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Mind the Gap: Gender Inequality in Europe's Twin Transition

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Mind the Gap: Gender Inequality in Europe's Twin Transition

Abstract

This paper examines gender disparities in the European labour market during the twin digital and green transitions. Using the European Skills and Jobs Survey matched with the ESCO occupational classification, it identifies digital and green occupations based on their skill content and analyses both access to these jobs and wage outcomes within them. Women are significantly less likely to work in digital and green occupations and, conditional on employment, face larger wage gaps than comparable men. They are also less likely to hold managerial positions and benefit less from STEM educational backgrounds, despite the positive returns associated with these qualifications. Finally, stronger regional STEM-oriented university environments are associated with smaller gender gaps in access to digital occupations and wages, suggesting that the twin transition may reinforce existing gender inequalities unless accompanied by targeted policies.

JEL classification

J16, J24, J31, O33, Q52

Keywords

gender disparities, gender wage gap, green jobs, digital jobs, STEM, labour market

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1. Introduction

The twin transition, namely the simultaneous expansion of digital technologies and environmentally sustainable production, is reshaping advanced economies. In Europe, it is a central policy priority, reflected in the European Green Deal (European Commission, 2019) and the Digital Decade strategy (European Commission, 2021), promoting sustainable, technologically advanced, and inclusive growth while reshaping employment and skill requirements.¹ Labour demand is consequently shifting towards digital, technical, managerial, and sustainability-related competences (ESCO, 2022; OECD, 2023, 2024a).

The implications of these changes for gender inequality remain theoretically ambiguous and empirically underexplored.² Digital and green activities may reinforce existing inequalities through women’s lower STEM³ and technical skills, occupational segregation, barriers to career progression, and unequal returns in high-paying occupations with non-linear wage structures (Bertrand et al., 2010; Blau and Kahn, 2017; Goldin, 2014; OECD, 2025; Vona et al., 2018). They may therefore disproportionately benefit workers whose skills are already aligned with emerging occupations while reinforcing labour market segmentation and precarious employment among vulnerable groups (Lan-dini et al., 2026). Conversely, remote work, broader access to STEM education, diversity policies, and women’s stronger pro-environmental attitudes may improve their access to higher-paying digital and green occupations (Echavarren, 2023; McCright and Xiao, 2014; OECD, 2024a). Whether the twin transition ultimately reduces or reinforces gender inequalities therefore remains an open empirical question.

To assess the relative importance of these contrasting mechanisms, this paper examines gender disparities in the European labour market during the twin transition, focusing on participation in digital and green occupations, wage outcomes, managerial positions, and the role of STEM education.

The empirical analysis uses the 2021 European Skills and Jobs Survey (ESJS2), covering 29 European countries and providing detailed information on workers’ characteristics and skills. Digital and green occupations are identified using the European Classification of Skills, Competences and Occupations (ESCO), adopting a skill-based classification at the ISCO 4-digit level, consistent with recent studies (Autor et al., 2003; ESCO, 2022; Vona et al., 2018). The analysis estimates gender gaps in employment, wages, and managerial positions in digital and green occupations, controlling for individual, firm, occupational, sector, and regional characteristics. It further examines whether STEM education, returns to STEM qualifications, and regional educational environments help explain these disparities.

The results reveal a persistent disadvantage for women both in accessing emerging occupations and in the returns they receive within them. Women are less likely to work in digital and green occupations (about -2.5 p.p.) and earn lower wages than comparable men (-9%), with larger penalties in digital (-13.5%) and green (-20%) occupations. They are also less likely to hold managerial positions and face an additional wage penalty

¹Digitalisation contributes to occupational polarisation and changing skill demands (Acemoglu and Restrepo, 2020; Autor and Dorn, 2013), while the low-carbon transition drives sectoral reallocation and demand for green and sustainability-related competences (Vona et al., 2019; Walker, 2013).

²Research has mainly examined the employment effects of the ecological transition, with less attention to its implications for gender and labour market inequality (Hanaček et al., 2020).

³STEM: Science, Technology, Engineering, and Mathematics.

when they do, consistent with evidence on glass-ceiling effects and non-linear returns in high-paying occupations (Bertrand and Hallock, 2001; Blau and Kahn, 2017; Goldin, 2014).

STEM education is an important mechanism. Women are less likely to hold STEM qualifications and, even when they do, remain less likely to enter digital occupations and receive lower wage returns than comparable men. However, stronger regional STEM-oriented university systems are associated with smaller gender gaps in digital employment and wages, suggesting that local educational environments can help mitigate these disparities.

This paper contributes to the literature on gender inequality, occupational segregation, and technological change by providing new evidence on the distributional implications of the twin transition. The findings highlight that the expansion of digital and green occupations does not automatically produce more inclusive labour market outcomes. Without targeted interventions addressing inequalities in skills, occupational entry, and career progression, the twin transition may reinforce existing gender disparities.

The remainder of the paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the data and the construction of the digital and green occupation indicators. Section 4 presents the empirical methodology and the main results on occupational participation, wage gaps, and managerial positions. Section 5 examines the role of STEM education, and Section 6 concludes.

2. Gender Inequality and the Twin Transition

Gender gaps in the labour market are a multidimensional phenomenon, encompassing employment, earnings, career progression, job quality, and access to emerging occupations. Despite improvements, women continue to earn less than men and remain under-represented in high-paying occupations and sectors (Bertrand, 2020). These disparities are increasingly linked to structural mechanisms, including occupational and sectoral segregation, field-of-study choices, unequal access to high-return jobs, and differences in job flexibility and work intensity (Blau and Kahn, 2017; Christofides et al., 2013; Goldin, 2014; Le Barbanchon et al., 2021).⁴

These mechanisms are particularly relevant in the context of the twin transition, which is shifting labour demand towards occupations requiring digital, technical, analytical, and green competences (ESCO, 2022). Whether these changes reduce or widen gender inequalities remains ambiguous, as they depend on how they interact with pre-existing differences in skills, occupational allocation, and access to high-return jobs (OECD, 2024a, 2025).

Digital occupations related to ICT, artificial intelligence, and data-intensive activities offer high wages and strong career prospects. Yet women account for only 11–24% of ICT specialists across OECD countries and are even less represented in AI-related occupations (OECD, 2024a, 2025; Young et al., 2023). Persistent barriers also limit their access to senior positions (Basso et al., 2026; Chang, 2018; Gomez-Herrera and Koeszegi, 2022). While digitalisation may improve work-family balance through remote work and flexible schedules (Chung and van der Horst, 2018; Goldin, 2014; van der Lippe and Lippényi,

⁴A substantial share of gender inequality also reflects the “child penalty”: the persistent reduction in women’s labour market outcomes following childbirth through lower labour supply, occupational sorting, and slower career progression (Angelov et al., 2016; Kleven et al., 2025, 2019).

2020), these opportunities are concentrated in high-skilled jobs and may therefore reinforce existing gender disparities.

Similarly, green jobs remain concentrated in male-dominated sectors such as energy, construction, manufacturing, transport, and engineering (Clancy and Feenstra, 2019; European Commission, 2023; Santero-Sánchez et al., 2025). They increasingly involve sustainability-related tasks within existing occupations rather than entirely new jobs (Consoli et al., 2016; Vona et al., 2018). Because these changes occur within already segregated sectors, they may reinforce existing inequalities: women hold only 28% of green-task jobs across OECD countries (OECD, 2023). This limits their ability to benefit from green growth and potentially reinforces labour market segmentation (Landini et al., 2026).

Educational choices and skill acquisition are key channels through which occupational segregation emerges. This is especially relevant for digital occupations, which require advanced cognitive, technical, and engineering competences (Bowen et al., 2018; Lennon et al., 2023).⁵ Women remain underrepresented in STEM, particularly in ICT and engineering, which provide the main entry routes into expanding digital occupations (Barone and Assirelli, 2020; Bovini et al., 2026; Charles and Bradley, 2009a; Delaney and Devereux, 2021; OECD, 2024a; Piazzalunga, 2018).⁶ Field-of-study segregation therefore limits women’s access to emerging occupations, firm wage premia, and career opportunities, creating a vicious cycle in which educational disparities reinforce occupational segregation and women’s underrepresentation in technology-intensive jobs (Gomez-Herrera and Koeszegi, 2022).

Occupational segregation also affects earnings within occupations. Gender wage gaps are larger in occupations rewarding long, continuous, and inflexible hours, the so-called “greedy work” (Blau and Kahn, 2017; Goldin, 2014; Goldin and Katz, 2016).⁷ This mechanism may be particularly relevant in digital occupations, where steep returns to experience and performance-based promotion magnify small differences in labour supply. Women’s underrepresentation in top-paying firms further widens earnings gaps (Albanesi et al., 2025; Card et al., 2016).

Evidence on gender wage gaps in green occupations remains limited. Existing cross-country evidence suggests that green occupations are associated with a wage premium, larger for women (around 12%) than for men (around 7%) (Alexander et al., 2024). However, the concentration of green jobs in male-dominated sectors, together with requirements for mobility, continuous employment, and inflexible working arrangements, may still disadvantage women. Consequently, the overall impact of the green transition on gender wage inequality remains uncertain, reflecting the interaction between occupational selection, sectoral composition, and job-specific wage-setting mechanisms.

⁵Digital and STEM-related competences may be less central in green occupations, whose skill requirements are more heterogeneous across sectors, tasks, and occupational profiles.

⁶These disparities reflect comparative advantages, gender norms, stereotypes, and biases among parents, teachers, and peers that shape educational choices from an early age (Bertrand, 2020; Bordalo et al., 2019; Buser et al., 2014; Carrell et al., 2010; Charles and Bradley, 2009b; Dee, 2007; Olivetti et al., 2024).

⁷This mechanism is related to compensating differentials: workers sort across jobs with different wage-amenity trade-offs (Bonhomme and Jolivet, 2009; Rosen, 1986), and women facing greater time constraints may select more flexible but lower-paying jobs (Goldin, 2021).

3. Data descriptions and preliminary statistics

3.1. The European Skills and Jobs Survey

The empirical analysis uses the second edition of Cedefop’s European Skills and Jobs Survey (ESJS2), conducted in 2021.⁸ The survey covers employees aged 25–64 in 29 European countries and provides harmonised information on demographics, education, occupations, skills, and job characteristics. The final sample consists of 44,103 respondents after excluding observations with missing information and non-binary respondents. ESJS2 combines detailed information on workers’ skills with occupational identifiers at the ISCO 4-digit level, allowing the identification of digital and green occupations using ESCO classifications (Section 3.2).

Table 1 summarises the variables used in the empirical analysis. The main outcomes are employment in digital and green occupations, hourly wages, and managerial status. Digital and green occupations are defined using the ESCO-based classification described in Section 3.2. Hourly wages are computed by dividing monthly net earnings by usual weekly hours multiplied by 4.33.^{9,10} Managerial status is defined according to the one-digit ISCO classification.

The main explanatory variable is gender. STEM education is measured by an indicator equal to one if the respondent’s highest educational qualification is in natural sciences, mathematics and statistics; ICT; or engineering, manufacturing and construction.¹¹

Control variables include age, education level, horizontal and vertical educational subjective mismatch, type of skills, skill mismatch, country or region of residence and living area. Job-related characteristics include occupation (1 to 4-digit ISCO), tenure, training, labour market status before current job, sector (1 or 2-digit NACE), and firm size.

Due to questionnaire design, horizontal mismatch and previous activity are not available for all the respondents.¹² We include a “no-response” category for either ineligible respondents or eligible respondents who did not answer and also replicate the analyses excluding those observations.

3.2. Defining Green and Digital Occupations using ESCO

To identify green and digital occupations, we rely on the European Classification of Skills, Competences and Occupations (ESCO), a standardised taxonomy developed by the European Commission that links occupations to their skill requirements. ESCO covers more than 3,000 occupations linked to the 436 four-digit ISCO-08 unit groups, and 14,000 skills that can be directly mapped to the ISCO-08 classification.

⁸Data are collected through a dual-mode design combining CATI and CAWI with a minimum of 500 respondents per country drawn from probabilistic telephone sampling and supplemented by a quota-based online panel. See the Appendix for survey details and Table A1 for the gender distribution by country and survey mode.

⁹ESJS2 reports net rather than gross earnings. Consequently, estimated wage differentials are not directly comparable to estimates based on gross wages (Christofides et al., 2013; Piazzalunga and Di Tommaso, 2019).

¹⁰Monthly earnings are missing for about 10,900 observations and are imputed using gender-, sector-, and occupation-specific means. Robustness checks using the non-imputed sample yield similar results.

¹¹Field-of-study information is available only for CAWI respondents with at least upper secondary education (26,538 observations).

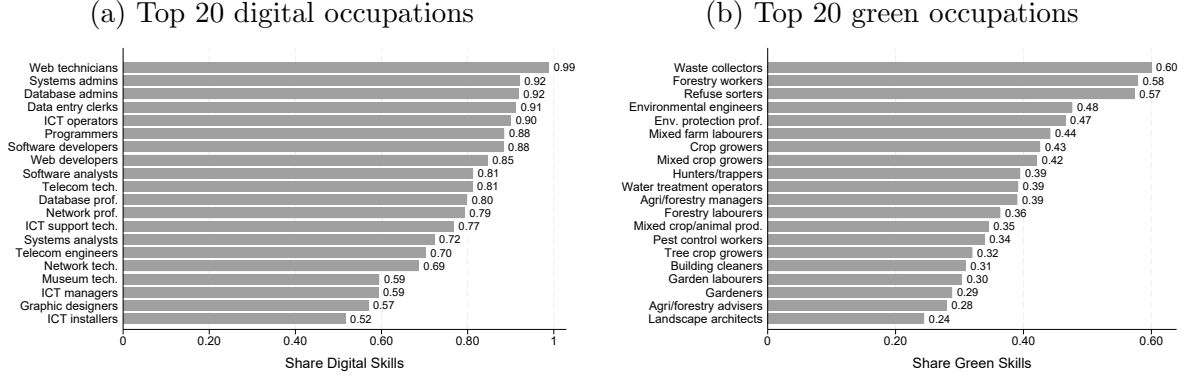
¹²Horizontal mismatch is available only for workers with at least upper secondary education (31,874 obs.) Information on previous activity is available only for 28,946 CAWI respondents.

Table 1: ESJS2 main variable descriptions

Variable	Notation	Description
Dependent and main variables		
	DigitalJob _i	Dummy=1 if the individual works in a digital job, 0 otherwise. (based on ESCO to ISCO-4 digit mapping; digital skills > 10%).
	GreenJob _i	Dummy=1 if the individual works in a green job, 0 otherwise. (based on ESCO to ISCO-4 digit mapping; green skills > 10%).
	HourlyWage _i	Continuous variable. Hourly net pay after compulsory deductions. (Monthly earnings divided by weekly hours*4.33)
	Manager _i	Dummy=1 if the individual is a manager (ISCO-1=1), 0 otherwise.
Gender		
	Female _i	Dummy = 1 if the individual is a woman, 0 otherwise.
Education		
Education level	PrimaryEdu _i	Dummy=1 if primary education or below; 0 otherwise.
	SecondaryEdu _i	Dummy=1 if secondary education, 0 otherwise.
	TertiaryEdu _i	Dummy=1 if tertiary education, 0 otherwise.
Educational mismatch	UnderEdu _i	Dummy=1 if undereducated (self-reported), 0 otherwise.
	MatchedEdu _i	Dummy=1 if educationally well matched (self-reported), 0 otherwise.
	OverEdu _i	Dummy=1 if overeducated (self-reported), 0 otherwise.
Field of study	STEM _i	Dummy=1 if upper secondary or tertiary education in STEM, 0 otherwise. (Natural sciences, math, statistics; ICTs; Engineering, manufacturing, constr.)
Field mismatch	ExactField _i	Dummy=1 for exact field of education required (self-rep.), 0 otherwise.
	RelatedField _i	Dummy=1 for related field of education required (self-reported), 0 otherwise.
	DifferentField _i	Dummy=1 for different field of education required (self-reported), 0 otherwise.
	NoSpecificField _i	Dummy=1 for no specific field of education required (self-reported), 0 otherwise.
	MissingFieldMism _i	Dummy=1 for non-respondent, 0 otherwise.
Skills		
Skills mismatch	UnderSkilled _i	Dummy=1 for under-skilled individual (self-assessed), 0 otherwise.
	MatchedSkills _i	Dummy=1 for well-matched skilled individual (self-assessed), 0 otherwise.
	OverSkilled _i	Dummy=1 for over-skilled individual (self-assessed), 0 otherwise.
Type of skill	LiteracySkill _i	Dummy=1 if high level of literacy skill, 0 otherwise.
	NumeracySkill _i	Dummy=1 if high level of numeracy skill, 0 otherwise.
	ProblemSolvSkill _i	Dummy=1 for high level of problem-solving skill, 0 otherwise.
	SocialSkill _i	Dummy=1 for high level of social skill, 0 otherwise.
	DigitalSkill _i	Dummy=1 for high level of digital skill, 0 otherwise.
	ManualSkill _i	Dummy=1 for presence of manual skill, 0 otherwise.
Job-related characteristics		
Occupation	Occupation _i	Categorical variable; individual's occupation (1 to 4-digit ISCO).
Work-related experience	Tenure _i	Individual's duration with current employer.
Training	Training _i	Dummy=1 if individual has participated in training, 0 otherwise.
Previous Activity	InEducation _i	Dummy=1 if in education before current job, 0 otherwise.
	Employed _i	Dummy=1 if previously employed before current job, 0 otherwise.
	NotEmployed _i	Dummy=1 if not employed (unempl., inactive) before current job, 0 otherwise.
	MissingPrevAct _i	Dummy=1 for non-respondent, 0 otherwise.
Other variables		
	Age _i	Individual's age (25-64).
Sector	Sector _i	Categorical variable; individual's firm sector (1 & 2-digit NACE).
Geographical location	Country _i	Categorical variable; Country where the individual lives (NUTS-0).
	Region _i	Categorical variable; Region where the individual lives (1-digit NUTS).
Living area	RuralArea _i	Dummy=1 if living in rural area, 0 otherwise.
	SmallTown _i	Dummy=1 if living in small town, 0 otherwise.
	LargeTown _i	Dummy=1 if living in large town, 0 otherwise.
Firm size	MicroFirm _i	Dummy=1 if working in micro firm (1-10 employees), 0 otherwise.
	SmallFirm _i	Dummy=1 if working in small firm (11-50 employees), 0 otherwise.
	MediumFirm _i	Dummy=1 if working in medium firm (51-250 employees), 0 otherwise.
	LargeFirm _i	Dummy=1 if working in large firm (> 250 employees), 0 otherwise.

Notes: The subscript i denotes the individual. *Source:* Author's elaboration based on ESJS2.

Figure 1: Top 20 ISCO 4-digit Occupations by Share of Digital Skills (left panel) and Share of Green Skills (right panel).



Notes: Observations: 44,103. Source: Author's elaboration based on ESJS2.

ESCO identifies both green and digital skills. Green skills refer to the knowledge and competences supporting environmentally sustainable production and resource efficiency,¹³ whereas digital skills capture the competences required to use, develop, and manage digital technologies in the workplace.¹⁴ These skills are increasingly central to labour market outcomes (Deming and Kahn, 2018; OECD, 2024b).

Following the recent literature (Bohnenberger, 2022; Consoli et al., 2016; Vona et al., 2019, 2018), occupations are classified according to their skill content rather than sector of employment. Using the information on green and digital skills, we construct measures of occupational intensity based on the share of specific skill types within each ISCO 4-digit occupation k . For each ISCO 4-digit occupation k , we compute the share of green or digital skills as

$$z_k = \frac{zc_k}{n_k}$$

where zc_k denotes the number of skills of type z (green or digital) associated with occupation k , and n_k is the total number of skills linked to that occupation.¹⁵ Following Vona et al. (2019) and OECD (2023), an occupation is classified as green or digital when the corresponding skill share exceeds 10%:

$$Z_k = \begin{cases} 1 & \text{if } z_k > 0.10 \\ 0 & \text{otherwise.} \end{cases}$$

The resulting indicators are matched to workers using ISCO 4-digit occupation codes.¹⁶

Applying this criterion identifies 57 green and 94 digital occupations among the 436 ISCO 4-digit occupations in the sample. Figure 1 reports the twenty occupations with the highest green and digital skill intensity. Green occupations are concentrated in envi-

¹³Examples include renewable energy, energy efficiency, waste management, environmental monitoring, sustainable construction, and natural resource management.

¹⁴Examples include ICT, programming, data analysis, digital problem solving, and the use of software and digital tools.

¹⁵For alternative definitions of green occupations, see Tomasi and Torre (202X).

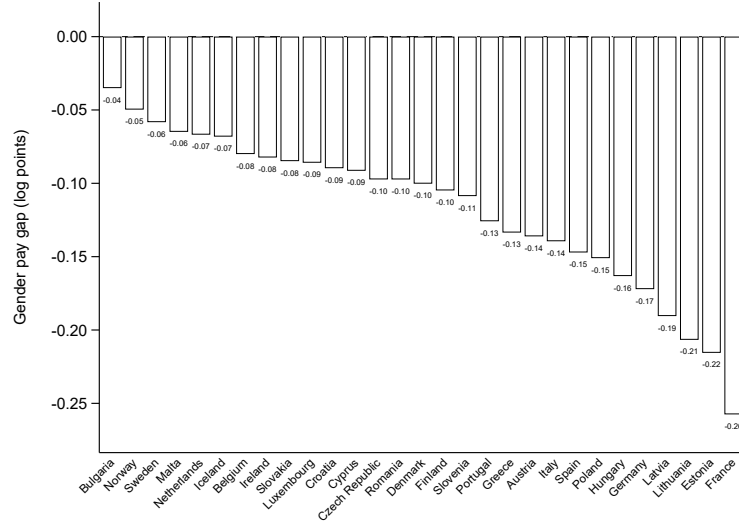
¹⁶Green and digital occupations are not mutually exclusive.

Table 2: Wages and hours worked, by gender

Variable	Male				Female			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Wages _i	1975.13	1480.07	2.75	16,000	1518.04	1092.83	2.26	12,000
HoursWorked _i	38.88	10.12	3	84	35.14	10.74	4	80
HourlyWage _i	13.11	12.73	1	184.76	11.37	10.12	1	148.06
Observations	21,750				22,353			

Notes: Wages_i refers to monthly wages, whereas HourlyWage_i refers to hourly wages. The subscript *i* denotes the individual. Total observations: 44,103. Source: Author's elaboration based on ESJS2.

Figure 2: The unadjusted gender wage gap across countries, net hourly wages



Notes: Observations: 44,103. Source: Author's elaboration based on ESJS2.

ronmental services, agriculture, forestry, and environmental engineering, whereas digital occupations are mainly found in ICT, software development, network services, and data-related activities. Overall, digital skills are more widespread across occupations, whereas green skills are concentrated in a smaller set of jobs.

3.3. Descriptive evidence

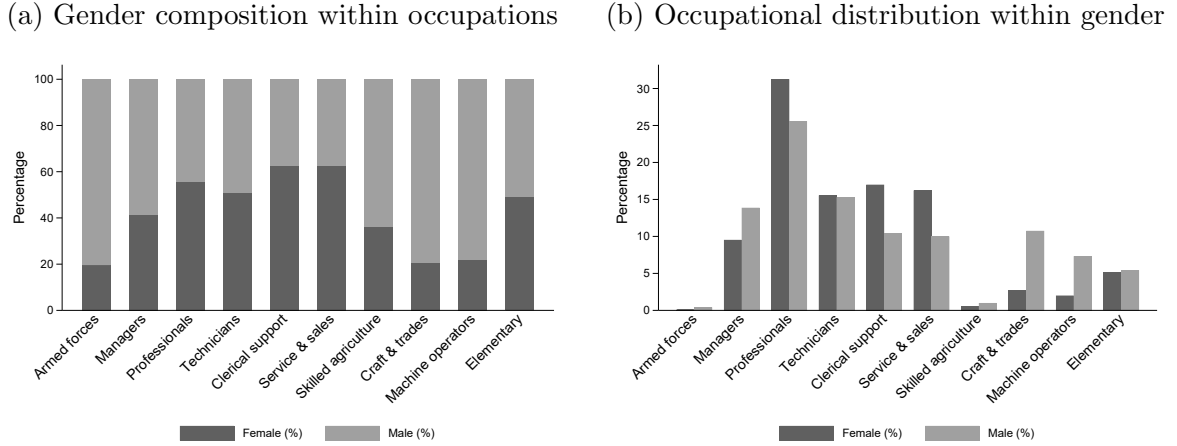
This section presents descriptive evidence on gender differences in wages, occupational allocation, and participation in digital and green jobs. These patterns motivate the multivariate analysis presented in the following sections.

Table 2 reports descriptive statistics for earnings and working hours. Women earn lower monthly and hourly wages than men (1,518 vs. 1,975 and 11.4 vs. 13.1 euros, respectively) and work fewer weekly hours (35 vs. 39), indicating that differences in working time explain only part of the observed earnings gap. Figure 2 shows that the unadjusted gender wage gap in hourly wages is negative in all countries, ranging from 4% in Bulgaria to 26% in France, highlighting substantial cross-country heterogeneity in the magnitude of gender wage inequality.¹⁷

Figure 3 documents substantial occupational segregation across ISCO 1-digit occupations. Men are overrepresented in managerial, craft, machine operator, and armed forces

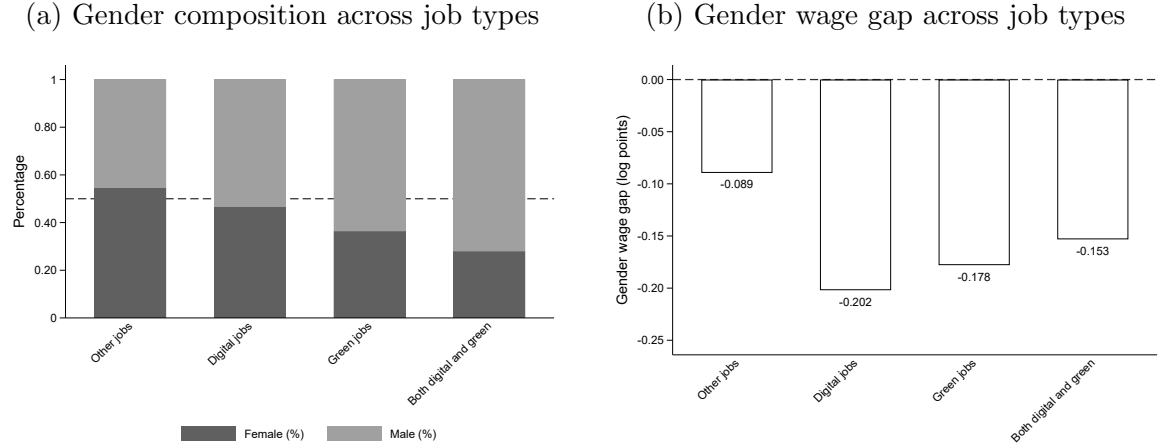
¹⁷Figure A1 in the Appendix reports the distribution of hourly wages by gender across countries, showing that gender disparities are particularly pronounced at the upper tail of the wage distribution and in Northern and Western European countries.

Figure 3: Gender segregation across occupations



Notes: Observations: 44,103. Source: Author's elaboration based on ESJS2.

Figure 4: Gender composition and wage gap across job types



Notes: Other jobs represents occupations which are neither digital nor green. The dashed line in panel (a) represents 50%. Observations: 44,103. Source: Author's elaboration based on ESJS2.

occupations, whereas women are concentrated in clerical, service, and professional occupations (Figure 3a). Women are also distributed across a narrower set of occupations than men, suggesting more limited occupational opportunities (Figure 3b).

Figure 4 shows that women are underrepresented in digital and green occupations, particularly in occupations combining both characteristics. Female representation declines from about 55% in other occupations to 47% in digital jobs, 36% in green jobs, and below 30% in occupations that are both digital and green. At the same time, the raw gender wage gap is larger in digital (20%) and green (17.8%) occupations than in other jobs (9%). These descriptive patterns suggest that occupations associated with the twin transition combine lower female representation with larger wage disparities.

Descriptive statistics for the control variables are reported in Table A2 in the Appendix. Women are, on average, more educated than men but are also slightly more likely to be overeducated. They are less likely to have been previously employed and more frequently work in micro and small firms, whereas men are more likely to be employed in large firms (Oi and Idson, 1999).

Table 3: Access to Digital and Green Jobs

Dep. Var.	DigitalJob _i			GreenJob _i		
	(1)	(2)	(3)	(4)	(5)	(6)
Female _i	-0.027*** (0.007)	-0.027*** (0.007)	-0.027*** (0.009)	-0.025*** (0.003)	-0.025*** (0.003)	-0.018*** (0.005)
Control Variables	✓	✓	✓	✓	✓	✓
Previous activity	-	✓	✓	-	✓	✓
Missing Previous activity var.	-	✓	-	-	✓	-
Field mismatch	-	✓	✓	-	✓	✓
Missing Field mismatch var.	-	✓	-	-	✓	-
δ_{sr}	✓	✓	✓	✓	✓	✓
δ_{isco1}	✓	✓	✓	✓	✓	✓
Adj. R ²	0.335	0.336	0.339	0.225	0.225	0.253
Obs.	42,849	42,849	16,964	42,849	42,849	16,964

Notes: The dependent variables are binary indicators for employment in digital (col. (1) to (3)) and green occupations (col. (4) to (6)). Estimates are based on linear probability models. Control variables include: age, age squared, level of education, educational mismatch, skills mismatch, type of skill, tenure, training, living area, firm size. Standard errors clustered at the country level are reported in parentheses. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

4. Empirical Evidence on Gender Disparities in the Twin Transition

4.1. Sorting into Digital and Green Occupations

To examine gender differences in access to occupations associated with the twin transition, we estimate the probability that an individual is employed in a digital or green occupation as a function of gender and a rich set of observable characteristics. Specifically, we estimate the following linear probability model:

$$JobType_i = \alpha + \beta Female_i + \gamma X_i + \delta_{sr} + \delta_{isco1} + \epsilon_i \quad (1)$$

where $JobType_i$ is a binary indicator equal to one if individual i is employed in a digital (or green) occupation. The coefficient of interest, β , measures the conditional difference in the probability of working in a digital or green occupation between women and men. The vector X_i includes the individual- and firm-level controls described in Section 3. We also include sector-region fixed effects (δ_{sr}) and 1-digit ISCO occupation fixed effects (δ_{isco1}), allowing identification to rely on variation across 4-digit occupations within broader occupational groups. Standard errors are clustered at the country level.

Table 3 reports estimates from linear probability models of access to digital and green occupations. The full set of coefficient estimates is reported in Table A3 of the Appendix.¹⁸ Columns (1) and (4) report the baseline specification. Columns (2) and (5), our preferred specification, additionally control for previous labour market status and field mismatch by retaining non-respondents through a separate category, thereby preserving the full sample.¹⁹ Columns (3) and (6) estimate the same specification on the restricted subsample, excluding individuals with missing information on field mismatch and previous labour market status.

Across all specifications, women are significantly less likely to work in both digital and green occupations. In the preferred specification, women are 2.7 percentage points less likely to be employed in digital occupations and 2.5 percentage points less likely to work in green occupations. These estimates remain remarkably stable across specifications, indicating that the results are robust to the inclusion of additional controls and to the

¹⁸The main specifications are estimated on 42,849 observations after removing singleton groups.

¹⁹Previous activity and field mismatch are observed only for a subsample of respondents (see Section 3).

Table 4: Gender Wage Gap

Dep. Var.	ln HourlyWage _i			
	OLS (1)	OLS (2)	OLS (3)	PSM (4)
Female _i	-0.102*** (0.015)	-0.101*** (0.015)	-0.087*** (0.021)	-0.099*** (0.015)
Control Variable	✓	✓	✓	✓
Previous activity	-	✓	✓	✓
Missing Previous activity var.	-	✓	-	✓
Field mismatch	-	✓	✓	✓
Missing Field mismatch var.	-	✓	-	✓
$\delta_{sr \times isco4}$	✓	✓	✓	✓
R^2	0.696	0.697	0.688	0.730
Adj. R^2	0.575	0.577	0.546	0.626
Obs.	20,786	20,786	7,010	15,127

Notes: The dependent variable is the logarithm of hourly wages. Control variables include: age, age squared, level of education, educational mismatch, skills mismatch, type of skill, tenure, training, living area, firm size. Standard errors clustered at the country level are reported in parentheses. All specifications include sector-region-4digit occupation fixed effects. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

treatment of missing information.²⁰

Among the control variables (Table A3), higher education and digital skills are positively associated with access to digital occupations, whereas manual and social skills are more strongly related to green occupations, reflecting the different skill requirements of the two job types, with green occupations involving a broader mix of manual, sustainability-related, and non-cognitive skills.

Overall, the results provide robust evidence that women face systematically lower access to occupations associated with the twin transition, even after accounting for a rich set of individual, firm, and labour market characteristics.

4.2. Gender Wage Gap

Having documented gender differences in access to digital and green occupations, we now examine wage outcomes. We first estimate the overall gender wage gap and then assess, in Section 4.3, whether it differs across occupations associated with the twin transition. The baseline specification is

$$\ln \text{HourlyWage}_i = \alpha + \beta \text{Female}_i + \gamma X_i + \delta_{sr \times isco4} + \epsilon_i. \quad (2)$$

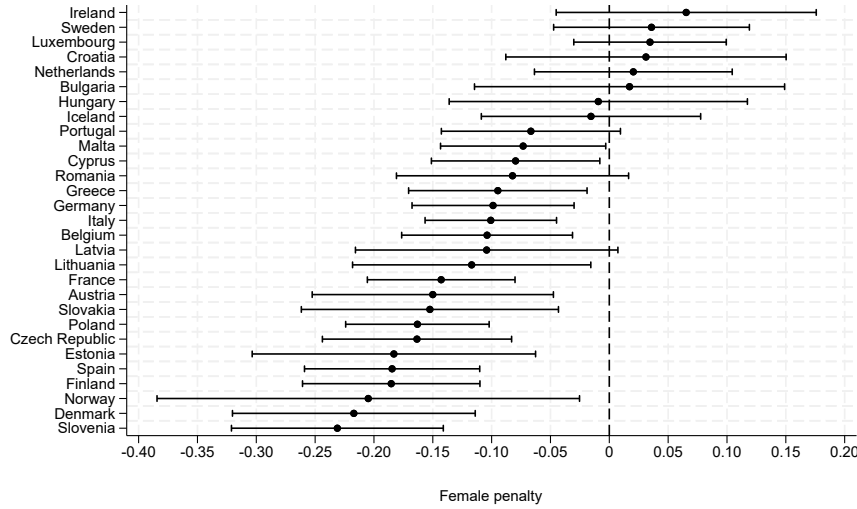
where HourlyWage_i denotes the hourly wage of individual i , X_i includes the control variables, and $\delta_{sr \times isco4}$ denotes sector-region by 4-digit occupation fixed effects. These fixed effects ensure that wage comparisons are made within narrowly defined labour market segments, thereby accounting for unobserved heterogeneity related to industrial structure, occupational sorting, and local labour market conditions. The coefficient of interest, β , measures the conditional gender wage gap. Standard errors are clustered at the country level.

Table 4 reports the estimation results for the wage gap, while the full set of coefficient estimates is reported in Table A5 of the Appendix.²¹ Column (1) reports

²⁰As explained in Footnote 8, we use both the probabilistic sample and the quota-based online panel of the Cedefop ESJS2 survey. As a robustness check, we replicate the analysis using survey weights. Weighted estimates are reported in Appendix Table A4.

²¹The number of observations is smaller than in Table 3 because the more demanding fixed-effects specification removes singleton groups.

Figure 5: Female wage penalty across countries



Notes: The figure reports the estimated coefficients from separate wage regressions, with 95% confidence intervals. Observations: 20,786. *Source:* Author's elaboration based on ESJS2.

the baseline specification. Column (2), our preferred specification, additionally controls for previous labour market status and field-of-study mismatch while retaining non-respondents through a separate category. Column (3) estimates the same specification on the restricted sample excluding individuals with missing information for these variables, whereas column (4) reports propensity score matching (PSM) estimates.

Across all specifications, a substantial and statistically significant gender wage gap emerges. In the preferred specification, women earn approximately 10% less than comparable men. The estimated penalty remains remarkably stable across specifications, including the restricted sample, suggesting that observable differences in education, skills, labour market history, and educational mismatch explain only a limited share of the gender wage gap.²²

To further assess robustness, column (4) reports estimates obtained using propensity score matching (PSM), where women are matched to observationally similar men based on the same set of observable characteristics included in the baseline specification.²³ As gender is not an exogenous treatment, the PSM estimates should be interpreted as a robustness check based on selection on observables rather than as a causal effect. The estimated coefficient on the female dummy remains negative and statistically significant, indicating that women earn approximately 9.9% less than comparable men. The persistence of the wage gap confirms that observable differences explain only a limited share of gender inequality in wages.

Figure 5 complements the regression results in Table 4 by reporting country-specific estimates of the female wage penalty. The gender wage gap is negative in most countries, although its magnitude varies considerably, ranging from about -24% to estimates

²²The results are robust to the use of survey weights (Table A4) and when using only reported wages (no imputation), available from the author upon request.

²³We use single nearest-neighbour matching with a caliper restriction, and then estimate the wage regression with conditional weighting. Figure A2 in the Appendix reports covariate balance before and after matching, showing that standardized biases are substantially reduced for all covariates.

Table 5: Gender Wage Gap in Digital and Green Jobs

Dep. Var.	ln HourlyWage _i					
	(1)	(2)	(3)	(4)	(5)	(6)
Female _i	-0.091*** (0.016)	-0.090*** (0.017)	-0.063*** (0.020)	-0.096*** (0.015)	-0.095*** (0.015)	-0.083*** (0.023)
Female _i × DigitalJob _i	-0.044* (0.025)	-0.043 (0.026)	-0.090* (0.044)			
Female _i × GreenJob _i				-0.113** (0.053)	-0.112** (0.053)	-0.139 (0.108)
Control Variables	✓	✓	✓	✓	✓	✓
Previous activity	-	✓	✓	-	✓	✓
Missing Previous activity var.	-	✓	-	-	✓	-
Field mismatch	-	✓	✓	-	✓	✓
Missing Field mismatch var.	-	✓	-	-	✓	-
$\delta_{SP \times isco4}$	✓	✓	✓	✓	✓	✓
Adj. R^2	0.576	0.577	0.546	0.576	0.577	0.546
Obs.	20,786	20,786	7,010	20,786	20,786	7,010

Notes: The dependent variable is the logarithm of hourly wages. Estimates are based on OLS regressions. Columns (1)–(3) include the interaction between Female_i and DigitalJob_i; columns (4)–(6) include the interaction between Female_i and GreenJob_i. Control variables include: age, age squared, level of education, educational mismatch, skills mismatch, type of skill, tenure, training, living area, firm size. Standard errors clustered at the country level are reported in parentheses. All specifications include sector-region by 4-digit occupation fixed effects. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

close to zero or slightly positive, none of which are statistically significant. Countries such as Bulgaria, Croatia, Ireland, Luxembourg, the Netherlands, and Sweden exhibit the smallest estimated penalties. Overall, the results point to substantial cross-country heterogeneity, suggesting that gender wage disparities also reflect differences in labour market institutions, occupational structures, and other country-specific factors.

4.3. Gender Wage Gap in Digital and Green Jobs

To examine whether gender wage gaps differ across occupations associated with the twin transition, we interact the female indicator with dummies identifying digital and green occupations. This allows the gender wage gap to vary between occupations associated with the twin transition and the rest of the labour market.

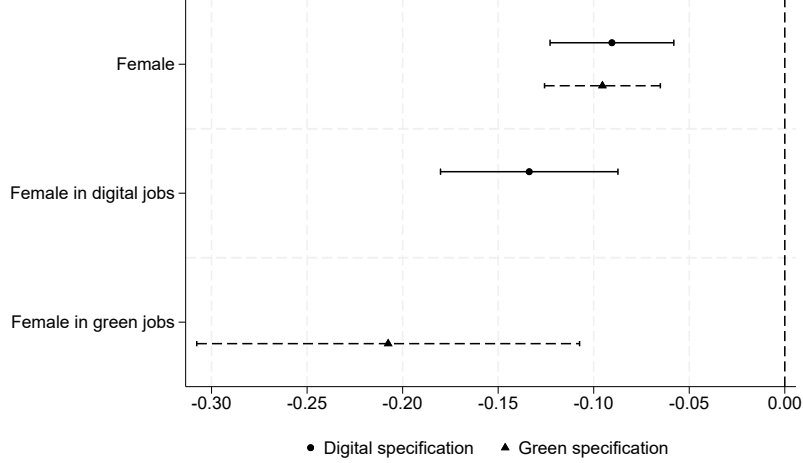
Table 5 reports the main results. The complete set of coefficient estimates is provided in Appendix Table A6. Columns (1)–(3) examine digital occupations, while columns (4)–(6) focus on green occupations. As in the previous section, columns (2) and (5) report the preferred specification, whereas columns (3) and (6) replicate the analysis on the restricted sample. The coefficient on Female_i remains negative and statistically significant across all specifications, indicating a persistent gender wage gap outside digital and green occupations. More importantly, the interaction terms are also negative, implying that women experience an additional wage penalty within occupations associated with the twin transition. In the preferred specification, women employed in digital occupations face an overall wage penalty of approximately 13.5%, compared with about 9% in other occupations. The corresponding wage gap exceeds 20% in green occupations, indicating even larger gender disparities. These estimates remain broadly stable across alternative specifications.²⁴

Figure 6 summarizes the combined female wage penalties and their confidence intervals, highlighting that the additional wage penalty is larger in green than in digital occupations.

One possible interpretation for the additional wage disadvantage in digital and green jobs is that occupations associated with the twin transition exhibit features similar to

²⁴The results are robust to the use of survey weights (Table A4) and when using only reported wages (no imputation), available from the author upon request.

Figure 6: Female wage penalty across digital and green jobs



Notes: Observations: 20,786. ‘Female in digital jobs’ represents the overall wage penalty for female working in digital jobs (female + female*digitaljobs), and the same applies for ‘Female in green jobs’. 95% confidence intervals. *Source:* Author’s elaboration based on ESJS2.

those of “greedy jobs” (Goldin, 2014, 2021). In these occupations, wage premia may depend not only on technical and task-specific skills, but also on continuous availability, long working or unpredictable hours, career continuity, and rapid progression into high-responsibility roles. To the extent that women face stronger constraints in meeting these requirements, digital and green occupations may be characterized by larger gender wage penalties. Digital occupations are also typically characterized by performance-based compensation. In such environments, relatively small differences in hours worked, career interruptions, bargaining, or access to high-reward tasks may translate into substantial wage gaps (Bovini et al., 2026). Moreover, women’s underrepresentation in digital occupations may reinforce network effects and implicit biases (Card et al., 2016).²⁵

Overall, the results indicate that the gender wage gap is significantly larger in occupations associated with digitalisation and the green transition. Combined with the evidence on occupational sorting, these findings point to a cumulative disadvantage: women are both less likely to enter digital and green occupations and earn less once employed in them.

4.4. Sensitivity to Omitted Variable Bias

Despite the inclusion of observed controls and fixed effects, the estimated gender gaps may still be affected by omitted variable bias. Unobserved factors such as unpaid care responsibilities, bargaining propensity, competitiveness, risk aversion, broader non-cognitive skills and preferences may be related to both gender and labour market outcomes. We therefore assess the sensitivity of our main results to selection on unobservables, based on our preferred specifications in previous estimates.

²⁵Evidence on gender wage gaps in math-intensive fields, including STEM and economics, is mixed. Although increasing women’s participation in STEM is important, it may not be sufficient to eliminate gender wage disparities (Blau and Kahn, 2017). Women are also more likely to leave STEM after graduation and move into lower-paying sectors (Delaney and Devereux, 2022). Our analysis instead focuses on occupations, examining gender disparities conditional on workers’ occupational sorting.

Table 6: Sensitivity of the results to omitted variables

Multiplier of R^2_{medium}	Specification	Dependent variable	Coefficient $\hat{\beta}_{\text{medium}}$	Explain-away breakdown point	Sign-change breakdown point		Obs.
				$\hat{\delta}^{\text{bp,exact}}(R^2_{\text{long}})$	$\hat{\delta}^{\text{bp,sign}}_{M = +\infty}$	$\hat{\delta}^{\text{bp,sign}}_{M = 10 \hat{\beta}_{\text{medium}} }$	
1.3 3	Sorting in digital jobs	Digital jobs	female	7.797 1.325	1 1	4.089 1.325	42,849
1.3 3	Sorting in green jobs	Green jobs	female	-30.035 -9.078	0.980 0.978	1.256 1.210	42,849
1.3 3	Gender wage gap	Hourly wage gap	female	11.799 2.884	1 1	2.196 2.058	20,786
1.3 3	Gender wage gap in digital jobs	Hourly wage gap	female	16.470 3.570	1 1	3.270 2.979	20,786
1.3 3	Gender wage gap in digital jobs	Hourly wage gap	female $\times$ digital	30.046 4.666	1 1	30.046 4.666	20,786
1.3 3	Gender wage gap in green jobs	Hourly wage gap	female	12.223 2.860	1 1	2.370 2.202	20,786
1.3 3	Gender wage gap in green jobs	Hourly wage gap	female $\times$ green	-171.173 -27.267	0.999 0.999	171.173 27.267	20,786

Notes: The medium regressions correspond to columns (2) and (5) of Table 3, column (2) of Table 4, and columns (2) and (5) of Table 5, respectively. The full sets of controls are reported in Table A3, A5, and A6, respectively, and are used to calibrate selection on unobservables. Region-by-sector and occupation fixed effects in the access specifications, and region-by-sector-by-occupation fixed effects in the wage specifications are included in the regressions but excluded from calibration.

We use the coefficient-stability approach developed by Oster (2019) and extended by Masten and Poirier (2026). Their methods use the changes in the coefficient of interest, β , and in the regression R^2 between specifications with fewer ($\hat{\beta}_{\text{short}}, R^2_{\text{short}}$) and more observed controls ($\hat{\beta}_{\text{medium}}, R^2_{\text{medium}}$) to assess sensitivity to omitted variables.²⁶ It requires assumptions about two parameters that can not be identified from the observed data: the sensitivity parameter, δ , which measures the strength of selection on unobservables relative to selection on observables (with $\delta = 1$ indicating equal selection), and R^2_{long} , which denotes the explanatory power of a hypothetical regression including both observed and omitted factors.

Following Masten and Poirier (2026), we report both explain-away and sign-change breakdown points. The explain-away breakdown point, $\hat{\delta}^{\text{bp,exact}}(R^2_{\text{long}})$, is the degree of selection on unobservables required to reduce the coefficient to zero, and corresponds to Oster’s approach. Values above one, in absolute terms, indicate robustness to omitted variable bias under the usual Oster benchmark. However, a coefficient may change sign at a lower degree of selection than that required to reduce it to zero (Masten and Poirier, 2026). The sign-change breakdown point, $\hat{\delta}^{\text{bp,sign}}(R^2_{\text{long}})$, thus measures the degree of selection required for the coefficient to change sign. This requires specifying a bound M on the maximum absolute omitted variable bias on $\hat{\beta}_{\text{medium}}$. We report results for $M = +\infty$ (Masten and Poirier (2026) formally show that $\delta^{\text{bp,sign}}$ is bounded above by one) and for $M = 10|\hat{\beta}_{\text{medium}}|$. We also consider both the benchmark $R^2_{\text{long}} = 1.3R^2_{\text{medium}}$ proposed by Oster (2019), where R^2_{medium} is the R^2 from the specification with observed controls, and the more demanding scenario $R^2_{\text{long}} = 3R^2_{\text{medium}}$.

Table 6 reports the results. The absolute values of the explain-away breakdown points exceed one for every coefficient examined under both choices of R^2_{long} . Thus, explaining away the estimated gender differences would require proportional selection on unobservables larger in magnitude than the conventional $\delta = 1$ benchmarks. For some coefficients,

²⁶The *short* regression includes the outcome and the coefficient of interest, together with the fixed effects; the medium regression includes the observed controls used for calibration, i.e. the one estimated above; the long regression is an hypothetical regression with both observed and unobserved controls.

Table 7: Manager Positions and Gender Wage Gaps

Dep. Var.	Full sample Manager _i (1)	Digital jobs only Manager _i (2)	Green jobs only Manager _i (3)	Full sample ln HourlyWage _i (4)
Female _i	-0.030*** (0.004)	-0.027*** (0.007)	-0.045** (0.017)	-0.104*** (0.010)
Female _i × Manager _i				-0.037* (0.019)
Control Variables	✓	✓	✓	✓
Previous activity	✓	✓	✓	✓
Missing Previous activity var.	✓	✓	✓	✓
Field mismatch	✓	✓	✓	✓
Missing Field mismatch var.	✓	✓	✓	✓
δ_{sp}	✓	✓	✓	✓
δ_{iscol}	-	-	-	✓
Adj. R^2	0.092	0.110	0.254	0.540
Obs.	42,849	11,792	2,551	42,849

Notes: Columns (1)–(3) report estimates from linear probability models for manager positions. Column (4) reports OLS estimates for log hourly wages. Control variables include: age, age squared, level of education, educational mismatch, skills mismatch, type of skill, tenure, training, living area, firm size. Standard errors clustered at the country level are reported in parentheses. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

the explain-away breakdown points are negative, indicating that the selection required to eliminate the estimate would operate in the opposite direction. According to the conventional cutoff, our results may therefore be considered robust to omitted variable bias.

The unrestricted sign-change breakdown points ($M = +\infty$) are always equal or very close to one, their theoretical upper bound, ranging from 0.978 to 1. When the magnitude of omitted variable bias is bounded at $M = 10|\hat{\beta}|$, all sign-change breakdown points are well above one, although, as expected, they are usually smaller than the corresponding explain-away breakdown points. This indicates that the signs of the estimates remain unchanged even when selection on unobservables is at least as strong as selection on observables. Overall, the results indicate substantial robustness to omitted variable bias.

4.5. Gender Gaps in Managerial Positions

To investigate whether career progression represents an additional channel of gender inequality, we examine women’s access to managerial positions and the associated wage premium. Occupations linked to the twin transition are often characterised by steeper career ladders and higher returns to leadership positions, making unequal access to managerial roles a potentially important source of gender disparities.

Table 7 reports the main estimates, whereas the full set of coefficient estimates is reported in Appendix Table A7. Columns (1)–(3) estimate the probability of holding a managerial position for the full sample, digital occupations, and green occupations, respectively, while column (4) examines whether managerial positions are associated with an additional gender wage penalty. Women are significantly less likely than men to hold managerial positions across all specifications. In the full sample, they are around 3 percentage points less likely to be managers, with similar penalties in digital occupations (2.7 percentage points) and even larger ones in green occupations (4.5 percentage points). Column (4) shows that women employed outside managerial occupations earn about 10.4% less than comparable men, while female managers face an additional wage penalty, implying an overall gender wage gap of roughly 14%.

These findings are consistent with the literature on the “glass ceiling”, according to which women face both lower access to leadership positions and lower returns once employed in them (Bertrand and Hallock, 2001; Blau and Kahn, 2017). Managerial

Table 8: STEM Education, Access to Twin-Transition Jobs and Wages

Dep. Var.	STEM _i (1)	DigitalJob _i (2)	GreenJob _i (3)	ln HourlyWage _i (4)
Female _i	−0.146*** (0.008)	0.008 (0.009)	−0.018*** (0.005)	−0.074*** (0.013)
STEM _i		0.098*** (0.011)	0.019*** (0.004)	0.048*** (0.015)
Female _i × STEM _i		−0.065*** (0.012)	0.006 (0.009)	−0.069*** (0.018)
Control Variables	✓	✓	✓	✓
Previous activity	✓	✓	✓	✓
Missing Previous activity var.	✓	✓	✓	✓
Field mismatch	✓	✓	✓	✓
Missing Field mismatch var.	✓	✓	✓	✓
δ_{sr}	✓	✓	✓	✓
δ_{iscol}	✓	✓	✓	✓
Adj. R^2	0.216	0.357	0.239	0.524
Obs.	25,188	25,188	25,188	25,188

Notes: Columns (1)–(3) report estimates from linear probability models. Column (4) reports OLS estimates for log hourly wages. Control variables include: age, age squared, level of education, educational mismatch, skills mismatch, type of skill, tenure, training, living area, firm size. Standard errors clustered at the country level are reported in parentheses. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

occupations often reward long and inflexible working hours, continuous career progression, and performance-based pay (Goldin, 2014), while unequal access to professional networks and promotion opportunities may further widen gender disparities. The evidence suggests that women are disadvantaged not only in entering occupations associated with the twin transition, but also in progressing to leadership positions within them.

5. Underlying mechanisms

5.1. STEM Education and Gender Inequality in the Twin Transition

A key mechanism through which gender inequalities may emerge during the twin transition is unequal access to STEM educational pathways, which provide many of the technical and analytical competences required in high-return digital occupations (Delaney and Devereux, 2021). We therefore examine whether women are less likely to hold STEM qualifications and whether the occupational and wage returns to STEM education differ by gender.

Table 8 reports the main results (Table A8 for completeness). Column (1) shows that women are about 14.6 percentage points less likely than men to hold a STEM educational background, consistent with the literature on gender segregation in STEM education (Charles and Bradley, 2009a; Delaney and Devereux, 2021; Smyth and Steinmetz, 2008). Columns (2) and (3) examine whether STEM education facilitates access to occupations associated with the twin transition. STEM qualifications substantially increase the probability of working in digital occupations, but women benefit significantly less from this premium. For men, a STEM background raises the probability of working in a digital occupation by about 9.8 percentage points, whereas the corresponding effect for women is only about 3.3 percentage points. This suggests that women are less able to translate STEM qualifications into employment in digital occupations (Blau and Kahn, 2017; Delaney and Devereux, 2022; Hunt et al., 2013; Speer, 2023). By contrast, STEM education has a much smaller association with access to green occupations (+1.9 p.p.), and the interaction with gender is small and not statistically significant, suggesting that STEM qualifications play a more limited role in shaping access to green jobs and do not generate different returns for women and men. Finally, column (4) examines the wage returns to STEM education. While STEM qualifications are associated with a positive

Table 9: Regional STEM Environment, Access to Digital and Green Jobs, and Wages

Dep. Var.	DigitalJob _i		GreenJob _i		ln HourlyWage _i	
	(1)	(2)	(3)	(4)	(5)	(6)
Female _i	-0.031*** (0.009)	-0.032*** (0.007)	-0.025*** (0.004)	-0.027*** (0.003)	-0.115*** (0.010)	-0.116*** (0.008)
Female _i × High STEM region, 50 th	0.007 (0.010)		0.001 (0.005)		0.014 (0.014)	
Female _i × High STEM region 75 th		0.018* (0.010)		0.008 (0.006)		0.033* (0.018)
Control Variables	✓	✓	✓	✓	✓	✓
Previous activity	✓	✓	✓	✓	✓	✓
Missing Previous activity var.	✓	✓	✓	✓	✓	✓
Field Mismatch	✓	✓	✓	✓	✓	✓
Missing Field mismatch var.	✓	✓	✓	✓	✓	✓
δ _{gr}	✓	✓	✓	✓	✓	✓
δ _{local}	✓	✓	✓	✓	✓	✓
Adj. R ²	0.336	0.336	0.225	0.225	0.540	0.540
Obs.	42,849	42,849	42,849	42,849	42,849	42,849

Notes: High STEM region is defined using regional STEM university intensity. Columns (1), (3), and (5) use the 50th percentile threshold, while columns (2), (4), and (6) use the 75th percentile threshold. Control variables include: age, age squared, level of education, educational mismatch, skills mismatch, type of skill, tenure, training, living area, firm size. Standard errors clustered at the country level are reported in parentheses. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

wage premium, women benefit significantly less than comparable men. The gender wage gap among workers without STEM background is about 7.4%, while women with STEM qualifications face an additional wage penalty of 6.9%, implying an overall gap of about 14.3%.

Taken together, these results shows that gender inequalities in the twin transition are not driven solely by differences in educational choices, but also by differences in persistence in STEM-related jobs and by unequal labour market returns to the same educational background. STEM education therefore represents an important channel through which access to emerging occupations and wage opportunities are structured, while simultaneously reproducing existing patterns of gender inequality.

5.2. The Role of the University Environment

The previous section showed that STEM qualifications increase access to digital occupations and wage outcomes, although women benefit less from these returns. These findings suggest that unequal access to STEM education is an important source of gender disparities during the twin transition. Policies promoting women's participation in STEM may therefore help reduce inequalities in access to emerging occupations and improve women's labour market outcomes, even if they are unlikely to eliminate gender gaps entirely.

To further investigate this mechanism, we examine whether the broader regional educational environment contributes to shaping gender disparities during the twin transition. Specifically, we analyse whether women face smaller participation and wage gaps in regions with a stronger STEM-oriented university system. To this end, we combine ESJS2 with the European Tertiary Education Register (ETER), which provides harmonised information on higher education institutions across Europe ([European Tertiary Education Register, 2024](#)).

Using ETER, we compute the regional share of university students enrolled in STEM disciplines and define high-STEM regions (NUTS-1) using the 50th and 75th percentiles of the regional distribution. We then examine whether women living in these regions experience smaller gender gaps in access to digital and green occupations and in wage outcomes.

Table 9 reports the results, while Table A9 in the Appendix reports the full estimates. Across all specifications, the coefficient on Female_i remains negative and statistically significant, confirming persistent gender disparities in access to digital and green occupations

and in hourly wages.

The interaction terms capture the role of the regional STEM environment. Interaction coefficients for regions above the 50th percentile of STEM intensity are small and statistically insignificant, suggesting that a moderate STEM presence is insufficient to reduce gender gaps. By contrast, stronger effects emerge in regions above the 75th percentile of the distribution. Women living in these regions face significantly smaller gaps in access to digital occupations, with the estimated female penalty roughly halved. A similar pattern emerges for wages: the female wage gap is reduced by about 3.3 percentage points in high-STEM regions. No significant effects emerge for green occupations, consistent with the more limited role of STEM qualifications documented in the previous subsection.

6. Conclusion

The twin transition is reshaping labour markets and has become a central policy priority. Although often regarded as an opportunity to promote more inclusive growth, its implications for gender inequality remain insufficiently understood.

This paper contributes to the literature by examining gender inequalities in the European labour market during the twin transition. Using Cedefop’s European Skills and Jobs Survey matched with the ESCO occupational classification, we identify digital and green occupations based on their skill content. To the best of our knowledge, this is one of the first attempts to classify digital and green jobs using granular occupation-level data at the European level, rather than relying on broader sectoral classifications. It is also one of the first attempts to use this classification to assess gender inequalities.

Our results reveal persistent gender disadvantages in emerging occupations. Even after controlling for a rich set of individual, educational, and job characteristics, women are 2.5–2.7 percentage points less likely to work in digital and green occupations. They also earn about 10% less than comparable men, with substantially larger wage gaps in digital (13.5%) and green (20%) occupations. Women are less likely to hold managerial positions and receive lower wage returns when they do.

We further show that STEM education is an important mechanism behind these disparities. While STEM qualifications substantially increase access to digital occupations and wages, women benefit less from these returns than comparable men. By contrast, STEM education plays a much smaller role in access to green occupations. At the regional level, stronger STEM-oriented university environments are associated with smaller gender gaps in access to digital occupations and wages.

Some limitations should be acknowledged. The cross-sectional nature of the data and the static ESCO classification do not allow us to analyse dynamic changes in occupations or skill requirements over time. Moreover, our results are associational and cannot distinguish the relative roles of preferences, social norms, discrimination, or other mechanisms underlying gender inequalities. Nevertheless, the richness of the data and the consistency of the results across alternative specifications and robustness checks support the robustness of our findings.

In terms of policy implications, our results contribute to the current debate on the twin transition and social inclusion, in line with existing studies on other disadvantaged groups. Without targeted policies, initiatives aimed at fostering technologically advanced and environmentally sustainable growth risk reinforcing existing gender inequalities.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT in order to enhance writing quality. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix

ESJS2 Survey

The ESJS2 survey provides detailed information on respondents’ demographics, occupations, skills, education, and job digitalisation. The target population consists of salaried employees aged 25 to 64 in 29 European countries, namely the 27 EU member states plus Norway and Iceland, excluding self-employed and family workers.²⁷ The sample includes residents of these countries,²⁸ living in private households,²⁹ and able to speak the national language sufficiently to participate.

The ESJS2 adopts a standardised methodology to collect “*harmonised international data, enabling cross-country comparisons across economic sectors, occupations, and other key socioeconomic and demographic variables*” (Cedefop, 2022). Data were collected using a dual-mode design combining computer-assisted telephone interviewing (CATI) and computer-assisted web interviewing (CAWI) in all countries except Malta and Cyprus, where only CATI was used. Table A1 reports the gender distribution by country and survey mode. Each country includes at least 500 respondents selected through probabilistic telephone sampling, ensuring broad coverage of the target population. To increase sample size and improve estimation precision, an additional quota-based top-up sample of at least 500 respondents was drawn from the Kantar LifePoints online panel. Although non-probabilistic, the panel is structured to approximate representativeness by key demographics (gender, age, and region). Due to panel limitations, Malta and Cyprus rely exclusively on the single-mode CATI design.

Overall, ESJS2 collected 46,213 interviews (15,512 CATI and 30,701 CAWI). The final analytical sample is reduced to 44,103: 30 respondents identified as non-binary and are excluded due to the study’s focus and limited cell size, and missing values in selected variables reduce usable observations. Despite these exclusions, the country composition remains balanced, without substantial gender imbalances, supporting the representativeness of the final dataset.

Variable construction

The main independent variable of interest is gender, captured by the binary indicator Female_i , which takes the value 1 for females and 0 for males.

Earnings-related variables include net monthly wages, hours typically worked per week, both self-reported, and hourly wages. Hourly wages, the main outcome in the wage-gap analysis, are calculated by dividing monthly wages by weekly hours multiplied by 4.33. To limit the influence of outliers, all earnings and hours variables are winsorised at the 1st and 99th percentiles by gender and country.

Educational characteristics include the highest level of education attained, grouped into primary or lower secondary, upper secondary, and tertiary education based on the

²⁷To ensure comparability within the EU, salaried employment follows EU-LFS definitions. Employment is defined as “a person who did any work for pay or profit during the reference week for at least one hour”, while an employee is “an individual who works for a public or private employer and who in return receives compensation in the form of wages, salaries, fees, gratuities, payment by results, or payment in kind” (Burnett, 2020).

²⁸Residents in the nine outermost EU regions and the 22 European Overseas Countries and Territories are excluded.

²⁹Private households exclude individuals residing in institutions such as military barracks, nursing homes, or long-term medical facilities.

original ISCED classifications. We also control for vertical and horizontal educational mismatch. Vertical educational mismatch is a self-reported measure indicating whether the education required by the job is below, equal to, or above the respondent’s attained level (subjective measure, see [McGuinness et al. \(2018\)](#)). Horizontal mismatch measures whether a respondent’s field of study matches the knowledge and skills required by their job. It is originally available only for workers with at least upper secondary education; we include an additional “no-response category” for ineligible respondents and eligible respondents who did not answer.³⁰ We also construct a binary STEM indicator, equal to 1 when the respondent’s highest educational qualification is in a STEM field (natural sciences, mathematics and statistics; ICT; or engineering, manufacturing and construction).³¹

Individual skills are measured using six distinct binary indicators: literacy, numeracy, problem-solving and creativity, social, digital, and manual skills. The indicators equal one for high proficiency, except for manual skills, which are defined more broadly and record only their presence or absence. We also include a subjective measure of skill mismatch, reflecting the alignment between the skills individuals possess and those required in their current job. This measure is based on respondents’ reported skill use at work and their perceived need for further skill development.

The analysis further incorporates job-related characteristics. Occupations are classified according to the International Standard Classification of Occupations (ISCO) and are available at four levels of aggregation (from 1 to 4 digit).³² Depending on the specification, different levels of aggregation are used to ensure an appropriate balance between precision and parsimony. Other job-related characteristics include tenure with the current employer, measured in months and ranging from 0 to 480 (40 years), participation in training, measured by a binary indicator, and a proxy for labour market history, based on individuals’ labour market status prior to their current job. The sector of employment is defined according to the NACE classification of economic activities and is available at both the 1-digit and 2-digit levels, comprising 21 or 88 industries, respectively. Firm characteristics are further captured by a categorical variable for firm size.

Demographic information completes the set of controls: age, measured discretely from 25 to 64 years; country and region, with regions defined according to the 1-digit NUTS classification, which divides the sample countries into 90 comparable regions; and living area, which captures the degree of urbanisation of the respondent’s place of residence.

³⁰The measure is available for 31,874 respondents. Around 8,400 eligible respondents have missing information and are assigned to the no-response category.

³¹Field-of-study information is available only for CAWI respondents with at least upper secondary education, yielding 26,538 observations. General upper secondary programmes are coded as generic and therefore not classified as STEM.

³²The 1-digit classification contains 10 broad groups, whereas the 4-digit level distinguishes 436 detailed occupations.

Table A1: ESJS2 sampling method by country and gender

	CATI			CAWI			TOTAL	
	Male	Female	Total	Male	Female	Total	Obs.	Perc.
Austria	216	257	473	439	540	979	1,452	3.29%
Belgium	213	240	453	449	509	958	1,411	3.20%
Bulgaria	229	239	468	407	624	1,031	1,499	3.40%
Croatia	186	295	481	241	244	485	966	2.19%
Cyprus	548	416	964	-	-	-	964	2.19%
Czech	219	266	485	512	538	1,050	1,535	3.48%
Denmark	259	215	474	229	217	446	920	2.09%
Estonia	202	272	474	273	287	560	1,034	2.34%
Finland	255	230	485	384	395	779	1,264	2.87%
France	274	204	478	1,169	1,236	2,405	2,883	6.54%
Germany	240	247	487	1,134	1,257	2,391	2,878	6.53%
Greece	234	252	486	756	717	1,473	1,959	4.44%
Hungary	280	194	474	503	473	976	1,450	3.29%
Iceland	227	252	479	265	248	513	992	2.25%
Ireland	260	196	456	291	510	801	1,257	2.85%
Italy	238	236	474	1,318	1,106	2,424	2,898	6.57%
Latvia	202	281	483	234	253	487	970	2.20%
Lithuania	192	252	444	208	277	485	929	2.11%
Luxembourg	220	264	484	275	232	507	991	2.25%
Malta	416	495	911	-	-	-	911	2.07%
Netherlands	244	222	466	430	517	947	1,413	3.20%
Norway	199	173	372	259	239	498	870	1.97%
Poland	252	224	476	1,239	1,255	2,494	2,970	6.73%
Portugal	243	237	480	494	511	1,005	1,485	3.37%
Romania	223	224	447	800	685	1,485	1,932	4.38%
Slovakia	217	249	466	257	225	482	948	2.15%
Slovenia	185	286	471	247	239	486	957	2.17%
Spain	255	228	483	1,300	1,145	2,445	2,928	6.64%
Sweden	253	220	473	456	508	964	1,437	3.26%
Observations	7,181	7,366	14,547	14,569	14,987	29,556	44,103	
Percentage			32.98%			67.02%		100%

Source: Author's elaboration based on ESJS2.

Table A2: Summary statistics by gender

Variable	Female	Male	Total
Female _i			0.507
Dependent and main variables			
DigitalJob _i	0.270	0.329	0.299
GreenJob _i	0.057	0.109	0.082
HourlyWage _i	11.368	13.108	12.226
STEM _i ^a (field of study)	0.197	0.455	0.323
Education level			
PrimaryEdu _i	0.082	0.097	0.089
SecondaryEdu _i	0.345	0.374	0.360
TertiaryEdu _i	0.573	0.529	0.551
Educational mismatch			
UnderEdu _i	0.114	0.122	0.118
MatchedEdu _i	0.596	0.611	0.603
OverEdu _i	0.290	0.267	0.279
Field mismatch			
ExactField _i	0.223	0.192	0.208
RelatedField _i	0.274	0.291	0.283
DifferentField _i	0.086	0.088	0.087
NoSpecificField _i	0.153	0.138	0.145
MissingFieldMism _i	0.264	0.291	0.277
Skills mismatch			
UnderSkilled _i	0.181	0.200	0.190
MatchedSkills _i	0.677	0.668	0.673
OverSkilled _i	0.142	0.132	0.137
Type of skill			
LiteracySkill _i	0.205	0.240	0.223
NumeracySkill _i	0.157	0.251	0.203
ProblemSolvSkill _i	0.169	0.183	0.176
SocialSkill _i	0.179	0.160	0.170
DigitalSkill _i	0.169	0.314	0.240
ManualSkill _i	0.419	0.512	0.465
Other variables			
Tenure _i	118.561	123.630	121.061
Training _i	0.636	0.647	0.641
Age _i	43.244	43.357	43.300
Firm size			
MicroFirm _i	0.227	0.181	0.204
SmallFirm _i	0.285	0.269	0.277
MediumFirm _i	0.253	0.269	0.261
LargeFirm _i	0.235	0.281	0.258
Living area			
RuralArea _i	0.245	0.220	0.233
SmallTown _i	0.361	0.357	0.359
LargeTown _i	0.394	0.423	0.408
Previous activity			
InEducation _i	0.151	0.149	0.150
Employed _i	0.401	0.425	0.413
NotEmployed _i	0.103	0.083	0.093
MissingPrevAct _i	0.345	0.343	0.344
Occupation (ISCO-1 digit)			
Armed Forces Occupations	0.001	0.004	0.002
Managers	0.095	0.139	0.117
Professionals	0.312	0.256	0.284
Technicians and Associate Professionals	0.155	0.153	0.154
Clerical Support Workers	0.170	0.104	0.138
Service and Sales Workers	0.162	0.100	0.131
Skilled Agricultural, Forestry and Fishery Workers	0.006	0.010	0.008
Craft and Related Trades Workers	0.027	0.107	0.067
Plant and Machine Operators, and Assemblers	0.020	0.073	0.046
Elementary Occupations	0.051	0.054	0.053
Sector (macro-categories)			
Agriculture	0.009	0.016	0.013
Industry excl. construction	0.102	0.207	0.153
Construction	0.018	0.059	0.038
Market services	0.484	0.524	0.504
Public and social services	0.383	0.192	0.289
Other activities	0.004	0.003	0.003
Observations	22,353	21,750	44,103

Notes: The subscript i denotes the individual. ^a STEM_i is observed only for 26,538 observations.
Source: Author's elaboration based on ESJS2.

Table A3: Access to Digital and Green Jobs: complete table

Dep. Var.	DigitalJob _i			GreenJob _i		
	(1)	(2)	(3)	(4)	(5)	(6)
Female _i	-0.027*** (0.007)	-0.027*** (0.007)	-0.027*** (0.009)	-0.025*** (0.003)	-0.025*** (0.003)	-0.018*** (0.005)
Education						
SecondaryEdu _i	0.026*** (0.007)	0.031*** (0.008)		-0.000 (0.008)	-0.003 (0.008)	
TertiaryEdu _i	0.001 (0.009)	0.015 (0.012)	-0.005 (0.010)	-0.006 (0.008)	-0.011 (0.010)	0.001 (0.004)
Education mismatch						
MatchedEdu _i	-0.003 (0.006)	-0.001 (0.006)	0.003 (0.016)	0.007** (0.003)	0.007** (0.003)	-0.003 (0.006)
OverEdu _i	0.003 (0.007)	-0.001 (0.007)	0.007 (0.015)	0.006 (0.004)	0.006 (0.004)	-0.002 (0.006)
Skills mismatch						
MatchedSkills _i	-0.007 (0.006)	-0.009 (0.006)	-0.011 (0.008)	0.003 (0.004)	0.004 (0.004)	0.003 (0.005)
OverSkilled _i	-0.007 (0.008)	-0.011 (0.008)	-0.006 (0.011)	-0.001 (0.005)	-0.001 (0.005)	-0.000 (0.006)
Type of Skills						
LiteracySkill _i	-0.008 (0.005)	-0.007 (0.006)	0.001 (0.009)	0.004 (0.003)	0.004 (0.003)	0.006 (0.005)
NumeracySkill _i	-0.015** (0.006)	-0.014** (0.006)	-0.030** (0.011)	-0.002 (0.003)	-0.002 (0.003)	-0.004 (0.004)
ProblemSolvSkill _i	0.017** (0.007)	0.018*** (0.006)	0.003 (0.011)	-0.002 (0.004)	-0.001 (0.004)	0.002 (0.006)
SocialSkill _i	-0.039*** (0.007)	-0.037*** (0.007)	-0.026** (0.010)	0.008** (0.003)	0.008** (0.003)	0.011** (0.005)
ManualSkill _i	-0.039*** (0.006)	-0.038*** (0.005)	-0.031*** (0.009)	0.015*** (0.003)	0.016*** (0.003)	0.007 (0.005)
DigitalSkill _i	0.106*** (0.006)	0.106*** (0.006)	0.117*** (0.007)	-0.020*** (0.004)	-0.019*** (0.004)	-0.029*** (0.006)
Other Individual and Firm Characteristics						
Tenure _i	-0.000*** (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000* (0.000)
Training _i	-0.023*** (0.004)	-0.022*** (0.004)	-0.013* (0.007)	0.006 (0.004)	0.006 (0.004)	0.008 (0.005)
Age _i	0.001 (0.002)	0.001 (0.002)	-0.001 (0.003)	-0.002** (0.001)	-0.002** (0.001)	-0.002 (0.002)
Age _i ²	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000* (0.000)	0.000 (0.000)
SmallFirm _i	-0.006 (0.006)	-0.005 (0.006)	-0.015 (0.012)	0.002 (0.004)	0.002 (0.004)	0.006 (0.008)
MediumFirm _i	0.004 (0.007)	0.004 (0.007)	-0.002 (0.015)	0.001 (0.004)	0.001 (0.004)	0.003 (0.006)
LargeFirm _i	0.043*** (0.007)	0.043*** (0.007)	0.036*** (0.013)	-0.002 (0.005)	-0.001 (0.005)	0.004 (0.009)
Rural _i	-0.009 (0.006)	-0.009 (0.006)	-0.010 (0.010)	0.007** (0.003)	0.007* (0.003)	0.000 (0.006)
SmallTown _i	-0.013** (0.005)	-0.013** (0.005)	-0.008 (0.008)	0.006** (0.003)	0.006** (0.003)	0.004 (0.004)
Previous activity^a						
Employed _i		0.003 (0.007)	-0.002 (0.010)		0.004 (0.004)	0.002 (0.004)
NotEmployed _i		0.021** (0.008)	0.016 (0.010)		-0.001 (0.004)	-0.008 (0.005)
MissingPrevAct _i		0.007 (0.007)			0.010* (0.005)	
Field mismatch^a						
ExactField _i		-0.039*** (0.012)	-0.046** (0.017)		-0.000 (0.005)	0.006 (0.005)
RelatedField _i		-0.003 (0.009)	-0.008 (0.011)		-0.002 (0.005)	0.004 (0.006)
NoSpecificField _i		0.012 (0.009)	0.023* (0.012)		-0.001 (0.005)	-0.001 (0.007)
MissingFieldMism _i		0.005 (0.010)			-0.006 (0.005)	
δ_{sr}	✓	✓	✓	✓	✓	✓
δ_{isco1}	✓	✓	✓	✓	✓	✓
Adj. R^2	0.335	0.336	0.339	0.225	0.225	0.253
Obs.	42,849	42,849	16,964	42,849	42,849	16,964

Notes: The dependent variables are binary indicators for employment in digital (col. (1) to (3)) and green occupations (col. (4) to (6)). Estimates are based on linear probability models. ^a The reference category for previous activity is InEducation_i, and for field mismatch is DifferentField_i (different/unrelated field of education required). Standard errors clustered at the country level are reported in parentheses. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A4: Robustness check with weights: complete table

Dep. Var.	DigitalJob _i (1)	GreenJob _i (2)	ln HourlyWage _i (3)	ln HourlyWage _i (4)	ln HourlyWage _i (5)
Female _i	-0.019* (0.011)	-0.026*** (0.007)	-0.132*** (0.021)	-0.119*** (0.021)	-0.125*** (0.021)
Female _i × DigitalJob _i				-0.051* (0.025)	
Female _i × GreenJob _i					-0.138** (0.053)
Education					
SecondaryEdu _i	0.045*** (0.008)	-0.005 (0.012)	0.012 (0.062)	0.011 (0.062)	0.012 (0.061)
TertiaryEdu _i	0.037** (0.014)	-0.008 (0.018)	0.077 (0.081)	0.076 (0.080)	0.077 (0.080)
Education mismatch					
MatchedEdu _i	0.002 (0.006)	0.008* (0.004)	-0.069*** (0.018)	-0.069*** (0.018)	-0.070*** (0.018)
OverEdu _i	-0.000 (0.009)	0.007 (0.006)	-0.115*** (0.022)	-0.114*** (0.022)	-0.115*** (0.022)
Skills mismatch					
MatchedSkills _i	-0.014 (0.009)	0.011* (0.006)	-0.018 (0.013)	-0.018 (0.013)	-0.018 (0.013)
OverSkilled _i	-0.018* (0.010)	0.009 (0.008)	-0.038 (0.030)	-0.039 (0.031)	-0.037 (0.030)
Type of Skills					
LiteracySkill _i	-0.002 (0.006)	-0.002 (0.004)	0.031** (0.015)	0.031* (0.015)	0.030* (0.015)
NumeracySkill _i	-0.017** (0.008)	-0.005 (0.005)	0.017 (0.013)	0.017 (0.013)	0.017 (0.013)
ProblemSolvSkill _i	0.007 (0.013)	-0.005 (0.006)	0.007 (0.012)	0.007 (0.012)	0.007 (0.012)
SocialSkill _i	-0.033*** (0.009)	0.012* (0.007)	-0.004 (0.014)	-0.004 (0.014)	-0.003 (0.014)
ManualSkill _i	-0.045*** (0.005)	0.016*** (0.002)	-0.047*** (0.013)	-0.048*** (0.013)	-0.048*** (0.013)
DigitalSkill _i	0.102*** (0.013)	-0.013*** (0.004)	0.082*** (0.017)	0.082*** (0.017)	0.083*** (0.017)
Other Individual and Firm Characteristics					
Tenure _i	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Training _i	-0.018*** (0.005)	0.012** (0.006)	0.030** (0.011)	0.029** (0.011)	0.030*** (0.011)
Age _i	-0.000 (0.002)	-0.002 (0.002)	0.005 (0.005)	0.005 (0.005)	0.004 (0.005)
Age _i ²				-0.000 (0.000)	-0.000 (0.000)
SmallFirm _i	0.003 (0.007)	-0.004 (0.004)	0.021* (0.012)	0.022* (0.012)	0.021* (0.012)
MediumFirm _i	0.011 (0.007)	-0.002 (0.007)	0.052*** (0.018)	0.052*** (0.018)	0.053*** (0.018)
LargeFirm _i	0.047*** (0.005)	-0.005 (0.009)	0.023 (0.022)	0.023 (0.022)	0.023 (0.022)
Rural _i	-0.005 (0.007)	0.003 (0.005)	-0.014 (0.012)	-0.014 (0.012)	-0.014 (0.012)
SmallTown _i	-0.016*** (0.005)	0.006 (0.004)	-0.009 (0.016)	-0.009 (0.016)	-0.009 (0.016)
Previous activity					
Employed _i	0.007 (0.011)	0.004 (0.005)	-0.050*** (0.015)	-0.050*** (0.015)	-0.050*** (0.015)
NotEmployed _i	0.024 (0.014)	0.005 (0.008)	-0.043* (0.022)	-0.043* (0.022)	-0.042* (0.022)
MissingPrevAct _i	0.008 (0.008)	0.015** (0.007)	-0.096*** (0.029)	-0.095*** (0.029)	-0.096*** (0.029)
Field mismatch					
ExactField _i	-0.027* (0.015)	-0.006 (0.005)	0.017 (0.028)	0.016 (0.028)	0.017 (0.028)
RelatedField _i	0.010 (0.013)	-0.009 (0.006)	-0.021 (0.027)	-0.021 (0.027)	-0.021 (0.027)
NoSpecificField _i	0.014 (0.008)	-0.010* (0.005)	-0.038** (0.018)	-0.038** (0.018)	-0.037** (0.017)
MissingFieldMism _i	0.016 (0.011)	-0.007 (0.007)	-0.017 (0.025)	-0.017 (0.025)	-0.016 (0.025)
δ_{sr}	✓	✓	-	-	-
δ_{isco1}	✓	✓	-	-	-
$\delta_{sr \times isco1}$	-	-	✓	✓	✓
Adj. R^2	0.386	0.306	0.568	0.569	0.569
Obs.	42,848	42,848	20,786	20,786	20,786

Notes: The dependent variables are binary indicators for employment in digital jobs (col. (1)) and in green jobs (col. (2)) (estimates based on linear probability models) and the logarithm of hourly wages (col. (3)-(5)). ^a The reference category for previous activity is InEducation_i, and for field mismatch is DifferentField_i (different/unrelated field of education required). Standard errors clustered at the country level are reported in parentheses. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A5: Gender Wage Gap: complete table

Dep. Var.	ln HourlyWage _i			
	OLS (1)	OLS (2)	OLS (3)	PSM (4)
Female _i	−0.102*** (0.015)	−0.101*** (0.015)	−0.087*** (0.021)	−0.099*** (0.015)
Education				
SecondaryEdu _i	0.016 (0.037)	0.022 (0.037)		0.031 (0.042)
TertiaryEdu _i	0.099** (0.045)	0.103** (0.045)	0.086*** (0.029)	0.117** (0.051)
Education mismatch				
MatchedEdu _i	−0.020* (0.012)	−0.023* (0.012)	−0.010 (0.042)	−0.039* (0.019)
OverEdu _i	−0.069*** (0.015)	−0.062*** (0.015)	−0.069 (0.041)	−0.070** (0.026)
Skills mismatch				
MatchedSkills _i	−0.008 (0.012)	−0.007 (0.012)	0.004 (0.022)	−0.007 (0.017)
OverSkilled _i	−0.032* (0.018)	−0.026 (0.018)	−0.009 (0.026)	−0.044** (0.021)
Type of Skills				
LiteracySkill _i	0.019 (0.012)	0.017 (0.011)	−0.001 (0.019)	0.022* (0.012)
NumeracySkill _i	−0.003 (0.011)	−0.005 (0.011)	0.009 (0.022)	−0.004 (0.017)
ProblemSolvSkill _i	0.023* (0.013)	0.019 (0.013)	0.003 (0.023)	0.033** (0.015)
SocialSkill _i	−0.009 (0.009)	−0.009 (0.009)	−0.001 (0.022)	−0.024* (0.014)
ManualSkill _i	−0.047*** (0.010)	−0.049*** (0.010)	−0.028* (0.015)	−0.052*** (0.013)
DigitalSkill _i	0.067*** (0.018)	0.063*** (0.018)	0.072*** (0.024)	0.063*** (0.022)
Other Individual and Firm Characteristics				
Tenure _i	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Training _i	0.028** (0.012)	0.027** (0.012)	0.024 (0.021)	0.007 (0.015)
Age _i	0.007 (0.004)	0.008* (0.004)	0.003 (0.006)	0.010* (0.006)
Age _i ²	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
SmallFirm _i	0.046*** (0.011)	0.044*** (0.011)	0.099*** (0.022)	0.041*** (0.015)
MediumFirm _i	0.060*** (0.014)	0.058*** (0.014)	0.091*** (0.023)	0.047** (0.018)
LargeFirm _i	0.048*** (0.016)	0.044*** (0.016)	0.070*** (0.020)	0.027 (0.022)
Rural _i	−0.021 (0.013)	−0.019 (0.012)	−0.011 (0.021)	−0.025 (0.017)
SmallTown _i	−0.026** (0.012)	−0.026** (0.012)	−0.033** (0.013)	−0.038** (0.015)
Previous activity^a				
Employed _i		−0.046*** (0.012)	−0.016 (0.021)	−0.027 (0.020)
NotEmployed _i		−0.043** (0.018)	−0.088*** (0.023)	−0.019 (0.022)
MissingPrevAct _i		−0.064*** (0.018)		−0.035 (0.026)
Field mismatch^a				
ExactField _i		0.036 (0.021)	0.045 (0.032)	0.044* (0.024)
RelatedField _i		0.003 (0.017)	0.025 (0.024)	0.018 (0.017)
NoSpecificField _i		−0.043** (0.017)	−0.032 (0.036)	−0.024 (0.025)
MissingFieldMism _i		0.007 (0.019)		0.040* (0.023)
$\delta_{sr \times isco4}$	✓	✓	✓	✓
R^2	0.696	0.697	0.688	0.730
Adj. R^2	0.575	0.577	0.546	0.626
Obs.	20,786	20,786	7,010	15,127

Notes: The dependent variable is the logarithm of hourly wages. ^a The reference category for previous activity is InEducation_i, and for field mismatch is DifferentField_i (different/unrelated field of education required). Standard errors clustered at the country level are reported in parentheses. All specifications include sector-region-4digit occupation fixed effects. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A6: Gender Wage Gap in Digital and Green Jobs: complete table

Dep. Var.	ln HourlyWage _i					
	(1)	(2)	(3)	(4)	(5)	(6)
Female _i	−0.091*** (0.016)	−0.090*** (0.017)	−0.063*** (0.020)	−0.096*** (0.015)	−0.095*** (0.015)	−0.083*** (0.023)
Female _i × DigitalJob _i	−0.044* (0.025)	−0.043 (0.026)	−0.090* (0.044)			
Female _i × GreenJob _i				−0.113** (0.053)	−0.112** (0.053)	−0.139 (0.108)
Education						
SecondaryEdu _i	0.016 (0.037)	0.021 (0.037)		0.016 (0.037)	0.022 (0.037)	
TertiaryEdu _i	0.098** (0.045)	0.103** (0.045)	0.087*** (0.029)	0.099** (0.045)	0.104** (0.045)	0.086*** (0.029)
Education mismatch						
MatchedEdu _i	−0.019 (0.011)	−0.022* (0.012)	−0.009 (0.043)	−0.020* (0.012)	−0.023* (0.012)	−0.010 (0.042)
OverEdu _i	−0.068*** (0.015)	−0.061*** (0.015)	−0.066 (0.041)	−0.069*** (0.015)	−0.062*** (0.015)	−0.068 (0.041)
Skills mismatch						
MatchedSkills _i	−0.008 (0.012)	−0.007 (0.012)	0.004 (0.022)	−0.008 (0.012)	−0.007 (0.012)	0.004 (0.022)
OverSkilled _i	−0.032* (0.019)	−0.027 (0.019)	−0.010 (0.026)	−0.032* (0.018)	−0.026 (0.018)	−0.008 (0.025)
Type of Skills						
LiteracySkill _i	0.018 (0.012)	0.017 (0.011)	0.000 (0.019)	0.018 (0.012)	0.016 (0.011)	−0.001 (0.019)
NumeracySkill _i	−0.003 (0.011)	−0.004 (0.011)	0.010 (0.023)	−0.002 (0.011)	−0.004 (0.011)	0.009 (0.022)
ProblemSolvSkill _i	0.023* (0.013)	0.019 (0.013)	0.003 (0.023)	0.023* (0.013)	0.019 (0.013)	0.003 (0.023)
SocialSkill _i	−0.009 (0.009)	−0.009 (0.009)	0.000 (0.022)	−0.009 (0.009)	−0.009 (0.009)	−0.001 (0.022)
ManualSkill _i	−0.047*** (0.010)	−0.049*** (0.010)	−0.029* (0.015)	−0.048*** (0.010)	−0.049*** (0.010)	−0.028* (0.015)
DigitalSkill _i	0.067*** (0.018)	0.063*** (0.018)	0.071*** (0.024)	0.068*** (0.018)	0.064*** (0.018)	0.072*** (0.024)
Individual and Firm Characteristics						
Tenure _i	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)
Training _i	0.027** (0.012)	0.027** (0.012)	0.024 (0.020)	0.027** (0.012)	0.027** (0.012)	0.025 (0.021)
Age _i	0.007 (0.004)	0.008* (0.004)	0.003 (0.006)	0.007 (0.004)	0.008* (0.004)	0.003 (0.006)
Age _i ²	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
SmallFirm _i	0.047*** (0.011)	0.044*** (0.011)	0.099*** (0.022)	0.046*** (0.011)	0.044*** (0.011)	0.100*** (0.022)
MediumFirm _i	0.060*** (0.014)	0.058*** (0.014)	0.092*** (0.023)	0.061*** (0.014)	0.058*** (0.014)	0.092*** (0.023)
LargeFirm _i	0.048*** (0.016)	0.044*** (0.015)	0.070*** (0.020)	0.048*** (0.015)	0.044*** (0.015)	0.071*** (0.020)
Rural _i	−0.021 (0.013)	−0.019 (0.012)	−0.012 (0.020)	−0.020 (0.013)	−0.019 (0.013)	−0.012 (0.020)
SmallTown _i	−0.026** (0.012)	−0.026** (0.012)	−0.033** (0.013)	−0.026** (0.012)	−0.026** (0.012)	−0.033** (0.013)
Previous activity ^a						
Employed _i		−0.046*** (0.012)	−0.016 (0.021)		−0.046*** (0.012)	−0.015 (0.021)
Unemployed _i		−0.043** (0.018)	−0.088*** (0.023)		−0.043** (0.018)	−0.087*** (0.023)
MissingPrevAct _i		−0.064*** (0.018)			−0.065*** (0.018)	
Field mismatch ^a						
ExactField _i		0.035 (0.021)	0.044 (0.033)		0.036 (0.021)	0.045 (0.032)
RelatedField _i		0.003 (0.017)	0.023 (0.024)		0.003 (0.017)	0.024 (0.024)
NoSpecificField _i		−0.043** (0.017)	−0.033 (0.036)		−0.042** (0.017)	−0.033 (0.036)
MissingFieldMism _i		0.006 (0.019)			0.007 (0.019)	
δ _{SP × ISCO4}	✓	✓	✓	✓	✓	✓
Adj. R ²	0.576	0.577	0.546	0.576	0.577	0.546
Obs.	20,786	20,786	7,010	20,786	20,786	7,010

Notes: The dependent variable is the logarithm of hourly wages. Estimates are based on OLS regressions. Columns (1)–(3) include the interaction between Female_i and DigitalJob_i; columns (4)–(6) include the interaction between Female_i and GreenJob_i. ^a The reference category for previous activity is InEducation_i, and for field mismatch is DifferentField_i (different/unrelated field of education required). Standard errors clustered at the country level are reported in parentheses. All specifications include sector-region by 4-digit occupation fixed effects. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A7: Managerial Positions and Gender Wage Gaps: complete table

Dep. Var.	Full sample Manager _i (1)	Digital jobs only Manager _i (2)	Green jobs only Manager _i (3)	Full sample ln HourlyWage _i (4)
Female _i	-0.030*** (0.004)	-0.027*** (0.007)	-0.045** (0.017)	-0.104*** (0.010)
Female _i × Manager _i				-0.037* (0.019)
Education				
SecondaryEdu _i	0.032*** (0.005)	0.013 (0.010)	0.069** (0.030)	0.005 (0.020)
TertiaryEdu _i	0.094*** (0.008)	0.069*** (0.016)	0.164*** (0.040)	0.119*** (0.022)
Education mismatch				
MatchedEdu _i	-0.036*** (0.007)	-0.012 (0.008)	-0.054 (0.032)	-0.027** (0.010)
OverEdu _i	-0.063*** (0.009)	-0.049*** (0.012)	-0.081* (0.039)	-0.066*** (0.015)
Skills mismatch				
MatchedSkills _i	0.010** (0.004)	0.011* (0.006)	0.007 (0.019)	-0.010 (0.006)
OverSkilled _i	-0.009 (0.006)	0.008 (0.011)	-0.028 (0.035)	-0.016 (0.013)
Type of Skills				
LiteracySkill _i	0.026*** (0.005)	0.018** (0.008)	-0.020 (0.023)	0.028*** (0.010)
NumeracySkill _i	0.025*** (0.005)	0.029*** (0.007)	0.051* (0.025)	0.026*** (0.008)
ProblemSolvSkill _i	0.017** (0.007)	0.017* (0.009)	0.044* (0.024)	0.020** (0.008)
SocialSkill _i	0.053*** (0.005)	0.086*** (0.013)	0.026 (0.025)	0.015** (0.007)
ManualSkill _i	-0.028*** (0.004)	-0.012* (0.006)	-0.049** (0.020)	-0.056*** (0.007)
DigitalSkill _i	0.001 (0.004)	-0.012 (0.008)	0.001 (0.021)	0.058*** (0.009)
Individual and Firm Characteristics				
Tenure _i	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)
Training _i	0.016*** (0.004)	0.012* (0.006)	-0.012 (0.017)	0.033*** (0.008)
Age _i	0.008*** (0.001)	0.010*** (0.002)	0.011 (0.007)	0.013*** (0.003)
Age _i ²	-0.000*** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000*** (0.000)
SmallFirm _i	0.014*** (0.004)	0.010 (0.009)	0.013 (0.022)	0.030*** (0.008)
MediumFirm _i	0.013** (0.005)	0.011 (0.010)	0.033 (0.022)	0.043*** (0.011)
LargeFirm _i	0.013*** (0.005)	0.010 (0.010)	0.031 (0.026)	0.048*** (0.011)
Rural _i	-0.008 (0.005)	-0.005 (0.009)	0.009 (0.020)	-0.013 (0.009)
SmallTown _i	-0.011** (0.005)	-0.007 (0.009)	0.003 (0.017)	-0.016 (0.009)
Previous activity^a				
Employed _i	0.013** (0.005)	0.001 (0.008)	0.042 (0.027)	-0.030*** (0.008)
NotEmployed _i	-0.013** (0.006)	-0.014 (0.010)	0.022 (0.027)	-0.019 (0.017)
MissingPrevAct _i	0.052*** (0.007)	0.033*** (0.011)	0.069** (0.032)	-0.063*** (0.020)
Field mismatch^a				
ExactField _i	-0.022*** (0.006)	-0.011 (0.011)	-0.019 (0.036)	0.045*** (0.014)
RelatedField _i	0.026*** (0.007)	0.037*** (0.011)	-0.008 (0.029)	0.017 (0.012)
NoSpecificField _i	-0.002 (0.009)	0.012 (0.014)	-0.000 (0.042)	-0.034*** (0.011)
MissingFieldMism _i	0.002 (0.008)	0.008 (0.019)	0.024 (0.030)	0.013 (0.013)
δ _{sr}	✓	✓	✓	✓
δ _{iscol}	-	-	-	✓
Adj. R ²	0.092	0.110	0.254	0.540
Obs.	42,849	11,792	2,551	42,849

Notes: Columns (1)–(3) report estimates from linear probability models for managerial positions. Column (4) reports OLS estimates for log hourly wages. ^a The reference category for previous activity is InEducation_i, and for field mismatch is DifferentField_i (different/unrelated field of education required). Standard errors clustered at the country level are reported in parentheses. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A8: STEM Education, Access to Twin-Transition Jobs and Wages

Dep. Var.	STEM _i (1)	DigitalJob _i (2)	GreenJob _i (3)	ln HourlyWage _i (4)
Female _i	-0.146*** (0.008)	0.008 (0.009)	-0.018*** (0.005)	-0.074*** (0.013)
STEM _i		0.098*** (0.011)	0.019*** (0.004)	0.048*** (0.015)
Female _i × STEM _i		-0.065*** (0.012)	0.006 (0.009)	-0.069*** (0.018)
Education				
TertiaryEdu _i	0.013 (0.012)	-0.005 (0.008)	-0.003 (0.004)	0.086*** (0.013)
Education mismatch				
MatchedEdu _i	-0.005 (0.011)	-0.005 (0.011)	0.007 (0.005)	-0.017 (0.013)
OverEdu _i	-0.003 (0.013)	-0.008 (0.010)	0.010 (0.006)	-0.064*** (0.018)
Skills mismatch				
MatchedSkills _i	-0.003 (0.006)	-0.015** (0.007)	0.005 (0.005)	-0.015 (0.009)
OverSkilled _i	0.008 (0.012)	-0.013 (0.010)	0.001 (0.006)	-0.016 (0.012)
Type of Skills				
LiteracySkill _i	-0.007 (0.009)	0.003 (0.007)	0.005 (0.004)	0.024*** (0.008)
NumeracySkill _i	0.073*** (0.009)	-0.031*** (0.009)	-0.005 (0.003)	0.016* (0.008)
ProblemSolvSkill _i	0.011 (0.009)	0.004 (0.008)	-0.003 (0.005)	0.022** (0.008)
SocialSkill _i	-0.047*** (0.009)	-0.026*** (0.008)	0.011** (0.005)	0.011 (0.009)
ManualSkill _i	0.017*** (0.006)	-0.038*** (0.007)	0.011*** (0.003)	-0.050*** (0.011)
DigitalSkill _i	0.121*** (0.010)	0.095*** (0.006)	-0.023*** (0.004)	0.069*** (0.009)
Individual and Firm Characteristics				
Tenure _i	-0.000 (0.000)	-0.000** (0.000)	-0.000*** (0.000)	0.000*** (0.000)
Training _i	-0.016* (0.008)	-0.016*** (0.004)	0.008* (0.004)	0.022* (0.012)
Age _i	-0.004 (0.003)	-0.002 (0.002)	-0.002 (0.001)	0.009* (0.004)
Age _i ²	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
SmallFirm _i	0.019** (0.007)	-0.017** (0.008)	0.008 (0.006)	0.018 (0.015)
MediumFirm _i	0.036*** (0.009)	-0.007 (0.010)	0.004 (0.005)	0.036** (0.014)
LargeFirm _i	0.035*** (0.010)	0.029*** (0.010)	0.001 (0.007)	0.036** (0.013)
Rural _i	0.005 (0.007)	-0.009 (0.008)	0.004 (0.004)	-0.003 (0.011)
SmallTown _i	-0.011 (0.008)	-0.009 (0.008)	0.004 (0.003)	-0.020* (0.012)
Previous activity^a				
Employed _i	0.008 (0.007)	0.002 (0.007)	0.001 (0.004)	-0.029*** (0.009)
NotEmployed _i	0.002 (0.012)	0.019** (0.008)	-0.006 (0.004)	-0.030* (0.017)
MissingPrevAct _i	-0.024 (0.018)	-0.029 (0.022)	-0.004 (0.012)	0.035 (0.023)
Field mismatch^a				
ExactField _i	-0.005 (0.014)	-0.048*** (0.016)	0.005 (0.005)	0.051*** (0.017)
RelatedField _i	0.018 (0.013)	-0.014 (0.012)	-0.001 (0.006)	0.030** (0.014)
NoSpecificField _i	-0.021 (0.016)	0.025* (0.012)	-0.004 (0.005)	-0.032** (0.015)
MissingFieldMism _i	-0.005 (0.016)	0.014 (0.012)	0.006 (0.007)	0.003 (0.018)
δ_{sr}	✓	✓	✓	✓
δ_{iscol}	✓	✓	✓	✓
Adj. R^2	0.216	0.357	0.239	0.524
Obs.	25,188	25,188	25,188	25,188

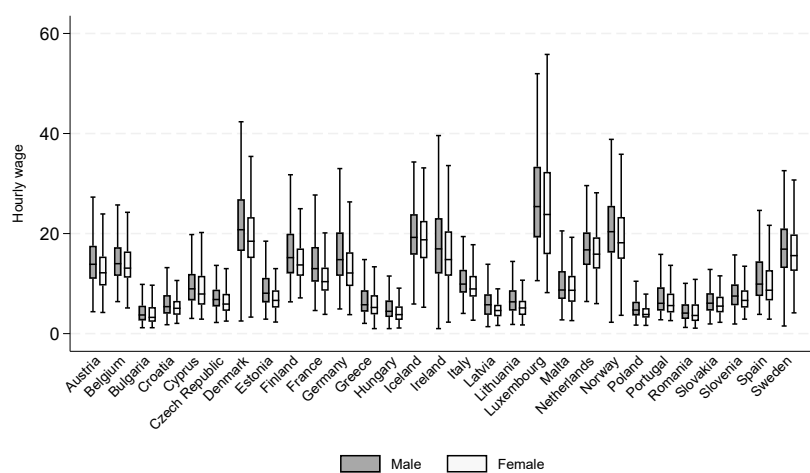
Notes: Columns (1)–(3) report estimates from linear probability models. Column (4) reports OLS estimates for log hourly wages. ^a The reference category for previous activity is InEducation_i, and for field mismatch is DifferentField_i (different/unrelated field of education required). Standard errors clustered at the country level are reported in parentheses. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A9: Regional STEM Environment, Access to Digital and Green Jobs, and Wages

Dep. Var.	DigitalJob _i		GreenJob _i		ln HourlyWage _i	
	(1)	(2)	(3)	(4)	(5)	(6)
Female _i	-0.031*** (0.009)	-0.032*** (0.007)	-0.025*** (0.004)	-0.027*** (0.003)	-0.115*** (0.010)	-0.116*** (0.008)
Female _i × High STEM region, 50 th	0.007 (0.010)		0.001 (0.005)		0.014 (0.014)	
Female _i × High STEM region 75 th		0.018* (0.010)		0.008 (0.006)		0.033* (0.018)
Education						
SecondaryEdu _i	0.031*** (0.008)	0.031*** (0.008)	-0.003 (0.008)	-0.003 (0.008)	0.004 (0.020)	0.004 (0.020)
TertiaryEdu _i	0.015 (0.012)	0.015 (0.012)	-0.011 (0.010)	-0.011 (0.010)	0.119*** (0.022)	0.119*** (0.022)
Education mismatch						
MatchedEdu _i	-0.001 (0.006)	-0.001 (0.006)	0.007** (0.003)	0.007** (0.003)	-0.027** (0.010)	-0.027** (0.010)
OverEdu _i	-0.001 (0.007)	-0.001 (0.007)	0.006 (0.004)	0.006 (0.004)	-0.066*** (0.015)	-0.066*** (0.015)
Skills mismatch						
MatchedSkill _i	-0.009 (0.006)	-0.009 (0.006)	0.004 (0.004)	0.004 (0.004)	-0.010* (0.006)	-0.010* (0.006)
OverSkilled _i	-0.011 (0.008)	-0.011 (0.008)	-0.001 (0.005)	-0.001 (0.005)	-0.017 (0.013)	-0.017 (0.013)
Type of Skills						
LiteracySkill _i	-0.007 (0.005)	-0.007 (0.006)	0.004 (0.003)	0.004 (0.003)	0.028*** (0.010)	0.028*** (0.010)
NumeracySkill _i	-0.014** (0.006)	-0.014** (0.006)	-0.002 (0.003)	-0.002 (0.003)	0.026*** (0.008)	0.026*** (0.008)
ProblemSolvSkill _i	0.018*** (0.006)	0.018*** (0.006)	-0.001 (0.004)	-0.001 (0.004)	0.020** (0.008)	0.020** (0.008)
SocialSkill _i	-0.037*** (0.007)	-0.037*** (0.007)	0.008** (0.003)	0.008** (0.003)	0.015** (0.007)	0.015** (0.007)
ManualSkill _i	-0.038*** (0.005)	-0.038*** (0.005)	0.016*** (0.003)	0.016*** (0.003)	-0.056*** (0.007)	-0.056*** (0.007)
DigitalSkill _i	0.106*** (0.006)	0.106*** (0.006)	-0.019*** (0.004)	-0.019*** (0.004)	0.058*** (0.009)	0.058*** (0.009)
Individual and Firm Characteristics						
Tenure _i	-0.000** (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.000** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Training _i	-0.022*** (0.004)	-0.022*** (0.004)	0.006 (0.004)	0.006 (0.004)	0.033*** (0.008)	0.033*** (0.008)
Age _i	0.001 (0.002)	0.001 (0.002)	-0.002** (0.001)	-0.002** (0.001)	0.013*** (0.003)	0.013*** (0.003)
Age _i ²	-0.000 (0.000)	-0.000 (0.000)	0.000* (0.000)	0.000* (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
SmallFirm _i	-0.005 (0.006)	-0.005 (0.006)	0.002 (0.004)	0.002 (0.004)	0.030*** (0.008)	0.030*** (0.008)
MediumFirm _i	0.004 (0.007)	0.004 (0.007)	0.001 (0.004)	0.001 (0.004)	0.043*** (0.011)	0.043*** (0.010)
LargeFirm _i	0.043*** (0.007)	0.043*** (0.007)	-0.001 (0.005)	-0.001 (0.005)	0.048*** (0.011)	0.048*** (0.011)
Rural _i	-0.009 (0.006)	-0.009 (0.006)	0.007* (0.003)	0.007* (0.003)	-0.013 (0.009)	-0.013 (0.009)
SmallTown _i	-0.013** (0.005)	-0.014** (0.005)	0.006** (0.003)	0.006** (0.003)	-0.015 (0.010)	-0.016 (0.010)
Previous activity^a						
Employed _i	0.003 (0.007)	0.003 (0.007)	0.004 (0.004)	0.004 (0.004)	-0.030*** (0.008)	-0.030*** (0.008)
NotEmployed _i	0.021** (0.008)	0.021** (0.008)	-0.001 (0.004)	-0.001 (0.004)	-0.019 (0.017)	-0.019 (0.017)
MissingPrevAct _i	0.007 (0.007)	0.007 (0.007)	0.010* (0.005)	0.010* (0.005)	-0.063*** (0.020)	-0.063*** (0.020)
Field mismatch^a						
ExactField _i	-0.039*** (0.012)	-0.039*** (0.012)	-0.000 (0.004)	-0.000 (0.005)	0.045*** (0.014)	0.045*** (0.014)
RelatedField _i	-0.003 (0.009)	-0.003 (0.009)	-0.002 (0.005)	-0.002 (0.005)	0.016 (0.012)	0.016 (0.012)
NoSpecificField _i	0.012 (0.009)	0.012 (0.009)	-0.001 (0.005)	-0.001 (0.005)	-0.035*** (0.011)	-0.035*** (0.011)
MissingFieldMism _i	0.005 (0.010)	0.004 (0.010)	-0.006 (0.005)	-0.006 (0.005)	0.013 (0.013)	0.012 (0.013)
δ_{sp}	✓	✓	✓	✓	✓	✓
δ_{iscol}	✓	✓	✓	✓	✓	✓
Adj. R^2	0.336	0.336	0.225	0.225	0.540	0.540
Obs.	42,849	42,849	42,849	42,849	42,849	42,849

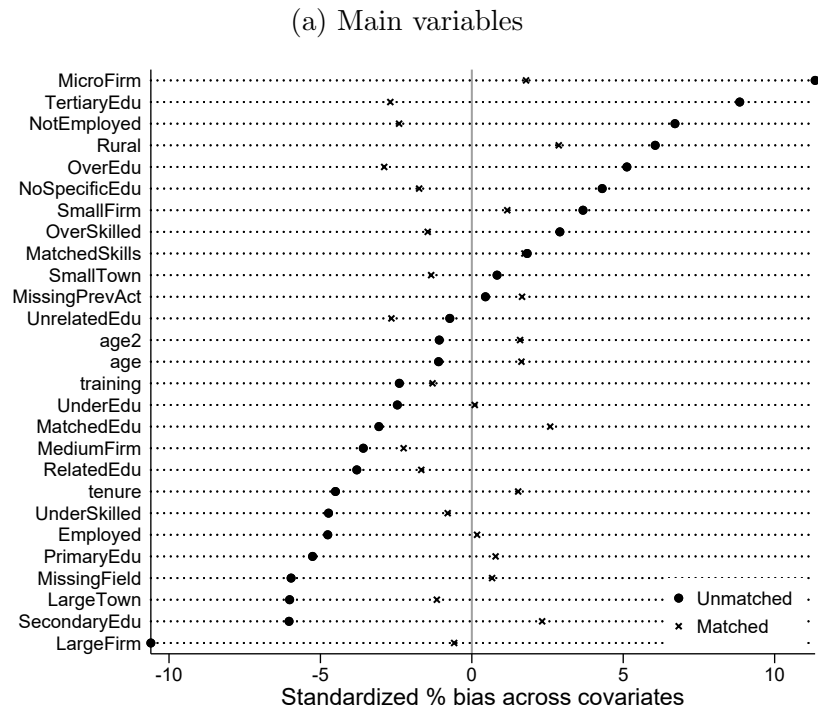
Notes: High STEM region is defined using regional STEM university intensity. Columns (1), (3), and (5) use the 50th percentile threshold, while columns (2), (4), and (6) use the 75th percentile threshold. ^a The reference category for previous activity is InEducation_i, and for field mismatch is DifferentField_i (different/unrelated field of education required). Standard errors clustered at the country level are reported in parentheses. Asterisks denote significance levels: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure A1: Hourly wage distribution by gender and country

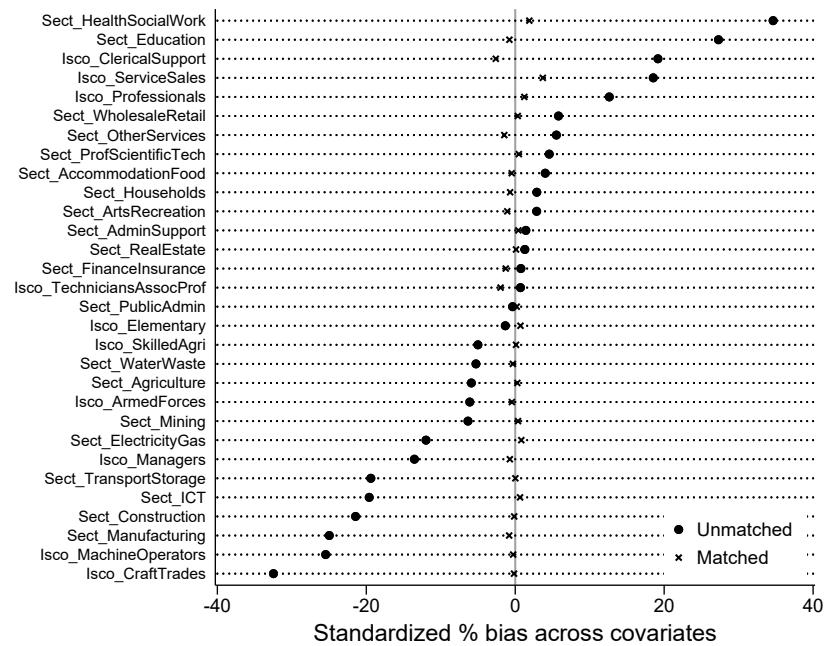


Notes: Observations: 44,103. *Source:* Author's elaboration based on ESJS2.

Figure A2: Balance Diagnostics: Standardized Bias Before and After Matching



(b) Occupations (ISCO-1 digit) and sectors (NACE-1 digit)



Notes: Observations: 44,103. Unmatched sample: mean standardised (std.) % bias=3.9 median std. % bias=1.8. Matched sample: mean std. % bias=0.9, median std. % bias=0.9. Negative std. bias indicates that the women have a lower mean than men, while positive std. bias indicates that women have a higher mean than men. Regions (NUTS-1 digit) are also included in the matching procedure, but not shown in the graph for parsimony. *Source:* Author's elaboration based on ESJS2.