Robots and Women in Manufacturing

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Setting the Scene

- Artificial intelligence and machine-learning technologies are fuelling concerns of job disruptions
- Different tasks and occupations are at different risk of automation
- At the same time, women and men concentrate in different jobs, occupations and industries
- Thus, robotization might lead to gendered labour market outcomes
- COVID-19 pandemic and technological adoption
- Studying the impact of automation of work in gender segregation in labour markets in the post COVID-19 era is timely

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Overview

1. Literature Review
2. Research Question
3. Data
4. Results
5. Conclusions

Literature Review

- Literature on the labour market implications of robots pays little attention to gendered labour market outcomes of automation [Graetz and Michaels, 2018, Acemoglu and Restrepo, 2020, De Vries et al., 2020]
- Gendered effects of robotization: robots affect gender pay gaps in Western countries [Aksoy et al., 2021, Ge and Zhou, 2020] ; No gender gap skill but skill utilisation in Japan, women at higher risk of computerization [Hamaguchi and Kondo, 2018, Brussevich et al., 2019] ; Firm-level data shows automation has no effect in gender pay gap in France but increases it in Estonia Domini et al. [2022], Pavlenkova et al. [2021] ; Robot adoption fosters egalitarian gender role attitudes Wang et al. [2022]
What about sectoral segregation?
- Technological upgrading reduces women in manufacturing employment [Saraçoğlu et al., 2018, Seguino and Braunstein, 2019, Tejani and Kucera, 2021]
The impact of robotization still remains unexplored in this strand.

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Research Question

Whether and how industrial robots affect female share in manufacturing employment

1. Why robots? AI and machine learning led to technological change that alters the domain of tasks done by humans.
2. Why manufacturing? Manufacturing plays a pivotal role in economic development [Kucera and Tejani, 2014]
3. How? Female labour force participation (FLFP) is associated with a "crowding out" effect of women in services sector Bergmann [1974], Seguino and Braunstein [2019] . Robotization might exacerbate the male "job-hoarding" of "good jobs" (i.e. manufacturing jobs)

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Data

Unbalanced panel dataset of 11 industries in 14 countries during 1993-2015

Industry-level data sources

- UNIDO INDSTAT 2 ISIC rev. 3: industrial statistics on output, value added, employment, wages and **female share** at country-industry level data disaggregation
- International Federation of Robotics (IFR) 2-digit level ISIC rev. 4: **operational stock** (annual robot deliveries assuming an average service life of 12 years and full depreciation thereafter) country-industry level data disaggregation
- UN COMTRADE 2-digit level SITC rev. 2: data on exports and imports of goods
- Graetz and Michaels [2018]: data on *replaceable hours* and *reaching and handling tasks* at industry level for IV models

Country-level data sources

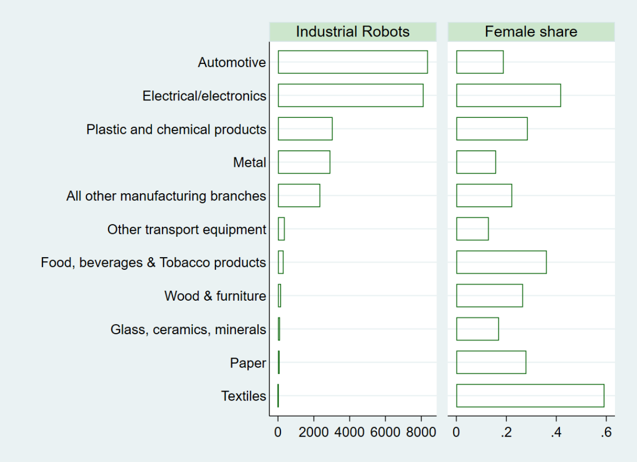
- World Development Indicators (World Bank)
- International Labour Organization (ILO)

Industries in the Sample

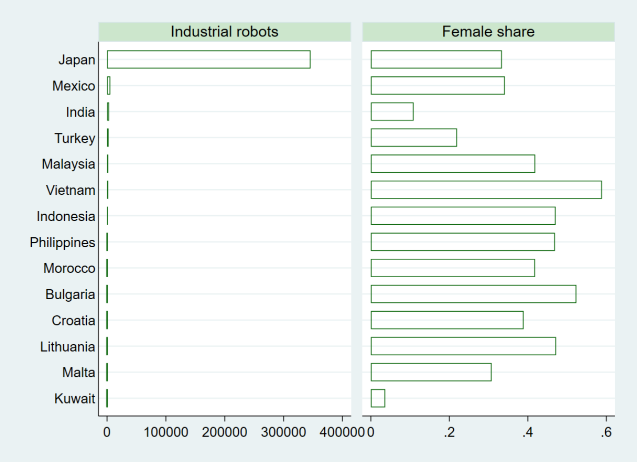
Draw on Klump et al. [2021] and Eurostat RAMON correspondence tables to convey 11 industrial categories

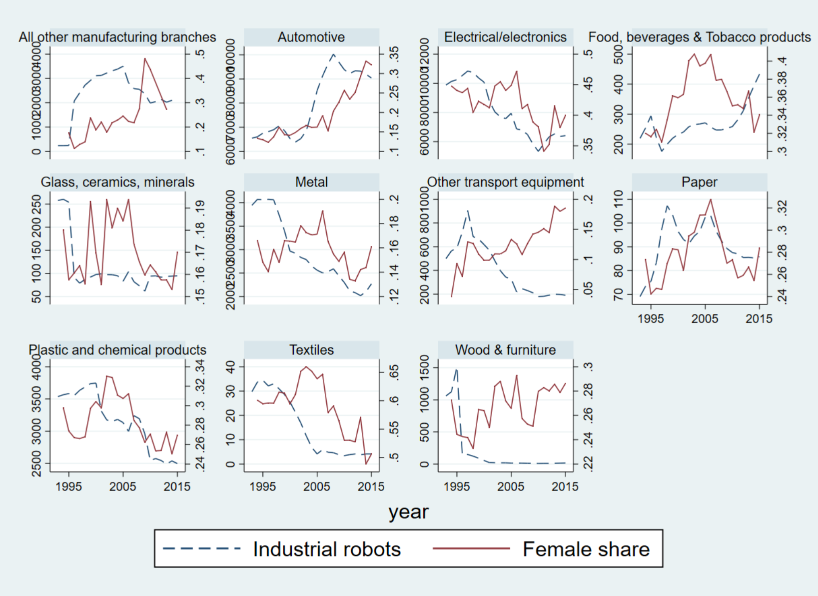
Table: Industry Classification

Food products and beverages; Tobacco products
Textiles, leather, wearing apparel
Wood and wood products (incl. furniture)
Paper and paper products, publishing & printing
Plastic and chemical products
Glass, ceramics, stone, mineral products n.e.c.
Metal
Electrical/electronics
Automotive
Other transport equipment
All other manufacturing branches

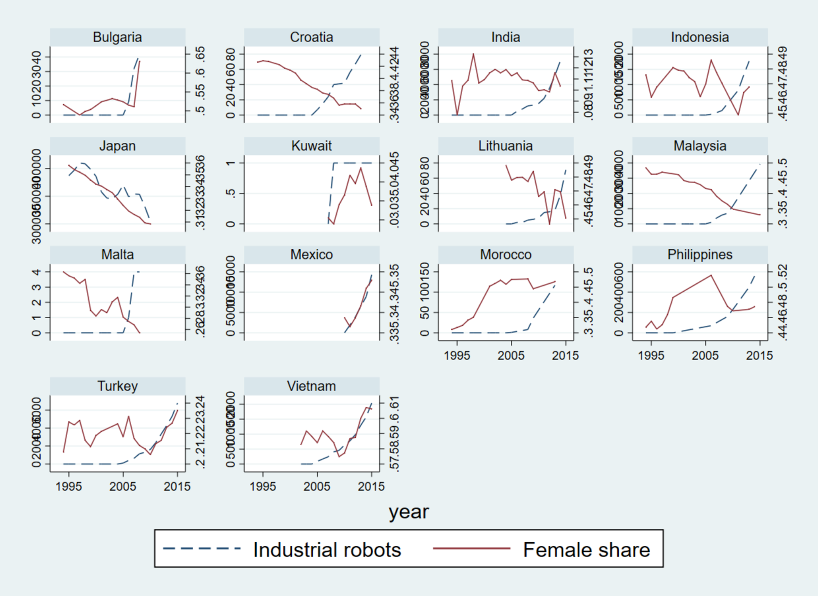


Industrial Robots
Female share
Automotive
Electrical/electronics
Plastic and chemical products
Metal
All other manufacturing branches
Other transport equipment
Food, beverages & Tobacco products
Wood & furniture
Glass, ceramics, minerals
Paper
Textiles
0
2000
4000
6000
8000
0
.2
.4
.6

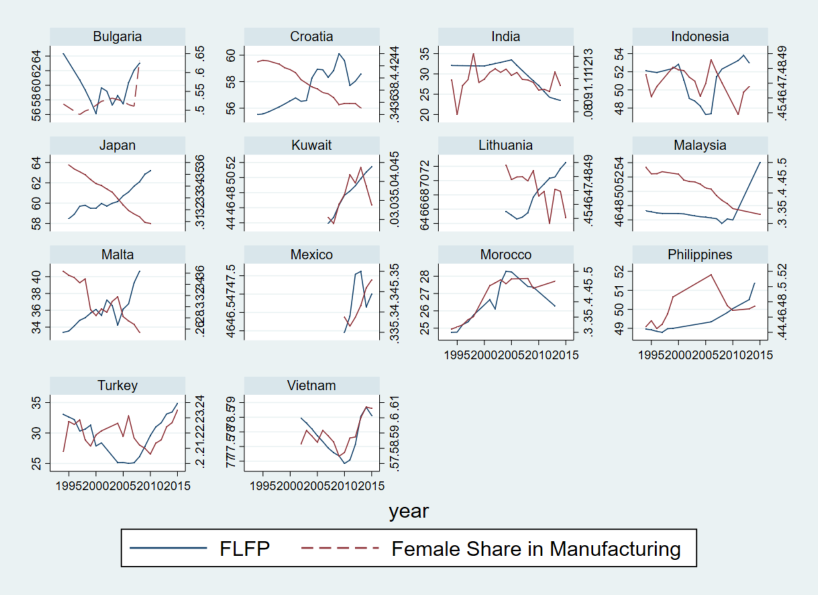

Industrial robots
Female share
Japan
Mexico
India
Turkey
Malaysia
Vietnam
Indonesia
Philippines
Morocco
Bulgaria
Croatia
Lithuania
Malta
Kuwait
0
100000
200000
300000
400000
0
.2
.4
.6



All other manufacturing branches
Automotive
Electrical/electronics
Food, beverages & Tobacco products
Glass, ceramics, minerals
Metal
Other transport equipment
Paper
Plastic and chemical products
Textiles
Wood & furniture
1995
2005
2015
year
Industrial robots
Female share


Bulgaria
Croatia
India
Indonesia
Japan
Kuwait
Lithuania
Malaysia
Malta
Mexico
Morocco
Philippines
Turkey
Vietnam
1995
2005
2015
year
Industrial robots
Female share

Female Labour Force Participation



Identification Strategy

$$
\begin{aligned}
FemaleShare_{ict} = \beta_0 + \beta_1 Bots_{ic,t-1} + \beta_2 FLFP_{c,t-1} + \\
\beta_3 Bots * FLFP_{c,t-1} + X'_{ic,t-1} + Z'_{c,t-1}\beta + v_{ict} \\
v_{ict} = \omega_i + \delta_c + \gamma_t + \epsilon_{ct} \\
i = indusry; c = country; t = year;
\end{aligned}
\tag{1}
$$

- $Bots_{ic,t-1}$ number of industrial robots at industry level
- $FLFP_{c,t-1}$ female labor force participation at country level
- $Bots * FLFP_{c,t-1}$ interaction term
- Country and industry-level controls
- Spatial and temporal correlation, and reverse causation issues

Endogeneity concerns: IV strategy

Reverse causation: share of women affecting the adoption of robots in the production function of industries. Instrumental variable strategy [Graetz and Michaels, 2018, De Vries et al., 2020, Aksoy et al., 2021]

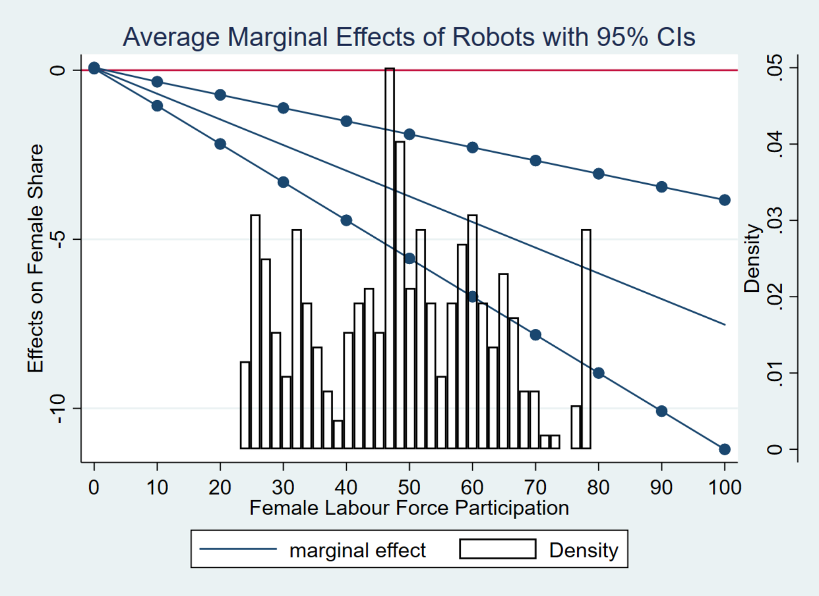
- **Replaceable hours** measures industry's labour input that is replaceable by robots. US occupations in each industry from the 1980 census, which dates back before the rise of robots. Occupations are defined as 'replaceable' if (part of) their tasks could have been replaced by robots in 2012. They then compute the fraction of hours worked in each industry in 1980 that was performed by occupations that subsequently became more prone to replacement by robots.
- **Reaching and handling tasks** measures the prevalence of occupations in each industry that require *reaching and handling* tasks compared to other physical demands in 1980 (aka robotic arms)

Limitations: based on calculations for the US labour shares, country and time invariant, not fully absent of reverse gendered causal effects

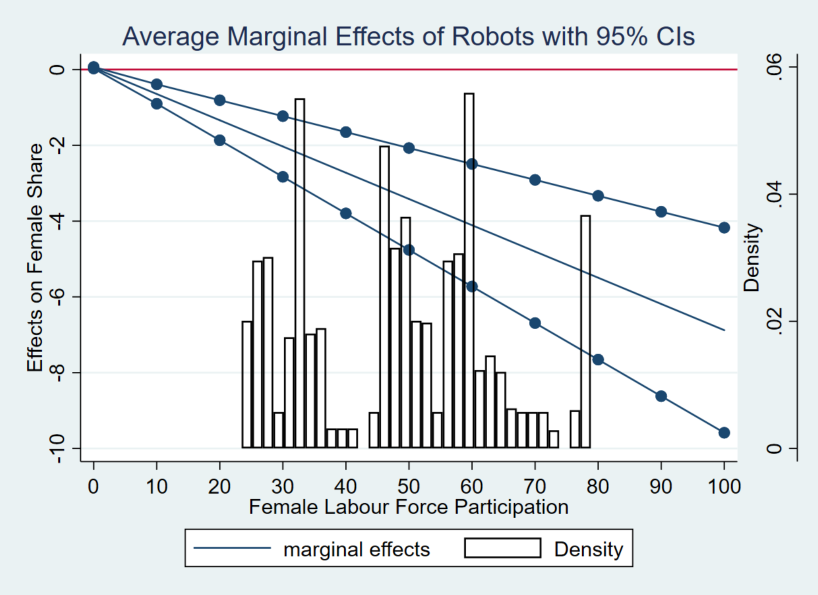
Table 1: Robots and Women in Manufacturing Employment

	(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.	1,804	1,804	1,804	1,648	1,786	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

FE estimates



IV estimates



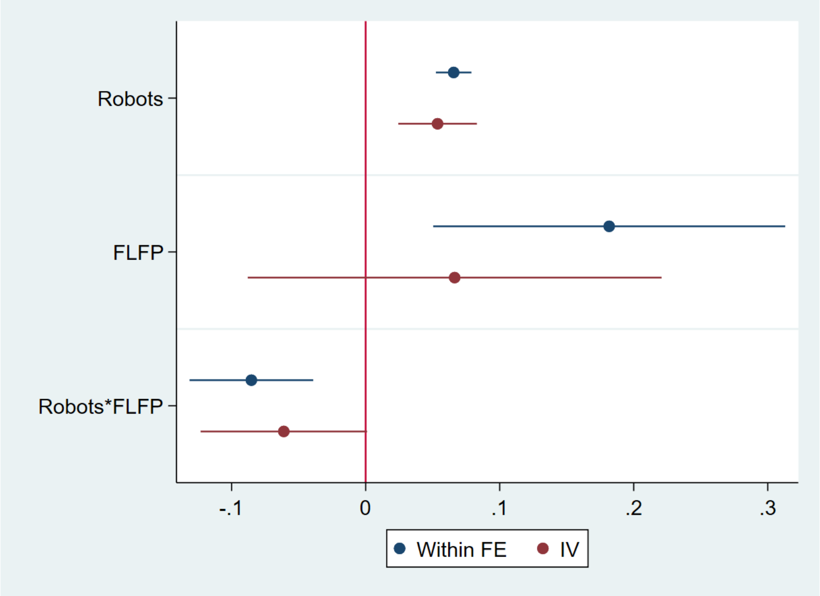
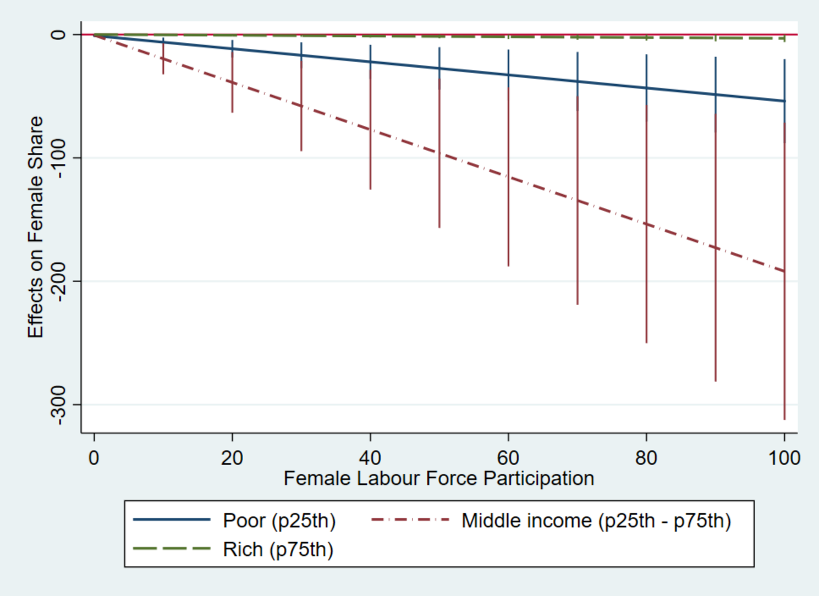

Robots
FLFP
Robots*FLFP
-.1
0
.1
.2
.3
Within FE
IV

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

	(1) Poor countries	(2) Middle income	(3) 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


Effects on Female Share
0
-100
-200
-300
0
20
40
60
80
100
Female Labour Force Participation
Poor (p25th)
Middle income (p25th - p75th)
Rich (p75th)

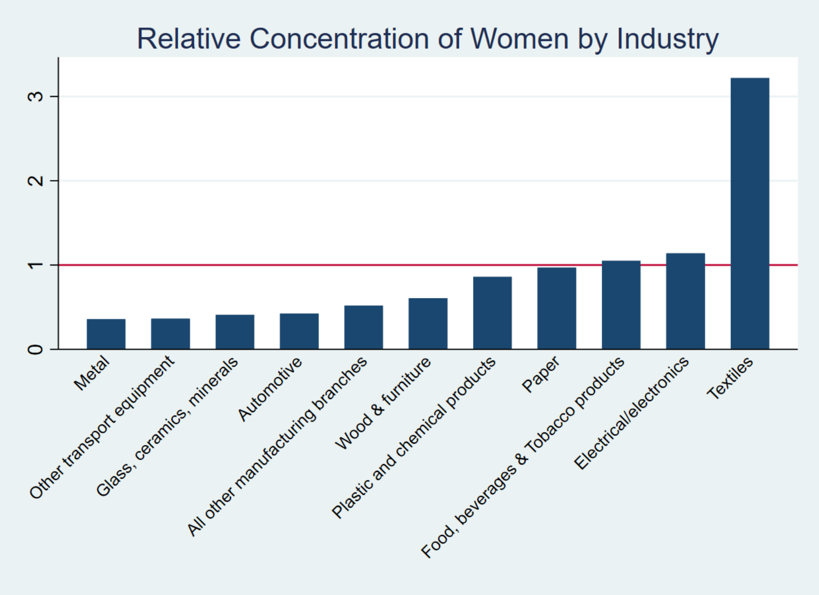
Identification Strategy II: alternative dependent variable

Following Greenstein and Anderson [2017], Seguino and Braunstein [2019] on differences in the male and female distribution across industries within manufacturing sector

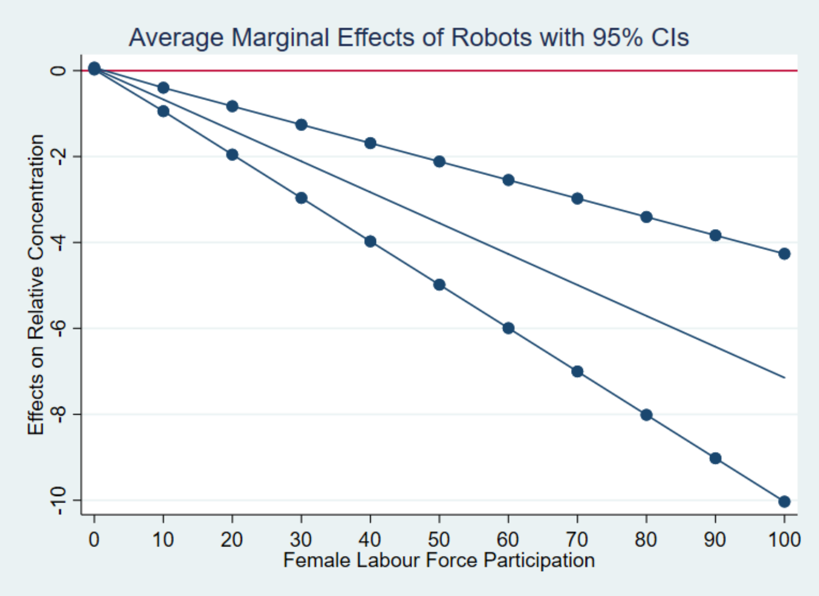
$$\begin{aligned} R_{ict} = \beta_0 + \beta_1 Bots_{ic,t-1} + \beta_2 FLFP_{c,t-1} + \\ \beta_3 Bots * FLFP_{c,t-1} + X'_{ic,t-1} + Z'_{c,t-1}\beta + v_{ict} \\ v_{ict} = \omega_i + \delta_c + \gamma_t + \epsilon_{ct} \\ i = indusry; c = country; t = year; \end{aligned} \tag{2}$$

Where $R_{ict} = \frac{\frac{f_i}{F}}{\frac{m_i}{M}}$, f_i number of women in industry i, F total number of women in manufacturing, m_i number of men in industry i, M total number of men in manufacturing

Relative female concentration



FE estimates



Effects in Employment (level and gender gaps)

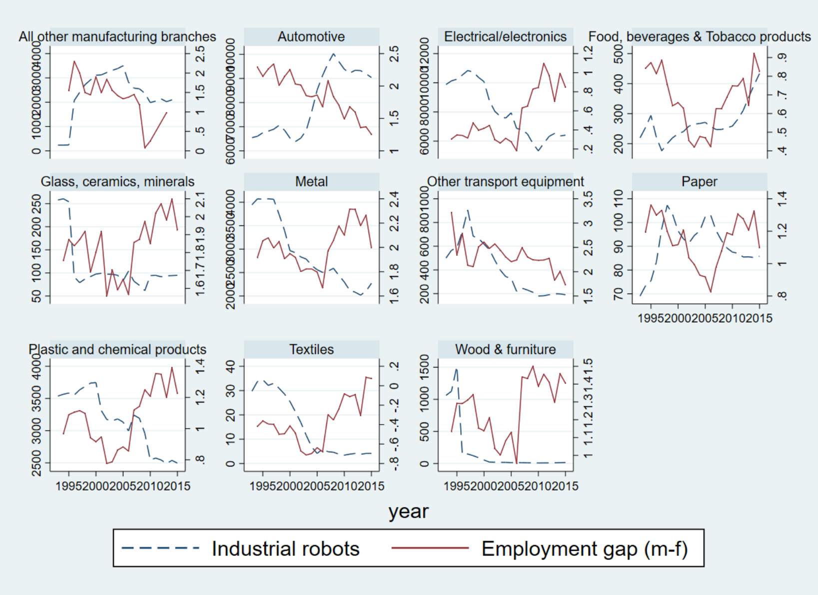
Employment level using partitions of the database for women and men

$$
\begin{aligned}
LogEmployees_{ict} = \beta_0 + \beta_1 Bots_{ic,t-1} + \beta_2 FLFP_{c,t-1} + \\
\beta_3 Bots * FLFP_{c,t-1} + X'_{ic,t-1} + Z'_{c,t-1}\beta + v_{ict} \\
v_{ict} = \omega_i + \delta_c + \gamma_t + \epsilon_{ct} \\
i = indusry; c = country; t = year;
\end{aligned}
\tag{3}
$$

Gender gaps in employment ($GG = male - female$)

$$
\begin{aligned}
GG_{ict} = \beta_0 + \beta_1 Bots_{ic,t-1} + \beta_2 FLFP_{c,t-1} + \\
\beta_3 Bots * FLFP_{c,t-1} + X'_{ic,t-1} + Z'_{c,t-1}\beta + v_{ict} \\
v_{ict} = \omega_i + \delta_c + \gamma_t + \epsilon_{ct} \\
i = indusry; c = country; t = year;
\end{aligned}
\tag{4}
$$

Gender Employment Gap



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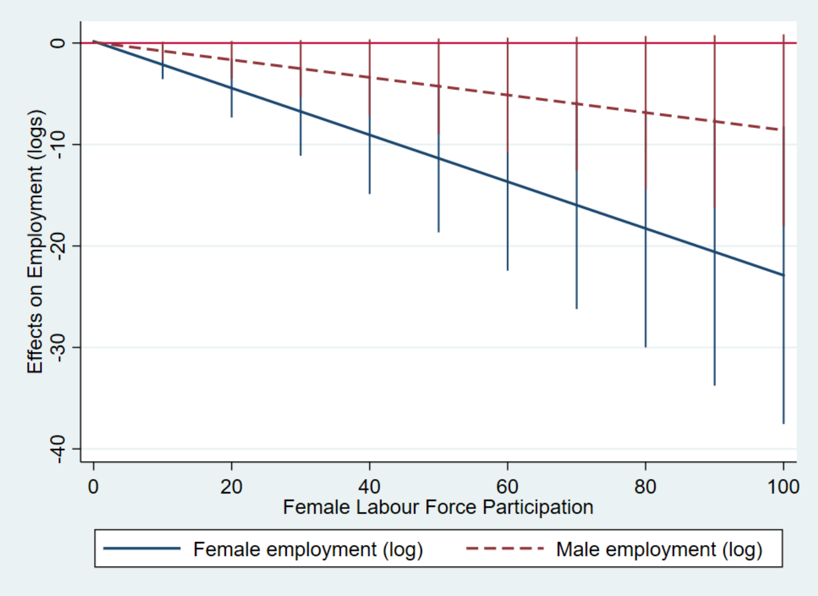

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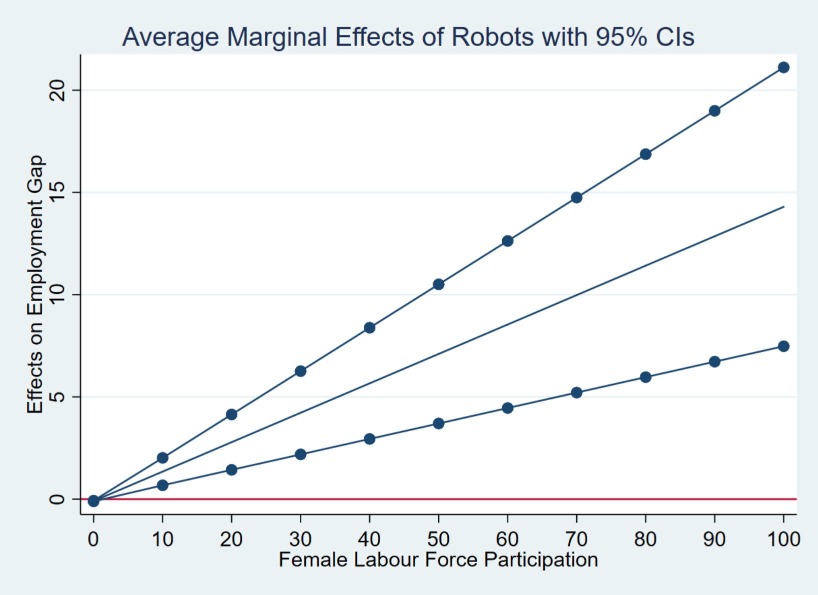

Takeaways

Panel data models using 11 industries, 14 countries during 1993-2015 show that

- Automation associates with reducing female share in manufacturing
- Gendered effects of automation in manufacturing hinge on FLFP
- Stronger effects in middle-income sample countries
- Automation also seems to alter the relative concentration of gender employment
- Female and male employment levels are negatively affected by automation, stronger effect for women
- Automation associated with increasing gender employment gap in manufacturing industries
- Further to explore: alternative measures of automation and causality issues

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Thank you for your attention!

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