Gendered Effects of Robotisation on Job Quality

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Abstract: This paper examines whether industrial robotisation is associated with gender-differentiated patterns in job quality across Europe. We combine individual-level data from the European Working Conditions Telephone Survey (EWCTS) 2021 with country–industry measures of robot exposure constructed from International Federation of Robotics (IFR) statistics. Job quality is captured along three dimensions—work intensity, physical risks, and autonomy—using harmonised EWCTS job-quality recodes. We estimate weighted logit models with individual and job controls as well as country and industry fixed effects, allowing robotisation effects to differ by gender through interaction terms. Overall, robot exposure is only weakly related to job-quality outcomes once controls and fixed effects are included. However, these associations are heterogeneous across dimensions: robotisation is associated with lower physical risks for both genders, a persistent female disadvantage in work intensity, and a narrowing gender gap in autonomy as robot exposure increases.

Keywords: Gender, Robotisation, Job quality

1. Introduction

Since the Industrial Revolution, technological progress has significantly influenced the functioning of the labour market. It first displaced some craft tasks while increasing output, then transformed production through Fordist mass production, and more recently, through computerisation, robotisation, and artificial intelligence, it has enabled the automation of routine manual and cognitive tasks. AI is now extending automation to perception, prediction, and content generation, reshaping jobs by reorganising tasks rather than replacing entire occupations.

Nowadays, next to rapidly developing AI, robot adoption is broad and still rising. According to World Robotics 2025 statistics on industrial robots, 542,000 robots were installed in 2024 - more than twice as many as ten years ago. The global operational stock reached about 4.664 million units in 2024 (+9% year-over-year). Europe is an important setting of two reasons: its a second region across the world with the highest number of annual installations (after Asia and Australia), and the first with robot density per worker (219 units per 10,000 employees in 2024, according to International Federation of Robotics (IFR) Press Room).

Due to the increasing role of robotization, many research is focused to analyse their impact on labour market, mainly on employment. Existing research document ambiguous outcomes, especially due to the country, sector, occupation/job and skills heterogeneity, e.g. higher exposure to industrial robots might be associated with cuts in employment and wages in case of US, but with increase in productivity and wages in Europe, see for review (Filippi, Bannò, & Trento, 2023; Guarascio, Piccirillo, & Reljic, 2025; Hötte, Somers, & Theodorakopoulos, 2023; Sharfaei, 2024).

However, less is known as far as the gender differences are taken into account. Scarce evidence for Europe shows that robot adoption and automation may increase gender pay gap (Aksoy, Özcan, & Philipp, 2021; Pavlenkova, Alfieri, & Masso, 2023).

Therefore, studying the impact of robotisation on gender inequalities in European labour markets is important. This study addresses this issue by developing a gender perspective on automation, asking how industrial robot adoption is associated with core dimensions of job quality for men and women. The main contribution of our research is to fill a persistent gap in the literature by providing EU-wide evidence on gender-differentiated relationships between robot exposure and job quality.

To do so, we employ a micro–macro linkage: individual job-quality indicators from the European Working Conditions Telephone Survey (EWCTS) 2021 matched to country–industry measures of robot density derived from International Federation of Robotics (IFR) data. Our empirical analysis focuses on three dimensions of job quality—work intensity, physical risks, and autonomy—captured as binary outcomes using harmonised EWCTS job-quality recodes. We estimate weighted logit models with rich individual and job controls and include country and industry fixed effects; we further allow the association between robotisation and job quality to vary by gender by interacting gender with a two-part robot-density measure (exposure versus intensity among exposed industries). Finally, we complement the regression evidence with Fairlie nonlinear decompositions to quantify the extent to which observed characteristics and sorting patterns account for female–male gaps in job-quality outcomes.

Our results indicate that, conditional on controls and fixed effects, robot density is only weakly associated with job-quality outcomes on average. Nonetheless, the patterns are heterogeneous across dimensions and by gender. Higher robotisation exposure is associated with lower physical-risk exposure for both women and men, while women display persistently higher work intensity than men. For autonomy, women exhibit lower predicted autonomy at low robotisation exposure, but this gap narrows with increasing robot density as women's predicted autonomy rises more strongly than men's. Decomposition results show that robot density explains little of the observed gender gaps in work intensity and autonomy in absolute terms, whereas occupation, work arrangements, and macro-level context (country and industry) account for substantially larger contributions.

The remainder of the paper is organised as follows. Section 2 reviews the literature and discusses mechanisms linking robotisation to gender inequality. Section 3 describes the EWCTS and IFR data, the construction of job-quality outcomes and robot exposure, and the empirical strategy. Section 4 presents the weighted logit estimates and the decomposition results. Section 5 discusses the findings, limitations, and implications. Section 6 concludes.

2. Related Literature

Nowadays, it is underlined that the automation and robotisation processes might be directly related not to the entire occupational groups but to distinct tasks performed by workers (Pető & Reizer, 2021). The distribution of men and women across occupations and performed tasks is different, what might be reflected in diversified treatment from robotisation. The risk of substitution could be therefore different for men and for women. The existing studies are non-conclusive in this matter (for review see (Filippi et al., 2023)), indicating that the final effect might be country, region, industry, firm and occupation-specific. The evidence for OECD countries presented by Brussevich, Dabla-Norris, and Khalid (2019) shows that women more often are engaged in conducting routine, automatable tasks, and therefore are at higher risk of displacement by automation (Brussevich et al., 2019). Importantly, the risk for women is heterogeneous: younger women and those at managerial positions are less prone to be replaced by robotisation processes. As women are underrepresented in STEM (Science, Technology, Engineering, and Mathematics) occupations (Eurostat, 2024), some of the negative effects related to the threat of automation can be mitigated, for example, by increasing the level of education of women and their performance of less routine work. Another branch of research reveals contrasting results for the EU labour market, showing that automation risk is higher for men than for women and is closely linked to differences in the skill and task profiles of their jobs (Pouliakas, 2018).

Apart from different risk of being substituted, the literature on gender disparities on labor market caused by robotization covers the issue of gender pay gap. In general, for Europe the gender wage gap has narrowed considerably over the last half-century, however a substantial gap remains (Kunze, 2018). An extensive literature has studied the factors that can explain this persistence of gender pay differences, but most research focuses on supply-side factors, while the evidence on how demand-side factors (such as automation) affect wage gap is much more scarce (Aksoy et al., 2021). As far as technology is considered the existing evidence is much more scarce. Aksoy et al. (2021) using data from 20 European countries indicates that for each 10 percent increase in robotization, the gender pay gap expands by 1.8 percent. This negative trend is mostly visible in countries with originally high level of gender inequalities and high level of robot density, at the same time. Moreover, robotization is linked with earnings premia for male workers in medium- and high skilled occupations thanks to the productivity gains. For women such effect is not observed. Similarly, using Estonian manufacturing and service data for the years 2006-2018, Pavlenkova et al. (2023) find that in firms where the automation processes were introduced the gender wage gap enlarge. According to Wicht, Müller, and Pollak (2024), who used German data for the years 2011, 2015 and 2019, women, in contrast to men, do not benefit thought performing more complex and autonomous job tasks, which consequently does not lead to wage returns from mowing to non-routine tasks. Albinowski and Lewandowski (2024), in turn, using sample of 14 European countries in the 2010-2018 period, find that the wage effects of robot adoption are minor, being young and prime-aged women more beneficial opposite to older women and prime-aged men. However, following Domini, Grazzi, Moschella, and Treibich (2022) the automation induced wage effects are homogeneous across workers of different skills/wage percentiles: French firms importing automation and AI related goods have not experienced higher wage inequalities (in the period 2012-2017).

3. Data and Methodology

Two main datasets are merged for our empirical analysis.

First, data about workers come from European Working Conditions Telephone Survey (EWCTS, hereafter) conducted in 2021. EWCTS is an extraordinary edition of European Working Conditions Survey (EWCS, hereafter) carried out, for the first time via computer-assisted telephone interviewing (CATI), due to the COVID-19 pandemic. Since 1990 EWCS has provided important source of working conditions in Europe on a harmonised basis. The 2021 wave covers over 70,000 detailed characteristics on European workers from 36 countries, including the EU Member States, the United Kingdom, Norway, Switzerland, Albania, Bosnia and Herzegovina, Kosovo, Montenegro, North Macedonia and Serbia.

Based on EWCTS data we use three indices of job quality: work intensity, physical environment and work autonomy. The selection of the job quality indices was driven both by the data availability as well as the previous literature on the impact from robotisation on working conditions. First, the use of robots might be related to an increased speed of work, reflected in work intensity (Antón, Fernández-Macías, & Winter-Ebmer, 2023). Second, at the the same time, robotisation can be beneficial in minimizing physical hazards in the workplace by replacing the most dangerous tasks with robots (Gihleb, Giuntella, Stella, & Wang, 2022). The third dimension of job quality is on work autonomy and related meaningfulness at work: past evidence shows that an increased use of robots might deteriorate the job meaningfulness and autonomy (Nikolova, Cnossen, & Nikolaev, 2024). Next, apart from capturing the different impact of robotization on job quality based on gender, we control for a range of workers' characteristics such age, educational level, type of employment contract, employment in public or private sector and company size. For the purpose of representatives we apply final calibrated sampling weights provided with the EWCTS 2021 data, which combine the inverse probability of selection with adjustments for unequal selection due to multiple phone numbers, non-response, and calibration to Labour Force Survey population margins by age, sex, region, occupation and sector (for more details see (Ipsos NV, 2022).

The second core data source are data derived from International Federation of Robotics (IFR, hereafter). It compiles a well-established annual statistical data on industrial robots, collected from industrial robot suppliers worldwide. The data covers 40 countries broken down into areas of application, customer industries, types of robots and other technical and economic aspects. We use the measure of the operational stock of robots that assumes an average service life of 12 years with an immediate withdrawal from service afterwards (more more detail see the annual World Robotics Industrial Robots reports, issued by IFR Statistical Department). Industrial robots, indeed, are described as 'automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment' (IFR, 2025). To control for differences in country and sector size, we use robot exposure, a measure commonly used to capture robot use (IFR, 2025). The robot exposure is calculated as a share of the industrial robots operational stock in given country/sector/year per 1000 employees. Data on employment are derived from Eurostat based on employment by detailed industry (NACE Rev.2) - national accounts (nama_10_a64_e).

3.1 Methodology

In our empirical analysis we focus on three job-quality indicators: work intensity, physical risks, and autonomy, constructed from the EWCTS job-quality recodes. Each indicator is binary and takes values in {0, 1}, which motivates the use of weighted logit models. In each case, the indicator equals 1 if the respondent is classified as having the given job-quality outcome (high work intensity/exposure to physical risks/high autonomy according to the EWCTS recode), and 0 otherwise. Our key explanatory variable is robots exposure, measured at the country-industry level. Robot exposure is a non-negative variable with a pronounced concentration at zero and a strongly right-skewed distribution for positive values. To accommodate this distributional pattern, we decompose robot exposure into two components, defined as follows:

$$robots\_ex_{cs} = \begin{cases} 1 \text{ if } exposure_{cs} > 0; \\ 0 \text{ if } exposure_{cs} = 0. \end{cases}$$

$$robots\_exp\_log_{cs} = \begin{cases} \log(exposure_{cs} & \text{if } exposure_{cs} > 0; \\ 0 & \text{if } exposure_{cs} = 0. \end{cases} \quad (1)$$

where c denotes country and s denotes industry.

This specification follows recommended practice for modelling covariates characterised by a mass point at zero, distinguishing between the presence of any exposure (the extensive margin) and variation in exposure intensity conditional on exposure (the intensive margin) (Dziak & Henry, 2017). In our context, this specification allows the association between robot exposure and job quality to differ between the presence of any robot penetration in an industry and marginal increases in robot density within industries that are already robotised.

Formally, to examine the relationship between robot exposure and job quality, we estimate the following baseline regression for individual i in country c and industry s:

$$\Pr(Y_{ics} = 1) = \Lambda(\alpha + \beta 1 \text{ robot\_ex}_{cs} + \beta 2 \text{ robot\_ex\_log}_{cs} + \beta 3 \text{ Female}_i + \beta 4 (\text{robot\_ex}_{cs} \times \text{Female}_i) + \beta 5 (\text{robot\_ex\_log}_{cs} \times \text{Female}_i) + X_i'\gamma + \mu_c + \mu_s) \quad (2)$$

where $\Lambda(\cdot)$ denotes the logistic CDF, Y_{ics} is a binary indicator equal to 1 if individual i in country c and industry s reports the job-quality outcome under consideration, and 0 otherwise. $Female_i$ is a gender indicator, X_i is a vector of individual and job controls, and μ_c and μ_s capture country and industry fixed effects. Standard errors are clustered at the country-industry level to reflect the aggregation level at which robot exposure varies.

For each binary job-quality indicator for work intensity, physical risk, work autonomy we estimate weighted logit models including the two-part robot exposure measure, a rich set of individual and job controls (demographics, work arrangements, workplace size, and occupation), and fixed effects for country and industry. To assess gender heterogeneity in the association between robotisation and job quality, we additionally estimate specifications interacting gender with both robot-exposure components. Because robot exposure varies at the country-industry level, standard errors are clustered at that level.

3.2 Descriptive Statistics

Table 1 reports descriptive statistics for the outcome indicators and the main explanatory variables separately for men and women. On average, women exhibit slightly higher work intensity than men and marginally higher exposure to physical risks. By contrast, men enjoy somewhat higher autonomy at work. With respect to background characteristics, the average respondent in both groups is in the mid-career age brackets (around 35–44 or 45–55 years), with women being only slightly older on average. The vast majority of workers in both groups hold open-ended contracts. Women are, on average, more highly educated than men. However, men are more likely to work full-time and more likely to be employed in the public sector. Tenure and workplace size are very similar across genders: both men and women on average fall between 5–9 and 10 or more years of seniority, and work in establishments of roughly comparable size.

Table 1: Descriptive statistics by gender

Variable	Male	Female	Diff. (F–M)	N
Work intensity (0/1)	0.65 (0.48)	0.68 (0.47)	0.03	71,543
Physical risks (0/1)	0.27 (0.44)	0.29 (0.45)	0.02	71,543
Autonomy (0/1)	0.51 (0.50)	0.47 (0.50)	-0.03	71,543
Age group (1–5)	3.16 (1.20)	3.25 (1.17)	0.09	71,543
Open-ended contract (0/1)	0.88 (0.33)	0.87 (0.34)	-0.01	57,886
Education (1–3)	2.42 (0.65)	2.57 (0.60)	0.14	71,182
Full-time (0/1)	0.89 (0.31)	0.77 (0.42)	-0.12	71,041
Public sector (0/1)	0.22 (0.41)	0.38 (0.48)	0.16	64,541
Seniority (1–4)	2.83 (1.07)	2.82 (1.08)	-0.01	71,346
Workplace size (1–4)	2.76 (0.84)	2.76 (0.80)	0.01	69,375

Notes: Reported values are means, with standard deviations in parentheses. “Diff.” reports the raw female–male difference in means. N denotes the number of non-missing observations for the given variable. Binary indicators are coded as 1 for the presence of the characteristic and 0 otherwise. Age groups: 1 = 16–24, 2 = 25–34, 3 = 35–44, 4 = 45–55, 5 = 56+. Education: 1 = low, 2 = medium, 3 = high. Seniority is coded as: 1 = less than 1 year, 2 = 1–4 years, 3 = 5–9 years, 4 = 10 years or more. Workplace size: 1 = working alone, 2 = 2–9 employees, 3 = 10–249 employees, 4 = 250+ employees.

Source: Own elaboration based on merged EWCTS 2021 and IFR 2021 data.

Turning to the second dataset, Table 2 shows substantial cross-country differences in robot penetration across European labour markets in 2021. Three broad groups of countries can be distinguished. First, the highest levels of robot exposure are observed in Germany, which records by far the largest value (62.8 robots per 10,000 workers), followed by Slovenia (55.9), the Czech Republic (44.6), Italy (38.7), and Slovakia (36.1). In these countries, robot exposure is approximately three to four times higher than in the low-adoption economies. Second, an intermediate group includes Austria, Sweden, Denmark, Switzerland, Hungary, Belgium, Finland, Spain, the Netherlands, and France, with robot exposure ranging from around 18 to 34 robots per 10,000 workers. Although these countries are more robotised than the less technologically advanced economies, they remain below the levels observed in the leading group. Third, a large group of countries displays relatively low robot penetration, with robot exposure below 15 robots per 10,000 workers. This group includes Portugal (14.2) and Poland (12.1), as well as Norway, Ireland, Romania, Estonia, Lithuania, Malta, Bulgaria, Croatia, Serbia, and Greece, where robot exposure falls to as little as 2.0. Overall, the disparity between the highest-and lowest-robotised countries is considerable: Germany's robot exposure is more than 30 times higher than that of Serbia or Greece.

Table 2: Robot exposure per 10,000 workers by country, 2021

Country	Robot exposure
Germany	62.8
Slovenia	55.9
Czech Republic	44.6
Italy	38.7
Slovakia	36.1
Austria	33.5
Sweden	32.3
Denmark	28.2
Switzerland	26.6
Hungary	24.9
Belgium	23.1
Finland	20.8
Spain	20.5
Netherlands	19.2
France	18.3
Portugal	14.2
Poland	12.1
Norway	6.8
Ireland	6.6
Romania	6.6
Estonia	6.5
Lithuania	5.1
Malta	5.0
Bulgaria	3.0
Croatia	2.1
Serbia	2.0
Greece	2.0

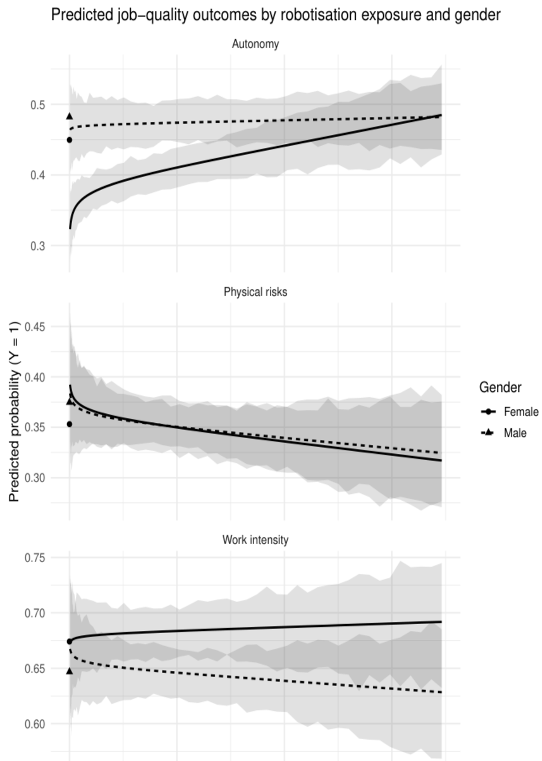
Note: Robot exposure calculated for all economic sectors available in the IFR dataset.

Source: Own elaboration based on IFR 2021 data.

4. Results

Figure 1 presents core weighted logit estimates with country and industry fixed effects and standard errors clustered at the country - industry level, following equation (2). The full set of coefficient estimates is reported in Appendix, Table A.1. Across all outcomes, the robots exposure effects are small once we include the full set of controls and fixed effects. This suggests that, in this specification, differences in industrial robot exposure are not strongly related to the job-quality indicators.

Basically, Figure 1 plots predicted probabilities of each job-quality outcome as a function of robotisation exposure, separately for women and men (with confidence intervals). Three main patterns emerge. First, work autonomy displays a clear gender gap at low levels of robotisation: predicted autonomy is lower for women than for men when robot exposure is near zero. However, the gap narrows with increasing exposure. Women's predicted autonomy increases steadily with robotisation intensity, whereas men's predicted autonomy is comparatively flat. At higher levels of robot density, the two profiles converge, suggesting that robotisation is associated with a relative improvement in women's autonomy compared with men.



Source: Own elaboration based on merged EWCTS 2021 and IFR 2021 data

Figure 1: Predicted job-quality outcomes by robotisation exposure and gender

Secondly, for physical risks, the predicted probability decreases with robotisation exposure for both genders. The gender profiles remain close throughout the distribution of robot density, indicating that robotisation is linked to lower physical-risk exposure overall, with only limited evidence that this association differs strongly between women and men. The decline appears slightly steeper for women, but the overlap of confidence bands suggests that gender differences in the slope are modest. Third, work intensity remains relatively high across the entire range of robotisation exposure, but the patterns differ by gender. Women exhibit consistently higher predicted work intensity than men at all exposure levels. Moreover, the gender gap appears to widen as robot density increases: women's predicted intensity is roughly stable or slightly increasing, while men's intensity declines slightly with exposure.

This implies that robotisation is associated with a small relative increase (or weaker reduction) in women's work intensity compared with men. Taken together, the figure suggests that higher robotisation exposure is not equally associated with better job quality. Instead, the associations differ across dimensions: robotisation correlates with higher autonomy for women relative to men, lower physical risks for both genders, and a persistent (and potentially slightly widening) female disadvantage in work intensity. These heterogeneous patterns are consistent with the idea that robotisation may reduce physically demanding tasks while simultaneously reshaping work organisation and pace in ways that do not benefit all dimensions of job quality equally.

Our results also indicate that the relationship between robotisation and job quality is not straightforward. Although the main coefficients for robot exposure are small and not statistically significant across all three dimensions, this does not necessarily mean that robotisation is irrelevant for workers' job quality. Rather, the estimates suggest that its association with job quality may differ across dimensions and between women and men. At the same time, the results point to persistent gender differences in job quality, even after controlling for demographic characteristics, work arrangements, workplace size, occupation, as well as country and industry fixed effects. In particular, women report higher work intensity, lower physical risk, and lower autonomy than otherwise comparable men in sectors without robot exposure.

Moreover, the association between robotisation and job quality seems to vary depending on the dimension considered. For work intensity and physical risk, the interaction terms with gender are not statistically significant, which suggests that robotisation is not associated with a systematic change in the gender gap in these two domains. In the case of autonomy, however, the pattern is more nuanced. The results show that in industries where robots are present, women experience a greater disadvantage in autonomy relative to men, while higher robot density within robot-using industries is associated with a reduction in this gap. That is, our estimates suggest that the presence of robots may initially coincide with less favourable autonomy outcomes for women, but that this disadvantage becomes smaller as robot exposure increases. Overall, our findings indicate that robotisation is linked less with broad average changes in job quality and more with differentiated patterns that depend on the specific job-quality dimension and on gender.

5. Discussion

The analysis provides EU-wide evidence on the association between industrial robotisation and gender differences in job quality. Our results suggest that this relationship is not uniform across dimensions. At the same time, the estimates indicate that gender differences in job quality remain visible even after accounting for a broad set of personal and job characteristics, as well as country and industry fixed effects.

In the case of physical risk, the coefficients for robot exposure are negative for both women and men, but they are not statistically significant. Thus, the results do not provide strong evidence that robotisation is associated with lower physical risk in the sample analysed here. At the same time, the direction of the coefficients is consistent with earlier studies suggesting that robots may substitute for more hazardous tasks and reduce workers' exposure to harmful physical conditions (Gihleb et al., 2022). In this sense, our findings do not contradict the view that one possible consequence of robot adoption is a reduction in dangerous manual work, although they do not allow for a strong conclusion on this point.

For work intensity, the pattern is different. The estimates show a persistent female disadvantage, while the interaction terms with robot exposure are not statistically significant. This suggests that the gender gap in work intensity does not vary systematically with robotisation. Earlier studies based on regional-level evidence have suggested that robot adoption may be associated with stronger work pressure, including faster pace of work, tighter targets, or more intensive monitoring (Antón et al., 2023). Although this is not directly comparable to our individual-level measure of job quality, it provides a useful context for interpreting the persistence of gender differences in work intensity observed in our results. At the same time, our estimates do not provide evidence that higher robot exposure is associated with any reduction in the female disadvantage in this dimension.

The results for autonomy are more differentiated. The estimates suggest that in industries where robots are present, women experience a greater disadvantage in autonomy relative to men, while higher robot density within robot-using industries is associated with a smaller gender gap. This indicates that the association between robotisation and autonomy is not linear and cannot be reduced to a single average effect. Earlier evidence has shown that robotisation may be associated with lower autonomy and reduced meaning at work on average (Nikolova et al., 2024). Our findings add nuance to this picture by suggesting that the relationship may also vary by gender and by the level of robot exposure within robot-using industries.

Overall, the findings suggest that robotisation is associated less with broad average differences in job quality and more with differentiated patterns across specific dimensions of work. In this respect, the results support the view that job quality should be treated as a multidimensional concept and that the relationship between technological change and job quality may take different forms for women and men.

6. Conclusions

The paper provides EU-wide evidence on the association between industrial robotisation and gender differences in job quality by linking EWCTS 2021 microdata with IFR-based measures of robot density at the country–industry level. Using weighted logit models with a broad set of controls and country and industry fixed effects, we examined whether robot exposure is associated with work intensity, physical risk, and autonomy, and whether these associations differ between women and men.

Our results suggest that the relationship between robotisation and job quality is not uniform across dimensions. Once personal characteristics, job attributes, and macro-level controls are taken into account, the overall association between robot density and job-quality outcomes remains limited. At the same time, the estimates indicate persistent gender differences in job quality. In particular, the results point to a stable female disadvantage in work intensity, while the coefficients for physical risk are negative but not statistically significant for both women and men. In the case of autonomy, the findings suggest a more differentiated pattern: in robot-using industries women experience a greater disadvantage relative to men, but this gap becomes smaller as robot density increases within those industries.

The study is based on cross-sectional data and therefore does not allow causal interpretation. In addition, the measure of robotisation used in the analysis refers to industrial robots and does not capture other technologies that may also be relevant for working conditions, especially in service activities. At the same time, the results suggest that the relationship between robotisation and job quality is differentiated across dimensions and cannot be reduced to a single general pattern.

In this sense, the analysis may be seen as a starting point for further research. In particular, it would be useful to examine whether the observed patterns differ across occupational groups, since the tasks performed in different occupations are likely to be linked to robotisation in different ways. A more detailed analysis could show more clearly whether robot exposure is associated mainly with physical risk, work intensity, or autonomy in particular occupations. It would also be worth exploring cross-country differences in greater detail, as the observed relationships may vary across national contexts. Another important direction would be to extend the robustness analysis by considering alternative measures of robot exposure, different model specifications, and more disaggregated samples. This would make it possible to assess whether the patterns identified here remain stable across alternative empirical approaches. More generally, the findings suggest that job quality should be treated as a multidimensional concept and that its different dimensions may be associated with technological change in different ways for women and men.

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Appendix A

Table A.1: Full weighted logit estimates with gender interactions

Covariate	Intensity	Physical risk	Autonomy
Robot exposure and gender			
Robot exposure > 0	0.026 (0.082)	-0.080 (0.099)	-0.049 (0.090)
log(robot exposure) for robots_ex > 0	-0.016 (0.026)	-0.029 (0.033)	0.007 (0.018)
Female	0.129*** (0.033)	-0.119** (0.047)	-0.144*** (0.034)
Female × (robots_ex>0)	0.005 (0.101)	0.130 (0.118)	-0.248*** (0.082)
Female × log(robots_ex) for robots_ex > 0	0.024 (0.038)	-0.008 (0.036)	0.058*** (0.022)
Demographics			
Age 25–34	0.106 (0.067)	0.072 (0.073)	0.081 (0.073)
Age 35–44	0.080 (0.067)	-0.013 (0.079)	0.056 (0.077)
Age 45–55	-0.060 (0.061)	-0.206*** (0.074)	0.059 (0.079)
Age 56+	-0.223*** (0.068)	-0.343*** (0.085)	0.051 (0.085)
Education			
Education: medium	0.222*** (0.053)	0.037 (0.068)	0.100* (0.051)
Education: high	0.376*** (0.059)	-0.282*** (0.075)	0.272*** (0.052)
Work arrangements			
Part-time	-0.292*** (0.036)	-0.112** (0.046)	0.006 (0.044)
Tenure 1–4 years	0.135*** (0.048)	0.110* (0.063)	0.070 (0.051)
Tenure 5–9 years	0.193*** (0.052)	0.202*** (0.063)	0.126*** (0.048)
Tenure 10+ years	0.380*** (0.050)	0.357*** (0.063)	0.110** (0.049)
Workplace size			
Workplace size 2–9 employees	-0.007 (0.059)	0.219*** (0.071)	-0.426*** (0.066)
Workplace size 10–249 employees	0.268*** (0.061)	0.180*** (0.069)	-0.651*** (0.059)
Workplace size 250+ employees	0.257*** (0.081)	-0.038 (0.083)	-0.634*** (0.067)
Occupation (ISCO major group)			
Occupation: Managers	-0.022 (0.226)	-1.099*** (0.242)	0.763*** (0.186)

Covariate	Intensity	Physical risk	Autonomy
Occupation: Professionals	-0.194 (0.208)	-0.838*** (0.243)	0.526*** (0.189)
Occupation: Technicians and associate professionals	-0.289 (0.210)	-0.533** (0.232)	0.279 (0.185)
Occupation: Clerical support workers	-0.465** (0.202)	-1.600*** (0.215)	0.225 (0.194)
Occupation: Service and sales workers	-0.379* (0.221)	0.138 (0.227)	-0.134 (0.192)
Occupation: Skilled agricultural, forestry and fishery workers	-0.179 (0.241)	0.847*** (0.280)	0.075 (0.240)
Occupation: Craft and related trades workers	-0.427** (0.211)	0.586*** (0.226)	0.014 (0.196)
Occupation: Plant and machine operators, and assemblers	-0.508** (0.219)	0.079 (0.228)	-0.404** (0.200)
Occupation: Elementary occupations	-0.560** (0.222)	0.395* (0.225)	-0.208 (0.206)

Notes: Entries are logit coefficients with clustered standard errors in parentheses (country × industry). All models use EWCTS calibrated weights. Reference categories: Male; Age: 16–24; Education: low; Full-time; Tenure <1 year; Workplace size: working alone; Occupation: Armed forces. Country and industry fixed effects are included in all models but not reported. Source: own elaboration based on merged EWCTS 2021 and IFR 2021 data