Robots and Women in Manufacturing

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Abstract

Automation transforms the combination of tasks performed by machines and humans, and reshapes existing labor markets by replacing jobs and creating new ones. This paper analyzes the extent to which these transformations can differ by gender. To do so, I focused on manufacturing, a widely robotized sector, to empirically analyze whether industrial robots are linked to female shares from an industry-level approach. Further, I surmise that robots and female shares can have a non-linear relationship which depends on female labor force participation. I construct an industry-level panel dataset consisting of 11 manufacturing industries operating in 14 countries during 1993-2015. Using dynamic panel data models and treating robotization as endogenous, the estimates associate robotization with a 0.1% to 0.4% increase in female shares. However, this association depends on female labor force participation rates. As female labor force participation increases, the positive association between robotization and female share decreases. These findings are robust to partitions of the sample, alternative measures of robot penetration and different estimation techniques.

JEL codes: C23, F16, J16, F14

Keywords: Robotization, manufacturing, gender, female labor force participation, dynamic panel data

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1 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 labor markets (Brynjolfsson & McAfee, 2014; Graetz & Michaels, 2018; Acemoglu & Restrepo, 2020). Industrial robots[1] have advanced rapidly since the 1990s and are mainly put to work in the manufacturing sector. Nonetheless, sectoral employment is at varying levels of exposure to automation, even within manufacturing, due to different compositions of routine and non-routine tasks and manual and analytical tasks (Autor et al., 2003; Reijnders & de Vries, 2018; Dauth et al., 2017; Acemoglu & Restrepo, 2020). At the same time, occupations and industries are overwhelmingly segregated by gender through history, where manufacturing shows an overall 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), and technological upgrading has been linked to lower shares of women in the industry and manufacturing (Seguino & Braunstein, 2019; Tejani & Kucera, 2021). Yet the net effect of robots and artificial intelligence (AI) in employment can be either negative, neutral or positive (Graetz & Michaels, 2018; Hamaguchi & Kondo, 2018), its impact can differ between women and men.

This paper brings together the literatures on the automation of work and the defeminization of the manufacturing to empirically analyze whether industrial robots impact the female share of manufacturing employment from an industry-level disaggregated approach. Gender approaches in the automation of work literature have focused primarily on the role of robotization and investments in AI in driving gender wage inequality (Ge & Zhou, 2020; Aksoy et al., 2021; Domini et al., 2022). Another body of literature that evolved in parallel tracks has focused on how technological upgrading, in the form of labor productivity gains rather than robot adoption, establishing a defeminization of manufacturing trend (Kucera & Milberg, 2000; Tejani & Milberg, 2016; Kucera & Tejani, 2014; Seguino & Braunstein, 2019; Tejani & Kucera, 2021). The defeminization of manufacturing literature finds technological upgrading together with rising female labor force participation to reduce women's opportunities in the industry (Seguino & Braunstein, 2019).

This paper hypothesizes that the impact of robots in female shares of manufacturing employment is non-linear and that it hinges upon the participation of women in the workforce. The incorporation of women in the labor market came along with a "crowding out" effect in the services sector of female employment

[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."

(Boserup, 1970; Ngai & Petrongolo, 2017; Seguino & Braunstein, 2019) and a subsequent defeminization of manufacturing employment (Tejani & Milberg, 2016; Kucera & Tejani, 2014). Relatedly, female labor force is considered in the literature of cultural values as a form of intergenerational transmission of gender roles (Fernández, 2013; Gaddis & Klasen, 2014; Uberti & Douarin, 2023). Thus, the direction and the intensity of the impact of robotization in female manufacturing employment can thus vary at different levels of female labor force participation.

The paper constructs an industry-level panel dataset consisting of 11 industries operating in 14 developed, emerging and developing countries over the period 1993-2015 to estimate the impact of industrial robots in the share of women in manufacturing employment. The dataset is built combining information from United Nations Industrial Development Organization (UNIDO), the International Federation of Robotics (IFR), UN Commodity Trade Statistics Database (COMTRADE), together with country-level data sources (World Bank, ILO). I specify status and dynamic panel data models and estimate them using fixed-effects and the Generalized Method of Moments (GMM). Thus, the models account for the influential role of previous levels of female shares in contemporary gender distribution of manufacturing employment, and treat robotization as endogenous using internal instruments.

The findings suggest that robotization increases the presence of women in manufacturing employment. However, this association depends on female labor force participation. As female labor force participation increases, the positive effect of robots in female shares in manufacturing industries is reduced, and at very high levels, the role of robotization becomes insignificant. A possible interpretation for this finding is that the robotization reduces the physical demands of manufacturing jobs, which can increase female-labor demand at initial levels of labor force participation of women (Galor & Weil, 1993; Rendall, 2013; Juhn et al., 2014; Rendall, 2017; Beaudry & Lewis, 2014). Nonetheless, the rise of female labor force could offset this increasing female-labor demand and divert female employment into the service economy (Ngai & Petrongolo, 2017; Petrongolo & Ronchi, 2020). Simultaneously, gender stereotypes, gender discrimination and the competition for jobs among genders in the advent of technological upgrading of manufacturing jobs can limit the rise in female-labor demand in robotized industries (Kucera & Tejani, 2014; Seguino & Braunstein, 2019).

The contribution of this article is two-fold. First, I expand existing works on the links between robots and gender differential effects (Brussevich et al., 2019; Aksoy et al., 2021; Ge & Zhou, 2020; Domini et al., 2022) and labor force participation (Grigoli et al., 2020) by using an industry-level disaggregated panel data approach that focuses on manufacturing employment. Second, I complement the literature on the effects of technological upgrading and structural change in the defeminization of manufacturing (Seguino & Braunstein, 2019; Tejani & Kucera, 2021) by identifying the role of robotization in female shares. Understanding the causal direction and magnitude of these mechanisms, specifically in the economic and social aftermath of the COVID-19 pandemic (Collins et al., 2021), is crucial to correct for the gendered imbalances in the sectoral composition of the workforce. To my best knowledge, this is the first attempt to test a non-linear association between industrial robots and female shares in manufacturing from an industry-level disaggregated dynamic panel data approach.

The paper is structured as follows. Section 2 provides a literature review and elaborates on the hypothesis to be tested. Section 3 explains the dataset and provides descriptive statistics. Section 4 presents the econometric model while Section 5 brings the first set of results. Section 6 expands the model and provides dynamic panel models that treat robots as endogeneous. Section 7 concludes.

2 Background and hypothesis

Existing literature establish direct links from robotization to gender differences in employment and wages. Brussevich et al. (2019) employ data on 30 advanced and emerging economies to show that women are at significantly higher risk for displacement by automation. To the contrary, Acemoglu & Restrepo (2020) use data on the US labor market and show that exposure to robots is related with a negative effect on employment for both women and men, although it is higher for men. Also for the US, P. Cortes & 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. Similarly, G. M. Cortes et al. (2020) look at the US and Portugal to find that less automation risk of women in the US and Portugal.

The association between robotization and gender wage gaps remains unclear in the literature. Aksoy et al. (2021) uses data from 20 European countries in two points in time (2006 and 2014) and relate industrial robots with increasing gender wage gaps. To the contrary, Ge & Zhou (2020) data on the variation in automation and gender gaps in US local labor markets between 1990 and 2015, and find that computer capital, but not industrial robots, increase gender pay gaps. Also for the US, together with Portugal, G. M. Cortes et al. (2020) do not find that automation leads to a significant effect in gender gaps. For the case of Japan, Hamaguchi & Kondo (2018) emphasize the role of gender gaps in skill utilization, rather than the skill gap itself. Finally, Domini et al. (2022) uses French firm-level data for the 2002-2017 period to that find that the adoption of automation and AI were not followed by an increase in gender wage inequality.

Previous econometric analyses of the role of technological change in the share of women in the manufacturing find support for the defeminization of the manufacturing hypothesis. Seguino & Braunstein (2019) use a panel of 94 developed and developing countries during 1991-2015 and find a significant and negative association between labor productivity and the relative concentration of women in industrial employment. Seguino & Braunstein (2019) also find that the female to male ratio of labor force participation is negatively associated with women in the industry. Nonetheless, they use a country-level aggregate data, and do not consider the interaction between technological upgrading and female labor force participation. In a related work, Tejani & Kucera (2021) use UNIDO database on 22 industries, 14 countries during 1990-2015 to analyze the role of rising productivity in the share of women in manufacturing industries. They find that technological upgrading is negatively correlated with the share of women in manufacturing industries. However, these two previous works on the defeminization of manufacturing do not consider industrial robots on their econometric models, nor consider a non-linear relationship between technological change and gender segregation. The econometric model provided in Section 4 also adds to these previous empirical works by using dynamic panel data models and this controlling for the significant role of previous female shares in manufacturing employment.

This paper draws on the above-mentioned findings on the gender impacts of automation and the defeminization of the manufacturing to study whether rising use of robots leads to a lower presence of women in manufacturing industries. Further, the paper hypothesizes that female labor force participation can counteract the role of robotization in the share of women in manufacturing industries. The argument for a non-linearity in the impact of robots on women is supported by two previous strands in gender economics literature, namely the cultural values literature (Fernández, 2013) and the structural change literature (Boserup, 1970). First, from the perspective of cultural values, the literature considers the intergenerational transmission of gender roles, for which female labor force participation is considered a yardstick of the economic behavior of future generations of women (Fernández et al., 2004; Fernández & Fogli, 2009; Fernández, 2013). Women's integration in the paid workforce serves as a reference for gender norms and cultural adequacy of existing jobs. Higher integration of women as paid workers can have countervailing effects in gender sectoral segregation. On the one side, it might reflect gender progressive ideals and gender equality in the social prescriptions, thus increasing the role of women in manufacturing with rising robotization. On the other, female labor force participation rates, can help create gender-typical conducts, where certain jobs and sectors are blocked for genders, and thus, factoring gender segregation.

Second, the participation of women in the workforce throughout the process of structural change can mediate the impact of robotization in the female share of manufacturing employment.[2] The increasing participa-

[2] The literature identifies complex interactions between gendered labor 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 agri-

tion of women in the labor market and the marketization of household production had led to a feminization of the service sector (Siminski & Yetsenga, 2022; Beaudry & Lewis, 2014). Specifically, the care sector has accrued female employment in the last decades. Structural changes can set into motion a gendered process, as for instance the U-shaped relation between female labor 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; Gaddis & Klasen, 2014; Uberti & Douarin, 2023). Although social norms and stigma attached to women working in manufacturing jobs shifted drastically after the 1950s (Dinkelman & Ngai, 2022), other gender gaps in preferences can emerge to reduce the presence of women in male-dominated sectors Falk & Hermle (2018); England et al. (2020). The types of tasks that women perform in male-dominated sectors, such as the manufacturing, can vary according the general level of women in the paid force. While robotization can shift toward cognitive over physical skills in the workplace, favoring opportunities for women (Rendall, 2013; Beaudry & Lewis, 2014), gender norms might ultimately divert this potential rising female-labor demand.

3 Data and descriptive statistics

I construct a country-industry panel dataset consisting of 11 industries operating in 14 countries during 1993-2015. This database contains information on industrial statistics, robot penetration and trade data at industry level, along with country-level data. The database combines information at industry-level and country-level from 5 main data sources, namely the UNIDO database, IFR, COMTRADE; Word Bank World Development Indicators (WDI) database and International Labor Organization (ILO). Supplementary material explains in detail the construction of the database and the methods used for the harmonization of the industrial classifications of the various data sources, and all the necessary information to replicate the econometric analysis.

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culture and service sector (Seguino & 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 labor market attachment and higher unpaid care work burden (Charmes, 2019) can intensify the stratification of the labor market by which women play a secondary role in the workforce.

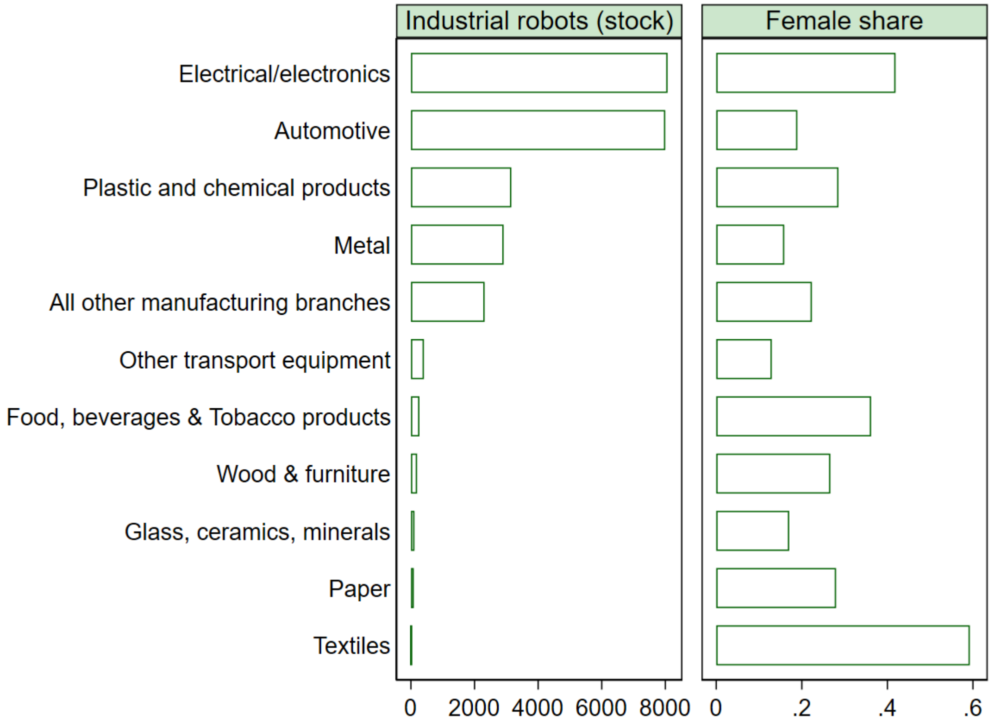

Figure 1: Industry Classification: Industrial Robots and Female Share by Industry

Figure 1 provides the resulting classification of industries after harmonizing the data sources of the database, which divides manufacturing in 11 industries. It plots the average number of industrial robots over the period considered and the average female share by industry (1993-2015). Women are over-represented in textiles, food, beverages and tobacco products, which are among the least robotized industries. Electrical/electronics has a female share above the average, and at the same time, show high levels of robotization. However, automotive, which is a highly robotized industry, employs a low fraction of women. It should be noted that the panel database here employed is unbalanced, and therefore, some cells are under-represented relative to others.[3]

Figure 2 compares the changes in robotization (x-axis) with changes in female shares in industry's employment (y-axis). As the panel database is unbalance, I consider the change between the first observation and last observation per country-industry cell.[4] Thus, I compare changes in female shares in manufacturing

[3]Figures A1 and A2 in the Appendix show respectively the evolution of the number of industrial robots and share of women by industries and by countries in the sample, and Figure A3 provides the evolution of female labor force and female share in manufacturing in the sample countries. Supplementary Data Appendix provides also information on the availability of countries by year in the database.

[4]Outliers are removed from the Figure 2 by considering data points in the range between the 5th and 95th percentiles.

industries and changes in the number of industrial robots for the period 1993-2015 attending to the time coverage for each cell. The correlation shows a slight negative slope, meaning that increasing robot penetration correlates with lower shares of women in manufacturing employment.

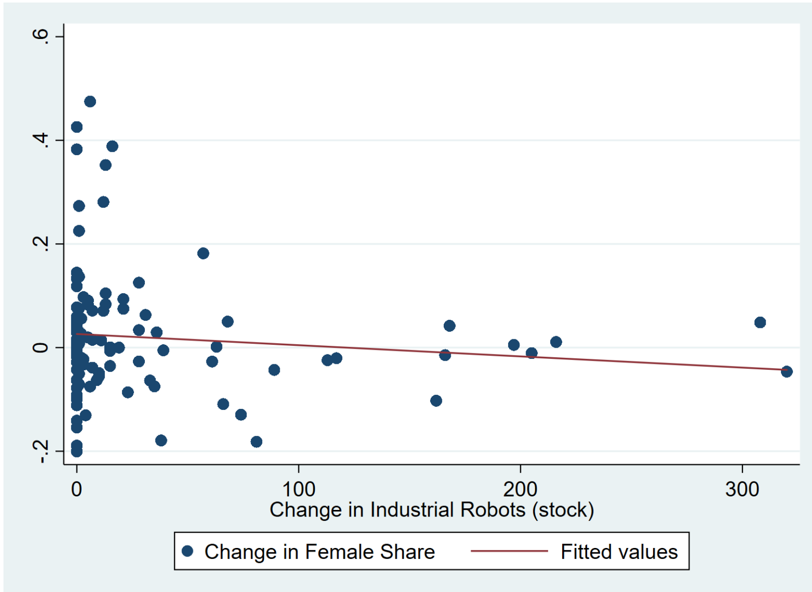

Figure 2: Changes in Industrial Robots and Female Shares (1993-2015)

4 Empirical strategy

I specify the following econometric model in Eq.1 to identify the role of industrial robots in female employment share in manufacturing industries. The database is therefore a three-way panel dataset with observations by industry (i), country (c) and year (t).

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

where f_{ict} is the female share in industry i, country c and year t, computed as the ratio of the number of women in industry i by total employment in industry i. The focal explanatory variables in this analysis are $Rob_{ic,t-1}$, $FLFP_{c,t-1}$ and $Rob * FLFP_{ic,t-1}$ which refer respectively to robotization, female labor force participation (FLFP) and the interaction between robotization and FLFP. $X'_{ic,t-1}$ is a set of country-industry level control variables whereas $Z`_{c,t-1}$ is a set of country-level covariates. The parameters ω_i, δ_c and γ_t constitute the idiosyncratic terms for industries, countries and time, whereas ϵ_{ict} stands for the error term.

Explanatory variables:

Robotization is measured using the inverse hyperbolic sine (IHS) transformation of the annual change in the stock of industrial robots per 10,000 workers in the corresponding country-industry in 1980, provided in Eq.2. The IHS transformation considers the skewness of the distribution of industrial robots and the high number of zeros in the variable. The logarithmic transformation is undefined at zero, and thus, observations with zero industrial robots would be dropped from the analysis and bias the estimates (G. De Vries et al., 2021). The IHS transformation behaves similarly to a log transformation for positive values, but has the added benefit of remaining defined for zeroes and negative values (Burbidge et al., 1988; Bellemare & Wichman, 2020).

$$Robotization_{ict} = IHS[\frac{Robots_{ict}}{10,000 * Employees_{ic,1980}} - \frac{Robots_{ic,t-1}}{10,000 * Employees_{ic,1980}}] \tag{2}$$

The choice of the base level of employment in 1980 draws on Graetz & Michaels (2018).[5] In principle, the level of employment back in 1980 should be less affected by the levels of industrial robots and robot penetration in contemporary trends and might overcome endogeneity concerns in the total number of employment. Nonetheless, using alternative reference years of industry employment, such as 1993 as the staring date of the database, does not alter the main results of the paper and are available on request.

[5]The influential work of Graetz & Michaels (2018) provides an instrument for analyzing the causal role of robotization in employment. For computing their instrument, they rely on employment levels in 1980. They argue this year was well before robots became ubiquitous, which can provide an exogenous baseline for changes in subsequent years after 1993, from which the IFR data is available.

Table 1: Descriptive Statistics of Selected Key Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Female share	1,147	.285	.199	0	.858
IHS male employment	1,147	11.33	2.145	3.527	15.403
IHS female employment	1,147	10.025	2.516	0	15.226
Industrial robots (stock)	1,147	2322.286	13870.87	0	151774
Installations	1,147	193.229	1269.738	0	20823
IHS Robotization (stock)	1,147	.003	.016	0	.159
IHS Robotization (installations)	1,147	0	.002	0	.024
Robots per 10,000 workers	1,147	2.513	29.228	0	460.815
Share of robots	1,147	.088	.193	0	1
Share of installations	1,147	.093	.217	0	1
Female labor force participation	1,147	.48	.152	.23	.78

Table 1 presents descriptive statistics of the main variables used in the analysis related to share of women in manufacturing, robot penetration and FLFP. Sources of data and definition of all variables are in Appendix. The main outcome variable in this paper is the industry female share, computed as the ratio of female employment to total employment in industry i, country c in time t. It ranges from 0, meaning that there are no women in that industry (the unique case is "All other manufacturing branches" in 1998 in Bulgaria), and the maximum share of women in the sample is 85%, which corresponds to "Textiles" in 2014 in Lithuania. Apart from the share of women by industries as the main dependent variable in the analysis below, I provide models that employ the IHS transformation of female and male employment as dependent variables as robustness checks.

Control variables:

The identification strategy in Eq. 1 includes a set of industry-level control variables that accounts for three main aspects: compositional shifts within the manufacturing, capital intensity and international trade. As female manufacturing employment is usually crowded into low value-added industries (Tejani & Kucera, 2021), the model controls for the share of employees in industry i to total manufacturing employment and gross fixed capital formation by industries. 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 globalization (Kucera & Milberg, 2000; Juhn et al., 2013). For this, the model includes the share of industry i in the total manufacturing exports of goods. Nonetheless, evidence suggests that technology is a more decisive factor in changing employment structure and drive inequality and job polarization than international trade (David & Dorn, 2013; Goos et al., 2014). Indeed, technological upgrading is associated with greater effects in the shifts of female employment than globalization (Tejani & Milberg, 2016).

A set of country-level control variables includes that captures the potential correlations between structural change, economic development, industrial policy or gender disparities in educational attainment with the dependent variable. One of the most relevant factors explaining unbalances in the gender distribution of industrial employment, apart from technological upgrading, is structural change (Gaddis & Klasen, 2014; Kucera & Tejani, 2014; Seguino & Braunstein, 2019). A decline in relatively good industrial sector employment during the process of structural change might lead to a consequent job competition among genders, which is proven in the literature to tend to be more costly for women than for men. Additionally, increasing the share of capital-intensive production might couple with gender norms designating men as breadwinners and women as secondary workers. On top of it, gender stereotypes fuelling discriminatory hiring practices might further deter the entrance of women in new capital-intensive, high-value-added employment in manufacturing. 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 & 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 industrial and trade policies. Finally, the gender parity gap in literacy of adults is included to control for educational attainment differences between women and men which could decisively impact on.[6]

Macroeconomic panel data are likely to be characterized by cross-sectional or spatial dependence, for which Driscoll & Kraay (1998) developed an estimator that computes alternative standard errors to alleviate such issues. Indeed, robot adoption in a country can unleash spillover effects in employment of neighbouring countries. 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 & Milberg, 2016) can also impose cross-dependency biases in the estimates. To alleviate endogeneity concerns due to cross-sectional correlation in the estimation of the above panel data model, I employ the Driscoll & Kraay (1998)'s standard errors in the fixed-effects models provided below. The estimates are thus well calibrated in the presence of cross-sectional or time dependence. I follow Hoechle (2007) to perform the

[6]Several other covariates were considered in separate models upon request, but came at the cost of significantly reducing the number of observations without improving the efficiency of the estimates. Among these other controls are the male rate of unemployment, the female share of mid-skill occupations, fertility rates, and different measures of educational attainment and disparities by gender.

adjusted Hausman test robust to spatial and temporal dependence, which justifies the use of fixed effects models in the panel dataset here used.

4.1 Limitations and potential solutions

The econometric analysis below is limited by at least two main challenges, namely data selection and endogneneity biases. The first challenge is related to the sample selection and data collection and rises concerns about the heterogeneity of the sample of countries here collected. Among these data selection concerns is the issueof the inclusion of Japan in the database. There are a number of reasons why including Japan in this analysis might distort the results. First, Japan is a world-wide exporter of industrial robots and is leading the automation of work.[7] Indeed, the diffusion of robots first started in the early 70s, to spread to other advanced economies such as Germany (Cette et al., 2021). Consequently, Japanese industries are likely to be highly robotized relative to the rest of sample countries and be outliers. Second, the IFR computes the stock of industrial robots as the sum of annual robot installations over 12 years with immediate withdrawal from service or replacement thereafter. However, this number is directly provided by the Japanese national robot association (JARA) (Jurkat et al., 2022), and thus, can suffer from measurement errors as being computed differently from the rest of countries in the IFR database. Finally, Japanese data were subject to substantial reclassification of the machines classified as robots (Graetz & Michaels, 2018), and Acemoglu & Restrepo (2020) and the IFR recommend excluding Japan for cross-country comparisons. Jurkat et al. (2022) suggest that starting from 2011, Japanese data should pose no problem in econometric models, but last data point available for the UNIDO industry-level data on the share of women in Japanese manufacturing industries is 2010. Therefore, there is no data availability to matching the IFR data from 2011 onwards and UNIDO data for Japanese country-industry cells.

Taking into account these potential threats, I include Japan to have a greater variability in the data, specifically relative to variability of educational trends, FLFP and country-level covariates and increase the number of observations. Having a counterfactual in the estimates, such as the case of a highly robotized economy with a relatively high level of FLFP and both declining use of robots and female shares in manufacturing, will provide the regression model with higher variability in the three key variables of the paper. Nonetheless, I systematically drop Japan from the sample to check the sensitivity of the results to the inclusion of Japanese data.[8]

[7] IFR https://ifr.org/news/japan-is-worlds-number-one-robot-maker/ last access 15 March 2023

[8] Some works of the reference literature includes Japan in empirical analyses without rising further concerns (Jung & Lim, 2020; Cette et al., 2021; Anelli et al., 2021). Other works that crucially drop Japan and provide a discussion on this issue are

Related to data selection issues is how representative the sample of countries employed here is in a world-wide context and its relevance for our understanding of the gender labor market effects of robot penetration. Figure 3 shows the share of the total of industrial robots of the sample industries to the total of industrial robots of the IFR database that contains information on 71 countries (see IFR data). When Japan is included in both the sample of countries and the world totals, the sample here used represents on average a 3% of the total IFR database.[9] When dropping Japan from both the sample and the total IFR database, the sample here employed represents 6% of the latter. In this context, "Other transport equipment" represents 15% of the total IFR database, "Electrical/electronics" around 13%.

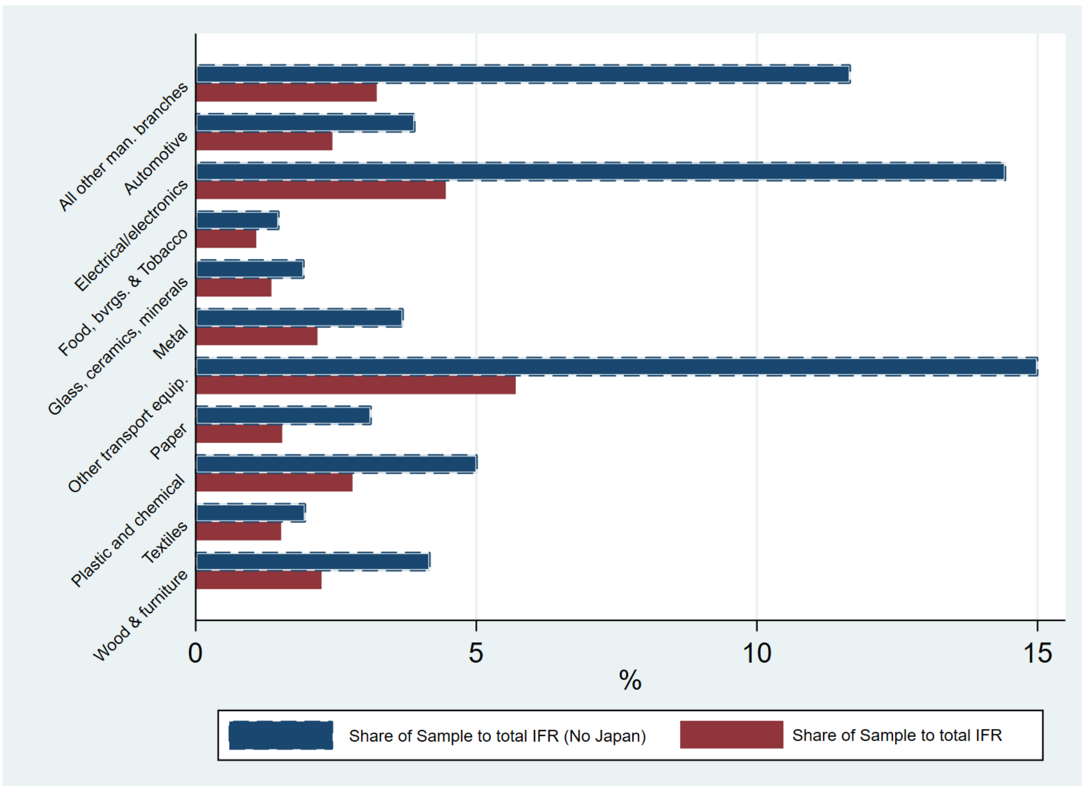

Figure 3: Share of Sample Industrial Robots to IFR Total Database

The second challenge relates to endogeneity issues emerging from omitted variable biases, feedback effects of previous levels of gender segregation in manufacturing, and reverse causation of robot penetration. 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 labor market. This in turn, can affect both hiring decision and the adoption of robots,

Graetz & Michaels (2018) and Acemoglu & Restrepo (2020).

[9]Notice that Japanese data is not available for few years in the database, as the last point observation of UNIDO database for female share of industries for Japan is 2010.

which will incur in a reverse causation problem (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.[10]

The issue of endogeneity has largely discussed in the literature of automation of work. One of the more popular instrumental variables approach in the literature is the one provided in Graetz & Michaels (2018), who construct two industry-specific instruments, namely *replaceable hours* and *reaching and handling tasks*. The first instrument is the share of labor input that can be replaceable by robots at industry level and was computed by Graetz & 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 & Michaels (2018) is a measure of the prevalence of the reaching and handling tasks, which are typically performed by industrial robots, where in each industry, relative to other physical demands, prior to 1980. The instruments in Graetz & Michaels (2018) are not free from limitations. Firstly, as already suggested in G. J. 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. Bekhtiar et al. (2021) provides an in-depth discussion of the instruments of Graetz & Michaels (2018), and other type of instruments are employed in Anelli et al. (2019).

Section 6 alleviates omitted variable biases and endogeneity issues related to robot penetration by specifying a dynamic panel data model that includes the first lag of the dependent variable (female share) in the set of explanatory variables. Using the Generalized Method of Moments (GMM) (Arellano & Bond, 1991; Blundell & Bond, 2000) avoids the so-called Nickel bias (Nickell, 1981) while allows accounting for the effect that previous share of women might have in contemporary (de)feminization trends of the manufacturing. To tackle the endogeneity concerns of a casual link from the share of women in the robot adoption, I treat robotization as an endogenous variable in the context of GMM. Due to the characteristics of the dataset here constructed, the GMM technique for circumventing endogeneity issues, that is using internal instruments, outperforms the use of the instrument in Graetz & Michaels (2018), as their instrument is time-invariant within industries, along to the limitations discussed in Bekhtiar et al. (2021).

[10] I note here the work of Jung & Lim (2020), who use IFR data and a simultaneous equation to consider two-way causal relationships between the expansion of industrial robots and labor characteristics, among them, the proportion of women in manufacturing.

5 Static panel data results

5.1 Main results

Table 2 shows the results of the regression model in Eq. 1 using panel data fixed-effects models. All the estimates associate robotization with an increasing share of women in manufacturing industries. Including year fixed effects, country and country-time fixed effects do not alter this finding. However, the interaction between robotization and FLFP is negative and significant (Columns 2-5). Therefore, the marginal association between robotization and women in manufacturing depends on the country level of women in the workforce. Dropping Japan from the database does not alter the results.

Alongside with the coefficients on the main independent variables (robotization, FLFP and its interaction), Table 2 shows the elasticities of the models to help the interpretation of the results. I compute the elasticity of robotization and the interaction with FLFP, and evaluate them at minimum, mean and maximum sample values of FLFP.[11] Column 1 associates a ten percent increase in robotization with a 0.16% increase in the share of women in industries within the manufacturing. Adding the interaction between robotization and FLFP (Columns 2-5) increases the coefficient of robotization up to 4.824 with an elasticity of 0.052 and elasticity of the interaction is -0.042 (Column 5, Table 2), meaning that an increase in FLFP reduces the elasticity of robotization relative to the share of women. The results of the model including year fixed effects, country-industry fixed effects and the whole set of controls suggest that a ten percent increase of robotization is linked to a 0.36% increase of women in industrial employment at the minimum level of FLFP. This elasticity is reduced when FLFP increases: a similar increase in robotization is associated with a 0.25% increase in female shares when FLFP is at its sample mean (FLFP of 48%) and drops to 0.12% when FLFP is at its maximum (FLFP of 78%). Column 6 replicates the saturated model in Column 5 without Japan, providing similar results albeit slightly lower in magnitude.

[11] All models in Table 2 are *linear-arcsinh*, meaning that the dependent variable is in levels and the independent variable is IHS transformed. The formula for computing the elasticities is given by $\hat{\xi_{yx}} = \frac{\hat{\beta}}{y} \frac{x}{\sqrt{x^2+1}}$ (Bellemare & Wichman, 2020). To keep the consistency of the IHS transformation of the measure of robot penetration, the results on the interaction are also expressed in elasticities.

Table 2: Robots and Women in Manufacturing: Baseline models

Dependent variable: Industry female share	(1) All	(2) All	(3) All	(4) All	(5) No Japan
Robotization	1.307***	3.794**	3.008**	4.824***	4.120**
	(0.272)	(1.340)	(1.106)	(1.171)	(1.618)
FLFP	0.001**	0.001*	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Robotization * FLFP		-0.047**	-0.037*	-0.066***	-0.048**
		(0.022)	(0.018)	(0.019)	(0.032)
Elasticity of coefficient	0.016	0.046	0.032	0.052	0.041
Elasticities of interaction coef.		-0.043	-0.028	-0.042	-0.042
Elasticity at min. FLFP (23%)		0.036	0.026	0.042	0.031
Elasticity at mean FLFP (48%)		0.025	0.018	0.031	0.02
Elasticity at max. FLFP (78%)		0.012	0.010	0.019	0.008
No. of Observations	1,147	1,147	1,147	1,030	895
No. of Groups	90	90	90	90	81
Within R-squared	0.021	0.044	0.272	0.240	0.231
Year fixed effects	no	yes	yes	yes	yes
Country-year fixed effects	no	no	yes	yes	yes
Industry-level controls	no	no	yes	yes	yes
Country-level controls	no	no	nos	yes	yes
Japan included	yes	yes	yes	yes	no

Table 2 notes: Independent variables are one-period lagged. Estimates are based on fixed effects models of equation in (1). Robotization is measured as the inverse hyperbolic sine transformation of change in robots per employees, see (Bellemare & Wichman, 2020). Driscoll-Kraay standard errors in parentheses. $^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$. Data Sources: own calculations based on UNIDO, IFR, COMTRADE, WDI and ILO.

Figure 4 shows the marginal effects of robotization in female share in industries (y-axis) as estimated in Column 5 (Table 2), by levels of FLFP (x-axis) where Japan is dropped from the database, with the histogram of FLFP in the background. Robotization is positively associated with female shares in manufacturing industries, although it reduces as FLFP increases. Nonetheless, for a certain threshold of FLFP, the association is not statistically significant.

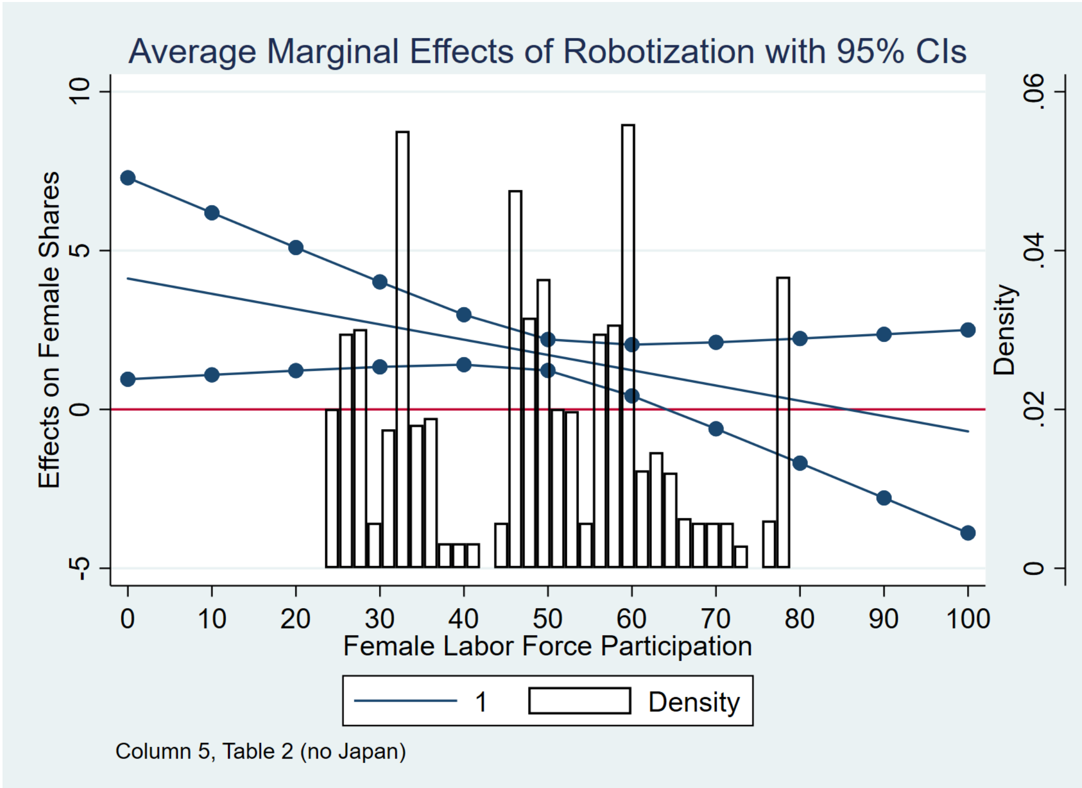

Figure 4: Marginal Effects of Robotization in Female Share (estimates from Column 6, Table 2)

The primary measure of robotization in this paper is the IHS transformation of annual change of industrial robots, with respect to the level of employment in the industry in 1980. I check the stability of the main findings in Table 2 by using alternative measures of robot penetration. Employing the number of industrial robots per 10,000 industrial workers (Table A3, Appendix), which allows using a substantial higher number of observations than in Table 2, provides similar results. Supplementary materials add additional sensitivity checks using alternative measures of robot penetration, and confirm the results of Table 1. For one of these sensitivity checks, I adapt the concept of distance to the World Technology Frontier of (Caselli et al., 2006) and (Acemoglu et al., 2006) to the case of robot penetration and deal in greater detail with the issues of the inclusion of Japanese data in the IFR database (Table S2). Finally, and following (Acemoglu & Restrepo, 2022), I replicate these analyses using the number of installations rather than the stock of industrial robots (see Figure S2, Table S3 and S4 in Supplementary materials).

5.2 Heterogeneity analysis

The sample of countries in the database differs greatly in terms of the participation of women in the paid workforce and economic development. Vietnam and Lithuania stand out in terms of FLFP with an average of respectively 78% and 68%, whereas India and Turkey have a FLFP level of around 30% (see Table A1 in Appendix). Regarding economic development, Kuwait and Japan surpass on average a GDP per capita of 30,000$, whereas India and Vietnam have a GDP per capita of around 1,000$. Although the fully saturated model in Column 4 (Table 2) controls for economic growth and structural change, which are crucial to consider the economic composition of the countries in the sample (e.g. oil exporters countries such as Kuwait), I consider here partitions of the database based on two different levels of FLFP and GDP per capita levels. Country-industry observations for which FLFP was lower than the sample average (48%) are here considered as low-FLFP (India, Indonesia, Kuwait, Malaysia, Malta, Mexico, Morocco, Turkey) and are used in model in Column 1, Table 3. Country-industry observations with a FLFP above or equal to the sample average are considered high-FLFP and are used in model in Column 2, Table 3.[12]

The results using low-FLFP and high-FLFP partitions of the database provide similar results. This suggests that FLFP per se, rather than the initial level of FLFP, mediates the impact of robotization on the share of women in manufacturing employment.

I also divide the database according to low and high levels of economic development.[13] Country-industry observations with low levels of income per capita are used in Column 3 of Table 3 (namely, Bulgaria, India, Indonesia, Malaysia, Morocco, Lithuania, Philippines, Turkey, Vietnam), whereas country-industry observations with high income levels are used in Column 4 of Table 3 (namely, Croatia, Japan, Kuwait, Malaysia, Malta, Mexico, Lithuania and Turkey). The results of the partition based on economic growth levels indicate that the main findings are mostly driven by countries with relatively high levels of economic growth. This might suggest that robotization is likely to influence the gender composition of manufacturing industries once a certain level of GDP per capita is reached. On the other hand, robotization has no effect on the gender distribution of manufacturing employment in countries with low levels of GDP per capita. One interpretation can be that the type of robots implemented in low-income countries are fundamentally different and less relevant than those in mid or high-income countries. Nonetheless, it falls beyond the scope of this paper to delve deeper on the type of robotization.

[12] All countries in the sample show at some data point in the period considered (1993-2015) a FLFP higher than the sample average

[13] This division in low and high economic development levels are made on the basis of the percentile 50th of the GDP per capita of the sample of countries (7055.936$).

Table 3: Robots and Women in Manufacturing: Baseline models, heterogeneous effects by FLFP and GDP

Dependent variable: Industry female share				
Partitions based on	FLFP		Economic Development	
	(1)	(2)	(3)	(4)
	Low FLFP	High FLFP	Low income	High income
Robotization	9.550***	9.378***	-9.061	4.092***
	(3.204)	(1.654)	(6.024)	(0.886)
FLFP	0.003***	0.002***	0.002***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Robotization*FLFP	-0.227**	-0.137***	0.507***	-0.056***
	(0.087)	(0.024)	(0.146)	(0.014)
Elasticity of coefficient	0.116	0.114		0.035
Elasticity of interaction coef.	-0.168	-0.101		-0.029
Elasticity at min. FLFP (23%)	0.077	-		0.029
Elasticity at mean FLFP (48%)	0.035	0.065		0.022
Elasticity at max. FLFP (78%)	-	0.035		0.013
No. of Observations	603	454	562	468
No. of Groups	63	45	63	45
Within R-squared	0.326	0.189	0.184	0.396
Year fixed effects	yes	yes	yes	yes
Country-year fixed effects	yes	yes	yes	yes
Industry-level controls	yes	yes	yes	yes
Country-level controls	yes	yes	yes	yes

Table 3 notes: Independent variables are one-period lagged. Estimates are based on fixed effects models of equation in (1). Robotization is measured as the inverse hyperbolic sine transformation of change in robots per employees, see (Bellemare & Wichman, 2020). Driscoll-Kraay standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: own calculations based on UNIDO, IFR, COMTRADE, WDI and ILO.

6 Dynamic panel data results and extensions

6.1 Persistence of female shares and endogenous robotization

Table 4 shows the results once the first lag of the dependent variable in Eq. 1 is included in the set of explanatory variables. Previous levels of female shares can influence current shares through different ways, as explained in Section 2. As a matter of fact, the estimates using dynamic panel data models suggest that previous realizations of the share of women in manufacturing industries have a significant role in the next period's female share, which is positive and indicate a path dependency of the presence of women in industries. Column 1 (Table 4) estimates the dynamic model using a fixed-effects estimator, and shows that a ten percent increase in robotization is associated with a 0.23% increase in female shares when at low levels of FLFP, and this elasticity drops to 0.01 at high levels of FLFP. [14]

The fixed-effects estimates in Column 1 (Table 4) suffer from the so-called Nickel bias as the correlation between the right-hand-side, lagged dependent variable ($f_{ic,t-1}$) and the error term (v_{ict}) does not tend to zero even with higher number of observations (N) (see (Nickell, 1981)). To solve for this bias, I estimate the dynamic version of the model in Eq. 1 using the difference Generalized Method of Moments (diff-GMM) (Arellano & Bond, 1991; Blundell & Bond, 2000; Roodman, 2009). The diff-GMM estimator applies first-diferences to the regression equation to cancel time-invariant idiosyncratic terms of industries and countries (ω_i and δ_c, respectively), and then it uses lagged values of female shares ($f_ic, t-1$) to internally instrument itself. One potential problem arisen from the use of diff-GMM instead of the system GMM, which estimates the equation in levels and applies first-diferences to the instruments, is that if female shares are highly persistent, diff-GMM might suffer from a version of the weak-instrument problem (Blundell & Bond, 1998). In separate models, I checked the consistency between the system GMM and the diff-GMM estimates, where postestimation tests show similar consistencies in both types of GMM models. However, in terms of efficiency, the diff-GMM outperformed system GMM as it uses a lower number of instruments (Roodman, 2009).

Column 2 (Table 4) treats robotization as exogenous, while Columns 3 and 4 endogeneize robotization using internal instruments in the context of diff-GMM. The results are slightly higher in magnitude than those using the fixed-effects model. When using the diff-GMM, the results associate a ten percent increase in robotization to an around 0.4% to 0.15% increase in female shares depending on the level of FLFP. Dropping Japan from the database produces similar results. Figure 5 plots this non-linear relationship between robotization and female share in manufacturing industries that depends on the level of FLFP based on the results of Column 4 (Table 4) when Japan is dropped from the database.

[14] This result remains when by dropping one industry and one country from the database at a time (see Tables A4 and A5 in Appendix).

Table 4: Dynamic Panel Data Models (FE and GMM)

Dependent variable: Industry female share				
	(1)	(2)	(3)	(4)
Robots treated as		Exogenous	Endogenous	
Estimator	FE	Δ-GMM	Δ-GMM	Δ-GMM
Sample	All	All	All	No Japan
Female share$_{t-1}$	0.734***	0.340**	0.382**	0.371**
	(0.066)	(0.165)	(0.143)	(0.148)
Robotization	2.374***	4.251**	3.116**	4.295**
	(0.662)	(1.996)	(1.295)	(2.042)
FLFP	0.002***	-0.007	-0.000	0.002
	(0.000)	(0.006)	(0.002)	(0.003)
Robotization * FLFP	-0.033***	-0.063**	-0.042**	-0.067*
	(0.011)	(0.030)	(0.019)	(0.036)
Elasticity of coefficient	0.029	0.051	0.038	0.052
Elasticity of interaction coef.	-0.024	-0.046	-0.032	-0.049
Elasticity at min FLFP (23%)	0.023	0.04	0.031	0.041
Elasticity at mean FLFP (48%)	0.017	0.029	0.023	0.028
Elasticity at max. FLFP (78%)	0.01	0.015	0.013	0.014
No. of Observations	1030	850	850	724
No. of Groups	90	90	90	81
Within R-squared	0.531			
AR(2)		0.496	0.486	0.449
Diff-hansen		0.119	0.688	0.208
No. of Instruments		24	58	58
Year fixed effects	yes	yes	yes	yes
Country-year fixed effects	yes	yes	yes	yes
Industry-level controls	yes	yes	yes	yes
Country-level controls	yes	yes	yes	yes
Japan included	yes	yes	yes	no

Table 4 notes: The models include one-period lagged dependent variable. All independent variables are one-period lagged. Robotization is measured as the inverse hyperbolic sine transformation of change in robots per employees, see (Bellemare & Wichman, 2020). Driscoll-Kraay standard errors in parenthesis (Column 1) * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: own calculations based on UNIDO, IFR, COMTRADE, WDI and ILO.

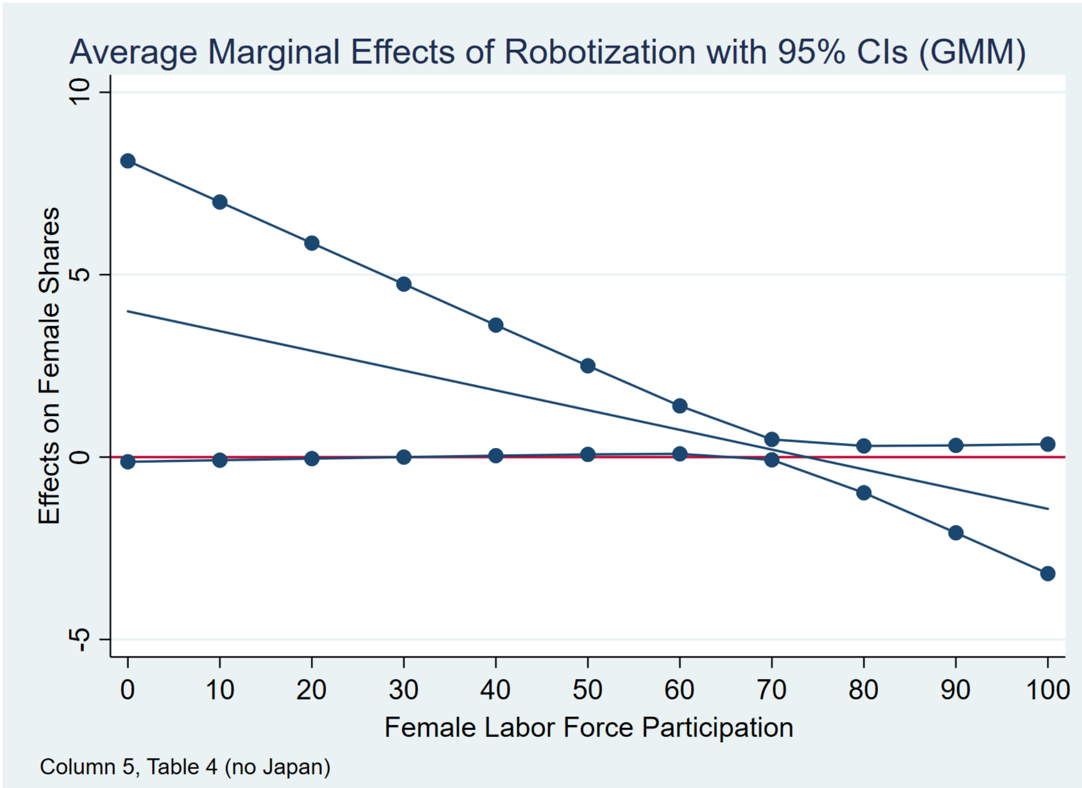

Figure 5: Marginal Effects of Robotization in Female Share (diff-GMM)

6.2 Robotization and employment level by gender

The previous estimates provide evidence on a statistically significant link between robot penetration and the gender distribution of manufacturing employment by industries. However, it remains to be tested the extent to which robotization is associated to the levels of female and male employment. I consider separate regression models for female and male employment as in Acemoglu & Restrepo (2020) to shed new light on the effects of automation in gender labor market outcomes when using industry-level disaggregated data on manufacturing. The models below use the IHS transformation of the level of female or male employment to solve for the skewness of the data and the presence of zeros.[15] The following estimates suggest that higher robotization leads to an increasing female employment, although there is no significant association in the case of male employment. This contrasts the findings in Acemoglu & Restrepo (2020), and thus suggests different gendered labor markets outcomes in the aftermath of robotization outside the US.

[15]Thus, these are *arcsinh-arcsinh* models. The formula for computing the elasticities is $\hat{\xi_{yx}} = \hat{\beta}\frac{\sqrt{y^2+1}}{y}\frac{x}{\sqrt{x^2+1}}$ as provided in Bellemare & Wichman (2020).

Columns 1-4 in Table 5 consider the IHS of female employment level while Columns 5-6 consider the IHS of male employment level. For women, the estimates show a statistically significant and positive association between robotization and employment, whereas for men the results are not statistically significant. Columns 1 and 2 use fixed-effects models to estimate respectively the static model and a dynamic model which includes female employment level in the set of explanatory variables. Columns 3 and 4 use diff-GMM treating robotization as an endogenous variable. The results suggest that one percent change increase of robotization is associated with a 0.17% increase in the presence of women in that precise industry, though at low levels of FLFP. The results here corroborate the main hypothesis of the paper, that is, the association between automation and gender distribution of sectoral employment in manufacturing hinges upon the participation of women in the paid workforce. At mean and maximum sample levels of FLFP, the effect of robots is also increasing female shares, although slightly lower in magnitude. These findings are robust to dropping Japan from the database (Column 4, Table 5). Figure 6 shows graphically the interaction between robotization and FLFP in female shares, showing the marginal effects obtained in the last Column that does not include Japan.

Table 5: Robots and Gender Employment in Manufacturing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimator	FE	FE	Δ-GMM	Δ-GMM	FE	FE	Δ-GMM
Sample			Women			Men	
				No Japan			
IHS female employment$_{t-1}$		0.588***	0.252***	0.250***			
		(0.105)	(0.052)	(0.052)			
IHS male employment$_{t-1}$						0.403**	0.558***
						(0.162)	(0.131)
Robotization	39.898***	21.318***	48.175***	63.809***	-10.773	-8.436	14.887
	(10.235)	(5.810)	(11.059)	(18.136)	(6.750)	(5.321)	(20.210)
FLFP	0.095***	0.058***	0.009	0.006	0.106***	0.080***	0.005
	(0.000)	(0.016)	(0.013)	(0.012)	(0.001)	(0.020)	(0.019)
Robotization * FLFP	-0.551***	-0.290***	-0.659***	-1.063***	0.190*	0.149	-0.183
	(0.161)	(0.092)	(0.175)	(0.364)	(0.108)	(0.088)	(0.313)
Elasticity of coefficient	0.138	0 .074	0.166	0.220			
Elasticity of interaction coef.	-0.002	-0.001	-0.002	-0.004			
Elasticity at min FLFP (23%)	0.138	0.074	0.166	0.219			
Elasticity at mean FLFP (48%)	0.137	0.074	0.165	0.218			

Elasticity at max. FLFP (78%)	0.136	0.073	0.164	0.217			
No. of Observations	1,030	1,030	850	724	1,030	1,030	850
No. of Groups	90	90	90	81	90	90	90
Within R-squared	0.641	0.745			0.809	0.849	
AR(2)			0.218	0.205		0.377	
Hansen Diff		0.763	0.957			0.052	
No. of Instruments			38	38			29

Table 5 notes: Female employment and male employment are transformed using the inverse hyperbolic sine method to correct for the skewness of their distribution (see Bellemare & Wichman (2020)). Independent variables are one-period lagged. Estimates are based on fixed effects models of equation in (1). Robotization is measured as the inverse hyperbolic sine transformation of change in robots per employees, see (Bellemare & Wichman, 2020). Driscoll-Kraay standard errors in parentheses (Columns 1, 2, 5 and 6). $^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$ Sources: own calculations based on UNIDO, IFR, COMTRADE, WDI and ILO.

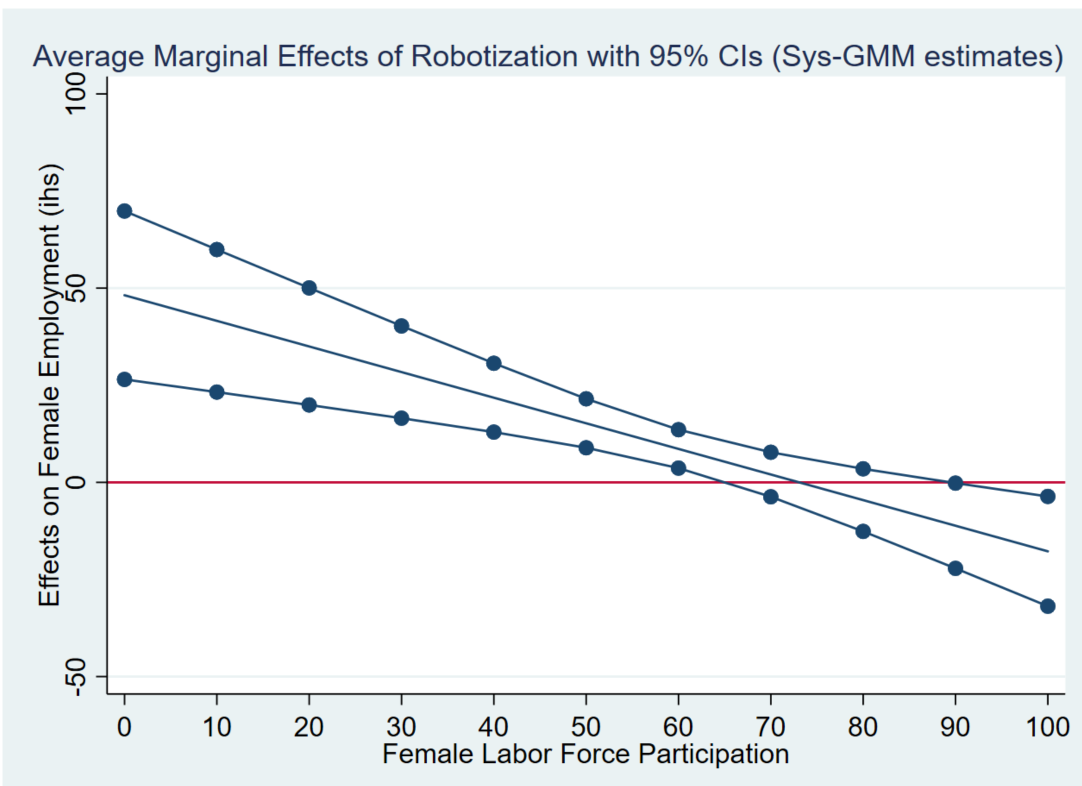

Figure 6: Marginal Effects of Robotization in Female Employment (diff-GMM)

7 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 labor. Against this backdrop, women and men play different roles in the labor market as well as in the household production, as they concentrate in different occupations and industries, accrue different educational paths and skills, and participate in the labor market at different rates. On top of this, cultural norms and gender stereotypes affect the economic role of women and men in sharply different forms, that drive gender wage gaps and usually crowd women labor-intensive sectors and low-skills occupations. This article makes the case of that technological change, specifically in the form of robot penetration, is not gender-neutral and that it will unleash differential employment effects for women and men. Further, I argue that the role of robotization in the gender distribution of sectoral employment might hinge upon the overall presence of women in the workforce, as a proxy of cultural values and prescriptions of gender economic roles.

This paper brought together two literatures that have evolved on parallel tracks: the literature on labor market effects of automation and the literature on the link between technological upgrading and the defeminization of the manufacturing. Although some attempts are welcome gender differences in labor market outcomes of automation (Aksoy et al., 2021; Ge & Zhou, 2020; Domini et al., 2022), they are mostly focused on gender wage gaps, rather than the distribution of women and men across sectors. On the side of gender segregation in manufacturing literature (Kucera & Tejani, 2014; Seguino & Braunstein, 2019; Tejani & Kucera, 2021), they usually consider technological upgrading as means of productivity gains, rather than conceptualizing robot penetration as a form of technological change.

The current paper addressed the question of whether and how the adoption of industrial robots impacts on the share of women in manufacturing industries. The paper built a panel database consisting of 11 industries from 14 countries during 1993-2015 to be able to identify the role of industrial robots in female shares. I specified dynamic panel data models, which include previous levels of female shares in industries, and estimated them using an instrumental variables approach that takes into consideration the endogeneity bias of the measure of robot penetration. To the best of my knowledge, this is the first attempt to consider how previous realizations of female shares might influence current gender distribution across industries within the manufacturing, while simultaneously, circumventing the endogeneity issues that robotization might impose on the econometric analysis.

The results point to a positive relationship between industrial robots and the share of women in manufacturing employment. Nonetheless, the estimates show a significant interaction between robotization and female labor force participation. Hence, the robotization-female share link is contingent upon the general participation of women in the workforce. The marginal effects of robotization in the share of women reduce as female labor force increases. Thus, a higher presence of women in the overall economy, the lower the positive effects of robotization in the share of women in manufacturing industries. The main results are robust to different estimation techniques and partitions of the sample, dropping influential observations such as Japan, or highly gender dominated sectors, such as textiles or automotive and electronics. Using female and male employment as the dependent variables, the results suggest that there is a small positive association between robotization and women in manufacturing, while there is no significant link to male employment.

The main findings of the paper are that industrial robots are linked to an increasing presence of women in manufacturing, but this effect fades away as female labor force participation increases. One interpretation of these findings is that the use of industrial robots in the production function might lower the need for physically demanding skills. This type of technological change is linked to an increasing impact in female-labor demand in the reference literature (Juhn et al., 2014; Rendall, 2013, 2017). Nonetheless, this positive effect of robotization in female-labor demand might be limited by the firm's preferences for male workers during industrial upgrading (Kucera & Tejani, 2014; Seguino & Braunstein, 2019). Gender stereotypes and gender differential skills (whether actual or perceived), along with unbalance gender distribution of unpaid household production, might reduce the potential gender equalizing effects of technological change. Relatedly, technological change is contextualized in the development process and structural change, where the increasing service economy crucially absorbs female employment and is linked to the rise in female labor force participation (Ngai & Petrongolo, 2017; Dinkelman & Ngai, 2022; Petrongolo & Ronchi, 2020). Thus, technological upgrading might benefit the entrance of women in manufacturing industries under certain circumstances, such as relatively low labor force participation of women or at relatively low levels of economic development. The significant relationship between robot penetration and female employment might suggest that robotization has a closer link to tasks performed by women than those performed by men.

This paper contributed to improve our understanding of the gender differential effects of robotization. As of its policy implications, the paper points at the role of development (measured by means of GDP per capita), and gender norms (measured by means of female labor force participation), to crucially shape the implications of technological upgrading in the gender distribution of manufacturing employment. Thus, and following the conclusions in Seguino & Braunstein (2019), countervailing forces in the process of technological upgrading can result in new forms of gender inequality in the context of automation and the future of work, even in light of improving other indicators, such as the participation of women in the paid workforce. Future research to complement this paper should look at the occupational gender composition of manufacturing industries, together with the sectoral perspective taken in this paper. Due to the lack of data on the gender distribution across occupations within manufacturing industries, this paper was silent on the effect that technological upgrading can have on the vertical segregation of women and men in the process of automation. Another replication of the present analysis might use information on the price of robots or a measure of the quality of industrial robots, instead of the number of industrial robots, to inform on the actual capacity of robots to replace tasks previously performed by humans. Finally, another interesting line of research to complement this article would consider the gender effects of robotization in informal employment and non-market economic activities such as household production, which can be specifically relevant for developing economies.

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Appendix

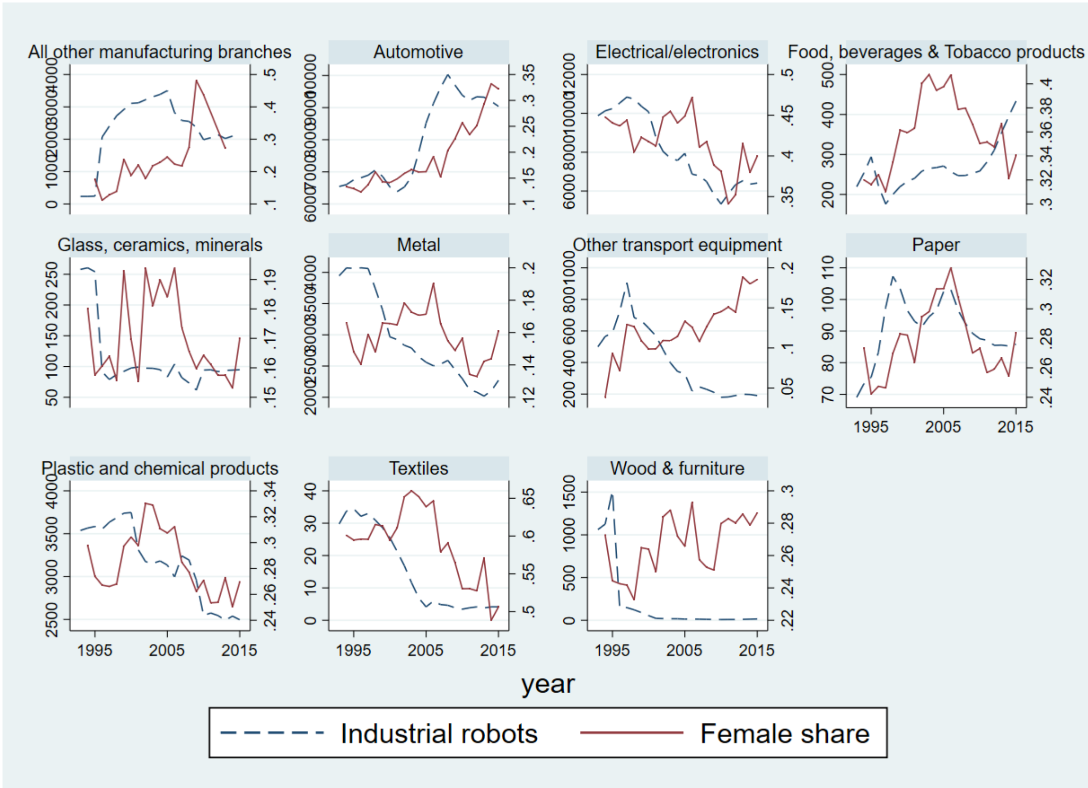

Figure A1: Evolution of Industrial Robots and Female Share by Industry

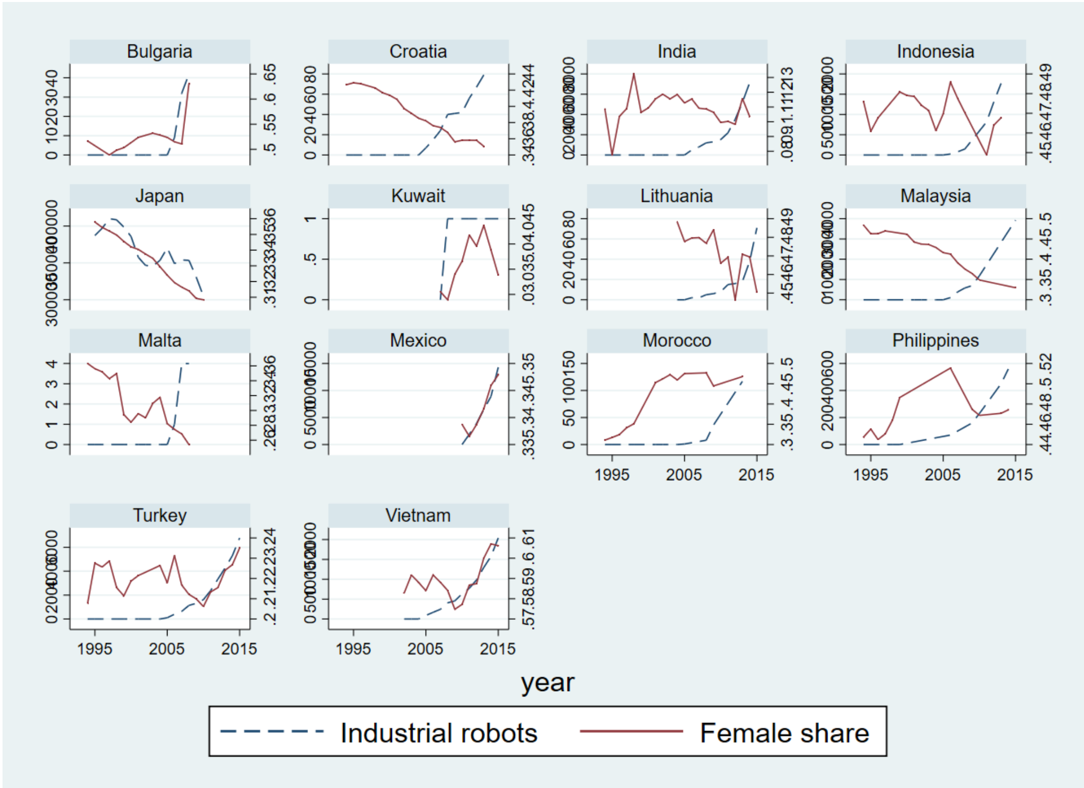

Figure A2: Evolution of Industrial Robots and Female Share by Country

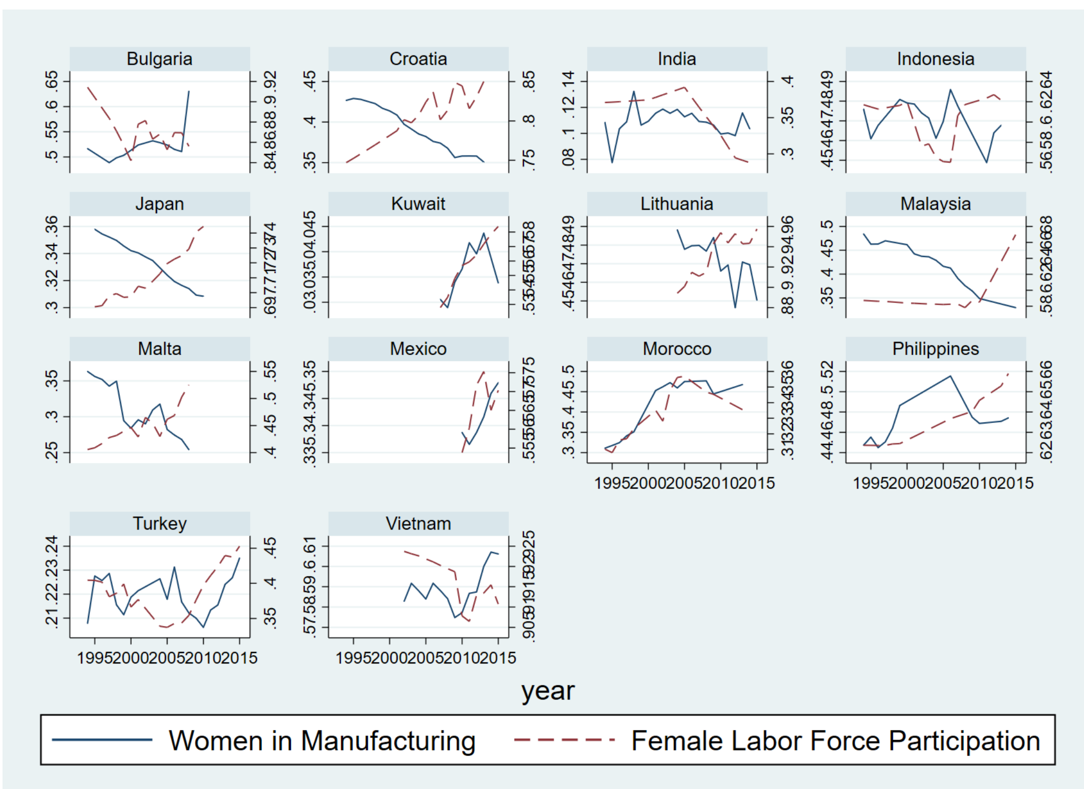

Figure A3: Female Labor Force Participation and Female Share in Manufacturing Industries (country avrg.)

Table A1: Sample Countries and Key Variables

Country	Female share	Industrial 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	Description	Source
Female share	Women in industry i to employment in industry i	UNIDO
GFKF	Gross fixed capital formation (in million dollars)	UNIDO
Employment share	Employment in industry i, c to total manufacturing employment in country c	UNIDO
Industrial robots (stock)	Number of industrial robots employed in industry i	IFR
Installations	New robot installations in industry i	IFR
Share of exports	Industry exports to total exports in in industry i	COMTRADE
FLFP	Labor force participation rate, % of female population ages 15+	ILO
GDP pc growth rate	Annual growth rate of per capita Gross Domestic Product	World Bank
GDP pc level	Per capita Gross Domestic Product	World Bank
Structural change	Industrial employment as a share of total employment (%)	World Bank
FDI	Foreign direct investment, net inflows (in million dollars)	World Bank
Tariffs	Tariff rate, applied, weighted mean, manufactured products in percentage terms	World Bank
GPI	Gender parity index (GPI) of literacy rate of adults	World Bank

Alternative measures of Robotization (A)

Table A3: Robots and Women in Manufacturing: Baseline models Appendix

Dependent variable: Industry female share					
	(1)	(2)	(3)	(4)	(5)
	All	All	All	All	No Japan
Robots per 10,000 workers	0.047***	0.475***	0.084	0.107*	0.241**
	(0.005)	(0.108)	(0.061)	(0.060)	(0.097)
FLFP	0.007**	0.004	-0.006***	-0.018***	-0.003***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Robots per 10,000 workers * FLFP		-0.007***	-0.001	-0.001	-0.004**
		(0.002)	(0.001)	(0.001)	(0.002)
No. of Observations	1798	1798	1798	1648	1486
No. of Groups	151	151	151	151	140
Within R-squared	0.010	0.030	0.194	0.182	0.182
Year fixed effects	no	yes	yes	yes	yes
Country-year fixed effects	no	no	yes	yes	yes
Industry-level controls	no	no	yes	yes	yes
Country-level controls	no	no	no	yes	yes
Japan included	yes	yes	yes	yes	no

Table A3 notes: Independent variables are one-period lagged. Estimates are based on fixed effects models of equation in (1). Robotization is measured as number of industrial robots per 10,000 employees. Driscoll-Kraay standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: own calculations based on UNIDO, IFR, COMTRADE, WDI and ILO.

Table A4: Dropping one industry at a time

Dep. variable: Industry female share											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Fem share$_{t-1}$	0.731***	0.723***	0.740***	0.731***	0.726***	0.741***	0.741***	0.760***	0.648***	0.731***	0.731***
	(0.070)	(0.066)	(0.062)	(0.067)	(0.065)	(0.063)	(0.064)	(0.066)	(0.073)	(0.064)	(0.064)
Robotization	2.457**	2.585***	2.436***	2.439***	2.490***	2.307***	2.368***	2.436***	2.866	2.465***	2.465***
	(0.902)	(0.754)	(0.707)	(0.746)	(0.740)	(0.676)	(0.656)	(0.785)	(2.385)	(0.719)	(0.719)
FLFP	0.002***	0.001***	0.001***	0.002***	0.001***	0.002***	0.001***	0.002***	0.001	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Robotization*FLFP	-0.035**	-0.035***	-0.033***	-0.034**	-0.034**	-0.032**	-0.033***	-0.034**	-0.042	-0.034***	-0.034***
	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.013)	(0.041)	(0.012)	(0.012)
No. of Observations	915	915	915	915	915	920	915	915	915	1030	1030
R^2											
No. of Groups	80	80	80	80	80	80	80	80	80	90	90
Within R-squared	0.486	0.434	0.475	0.469	0.465	0.496	0.478	0.479	0.457	0.469	0.469
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country-year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry-level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country-level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table A4 notes: Columns 1-11 drop respectively the industries: ”Food, beverages Tobacco products” , ”Textiles”, ”Wood furniture”, ”Paper” , ”Plastic and chemical products” , ”Glass, ceramics, minerals”, ”Metal” , ”Electrical/electronics”, ”Automotive” , ”Other transport equipment.” Independent variables are one-period lagged. Estimates are based on fixed effects models of equation in (1). Robotization is measured as the IHS transformation on the share of robots (see Bellemare & Wichman (2020)). Driscoll-Kraay standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: own calculations based on UNIDO, IFR, COMTRADE, WDI and ILO.

Table A5: Dropping one country at a time

Dep. variable	Industry female share												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Fem share$_{t-1}$	0.750***	0.731***	0.726***	0.761***	0.731***	0.735***	0.722***	0.754***	0.731***	0.715***	0.664***	0.731***	0.723**
	(0.073)	(0.064)	(0.063)	(0.057)	(0.064)	(0.066)	(0.065)	(0.058)	(0.064)	(0.070)	(0.079)	(0.064)	(0.069
Robotization	2.394***	2.465***	2.166***	2.221***	2.465***	2.391***	2.657***	2.594***	2.465***	2.538***	2.742***	2.465***	2.904*
	(0.690)	(0.719)	(0.648)	(0.685)	(0.719)	(0.743)	(0.839)	(0.710)	(0.719)	(0.792)	(0.538)	(0.719)	(1.212
FLFP	0.001	0.001***	0.001***	0.001***	0.001***	0.002***	0.001**	0.001***	0.001***	0.002***	0.001***	0.001***	0.002**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000
Robotization*FLFP	-0.033***	-0.034***	-0.029**	-0.032***	-0.034***	-0.033**	-0.037**	-0.036***	-0.034***	-0.035**	-0.038***	-0.034***	-0.041*
	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.014)	(0.012)	(0.012)	(0.013)	(0.009)	(0.012)	(0.018
No. of Observations	931	1030	877	927	1030	958	931	904	1030	985	967	1030	895
No. of Groups	81	90	81	81	90	81	81	81	90	81	81	90	81
Within R-squared	0.566	0.469	0.493	0.511	0.469	0.471	0.454	0.467	0.469	0.438	0.390	0.469	0.468
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes		
Country-year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes		
Industry-level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes		
Country-level controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes		

Table A5 notes: Columns 1-13 drop respectively the countries: Bulgaria, Croatia ,India,Indonesia, Kuwait, Lithuania , Malaysia, ,Malta, Mexico, Morocco, , Philippines, Turkey, Vietnam . Independent variables are one-period lagged. Estimates are based on fixed effects models of equation in (1). Robotization is measured as the IHS transformation on the share of robots (see Bellemare & Wichman (2020)). Driscoll-Kraay standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: own calculations based on UNIDO, IFR, COMTRADE, WDI and ILO.

Supplementary materials

S1. Database construction and data cleaning

This database is built upon three main data sources at country-industry level of disaggregation, 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) at ISIC revision 4, the United Nations Statistical Division (COMTRADE) Standard International Trade Classification (SITC) revision 2. These country-industry cells are merged with two other data sources at country-level information collected from the World Bank and the International Labour Organization (ILO). The countries included in the sample are Bulgaria, Croatia, India, Indonesia, Japan, Kuwait, Lithuania, Malaysia, Malta, Mexico, Morocco, Philippines, Turkey and Vietnam. The sample selection is influenced by the demanding data requirements of the industry level of disaggregation of manufacturing industries, and this issue is further discussed below in the data limitations subsection.

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. As noted in Rodrik (2013), UNIDO information on industrial statistics database is derived largely from industrial surveys which exclude micro-enterprises and informal firms. Thus, the analysis provided here might not be universally valid across all types of manufacturing activities, but to the organized, formal parts of manufacturing. As of data on automation, the IFR database is the best accessible source of data on robots (Ge & Zhou, 2020), and it is widely used in the reference literature on automation (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2020; Aksoy et al., 2021). The IFR provides data on the stock of robots and new robot installations by industry, country, and year, starting from 1993. This article primarily relies on IFR data on industrial robots (stock) to measure the extent of automation by country and industry during the period at scrutiny. Nonetheless, in alternative models I also employ the number of new installations as a sensitivity check. A crucial feature of the IFR data for this paper is that IFR provides information at a higher level of disaggregation for manufacturing than other sectors. 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. To maintain consistency in the classification of industries across these three data sources, namely UNIDO, IFR and COMTRADE, I combine the 23 ISIC 2-digit level industries from UNIDO into 11 industries.[16].

[16]For the harmonization of the industrial classification, I draw on Klump et al. (2021) and M Affendy et al. (2010) together with Eurostat RAMON correspondence tables to accurately combine the industrial classification `https://`

The high level of data disaggregation employed in this paper allows to uncover potential gender differential effects of robotization across industries within the manufacturing. Nonetheless, this comes at the cost of country coverage and time frame. The UNIDO data shows jumps in the data, as well as discrepancies with other data sources on total employment level in manufacturing (e.g. Economic Transformation Database constructed by G. De Vries et al. (2021) or the World Bank data). Likewise, the IFR data covers only a subset of countries, and it is not free from limitations (see Klump et al. (2021)). Linking UNIDO and IFR information, together with the COMTRADE data to account for industrial-level trade flows, implied strong limitations in the number of countries for which data is available. The selection of countries here provide was based on data availability, for which all country-industry observations fulfil the rule of showing consistent time series of at least 5 years in a row.

Table S1: 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	1994-2010		16
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

ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL&StrLanguageCode=EN&IntCurrentPage=4 last access 7/02/2023

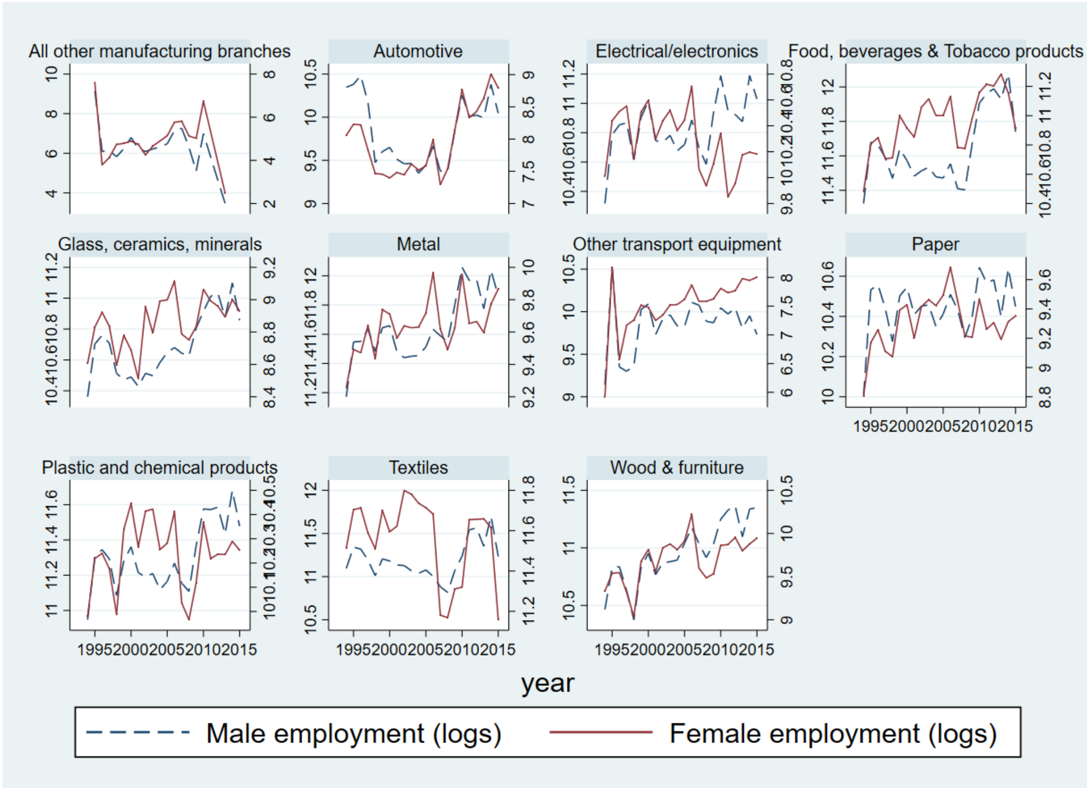

Figure S1: Evolution of Industrial Robots and Female and Male Employment by Industry

S2. Alternative measures of robot penetration (S)

S2.1 Distance to the World Robotization Frontier

The measure of robot penetration used in the manuscript was the IHS transformation of the annual change in the stock of industrial robots relative to the level of industry employment in 1980. As an extension of this model, I adapt the concept of Distance to the World Technological Frontier provided in (Caselli et al., 2006) and (Acemoglu et al., 2006) to the context of robot perpetration. To pay tribute to its first proponents, I call this measure the Distance to the World Robotization Frontier (WRF). The WRF is given by Eq.S1:

$$Distance_{ict} = 1 - \frac{IndustrialRobots_{ict}}{max_{c'} IndustrialRobots_{it}} \tag{S1}$$

where $IndustrialRobots_{ict}$ are the number of industrial robots in an industry i, country c and year t and $max_{c'} IndustrialRobots_{it}$ is the maximum number of industrial robots within an industry across countries. This measure is therefore the distance between each country-industry cell and the country that sets the robotization frontier for each industry, and thus, the higher the distance, the lower the robotization level of that country-industry cell.

Table S2 uses the shares of country-industry robots to the total of industrial robots per industry in the IFR database and the Distance to the WRT as two alternative extensions of the measure of robotization in the baseline model of the manuscript (Table 2). Columns 1 and 2 consider the share of robots to the total number of industrial robots in the IFR database, and Columns 3 and 4 use the distance to the WRT. When Japan is dropped from the analysis, I also drop it from the computation of the total of industrial robots in IFR database and the world robotization frontier to compute the distance measure. The results provide further evidence to the main findings of the paper. Increasing robotization is associated with higher share of women in manufacturing employment, and this effect hinge upon the level of female labor force participation. When using the distance to the WRF, higher distance to the WRF is associated with a negative effect in female shares in manufacturing industries, and this depends positively on the level of female labor force participation. Therefore, these models point to the same relationship between robotization and women in manufacturing. robot penetration favors women in manufacturing, but this effect depends on the level of women that participate in the workforce. The higher the women in the workforce, the lower the positive association between robotization and women in manufacturing industries.

Table S2: Robots and Women in Manufacturing: Distance to the World Robotization Frontier (WRT)

Dependent variable: Industry female share				
	(1)	(2)	(3)	(4)
	Share robots to total IFR		Distance to WRF	
	All	No Japan	All	No Japan
Share IFR robots	0.657***	2.613***		
	(0.059)	(0.836)		
FLFP	0.003***	0.002***	0.002***	-0.003
	(0.000)	(0.000)	(0.000)	(0.002)
Share IFR robots*FLFP	-0.011***	-0.060***		
	(0.001)	(0.019)		
Distance WRF			-0.002**	-0.513***
			(0.001)	(0.165)
Distance WRF*FLFP			0.000*	0.012***
			(0.000)	(0.003)
No. of Observations	1,648	1,486	1,648	1,486
No. of Groups	151	140	151	140
Within R-squared	0.180	0.173	0.179	0.173
Year fixed effects	yes	yes	yes	yes
Country-year fixed effects	yes	yes	yes	yes

Industry-level controls	yes	yes	yes	yes
Country-level controls	yes	yes	yes	yes
Japan included	yes	no	yes	no

Table S2 notes: Independent variables are one-period lagged. Estimates are based on fixed effects models of equation in (1). Robotization is measured as share of robots to total IFR database (Columns 1 and 2) and Distance to the World Robotization Frontier (Columns 3 and 4). Driscoll-Kraay standard errors in parentheses. $^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$ Sources: own calculations based on UNIDO, IFR, COMTRADE, WDI and ILO.

IFR total database sample of countries: Argentina , Australia , Austria , Belarus , Belgium , Brazil , Bulgaria , Canada , Chile , China , Colombia , Croatia , Czech Republic Denmark , Egypt , Estonia , Finland , France , Germany , Greece , Hong Kong Hungary , Iceland , India , Indonesia , Iran , Ireland , Israel , Italy , Japan , Kuwait , Latvia , Lithuania , Macau , Malaysia , Malta , Mexico , Moldova , Morocco , Netherlands , New Zealand North Korea Norway , Oman , Pakistan , Peru , Philippines , Poland , Portugal , Puerto Rico Romania , Russian Federation Saudi Arabia Serbia , Singapore , Slovakia , Slovenia , South Africa Spain , Sweden , Switzerland , Thailand , Tunisia , Turkey , Ukraine , United Arab United Kingdom United States Uzbekistan , Venezuela , Vietnam .

S2.2. Installations

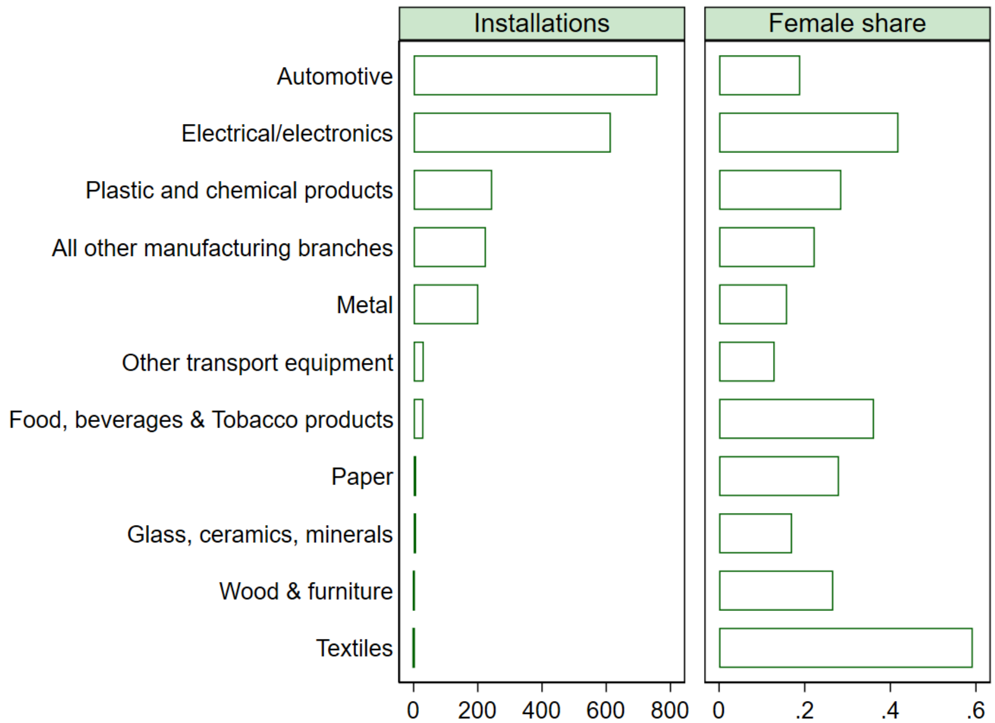

Figure S2: Installations and Female Share by Industry

Table S3: Robots and Women in Manufacturing: Baseline models IHS Installations share

Dependent variable: Industry female share					
	(1)	(2)	(3)	(4)	(5)
	All	All	All	All	No Japan
Robotization (installations)	1.414	12.363***	9.628***	12.023***	12.327**
	(1.611)	(3.265)	(2.802)	(4.218)	(4.451)
FLFP	0.001**	0.001*	0.004***	0.001***	0.002***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Robotization (installations) * FLFP		-0.211***	-0.139**	-0.178**	-0.180*
		(0.055)	(0.051)	(0.069)	(0.102)
No. of Observations	1147	1147	1147	1030	895
No. of Groups	90	90	90	90	81
Within R-squared	0.006	0.032	0.268	0.232	0.233
Year fixed effects	no	yes	yes	yes	yes
Country-year fixed effects	no	no	yes	yes	yes
Industry-level controls	no	no	yes	yes	yes

Country-level controls	no	no	no	yes	yes
Japan included	yes	yes	yes	yes	no

Table S3 notes: Independent variables are one-period lagged. Estimates are based on fixed effects models of equation in (1). Robotization is measured as the IHS transformation on the share of installations (see Bellemare & Wichman (2020)). Driscoll-Kraay standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: own calculations based on UNIDO, IFR, COMTRADE, WDI and ILO.

Table S4: Robots and Women in Manufacturing: Baseline models Installations per 10,000 workers

Dependent variable: Industry female share					
	(1)	(2)	(3)	(4)	(5)
	All	All	All	All	No Japan
Installations per 10,000 workers	0.011	0.443**	0.198*	0.189	0.343
	(0.008)	(0.189)	(0.114)	(0.126)	(0.221)
FLFP	0.006**	0.004	-0.009***	-0.015***	-0.011***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Installations per 10,000 workers * FLFP		-0.007**	-0.003	-0.003	-0.006
		(0.003)	(0.002)	(0.002)	(0.004)
Year fixed effects	no	yes	yes	yes	yes
Country-year fixed effects	no	no	yes	yes	yes
Industry-level controls	no	no	yes	yes	yes
Country-level controls	no	no	no	yes	yes
Japan included	yes	yes	yes	yes	no
N	1798	1798	1798	1648	1486
No. of Groups	151.000	151.000	151.000	151.000	140
log-likelihood					
Within R-squared	0.005	0.025	0.192	0.180	0.180

Table S4 notes: Independent variables are one-period lagged. Estimates are based on fixed effects models of equation in (1). Robotization is measured as number of industrial installations per 10,000 employees. Driscoll-Kraay standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$ Sources: own calculations based on UNIDO, IFR, COMTRADE, WDI and ILO.