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Robots and Women in Manufacturing Employment

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Abstract

Automation transforms the combination of tasks performed by machines and humans, and reshapes existing labour markets by replacing jobs and creating new ones. The implications of these transformations are likely to differ by gender as women and men concentrate in different tasks and jobs. This article argues that a gender-biased technological change framework will advance our understanding of the differentiated role of robots in labour market outcomes of women and men. The article empirically analyses the impact of industrial robots in gender segregation and employment levels of women and men using an industry-level disaggregated panel dataset of 11 industries in 14 developed and developing countries during 1993-2015. Within fixed-effects and instrumental variables estimates suggest that robotization increases the share of women in manufacturing employment. However, this impact hinges upon female labour force participation. As female labour participation rate increases, robots are associated with a negative effect of robotization in the female share of manufacturing employment. Results also show that the impact of robotization varies at different levels of economic development. The estimates point to a reducing employment effects of robotization, although the effect for women is larger. The results are robust to a variety of various sensitivity checks.

JEL codes: C23, F16, J16, F14

Keywords: Gender-biased technological change, robotization, manufacturing employment, gender industrial segregation

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INTRODUCTION

Technological change and the automation of work are shifting the frontier between tasks performed by humans and those performed by machines, growing concerns about its impact on labour markets (Brynjolfsson and McAfee, 2014; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Industrial robots[1] have advanced rapidly since the 1990s and are mainly put to work in the manufacturing sector. However, robotization affects sectoral employment differently since industries are at varying levels of exposure to automation due to different compositions of routine and non-routine tasks and manual and analytical tasks (Autor et al., 2003; Reijnders and de Vries, 2018; Dauth et al., 2017; Acemoglu and Restrepo, 2020). Against this backdrop, occupations and industries are overwhelmingly segregated by gender through history, where manufacturing shows a remarkable male domination (Goldin, 2014; England et al., 2020). Women tend to concentrate in industries and perform tasks that are more prone to automation (Brussevich et al., 2019; Tejani and Kucera, 2021). Yet the net effect of robots and artificial intelligence (AI) in employment can be either negative, neutral or positive (Graetz and Michaels, 2018; Hamaguchi and Kondo, 2018), its impact can be different for female and male employment.

Technological upgrading in the form of labour productivity gains is associated with the defeminization of manufacturing employment (Kucera and Milberg, 2000; Tejani and Milberg, 2016; Seguino and Braunstein, 2019; Tejani and Kucera, 2021). At the same time, robotization has been found to impact on gender wage gaps (Ge and Zhou, 2020; Aksoy et al., 2021). In this article, I merge these two strands of the gendered impacts of technological change to study gender differences in the employment effect of robotization. I propose a gender-biased technological change framework by which robotization can interplay with gendered labour markets to influence industrial gender segregation in manufacturing.[2] Gender skill differentials and stereotypes about gendered aptitudes can mediate to both drive the adoption of robots in female-dominated industries, and at the same time, the share of women in increasingly automated industries. Understanding the causal direction and magnitude of these mechanisms, specifically in the economic and social aftermath of the COVID19 pandemic (Collins et al., 2021), is crucial to correct for the gendered imbalances in the composition of the workforce.

[1]The International Federation of Robotics (IFR) defines industrial robots as "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications."

[2]Gender segregation exists along a vertical or occupational axis and along a horizontal or industrial axis. Industrial gender disparities do not clearly define hierarchical structures relative to occupational disparities, and thus could be less easily undermined (Goldin, 2006).

I estimate the impact of industrial robots in the share of women in manufacturing employment using industry-level disaggregated panel dataset of 11 industries operating in 14 countries over the period 1993-2015. Further, I surmise that the role of robotization in female share of manufacturing employment hinges upon the country-level participation of women in the paid workforce. The incorporation of women in the labour market came along with a ”crowding out” effect in services sector of female employment (Ngai and Petrongolo, 2017; Seguino and Braunstein, 2019) and the defeminization of manufacturing employment (Tejani and Milberg, 2016; Kucera and Tejani, 2014). Thus, the direction and the intensity of the impact of robotization in female manufacturing employment can thus vary at different levels of female labour force participation. These hypotheses are empirically tested by specifying hierarchical and interactive regression equations combining country-industry observations and country-level macroeconomic indicators during a period of time, and allowing the effect of robotization in female employment vary at different levels of female labour force participation.

The contribution of this article is three-fold. First, I add to the growing literature on the labour market consequences of automation (Frey and Osborne, 2017; Brynjolfsson and McAfee, 2014; Acemoglu and Restrepo, 2020) by focusing specifically in gender differences in the way robots impact in manufacturing employment. Second, I expand existing works on the links between robots and gender wage gaps (Brussevich et al., 2019; Aksoy et al., 2021; Ge and Zhou, 2020) and labour force participation (Grigoli et al., 2020) by using an industry-level disaggregated panel data approach. Finally and more specifically, I complement the literature on the effects of technological change and deindustrialization in the defeminization of manufacturing. I add to the econometric approaches in Seguino and Braunstein (2019), who use a country-level panel data, and Tejani and Kucera (2021), who pool industry-level panel data across countries, in in including the role of robots, as a manner of technological innovation, while controlling for their focal variables, namely capital-labour ratio and labour productivity growth.

The remainder of the text is structured as follows. Section 2 proposes a gender-biased technological change approach. Section 3 explains the dataset and descriptives. Section 4 presents the econometric model while Section 5 brings the results. Section 6 concludes.

GENDER-BIASED TECHNOLOGICAL CHANGE

Background

Historically, sectors have faced processes of automation that produce large substitutions between human labour and capital-intensive inputs or machines (Brussevich et al., 2019). Current automation trends differ from previous ones insofar the ability of machine learning and AI further expands the set of activities more efficiently performed by machines than by humans (Brynjolfsson et al., 2018). Despite the growing body of research, there is still a lack of consensus on the ultimate effects of automation.[3] The employment effects of automation thus depend on the degree of replaceability or complementarity of robots with workers' skills, whether these skills are real or perceived. In that respect, the skill-biased technical change (SBTC) hypothesis suggests that new technologies will increase highly skilled workers' demand (Card and DiNardo, 2002). Recent contributions to the SBTC hypothesis show that skill-biased technologies reduce the number of hours and works differently on a migrant status basis, thus posing a challenge for employment development and equality of access to it of different groups of workers (Hutter and Weber, 2021; ten Berge and Tomaskovic-Devey, 2021). A gender-biased technological change approach can contribute to this general literature by providing stylized facts on gendered labour market outcomes and disentangle the complex interplay between technological innovations and occupationally and industrially gender segregated labour markets. In this article, I use this framework to estimate the impact of robots in industry-level displacement of female employment.

The gender differentials in job displacement effects of robotization are far from clear. On the one hand, women outnumber men in higher education, and thus, can dominate skilled positions (Blau and Kahn, 2017). On the other hand, women are less likely to major in technical-related fields of education, limiting their opportunities in the digital era (Brussevich et al., 2018; Frenette and Frank, 2020). The female over-representation in retail sales or office support occupations can make women more susceptible to automation. Nonetheless, other female-dominated occupations and industries, such as the care sector which is difficult

[3]Works on the labour market impacts of automation show alternative results for different sample countries and types of workers (Frey and Osborne, 2017; Brynjolfsson and McAfee, 2014; Acemoglu and Restrepo, 2020). While Graetz and Michaels (2018) find that robotization spurs labour productivity and wages without influencing employment, other works find that automation reduces routine manual jobs and alters the employment industrial composition displacing manufacturing employment (Dauth et al., 2017; De Vries et al., 2020). Jung and Lim (2020) find that industrial robots tends to suppress employment growth, confirming the labor-substituting effect of industrial robots, with disproportional affects for low-skilled labour.

to automate, are less vulnerable to the increasing use of industrial robots. On average, women perform more routine tasks than men across all sectors and occupations, which are those more prone to automation (Brussevich et al., 2019; Frenette and Frank, 2020). Moreover, women perform fewer tasks requiring analytical input or abstract thinking (e.g., information-processing skills), where technological change can be complementary to human skills. This article considers this puzzle by estimating the role of industrial robots in the female share of manufacturing employment using an industry-level panel data approach.

Previous literature shows a causal link from robotization to gender differences in employment and wages. Brussevich et al. (2019) employ data on advanced and emerging economies to show that women are significantly at higher risk for displacement by automation. To the contrary, Acemoglu and Restrepo (2020) show that exposure to robots is related with a negative effect on employment for both women and men, although it is higher for men in the US labour market. Also for the US, Cortes and Pan (2019) explore the interplay between skills and gender impacts of automation, and find that women experience larger employment displacement in the middle of the skill distribution relative to men. Apart from the gendered impact of automation in job displacement, robotization is also associated with gender wage gaps. Aksoy et al. (2021) relate industrial robots with an increasing gender wage gaps in 20 European countries, whereas Ge and Zhou (2020) industrial robots are found to reduce gender pay gaps but computer capital increases gender wage gap using a panel dataset of US local labour markets. Importantly, Hamaguchi and Kondo (2018) show that what matters is gender gaps in skill utilization, rather than skill gap itself, and argue that gender is a crucial aspect to consider when studying AI's employment effects. A common feature of these works is cross-country heterogeneity in gendered implications of the automation of work.

Robots and Women in Manufacturing

Robotization might reduce the share of women in manufacturing employment through different channels mediated by, among other macroeconomic settings, educational segregation and hiring-decisions, structural transformation and gendered labour markets. The lack of women in technical fields of education (Blau and Kahn, 2017) can couple with the rise of demand for technical skills due to the robotization of the production function to reduce female employment in manufacturing. The pre-existing gender segregation in both educational systems and labour market can limit the complementary skills of female workers with new technologies. At the same time, hiring decisions can be influenced by perceived skills or gender stereotypes about technical skills (Seguino and Braunstein, 2019; Tejani and Kucera, 2021), even in the absence of gender differentials in real skills. Robotization of the production function happened within gendered institutions, as the labour market, where gender discriminatory practices are rampant. Persisting gender essentialist ideals of male superiority in technical and mathintensive skills and female advantage in nurturing and care-related skills might perpetuate a traditional gender division of labour Charles and Bradley (2009), and block the access of women to technological-intensive employment. Complementary jobs to robotization can thus be located for men, while substitution effects can displace female jobs in manufacturing due to discriminatory hiring practices based on perceived skill differentials between women and men. This mechanism by which technological upgrading, measured by labour productivity growth or capital-labour ratio, reduces female shares of manufacturing employment (Kucera and Tejani, 2014; Seguino and Braunstein, 2019; ten Berge and Tomaskovic-Devey, 2021).

Structural change and the participation of women in the workforce can also mediate the impact of robotization in the female share of manufacturing employment. The increasing participation of women in the labour market and process of modernization and marketization of household production had led to a feminization of the service sector. Specifically, the care sector has crowded female employment. Structural changes can set into motion gendered process, as for instance the U-shaped relation between female labour force participation and economic development in the U.S. that came together with first a decline in agricultural employment, and second, a rise of the service employment (Goldin, 1994). Although social norms around and stigma attached to women working in manufacturing jobs shifted dramatically after the 1950s (Dinkelman and Ngai, 2022), other gender gaps in preferences can emerge to reduce the presence of women in male-dominated sectors or occupations Falk and Hermle (2018); England et al. (2020).

Complex interplays between gendered labour markets and skill-biased adoption of industrial robots can limit the share of manufacturing employment with relatively better working conditions and wages than other jobs in agriculture and service sector (Seguino and Braunstein, 2019). In addition to that, the process of deindustrialization as part of the structural transformation can increase the competition for manufacturing jobs (Rodrik, 2016). The relatively lower female labour market attachment and higher unpaid care work burden (Charmes, 2019) can intensify the stratification of the labour market by which women play a secondary role in the workforce.

Finally, one might argue that gender can play a pivotal role in both the employment impact of robotization and the adoption of robots by industries, which might incur in reverse causation issues in the specifications below. As women tend to major in non-technical fields of study and be employed in lower hierarchical occupations, it could be plausible that the adoption of innovations differ in female and male-dominated industries. At the same time, the adoption of robots can influence hiring decisions governed by gender traditional views of capabilities, to reduce the access of women to manufacturing employment in the event of technological upgrading/robotization. This article makes the case of the latter direction of the causal link, and thus, assumes that the adoption of robots affects the level of women employed at industry levels. Nevertheless, to reduce causality issues in the estimates, the article uses instrumental variables as performed in the reference literature (Graetz and Michaels, 2018; Ge and Zhou, 2020). Specifically, I focus on the case of manufacturing industries, since robots are mainly employed in the manufacturing sector to perform tasks such as assembling, painting and welding.

DATA AND DESCRIPTIVE STATISTICS

I build an unbalanced panel dataset with information on 11 industries from 14 developed and developing countries[4] during 1993-2015 with information on industrial statistics, robot penetration and trade data at industry level, along with country-level data. This research employs six different data sources to obtain country-industry level disaggregated data, namely the United Nations Industrial Development Organization (UNIDO) INDSTAT 2 2021 at 2-digit level Industrial Statistics International Classification (ISIC) revision 3, the International Federation of Robotics (IFR) ISIC revision 4, the United Nations Statistical Division (COMTRADE) Standard International Trade Classification (SITC) revision 2, and data on instrumental variables collected from Graetz and Michaels (2018). These country-industry observations are merged with two data sources at country-level information collected from the World Bank and the International Labour Organization (ILO).

The variables collected from the UNIDO INDSTAT database provide statistics on 23 ISIC 2-digit level manufacturing industries by country and year, such as output, value added, gross fixed capital formation, employees, female employees, wages and salaries, and number of establishments.[5] As of data on automation, the IFR database is the best accessible source of data on robots (Ge and Zhou, 2020), which complies survey information on industrial robots at country and industry levels, annually starting from 1993. In this article, I use IFR data on industrial robots to measure the extent of automation by country and industry during the period at scrutiny. It provides information at industry level, and with a higher level of disaggregation

[4]The countries included in the sample are Bulgaria, Croatia, India, Indonesia, Japan, Kuwait, Lithuania, Malaysia, Malta, Mexico, Morocco, Philippines, Turkey and Vietnam.

[5]As noted in Rodrik (2013), UNIDO information on industrial statistics database is derived largely from industrial surveys which exclude microenterprises and informal firms. Thus, the results below might not be universally valid across all types of manufacturing activities, but to the organized, formal parts of manufacturing.

for manufacturing. The COMTRADE database provides information on raw trade data on goods which I merge at industry level in the database constructed for the econometric analysis below. Finally, I collect data from Graetz and Michaels (2018) on replaceable hours and reaching and handling tasks at industry level.[6] To maintain consistency in the classification of industries across different data sources, I combine the 23 ISIC 2-digit level industries from UNIDO into 11 industries.[7] Figure 1 shows the mean values of industrial robots and share of women employed in each industry for the period 1993-2015. There is a great heterogeneity in the use of industrial robots and the presence of women. ”Automotive” and ”Electrical/electronics” are the industries that employ more industrial robots, while their employees are respectively, 20% and 40% women. The industry that employs women to a greater extend is ”Textiles” with a low use of industrial robots. Nonetheless, there is an important heterogeneity in the trends and magnitude in both automation and defeminization in the industries and countries in the sample. Figures A2 and A5 in Appendix show the evolution of automation and share of women by each industry and country, respectively. Sample average evolution of industrial robots and share of women are displayed in Figures A3 and A4, respectively, in Appendix.

Figure 1 here

EMPIRICAL STRATEGY

I specify the following econometric model to identify the causal role of industrial robots in female employment shares at country-industry and time level. The database is therefore a three-way panel dataset that pools observations by industry (i), country (c) and year (t).

$$\begin{aligned} f_{ict} &= \beta_0 + \beta_1 robots_{ic,t-1} + \beta_2 FLFP_{c,t-1} + \beta_3 robots * FLFP_{ic,t-1} + X'_{ic,t-1} + Z'_{c,t-1}\beta + v_{ict} \\ v_{ict} &= \omega_i + \delta_c + \gamma_t + \epsilon_{ict} \\ i &= industry; c = country; t = year; \end{aligned} \tag{1}$$

[6] It should be clarified that due to the different classification of industries in the database here employed and in Graetz and Michaels (2018), there are two industries for which I do not have data, which are ”Other transport equipment” and ”All other manufacturing branches.”

[7] I draw on Klump et al. (2021) and M Affendy et al. (2010) along with Eurostat RAMON correspondence tables to combine an accurate the industrial classification `https://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL`

where f_{ict} is the share of women in industry i, country c and year t, which is computed as the ratio of the number of women in industry i by total employment in that industry i.

Explanatory Variables

The set of explanatory variables is composed primarily by $bots_{ic,t-1}$, which is the number of industrial robots by industry, country and year, and $flfp_{c,t-1}$, that is the ratio of female labor force participation (FLFP, hereafter) by country and year. [8] Recall that FLFP does not vary across industries within a country and year, hence is a country-level variable. Importantly, the econometric model in Equation 1 includes the interaction between industrial robots and FLFP to explore whether the impact of robotization in female shares by industries hinges on the participation of women in the paid workforce ($bots * flfp_{ic,t-1}$). Notice that the explanatory variables in the specification are one-period lagged in order to circumvent reverse causation biases in the estimates.[9]

Control Variables

Some of the specifications above include industry-level ($X'_{ic,t-1}$) and country-level ($Z'_{ic,t-1}$) controls. The set of industry-level control variables includes the share of employees in industry i to total manufacturing employment and gross fixed capital formation to consider whether the relative importance of an industry in the total manufacturing sector plays a role on the feminization of employment. Real wages and salaries are included to account for varying levels of bargaining power in different industries. Female manufacturing employment is usually crowded into low value-added industries, and thus, women have limited bargaining power (Tejani and Kucera, 2021). Finally, the set of industry-level covariates includes the share of industry i in manufacturing exports of goods. Exposure to international trade at industry-level is an important factor to control for since previous research finds gender bias in the employment effects of the expansion of international trade (Kucera and Milberg, 2000).[10]

[8] One might consider the adjustment of industrial robots conducted in Acemoglu and Restrepo (2020) or Ge and Zhou (2020). Due to limited data availability at industry level for employment in 1990, that adjustment cannot be conducted in the regression analysis here, and rather, I conduct yearly panel data models.

[9] Specifications using longer lags of the independent variables confirm the results of the article, and are available upon request.

[10] Globalization and defeminization of manufacturing has been widely studied in the reference literature, providing empirical evidence on that trade openness can lead to feminization by means of hiring cheap labour due to competition forces. The so-called

The set of country-level controls includes firstly a measure of deindustrialization. Premature deindustrialization characterizes the conversion towards service economies without having had a proper experience of industrialization, with crucial economic consequences such as the loss of good jobs, rising inequality, and declining innovation capacity (Timmer et al., 2015; Rodrik, 2016). It is likely to amplify the male bias of industrial upgrading, as the scarcity of industrial jobs might couple with stereotypes and discrimination to reduce the presence of women in manufacturing employment (Greenstein and Anderson, 2017; Seguino and Braunstein, 2019). The country-level control variables set includes also the share of women in the manufacturing to capture whether the general presence of women in the sector can cause a less gender segregation within industries. Per capita GDP annual growth rate is included on the assumption that higher levels of economic development might ease job competition and provide better access of women to jobs of quality (Seguino and Braunstein, 2019). Foreign direct investment (FDI), together with tariffs weighted in manufacturing are also included as proxies of the global integration of the economy and country trade policy. Finally, the specification in Eq. 1 includes industry fixed effects, ω_i, country fixed effects δ_c and time fixed effects γ_t, and the error term ϵ_{ict}. The models are first estimated using a within fixed effects model that corrects for cross-sectional and temporal correlation, although an instrumental variable strategy is also used to solve for reverse causation from female share in manufacturing towards the adoption of robots at industry level. Table A1 in Appendix provides mean values on industrial robots, share of women in manufacture industries and FLFP for the sample of countries. Table A2 provides information on the source of data for each variable, while Table A4 shows the time coverage at country level.

Cross-sectional and Temporal Dependency

Robot adoption in a country can unleash spillover effects in employment of neighbouring countries.[11] Faber (2020) shows sizeable negative impacts from US robotization on employment in Mexico. Along similar lines, the linkages between trade openness and defeminization of manufacturing (Tejani and Milberg, 2016) can also impose cross-dependency biases in the estimates. All these accounts for the necessity to use tech-

Wood (1991)'s asymmetry suggests that trade between developed and developing countries is increasing female employment in developing countries and had no noticeable negative symmetric effect on female employment in the traded-goods sector of developed countries. Nonetheless, evidence suggests that technology is a more decisive factor in changing employment structure and drive inequality and job polarization than international trade David and Dorn (2013); Goos et al. (2014). Indeed, technological upgrading is associated with greater effects in the shifts of female employment than globalization (Tejani and Milberg, 2016)

[11]Macroeconomic panel data are likely to be characterized by cross-sectional or spatial dependence, for which Driscoll and Kraay (1998) developed a estimator that computes alternative standard errors to alleviate such issues.

niques that at the very least, alleviate for cross-sectional endogeneity sources since ignoring cross-sectional correlation in the estimation of panel models can lead to severely biased statistical results (Hoechle, 2007). To do that, I employ Driscoll and Kraay (1998)'s standard errors in the specifications below. The estimates are thus well calibrated in the presence of cross-sectional or time dependence. I follow Hoechle (2007) to perform the adjusted Hausman test robust to spatial and temporal dependence, which justifies the use of fixed effects models in the panel dataset here used.

Instrumental Variables

One important limitation of the econometric specification in Eq. 1 is caused by potential reverse causation between women in manufacturing employment and robotization, as technological innovation is found to be driven by labour (Jung and Lim, 2020). Previous research found that technological innovation is generally affected by the skill distribution of workers (Acemoglu and Autor, 2010) and employment structure within firms (McGuirk et al., 2015). Specific to the regression equation 1 is the role of women in employment as a factor of robotization of industries. Female share of employment at industry levels can be influenced by industry-specific policies that try to involve more women in those industries, or country-level policies focus to reduce industrial segregation and gender equality in the labour market. This in turn, can affect both hiring decision and the adoption of robots (Aksoy et al., 2021). Alternatively, firms may adopt robots in response to economic shocks at both country and industry levels, which can further affect the gendered hiring decisions.

I collect data from Graetz and Michaels (2018) to conduct an instrumental variables strategy similar to related literature (De Vries et al., 2020; Aksoy et al., 2021). Graetz and Michaels (2018) provides two industry-specific instruments, namely *replaceable hours* and *reaching and handling tasks*.[12] The first instrument is the share of labour input that can be replaceable by robots at industry level and was computed by Graetz and Michaels (2018) using the IFR data in 2012 and information on the distribution of hours across occupations and industries from the 1980 U.S. Census, dating back to the rise of robotization. They identified those occupations that could have been replaced by robots in 2012, and the occupational distribution by industry in 1980, to provide an industry-level replaceability measure. The other instrument provided in Graetz and Michaels (2018) is a measure of the prevalence of the reaching and handling tasks, which are

[12] In this manuscript, I present results using the replaceable hours instrument. Specifications using the reaching and handling tasks instrument yield similar results. Using specifications that combine both instruments also provide similar results, although this comes at the cost of a great number of observations. In any case, these results are available upon request.

typically performed by industrial robots, were in each industry, relative to other physical demands, prior to 1980. In the analysis below, I employ as the main proxy for industrial robots the variable replaceable hours because, as suggested in Aksoy et al. (2021), reaching and handling tasks, the other instrument available, can be less relevant in current robotization patterns than in the period considered in Graetz and Michaels (2018) (1993-2007). Current robots' capabilities trends are more oriented towards precision, added functionalities or increased automatability (of Robotics, 2018; Aksoy et al., 2021).

The instruments in Graetz and Michaels (2018) are not free from limitations. Firstly, as already suggested in De Vries et al. (2020), these instruments are based on US data and thus they might differ if constructed using data from other countries. Secondly, the data do not vary across time, and thus do not allow for controlling for country and industry heterogeneity across time.[13]

Omitted Variable Bias

Finally, other sources of endogeneity can be caused by omitted variable biases in the specification in Eq. 1. To alleviate this issue, I specify augmented regression equations that control for a variety of possible demand-side and supply-side factors behind the share of women in manufacturing industries' employment. These specifications can serve as sensitivity checks of the baseline regression equation.

RESULTS

Table 1 presents fixed effects within estimates and instrumental variables results on link between robotization and female share of manufacturing employment at industry level. The results generally associate industrial robots with a negative effect on female share which depends on the overall participation of women in the labour market. Estimates in Column 1 (Table 1), that include the baseline regression equation with industry-level controls, and Column 2 which adds FLFP, associate industrial robots with an increasing share of women in manufacturing employment. Previous attempts using demographic cells by occupations and industries failed to associate a significant role of industrial robots in the gender composition of workers (Aksoy et al., 2021). Here I use a higher level of data disaggregation and a focus on manufacturing industries to provide some evidence on a significant role of robots in the gender distribution of manufacturing

[13] Bekhtiar et al. (2021) provides an in-depth discussion of the instruments of Graetz and Michaels (2018)

employment.

I find a a positive effect of robotization in the share of women in manufacturing can be explained by the type of robots implemented, which could be complementary to the type of tasks undergone by women at country-industry levels. An explanation behind this preliminary result is that industrial robots, relative to other computer-assisted technologies, are not directly complementing high-skill workers (Acemoglu and Restrepo, 2020). Thus, as women are under-represented in the high-skill workforce, this can lead to an increasing effect of robotization in the share of women in the manufacturing. This positive effect goes also along the lines of the results in Ge and Zhou (2020), that associate industrial robots with a reducing gender wage gap in the U.S.

The subsequent specifications in Table 1 suggest that FLFP and its interaction with automation are significant factors of the dependent variable, and thus, should be accounted for to estimate the ultimate effect of robots in women in manufacturing. Column 3 includes the interaction between industrial robots and FLFP, which is statistically significant. Thus, the female employment effect of robotization varies at different levels of FLFP. Column 4 includes country-level control variables. Columns 5 and 6 replicates the regression equations estimated in Columns 3 and 4 respectively, but address potential endogeneity issues through the use of instrumental variables. Using replaceable hours to instrument industrial robots in the first stage, the F-statistics corroborates the suitability of the instrument.

TABLE 1 here

The estimates in Table 1 associate one standard deviation (s.d.) increase in robotization with a 0.034 to 0.036 s.d. increase in female employment when the interaction is not considered in the specification. Once FLFP and its interaction with robotization are accounted, the effect of one additional robot at industry-level in period $t-1$ is associated with a lower female share at industry level in period t. Both fixed effects and instrumental variables estimates point to a negative effect of robotization, which hinges upon the level of FLFP.[14] The instrument employed in Columns (5) and (6) in Table 1, namely replaceable hours, is positively and statistically significantly correlated with robot adoption in the first stage. The F-statistic is around 30, indicating that the replaceability measure is a strong instrument. Figure 2 plots the marginal effects of robotization on female share at different levels of FLFP estimated using regression model in Column (4) (Table 1), and with the histogram of the FLFP in the background. At every level of FLFP, robotization is associated with a reducing female share in employment. The negative effect of robotization is greater the higher the

[14] It should be noted that Graetz and Michaels (2018) data on replaceable hours at industry level did not allow for including ”All other manufacturing branches” and ”Other transport equipment” industries, and thus, the instrumental variable estimates are computed in a smaller database.

FLFP. More precisely, at the sample minimum of FLFP (23.46%), one sd increase of robotization leads to a 1.45 sd reduction in female share in manufacturing employment. However, this effect increases up to -3.7 sd at FLFP sample mean value (49.35%) and around -6 in the sample maximum (78.84%). Thus, the estimates here suggest that robotization impacts more severely the in female manufacturing employment in industries operating in countries where the overall participation of women in the paid workforce is higher.

Figure 2 here

Sensitivity Checks

Economic Development

The sample of countries employed in the previous estimates combines information on advanced, emerging and developing countries. The first sensitivity check of the empirical analysis is to analyse whether the interaction between robots and the participation of women in the paid workforce has different implications for the share of women in manufacturing at varying stages of country-level economic development. Table 2 shows the estimates of the previous regression model (Column 3, Table 1) using partitions of the database on the basis of average GDP per capita (in constant US dollars, 2010) during 1993 and 2015. Countries are grouped as follows: a set of poor countries, with an average GDP pc below the 25th percentile of the sample (2,550 US dollars), middle income countries that are in between the 25th and 75th percentiles (ranging between 2,550 and 10,903 US dollars) and rich countries that have an average GDP pc above the 75th percentile (10,903 US dollars). Using partitions of the sample of countries, the results suggest that the link between robotization and FLFP in the share of women in manufacturing is stronger in those industries operating in middle income countries. For higher levels of economic development, the marginal effect of robotization in the presence of women in manufacturing is still negative, although lower in magnitude. Figure 3 better displays the comparison among the results of the econometric model for the three set of countries based on economic development. The stronger and more negative marginal effect of robotization in the female share of manufacturing employment is found in those countries in the middle of the economic development, that are Bulgaria, Indonesia, Lithuania, Malaysia, Mexico and Turkey. In these countries, however, there is an indirect effect of automation on gender segregation in manufacturing mediated through the level of FLFP. In the case of poor countries in the sample, which are India, Morocco, Philippines and Vietnam, I find a strong negative effect of robotization. Finally, for the richest countries in the sample, namely Croatia, Japan, Kuwait and Malta, the effect of robots is positive, although the interaction with FLFP rends the marginal effect of one additional robot to reduce female shares of manufacturing employment.

Table 2 here

Figure 3 here

Dropping outliers

I further conduct a range of sensitivity checks to study the sensitivity of the above results. I first rule out the effect of influential country or industry-level observations both in terms of robotization and share of women in industry employment. According to the IFR[15], Japan is the world's predominant industrial robot manufacturer, supplying almost half of the global supply of robots, in which ”Automotive” and ”Electrics/electronics” industries dominate. Related to the presence of women at industry level, Viet Nam is the sample country that shows the higher rate of women by industry (45%), specifically in the textile industry, where women account for almost 80% of employment during the period under scrutiny. Finally, automation is the industry which shows the higher level of robotization.

Table 3 shows fixed effects and instrumental variable estimates that check whether the main results are driven by influential country-industry observations coming from Japan or Viet Nam, or from automative industry. Column 1 and Column 2 drop respectively Japan and Viet Nam from the sample of countries, while Column 3 excludes from the sample the automotive industry. The results point again to a positive effect of robotization that however hinges upon the level of FLFP: additional industrial robots always impact negatively on the share of women in industry employment, and it increases with the level of FLFP.

TABLE 3 here

Demand-side and supply-side factors

I also check the sensitivity of the main results of the article by augmenting the regression equation 1 to control for demand-side and supply-side factors behind female share of employment. Table 4 shows similar results once the potential effects of the male unemployment rate to capture the added-worker effect (Column 1) and the percentage of government expending to GDP (Column 2). Accounting for fiscal policies in the form of government expending might importantly control first for public sector opportunities for women, which generally concentrate in services sector (Karamessini and Rubery, 2014). Second, government expending can also be associated with higher industrial activity or higher provisioning of social infrastructure that can alleviate women's care burden or easy their participation in the paid workforce (Seguino and Braunstein, 2019). Finally, the equation 1 is augmented by adding labour productivity growth rates (Column 3), as it is done in Tejani and Kucera (2021). Subsequent Columns in Table 4 shows instrumental variables

[15]https://ifr.org/post/why-japan-leads-industrial-robot-production

estimates of these three specifications. The results after adding these controls remain the same.

TABLE 4 here

Table 5 includes country-level supply-side control variables, such as fertility rates, the gender gaps in literacy and the proportion of women in mid-skill occupations. Fertility correlates with representation of women in the paid workforce and can alter gendered patterns in labour market attachment differently at varying levels of economic development (Goldin and Katz, 2002; Kabeer, 2001). The increasing household production due to motherhood might couple with the lack of family policies at country level or gender traditional roles in the childcare labour to deter women to enter the paid workforce. To the contrary, the educational upgrading of women can play an important role in reducing gender differences in labour market prospects, and foster female employment in all manufacturing industries.[16]

Columns 1 and 2 in Table 5 include separately these controls, yielding again a negative female employment effect of robots that increases in FLFP, while Column 3 controls for the share of women in medium skills occupations.[17] As discussed above, technological change has alternative employment effects depending on the skill composition of occupations (Reijnders and de Vries, 2018; De Vries et al., 2020). Autor et al. (2003) establish that a replaceable effect of robotization will be more powerful in routine jobs, as tasks in such occupations follow explicit, clearly defined rules. However, non-routine jobs, even with limited skill requirements, are more likely to be complementary to robots, and thus, workers in such jobs are at lower risk of being displaced. Mid-skill workers, instead, can be at higher risk of displacement at AI is able to perform high-skill, routine tasks. The gender distribution of the occupational skill composition can thus be a factor behind the results found in the current article. The coefficient associated to the share of women in mid-skill occupations is positive and significant at 5% in the fixed effects model (Column 3 Table **??**), and the main results associated with robotization and its interaction with FLFP remain unchanged. Using the instrumental variables strategy, the coefficient associated with the female share of mid-skill workers is not significant, and the interaction between robotization and FLFP is not significant. Nevertheless, using this variable comes at the cost of reducing the sample of country-industry observations (from 1,648 to 952), and the time coverage is limited to 2001-2015.

[16]Ideally, the specification in this robustness check would control for the share of women by major of education to rule out the possible gender distributional effects in employment due to the segregation of women in care-related and nurturing fields of education and men in technical-related fields of education. However, there is no availability of panel data information that can be comparable for the sample of countries.

[17]I employ the skill level 2 of the ILOSTAT classification. These occupations are clerical support workers, service and sales workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, and plant and machine operators and assemblers (based on ISCO-08).

TABLE 5 here

Alternative segregation measures

This subsection considers other measure of gender segregation and labour market outcomes as dependent variables in Eq. 1. First, I follow Seguino and Braunstein (2019) to use the relative concentration of women in each manufacturing industry given by Equation 2, and regress against the independent variables in regression equation in Column (3) of Table 4.

$$r_i = \frac{\frac{f_i}{F}}{\frac{m_i}{M}} \tag{2}$$

where f_i refers to the number of women in industry i and F the total number of women in manufacturing, whereas m_i is the number of men in industry i and M the total number of men in manufacturing. Recall that the preferred regression model includes the labour productivity growth in the set control variables to draw parallels to the models in the reference literature in gender segregation in manufacturing.

The estimates displayed in Table A5 in Appendix use within fixed effects and instrumental variables, and associate robots with an increasing concentration of women in manufacturing industries. However, this effect depends on the level of female labour force participation: as previously found in the current article, the higher the participation of women in the paid workforce, the lower the concentration of women in manufacturing employment. Figure 4 provides the marginal effects of one s.d. increase of industrial robots in the relative concentration of women in manufacturing industries by levels of FLFP. Once again, the estimates suggest that automation reduces the presence of women in manufacturing employment, and this effect is stronger the higher the participation of women in the labour market.

Figure 4 here

Female and Male Employment Effects

My empirical analyses so far have focused on the effects of industrial robots, along with a variety of industry-level controls such as trade exposure or wages, and country-level controls such as premature deindustrialization, on the share of women in manufacturing employment. In this subsection, I focus on the role of industrial robots in the level of employment of women and men in manufacturing, as well as the gender gap in employment. The results of the subsequent specifications will provide further leverage of the findings above, and will help identify other gender differences in labour market outcomes of robotization.

Figure 5 shows the difference in the gender employment gap (male minus female employment) at the beginning and at the end of the period considered. Some industries, such as "Automotive" and "Other transport equipment” have reduce the employment gap considerably. Except for the case of ”Textiles,” all gaps show a lack of women in manufacturing, yet the gender gap in ”Textiles” in 2015 is positive, meaning that on average men outnumber women in that industry in the sample. Figure A6 and Figure A7 in Appendix show respectively the female and male employment in logs and the evolution of the adoption of robots and the gender employment gap by industry during the time at scrutiny.

Figure 5 here

Table 6 uses the log of employment for women and men, and gender employment gaps separately, as dependent variables, and regresses the preferred model (Column 3, Table 4). The results first associate industrial robots with a positive effect in employment, both for women and men, although the coefficient for women is higher (0.172 sd and 0.08 sd., respectively). Nonetheless, the interaction between robots and FLFP is significant and negative, rending the marginal effect of one additional sd. increase of industrial robots to be between -4.4 sd to -15.9 sd for the minimum and maximum sample values of FLFP, respectively, in the case of female employment. The effect of robotization in male employment is similar, although is lower at every level of the interaction with FLFP. At the sample minimum of FLFP, one additional sd in robots is associated with a -1.65 sd change in male employment, while at the sample maximum this effect is of -5.9. This lower, although still negative, effect of robots in male employment might led to greater gender inequality in the labour market as a consequence of the automation of work. The different level of robotization effects in female and male employment can be easily seen in Figure 6, where the blue (solid) line is the effect for log female employment, and the red (dashed) line, is the marginal effect on log male employment. For every point in the FLFP, the effect for female employment is always higher in magnitude than for male employment. This result contradicts those in Acemoglu and Restrepo (2020), who find that the employment effect of robots is larger for men.

Figure 6 here

Finally, Figure 6 shows the estimates of regression model in Column (3) in Table 6 shows that the effect of robotization increases the gender employment gap in manufacturing industries, which corroborates the previous findings of the article. It is important to acknowledge that the instrumental variable strategies in Columns (4-6) (Table 6) show a significant relationship between robots and female employment, whereas for the case of male employment the level of significance is 10%, and there is not a significant role of robots in gender employment gaps in the instrumental variable estimates.

Figure 7 here

Industry-level Estimates

For the purpose of this manuscript, country-industry panel data models are the most appropriate specifications. In this way, the estimates control for time-invariant factors that characterize industries operating in specific countries, such as industrial structural factors, and at the same time, country-institutional settings specific at industry levels, or cultural norms that can be vary across industries and countries. Nonetheless, I check the validity of the results above running regression models separately for each industry on key dependent variables, namely, the female share in manufacturing industries, and log of employment of women and men and gender employment gap. By doing so, I am able to compare the results of the current article with that of Tejani and Kucera (2021), who use labour productivity growth as a focal variable of technological upgrading. Hence, labour productivity growth rates are included in the models to reduce omitted variable bias and reproduce the model in Tejani and Kucera (2021).

Hence, the final step of this article is to estimate the specification in Eq. 1 separately for each industry pooling data across countries.[18] Table A6 in Appendix shows estimates that generally confirm a statistical significant role of robotization and its interaction with FLFP in female share in manufacturing industries. In 7 out of 11 industries, industrial robots are associated with a significant effect in the presence of women in manufacturing industries. However, the interaction between robotization and FLFP is negative and significant in ”Food, beverages and Tobacco products”, ”Wood and furniture”, ”Glass” and ”Metal.” In ”Textiles”, the interaction is positive although significant at 10% level. This positive effect of technological change in textile industry is consistent with the findings in Tejani and Kucera (2021), who show a positive causal effect of technological upgrading in the wearing apparel, fur, leather products and footwear industry.[19] Robotization is not associated with a significant role in ”Paper”,”Electrical/electronics”, ”Automotive”, and ”All other manufacturing branches,” but it should be considered that the number of observations is smaller relative to the other models.

Similarly, I pool data across countries to focus on the employment effects for women and men separately of robotization and its interaction with FLFP, and conduct separate models for the 11 industries in the database. Table A7 shows estimates on female employment: the estimates in the industries of ”Food”, ”Paper”, ”Glass”, ”Metal” and ”All other manufacturing branches” confirm the hypothesis that robotization has

[18] Since the instruments in (Graetz and Michaels, 2018) vary across industries but not across countries, these specifications cannot be estimated using instrumental variable regression models as in the previous results of the current research. Separate regression equations for each industry are thus solely estimated with within fixed-effects models.

[19] It should be noted that the industrial classification derived from the merge of UNIDO and IFR data differs slightly with the ISIC revision 2 employed in Tejani and Kucera (2021).

a negative effect in the share of women in manufacturing industries when FLFP is increasing. Regression models in Table A8 show that in 8 out of the 11 industries in the sample, robotization plays a significant role in female employment. In the industries of ”Food”, ”Textiles”, ”Paper”, ”Glass”, ”Metal”, and ”All other manufacturing branches” a interplay between robotization and FLFP is significant, supporting the previous results in the article. ”Plastic” and ”Electronics” appear to be positively affected by robotization. Finally, Table A9 identifies the industries for which robotization and FLFP plays a role in gender employment gap, which generally confirm the estimates at country-industry pairs in the above subsections.

CONCLUSIONS

The automation of work profoundly transforms the set of activities that can be performed by robots and humans, and thus, alter the extent to which machines are substitutes or complementarities of human labour. In this article, I laid out a gender-biased technological change framework that can advance our understanding of the implications of technological upgrading in labour market outcomes for women and men. Yet a skill-biased technological change hypothesis by which technical innovations can affect individuals different on the basis of different skills is already documented in the literature, a gender-biased technological change is still to be defined. Existing literature heed relative little attention to the implications of robots for gender equality in labour market outcomes, with the exception of few cases that measure the effect of robots in gender wage gaps (Ge and Zhou, 2020; Aksoy et al., 2021). Here I focused on the role of robotization of the production function in the share of women employed in manufacturing industries.

This article empirically addressed the impact of robots in gender segregation and level of employment of women and men using an industry-level disaggregated panel dataset for a set of 14 advanced and emerging economies. I specified within fixed-effects that control for spatial and temporal serial correlation issues. Additionally, I employed instrumental variables techniques to instrumentalize robotization as first proposed by (Graetz and Michaels, 2018). These alternative techniques yield similar results, that associate automation with a positive impact on the presence of women in manufacturing. Nonetheless, this impact hinges upon the rate of female labour force participation as its interaction with robots is significant. The net effect of robots is thus always negative and increases the greater the presence of women in the labour market. More precisely, the results suggest that one sd increase in robotization will lead to a 1.45 sd reduction of female share in manufacturing employment when female labour force participation is low (20%). Nonetheless, the effect of robots increases in magnitude as female labour force participation increases. Evaluated at the

sample mean of female labour force participation (49.35%), one sd increase in robotization leads -2.97 sd of female share in manufacturing. Finally, in countries with high levels of female labour force participation (80%), one sd increase of robotization is found to reduce -6 sd the presence of women in manufacturing employment at industry level. The patterns of economic development seem to interplay in the effect of robots in gender segregation. The results further show that the link is stronger for middle income countries in the sample. Nonetheless, the marginal effect is always negative no matter the level of economic development.
The results using female and male employment, and gender employment gaps as dependent variables provide further leverage to the gender disparity effects of robots in manufacturing. Separate panel data models that pool data across countries for each industry corroborate the negative link between technological upgrading and women in manufacturing, and identify the industries where this link is more important.
Existing empirical evidence shows that as women increase their participation in the paid workforce, they tend to concentrate in service sector, a process that is also influenced by economic development. My results add to these stylized facts by suggesting one causal factor behind the feminization of the service sector and the defeminization of the manufacturing at different levels of economic development. These mechanisms can be triggered by the automation of the manufacturing, as gender stereotypes about skill differentials and discrimination can block the access of women to more technological jobs. The econometric models above controlled for important industry-level factors of female manufacturing employment, such as international trade and real wages. At country level, the specifications control for a variety of demand-side and supply-side covariates that can drive the presence of women in the manufacturing, such as male unemployment, public spending or the share of women in mid-skill jobs, among other factors.
The conclusions of the article go along the lines of Seguino and Braunstein (2019) and Tejani and Kucera (2021) insofar technological upgrading is found to reduce the presence of women in manufacturing employment. The econometric specifications here proposed augmented previous econometric models by adding the role of robots, as well as included the interaction between technological upgrading and country-level participation of women in the paid workforce. Importantly, in this article I directly tackled reverse causation by using instrumental variables estimates, as performed other studies of the gendered implications of robots (Aksoy et al., 2021). The results ultimately complement the regressions in Aksoy et al. (2021) in the effects of industrial robots in the gender composition of workers by focusing on a higher data-level disaggregation of the manufacturing. Finally, my results complement those in Acemoglu and Restrepo (2020) by showing that the effect of robots in employment in manufacturing is negative and greater for women than for men.
The results here documented can inform labour market policies to provide a better designed of industrial policies to foster an even distribution of women and men in manufacturing employment. Technological

innovations can displacement of jobs and create of new ones, and at the same time, trigger new forms of gender inequality. Pervasive effects from rising participation of women in the paid labour force can couple with technological upgrading to unleash new gender inequalities. Policies that can countervail the opposite forces of rising female paid labour in reaching higher levels of gender equality in the labour market should include the reduction of educational horizontal segregation to provide an even skill distribution between women and men.

The next natural steps of the current article are divided in three strands. First, a replication of the present analysis using the price of robots instead of the number of robots at industry level will inform on the actual capacity of robots to replace tasks previously performed by humans. Second, the complexity of occupational gender segregation and task gender segregation and its interplay with industrial gender segregation should be address empirically at the same time. The concentration in skills and tasks in different industries might be at the core of gender disparities in employment in the era of automation of work. Third, a final line of research to complement this article is to consider the gendered effects of robotization on informal employment and non-market economic activities, which can be specifically important in developing economies.

Figures in text

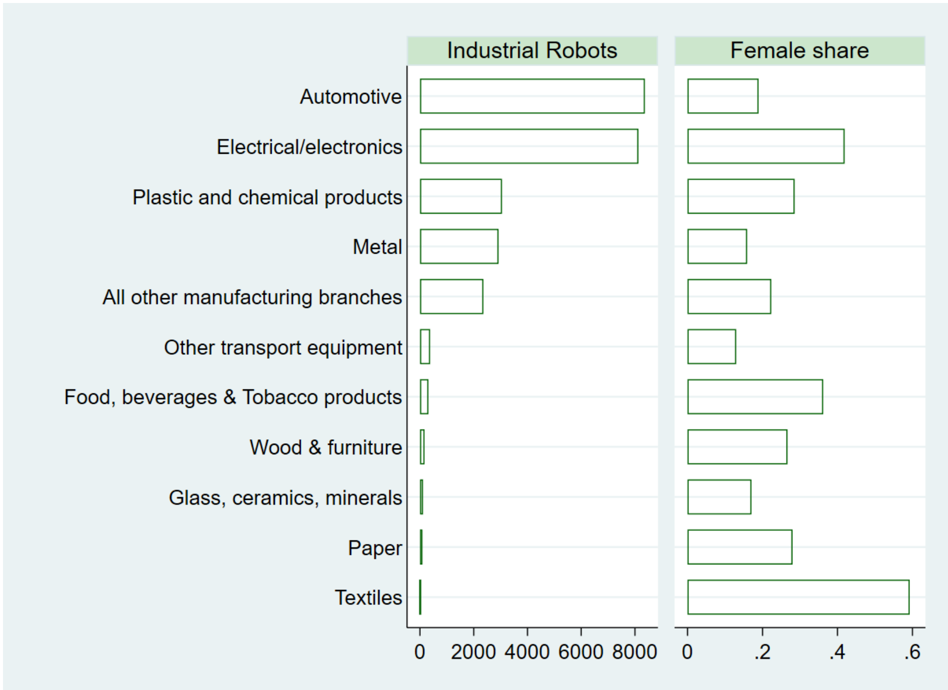

Figure 1: Average Industrial Robots and Female Share in Manufacturing Industries (1993-2015)

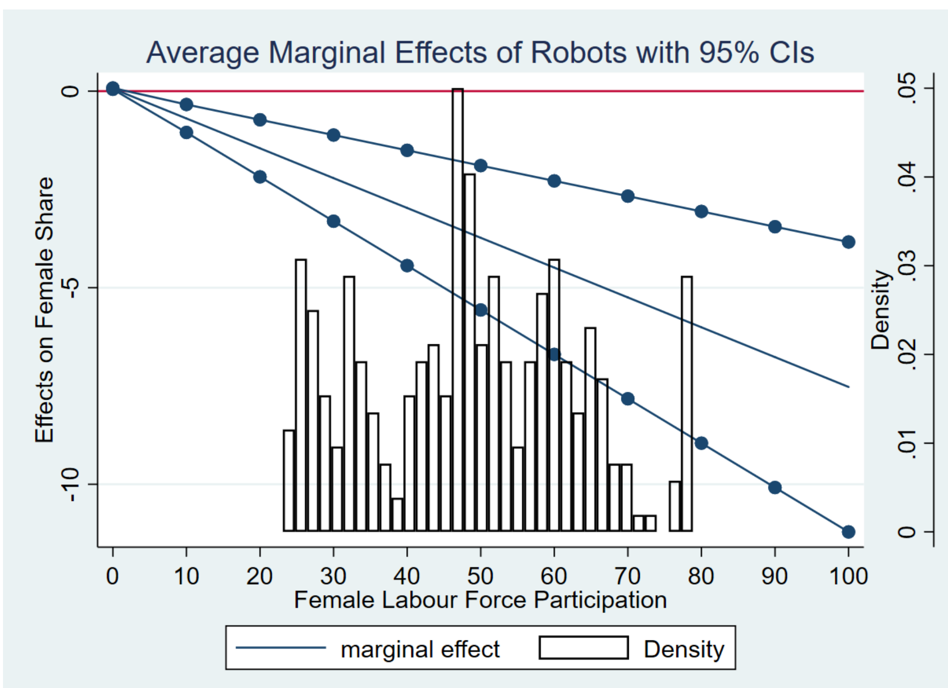

Figure 2: Marginal effects of Industrial Robots in Female Share

Figure 2 notes: Marginal effects of one sd increase in robotization in the female share in manufacturing industries (left y-axis) at different levels of female labour force participation in x-axis. Histogram of female labour force participation in the background (density in right, y-axis)

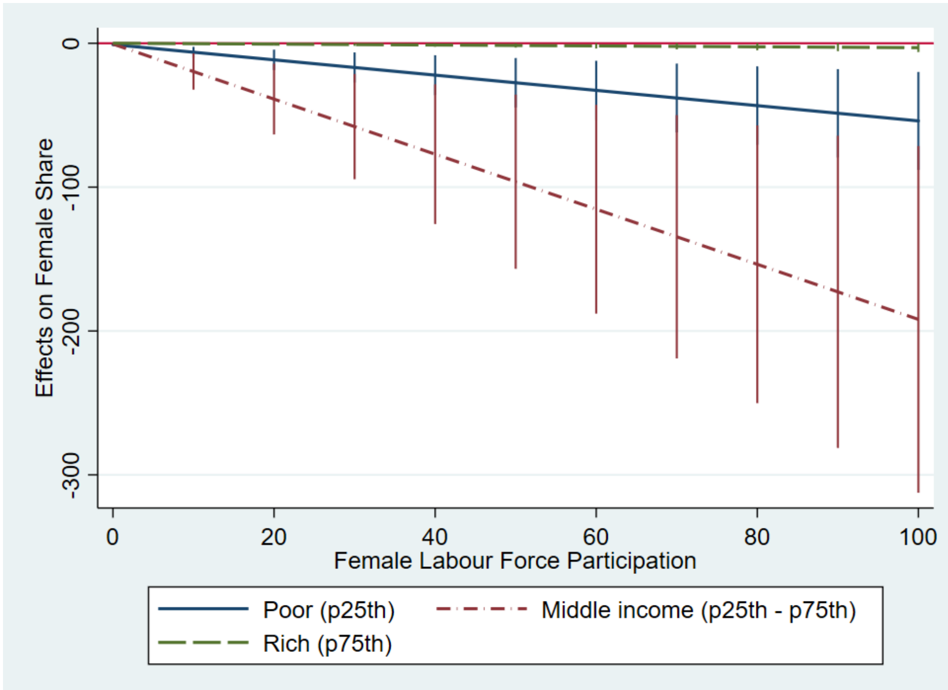

Figure 3: Robots and Women in Manufacturing Employment by GDP per capita percentiles

Figure 3 notes: Marginal effects of one sd increase in robotization in the female share in manufacturing industries (left y-axis) at different levels of female labour force participation in x-axis at different levels of economic development. Blue line shows estimates using developing countries (GDP pc below 2,55 US dollars), red dot-dashed line shows estimates using emerging countries (GDP pc between 2,550 and 10,903 US dollars), and green dashed line shows estimates using relatively advanced sample countries (GDP pc above 10,903)

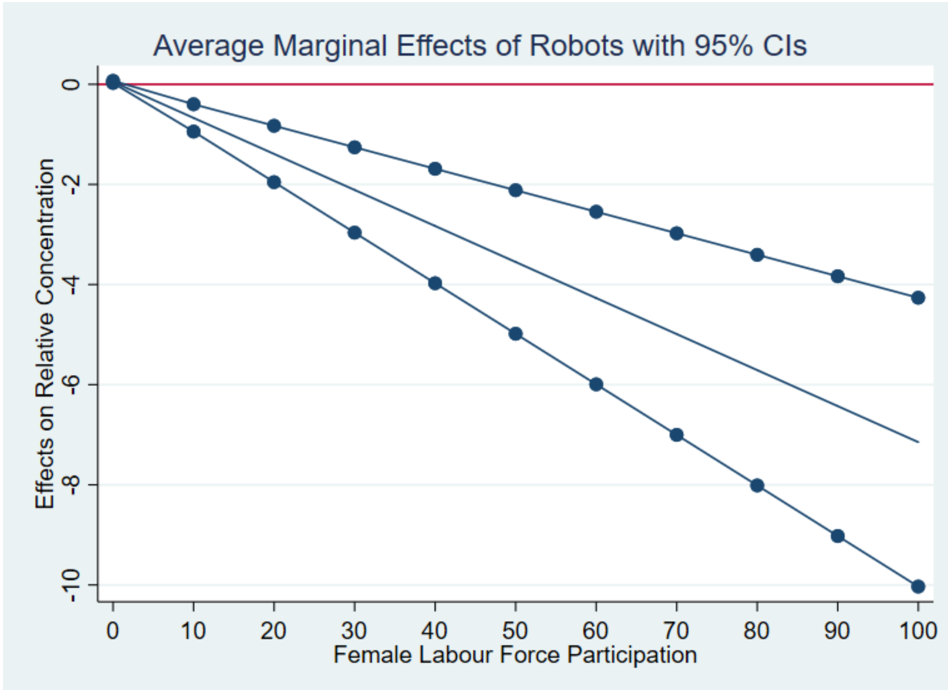

Figure 4: Marginal effects of Industrial Robots in Female Industrial Concentration

Figure 4 notes: Marginal effects of one sd increase in robotization in the relative concentration of women in manufacturing industries (left y-axis) at different levels of female labour force participation in x-axis. Histogram of female labour force participation in the background (density in right, y-axis)

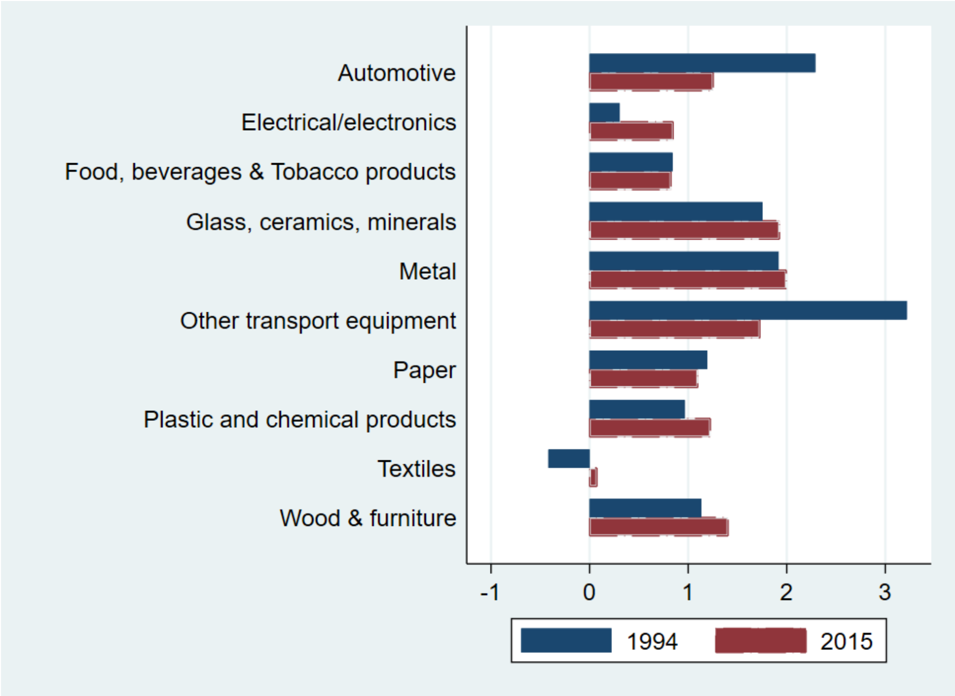

Figure 5: Gender Employment Gap

Figure 5 notes: Gender gap in employment in 1994 and 2015 by industry. Sources: UNIDO, own calculations. The gender gap is calculated as the log-difference between male employment and female employment.

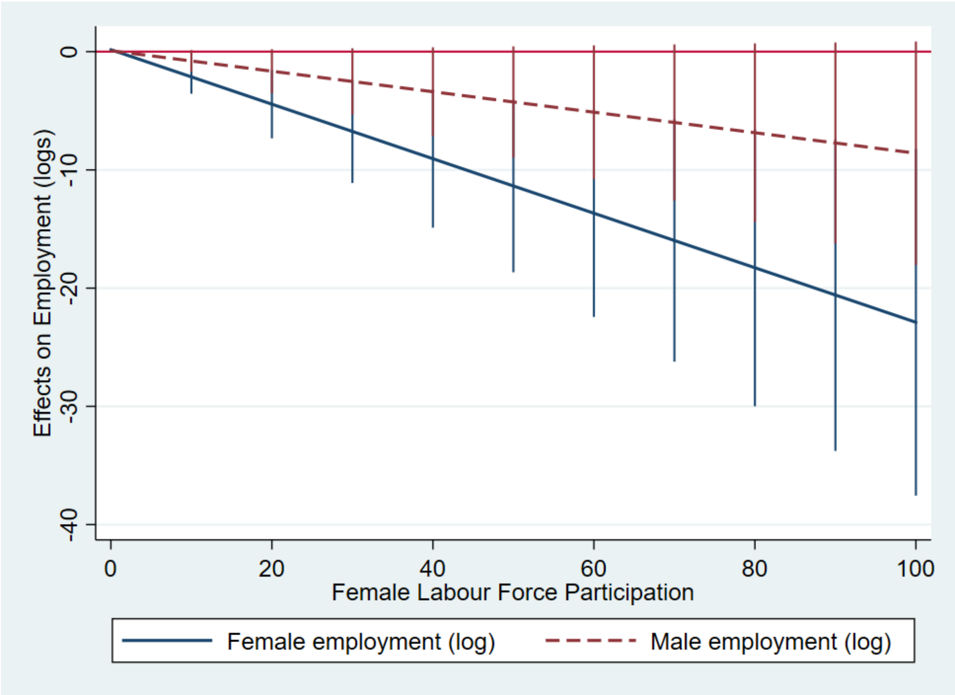

Figure 6: Marginal effects of Industrial Robots in Female and Male Employment

Figure 6 notes: Marginal effects of one sd increase in robotization in female employment (blue, solid line) and male employment (red, dashed line), based on models (1) and (2) respectively in Table 6.

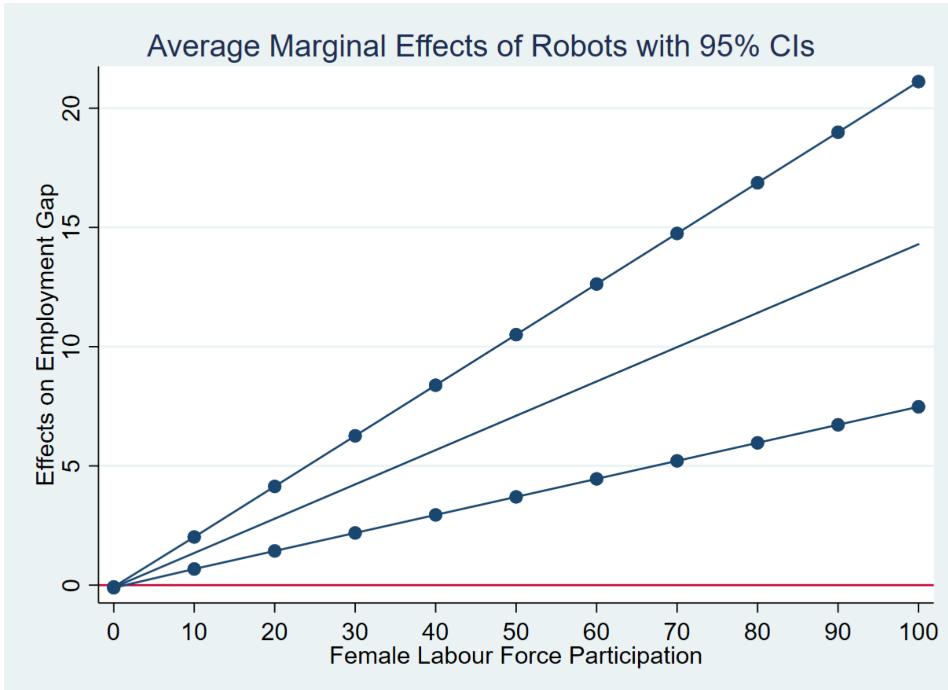

Figure 7: Marginal effects of Industrial Robots in Gender Employment Gap

Figure 7 notes: Marginal effects of one sd increase in robotization in gender employment gap (male minus female employment), based on model (3) in Table 6.

Tables in text

Table 1: Robots and Women in Manufacturing Employment

	(1)	(2)	(3)	(4)	(5)	(6)
		FE		—	IV	
First stage dependent variable: industrial robots						
Replaceable hours					2.732***	2.991***
					(0.501)	(0.549)
Second stage dependent variable: female share						
Robots	0.034***	0.036***	0.070***	0.066***	0.073***	0.064***

	(0.004)	(0.004)	(0.004)	(0.006)	(0.012)	(0.017)
FLFP		0.122***	0.123***	0.182***	0.114	0.159**
		(0.037)	(0.034)	(0.063)	(0.078)	(0.068)
Robots*FLFP			-0.099***	-0.085***	-0.095***	-0.076**
			(0.018)	(0.022)	(0.025)	(0.036)
No. of Obs.	1,798	1,798	1,798	1,648	1,804	1,642
No. of Groups	151	151	151	151	126	126
No. of Industries	11	11	11	11	9	9
Within R-squared	0.104	0.108	0.110	0.102	0.140	0.145
F-stat First stage					29.76	29.68
Industry-level controls	yes	yes	yes	yes	yes	yes
Country-level controls	no	no	no	yes	no	yes
Year fixed effects	yes	yes	yes	yes	yes	yes

Table 1 notes: Columns 1-4 present fixed effects (within) estimates, while Columns 5-6 present instrumental variables estimates using replaceable hours as instrument for industrial robots. All models include constant terms, independent variables are one-period lagged and include time effects and country-time fixed effects. Dependent and independent variables are standardized to ease the interpretation of the results. Driscoll-Kraay standard errors in parentheses in fixed effects within estimates. Columns 5-6 do not include All other branches and Other transport industries because inconsistency in correspondence with Graetz and Michaels (2018) data. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: UNIDO, IFR, COMTRADE, WDI, ILO, own calculations

Table 2: Robots and Women in Manufacturing Employment:
Different levels of Development

	(1)	(2)	(3)
	Poor countries	Middle income	Rich countries
Robots	-0.902***	-0.507	0.037***
	(0.207)	(0.337)	(0.008)
FLFP	0.238**	-0.411**	0.319
	(0.100)	(0.181)	(0.420)
Robots*FLFP	-0.531***	-1.914***	-0.031*
	(0.172)	(0.612)	(0.016)

No. of Obs.	474	700	474
No. of Groups	54	97	54
No. of Countries	4	6	4
Within R-squared	0.175	0.119	0.202

Table 2 notes: Fixed effects (within) estimates using partitions of the database on the basis of development. Column 1 uses India, Morocco, Philippines and Vietnam. Column 2 uses Bulgaria, Indonesia, Lithuania, Malaysia, Mexico and Turkey. Column 3 uses Croatia, Japan, Kuwait and Malta. All models include constant terms, independent variables are one-period lagged and include time effects and country-time fixed effects. Dependent and independent variables are standardized to ease the interpretation of the results. Driscoll-Kraay standard errors in parentheses in fixed effects within estimates. Columns 5-6 do not include All other branches and Other transport industries because inconsistency in correspondence with Graetz and Michaels (2018) data. * $p < .1$, ** $p < .05$, *** $p < .01$. Sources: UNIDO, IFR, COMTRADE, Graetz and Michaels (2018), WDI, ILO, own calculations

Table 3: Robots and Women in Manufacturing Employment: Dropping Outliers

	(1)	(2)	(3)	(4)	(5)	(6)
		FE		—	IV	
	No Japan	No VN	No Auto.	No Japan	No VN	No Auto.
First stage dependent variable: industrial robots						
Replaceable hours				0.067***	3.313***	1.772***
				(0.019)	(0.602)	(0.400)
Second stage dependent variable: female share						
Robots	0.013***	0.075***	0.065***	0.013***	0.014***	0.014***
	(0.001)	(0.005)	(0.007)	(0.003)	(0.003)	(0.003)
FLFP	0.035***	0.166***	0.097	0.029**	0.029**	0.029**
	(0.012)	(0.051)	(0.061)	(0.014)	(0.014)	(0.014)
Robots*FLFP	-0.017***	-0.102***	-0.118***	-0.016**	-0.018***	-0.018***
	(0.004)	(0.019)	(0.035)	(0.007)	(0.006)	(0.006)
No. of Obs.	1,462	1,478	1,459	1,606	1,489	1,489

No. of Groups	117	139	136	126	117	117
No. of Industries	11	11	10	9	9	8
No. of Countries	13	13	14	13	13	14
Within R-squared	0.105	0.097	0.132	0.145	0.143	0.143
F-stat first stage				12.31	30.31	19.60
Industry-level controls	yes	yes	yes	yes	yes	yes
Country-level controls	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes

Table 3 notes: Columns 1-3 present fixed effects (within) estimates, while Columns 4-6 present instrumental variables estimates using replaceable hours as instrument for industrial robots. Columns 1 and 4 do not include Japan, Columns 2 and 5 do not include Vietnam and Columns 3 and 6 do not include ”Automotive” industry. All models include constant terms, independent variables are one-period lagged and include time effects and country-time fixed effects. Dependent and independent variables are standardized to ease the interpretation of the results. Driscoll-Kraay standard errors in parentheses in fixed effects within estimates. Columns 4-6 do not include ”All other branches” and ”Other transport” industries because inconsistency in correspondence with Graetz and Michaels (2018) data. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: UNIDO, IFR, COMTRADE, Graetz and Michaels (2018), WDI, ILO, own calculations

Table 4: Robots and Women in Manufacturing Employment:
Demand-side Controls

	(1)	(2)	(3)	(4)	(5)	(6)
		FE	—		IV	
First stage:				2.991***	2.991***	3.069***
				(0.549)	(0.549)	(0.559)
Robots	0.065***	0.062***	0.067***	0.064***	0.062***	0.066***
	(0.006)	(0.005)	(0.006)	(0.017)	(0.015)	(0.017)
FLFP	0.191***	0.156**	0.184***	0.161**	0.151**	0.153**
	(0.062)	(0.070)	(0.063)	(0.064)	(0.069)	(0.071)
Robots*FLFP	-0.084***	-0.079***	-0.088***	-0.076**	-0.073**	-0.080**
	(0.022)	(0.020)	(0.021)	(0.036)	(0.032)	(0.037)
Male unemployment rate	0.011			0.003		

	(1)	(2)	(3)	(4)	(5)	(6)
	(0.021)			(0.032)		
Govern. exp.		-0.008			-0.004	
		(0.007)			(0.010)	
Labour productivity growth			-0.002			-0.007
			(0.005)			(0.010)
No. of Obs.	1648	1648	1606	1642	1642	1606
No. of Groups	151	151	150	126	126	126
No. of Industries	11	11	11	9	9	9
Within R-squared	0.103	0.104	0.105	0.145	0.145	0.145
F-stat First stage				29.68	29.68	30.13

Fixed-effects within estimates with one-period lagged independent variables and time fixed effects included

All independent variables are standardized

Driscoll-Kraay standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 4 notes: Columns 1-3 present fixed effects (within) estimates, while Columns 4-6 present instrumental variables estimates using replaceable hours as instrument for industrial robots. Columns 1 and 4 include male unemployment rates, Columns 2 and 5 include government spending and Columns 3 and 6 include labour productivity growth rate. All models include constant terms, independent variables are one-period lagged and include time effects and country-time fixed effects. Dependent and independent variables are standardized to ease the interpretation of the results. Driscoll-Kraay standard errors in parentheses in fixed effects within estimates. Columns 4-6 do not include ”All other branches” and ”Other transport” industries because inconsistency in correspondence with Graetz and Michaels (2018) data. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: UNIDO, IFR, COMTRADE, Graetz and Michaels (2018), WDI, ILO, own calculations

Table 5: Robots and Women in Manufacturing Employment:
Supply-side Controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects			— Instrumental Variables		
First-stage dependent variable: industrial robots						
Replaceable hours				3.069***	0.212***	3.307***
				(0.559)	(0.072)	(0.779)

Second stage dependent variable: female share						
Robots	0.069***	-0.394**	0.059***	0.013***	-0.129**	0.010**
	(0.005)	(0.157)	(0.014)	(0.004)	(0.063)	(0.004)
FLFP	0.173***	0.021	0.227**	0.027*	-0.001	0.031
	(0.059)	(0.151)	(0.079)	(0.015)	(0.033)	(0.023)
Robots*FLFP	-0.092***	-1.292***	-0.025	-0.017**	-0.349**	-0.004
	(0.020)	(0.368)	(0.029)	(0.007)	(0.149)	(0.009)
Fertility	0.028			0.010		
	(0.040)			(0.022)		
Literacy Gender gap		0.800			0.110	
		(0.696)			(0.178)	
Fem share mid-skill			0.844**			0.091
			(0.293)			(0.101)
No. of Obs.	1,606	356	952	1,606	349	912
No. of Groups	150	136	140	126	117	117
No. of Industries	11	11	11	9	9	9
No. of Countries	14	13	13	14	13	13
Within R-squared	0.105	0.196	0.097	0.146	0.219	0.114
F-stat first stage				30.13	8.72	18.03

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 5 notes: Columns 1-3 present fixed effects (within) estimates, while Columns 4-6 present instrumental variables estimates using replaceable hours as instrument for industrial robots. Columns 1 and 4 include fertility rates, Columns 2 and 5 include literacy gender gap and Columns 3 and 6 include female share in mid-skill occupations. All models include constant terms, independent variables are one-period lagged and include time effects and country-time fixed effects. Dependent and independent variables are standardized to ease the interpretation of the results. Driscoll-Kraay standard errors in parentheses in fixed effects within estimates. Columns 4-6 do not include ”All other branches” and ”Other transport” industries because inconsistency in correspondence with Graetz and Michaels (2018) data. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: UNIDO, IFR, COMTRADE, Graetz and Michaels (2018), WDI, ILO, own calculations

Table 6: Female and Male Employment effects and Gender Employment Gap

	(1)	(2)	(3)	(4)	(5)	(6)
	Fixed Effects		—	Instrumental Variables		
First-stage dependent variable: industrial robots						
Replaceable hours				3.069***	3.069***	3.069***
				(0.559)	(0.559)	(0.559)
Second-stage dependent variables:						
	Fem. Emp.	Male Emp.	Emp Gap	Fem. Emp.	Male Emp.	Emp. Gap
Robots	0.172***	0.080***	-0.092***	0.147***	0.053*	0.030
	(0.029)	(0.023)	(0.009)	(0.047)	(0.031)	(0.067)
FLFP	-0.408	-0.615***	-0.207**	-0.411***	-0.575***	-0.553***
	(0.256)	(0.202)	(0.074)	(0.145)	(0.112)	(0.120)
Robots*FLFP	-0.239***	-0.091*	0.148***	-0.209**	-0.067	-0.017
	(0.075)	(0.049)	(0.034)	(0.081)	(0.052)	(0.091)
No. of Obs.	1,606	1,606	1,606	1,606	1,606	1,606
No. of Groups	150	150	150	126	126	126
Within R-squared	0.332	0.412	0.082	0.359	0.452	0.360
F-stat first stage				30.13	30.13	30.13

Table 6 notes: Columns 1-3 present fixed effects (within) estimates, while Columns 4-6 present instrumental variables estimates using replaceable hours as instrument for industrial robots. Columns 1 and 4 include fertility rates, Columns 2 and 5 include literacy gender gap and Columns 3 and 6 include female share in mid-skill occupations. All models include constant terms, independent variables are one-period lagged and include time effects and country-time fixed effects. Dependent and independent variables are standardized to ease the interpretation of the results. Driscoll-Kraay standard errors in parentheses in fixed effects within estimates. Columns 4-6 do not include "All other branches" and "Other transport" industries because inconsistency in correspondence with Graetz and Michaels (2018) data. $^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$ Sources: UNIDO, IFR, COMTRADE, Graetz and Michaels (2018), WDI, ILO, own calculations

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Appendix

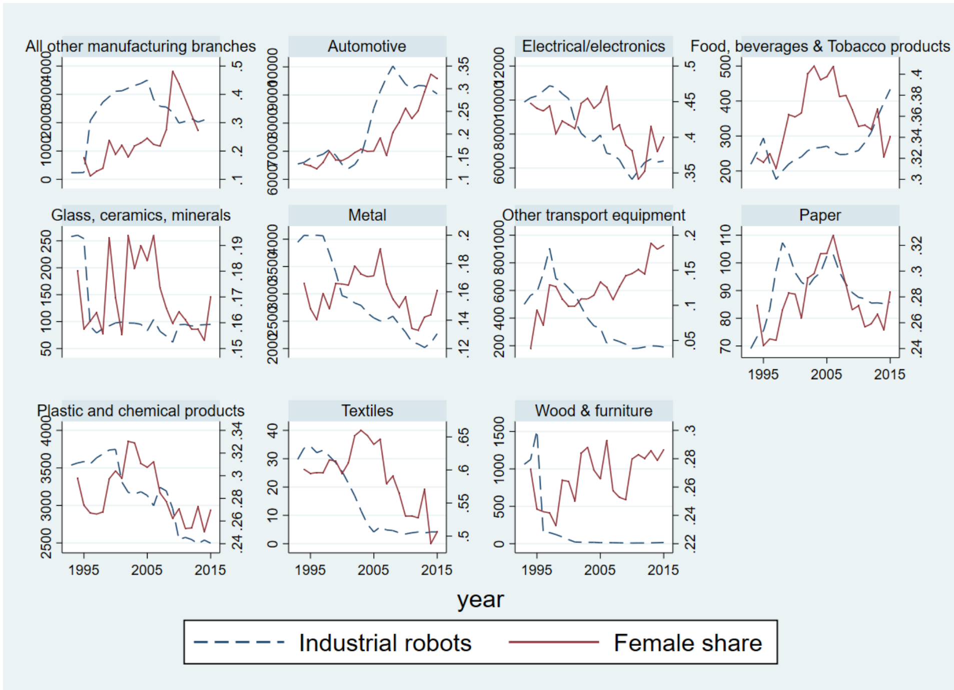

Figure A1: Evolution of Industrial Robots and Women in Manufacturing by Industry

Figure A5 notes: Evolution of adoption of industrial robots and female employment share by manufacturing industries. Data sources: IFR data on industrial robots and UNIDO data on share of women by manufacturing industry.

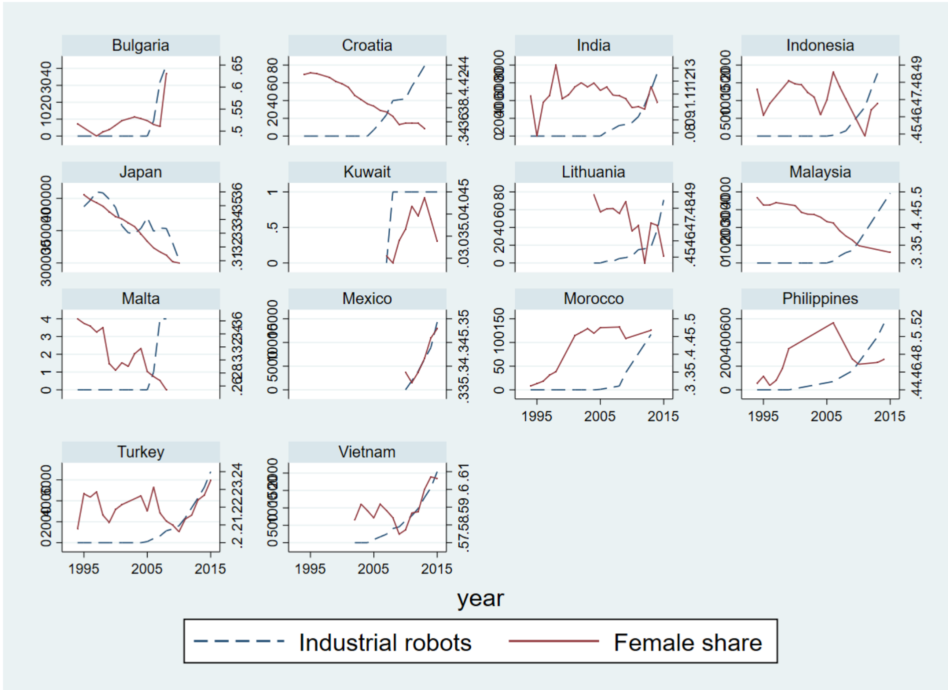

Figure A2: Evolution of Industrial Robots and Women in Manufacturing by Country

Figure A2 notes: Evolution of adoption of industrial robots and female employment share in total manufacturing by sample countries. Data sources: IFR data on industrial robots and UNIDO data on share of women by manufacturing industry.

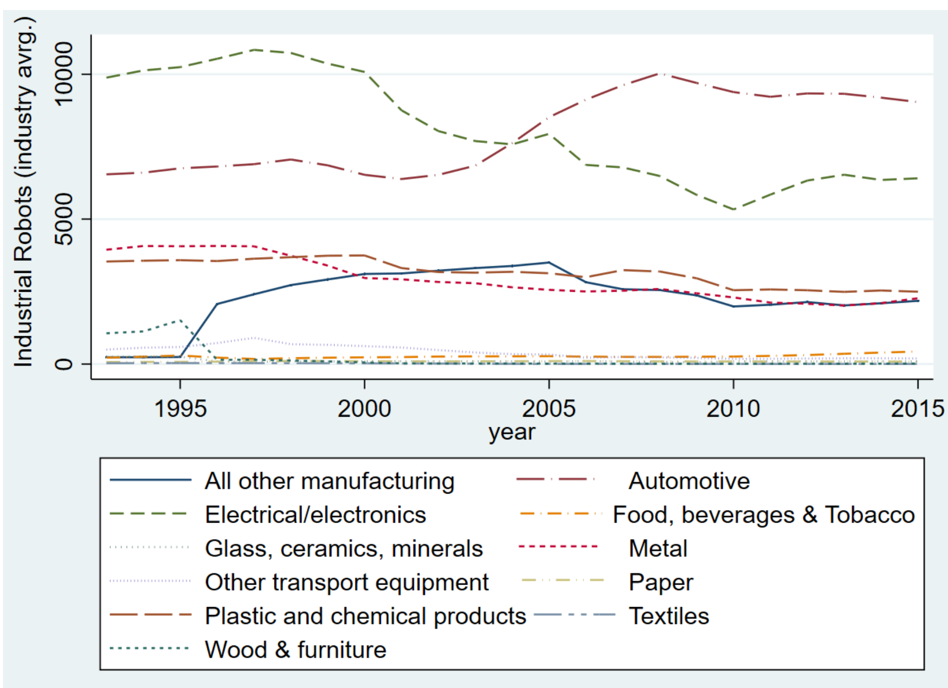

Figure A3: Evolution of Industrial Robots Adoption by Industry

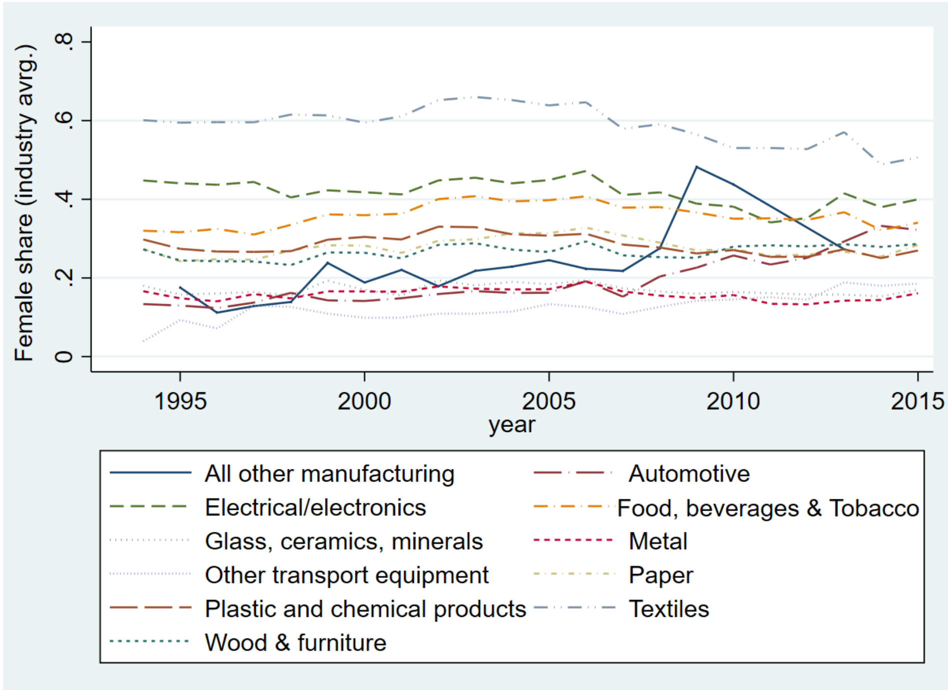

Figure A4: Evolution of Female Employment Share by Industry

Table A1: Sample Countries

Country	Female share	Robots	FLFP
Bulgaria	0.41	3.04	59.62
Croatia	0.35	2.33	57.54
India	0.08	127.71	30.22
Indonesia	0.36	39.85	50.98
Japan	0.31	31976.70	60.41
Kuwait	0.03	0.03	47.98
Lithuania	0.41	0.72	67.95
Malaysia	0.34	64.05	46.99
Malta	0.22	0.26	35.99
Mexico	0.33	140.37	46.86
Morocco	0.26	2.81	26.54
Philippines	0.37	12.04	49.53
Turkey	0.17	107.85	29.62
Vietnam	0.45	34.27	77.83

Table A2: Sources of Data

Variable	Explanation	Source
Female share	Women in industry i to employment in industry i	UNIDO
Relative concentration	Ratio of womens concentration in industry i employment to mens concentration	UNIDO
Robots	Number of industrial robots employed in industry i	IFR
Labor productivity growth rate	Growth rate of value added per employee (industry level)	UNIDO
Female Labor Force Participation (FLFP)	Labor force participation rate, % of female population ages 15+ (country level)	World Bank ILO
Employment share	Employees in industry i to total manufacturing employment (industry level)	UNIDO
Female share in Manufacturing	Ratio of total number of women in manufacturing employment to total manufacturing employment	UNIDO
Real wages	Wages and salaries are deflated to the year 2010 (industry level)	UNIDO World Bank
Export share	Industry exports to total exports in manufacturing (industry-level)	COMTRADE
GDP per capita annual growth	Annual growth rate of gross domestic product per capita, in constant terms (2010), international dollars	World Bank
Tariffs	Tariff rate, applied, weighted mean, manufactured products in percentage terms (country level)	World Bank

Table A3: Sources of Data (cont.)

Variable	Explanation	Source
FDI	Foreign direct investment, net inflows (country level)	World Bank
Deindustrialization	Industrial employment as a share of total employment (%)	World Bank
Male unemployment	Unemployment, male (% of male labor force)	ILO
Governement expenditure	General government final consumption expenditure (% of GDP)	World Bank
Replaceable hours	Index of replaceability of robots by industry. It is the fraction of each industrys hours worked in 1980 in the United States that was performed by occupations that became replaceable by robots by 2012 (industry-level time, country and time invariant)	Graetz and Michaels (2018)

Table A4: Data Availability by Country

Country	Time Coverage	Missing years	Number of Years
Bulgaria	1993-2015	1995	22
Croatia	1993-2015		23
India	1993-2015		23
Indonesia	1993-2015		23
Japan	1994-2012	2011	18
Kuwait	2006-2015		20
Lithuania	1996-2015	2000, 01, 02	27
Malaysia	1993-2015	1998, 11, 13	20
Malta	1993-2008		16
Mexico	2009-2015		7
Morocco	1993-2010	1999, 06	16
Philippines	1993-2015	2000, 02, 04, 07, 11	18
Turkey	1993-2008	2002	15
Viet Nam	1998-2015	1999, 00	16

Table A5: Robots and Women in Manufacturing Employment: Relative Concentration

	(1)	(2)	(3)	(4)	(5)	(6)
		Within	—		2SLS	
First-stage dependent variable: industrial robots						
Replaceable hours				2.991***	2.991***	3.069***
				(0.549)	(0.549)	(0.559)
Dependent variable: relative concentration						
Robots	0.047***	0.043***	0.049***	0.040	0.036	0.042
	(0.010)	(0.010)	(0.011)	(0.029)	(0.027)	(0.029)
FLFP	0.076	0.034	0.064	0.056	0.022	0.021
	(0.059)	(0.062)	(0.061)	(0.086)	(0.083)	(0.090)
Robots*FLFP	-0.068***	-0.062***	-0.072***	-0.062	-0.055	-0.066
	(0.013)	(0.012)	(0.015)	(0.042)	(0.039)	(0.041)
Male unemployment rate	0.015			0.020		
	(0.017)			(0.022)		
Govern. exp.		-0.009***			-0.009	
		(0.003)			(0.010)	
Labour productivity growth			0.003			0.015
			(0.007)			(0.019)
No. of Obs.	1,648	1,648	1,606	1,642	1,642	1,606
No. of Groups	151	151	150	126	126	126
No. of Industries	11	11	11	9	9	9
Within R-squared	0.061	0.062	0.063	0.067	0.068	0.069

Table A5 notes: Columns 1-4 present fixed effects (within) estimates, while Columns 5-6 present instrumental variables estimates using replaceable hours as instrument for industrial robots. All models include constant terms, independent variables are one-period lagged and include time effects and country-time fixed effects. Dependent and independent variables are standardized to ease the interpretation of the results. Driscoll-Kraay standard errors in parentheses in fixed effects within estimates. Columns 5-6 do not include All other branches and Other transport industries because inconsistency in correspondence with Graetz and Michaels (2018) data. * $p < .1$, ** $p < .05$, *** $p < .01$. Sources: UNIDO, IFR, COMTRADE, Graetz and Michaels (2018), WDI, ILO, own calculations

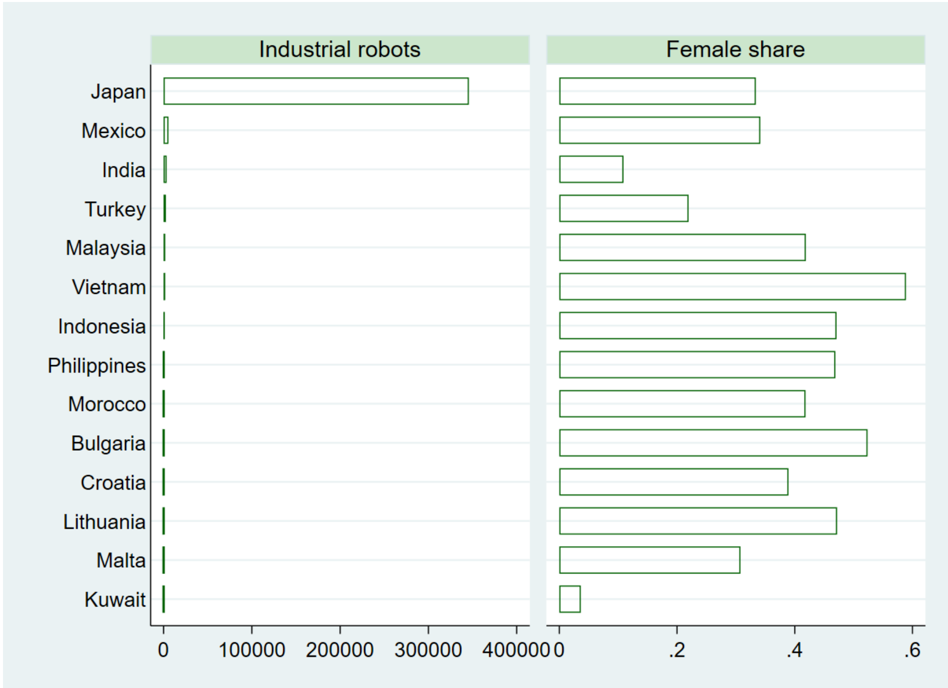

Figure A5: Industrial Robots and Female Share in Manufacturing Industry by Country

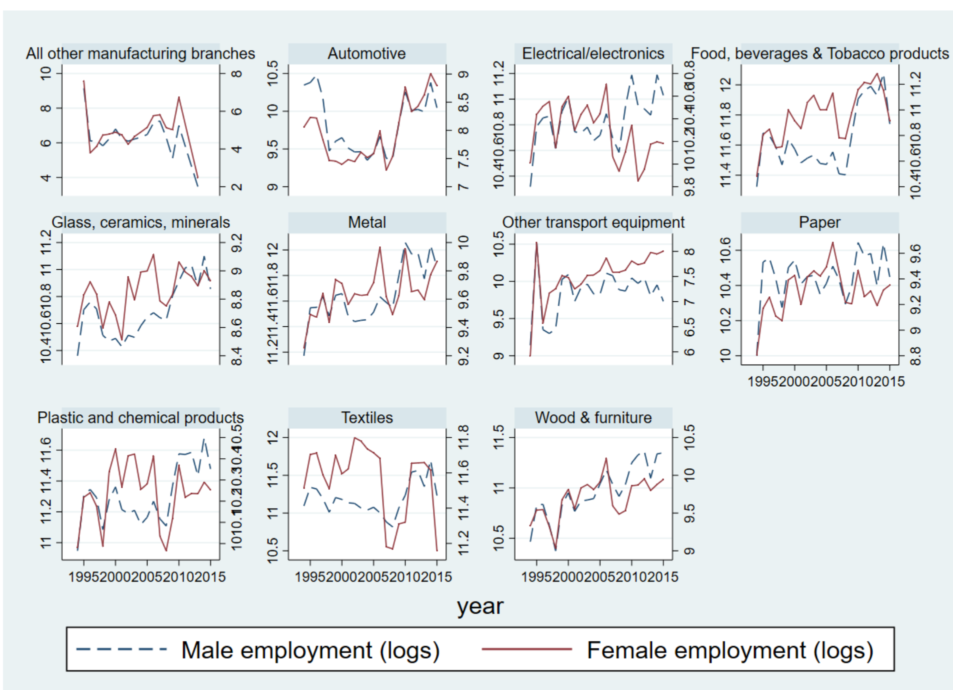

Figure A6: Evolution of Female and Male Employment by Industry

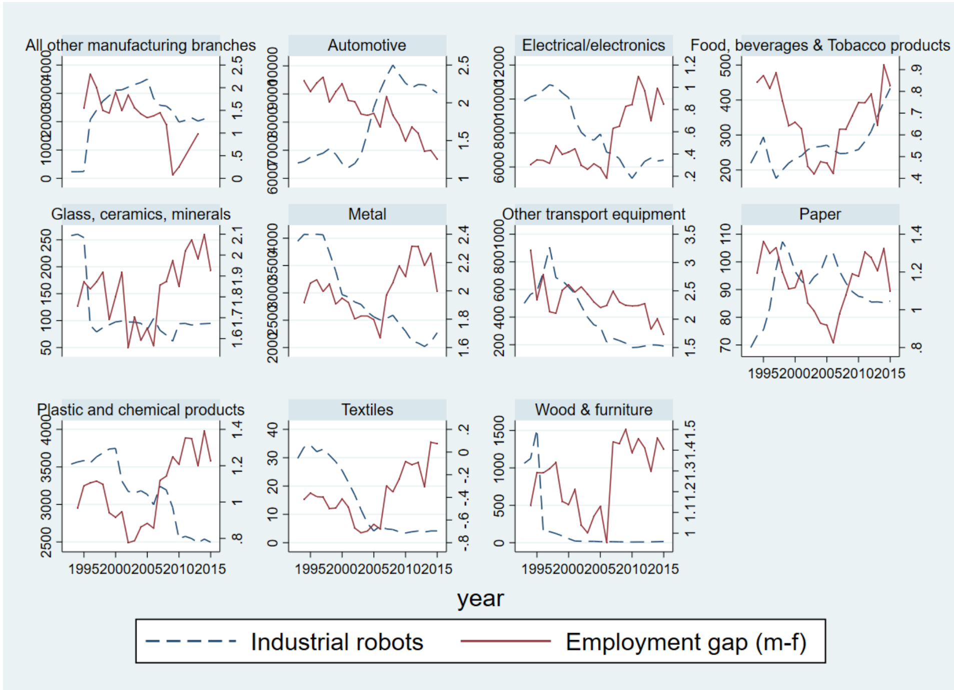

Figure A7: Evolution of Industrial Robots and Gender Employment Gap by Industry

Table A6: Robots and Women in Manufacturing Employment: Regressions by Industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Food	Textiles	Wood	Paper	Plastic	Glass	Metal	Elec.	Auto	Other T.	All other
Robots	1.510**	-23.700**	-3.997***	-5.415**	0.024	3.172***	0.123***	0.016	-0.303	0.958*	0.153
	(0.567)	(8.931)	(1.149)	(2.012)	(0.050)	(1.113)	(0.015)	(0.016)	(0.243)	(0.462)	(0.543)
FLFP	-0.473**	8.266*	2.301***	0.322	0.180*	-1.578**	-0.137	-0.042	1.002**	-0.139	1.074
	(0.201)	(4.027)	(0.580)	(0.450)	(0.093)	(0.582)	(0.081)	(0.154)	(0.387)	(0.227)	(0.649)
Robots*FLFP	-4.097***	57.576*	14.198***	2.042	-0.115	-10.923**	-0.424***	-0.043	0.202	-2.335	-0.233
	(1.058)	(29.045)	(3.970)	(3.230)	(0.126)	(4.519)	(0.073)	(0.058)	(0.292)	(1.439)	(1.230)
No. of Obs.	158	158	158	158	158	153	158	147	147	136	75
No. of Countries	14	14	14	14	14	14	14	14	14	14	10
Within R-squared	0.544	0.624	0.311	0.547	0.351	0.365	0.337	0.663	0.546	0.518	0.600
Country-level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table A6 note: Columns show estimates of the model in Column 3 in Table 4 regress separately for each industry, thus observations vary at country level. All models include constant terms, independent variables are one-period lagged and include time effects. Dependent and independent variables are standardized to ease the interpretation of the results. The set of control is the one of model in Column 3 in Table 4. Fixed effects within estimates using Driscoll-Kraay standard errors in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$ Sources: UNIDO, IFR, COMTRADE, Graetz and Michaels (2018), WDI, ILO, own calculations

Table A7: Robots and Log Female Employment: Regressions by Industry

	(1) Food	(2) Textiles	(3) Wood	(4) Paper	(5) Plastic	(6) Glass	(7) Metal	(8) Elec.	(9) Auto	(10) Other T.	(11) All other
Robots	3.015**	19.916	-9.885*	2.578	0.310***	17.152***	0.446***	0.143***	-0.437*	-1.528	2.089***
	(1.441)	(12.993)	(5.082)	(8.012)	(0.083)	(4.112)	(0.065)	(0.038)	(0.242)	(1.103)	(0.506)
FLFP	-1.191***	-8.993	4.678*	-3.970**	-0.101	-9.492***	-0.714***	-0.393*	0.802**	-0.011	2.844*
	(0.263)	(5.316)	(2.338)	(1.585)	(0.297)	(2.301)	(0.163)	(0.223)	(0.372)	(0.651)	(1.387)
Robots*FLFP	-7.514***	-64.134	35.335*	-25.263**	-0.128	-64.796***	-1.251***	-0.218	0.222	5.245	-5.346***
	(2.003)	(39.421)	(17.514)	(11.711)	(0.249)	(16.982)	(0.338)	(0.154)	(0.231)	(3.222)	(1.426)
No. of Obs.	158	158	158	158	158	153	158	147	147	136	75
No. of Countries	14	14	14	14	14	14	14	14	14	14	10
Within R-squared	0.534	0.846	0.654	0.595	0.527	0.456	0.628	0.649	0.711	0.481	0.775
Country-level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table A7 note: Dependent variable is log of female employment. Columns show estimates of the model in Column 3 in Table 4 regress separately for each industry, thus observations vary at country level. All models include constant terms, independent variables are one-period lagged and include time effects. Dependent and independent variables are standardized to ease the interpretation of the results. The set of control is the one of model in Column 3 in Table 4. Fixed effects within estimates using Driscoll-Kraay standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: UNIDO, IFR, COMTRADE, Graetz and Michaels (2018), WDI, ILO, own calculations

Table A8: Robots and Log Male Employment: Regressions by Industry

	(1) Food	(2) Textiles	(3) Wood	(4) Paper	(5) Plastic	(6) Glass	(7) Metal	(8) Elec.	(9) Auto	(10) Other T.	(11) All other
Robots	1.455	42.927**	-3.595	5.877	0.212***	8.589***	0.255***	0.123***	-0.328**	-2.093	2.544
	(1.315)	(19.440)	(4.171)	(4.782)	(0.071)	(2.450)	(0.058)	(0.036)	(0.133)	(1.523)	(1.693)
FLFP	-0.767***	-17.689*	1.069	-3.340***	-0.377	-5.204***	-0.402***	-0.430***	-0.457***	-0.028	0.658
	(0.184)	(8.636)	(1.846)	(0.955)	(0.224)	(1.417)	(0.125)	(0.126)	(0.130)	(0.797)	(1.223)
Robots*FLFP	-3.467**	-124.189*	13.100	-20.130***	0.035	-35.094***	-0.609*	-0.163	0.391***	5.971	-7.262*
	(1.548)	(63.055)	(14.318)	(7.033)	(0.163)	(10.031)	(0.299)	(0.128)	(0.130)	(4.673)	(4.038)
No. of Obs.	158	158	158	158	158	153	158	147	147	136	75
No. of Countries	14	14	14	14	14	14	14	14	14	14	10
Within R-squared	0.665	0.658	0.721	0.579	0.659	0.700	0.780	0.702	0.746	0.607	0.564
Country-level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table A8 note: Dependent variable is log of male employment. Columns show estimates of the model in Column 3 in Table 4 regress separately for each industry, thus observations vary at country level. All models include constant terms, independent variables are one-period lagged and include time effects. Dependent and independent variables are standardized to ease the interpretation of the results. The set of control is the one of model in Column 3 in Table 4. Fixed effects within estimates using Driscoll-Kraay standard errors in parentheses. $^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$ Sources: UNIDO, IFR, COMTRADE, Graetz and Michaels (2018), WDI, ILO, own calculations

Table A9: Robots and Gender Employment Gap: Regressions by Industry

	(1) Food	(2) Textiles	(3) Wood	(4) Paper	(5) Plastic	(6) Glass	(7) Metal	(8) Elec.	(9) Auto	(10) Other T.	(11) All other
Robots	-1.560**	23.011**	6.290***	3.299	-0.097**	-8.563***	-0.191***	-0.020	0.109	-0.564	0.455
	(0.560)	(9.633)	(1.371)	(3.319)	(0.046)	(1.806)	(0.021)	(0.018)	(0.283)	(0.924)	(1.306)
FLFP	0.424**	-8.696*	-3.609***	0.630	-0.276**	4.287***	0.312***	-0.038	-1.258***	-0.017	-2.187**
	(0.170)	(4.403)	(0.700)	(0.650)	(0.101)	(0.985)	(0.090)	(0.118)	(0.421)	(0.523)	(0.943)
Robots*FLFP	4.047***	-60.055*	-22.235***	5.133	0.163	29.701***	0.643***	0.054	0.169	0.726	-1.916
	(0.899)	(31.551)	(4.760)	(4.871)	(0.131)	(7.710)	(0.113)	(0.056)	(0.281)	(2.843)	(3.006)
No. of Obs.	158	158	158	158	158	153	158	147	147	136	75
No. of Countries	14	14	14	14	14	14	14	14	14	14	10
Within R-squared	0.525	0.580	0.361	0.552	0.500	0.422	0.380	0.553	0.544	0.421	0.624
Country-level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table A9 note: Dependent variable is gender employment gapc. Columns show estimates of the model in Column 3 in Table 4 regress separately for each industry, thus observations vary at country level. All models include constant terms, independent variables are one-period lagged and include time effects. Dependent and independent variables are standardized to ease the interpretation of the results. The set of control is the one of model in Column 3 in Table 4. Fixed effects within estimates using Driscoll-Kraay standard errors in parentheses. $^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$ Sources: UNIDO, IFR, COMTRADE, Graetz and Michaels (2018), WDI, ILO, own calculations

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