Robots, Labor Markets, and Demographic Behavior*

Massimo Anelli
Bocconi University

Osea Giuntella
University of Pittsburgh and IZA†

Luca Stella
Bocconi University and IZA‡

September 13, 2018

Abstract

Previous studies have shown that the declining labor-market opportunities of men induced by trade shocks to manufacturing industries can degrade men marriage-maket value, reduce fertility and contribute to the rising rate of out-of-wedlock childbearing and single-headed childrearing in the US. Recent evidence has also shown large negative effects of robots on employment and wages. These effects are distinct from the impact of trade and other labor market shocks (e.g. decline of routine jobs etc.). In this study, we examine the impact of exposure to robot penetration on the labor market opportunities of men and women. Following the empirical strategy adopted by Acemoglu and Restrepo (2017), we find that in commuting zones that were more exposed to robots, the gender-wage gap declined and female employment increased. We then explored the impact of robots on marriage and fertility. We find that individuals were less likely to marry and also more likely to divorce. Furthermore, exposure to robots reduced the overall fertility rate, but increased the number of children born out of wedlock.

JEL Codes: J12, J13, J21, J23, J24
Keywords: Automation, marriage market, fertility

1 Introduction

Million of workers across the world feel the growing pressure and fear of machines replacing their jobs. Artificial intelligence (AI), machine learning, robots, and the Internet have already

*This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement n. 694262), project *DisCont - Discontinuities in Household and Family Formation*. We are grateful to XXX for comments and suggestions.

†University of Pittsburgh. Email: osea.giuntella@pitt.edu.

‡Carlo F. Dondena Centre for Research on Social Dynamics and Public Policy, Bocconi University. Email: luca.stella@unibocconi.it

transformed the nature of jobs and will continue to rapidly change our labor markets. The debate on the effects that the development of robotics and automation will have on the future of jobs has been lively (Brynjolfsson and McAfee, 2014; Autor et al., 2015; Graetz and Michaels, 2015). However, despite the growing interest on the labor market effects of automation, we know very little about how these economic changes will reshape life-course choices. The goal of this paper is to contribute to fill this gap in the literature.

Over the last 3 decades, the stock of operational industrial robots in the US increased by more than 5 times (see Figure 1). In 2016 robot sales increased by 16% reaching a new peak for the fourth year in a row. This increase is driven by the increase in electrical/electronics industry. Yet, the automotive industry still accounts for the highest share of industrial robots. Between 2011 and 2016, the average robot sales increase was at 12% per year. This continued growth was pushed by the trend to automate production as a way to strengthen American industries and keep manufacturing in the US. Just since 2005, and despite the slow-down caused by the great recession, the number of robots per thousand worker grew from 1.3 to 2.4 (Figure 2).

Recent evidence shows that the recent rise of automation and the growing stocks of industrial robots had significant negative effects on the employment and wages of workers (Acemoglu and Restrepo, 2017). There is also increasing evidence that the labor market shocks induced by the exposure to imports from China and Mexico negatively impacted the marriage opportunities of men, with consequences on fertility rates and the rate of out-of-wedlock childbearing (Dorn et al., 2017). The effects of robot penetration on labor market has been shown to be independent from other labor market shocks (trade, decline of routine jobs etc.).

Our paper contributes to this literature by examining the effects of robots penetration on the labor market opportunities of men and women. Furthermore, we investigate how this shock may affect marital decision-making and fertility choices.

Following Acemoglu and Restrepo (2017), we focus on the US labor market and construct a measure of exposure to robots using data from the International Federation of Robotics (IFR). These data allow us to estimate the effects of industrial robots, fully autonomous machines that are automatically controlled, do not need a human operator and can be programmed to perform several tasks.

To identify the effects of industrial robots, we exploit changes in the use of robots across industries and exploit the variation in the distribution of industrial employment across commuting zones to create a measure of robots peneteration in US labor markets (Figure 3). To mitigate the concern that the adoption of robots could be correlated with other trends within an industry or a commuting zone, we follow Acemoglu and Restrepo (2017) and use the industry-level spread of robots in other advanced economies as an instrument for the adoption of robots in the US. In this way, we only exploit the variation resulting from industries that exhibited an increase in the use of robots in other advanced economies.

Using this empirical strategy we first we confirm the strong effect of robot penetration on labor market outcomes found by (Acemoglu and Restrepo, 2017). Second, we investigate the effects of this labor market shocks on marriage markets and fertility. We find that a one standard deviation increase in our measure of robot exposure had a modest increase on labor female participation (+1.6% with respect to the mean), but had a substantial negative effect on the gender earning gap, reducing it by 13% (or .38 standard deviation). Commuting zones that were more exposed to robots penetration exhibit a reduction in the marriage (-4.5%) and fertility rates (-6%), and a marginally significant increase in divorce rate in the previous year (+4.6%). Effects are small but sizable and the magnitude is comparable to (Dorn et al., 2017) who find that a 1 unit trade shock (1.33 standard deviation) reduced fertility by 4%. However, similarly to Dorn et al. (2017), we find that exposure to robots increased the rate of children born out of wedlock.

This study is closely related to a handful of recent studies analyzing the impact of robots on labor markets. Acemoglu and Restrepo (2017) find significant negative effects of robot exposure on wages and employment. We rely on the same data and adopt a very similar empirical strategy. Although, Acemoglu and Restrepo (2017) explore the effects of robots penetration on men and women labor market outcomes, they do not focus on gender differences. Furthermore, they do not explore the effects of robots penetration on marital behavior and fertility. In an earlier study, Graetz and Michaels (2015) used variation in the adoption of industrial robots across industries in different countries to estimate the effects of automation on productivity and wages. They find that robots had positive effects on productivity and wages, but negatively affected the employment of low-skilled workers. Dauth et al. (2017) estimate that robots accounted for almost 23% of the overall decline of manufacturing employment in Germany between 1994 and 2014, but this loss was offset by the jobs created in the service sector.

Our work is also related to Dorn et al. (2017), who analyze the effects of trade on the marriage market value of men and find that trade-impacted labor markets exhibited lower fertility rates, higher rate of out-of-wedlock childbearing and single-headed child-rearing.

More generally, our study contributes to previous work on the effects of technology on female labor force participation, gender wage gap, marital and fertility behavior (Greenwood et al., 2005; Goldin, 2006; Albanesi and Olivetti, 2016; Guldi and Herbst, 2017; Dettling, 2017). Finally, our research relates to the studies linking labor demand shocks to marriage and fertility outcomes (Ananat et al., 2013; Kearney and Wilson, 2017; Schaller, 2016; Shenhav, 2016).

The rest of the paper is organized as follows. Section 2 describes the data. In Section 3 we illustrate our empirical strategy. Section 4 presents our main results. Our concluding remarks are in Section 5.

2 Data

Our data are drawn from two main sources. The data on the stock of robots by industry, country and year are drawn from the International Federation of Robotics (IFR). These data are based on yearly surveys of robots suppliers. The data contain information on 70 countries from 1993 to 2014, covering more than 90% of the industrial robots market.

Unfortunately, information on the stock of industrial robots by sector is limited to a subsample of countries for the period 1990-2003. Data for the United States provide the industry background only since 2004, although we do have information on the total stock of industrial robots in the US since 1993.

The IFR data present several limitations. Within manufacturing, we have detailed data on robots stocks for 13 industries, while outside of manufacturing data are available in six broad categories. Furthermore, approximately a third of robots are not classified. Following **?**, we allocate unclassified robot in the same proportion as in the classifed data. Before 2004, the overall stock of robots is only reported for North America aggregating data from US, Canada and Mexico. In addition, there is no information on dedicated industrial robots. IFR data were combined with the 1990 employment counts by country and industry drawn from the EUKLEMS dataset to construct a measure of the number of robots per thousand workers by country, industry, and year.

Our analysis focuses on 741 commuting zones covering the entire US. We use data from the 1970 and and 1990 Censuses to construct the share of employment by industry in each commuting zone. Our main outcomes of interest are instead drawn from the American Community Survey (ACS, 2005-2016). We use data from the ACS to construct measures of employment, wages, fertility, marriage, and divorce for each commuting zone.

2.1 Exposure to Robots

Building on Acemoglu and Restrepo (2017), we construct our measure of exposure to robots as follows:

$$Exposure\_to\_robots_{t,c} = \sum l_{ci}^{1970}(p30(\frac{R_{i,t}}{L_{i,1990}}) \tag{1}$$

where the sum runs over all industries in the IFR data, l_{ci}^{1970} is the 1970 share of commuting zone c employment in industry i, as computed from the 1970 Census, and $(p30(\frac{R_{i,t}}{L_{i,1990}})$ represents the 30th percentile of robot usage among European countries in industry i and year t. Following Acemoglu and Restrepo (2017), we use the 1970 distribution of employment across industries to construct an exogenous measure of exposure to robots. By doing so, we exploit historical and persistent differences in the industry specialization across commuting zones. Similarly, we construct our endogenous measure of US exposure to robots:

$$US\_exposure\_to\_robots_{t,c} = \sum l_{ci}^{1990}(\frac{R_{i,t}}{L_{i,1990}}) \tag{2}$$

where l_{ci}^{1990} identifies the 1990 distribution of employment across industries.

3 Empirical Methodology

3.1 First Stage

Our first-stage is specified as follows

$$\sum l_{ci}^{1990}(\frac{R_{i,t}}{L_{i,1990}}) = \pi(\sum l_{ci}^{1970}(p30(\frac{R_{i,t}}{L_{i,1990}}) + \Gamma X_{c,t} + \eta_c + \tau_t + v_{ct} \tag{3}$$

where $X_{c,t}$ is a vector of time-varying controls, η_c are commuting zone fixed effects, and τ_t are year fixed effects.

3.2 Baseline specification

To identify the impact of robot exposure on our outcomes of interest we estimate the following regression

$$Y_{c,t} = \beta * Exposure\hat{t}orobots_{t,c} + \Lambda X_{c,t} + \eta_c + \tau_t + \epsilon_{c,t} \tag{4}$$

where $Y_{c,t}$ is one of our outcomes of interest; $Exposure\hat{t}orobots_{t,c}$ is the exposure to robots of community zone c at time t as predicted instrumenting it with the sectoral trends in other advanced economies; $X_{c,t}$ is a vector of time-varying controls; and η_c are commuting zone fixed effects, and τ_t are year fixed effects.

4 Empirical Results

4.1 Effects on employment

Table 1 presents the results of robot penetration on labor force participation, employment and unemployment rate by gender. Differently from (Acemoglu and Restrepo, 2017), we consider the ACS sample (2004-2016) and use a fixed effect model to exploit within commuting zones changes over time. Standard errors are clustered at the state level. We start by examining the impact of robot exposure on labor force participation. OLS estimates are positive (column 1) but non-significantly different from zero for men (Panel A), while the coefficient is statistically significant but relatively small for women (0.005%, Panel B). Column 2 reports the results from the reduced form model using the exposure to robots imputed using the trends in European countries confirming a positive but relatively small effect. 2SLS estimates (column 3) are twice as large as the OLS. A 1 standard deviation increase in the our measure of robot exposure has a small positive effect on labor force participation of both men (+0.082%) and women (+0.083%).

We find similar effects on employment and unemployment rate. Focusing on the 2SLS estimates a 1 standard deviation increase in robot exposure was associated with a 2.6% (2%) increase in employment among men (women). While for an equivalent change in robot exposure unemployment went down by 22% among men and by 24% among women.

4.2 Effects on wages

Table 2 reports the effects of exposure to robots on wages. 2SLS estimates show that a 1 standard deviation increase in robot exposure decreased female wages by 5% (column 3) and male wages by 10% (column 6). Thus, the gender wage-gap shrank significantly in areas that were more exposed to robots penetration. A one standard deviation increase in robot exposure decreased the gender wage gap by 16% with respect to its mean (column 9).

4.3 Effects on marital behavior

In Table 3 we investigate the effects of robot exposure on marital behavior. Column 1 shows that a 1 standard deviation increase in robot exposure was associated with a 1.1% decrease in the fraction of new marriages. In column 2, we report the reduced form coefficient obtained regressing the share of last year marriages on our exogenous measure of robot exposure based on the industrial robots stocks in Europe. The coefficient suggests that a 1 standard deviation increase decreases fertility by 2%. The 2SLS coefficient is 5 times larger than the OLS (column 3). A 1 standard deviation increase in the exposure to robots decreased marriage in the previous year by 4.5%.

We instead find an opposite pattern when examining divorce rates. A one standard deviation increase in robot exposure was associated with a 2.3% increase in divorce. 2SLS estimates are larger pointing at a 4.7% increase with respect to the mean for a 1 standard deviation change in our metric of robot exposure.

A 1 standard deviation increase in the exposure to robots increased divorce in the previous year by 4.6%.

4.4 Effects on fertility

In Table 4, we analyze the effect of automation on fertility. Column 1 reports the OLS relationship between our measure of robot exposure across commuting zones and the share of individuals reporting that they had a child in the past year. A 1 standard deviation increase in the exposure to robots (1.90) is associated with a 2% decrease in fertility with respect to the mean (0.05). The reduced-form coefficient suggests that a one standard deviation (1.90) in the exposure to robots as measure using data from European countries decreased fertility by approximately 3.6% with respect to the mean (column 2). 2SLS estimates (column 3) are twice as large as the OLS estimates suggesting that the exposure to robots penetration may be negatively correlated with unobserved determinants of fertility. A 1 standard deviation increase in the exposure to robots decreased fertility in the previous year by 6%.

In Table 5 we examine whether robot exposure had different effects when examining the likelihood of having children born out of wedlock. Interestingly robot exposure increase the fraction of children born out of wedlock (+5%, Table 5). This result is consistent with what found by Dorn et al. (2017) analyzing the effects of trade on fertility.

4.5 Robustness

5 Concluding Remarks

The impact of automation, robots and artificial intelligence on labor markets is likely to have fundamental shifts on our daily lifes. A handful of pioneering studies has examined the impact of robots on labor markets (Acemoglu and Restrepo, 2017; Graetz and Michaels, 2015). Yet, we know little about the effects the ways in which these labor market shocks may affect gender differences in labor market opportunities and in turn family and fertility decisions.

This study estimates the impact of exposure to industrial robots on labor market opportunities of men and women and on their demographic behavior.

We show that women living in commuting zones that were more exposed to robots penetration were more likely to work and suffered a lower gender wage gap. Furthermore, we find evidence that exposure to robots decreased marriage, while it slightly increased divorce rate. Finally, exposure to industrial robots reduced fertility, but increased the fraction of children born out of wedlock.

References

Acemoglu, Daron and Pascual Restrepo, "Robots and jobs: Evidence from US labor markets," 2017.

Albanesi, Stefania and Claudia Olivetti, "Gender roles and medical progress," *Journal of Political Economy*, 2016, *124* (3), 650–695.

Ananat, Elizabeth Oltmans, Anna Gassman-Pines, and Christina Gibson-Davis, "Community-wide job loss and teenage fertility: evidence from North Carolina," *Demography*, 2013, *50* (6), 2151–2171.

Autor, David H, David Dorn, and Gordon H Hanson, "Untangling trade and technology: Evidence from local labour markets," *The Economic Journal*, 2015, *125* (584), 621–646.

Brynjolfsson, Erik and Andrew McAfee, *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*, WW Norton & Company, 2014.

Dauth, Wolfgang, Sebastian Findeisen, Jens Südekum, and Nicole Woessner, "German robots-the impact of industrial robots on workers," 2017.

Dettling, Lisa J, "Broadband in the labor market: the impact of residential high-speed internet on married womens labor force participation," *ILR Review*, 2017, *70* (2), 451–482.

Dorn, David, Gordon Hanson et al., "When work disappears: manufacturing decline and the falling marriage-market value of men," Technical Report, National Bureau of Economic Research 2017.

Goldin, Claudia, "The quiet revolution that transformed women's employment, education, and family," *American economic review*, 2006, *96* (2), 1–21.

Graetz, Georg and Guy Michaels, "Robots at work," 2015.

Greenwood, Jeremy, Ananth Seshadri, and Mehmet Yorukoglu, "Engines of liberation," *The Review of Economic Studies*, 2005, *72* (1), 109–133.

Guldi, Melanie and Chris M Herbst, "Offline effects of online connecting: the impact of broadband diffusion on teen fertility decisions," *Journal of Population Economics*, 2017, *30* (1), 69–91.

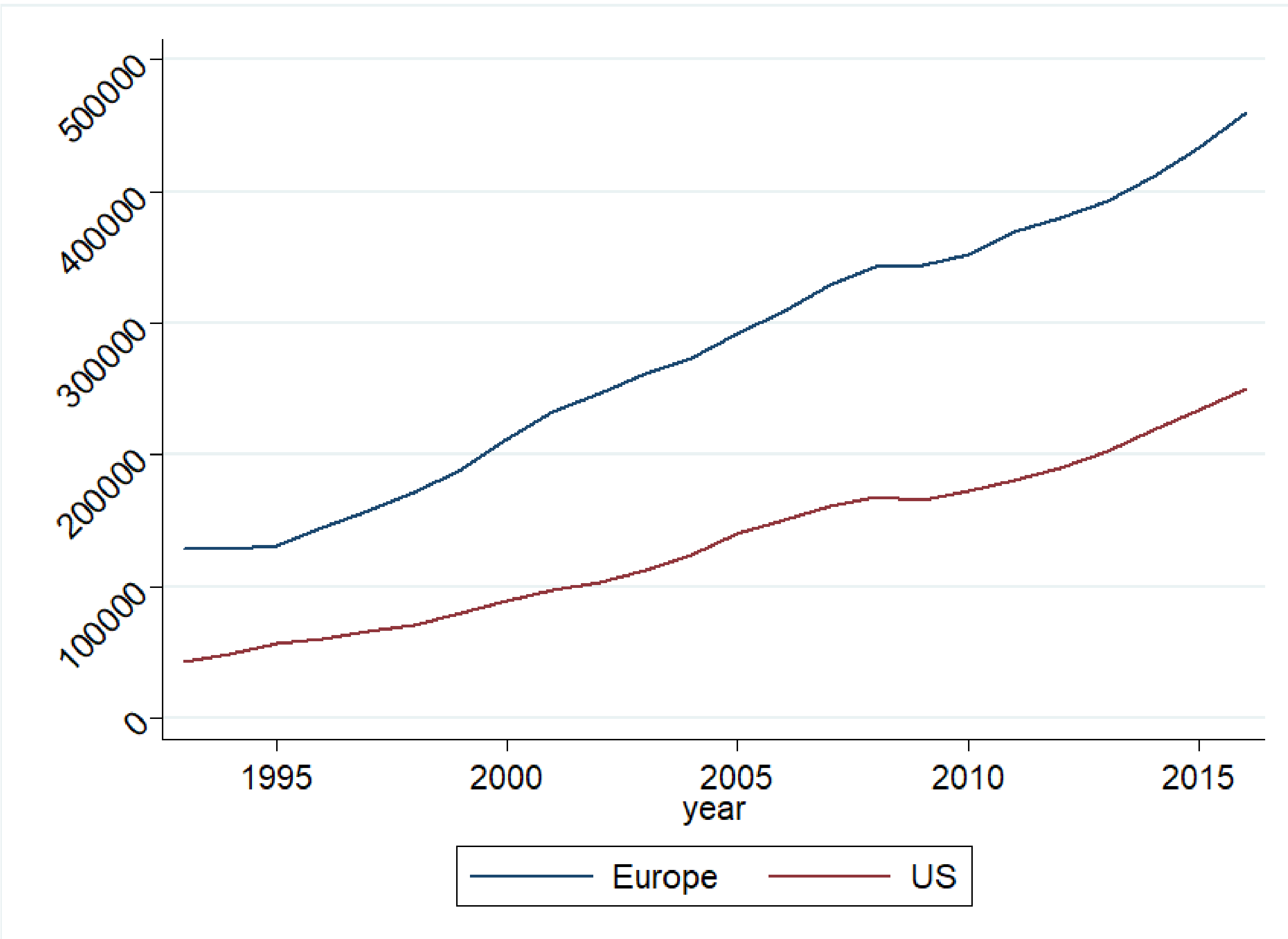
Kearney, Melissa S and Riley Wilson, "Male Earnings, Marriageable Men, and Non-Marital Fertility: Evidence from the Fracking Boom," *Review of Economics and Statistics*, 2017, (0).

Schaller, Jessamyn, "Booms, Busts, and Fertility Testing the Becker Model Using Gender-Specific Labor Demand," *Journal of Human Resources*, 2016, *51* (1), 1–29.

Shenhav, Naama, "Bribed to Wed? Family Formation and Labor Market Responses to the Gender Wage Gap," 2016.

Figures and Tables

Figure 1: Industrial Robots in the US

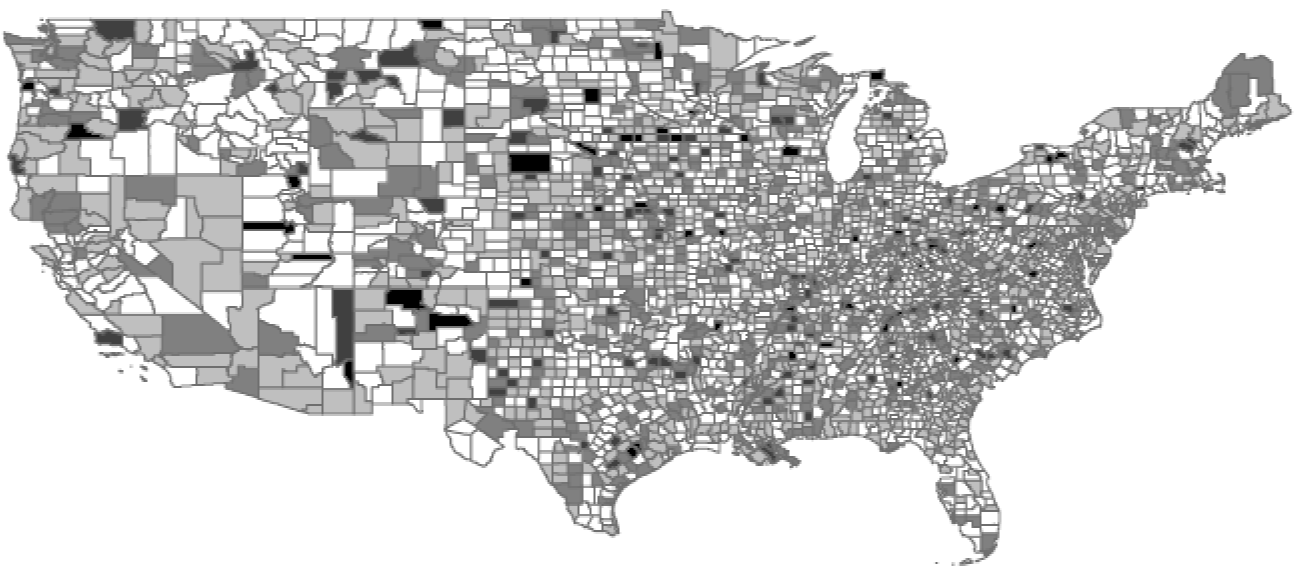


Notes - Data are drawn from the International Federation of Robotics.

Figure 2: Industrial Robots in the US

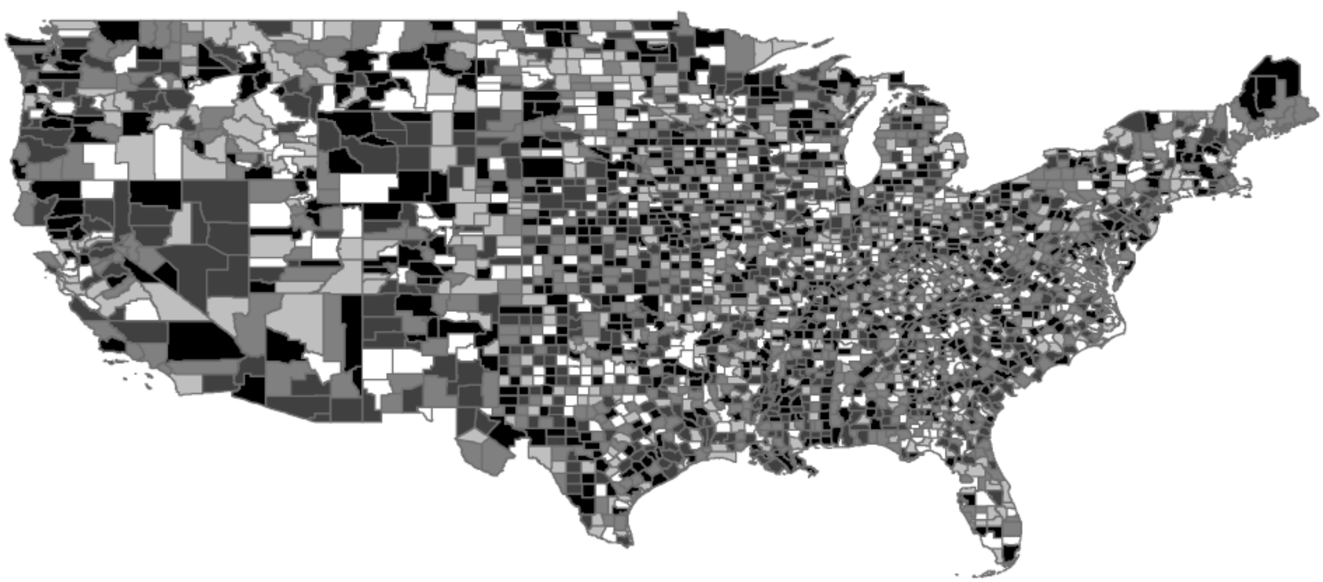
Notes - Data are drawn from the International Federation of Robotics.

Figure 3: Industrial Robots Across US Commuting Zones, 2016



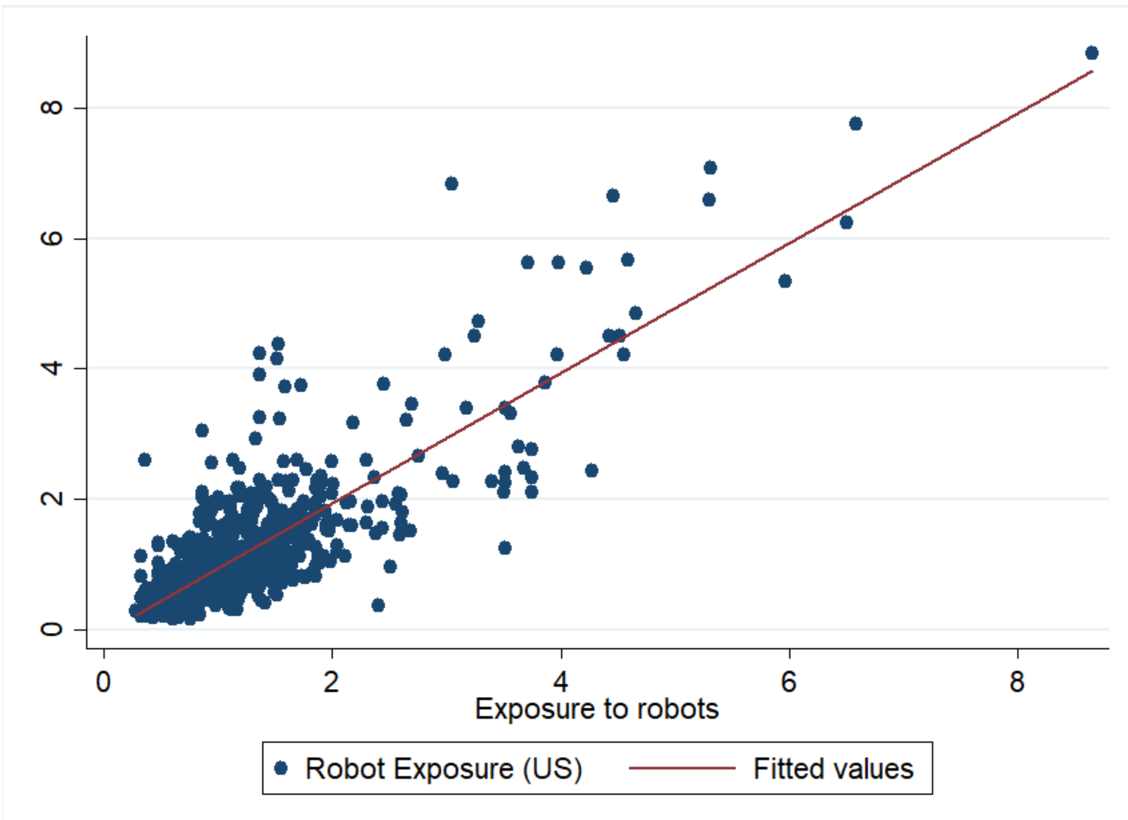
Notes - Data are drawn from the International Federation of Robotics.

Figure 4: Industrial Robots Across US Commuting Zones, $\Delta_{2004-2016}$



Notes - Data are drawn from the International Federation of Robotics.

Figure 5: Robots Exposure in the US and Exposure to Robots, 2004-2016



Notes - Data are drawn from the International Federation of Robotics.

Table 1: Robot exposure, labor force participation, and employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Labor force participation				Employment			Unemployment	
					Men				
robot_exposure_us	0.0015		0.0032**	0.0060***		0.0095***	-0.0028***		-0.0086***
	(0.001)		(0.002)	(0.001)		(0.002)	(0.000)		(0.001)
robot_exposure_IV		0.0031*			0.0086***			-0.0023***	
		(0.002)			(0.002)			(0.001)	
Observations	8,892	8,892	8,892	8,892	8,892	8,892	8,892	8,892	8,892
R-squared			0.576			0.606			0.549
Number of czone	741	741	741	741	741	741	741	741	741
Mean of Dep. Var.	0.747	0.747	0.747	0.693	0.693	0.693	0.0748	0.0748	0.0748
Std.Dev. of Dep. Var.	0.0718	0.0718	0.0718	0.0825	0.0825	0.0825	0.0365	0.0365	0.0365
					Women				
robot_exposure_us	0.0013**		0.0029***	0.0047***		0.0073***	-0.0016***		-0.0065***
	(0.001)		(0.001)	(0.001)		(0.001)	(0.000)		(0.001)
robot_exposure_IV		0.0027***			0.0070***			-0.0015***	
		(0.001)			(0.001)			(0.001)	
Observations	8,892	8,892	8,892	8,892	8,892	8,892	8,892	8,892	8,892
R-squared			0.279			0.350			0.449
Number of czone	741	741	741	741	741	741	741	741	741
Mean of Dep. Var.	0.685	0.685	0.685	0.641	0.641	0.641	0.0659	0.0659	0.0659
Std.Dev. of Dep. Var.	0.0626	0.0626	0.0626	0.0702	0.0702	0.0702	0.0284	0.0284	0.0284

Notes - Data on wages, employment, marriage and fertility are drawn from the American Community Survey (2005-2016). Data on robot exposure are drawn from the International Federation of Robotics (IFR). All estimates include controls for the share of over 65, under 25, and 25-54 years old.

Table 2: Robot exposure, wages, and wage-gender gap

		Income				Gender wage gap		
	women			men				
-300.1093***		-392.8575***	-615.8139***		-1,306.4719***	-242.7929***		-913.6144***
(46.783)		(60.172)	(89.281)		(152.472)	(52.561)		(121.470)
	-379.6714***			-1,267.7542***			-657.6746***	
	(82.378)			(166.757)			(102.404)	
8,892	8,892	8,892	8,892	8,892	8,892	8,892	8,892	8,892
		0.622			0.470			0.179
741	741	741	741	741	741	741	741	741
14563	14563	14563	25127	25127	25127	10563	10563	10563
3482	3482	3482	6309	6309	6309	3755	3755	3755

Notes - Data on wages, employment, marriage and fertility are drawn from the American Community Survey (2005-2016). Data on robot exposure are drawn from the International Federation of Robotics (IFR). All estimates include controls for the share of over 65, under 25, and 25-54 years old.

Table 3: Robot exposure and marital behavior

	(1)	(2)	(3)	(4)	(5)	(6)
		Married last year			Divorced last year	
	OLS	Reduced-form	2SLS	OLS	Reduced-form	2SLS
Robot exposure US	-0.0001*		-0.0005*	0.0001***		0.0002*
	(0.000)		(0.000)	(0.000)		(0.000)
Robot expoure IV		-0.0004***			0.0002**	
		(0.000)			(0.000)	
Observations	8,892	8,892	8,892	8,892	8,892	8,892
R-squared			0.828			0.810
Number of czone	741	741	741	741	741	741
Mean of Dep. Var.	0.0161	0.0161	0.0161	0.00888	0.00888	0.00888
Std.Dev. of Dep. Var.	0.0107	0.0107	0.0107	0.00602	0.00602	0.00602

Notes - Data on wages, employment, marriage and fertility are drawn from the American Community Survey (2005-2016). Data on robot exposure are drawn from the International Federation of Robotics (IFR). All estimates include controls for the share of over 65, under 25, and 25-54 years old.

Table 4: Robot Expsoure and Fertility

	(1)	(2)	(3)
	OLS	Reduced-form	2SLS
robot exposure (US)	-0.0005***		-0.0013***
	(0.000)		(0.000)
robot exposure IV		-0.0021***	
		(0.000)	
Observations	8,892	8,892	8,892
R-squared			0.056
First-stage F			611.52
Number of czone	741	741	741
Mean of Dep. Var.	0.0553	0.0553	0.0553
Std.Dev. of Dep. Var.	0.0139	0.0139	0.0139

Notes - Data on wages, employment, marriage and fertility are drawn from the American Community Survey (2005-2016). Data on robot exposure are drawn from the International Federation of Robotics (IFR). All estimates include controls for the share of over 65, under 25, and 25-54 years old.

Table 5: Robot Exposure and Fertility

	(1) Fertility	(2) Fertility	(3) Out of Wedlock	(4) Out of Wedlock
Robot exposure	-0.0012**	-0.0013***	0.0001	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8,892	8,892	8,892	8,892
R-squared	0.021	0.056	0.018	0.043
Number of czone	741	741	741	741
Mean of Dep. Var.	0.0553	0.0553	0.00330	0.00330
Std.Dev. of Dep. Var.	0.0139	0.0139	0.00202	0.00202

Notes - Data on wages, employment, marriage and fertility are drawn from the American Community Survey (2005-2016). Data on robot exposure are drawn from the International Federation of Robotics (IFR). All estimates include controls for the share of over 65, under 25, and 25-54 years old.

Appendix A: Supplemental Figures and Tables