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ABSTRACT

We examine the link between the diffusion of artificial intelligence (AI) enabled technologies and changes in the female employment share in 16 European countries over the period 2011-2019. Using data for occupations at the 3-digit level, we find that on average female employment shares increased in occupations more exposed to AI. Countries with high initial female labor force participation and higher initial female relative education show a stronger positive association. While there exists heterogeneity across countries, almost all show a positive relation between changes in female employment shares within occupations and exposure to AI-enabled automation.

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1 Introduction

Technological change transforms the range of activities that workers engage in and typically has distributional consequences. Skill biased technological change during the 1970s and 1980s increased the demand for educated workers at the expense of those with lower levels of formal education (Autor et al. (1998), Autor and Katz (1999), and Acemoglu (2020)), whereas automation technologies widely adopted starting in the 1990s reduced demand for routine jobs in the middle of the wage distribution (Autor et al. (2003) and Goos and Manning (2007)). The effect of these technologies also differ by gender. Mechanization and skill biased technological change favored women due to their comparative advantage in intellectual activities compared to physical labor (Galor and Weil (2000)). Though women were more exposed to the adverse effects of automation (Cortes and Pan (2019), Albanesi and Kim (2021)), their educational advancements and superior interpersonal skills allowed them to gain in employment by shifting to professional occupations, whereas men shifted into lower level service jobs (Cortés et al. (2024)).

The most recent wave of innovation has been driven by the development of artificial intelligence (AI) enabled technologies. These applications are based on algorithms that learn to perform tasks by following statistical patterns in data and generate a general-purpose technology that enables automation of non-routine tasks, both in manufacturing and services. The fast growth and diffusion of these technologies (Agrawal et al. (2018)) has generated an active debate on their potential impact on jobs (Frey and Osborne (2017), and Acemoglu and Restrepo (2020)), particularly in light of the emergence of even more powerful generative AI technologies. A natural question is whether the diffusion of these technologies will have differential impacts by gender.

We quantify the impact of AI-enabled technologies on the female share of employment in 16 European countries between 2011 and 2019.[1] We measure exposure to these technologies using the measures developed by Felten et al. (2019) and Webb (2020). We find that high exposure to AI-enabled technologies substantially increases an occu-

[1]These include Austria (AT), Belgium (BE), Germany (DE), Estonia (EE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), Lithuania (LT), Luxembourg (LU), Latvia (LV), the Netherlands (NL), Portugal (PT) and the United Kingdom (UK).

pation's share of female employment. A rise in exposure distribution of ten percentiles is associated with 2.2-2.9% increase in the share of female employment overall. The positive effect is larger in countries with higher female educational attainment and where women have experienced more gains in education relative to men over the sample period. Additionally, the impact is greater in countries with higher initial female participation. The positive relation between exposure to AI and female employment shares also holds at the country level with few exceptions.

Our findings are consistent with the notion that the diffusion of AI-enabled technologies may benefit women's employment and that this benefit may be amplified by improvements in educational attainment. While there are no studies on the impact of AI on employment by gender in the United States, this pattern is consistent with with Cortes and Pan (2019) and Cortés et al. (2024), who find strong negative correlation between changes in the female employment share and exposure to automation in the United States between 1980 and 2017, due to the movement out of routine occupations and into occupations with high abstract task inputs, bolstered by the rise in women's educational attainment.

2 Exposure to AI by Gender

We measure exposure to AI at the occupation level with two existing measures developed for the United States. The first is the AI Occupational Impact score in Felten et al. (2019). This measure links advances in AI applications, such as finding patterns in data and making predictions about the future, to the abilities required by an occupation. The second measure from Webb (2020) quantifies AI exposure based on the textual overlap of patents from Google Patents Public Data with task based occupation descriptions, such as predicting prognosis and treatment, detecting cancer, identifying damage, detecting fraud. Both measures are based on the U.S. SOC, which we translate to the 3-digit level ISCO using crosswalks from Hardy et al. (2018), and using the classification from the US Bureau of Labor Statistics and from the International Labor Organization, see Albanesi et al. (2024) for details. These measures capture the extent to which occupations could be performed by AI, and can therefore serve as proxies for potential AI-enabled automation.

To understand how exposure to AI varies by gender, we report the female share of employment for occupations by decile of the technology exposure distribution in 2011 and 2019.

The results, displayed in Figure 1, suggest that men and women are not equally exposed to AI. Female shares of employment are relatively high in occupations with mid to high exposure to the Felten et al. measure, suggesting women are more exposed to AI than men. By contrast, the share of female employment is higher in occupations with low exposure to the Webb measure.

3 Analysis

We now explore the relationship between occupations' exposure to AI and the female share of employment in our pooled sample and by country. We report these relationships by means of the coefficients β in the following regression:

$$y_{so} = \alpha_s + \beta X_{so} + \epsilon_{so} \tag{1}$$

Our unit of analysis is a sector-occupation-country cell, so, occupations are categorised according to ISCO-2008 at the three-digit disaggregation level and sectors, s, are grouped into six major aggregates (see Albanesi et al. (2024)).

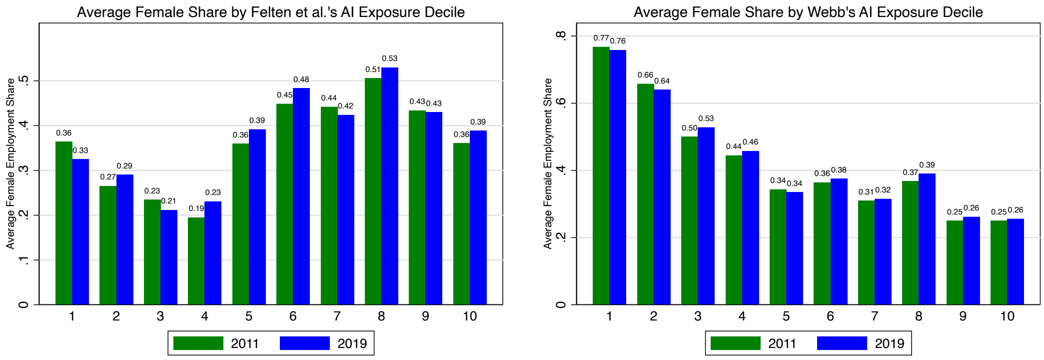
Our dependent variable y_{so} is the percentage change in female share of overall employment in the cell so from 2011 to 2019.[2]

X_{so} captures the relative exposure of the cells to AI. Specifically, we convert the AI measures to employment-weighted percentiles, so that we can interpret our results in terms of workers, using the employment in each cell in the initial year of the sample as weights. This transformation also allows us to compare our results with other results in the literature, such as Webb (2020), Albanesi et al. (2024). The estimated β coefficient measures the potential impact of AI-enabled automation on changes in the female employment shares

Higher exposure to AI with both measures is associated with an increase in the cells' share of overall female employment. On average, moving up 10 centiles along the

[2]Calculated relative to the midpoint This is a second-order approximation to the log change for growth and used in related literature to deal with entry and exit of units of observation, see for example Davis et al. (1996) and Webb (2020).

Figure 1: Average Female Employment Share By Technology Exposure Deciles



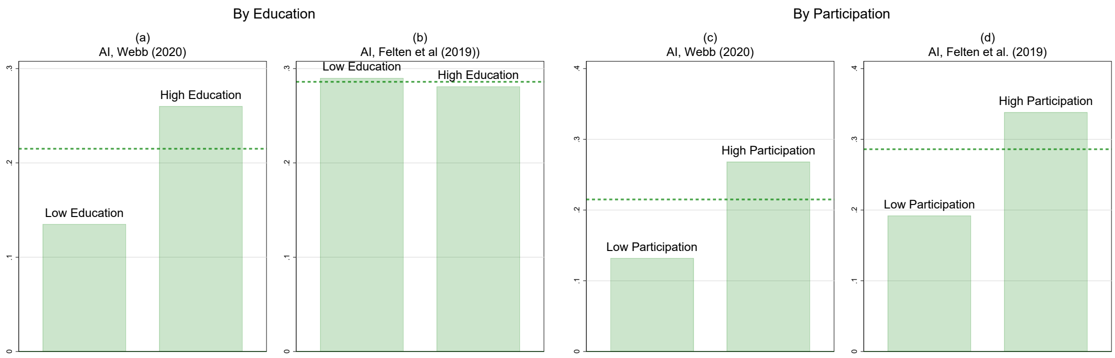
Notes: Plots show the 2011 and 2019 occupation-sector cell's average level of female employment share, all by technology exposure decile of the respective cell. Data are winsorised at the top and bottom 1 percent with respect to income.

distribution of exposure to AI is associated with an increase in the female employment share in the cell of 2.2% for the Webb measure and of 2.9% for the Felten et al. measure. These estimates are approximately double than for the total employment share, in Albanesi et al. (2024). Also, the statistically positive association between AI exposure and the female employment share is more robust across occupations than the association between the total employment share and exposure to AI, which was largely driven by professional occupations (see Table 3 in the Appendix).

Educational attainment is an important factor for the impact of new technologies on employment, with highly educated workers most likely to reap any benefits in employment from the diffusion of new technologies (Albanesi et al. (2024)). Given the large variation in women's educational attainment in our sample (see Table 1 in the Appendix), we stratify the results by countries' average female educational attainment. We find a stronger association between exposure to AI-enabled technologies and the female share of employment for countries that have experienced greater increases in female education attainment. In those countries, moving 10 centiles up along the distribution of exposure to AI is estimated to be associated with an increase of sector-occupation female employment share of 2.7% using Webb's exposure measure, and of 3.4% using the measure by Felten et al., as seen in Panels (a) and (b) in Figure 2.[3]

[3]Table 2 in the Appendix also reports estimates by female educational attainment relative to the U.S., with a stronger positive association between AI exposure and female employment share for both

Figure 2: Exposure to AI and changes in female employment shares, by Female Participation and Education



Notes: Regression coefficients measuring the association between exposure to technology and changes in the female employment share. Each observation is an ISCO 3-digit occupation times sector cell. Observations are weighted by the average labor supply in the cell. Industry and country dummies included. Sample: 16 European countries, 2011-2019. The coefficient for the full sample is indicated by the horizontal dashed line. The bars in panels (a) and (b) show the coefficient estimated for the subsample of countries according to the average change between 2011 and 2019 in women's educational attainment relative to that of men in the same country. The bars labeled High Education show the results for the group of countries with a high relative increase in women's educational attainment, while those labeled Low Education show the results for the group of countries where the relative increase in women's educational attainment is lower than the average of all countries in the sample. The bars in panels (c) and (d) show the estimated coefficient for the subsample according to the women's participation rate in 2011. Low/high participation countries are those where female participation in 2011 was lower/higher than the average for all countries in the sample. Full results are in Table 2 in the Appendix.

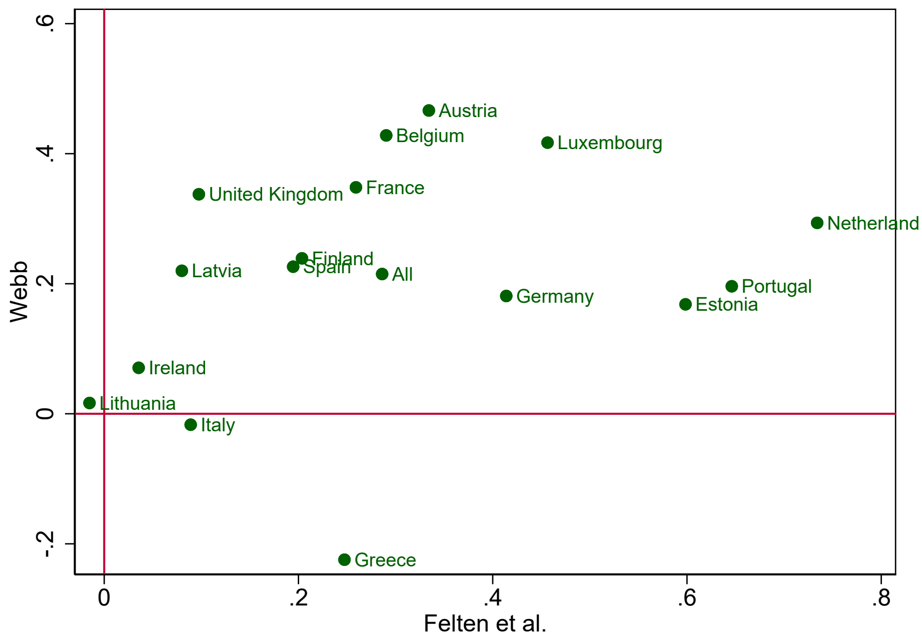
Labor market attachment is also an important factor in the response to economic shocks, with higher participation associated with higher employment rates and lower unemployment rates for women (Albanesi and Şahin (2018)). In our sample, countries with lower initial levels of female participation exhibit stronger positive trends in female employment growth (see Table 1 in the Appendix). This underlying trend could affect female employment shares independently of AI exposure. To account for this potential confounding effect, we stratify our analysis based on women's labor force participation rates in 2011. Our findings indicate that the association between the female share of employment and AI exposure is stronger in countries with high initial levels of female participation for both measures of AI exposure, as shown in Panels (c) and (d) of

measures for countries with higher relative female education.

Figure 2. This pattern suggests that greater attachment to the labor force enables women to minimize any displacement effects associated with the diffusion of these technologies and the positive association between female employment share and AI exposure is not mechanically driven by faster growth in women's employment in lower initial participation countries.

Figure 3 displays the country level results, with regression coefficients for the Webb measure on the vertical axis and those for the Felten et al. measure on the horizontal axis. There is a large cross-country variation in the association between exposure to AI and the female employment share, but almost all countries show positive coefficients. Despite the differences in exposure by gender across the two measures, the changes in female employment shares associated with exposure are positively correlated. The Netherlands, Portugal and Estonia show the largest coefficients according to the Felten et al. measure, while Austria, Belgium and Luxembourg show the largest coefficients for the Webb measure.

Figure 3: Exposure to AI and changes in female employment shares, by country



Notes: βc and β coefficients from employment shares regressions. See notes in Table 2.

4 Conclusions

Our results are consistent with the idea that the diffusion of AI-enabled technologies can benefit female employment, and that this benefit is amplified by higher levels of education. Moreover, the finding that the positive association between female employment share and exposure to AI-enabled technologies is stronger in countries with higher initial female labor force participation suggests that greater labor force attachment and work experience enable women to minimize any displacement effects associated with the diffusion of these new technologies. These findings also support the notion in UNESCO (2022) that educational credentials are crucial for harnessing any beneficial impacts of AI for female employment.

Acemoglu et al. (2022) show that older workers are employed in occupations that differ from younger workers in many ways, and that AI seems to have the potential to create an 'age-friendly work environment'. Similarly, our findings suggest that AI also has the potential to promote gender-friendly jobs.

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Appendix

Table 1: Education and Participation Rates

	Education				Participation			
	2011		2019		2011		2019	
	Female	Gap to Male	Female	Gap to Male	Female	Gap to Male	Female	Gap to Male
Austria	11.3	-0.9	12.7	0.1	72.4	-10.8	75.8	-9.5
Belgium	11.2	-0.5	12.3	-0.1	66.1	-12.4	69.9	-9.1
Estonia	13.8	0.8	14.0	0.8	77.5	-6.9	81.5	-5.4
Finland	12.6	0.2	13.1	0.4	75.5	-5.7	78.8	-4.6
France	10.6	-0.5	11.4	-0.4	72.1	-8.4	75.4	-6.7
Germany	13.5	-0.9	13.9	-0.6	74.1	-11.3	77.5	-8.8
Greece	10.0	-0.7	10.8	-0.7	61.4	-22.1	65.1	-18.0
Ireland	11.2	0.4	11.8	0.5	68.4	-15.0	71.9	-13.6
Italy	9.7	-0.5	10.5	-0.3	54.7	-22.8	60.5	-20.0
Latvia	12.9	0.6	13.6	0.7	75.5	-7	80.0	-5.3
Lithuania	12.5	-0.1	13.5	0.2	76.5	-5.4	82.1	-2.9
Luxembourg	12.5	-0.7	13.0	0.0	65.9	-15.2	71.9	-9.7
Netherlands	11.7	-0.6	12.2	-0.5	75.9	-11.3	79.7	-9.0
Portugal	8.3	0	9.4	0.1	72.1	-9.6	77.6	-6.3
Spain	9.3	-0.4	10.3	-0.2	71.3	-13.9	73.7	-10.5
United Kingdom	13.1	-0.2	13.4	0.1	71.7	-13.5	76.6	-9.8
Average	11.51	-0.25	12.24	0.01	70.69	-11.96	74.88	-9.33

Source: Eurostat, OECD and UNDP, Human Development Report (2024). Participation rates for the age group 20-64.

Table 2: Change in female employment vs. Exposure to technology. 2011_19. Countries' subsample by female initial participation in the labor market and by educational attainment

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
AI, Webb	0.215***	0.160**	0.263***	0.132	0.268***	0.260***	0.135*	0.250***	0.181**
	(0.041)	(0.078)	(0.036)	(0.088)	(0.032)	(0.044)	(0.079)	(0.038)	(0.071)
Observations	4763	2081	2682	1753	3010	3059	1704	2191	2572
AI, Felten	0.286***	0.194***	0.358***	0.192***	0.338***	0.281***	0.293***	0.335***	0.235***
	(0.043)	(0.051)	(0.059)	(0.059)	(0.054)	(0.050)	(0.081)	(0.066)	(0.053)
Observations	3922	1716	2206	1443	2479	2520	1402	1798	2124
Observations	3922	2107	1815	2520	1402	823	1301	1053	745

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. ** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country change in female employment in each cell over country's total employment from 2011 to 2019, winsorised at the top and bottom 1 per cent. Sample: 16 European countries, 2011-2019. Column (1) presents the estimated β coefficient for the full sample of countries. The remaining columns group countries by female educational attainment and female labor market participation. The subsample in columns (2) to (5) is based on female labor market participation in the starting year of the sample, 2011. Column (2) shows the estimates for countries in the sample where female participation relative to male participation in 2011 was lower than the average for all countries in the sample, and (3) for those countries where relative female participation was higher than the sample average. Columns (4) and (5) divide the countries according to the level of female participation also in 2011, (4) showing the results for countries where female participation is lower than the average for all countries in the sample and (5) for countries where female participation was higher than the average. The classification of countries in columns (6) to (7) groups countries according to the average change between 2011 and 2019 in women's educational attainment compared with that of men in the same country. Column (6) shows the results for the group of countries with a high relative increase in women's educational attainment, while column (7) shows the results for the group of countries where the relative increase in women's educational attainment is lower than the average of all countries in the sample. The classification of countries in columns (8)-(9) is based on the level of female education in the country compared to the US in 2011. The sample of countries in column (8) consists of those where female education in 2011 is within 1 standard deviation of that in the US, while column (9) includes those where female education in 2011 is at least 2 standard deviations lower than in the US. Educational attainment is measured as the average number of years that adults aged 25 and over have participated in formal education.

Table 3: Change in female employment vs. Exposure to technology. 2011_19. Occupations

	(All)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI, Webb	0.215***	0.222***	0.112**	0.216***	0.183***	0.221***	0.236***	0.200***	0.263***	0.232***
	(0.041)	(0.043)	(0.047)	(0.047)	(0.041)	(0.042)	(0.043)	(0.042)	(0.038)	(0.046)
Observations	4763	4301	3627	3897	4242	4240	4647	4340	4439	4371
AI, Felten	0.286***	0.291***	0.166***	0.303***	0.286***	0.307***	0.280***	0.278***	0.275***	0.344***
	(0.043)	(0.042)	(0.054)	(0.044)	(0.044)	(0.047)	(0.043)	(0.042)	(0.046)	(0.058)
Observations	3922	3499	2959	3064	3764	3477	3803	3499	3736	3575

Notes: Linear regression. Robust standard errors in parentheses, two-way clustered by country and sector. ** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each observation is a ISCO 3 digits occupation times sector cell. Observations are weighted by cells' average labour supply. Sector and country dummies included. Dependent variable: within country change in female employment in each cell over country's total employment from 2011 to 2019, winsorised at the top and bottom 1 per cent. Sample: 16 European countries, 2011-2019. Column named (All) includes the whole sample. The rest of the columns exclude occupations in one of ISCO major groups. Column named (1) excludes managers; (2) excludes professional; (3) excludes technicians; (4) excludes clerical support workers; (5) excludes services and sales workers; (6) excludes skill agriculture, forestry and fishing; (7) excludes craft workers; (8) excludes plant and machine operators; and (9) excludes elementary occupations.