern and Eastern European countries the gap remains very large even after controls. For example, countries like Poland, Portugal, and Czechia have among the smallest adjusted gaps, while countries such as Latvia, Ireland and Slovakia exhibit much larger gaps. However, no country in our sample (apart from Croatia, which essentially exhibits no gap) achieves gender parity on this metric and across all countries the sign of the gap is that women are less likely to perform advanced digital tasks, differing only in magnitude. We also conduct country-specific Blinder-Oaxaca decompositions for our digital skills variables and find that the proportion of the gap that is explained versus unexplained can differ by country or region. For instance, in some Western European countries with more women in STEM fields, a greater share of the gap is explained by remaining differences, whereas in others the unexplained component (potentially reflecting cultural factors or workplace practices) remains high. These geographic patterns, while descriptive, suggest that policy and social context may matter.

In summary, this paper provides the first comprehensive analysis of gender disparities in actual usage of digital skills at work across European countries. By shifting the focus to what workers actually do on the job and using task-based measures, we align with and extend the labour economics literature on skill-biased technological change and task specialisation (e.g., Autor et al., 2003; Acemoglu and Autor, 2011), bringing a gender perspective into that framework. Furthermore, this paper contributes to the growing body of research on gender inequality in the labour market by showing that women face a form of “digital glass ceiling”. While parity is largely observed in low-intensity digital work, women are systematically less likely to access roles requiring complex digital engagement. The results indicate that while

part of the gap can be explained by women's choices and/or constraints in terms of education and occupation, a large portion cannot, implying that simply attaining equal qualifications in STEM may not be sufficient for women to achieve equal digital engagement in the workplace. Addressing the gender gap in digital task use will likely require both: (i) policies that reduce gendered sorting into less digital pathways, and (ii) measures within firms that support equal access to advanced digital tasks, training opportunities and progression. These findings contribute to the literature on the gender digital divide (Huyer, 2015; Perifanou and Economides, 2020) by focusing specifically on workplace skill utilisation, and to the broader gender gaps in skills and tasks literature (Blau and Kahn, 2017; Brussevich et al., 2019), potentially providing new evidence for Europe during an era of ongoing digital transformation. As digital tools become increasingly central to productivity, wages, and career advancement, ensuring equitable access to high-digital-intensity roles will be critical for both gender equality and inclusive economic growth.

7. References

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8. Appendix

Table A1: Additional Variable Descriptives

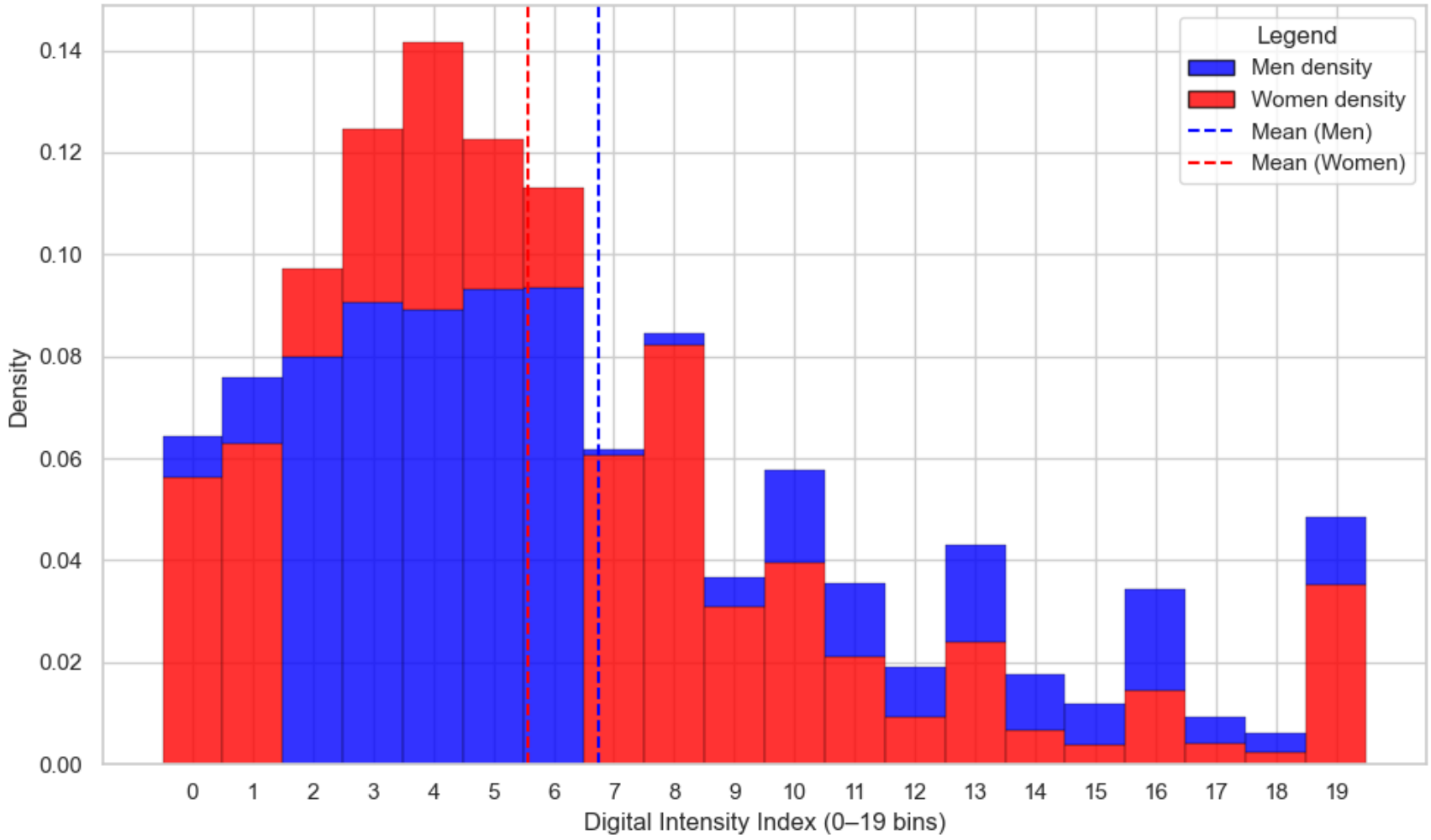
Variable	Observations	Overall Prevalence	Male Prevalence	Female Prevalence
Female	44,178	0.49	0	1
Tenure	43,665	9.9	10.07	9.74
Age	44,208	43.41	43.28	43.54
Part-time	44,208	0.21	0.13	0.29
contract type				
Permanent	44,132	0.84	0.86	0.82
Temporary	44,132	0.13	0.12	0.15
No contract	44,132	0.02	0.02	0.03
Education level				
Low	44,122	0.11	0.13	0.09
Middle	44,122	0.46	0.5	0.41
High	44,122	0.43	0.37	0.49
Area of residence				
Rural	44,181	0.25	0.24	0.25
Small/Medium town	44,181	0.37	0.37	0.37
City	44,181	0.38	0.39	0.37
Firm size				
1 to 10	43,908	0.21	0.2	0.23
11 to 49	43,908	0.28	0.27	0.29
50 to 249	43,908	0.26	0.26	0.25
250 or more	43,908	0.25	0.27	0.23
Sector				
Private	44,055	0.63	0.72	0.54
Public	44,055	0.29	0.21	0.37
Not-for-profit	44,055	0.03	0.02	0.03
Other	44,055	0.05	0.05	0.05
education field				
Arts and humanities	27,409	0.07	0.03	0.1
Generic p..	27,409	0.08	0.05	0.11
Education	27,409	0.1	0.11	0.09
Social sciences	27,409	0.04	0.03	0.05
Business, Admin and Law	27,409	0.18	0.14	0.22
Natural sciences, maths and stats	27,409	0.08	0.09	0.08
ICT	27,409	0.08	0.12	0.04
Engineering and Construction	27,409	0.18	0.27	0.08
Agriculture	27,409	0.03	0.03	0.02
Health	27,409	0.08	0.04	0.13
Services	27,409	0.08	0.09	0.06
occupation				
Commissioned armed forces officers	43,352	0.11	0.18	0.04

Non-commissioned armed forces officers	43,352	0.02	0.01	0.02
Armed forces occupations, other ranks	43,352	0.15	0.21	0.08
Chief executives, senior officials and Legislators	43,352	0.86	0.98	0.73
Administrative and commercial managers	43,352	3.08	3.29	2.85
Production and specialised services managers	43,352	4	4.89	3.07
Hospitality, retail and other services	43,352	1.27	1.27	1.26
Science and engineering professionals	43,352	3.11	3.9	2.27
Health professionals	43,352	2.9	1.11	4.79
Teaching professionals	43,352	6	2.67	9.51
Business and administration professionals	43,352	4.4	3.39	5.47
Information and communications technology professionals	43,352	2.91	4.14	1.59
Legal, social and cultural professional	43,352	2.61	1.76	3.5
Science and engineering associate professionals	43,352	2.68	3.91	1.39
Health associate professionals	43,352	1.85	0.96	2.79
Business and administration associate professionals	43,352	8.12	6.22	10.13
Legal, social, cultural and related assistants	43,352	1.41	1.22	1.61
Information and communications technicians	43,352	1.9	2.7	1.06
General and keyboard clerks	43,352	3.84	2.27	5.5
Customer services clerks	43,352	3.27	2.42	4.17
Numerical and material recording clerks	43,352	3.2	2.81	3.61
Other clerical support workers	43,352	1.33	0.93	1.76
Personal service workers	43,352	2.99	2.32	3.68
Sales workers	43,352	4.65	3.06	6.34
Personal care workers	43,352	3.75	1.03	6.62
Protective services workers	43,352	1.8	2.82	0.72
Market-oriented skilled agricultural workers	43,352	1.04	1.21	0.85
Market-oriented skilled forestry, fishery, hunting workers	43,352	0.23	0.36	0.09
Subsistence farmers, fishers, hunters	43,352	0.01	0.01	<1%
Building and related trades workers, excluding electricians	43,352	2.71	4.79	0.5
Metal, machinery and related trades workers	43,352	3.3	5.8	0.66
Handicraft and printing workers	43,352	0.81	1.14	0.47
Electrical and electronic trades worker	43,352	2.25	3.91	0.49
Food processing, wood working, garment manufacturers	43,352	2.16	2.36	1.96
Stationary plant and machine operators	43,352	2.31	3.16	1.41
Assemblers	43,352	1.23	1.75	0.68
Drivers and mobile plant operators	43,352	3.9	6.7	0.95
Cleaners and helpers	43,352	2.16	0.8	3.59
Agricultural, forestry and fishery labourers	43,352	0.48	0.61	0.34
Labourers in mining, construction, manufacturing	43,352	3.72	5.39	1.95
Food preparation assistants	43,352	0.77	0.51	1.04
Street and related sales and service workers	43,352	0.06	0.08	0.05

Refuse workers and other elementary workers	43,352	0.69	0.96	0.39
NACE-1 Industry				
Agriculture, Forestry & Fishing	43,434	0.02	0.02	0.01
Mining & Quarrying	43,434	<1%	0.01	<1%
Manufacturing	43,434	0.18	0.25	0.11
Energy Supply	43,434	0.02	0.02	0.01
Water & Waste Management	43,434	0.01	0.01	0.01
Construction	43,434	0.05	0.08	0.02
Wholesale & Retail Trade	43,434	0.09	0.09	0.1
Transportation & Storage	43,434	0.06	0.09	0.03
Accommodation & Food Services	43,434	0.04	0.04	0.05
Information & Communication	43,434	0.06	0.07	0.04
Finance & Insurance	43,434	0.03	0.03	0.04
Real Estate	43,434	0.01	0.01	0.01
Professional & Technical Services	43,434	0.06	0.05	0.07
Admin & Support Services	43,434	0.06	0.06	0.07
Public Admin & Defense	43,434	0.06	0.05	0.06
Education	43,434	0.09	0.04	0.15
Health & Social Work	43,434	0.11	0.04	0.18
Arts & Recreation	43,434	0.02	0.01	0.02
Other Services	43,434	0.02	0.01	0.02
Household Activities	43,434	<1%	<1%	<1%
Extraterritorial Organizations	43,434	<1%	<1%	<1%

Note: Descriptive statistics by gender. Weighted

Figure A1: Raw Distribution of JDII by Gender (no rescaling and no smoothing 0-19)



Notes: Raw Distribution of JDII (0-19 scale), unsmoothed. Weighted

Table A2: Detailed Regression Results for Digital Skills Use (pooled): Intermediate+, Advanced Tasks, and JDII (Marginal Effects)

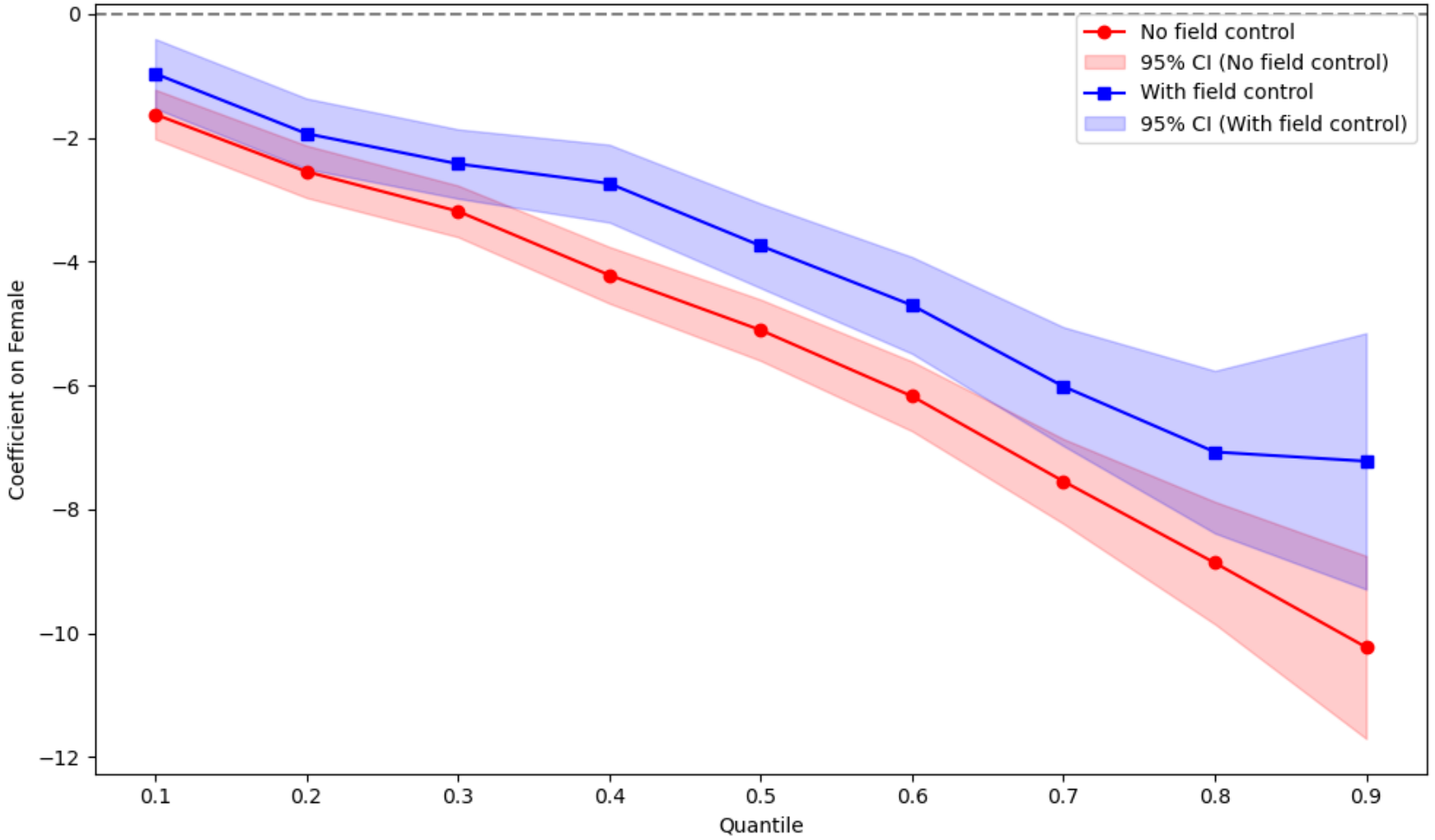
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Intermediate or above tasks (Probit ME)			Advanced tasks (Probit ME)			JDII (OLS)		
Female	-0.064***	-0.060***	-0.043***	-0.134***	-0.101***	-0.093***	-5.66***	-5.64***	-4.56***
	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)	(0.007)	(0.30)	(0.31)	(0.39)
Age (years)	-0.004***	-0.004***	-0.004***	-0.006***	-0.005***	-0.005***	-0.36***	-0.31***	-0.34***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.01)	(0.01)	(0.02)
Part-time		-0.009	-0.017**		0.038***	0.029***		1.21***	0.52
		(0.007)	(0.008)		(0.007)	(0.008)		(0.41)	(0.47)
Contract type (ref: Permanent)									
Temporary		-0.047***	-0.045***		-0.024***	-0.029***		-2.78***	-3.14***
		(0.009)	(0.010)		(0.007)	(0.009)		(0.47)	(0.56)
No contract		-0.110***	-0.091***		-0.041**	-0.045**		-5.69***	-6.30***
		(0.021)	(0.024)		(0.017)	(0.021)		(1.09)	(1.19)
Education Level (ref: low)									
Middle		0.033***			-0.047***			-1.60**	
		(0.012)			(0.011)			(0.72)	
High		0.114***	0.070***		-0.018	0.039***		4.13***	5.89***
		(0.012)	(0.007)		(0.011)	(0.007)		(0.73)	(0.40)
Area of residence (ref: rural)									
Small/mid-sized town	0.026***	0.006	-0.004	0.021***	0.017**	0.000	1.94***	1.01***	0.68
	(0.008)	(0.007)	(0.009)	(0.007)	(0.007)	(0.009)	(0.40)	(0.37)	(0.48)
City	0.061***	0.007	-0.003	0.050***	0.028***	0.019**	5.01***	1.94***	1.99***
	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)	(0.009)	(0.41)	(0.39)	(0.50)
Firm size (ref: 1 to 10)									
11 to 49		0.036***	0.033***		0.026***	0.021**		2.61***	2.59***
		(0.008)	(0.010)		(0.008)	(0.010)		(0.43)	(0.54)
49 to 249		0.052***	0.045***		0.026***	0.023**		3.95***	4.31***
		(0.009)	(0.010)		(0.008)	(0.010)		(0.44)	(0.56)
250 or more		0.058***	0.046***		0.019**	0.011		3.43***	3.22***

		(0.009)	(0.011)		(0.008)	(0.010)		(0.45)	(0.57)
Sector (ref: Private)									
Public		-0.005	0.009		0.040***	0.047***		1.93***	2.33***
		(0.008)	(0.009)		(0.007)	(0.009)		(0.43)	(0.53)
Not-for-profit		-0.002	0.010		0.090***	0.102***		4.24***	4.14***
		(0.016)	(0.018)		(0.016)	(0.020)		(0.91)	(1.11)
Other		0.025**	0.022		0.080***	0.055***		4.14***	2.74***
		(0.013)	(0.014)		(0.013)	(0.015)		(0.74)	(0.82)
Education Field (ref: Arts and Humanities)									
Generic			0.014			0.077***			5.21***
			(0.017)			(0.016)			(0.94)
Education			-0.027			0.027*			0.97
			(0.017)			(0.016)			(0.83)
Social Sciences			-0.030			0.009			-0.45
			(0.019)			(0.016)			(0.87)
Business, admin, Law			0.064***			0.019			2.97***
			(0.013)			(0.012)			(0.65)
Natural Sciences, Maths, Stats			0.089***			0.131***			8.44***
			(0.015)			(0.015)			(0.86)
ICT			0.134***			0.242***			12.94***
			(0.016)			(0.017)			(0.93)
Engineering and construction			0.066***			0.061***			4.12***
			(0.015)			(0.013)			(0.76)
Agriculture			0.016			0.040			1.36
			(0.026)			(0.025)			(1.37)
Health			0.031*			0.057***			2.27**
			(0.017)			(0.017)			(0.93)
Services			0.015			0.071***			2.30**
			(0.017)			(0.016)			(0.90)
Constant							47.88***	39.31***	41.66***
							(0.99)	(3.83)	(5.74)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

ISCO-2 FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
NACE-1 FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
Observations	39,756	38,589	24,639	39,769	38,601	24,634	39,598	38,455	24,605
R-squared	-	-	-	-	-	-	0.07	0.20	0.21

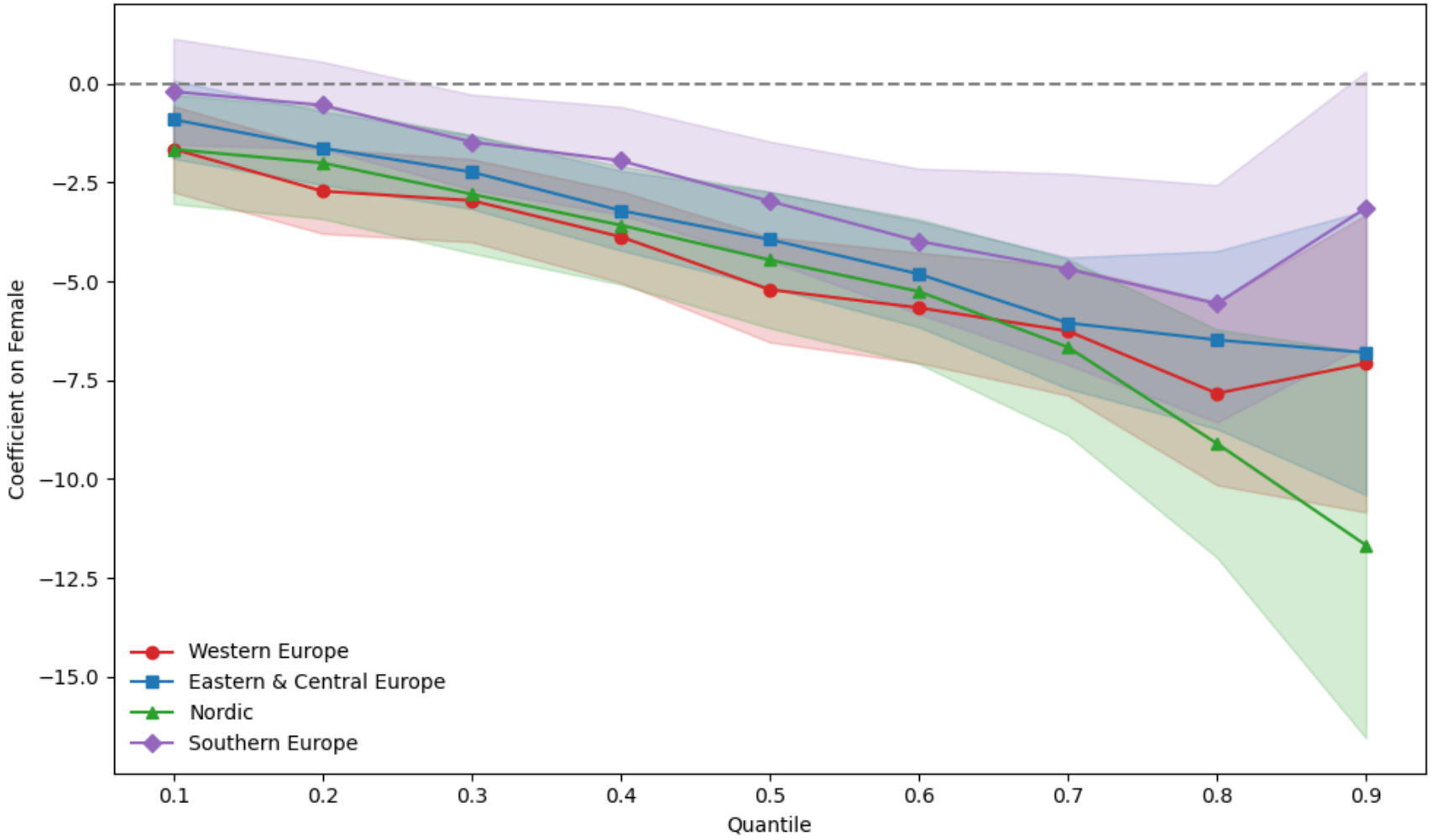
Note: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1. Field of education is only recorded for a limited sample, thus these specifications only include individuals with High-school education or above. Weighted.

Figure A2: Gender Gap in Job Digital Intensity Index in Europe



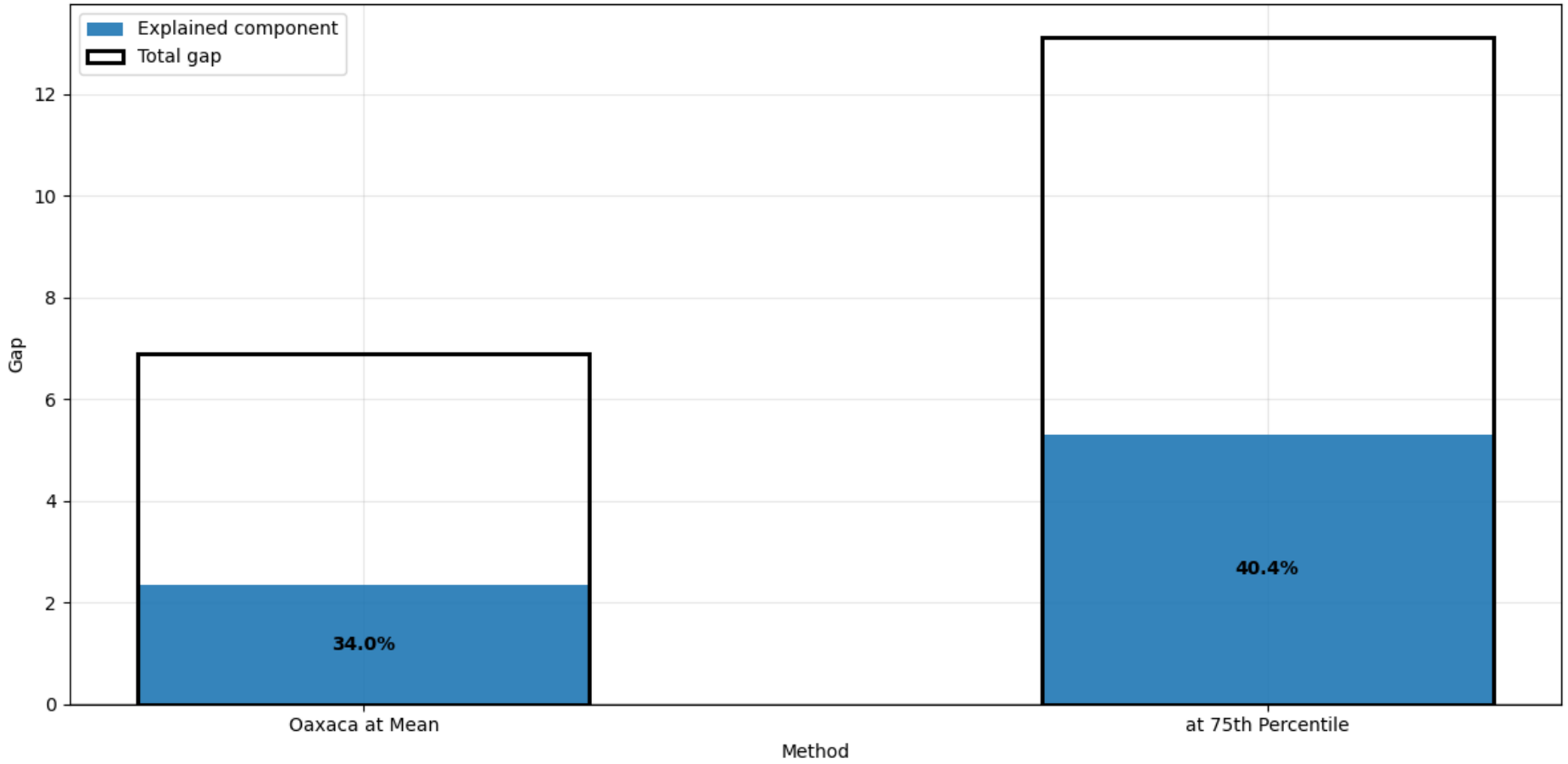
Notes: Female coefficient at various deciles from quantile regression on JDII. Both specifications include detailed controls.

Figure A3: Gender Gap in Digital-Intensity Index by Region with Field (Quantile Regression)



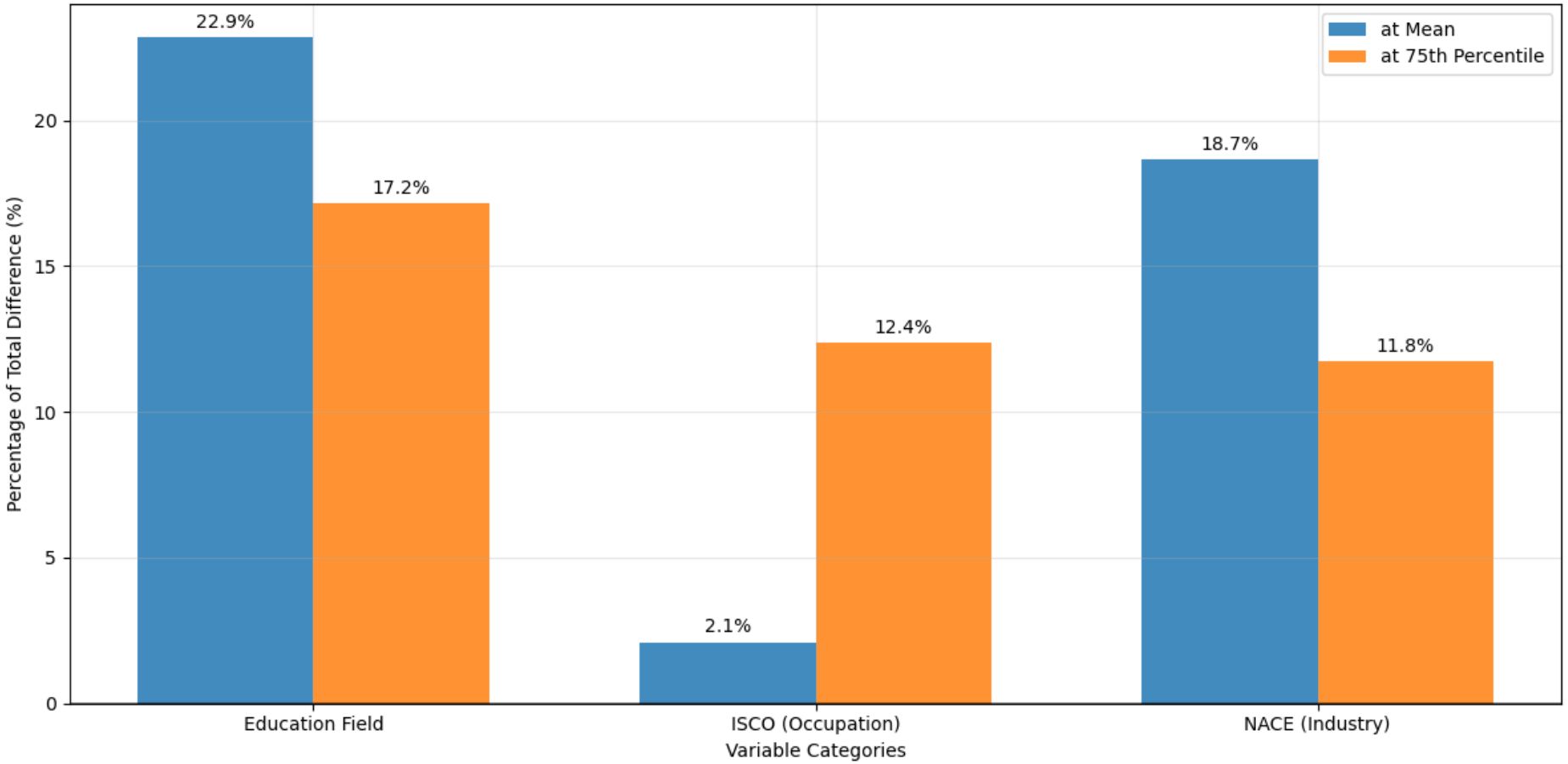
Notes: Female coefficient at various deciles from quantile regression on JDII. All specifications include detailed controls and Field of education.

Figure A4: Overall Gender Gap in JDII and % Explained at Mean and at 75th Percentile



Note: 75th percentile uses decomposition of RIF-regression at 75th percentile of outcome variable

Figure A5: Explained Contribution to Overall Gender Gap in JDII by Characteristic at Mean Vs at 75th Percentile



Note: 75th percentile uses decomposition of RIF-regression at 75th percentile of outcome variable

Table A3: Detailed NACE-1 Industry Explained Components

Rank	NACE-1 Industry	Expl. % (μ)	Expl. % ($Q_{0.75}$)	Mean JDII	Pctil. Mean JDII	% Female
1	Health & Social Work	8.9	4.4	25.6	42.0	80.6
2	Education	7.7	3.4	29.5	52.3	76.7
3	Information & Communication	2.5	1.3	51.6	79.1	32.7
4	Public Admin & Defense	1.5	0.6	32.4	62.2	55.9
5	Wholesale & Retail Trade	0.3	0.1	30.9	52.3	51.0
6	Arts & Recreation	0.3	0.1	29.6	52.3	57.8
7	Mining & Quarrying	0.2	0.1	35.9	62.2	25.8
8	Agriculture, Forestry & Fishing	0.1	0.4	33.4	62.2	34.2
9	Household Activities	0.1	0.0	36.9	68.0	55.0
10	Accommodation & Food Services	0.1	0.1	28.2	52.3	49.7
11	Other Services	0.0	0.0	30.8	52.3	55.3
12	Finance & Insurance	0.0	0.0	39.9	68.0	50.5
13	Real Estate	0.0	0.0	35.3	62.2	54.2
14	Admin & Support Services	0.0	0.0	33.7	62.2	48.5
15	Extraterritorial Organizations	0.0	0.0	26.1	42.0	54.6
16	Manufacturing	-0.1	0.9	33.6	62.2	29.1
17	Water & Waste Management	-0.3	0.1	30.5	52.3	29.7
18	Professional & Technical Services	-0.4	-0.2	40.4	68.0	55.7
19	Energy Supply	-0.6	-0.1	32.9	62.2	23.7
20	Construction	-0.6	0.6	31.3	52.3	20.4
21	Transportation & Storage	-1.3	0.0	28.0	52.3	27.0
	Total	**18.7**	**11.8**			

Note: Industries that contribute most to explained proportion in mean on JDII. Expl. % ($Q_{0.75}$) shows the proportion explained at the 75th percentile. Mean JDII shows mean JDII in that industry, Pctil. Mean JDII is the percentile of that JDII value. % Female is the proportion of that industry that are women. Weighted.

Table A4: Detailed Education Field Explained Components

Rank	Education field	Expl. % (μ)	Expl. % ($Q_{0.75}$)	Mean JDII	Pctil. Mean JDII	% Female
1	Information and Communication Technology	11.1	6.1	52.9	80.6	26.0
2	Arts, humanities and foreign languages	3.3	2.8	31.7	58.1	68.6
3	Education	2.6	3.0	29.4	48.7	74.2
4	Health and welfare (including care and	2.0	0.6	28.2	48.7	78.7
5	Social sciences, journalism and information	1.6	0.9	33.1	58.1	66.1
6	Engineering, manufacturing and construction	1.3	4.2	36.2	58.1	23.1
7	Business, administration and law	0.8	-0.5	36.2	58.1	59.9
8	Natural sciences, mathematics and statistics	0.7	0.4	42.8	72.3	47.0
9	Generic programmes and qualifications	0.3	-0.2	34.0	58.1	45.4
10	Agriculture, forestry, fisheries and veterinary	-0.2	0.0	30.2	48.7	43.7
11	Services (Personal, security, transport)	-0.6	-0.1	30.3	48.7	39.5
	Total	**22.9**	**17.2**			

Note: Education Fields that contribute most to explained proportion in mean on JDII. Expl. % ($Q_{0.75}$) shows the proportion explained at the 75th percentile. Mean JDII shows mean JDII in that field, Pctil. Mean JDII is the percentile of that JDII value. % Female is the proportion of that field that are women. Weighted.

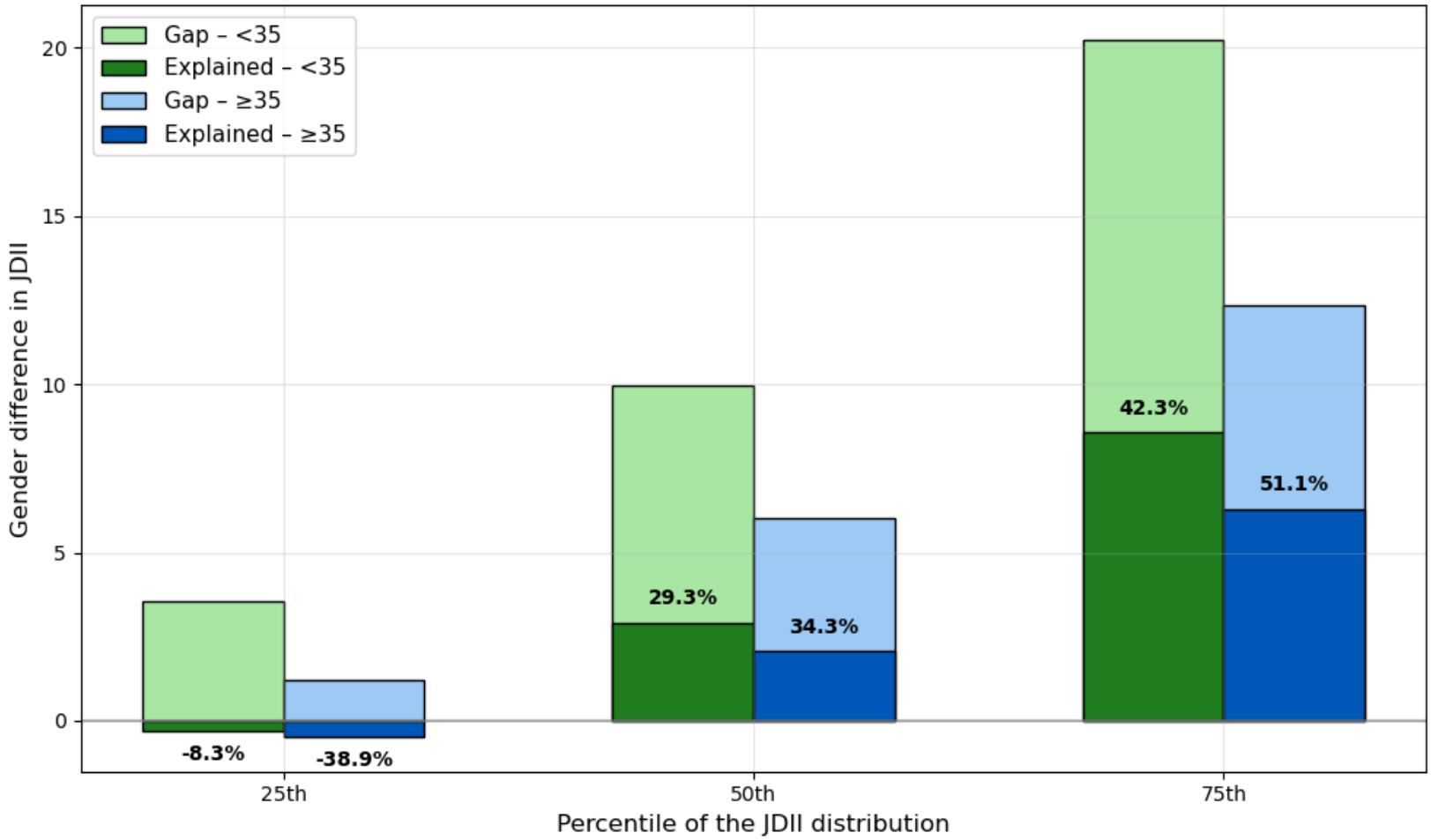
Table A5: Detailed ISCO-2 Occupation Explained Components

Rank	ISCO-2 Occupation	Expl. % (μ)	Expl. % ($Q_{0.75}$)	Mean JDII	Pctil. Mean JDII	% Female
1	Information and communications technology managers	7.6	4.7	60.4	86.5	26.7
2	Production and specialised services managers	4.2	1.9	44.2	76.0	37.1
3	Personal care workers	3.6	2.0	19.5	31.0	84.6
4	Information and communications technicians	3.5	2.7	52.0	79.1	26.8
5	Health professionals	2.2	2.4	26.2	42.0	79.7
6	Administrative and commercial managers	0.9	0.9	41.8	68.0	44.9
7	Science and engineering professionals	0.9	0.4	41.0	68.0	35.8
8	Sales workers	0.9	1.1	27.0	52.3	64.1
9	Chief executives, senior officials and legislators	0.7	0.3	43.6	76.0	41.7
10	Health associate professionals	0.6	0.7	26.7	52.3	72.8
11	Teaching professionals	0.5	1.5	29.5	52.3	76.8
12	Cleaners and helpers	0.4	0.2	25.2	42.0	71.8
13	Other clerical support workers	0.3	-0.2	29.8	52.3	64.5
14	Market-oriented skilled agricultural workers	0.2	0.1	31.0	52.3	43.0
15	Legal, social and cultural professional	0.2	0.1	31.8	62.2	65.9
16	Legal, social, cultural and related assistants	0.2	0.1	27.6	52.3	56.9
17	Armed forces occupations, other ranks	0.1	0.3	33.0	62.2	23.4
18	Personal service workers	0.1	0.1	26.2	42.0	55.5
19	Hospitality, retail and other services	0.1	0.1	38.3	68.0	47.1
20	Customer services clerks	0.1	0.1	31.2	52.3	62.4
21	Food preparation assistants	0.0	0.1	26.8	52.3	57.1
22	Non-commissioned armed forces officers	0.0	0.0	21.0	31.0	62.8
23	Commissioned armed forces officers	0.0	-0.1	30.6	52.3	17.6
24	Subsistence farmers, fishers, hunters and forestry workers	0.0	0.0	22.5	42.0	27.8
25	Street and related sales and service workers	-0.1	0.0	21.5	42.0	29.9
26	Agricultural, forestry and fishery labourers	-0.1	0.0	33.5	62.2	29.9
27	Market-oriented skilled forestry, fishery workers	-0.1	-0.1	22.8	42.0	12.4

28	Food processing, wood working, garment makers	-0.1	-0.1	32.9	62.2	39.7
29	Science and engineering associate professionals	-0.2	0.3	34.2	62.2	25.4
30	Refuse workers and other elementary workers	-0.2	-0.1	24.8	42.0	27.1
31	Handicraft and printing workers	-0.5	-0.6	27.8	52.3	23.4
32	Numerical and material recording clerks	-0.6	-0.6	34.8	62.2	56.0
33	Assemblers	-0.7	0.1	26.7	52.3	24.4
34	Electrical and electronic trades workers	-1.3	0.4	31.5	52.3	10.6
35	General and keyboard clerks	-1.5	-0.6	35.6	62.2	70.1
36	Business and administration professionals	-1.6	-1.4	40.2	68.0	60.5
37	Building and related trades workers, excluding electricians	-1.7	3.7	26.1	42.0	6.4
38	Business and administration associate professionals	-1.7	-1.3	34.6	62.2	60.7
39	Protective services workers	-1.9	-1.7	24.3	42.0	19.4
40	Labourers in mining, construction, manufacturing	-2.0	-1.2	27.5	52.3	22.6
41	Stationary plant and machine operators	-2.1	-1.7	27.5	52.3	21.2
42	Metal, machinery and related trades workers	-3.3	-0.3	27.9	52.3	9.2
43	Drivers and mobile plant operators	-5.5	-1.7	17.9	31.0	12.3
	Total	**2.1**	**12.4**			

Note: occupations that contribute most to explained proportion in mean on JDII. Expl. % ($Q_{0.75}$) shows the proportion explained at the 75th percentile. Mean JDII shows mean JDII in that occupation, Pctil. Mean JDII is the percentile of that JDII value. % Female is the proportion of that occupation that are women. Weighted.

Figure A6: JDII Gap Decomposition at Different Quantiles by Age Cohort



Note: Gap and explained proportion of the gender gap in JDII at 25th-, 50th- and 75th-percentile of the JDII distribution, by age sample. Weighted