Gender Differences in the Effects of Robot Adoption: Evidence from the US*

Azat Nurmukhametov†

October 11, 2023

Abstract

A significantly growing robotics technology may have considerably influenced labor market dynamics over the recent decades. This paper delves into the implications of increased industrial robot installations on changes in population size and employment in local labor markets. The cross-sectional study reveals discernible gender disparities in the impacts of robot adoption. The effect of robotization on the labor force participation rate is negative for men and unmarried women yet positive for married women. As industrial robots are predominantly programmed to perform routine tasks in manufacturing industries traditionally associated with heavy manual male-dominated labor, the anticipated impact of robot exposure on employment in the manufacturing sector is predictably negative for male workers. For women, this effect is conversely positive. It was also found that robot penetration leads to an increase in the share of family income attributed to females within married-couple households.

JEL Codes: J16, J21, J23, J24, J61, O33

Keywords: Industrial robots, migration, employment, gender differences

*First draft: May 2023. I cannot thank enough my academic adviser, Dr. Suqin Ge, for her constant support, patience, and valuable guidance. I am also grateful to Dr. Susan Chen, my committee member, for indispensable feedback and editing help.

†Department of Economics, Virginia Tech, Blacksburg, VA 24061, USA. azatn@vt.edu

1 Introduction

The term "robot" is relatively recent, originating from the creative works of Czech author and playwright Karel Čapek (1880-1938) in his 1920 science-fiction masterpiece, "R.U.R." or "Rossum's Universal Robots."[1] This neologism finds its roots in the Czech word "robota," signifying servitude or involuntary labor. Its linguistic counterparts can be observed in various European languages, including German, Polish, and Russian. Within the narrative of "R.U.R.," a fictional factory employs principles of biochemistry and physiology to engage in the mass production of a novel type of laborer who possesses every attribute except for a soul.

In the opening scenes of the play, Harry Domin, the general manager of Rossum's Universal Robots, recounts the company's historical background and explains the pivotal role of robots in driving down labor costs across the world. By the time the events of the play unfold, situated approximately in the year 2000, the use of robot laborers is already both economical and readily available. Domin anticipates a future where, within a mere decade, everything will be done by robots worldwide (Čapek, 1923). Automation will permeate every facet of global productivity and robots will produce "so much of everything that nothing will cost anything," bringing the human need to work to a close. As a result, people will not work; they "will do only the things they want to do." But the narrative takes a twist as the robots rebel against their creators, embarking on a campaign to exterminate humanity, thereby thwarting the realization of Domin's vision. However, evaluating the accuracy of the robot creator's predictions through the lens of contemporary labor economics is thought-provoking.

In the current era, approximately a century after the coining of the term "robot," our world is witnessing a groundbreaking shift in the realm of employment, driven by technological progress. This transformation is reshaping the labor landscape, diminishing the need for certain occupations while expanding the demand for others. Among the pioneering domains of technology underpinning these changes, robotics stands as a formidable force. The International Federation of Robotics (IFR) provides a succinct definition of an industrial robot as "an automatically controlled, reprogrammable, and multipurpose machine." These machines exhibit the capacity to supplant human labor across a diverse array of tasks. Although there are several other types of robots (androids, telechir robots, smart robots, etc.), the primary focus of this study centers on industrial robots, and the terms "robots" and "industrial robots" will be used interchangeably.

[1] first premiered on January 2, 1921 in Hradec Králové, Czechoslovakia, https://www.uhk.cz/cs/pedagogicka-fakulta/pdf/aktualne/svetova-premiera-r.u.r.-byla-pred-100-lety-v-hradci-kralove

According to the IFR's definition, industrial robots are entirely autonomous machines, programmed to execute manual, repetitive tasks without the necessity of human intervention (Acemoglu and Restrepo, 2020). Given their capacity to operate independently of direct people's participation in the production process, robots may be categorized as a form of physical capital. Analogous to other forms of physical capital, such as tools and equipment utilized in the production of goods and services, industrial robots can effectively serve as replacements for human labor. However, the adoption of these highly efficient manufacturing tools is likely to result in increased output, thereby leading to a heightened demand for labor. While labor demand for certain routine occupations may decline due to the substitution by robots, there emerges a complementary demand for other occupations, primarily those necessitating higher skill levels. Thus, industrial robots act as substitutes for particular manual routine occupations and complements to other, often more skill-intensive, roles (albeit not necessarily in a direct manner). In addition, this supplanting by robots for routine work may contribute to employment polarization, whereby lower-skilled labor is redirected toward service sectors characterized by lower income and slower career advancement (Autor and Dorn, 2013; Dauth et al., 2018). Consequently, the employment effects of robotization can spill over to other industries not directly affected by this labor market shock.

Presently, the appeal of industrial robots as replacements for human labor continues to intensify due to the compelling cost-effectiveness it offers to manufacturers in automating routine tasks. Over the recent decades, the field of robotics has experienced rapid technological advancement, resulting in a notable upswing in the prevalence of robots in the United States and Western Europe. Figure 1 underscores this trend, illustrating a more than fourfold increase in the number of industrial robots in the USA from 1995 to 2017.

The growing robotics technology significantly impacts our society, including the labor market. A series of papers have linked the rise of robots to essential effects on overall employment, manufacturing employment, earnings, and migration (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Grigoli et al., 2020; Faber et al., 2019). It has been ascertained that exposure to industrial robots amplifies both productivity and wages, but concurrently diminishes employment opportunities for low-skill workers. However, this impact does not affect overall employment in the USA, South Korea, Australia, and 14 European countries (Graetz and Michaels, 2018). Other studies assert that the adoption of robots leads to reduced employment and wages for American workers (Acemoglu and Restrepo, 2020). Within German local labor markets that specialize in industries characterized by extensive robot usage, the introduction of robots does not exhibit an unfavorable effect on total employment, as the gains experienced within the business service sector offset the job losses in manufacturing (Dauth et al., 2018).

Artificial Intelligence (AI) has the potential to impact labor markets in a manner akin to industrial robots, replacing certain occupations and complementing others. Recent studies highlight the differential influence of AI on various skill groups within the workforce. According to Webb (2019), high-skilled workers constitute the most vulnerable segment of the labor force to artificial intelligence. In stark contrast to robots, AI tends to exert a more pronounced effect on highly educated and older workers. This divergence is attributed to the nature of artificial intelligence, which entails the development of algorithms and computer programs capable of learning to perform tasks traditionally reliant on human intelligence, whereas industrial robots primarily adhere to instructions provided by humans.

The negative impact of robotization on employment displays relatively limited variation across different skill groups. Industrial robots similarly reduce high-skilled (some college or more) and low-skilled (less than college) employment (Faber et al., 2019; Acemoglu and Restrepo, 2020). An unexpected and to some extent intriguing observation is the absence of a positive effect on workers holding master's or doctoral degrees, which might be elucidated by reduced demand for highly educated workers within the non-tradable sector. Another conceivable explanation is that industrial robots do not directly complement high-skilled workers, in contrast to other computer-assisted technologies such as AI.

Given that industrial robots act as substitutes for labor in some occupational categories and complements in others, and considering the foreseeable differences in the socio-demographic characteristics of these occupations, the impact of robot penetration on key labor market outcomes may exhibit discrepancies among specific socio-demographic groups within local labor markets. Historically, following the Industrial Revolution, roles in manufacturing that required physical strength tended to offer higher wages and became more appealing to men. For that reason, many sectors associated with strenuous manual labor are characterized by a male-dominated workforce. Owing to this substantial diversity in the gender composition of industries, one can anticipate differing gender-related effects of robotization. Nevertheless, recent literature has yet to empirically explore the distinctions in the consequences of robot adoption on employment and migration for female and male workers. The ultimate goal of this paper is to fill this gap in the existing research.

One of the primary outcomes of robot exposure in local labor markets is the job transitions undergone by workers replaced by robots. Typically, patterns of job mobility exhibit gender-based variations. An earlier study by Viscusi (1980) identified that women tend to resign from their positions more frequently than men, although this observation lacks informativeness due to the inherent heterogeneity of worker characteristics, job attributes, and regional economic conditions. Royalty (1998) suggests that disparities between the job mobility of men and women are primarily rooted in the turnover behavior of less educated women. Their job mobility diverges from that of more educated women and both educational strata of men, with more educated women closely resembling men in their turnover behavior. In addition to this, research by Cotton and Tuttle (1986) reveals that unmarried workers of both genders exhibit a higher likelihood of leaving their jobs in comparison to their married counterparts.

The potential responses of workers who are forced out from the labor market due to robots can be twofold. Some individuals who have lost their jobs might opt to relocate to local labor markets with lower exposure to robots, seeking opportunities in the same occupations. Overall, robots have been linked to a notable reduction in the population size of local labor markets (Faber et al., 2019). Alternatively, another response pertains to occupational mobility, where unemployed workers may decide to change their occupations while remaining within the same local labor markets. Empirical evidence concerning gender as a determinant of occupational mobility is varied. While some studies have reported that men exhibit a greater tendency to change occupations than women (Felmlee, 1982; Markham et al., 1983; Blau, 2000), other researchers have implied little difference in overall occupational mobility between males and females (Rosenfeld and Sorensen, 1979; Gabriel, 2003), or have posited that women are more likely than men to switch occupations (Ranson, 2003). Additionally, it was found that female workers face a significantly higher risk of displacement due to automation[2] compared to their male counterparts (Brussevich et al., 2019).

A similar scenario of automating specific occupations to substitute human labor transpired about a century ago. During the first half of the previous centenary, automation led to the elimination of an essential number of manual telephone operation roles, a field primarily occupied by young American women. However, this transformation did not impact the overall employment prospects of future cohorts, as the decline in operators was offset by a resurgence in demand for middle-skill clerical positions and lower-skill service jobs (Feigenbaum and Gross, 2022). In the contemporary context, industrial robots are capable of executing physical tasks, thereby supplanting "brawn" skills traditionally associated with male-dominated industries. As a result, the comparative advantage held by low-skilled male workers in contrast to their female counterparts may be diminished (Rendall, 2017).

Empirical findings in recent literature concerning the effect of robotization on the gender wage gap present a mixed picture. It has been observed that exposure to industrial robots tends to reduce the gender wage gap in the USA but increase it in European countries. In

[2]Although the terms "automation" and "robotics" are occasionally used interchangeably and can yield comparable effects on labor market outcomes, there exists a conceptual distinction between them. Automation refers to the utilization of technology to execute a range of human tasks, whereas robotics pertains to the creation and deployment of robots (including industrial robots) designed to perform only specific functions.

the United States, the negative impact of robots on male wages substantially exceeds that on female wages, thus diminishing the gender income disparity (Anelli et al., 2019; Ge and Zhou, 2020). However, across 20 European nations, the adoption of industrial robots results in higher earnings for both men and women while simultaneously widening the gender pay gap (Aksoy et al., 2021). This stark difference in outcomes is predominantly influenced by Eastern European countries characterized by significant initial gender inequality. Besides, the productivity effect allows male middle-skill and high-skill workers in Europe disproportionately benefit from upscaled robot penetration. These divergent results imply that the influence of robot exposure on local labor markets may be context-specific.

There are general predictions indicating that the impact of automation and robotics on Americans will be uneven. Given that occupations principally held by male workers often involve more manual tasks that are relatively easier to be substituted by industrial robots, men are at a higher risk of experiencing job displacement due to robotization (Muro et al., 2019). In recent decades, male workers have been mainly concentrated in occupations related to construction, production, and transportation – occupational groups characterized by tasks that are relatively more exposed to automation and robotization.

On the other hand, women are disproportionately represented in occupations that revolve around human interaction, including education, healthcare, and social work – roles that are considerably reliant on human labor (Ngai and Petrongolo, 2017). Furthermore, women are currently more likely to achieve higher education degrees than men. Consequently, female workers' occupations may be somewhat more resilient to displacement by automation tools, including industrial robots. In line with these assertions, the effect of robot adoption is anticipated to be relatively more advantageous for female workers.

Nonetheless, it is likely that skilled men stand to gain more from the productivity enhancements driven by robots (Aksoy et al., 2021). This conclusion is primarily attributed to the overrepresentation of male workers in higher positions within the occupational hierarchy of companies. In addition, men are disproportionately prevalent in STEM (science, technology, engineering, mathematics) occupations that hold relevance in this context. For these reasons, the foreseeable influence of robotization is expected to exhibit variations across skill-based occupational groups for both genders.

The main objective of this paper is to examine potential discrepancies in the consequences of robot exposure on various aspects of the local labor markets in the USA such as migration, labor force participation, total employment, private employment, and public employment, focusing on diverse socio-demographic groups categorized by gender.

To delve deeper into the distinctions in the impact of robot penetration and provide a comprehensive explanation, the supplementary analysis within gender groups is extended to different socio-demographic subgroups, including those distinguished by marital status, broad industry categories, and occupational groups. Moreover, this study explores the intricacies of intra-household adjustments in response to robotization. A similar analysis in recent literature uncovers that heightened competition from Chinese imports, representing another potent and localized shock to American local labor markets, led to an increase in married female labor force participation (Besedeš et al., 2021).

This paper makes contributions to various strands of literature. It endeavors to investigate gender discrepancies in the consequences of exposure to industrial robots. The empirical findings indicate that, on the whole, the negative effects of robot adoption on the working-age population and total employment are more pronounced for females. However, the impact of robot penetration on private employment tends to have a more negative effect on the male population. Notably, the influence of robot exposure is comparatively less negative for married workers of both genders.

Within the context of three broad industry categories, the unfavorable impact of robotization is found to be more substantial within low-skilled non-manufacturing industries, regardless of gender. In line with the predictions, the influence of robot adoption in manufacturing industries is negative for the male population and conducive for females. This positive impact is mostly attributed to married female workers and women in cognitive routine manufacturing occupations. In addition, robot penetration exerts a positive effect on labor force participation and the proportion of family income among married women.

The rest of the paper is organized as follows. Section 2 demonstrates the data and descriptive statistics. Section 3 describes the empirical framework. The results are presented in Section 4. Finally, Section 5 concludes.

2 Data and Descriptive Statistics

This section of the paper introduces the data sources utilized in constructing the commuting zone's level of robotization variable, several outcome variables, and the covariates. In addition to this, it provides essential descriptive statistics for rendering an initial overview.

2.1 Robot Adoption

In alignment with Acemoglu and Restrepo (2020), this study draws upon data encompassing the United States and five European countries (Denmark, Finland, France, Italy, and Sweden) sourced from the International Federation of Robotics (IFR). The dataset provided by the IFR includes counts of the operational stock of industrial robots categorized by industry, country, and year within the time frame of 1993 to 2017. Additionally, data on industry employment and output growth rates are extracted from the EU KLEMS database. Consistent with recent literature, robot capital is quantified as the number of robots per thousand workers.

This paper relies on robot data spanning 15 industries. Within these, nine belong to the manufacturing sector, which includes food and beverages; textiles (including apparel); wood, furniture, paper, and printing; plastic, chemicals, glass, and non-metals; basic metals and metal products; electronics; industrial machinery; automotive, shipbuilding, and aerospace; and miscellaneous manufacturing. Outside of the manufacturing domain, the dataset consists six broad industries, namely agriculture, forestry, and fishing; mining; construction; utilities; education, research, and development; and services.

The data regarding the numbers of robots per thousand workers across IFR industries in the United States for the years 1997, 2007, and 2017 are provided in Table 1. It is evident that the distribution of robots across these industries is not uniform. Specifically, the automotive, shipbuilding, and aerospace sectors exhibited the highest numbers of robots per thousand workers in 1997, 2007, and 2017, while all other industries displayed considerably lower figures.

One limitation of the IFR data is that industry-specific data for the USA is reported only after 2004. To address this, the distribution across industries in 2004 is employed to allocate the total number of the operational stock of robots in preceding years to the IFR industries. Moreover, the IFR categorizes some robot stocks as "unspecified" when the number of suppliers to a particular industry is less than four. To assign these unspecified robots to each industry, the proportions across industries in the specified data from 2017 are used as weighting factors.

2.2 Dependent Variables

In line with recent literature, this study adopts commuting zones (CZs) as the unit of observation. CZs are characterized as clusters of counties exhibiting strong commuting connections within the zone but weak commuting ties across different CZs (Autor and Dorn, 2013). Unlike alternative definitions of local labor markets such as counties, states, or metropolitan areas, CZs are considered economically relevant boundaries (unlike counties or states) that also cover rural regions of the country (unlike metropolitan areas). It is assumed that individuals residing in a particular CZ are highly likely to work within the same CZ. The dataset contains 722 commuting zones, providing comprehensive coverage of the entire continental United States (Tolbert and Sizer, 1996).

The dependent variables in this paper include migration, employment, private employment, and public employment. The examination of two distinct employment types is conducted separately, as women are more inclined to work in the public sector (Lewis and Frank, 2002). The first outcome variable, migration, is defined as the change in the logarithm of the number of working-age individuals (aged 15-64) residing in CZ c between periods t and $t+1$, within the subgroup Y:

$$\Delta lnY_{c,t:t+1} = lnY_{c,t+1} - lnY_{c,t} \tag{1}$$

The remaining three similar outcome variables represent the changes in the logarithm of the count of the employed population and the employed population in the private and public sectors, respectively.

This study also employs labor force participation and employment rate changes as dependent variables. The total, private, and public employment rates of various socio-demographic subgroups of the population are determined as the proportion of the population within these subgroups that are employed, employed in the private sector, and employed in the public sector, respectively. The labor force participation rate denotes the proportion of the population engaged in the labor force.

The dependent variables are constructed using IPUMS census samples for 1970, 1990, and 2000, as well as data from the American Community Survey (ACS) for 2007 and 2017 (Flood et al., 2023). The sample size is 1% for 1970 and 5% for the other samples. To enhance the sample size, following Autor et al. (2013), the outcomes for 2007 and 2017 are measured using the ACS data for 2005–2009 and 2015-2019.

For intra-household analysis, the IPUMS and ACS samples are limited to households containing married or cohabiting working-age couples who are not on active military duty. Households with more than one married couple and households with same-sex married couples are excluded from the dataset used for the intra-household analysis.

Descriptive statistics for the dependent variables are detailed in Table 2. The table presents unweighted means of these variables across all 722 CZs over the period from 1990 to 2017 and three subperiods (1990-2000, 2000-2007, and 2007-2017). Consistent with the approach of

Autor et al. (2013) and Acemoglu and Restrepo (2020), changes in the second period in this paper are adjusted to 10-year equivalents. This adjustment is achieved by dividing shifts in the dependent and explanatory variables over the 2000-2007 subperiod by 0.7, effectively rescaling the seven-year changes to the ten-year period for comparability.

This table demonstrates notable disparities in changes for certain dependent variables between men and women. These distinctions are most pronounced when examining changes in the labor force participation rate, total employment rate, and the logs of total and public employment. The primary source of these gender differences is the first subperiod (1990-2000), while gender discrepancies in the two subsequent subperiods are less perceptible.

The preliminary step of this study involves a visual inspection of the correlation between robotization and the dependent variables. Figures 2 and 3 reveal that robot exposure is primarily concentrated in the Eastern part of the US, particularly within the Rust Belt region. The second panels of these figures depict that the Eastern part of the country in general, and the Rust Belt in particular, experienced relatively low increases in population and total, private, and public employment. In contrast, the western part of the country exhibits lower levels of the adoption of robots but relatively high changes in all four dependent variables. Therefore, it is anticipated that there is a negative correlation between robot penetration and the dependent variables. However, Figures 4-7 do not illustrate significant visual dissimilarities in changes in the dependent variables between men (panel C) and women (panel D). The geographic distribution of all four outcome variables for both gender groups closely resembles the overall distribution among CZs (panel B).

2.3 Covariates

The first covariate employed in this paper is the exposure to Chinese imports per worker, which is constructed following the method of Autor et al. (2013). This covariate is included to control for potentially confounding changes in trade patterns. Recent literature has highlighted the significant impact of Chinese import competition on local labor markets. The substantial growth in Chinese exports to the USA and other Western countries was particularly consolidated in labor-intensive industries within the manufacturing sector, such as electronics and electrical, industrial machinery, and textiles and apparel (Faber et al., 2019). This crucial covariate is computed using data from two sources: industry-level data on the value of Chinese imports by year and destination country from the UN Comtrade database, as well as data on industry employment shares by commuting zone from the IPUMS samples. The variable is created utilizing crosswalks from Autor et al. (2013) and Autor et al. (2019).

Other covariates in the model consist of the following baseline CZ characteristics. Census division dummies are included to account for the general geographic characteristics of commuting zones. Changes in the outcome variables between 1970 and 1990 are added to capture secular labor market trends that might act as potential confounders. In order to control for the initial (before exposure to industrial robots) characteristics of commuting zones, the model has different demographic characteristics and shares of employment in broad industries in 1990. These variables are constructed from the IPUMS samples. Finally, contemporaneous changes to the demand for certain skills as potential confounders are represented by the initial shares of routine jobs and the average offshorability index (the share of tasks in an industry that can be offshored) in 1990. In alignment with Autor and Dorn (2013), these two variables are included in the model to control the potential susceptibility of a CZ's routine-intensive occupations to the substitution of routine tasks by technology or task offshoring to cheaper labor markets.

3 Empirical Framework

The effect of robot adoption on outcome variables (changes in population size, labor force participation rate, different employment rates, and various types of employment) within the subgroup Y can be written as follows:

$$\begin{aligned}\Delta Y_{c,t:t+1} =& \beta_0 + \beta_1 \text{US Robot Adoption}_{c,t:t+1} + \beta_2 \text{US Exposure to Chinese Imports}_{c,t:t+1} + \\ & X'_{c,1990}\gamma_{t:t+1} + \varepsilon_{c,t:t+1}, \end{aligned} \tag{2}$$

where $\Delta Y_{c,t:t+1}$ represents the change in the log count of the population, employed population, and employed population in the private and public sector in the local labor market c between periods t and $t+1$, multiplied by 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. $\Delta Y_{c,t:t+1}$ also denotes the change in the labor participation rate, total employment rate, private employment rate, and public employment rate within commuting zone c between two periods.

US Exposure to Chinese Imports$_{c,t:t+1}$ in this estimation equation is the change in the values of Chinese imports to the US in commuting zone c between periods t and $t+1$ (Autor et al., 2013). $X'_{c,1990}\gamma_{t:t+1}$ represents a vector of interactions between baseline CZ characteristics ($X'_{c,1990}$) and period dummies ($\gamma_{t:t+1}$), and $\varepsilon_{c,t:t+1}$ is a random error.

The US robot exposure variable for a commuting zone is constructed following the method employed by Acemoglu and Restrepo (2020). It is a Bartik-style measure that is based on the change in robot density within each industry in the US between t and $t+1$, as well as the baseline industry employment shares within CZ c in 1990:

$$\text{US Robot Adoption}_{c,t:t+1} \equiv \sum_{i \in I} l_{ci,1990} \left(\frac{R^{US}_{i,t+1} - R^{US}_{i,t}}{L^{US}_{i,1990}} - g^{US}_{i,t:t+1} \frac{R^{US}_{i,t}}{L^{US}_{i,1990}} \right), \tag{3}$$

where, $L^{US}_{i,t}$ and $R^{US}_{i,t}$ indicate the number of employed individuals and robots in industry i at time t, $g^{US}_{i,t:t+1}$ denotes the output growth rate of industry i in the US between time t and $t+1$, and $l_{ci,1990}$ represents the employment share of industry i within CZ c in 1990.

The dependent variables, including changes in population size and employment, can directly influence manufacturers' decisions within local labor markets, conceivably affecting robot adoption choices. To address this anticipated endogeneity issue, the measure of US robot penetration is instrumented, replacing the robotization of American industries with average robotization in five European countries that were ahead of the USA in this regard (Acemoglu and Restrepo, 2020). To mitigate any potential correlation related to robot exposure before the 1990s, the employment shares in 1990 are replaced with those from 1970:

$$\text{EU Robot Adoption}_{c,t:t+1} \equiv \sum_{i \in I} l_{ci,1970} \frac{1}{5} \sum_{j \in EU5} \left(\frac{R^{j}_{i,t+1} - R^{j}_{i,t}}{L^{j}_{i,1990}} - g^{j}_{i,t:t+1} \frac{R^{j}_{i,t}}{L^{j}_{i,1990}} \right), \tag{4}$$

where j represents the five European countries Denmark, Finland, France, Italy, and Sweden.

Europe indeed provides a valuable context for this analysis due to the notable divergence in the adoption of industrial robots in comparison to the USA, experiencing a 19% higher exposure in 2016 (Chiacchio et al., 2018). Besides, an examination of Figure 1 reveals a convergence in the average growth trends of the industrial robot stock in Denmark, Finland, France, Italy, and Sweden with the patterns observed in the United States, particularly evident in the period preceding 2010.

In line with the methodology outlined in recent literature, the exposure to Chinese imports is instrumented by substituting imports to the USA with imports to eight high-income countries to alleviate the analogous endogeneity concerns related to consequent shifts in US demand. (Autor et al., 2013). Both the robot penetration variable and this instrument are standardized, yielding a mean of 0 and a standard deviation of 1.

In this study, the 27-year timeframe spanning from 1990 to 2017 is divided into three distinct periods: 1990-2000, 2000-2007, and 2007-2017. It is important to point out that all regression models employ weighting, with the weights assigned based on a commuting zone's national share of the outcome group as of 1990. The standard errors are robust against heteroskedasticity and correlation within US states.

4 Results

4.1 General Effects of Robotization

The general findings of this paper align with existing literature. Table 3 presents the results, indicating an overall negative relationship between a commuting zone's exposure to industrial robots and population size (-0.48), labor force participation rate (-0.06), total employment rate (-0.14), and private employment rate (-0.26). However, there is a positive overall impact on public employment (0.14). The statistical significance of these coefficients varies, with all being significant at conventional levels except for the labor force participation rate. The study reveals that the negative effects of robotization on population size and the public employment rate are more pronounced for women (-0.55 compared to -0.42 and -0.68 compared to -0.05, respectively). In contrast, for the other three dependent variables, the negative impact is more substantial among male respondents (-0.15 vs. zero, -0.94 vs. -0.85, and -1.24 vs. -1.07). It is also worth noting that the adoption of robots has a more prominent negative effect on all dependent variables for the unmarried population, for instance, on the labor force participation rate (-0.19 compared to 0.03) and the total employment rate (-1.23 compared to -0.86).

The table additionally illustrates the differential impact of robot penetration on the labor force participation rate across various demographic groups. The findings display a negative and statistically significant effect on male labor force participation (-0.15), whereas there is no impact on women. This effect on male respondents has similar magnitudes for unmarried and married men (-0.19 and -0.14, respectively). The negative and statistically significant impact of robot adoption is nearly identical for both genders within the unmarried population (-0.19 for men and -0.20 for women). All the coefficients mentioned above are statistically significant.

One may find that the effect of robot exposure on the alteration in female labor force participation significantly depends on marital status. The impact of robotization is negative for unmarried females (-0.20) and positive for women in married or cohabiting households (0.14). Both coefficients are statistically significant. This discrepancy might be attributed to the hypothesis that married women might enter the labor force to compensate for the income lost when their husbands withdraw from the labor force. If this assumption holds, the observed increase in labor force participation among married women may lead to a more conspicuous contribution of wives to household income in married couples. The analysis of the effect of robots on intra-household work dynamics in the fourth section of this chapter will further investigate this proposition.

Lastly, upon scrutinizing the statistically significant coefficients related to changes in population size and employment rates, an essential pattern emerges: the influence of robot penetration appears to be least negative for married women, with coefficients of -0.46 for migration, -0.54 for total employment, and -0.73 for private employment. Conversely, this unfavorable impact is notably more pronounced for other demographic groups.

The further analysis is expanded by estimating a relationship between a commuting zone's exposure to industrial robots and its labor market outcomes within three broad industry groups: manufacturing industries (including construction and mining) and two groups encompassing non-manufacturing industries[3]. Since these industry groups are contingent on employment, the dependent variables are solely the changes in different employment categories. The effect of robot adoption on the working-age population is not assessed for these subgroups of workers, as it is assumed that only employed respondents provide information about their respective industries and occupations.

Table 4 discloses compelling evidence that robotization reduces total employment, private employment, and public employment, as reflected in the respective changes in log counts. The coefficients associated with the robot penetration variable demonstrate the extent of this impact, revealing values of -0.71, -0.96, and -0.35, respectively. All of them, except the coefficient on public employment, are statistically significant. It is noteworthy that this negative effect on two variables is more distinct for females, where the coefficients for total employment (-0.85 compared to -0.67) and public employment (-0.58 compared to -0.11) exhibit greater magnitudes. On the other hand, male workers experience a more substantial negative impact on private employment (-1.05 against -0.96). All coefficients, except the one pertaining to public employment for men, indicate statistical significance at conventional levels.

The negative effect of robot exposure on all three dependent variables is notably more prominent among unmarried respondents. The estimated coefficients for total and private employment are -1.16, contrasting with -0.51, and -1.37, contrasting with -0.72, respectively. Both coefficients on public employment are statistically insignificant.

The findings outlined in this table suggest that robotization diminishes total employment, private employment, and public employment in both categories of non-manufacturing industries. This negative influence is stronger for low-skilled non-manufacturing industries. Remarkably, the impact of robot adoption on all three dependent variables within manufacturing industries is nearly zero and lacks statistical significance.

[3]High-skilled non-manufacturing industries include Finance and Insurance, and Real Estate; Professional, Scientific, and Technical Services; Management of companies and enterprises; Educational and Health Care Services; Public Administration. Other non-manufacturing industries are considered as low-skilled.

4.2 Gender Effects of Robotization on Industry Groups

To investigate further the gender-specific impact of robotization, the analysis is extended to diverse socio-demographic subgroups. The results in Table 5 reveal that the negative effect of robot penetration on total employment, private employment, and public employment is particularly more pronounced in low-skilled non-manufacturing industries, while it is comparatively weaker in manufacturing industries, irrespective of gender. It is worth noting one exception – the impact of robot exposure on male public employment, which is more negative in high-skilled non-manufacturing industries. The most noteworthy discovery from this table is that among the female population, there is a positive and statistically significant effect of robot adoption on all three outcome variables within manufacturing industries. The estimated coefficients stand at 1.66 for total employment, 1.65 for private employment, and 2.31 for public employment. In comparison, the coefficients for males are negative, measuring at -0.57, -0.61, and -0.27, respectively.

It is also noticeable that within low-skilled non-manufacturing industries, the negative impact of the primary variable of interest on all three outcome variables is more conspicuous among female workers. However, in the case of high-skilled non-manufacturing industries, the unfavorable effect on two of the response variables, namely private and public employment, is more discernible among male employees.

Table 6 illustrates that the negative impact of exposure to robots on the three dependent variables is notably more distinct among unmarried male workers. All coefficients in this table, except for two, exhibit greater negativity for unmarried men. The first deviation pertains to the influence of robotization on private employment in low-skilled non-manufacturing industries, where married male workers experience a more negative effect of robot penetration (-1.72 compared to -1.58 for unmarried men). The second exception is seen in the coefficient related to public employment in manufacturing industries. In this instance, the impact on unmarried men is not only less negative compared to their married counterparts but even turns positive (1.18). However, it is important to note that neither of the coefficients in this comparison is statistically significant.

The examination of female workers in manufacturing industries indicates that the positive relationship between robot adoption and both total and private employment primarily stems from married females. Table 7 displays that the coefficients of the predictor variable for married women are 2.23 and 2.31, both of which are statistically significant. On the contrary, for unmarried female workers, these coefficients are 0.75 and 0.66, respectively, and both are statistically insignificant. The results are inverted for public employment. The effect of robotization on unmarried women is positive and statistically significant (3.22). In contrast, the same coefficient for married females is also positive but considerably smaller and statistically insignificant. The negative impact of robot exposure on all three response variables for female workers in both non-manufacturing industry groups is more prominent for unmarried women.

The analysis of gender disparities in the impact of robotization is further expanded by considering a breakdown of workers into various broad occupational groups. These occupational groups represent detailed occupation recodes based on census occupation codes, resulting in a total of 22 distinct categories (as depicted in Table 8). Following recent literature (Autor and Dorn, 2013; Cortes, 2016), these occupational groups are categorized into four broader groups: cognitive non-routine, cognitive routine, manual routine, and manual non-routine occupations.

According to the results presented in Table 9, the effect of robot penetration on the four broad occupational groups is predominantly unfavorable for both male and female workers. An exception to this pattern is observed in the case of male employees engaged in cognitive routine occupations, where the adoption of robots has a positive and statistically significant impact on public employment (1.41). However, the effect of robot exposure on private employment in this particular occupational group is more negative for male workers (-0.98, contrasting with -0.60). All three of these coefficients attain statistical significance.

In cognitive non-routine occupations, the negative influence of robotization on total employment and public employment is more pronounced for women (-1.16 compared to -0.92 and -0.73 compared to -0.18, respectively) and on private employment is stronger for men (-1.72 compared to -1.63). For male workers in manual routine occupations, the impact of robot penetration on total and private employment is noticeably more negative (-0.91 and -1.04) in comparison to women, where both effects are close to zero. Finally, in manual non-routine occupations, the negative impact of robot adoption on total and private employment is more substantial for female workers (-1.42, contrasting with -0.95 and -1.64, contrasting with -1.31, respectively) and on public employment for their male colleagues (-1.05, contrasting with -0.94). All these coefficients, except the one concerning public employment for men in cognitive non-routine occupations, are statistically significant at conventional levels.

4.3 Gender Effects of Robotization in Manufacturing Industries

The subsequent phase of this study involves an examination of four broad occupational groups within manufacturing industries. Table 10 demonstrates the impact of robot penetration on these occupational groups for both male and female workers. This table reveals that the most conspicuous negative effects on total and private employment are observed among male employees engaged in manual non-routine occupations (-3.09 and -3.03). Although the unfavorable influence on these two dependent variables is somewhat less discernible, it remains statistically significant for males in manual routine occupations as well (-1.08 and -1.16).

Among women, robot exposure effects are statistically significant only for cognitive routine workers, indicating a positive impact on total employment, private employment, and public employment (1.26, 1.20, and 3.31, respectively). None of the other coefficients attain statistical significance. It is also worth noting that the adoption of robots has a negative impact only on manual non-routine female workers.

To advance the analysis of robotization within manufacturing industries, the robot penetration effect on different occupational groups is explored separately. In the Appendix, one can find the average numbers of total employment, private employment, and public employment within manufacturing industries for male and female workers in 1990, 2000, 2007, and 2017 (Tables A1, A4, and A7, respectively). For a more comprehensive view of the workforce composition, Tables A2, A5, and A8 illustrate the distribution of workers across occupational groups by gender and Tables A3, A6, and A9 display workers' shares of occupational groups.

The data presented in Tables A1 and A2 within the Appendix depict perceptible shifts in the gender composition of the workforce in manufacturing industries over the years. The average number of women in total manufacturing employment declined from 10,298 in 1990 to 7,457 in 2017, corresponding to an overall reduction in the average share of women from 24.6% in 1990 to 19.1% in 2017. Remarkably, there is a distinct increase in both the average numbers and percentages of female workers in specific occupational groups. For instance, business and financial operations occupations witnessed an uptick from 443 workers and a 43% share in 1990 to 618 workers and 51.9% in 2017, while legal occupations experienced a rise from 12 workers and 35.1% in 1990 to 26 workers and 53.1% in 2017.

In some other occupational groups, such as farming, fishing, and forestry occupations; life, physical, and social science occupations; and protective service occupations, the expansion in the share of women can be attributed to a significant reduction in the average number of male workers. Conversely, a substantial increase in the average numbers and proportions of men was observed in the two most populous occupational groups – construction and extraction occupations, which increased from 7,212 and 96.9% in 1990 to 9,276 and 97.2% in 2017, and production occupations, which changed from 8,067 and 67.2% in 1990 to 6,286 and 75.6% in 2017. These tables point to an essential growth in the average number of male workers in the first case and a prominent augmentation in their proportion in the second.

Table A3 demonstrates that two most prevalent occupational groups for men remained consistent over time – construction and extraction occupations (29.9% in 1990 and 34.7% in 2017) and production occupations (28.8% in 1990 and 25.3% in 2017). However, the fraction of the third group, transportation and material moving occupations, decreased from 11.8% in 1990 to 9.4% in 2017, which is lower than the 10.6% share held by management occupations in 2017 (increased from 7.3% in 1990).

A similar pattern can be observed among female workers. The two most prevailing groups are the same – production occupations (43.6% in 1990 and 34.6% in 2017) and office and administrative support occupations (26.3% in 1990 and 25.0% in 2017). These occupational groups remained relatively stable in terms of their proportions. Notably, there was a substantial increase in the percentage of women in management occupations, rising from 4.9% in 1990 to 9.4% in 2017. The share of the third group in 1990, transportation and material moving occupations, increased from 6.7% to 6.9%.

Table 11 illustrates the impact of exposure to robots on three types of employment in manufacturing industries, considering gender and 22 occupational groups. The consequences of robotization on total and private employment are mostly similar for male manufacturing workers. This effect is negative in the majority of occupational groups, including the two most populous groups such as construction and extraction occupations (-1.54 and -1.74) and production occupations (-0.83 and -0.93), as well as installation, maintenance, and repair occupations (-3.09 and -3.18) and business and financial operations occupations (-2.71 and -2.76). However, there is a positive impact of robot adoption in arts, design, entertainment, sports, and media occupations (2.42 and 1.82). Results diverge in the case of male public employment. Robot penetration exhibits a positive influence on certain occupational groups, such as business and financial operations (12.68), computer and mathematical science (14.38), arts, design, entertainment, sports, and media (20.49), and food preparation and serving-related occupations (27.18). The effect of industrial robots on public employment is only negative for healthcare practitioners and technical occupations (-13.06). All these coefficients are statistically significant.

The relationship between robot exposure and employment indicates variation among female manufacturing workers. The impact of robotization is favorable for total employment within specific occupational groups, namely arts, design, entertainment, sports, and media (4.55); healthcare support (17.27); personal care and service (19.36); production (2.05); and transportation and material moving occupations (2.05). There is a positive influence of robot adoption on private employment in another set of occupational groups, including legal (8.35); education, training, and library (9.62); healthcare support (22.55); production (1.96); and transportation and material moving occupations (2.13). In terms of public employment, the robot penetration effect is positive for certain occupational groups like management (12.08); life, physical, and social science (12.50); protective service (12.40); installation, maintenance, and repair (24.71); and production occupations (4.35), but negative for others such as legal (-17.82) and farming, fishing, and forestry occupations (-6.33). All coefficients mentioned in this paragraph attain statistical significance at conventional levels.

4.4 Effects of Robotization on Intra-household Work Dynamics

The final segment of this study delves into the impact of industrial robot adoption on intra-household employment dynamics. It is observed that the robotization effect on the labor force participation rate is negative for unmarried females and positive for women in married households, as depicted in Table 3. This divergence in outcomes may be elucidated by the assumption that married women, when faced with their husbands exiting the labor force due to the influence of robot penetration, are motivated to enter the labor force themselves to compensate for the lost household income.

The negative consequences of exposure to robots are mostly concentrated within male-dominated manufacturing industries characterized by heavy manual labor and repetitive routine tasks. The displaced male workers have the options of relocating to other commuting zones or shifting to different occupations within the same geographic areas. However, for married men, particularly those with children, the prospect of migrating to a different local labor market poses substantial challenges. The logistical complexities and social considerations associated with relocating an entire family can be formidable. Consequently, this group of men affected by robotic technology will probably tend to remain within the same commuting zones in their efforts to secure new employment opportunities.

Given that not all of these unemployed men will immediately find success in the labor market, their wives are likely compelled to join the labor force. This response on the part of married women serves as a pragmatic measure to ameliorate the economic deficits that result from husbands departing the labor force due to robotization. In this context, the entrance of married women into the labor force can be viewed as a strategy to offset the negative economic consequences of husbands' unemployment stemming from the changing employment landscape induced by robotics.

The results in Table 12 provide confirmation for this hypothesis. The effect of robot adoption on the change in the proportion of households with only the husband engaged in the labor force is observed to be negative and statistically significant (-0.12). The impact on the other three dependent variables (both spouses, only the wife, and neither of the spouses entering the labor force) is positive but statistically significant solely for the third coefficient, where both spouses are not participating in the labor force (0.05).

The effect of robot penetration on the composition of households in terms of employment is also noteworthy. Specifically, there is a positive and statistically significant influence on the shares of married households where only the wife is employed (0.07) and those where neither of the spouses is employed (0.09). The impact on the change in the fractions of households with both spouses employed and with only the husband employed is negative, although these effects are not statistically significant. Furthermore, it is evident that in commuting zones characterized by higher levels of robotization, there is an increase in the female share of family income in married or cohabiting households (0.14), and this coefficient holds statistical significance.

As a result, it might be concluded that potentially lower labor market opportunities associated with the significantly growing robotics technology have contributed to a reduction in gender inequality among married workers. Nevertheless, this notable upswing in the role of wives in income-earning within married households could also be attributed to other factors, including declining fertility rates or structural shifts in available employment opportunities that favor women.

4.5 Robustness Checks

This section outlines various robustness checks. Tables 13 and 14 present a series of robustness checks for the general robot adoption impact and the effects of robotization in manufacturing industries. In both tables, Column 2 demonstrates the coefficients of the robot exposure variable in 2SLS models weighted by population.

To address a potential concern that robot adoption effects may be primarily driven by commuting zones with the highest levels of robotization, the sample omits the top one percent of CZs with the greatest robot penetration. The estimates of the robot exposure coefficients for these models are illustrated in Column 3 of both tables.

Additionally, the robotization effect for both gender groups is assessed, excluding the post-2007 time period. This methodology permits researchers to account for the potential influence of variations in the macroeconomic landscape following the Great Recession, which could have a significant impact on the robot penetration effects. The results of this exercise are indicated in Column 4 of both tables.

Tables 13 and 14 highlight that when utilizing 2SLS models weighted by the national population share of commuting zones in 1990, rather than the share of the outcome variable (total employment, etc.), the estimation results closely resemble those of the baseline specification. The disparities in estimated effects of robot exposure on male and female workers largely remain robust after omitting the top 1% of CZs with the highest levels of robot penetration and eliminating the third period from the analysis. However, it is worth noting that the impact of robotization on private employment becomes more negative for women than men when the commuting zones with the most substantial robot adoption levels are excluded.

5 Conclusion

This study reveals that the negative influence of robot adoption on the working-age population, total employment, and public employment is more pronounced for women, while the impact of robot penetration on private employment is more negative among men. This observation underscores the differential responses of the two gender groups to the adverse economic shock. In addition to this, the negative effect of exposure to robots is found to be more conspicuous for the unmarried population, irrespective of gender.

Furthermore, there is a negative effect of robotization on the labor force participation rate of both unmarried and married men. Conversely, for female respondents, robot penetration has a positive impact on married women and a negative influence on unmarried females. This conclusion suggests that married women might be compelled to enter the labor force to compensate for any potential decline in household income caused by their husbands leaving the labor force. Supporting this substitution assumption, the intra-household analysis implies that robot exposure negatively affects the percentage of households where only the husband is in the labor force or employed, while positively impacting the proportion of households with only the wife participating in the labor force or being employed. Additionally, robot adoption has a positive effect on the proportion of household income contributed by females in married couples.

According to the findings presented in this paper, the introduction of industrial robots leads to a reduction in all outcome variables within both categories of non-manufacturing industries. This negative effect is notably more discernible in low-skilled industries of non-manufacturing sector, and it persists irrespective of gender. In low-skilled industries, the negative impact of robotization is particularly heightened for female workers. Oppositely, in non-manufacturing industries with high-skilled workers, the negative effect on private and public employment is more prominently amplified among male employees.

Nevertheless, within manufacturing industries, the influence of robot penetration exhibits a conducive trend among female participants but conversely impacts their male colleagues in a negative way. This observation could be elucidated by the divergence in the automation potential of jobs typically held by men and women. Professions traditionally associated with men tend to have a significantly higher susceptibility to automation and robotization, implying that a larger proportion of these positions could be automated using current technological capabilities (Muro et al., 2019). The positive relationship between robot exposure and employment among women in manufacturing industries is determined to be predominantly resulting from the married segment of female employees.

Further analysis of manufacturing industries demonstrates that the positive influence of robotization on three types of employment for women can be primarily attributed to workers in cognitive routine manufacturing occupations. The impact of robot penetration on total and private employment tends to be negative for men employed in manual routine and non-routine occupational groups. Moreover, it is noteworthy that the effect of robot adoption on employment within one of the most extensive occupational groups in manufacturing industries, namely production occupations, is distinct for males and females. Specifically, it is unfavorable for male workers but advantageous for women.

Some recent studies have aimed to discern the gender-specific ramifications of automation by linking occupation-specific assessments of automation probability with data on job task compositions. As noted by Brussevich et al. (2019), female employees across 30 countries, including 28 OECD member states, Cyprus, and Singapore, face a remarkably upscaled risk of displacement by automation technologies compared to their male counterparts, albeit with noticeable cross-country variations. This conclusion is primarily rooted in the observation that "female workers engage in fewer tasks that require analytical and interpersonal skills or physical labor and more tasks characterized by routine attributes, limited job flexibility, minimal on-the-job learning, and heightened repetitiveness" (Brussevich et al., 2018). The probability of replacement by automation is ascertained to be lower for younger female workers and women in managerial roles.

On the other hand, employers in manufacturing industries are increasingly seeking workers with the expertise to efficiently operate tools and equipment in highly automated environments. Data from the Census Bureau, as well as trends within the manufacturing sector, suggest that these changes could present essential opportunities for females. This shift may allow them to reduce the underrepresentation of women, which has long been a considerable problem in the manufacturing sector.

Besides this, as more women gain access to education and skills training, their presence in the industry has significantly expanded over the past few decades. Women are now occupying various roles within manufacturing organizations, spanning from executive positions to production roles and everything in between. According to Benjamin Wann, an expert in manufacturing product costs, the top typical positions women hold within the manufacturing sector include such roles as designers, engineers, operators, quality control specialists, and logistics professionals[4]. The majority of these key positions are not easily replaceable by robots. The findings presented in this paper align with this side of the discussion.

One of the limitations of this study pertains to the use of cross-sectional data, which may not definitively establish cause-and-effect relationships between robotization and labor market outcomes. Another concern is that this paper's aggregate findings at the commuting zone level may be driven by unobservable individual-level factors. Consequently, there is a clear need for additional empirical research in this field to explore the impact of robot adoption on outcomes of interest at the individual level. A promising approach for gaining a more nuanced understanding of the effects of robot penetration regarding gender and marital status differences involves utilizing longitudinal data on migration and job mobility, such as the National Longitudinal Survey of Youth 1997 (NLSY97).

Using this dataset would complement the aggregate results by examining the relationship between a local labor markets' exposure to industrial robots and the propensity of young adults to move and change occupations in response to the adverse shock employing panel microdata from the BLS. The NLSY97 data would allow for tracking migration and employment behavior among young millennials while controlling for a broad range of individual-level characteristics. The aforementioned method would presumably mitigate concerns related to the aggregate-level findings of this paper.

[4]https://benjaminwann.com/blog/the-impact-and-role-of-women-in-manufacturing-what-can-they-do

Figure 1:
Industrial robots per thousand workers in USA and Europe [cited on pages 2 and 11]

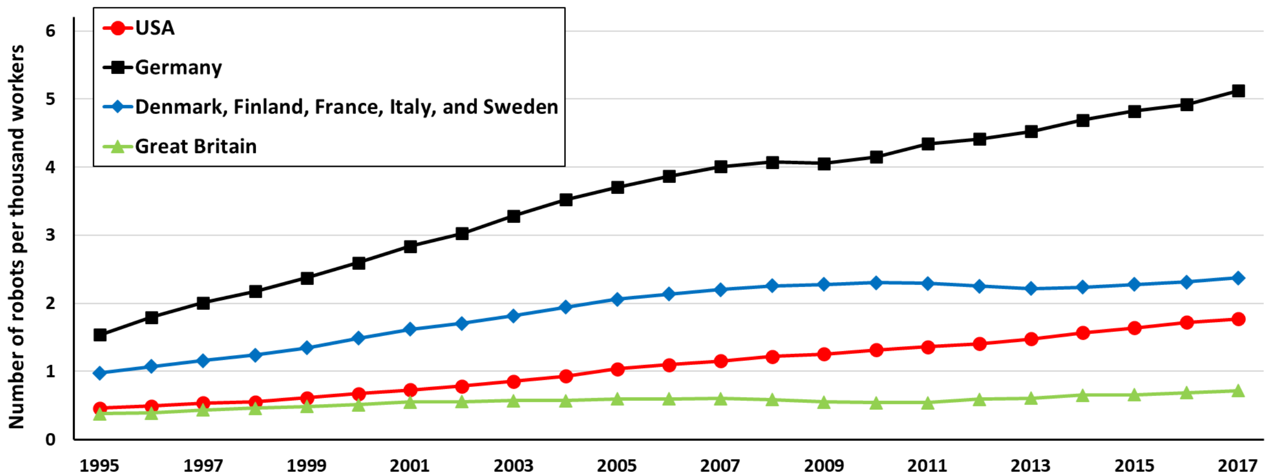


Table 1: Robot Capital (the Number of Robots (Operational Stock) per Thousand Employees) by Industries in the USA [cited on page 7]

Industries	1997	2007	2017
Manufacturing industries			
Food and beverages	0.1861	1.5892	5.8512
Textiles (including apparel)	0.0000	0.0031	0.4270
Wood, furniture, paper, and printing	0.0000	0.0048	0.4616
Plastic, chemicals, glass, and non-metals	0.2350	2.6568	10.0728
Basic metals and metal products	0.3120	3.0568	9.7648
Electrical/electronics	0.2915	5.7418	32.6076
Industrial machinery	0.0000	0.0008	3.0704
Automotive, shipbuilding, and aerospace	2.2772	22.4319	73.1389
Miscellaneous manufacturing	0.0000	0.3636	10.7061
Non-manufacturing industries			
Agriculture, forestry, and fishing	0.0000	0.0009	0.0366
Mining	0.0000	0.0029	0.0642
Construction	0.0000	0.0021	0.0185
Utilities	0.0000	0.0000	0.0921
Education, research, and development	0.0000	0.0210	0.2553
Services	0.0000	0.0000	0.0031

Notes: Robot capital is measured by the number of industrial robots per thousand workers. The numbers of industrial robots in industries come from the IFR and the numbers of workers come from the EU KLEMS.

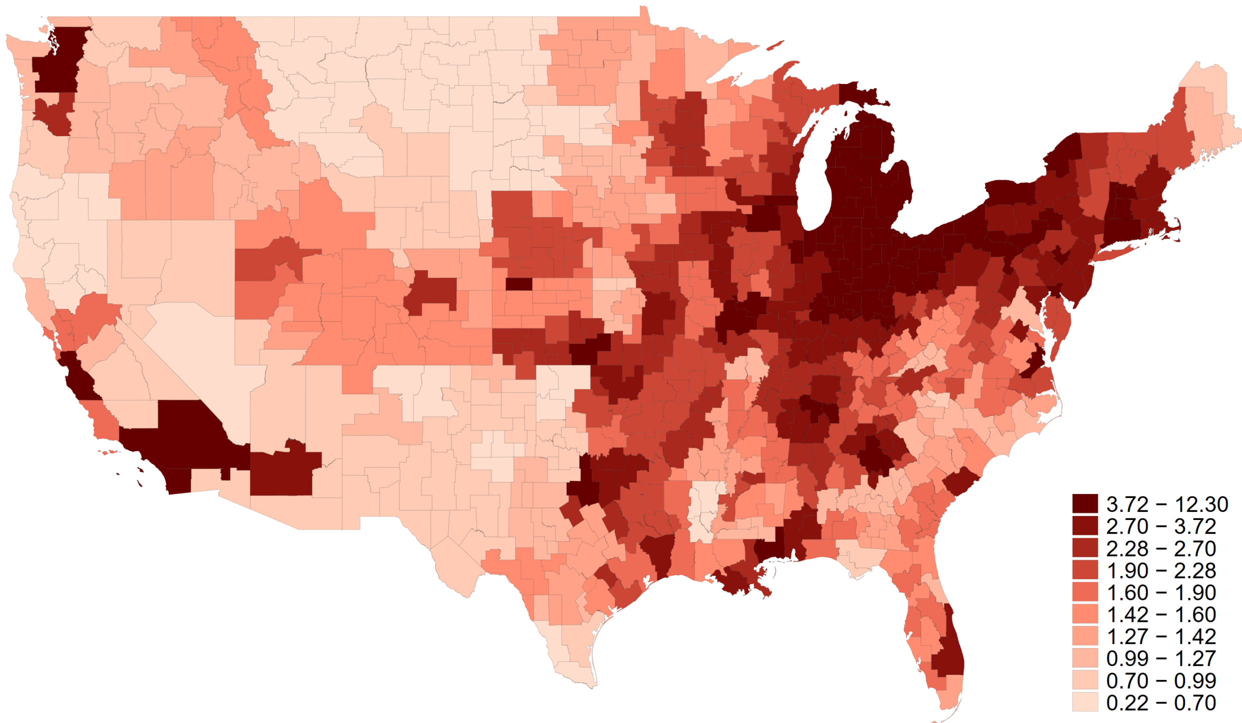
Table 2: Descriptive Statistics [cited on page 8]

	1990-2017		1990-2000		2000-2007		2007-2017	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Robot Adoption	2.05	(1.54)	0.58	(0.46)	0.85	(0.70)	0.94	(0.59)
Change in Log Working-Age Population								
All	17.62	(20.01)	11.35	(11.15)	6.19	(9.04)	1.93	(7.42)
Men	19.43	(19.61)	12.49	(11.41)	6.75	(8.87)	2.22	(7.65)
Women	15.76	(20.67)	10.20	(11.24)	5.61	(9.51)	1.63	(7.49)
Change in Labor Force Participation Rate								
All	-1.06	(3.09)	-0.65	(2.67)	0.92	(2.63)	-1.05	(1.81)
Men	-5.64	(3.88)	-4.05	(3.43)	-0.02	(3.18)	-1.58	(2.41)
Women	3.39	(3.39)	2.67	(3.01)	1.83	(2.86)	-0.56	(1.88)
Change in Total Working-Age Employment Rate								
All	-0.03	(3.48)	-0.10	(2.88)	-0.08	(3.51)	0.12	(1.92)
Men	-4.42	(4.23)	-3.31	(3.56)	-1.12	(4.21)	-0.33	(2.53)
Women	4.23	(3.67)	3.03	(3.17)	0.94	(3.48)	0.54	(1.94)
Change in Private Working-Age Employment Rate								
All	2.20	(4.45)	0.76	(3.26)	-0.20	(3.54)	1.58	(2.11)
Men	1.02	(5.79)	-0.30	(4.08)	-0.63	(4.57)	1.76	(2.99)
Women	3.18	(3.96)	1.71	(3.22)	0.15	(3.26)	1.36	(2.05)
Change in Public Working-Age Employment Rate								
All	-0.20	(2.33)	-0.21	(1.92)	0.57	(1.44)	-0.39	(1.42)
Men	-1.95	(3.12)	-1.73	(2.77)	0.23	(1.68)	-0.38	(1.80)
Women	1.69	(2.15)	1.40	(1.70)	0.97	(1.88)	-0.40	(1.61)
Change in Log Total Working-Age Employment								
All	17.46	(20.37)	11.13	(11.55)	6.07	(9.78)	2.08	(8.43)
Men	13.04	(21.34)	7.82	(12.60)	5.08	(10.29)	1.67	(9.06)
Women	22.72	(19.73)	15.15	(10.97)	7.21	(10.15)	2.51	(8.35)
Change in Log Private Working-Age Employment								
All	23.14	(22.11)	13.24	(13.09)	6.03	(11.29)	5.68	(10.22)
Men	21.95	(23.74)	11.93	(14.47)	5.78	(12.26)	5.97	(11.52)
Women	24.78	(21.19)	15.04	(12.46)	6.32	(12.13)	5.32	(9.92)
Change in Log Public Working-Age Employment								
All	17.16	(21.14)	10.69	(13.89)	9.81	(11.08)	-0.39	(10.38)
Men	7.25	(24.68)	1.37	(17.99)	8.87	(14.10)	-0.32	(13.67)
Women	24.98	(20.23)	18.02	(13.07)	10.62	(12.05)	-0.47	(10.28)

Notes: This table presents unweighted averages and standard deviations of several variables across 722 commuting zones. The changes in the log counts of working-age population, total employment, private employment, and public employment are multiplied by 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$.

Figure 2: Geographic
Distribution of Exposure to Robots and Changes in Population [cited on page 9]

Panel A. US Exposure to Robots. 1993-2017



Panel B. Changes in Population. 1990-2017

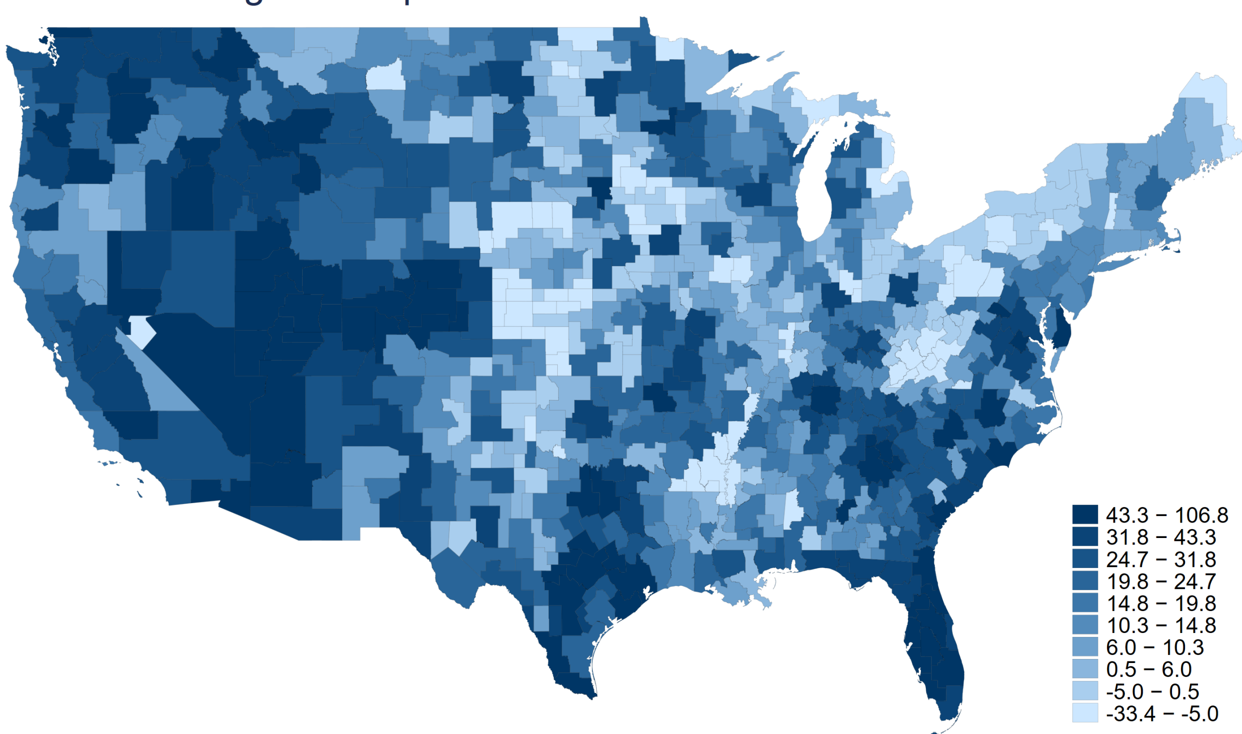


Figure 3: Geographic
Distribution of Exposure to Robots and Changes in Employment [cited on page 9]

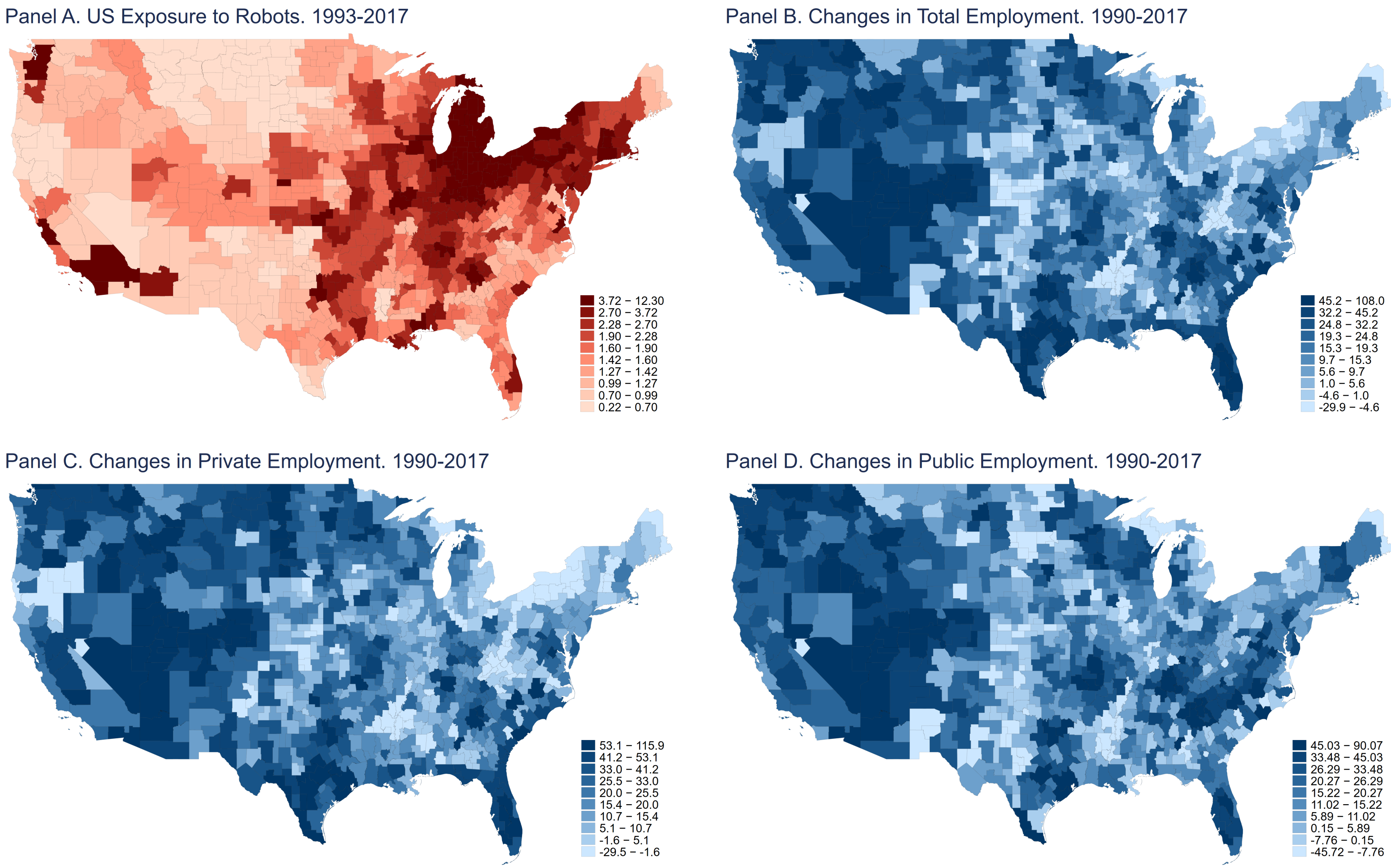


Figure 4: Geographic Distribution of Exposure to Robots and Changes in Population by Gender [cited on page 9]

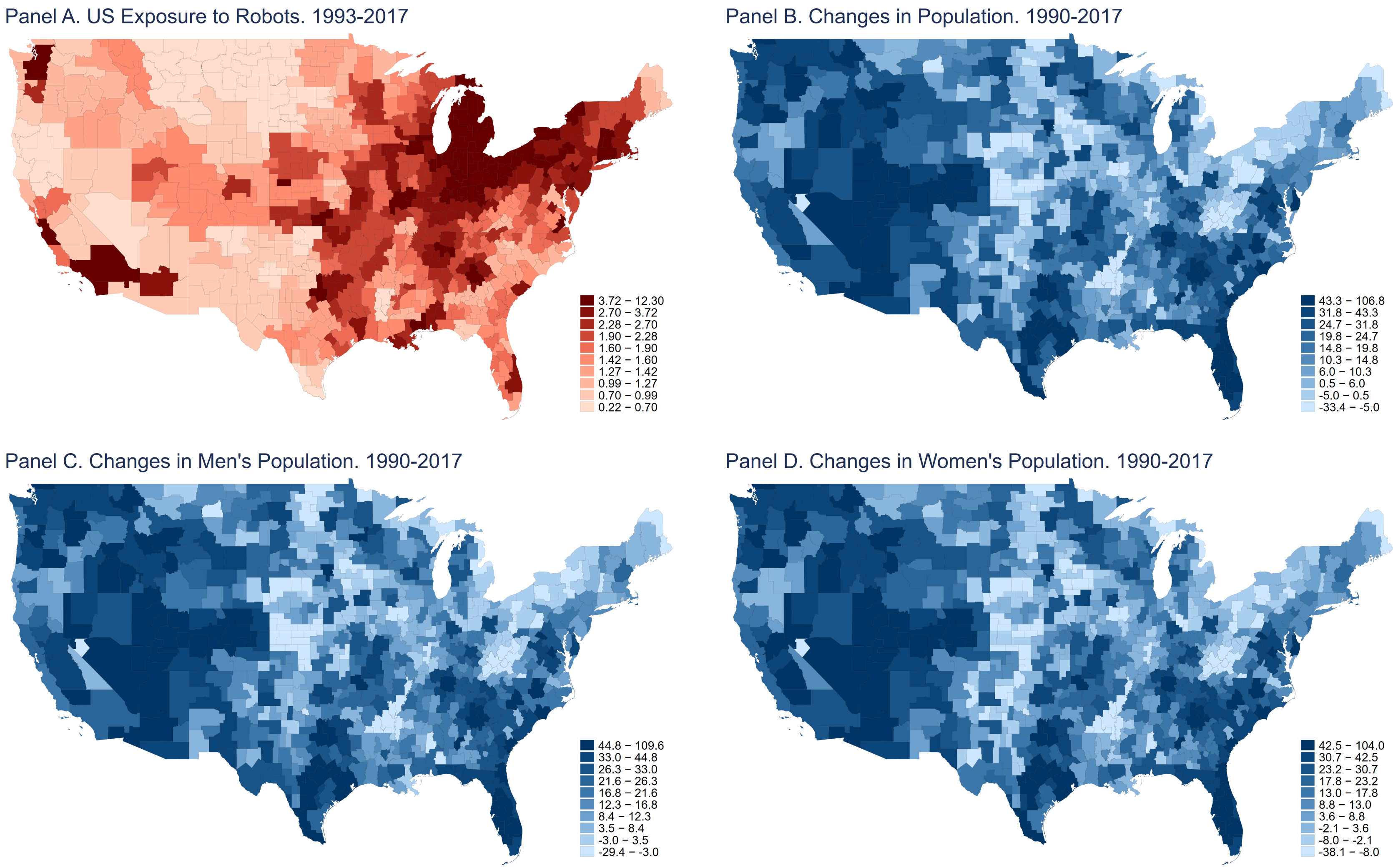


Figure 5: Geographic Distribution of Exposure to Robots and Changes in Total Employment by Gender [cited on page 9]

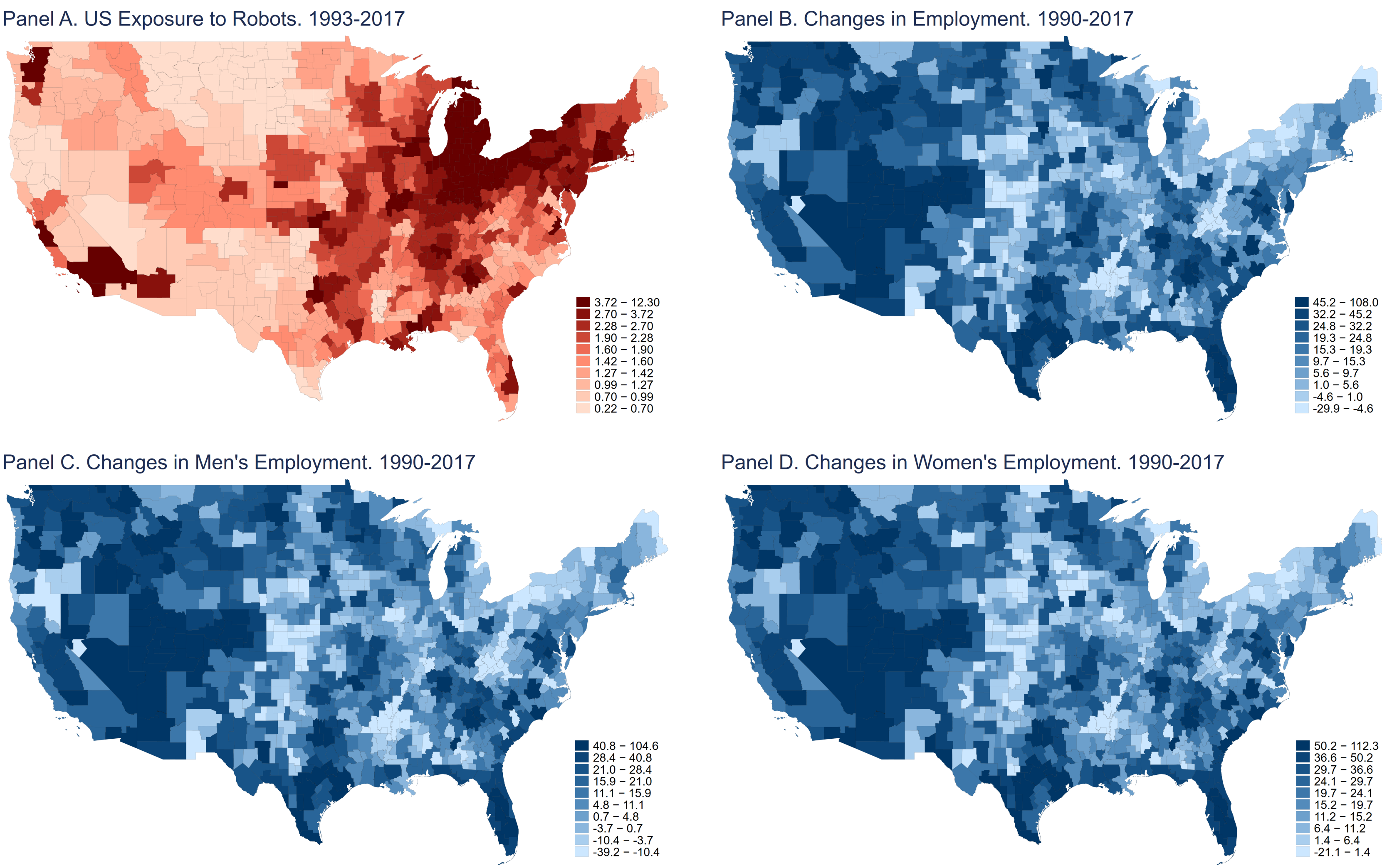


Figure 6: Geographic Distribution of Exposure to Robots and Changes in Private Employment by Gender [cited on page 9]

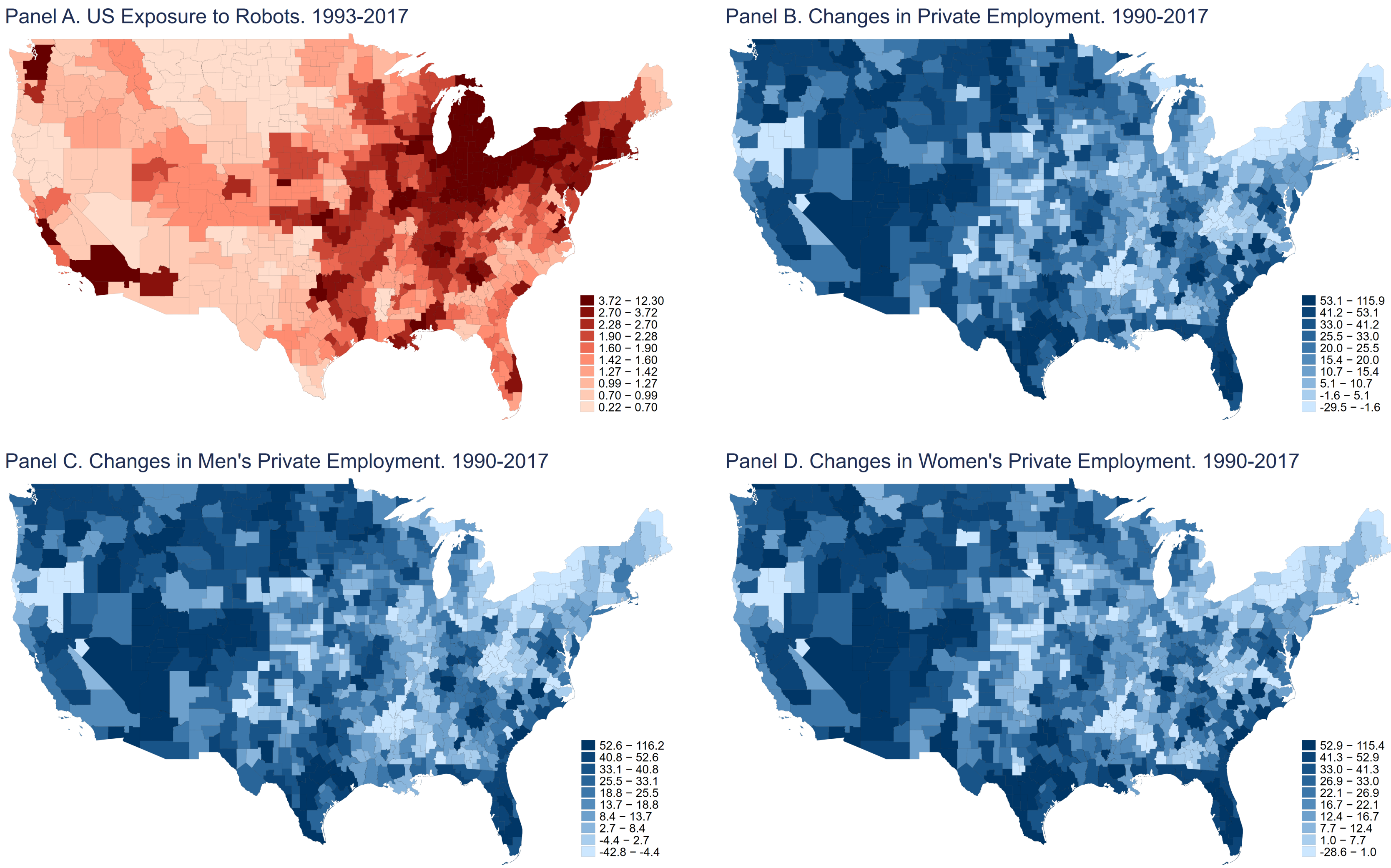


Figure 7: Geographic Distribution of Exposure to Robots and Changes in Public Employment by Gender [cited on page 9]

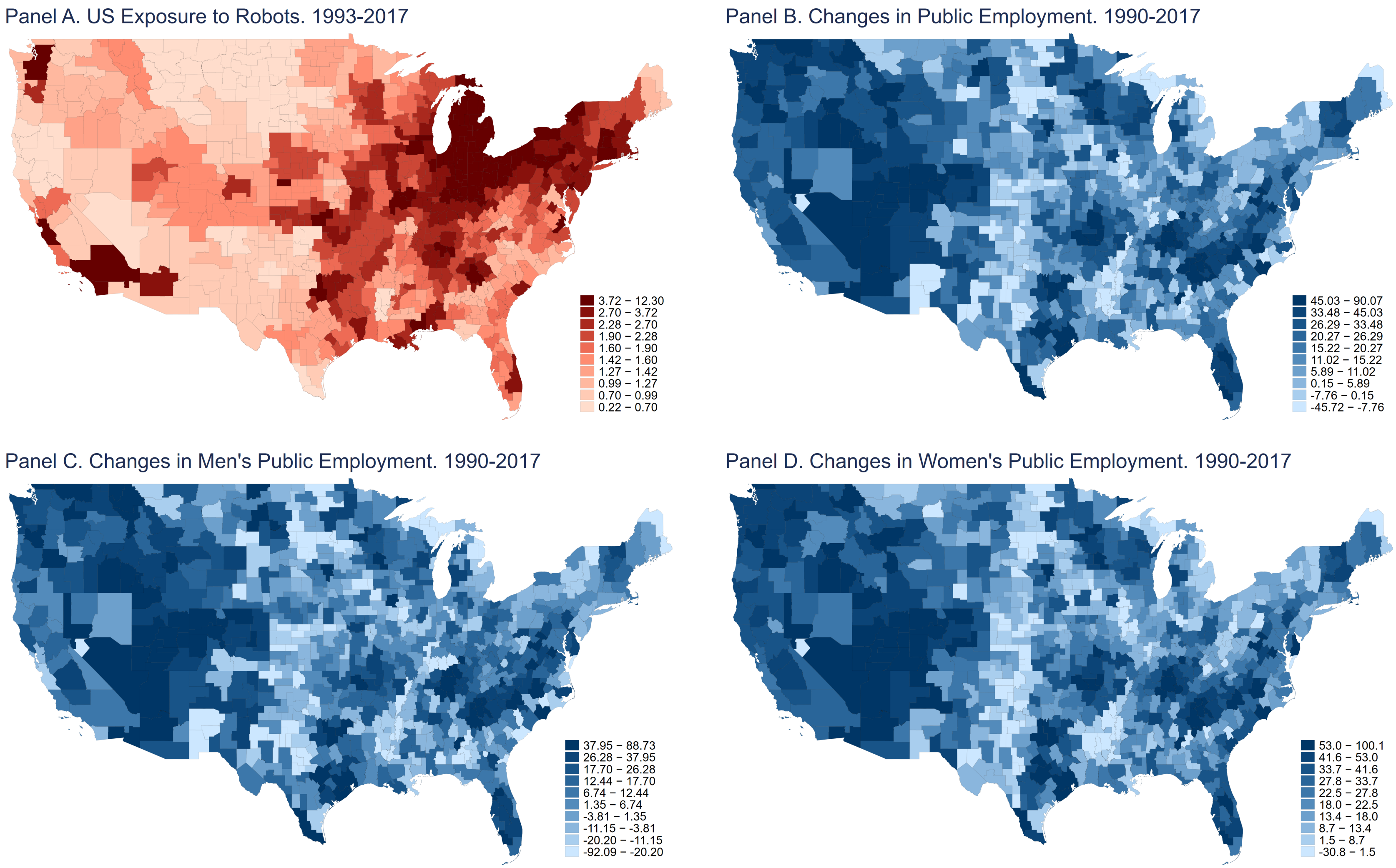


Table 3: General Robot Adoption Effects (2SLS) [cited on pages 12 and 18]

	(1)	(2)	(3)	(4)	(5)
	Dependent Variables				
Samples	Population	Labor Force Participation Rate	Total Employment Rate	Private Employment Rate	Public Employment Rate
Total sample	-0.48*	-0.06	-0.14*	-0.26***	0.14**
	(0.21)	(0.05)	(0.06)	(0.04)	(0.05)
Male respondents	-0.42*	-0.15**	-0.94**	-1.24***	-0.05
	(0.20)	(0.05)	(0.30)	(0.30)	(0.36)
Female respondents	-0.55*	0.00	-0.85**	-1.07**	-0.68
	(0.22)	(0.06)	(0.31)	(0.32)	(0.42)
Unmarried respondents	-0.76**	-0.19**	-1.23**	-1.50***	-0.44
	(0.25)	(0.06)	(0.36)	(0.36)	(0.45)
Married respondents	-0.40*	0.03	-0.86**	-1.05**	-0.05
	(0.24)	(0.05)	(0.31)	(0.32)	(0.35)
Unmarried male	-0.68**	-0.19*	-1.13**	-1.54***	-0.19
respondents	(0.23)	(0.08)	(0.39)	(0.38)	(0.49)
Married male	-0.33	-0.14*	-0.86**	-1.11***	0.08
respondents	(0.24)	(0.06)	(0.29)	(0.29)	(0.35)
Unmarried female	-0.85**	-0.20**	-1.34***	-1.51***	-0.96*
respondents	(0.29)	(0.06)	(0.36)	(0.36)	(0.47)
Married female	-0.46*	0.14*	-0.54*	-0.73*	-0.49
respondents	(0.23)	(0.06)	(0.31)	(0.36)	(0.38)

Notes: The dependent variables in columns (1)-(5) are the changes in the log count of the working-age population, multiplied by 100, in the labor force participation rate, in total employment, private employment, and public employment rates, respectively. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions are weighted by a commuting zone's national share of the population (columns 1-2), total employment (3), private employment (4), and public employment (5) in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 4: General Robot Adoption Effects (2SLS) [cited on page 13]

	(1)	(2)	(3)
	Dependent Variables		
	Total	Private	Public
Samples	Employment	Employment	Employment
Total sample	-0.71***	-0.96***	-0.35
	(0.24)	(0.25)	(0.28)
Male respondents	-0.67**	-1.05***	-0.11
	(0.25)	(0.27)	(0.33)
Female respondents	-0.85**	-0.96***	-0.58*
	(0.25)	(0.26)	(0.29)
Unmarried respondents	-1.16***	-1.37***	-0.53
	(0.30)	(0.32)	(0.41)
Married respondents	-0.51*	-0.72**	-0.20
	(0.23)	(0.24)	(0.27)
Manufacturing industries	0.05	0.07	0.36
	(0.33)	(0.35)	(0.81)
High-skilled non-manufacturing	-0.95**	-1.40***	-0.63*
industries	(0.28)	(0.37)	(0.30)
Low-skilled non-manufacturing	-1.62***	-1.86***	-0.84*
industries	(0.33)	(0.37)	(0.33)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions are weighted by a commuting zone's national share of the outcome group in 1990
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 5: Robot Adoption Effects on Industry Groups (2SLS) [cited on page 14]

	(1)	(2)	(3)
	Dependent Variables		
Samples	Total Employment	Private Employment	Public Employment
	Male respondents		
All industries	-0.67**	-1.05***	-0.11
	(0.25)	(0.27)	(0.33)
Manufacturing industries	-0.57*	-0.61*	-0.27
	(0.32)	(0.34)	(0.92)
High-skilled non-manufacturing industries	-0.85**	-1.50***	-0.63*
	(0.27)	(0.33)	(0.31)
Low-skilled non-manufacturing industries	-1.34***	-1.65***	-0.45
	(0.34)	(0.37)	(0.49)
	Female respondents		
All industries	-0.85**	-0.96***	-0.58*
	(0.25)	(0.26)	(0.29)
Manufacturing industries	1.66**	1.65**	2.31*
	(0.50)	(0.53)	(1.16)
High-skilled non-manufacturing industries	-0.95**	-1.32***	-0.57*
	(0.31)	(0.41)	(0.34)
Low-skilled non-manufacturing industries	-1.80***	-2.03***	-1.24***
	(0.35)	(0.40)	(0.29)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 6: Robot Adoption Effects on Male Socio-Demographic Groups (2SLS)
[cited on page 14]

	(1)	(2)	(3)
	Dependent Variables		
	Total	Private	Public
Samples	Employment	Employment	Employment
	Unmarried male respondents		
All industries	-1.07**	-1.34***	-0.20
	(0.33)	(0.36)	(0.50)
Manufacturing industries	-0.82*	-0.98*	1.18
	(0.49)	(0.54)	(1.36)
High-skilled non-manufacturing	-1.40***	-2.34***	-0.83*
industries	(0.34)	(0.44)	(0.40)
Low-skilled non-manufacturing	-1.56***	-1.58***	-1.24*
industries	(0.38)	(0.39)	(0.68)
	Married male respondents		
All industries	-0.51*	-0.95***	0.01
	(0.24)	(0.26)	(0.30)
Manufacturing industries	-0.55*	-0.54*	-0.92
	(0.29)	(0.31)	(1.00)
High-skilled non-manufacturing	-0.55*	-0.92*	-0.57*
industries	(0.30)	(0.41)	(0.33)
Low-skilled non-manufacturing	-1.18**	-1.72***	-0.00
industries	(0.38)	(0.47)	(0.49)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 7: Robot Adoption Effects on Female Socio-Demographic Groups (2SLS)
[cited on page 14]

	(1)	(2)	(3)
	Dependent Variables		
	Total	Private	Public
Samples	Employment	Employment	Employment
	Unmarried female respondents		
All industries	-1.25***	-1.43***	-0.85*
	(0.30)	(0.31)	(0.39)
Manufacturing industries	0.75	0.66	3.22*
	(0.58)	(0.61)	(1.29)
High-skilled non-manufacturing	-1.24**	-1.51**	-0.96*
industries	(0.39)	(0.55)	(0.43)
Low-skilled non-manufacturing	-2.18***	-2.36***	-1.38***
industries	(0.37)	(0.40)	(0.38)
	Married female respondents		
All industries	-0.60*	-0.61*	-0.46
	(0.25)	(0.27)	(0.31)
Manufacturing industries	2.23***	2.31***	1.34
	(0.48)	(0.49)	(2.45)
High-skilled non-manufacturing	-0.87**	-1.37***	-0.36
industries	(0.32)	(0.38)	(0.35)
Low-skilled non-manufacturing	-1.52**	-1.65**	-1.27**
industries	(0.44)	(0.52)	(0.39)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 8: List of Occupational Groups [cited on page 15]

Occupational Group Description	Occ Codes	Cognitive or Manual	Routine or Non-routine
Management occupations	0010-0430	C	NR
Business and financial operations occupations	0500-0950	C	NR
Computer and mathematical science occupations	1000-1240	C	NR
Architecture and engineering occupations	1300-1560	C	NR
Life, physical, and social science occupations	1600-1965	C	NR
Community and social service occupation	2000-2060	C	NR
Legal occupations	2100-2160	C	NR
Education, training, and library occupations	2200-2550	C	NR
Arts, design, entertainment, sports, and media occupations	2600-2960	C	NR
Healthcare practitioner and technical occupations	3000-3540	C	NR
Healthcare support occupations	3600-3655	C	NR
Protective service occupations	3700-3955	C	NR
Food preparation and serving related occupations	4000-4160	M	NR
Building and grounds cleaning and maintenance occupations	4200-4250	M	NR
Personal care and service occupations	4300-4650	M	NR
Sales and related occupations	4700-4965	C	R
Office and administrative support occupations	5000-5940	C	R
Farming, fishing, and forestry occupations	6000-6130	M	R
Construction and extraction occupations	6200-6940	M	R
Installation, maintenance, and repair occupations	7000-7630	C	R
Production occupations	7700-8965	C	R
Transportation and material moving occupations	9000-9750	M	R

Note: the second column represents 2010 Census codes of occupations.

Table 9: Robot Adoption Effects on Broad Occupational Groups (2SLS) [cited on page 15]

	(1)	(2)	(3)
	Dependent Variables		
	Total	Private	Public
Samples	Employment	Employment	Employment
	Male respondents		
Cognitive Non-routine	-0.92**	-1.72***	-0.18
occupations	(0.30)	(0.44)	(0.36)
Cognitive Routine	-0.37	-0.98**	1.41*
occupations	(0.43)	(0.38)	(0.62)
Manual Routine	-0.91*	-1.04*	-0.85
occupations	(0.51)	(0.55)	(0.76)
Manual Non-routine	-0.95*	-1.31*	-1.05*
occupations	(0.48)	(0.52)	(0.54)
	Female respondents		
Cognitive Non-routine	-1.16***	-1.63***	-0.73*
occupations	(0.29)	(0.37)	(0.34)
Cognitive Routine	-0.48	-0.60*	0.02
occupations	(0.32)	(0.31)	(0.43)
Manual Routine	-0.12	0.07	-1.62
occupations	(0.53)	(0.58)	(1.10)
Manual Non-routine	-1.42**	-1.64**	-0.94*
occupations	(0.47)	(0.52)	(0.52)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 10: Robot Adoption Effects on Broad Occupational Groups in Manufacturing Industries (2SLS) [cited on page 15]

	(1)	(2)	(3)
	Dependent Variables		
	Total	Private	Public
Samples	Employment	Employment	Employment
	Male respondents		
Cognitive Non-routine	-0.04	0.08	0.36
occupations	(0.75)	(0.84)	(1.35)
Cognitive Routine	-0.75	-0.85	0.14
occupations	(0.54)	(0.56)	(1.98)
Manual Routine	-1.08*	-1.16*	-0.91
occupations	(0.53)	(0.63)	(0.95)
Manual Non-routine	-3.09**	-3.03**	8.01
occupations	(1.03)	(1.08)	(6.25)
	Female respondents		
Cognitive Non-routine	1.09	1.15	2.11
occupations	(0.84)	(0.87)	(2.10)
Cognitive Routine	1.26*	1.20*	3.31*
occupations	(0.61)	(0.64)	(1.46)
Manual Routine	1.35	1.69	-1.59
occupations	(1.11)	(1.19)	(5.32)
Manual Non-routine	-2.06	-2.10	-9.63
occupations	(1.72)	(1.87)	(10.26)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 11: Robot Adoption Effects on Occupational Groups in Manufacturing Industries (2SLS) [cited on page 17]

	Total Employment				Private Employment				Public Employment			
Occupational groups	Male		Female		Male		Female		Male		Female	
Management	-0.27	(0.57)	0.88	(0.90)	-0.33	(0.67)	0.92	(0.92)	-0.09	(2.39)	12.08*	(5.50)
Business and financial operations	-2.71*	(1.30)	0.08	(1.05)	-2.76*	(1.36)	0.29	(1.11)	12.68*	(6.96)	-0.23	(6.10)
Computer and mathematical science	1.52	(1.96)	-0.06	(1.67)	1.81	(2.00)	-0.40	(1.72)	14.38*	(8.03)	10.74	(10.50)
Architecture and engineering	-0.46	(1.20)	1.23	(1.49)	-0.33	(1.28)	1.50	(1.61)	0.12	(2.09)	-1.57	(6.61)
Life, physical, and social science	0.47	(1.82)	-1.00	(1.84)	0.61	(1.84)	-0.86	(2.00)	-9.24	(8.99)	12.50*	(7.36)
Community and social service occupations	-13.84*	(7.03)	4.71	(9.96)	-7.10	(8.51)	-5.83	(10.09)	2.71	(3.19)	5.28	(6.21)
Legal	-4.37	(4.17)	3.13	(4.86)	-4.73	(4.30)	8.35*	(4.68)	-9.99	(6.40)	-17.82**	(5.21)
Education, training, and library	6.43	(5.24)	9.23	(5.87)	5.16	(5.70)	9.62*	(5.82)	-0.88	(6.01)	-7.53	(10.18)
Arts, design, entertainment, sports, and media	2.42*	(1.04)	4.55**	(1.75)	1.82*	(1.05)	2.80	(1.78)	20.49*	(8.58)	3.51	(10.28)
Healthcare practitioner and technical	-2.46	(3.55)	-0.59	(4.68)	-1.49	(3.56)	-1.65	(5.16)	-13.06*	(5.28)	-3.14	(4.76)
Healthcare support	-13.49*	(7.95)	17.27*	(8.96)	-4.50	(9.12)	22.55*	(11.55)	1.85	(2.65)	-1.76	(2.49)
Protective service	-5.70**	(1.71)	6.42	(5.01)	-4.06*	(1.83)	9.13	(5.66)	-6.46	(9.58)	12.40*	(7.36)
Food preparation and serving related occupations	0.39	(5.96)	-5.79	(4.28)	1.89	(5.91)	-4.84	(4.76)	27.18***	(6.51)	6.76	(6.57)
Building and grounds cleaning and maintenance	-3.36***	(0.92)	-2.80	(2.00)	-3.61***	(0.95)	-1.66	(2.24)	10.04	(6.28)	11.25	(7.72)
Personal care and service	-4.13	(8.74)	19.36***	(5.36)	-5.34	(8.93)	6.99	(6.16)	3.29	(4.98)	1.31	(4.53)
Sales and related occupations	0.31	(0.59)	0.23	(1.02)	0.19	(0.54)	0.30	(1.09)	11.89	(7.89)	14.08	(9.31)
Office and administrative support	-0.70	(0.78)	-0.66	(0.55)	-0.67	(0.83)	-0.81	(0.63)	2.78	(3.98)	4.82	(4.30)
Farming, fishing, and forestry	-7.17	(7.07)	8.73	(12.85)	-8.23	(7.31)	19.87	(19.57)	-2.02	(8.43)	-6.33*	(2.84)
Construction and extraction	-1.54**	(0.54)	-1.00	(1.51)	-1.74*	(0.69)	-0.02	(1.75)	-1.37	(1.04)	2.48	(8.87)
Installation, maintenance, and repair	-3.09**	(0.91)	-0.32	(2.02)	-3.18**	(0.97)	-1.30	(2.19)	-3.85	(2.67)	24.71**	(8.30)
Production	-0.83*	(0.49)	2.05*	(0.87)	-0.93*	(0.53)	1.96*	(0.94)	0.82	(2.69)	4.35*	(2.46)
Transportation and material moving	-0.47	(0.67)	2.05*	(1.04)	-0.57	(0.67)	2.13*	(1.06)	1.94	(2.05)	11.49	(9.11)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions are weighted by a commuting zone's national share of the outcome group in 1990.

Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 12: Robot Adoption Effects on Intra-Household Working Outcomes (2SLS) [cited on page 18]

	(1)	(2)	(3)
	Dependent Variables		
Samples	Fraction of Households	Fraction of Households	Share of Income in Household Income
Both spouses are in the labor force	0.08		
	(0.06)		
Only husband is in the labor force	-0.12*		
	(0.05)		
Only wife is in the labor force	0.05		
	(0.03)		
Both spouses are not in the labor force	0.05*		
	(0.03)		
Both spouses are employed		-0.02	
		(0.08)	
Only husband is employed		-0.08	
		(0.05)	
Only wife is employed		0.07*	
		(0.03)	
Both spouses are not employed		0.09**	
		(0.04)	
Share of female income			0.14***
			(0.04)

Notes: The dependent variables in columns (1)-(3) are the changes in the fraction of households with both spouses or just one spouse (either husband or wife) or neither of spouses in the labor force (1) or employed (2) and in the share of income earned by women in married or cohabiting households. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions are weighted by a commuting zone's national share of the population in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 13: Robustness Checks of General Robot Adoption Effects (2SLS) [cited on page 20]

	(1)	(2)	(3)	(4)
	Specifications			
Dependent Variables	Baseline Specification	Weighted by Population	Without 1% Top Robot Adoption CZs	Without 2007-2017
	Male respondents			
Population	-0.42*	-0.42*	-0.53	-0.29
	(0.20)	(0.20)	(0.41)	(0.26)
Total Employment	-0.67**	-0.69**	-0.60	-0.81*
	(0.25)	(0.25)	(0.44)	(0.34)
Private Employment	-1.05***	-1.07***	-1.15*	-1.32**
	(0.27)	(0.28)	(0.51)	(0.42)
Public Employment	-0.11	-0.04	0.03	0.05
	(0.33)	(0.33)	(0.58)	(0.40)
	Female respondents			
Population	-0.55*	-0.55*	-0.61	-0.53*
	(0.22)	(0.22)	(0.44)	(0.24)
Total Employment	-0.85**	-0.85**	-1.01*	-0.92**
	(0.25)	(0.25)	(0.46)	(0.28)
Private Employment	-0.96***	-0.97***	-1.25*	-1.20***
	(0.26)	(0.26)	(0.49)	(0.32)
Public Employment	-0.58*	-0.58*	-0.70	-0.31
	(0.29)	(0.29)	(0.53)	(0.31)
Observations	2,166	2,166	2,145	1,444

Notes: The dependent variables are the change in the log count of the working-age population, total employment, private employment, and public employment, respectively, multiplied by 100: $[ln(Y_{t+1})-ln(Y_t)]\cdot 100$. The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions in columns 1, 3, and 4 are weighted by a commuting zone's national share of the outcome group in 1990, in column 2 they are weighted by a commuting zone's national share of the population in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 14: Robustness Checks of Robot Adoption Effects in Manufacturing Industries (2SLS) [cited on page 20]

	(1)	(2)	(3)	(4)
	Specifications			
Dependent Variables	Baseline Specification	Weighted by Population	Without 1% Top Robot Adoption CZs	Without 2007-2017
	Male respondents			
Total Employment	-0.57*	-0.59*	-0.43	-0.83
	(0.32)	(0.32)	(0.62)	(0.54)
Private Employment	-0.61*	-0.63*	-0.56	-0.91
	(0.34)	(0.35)	(0.66)	(0.60)
Public Employment	-0.27	0.76	-1.80	0.70
	(0.92)	(0.81)	(1.27)	(1.13)
	Female respondents			
Total Employment	1.66**	1.68**	2.54**	1.17
	(0.50)	(0.51)	(0.77)	(0.72)
Private Employment	1.65**	1.69**	2.53**	1.11
	(0.53)	(0.54)	(0.81)	(0.76)
Public Employment	2.31*	2.56*	2.75	3.22*
	(1.16)	(1.22)	(1.76)	(1.91)
Observations	2,166	2,166	2,145	1,444

Notes: The dependent variables are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Regressions include such covariates as instrumented US exposure to Chinese imports; census division dummies interacted with time period dummies; the change in the outcome variable between 1970 and 1990; 1990 demographic characteristics (log population, share of population above 65 years old, share of population with less than a college degree, share of population with some college or more, population shares of Hispanics, Blacks, Whites, and Asians), each interacted with time period dummies; shares of employment in broad industries in 1990 (agriculture, mining, construction, manufacturing), each interacted with time period dummies; the share of routine jobs and the average offshorability index in 1990, each interacted with time period dummies. Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the state level. Regressions in columns 1, 3, and 4 are weighted by a commuting zone's national share of the outcome group in 1990, in column 2 they are weighted by a commuting zone's national share of the population in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

References

1. Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6):2188–2244. [Cited on pages 2, 3, 7, 9, 10, and 11.]

2. Aksoy, C. G., Özcan, B., and Philipp, J. (2021). Robots and the gender pay gap in Europe. *European Economic Review*, 134:103693. [Cited on page 5.]

3. Anelli, M., Giuntella, O., and Stella, L. (2019). Robots, labor markets, and family behavior. *IZA Discussion Paper*, No. 12820. [Cited on page 5.]

4. Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US Labor Market. *American Economic Review*, 103(5):1553–1597. [Cited on pages 2, 7, 10, and 15.]

5. Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, 103(6):2121–2168. [Cited on pages 8, 9, 10, and 11.]

6. Autor, D. H., Dorn, D., and Hanson, G. H. (2019). When work disappears: Manufacturing decline and the falling marriage-market value of young men. *American Economic Review: Insights*, 1(2):161–178. [Cited on page 9.]

7. Besedeš, T., Lee, S. H., and Yang, T. (2021). Trade liberalization and gender gaps in local labor market outcomes: Dimensions of adjustment in the United States. *Journal of Economic Behavior and Organization*, 183:574–588. [Cited on page 6.]

8. Blau, G. (2000). Job, organizational, and professional context antecedents as predictors of intent for interrole work transitions. *Journal of Vocational Behavior*, 56(3):330–345. [Cited on page 4.]

9. Brussevich, M., Dabla-Norris, E., Kamunge, C., Karnane, P., Khalid, S., and Kochhar, K. (2018). *Gender, technology, and the future of work*. International Monetary Fund. [Cited on page 21.]

10. Brussevich, M., Dabla-Norris, E., and Khalid, S. (2019). *Is technology widening the gender gap? Automation and the future of female employment*. International Monetary Fund. [Cited on pages 4 and 21.]

11. Chiacchio, F., Petropoulos, G., and Pichler, D. (2018). The impact of industrial robots on EU employment and wages: A local labour market approach. *Bruegel working paper*, 02. [Cited on page 11.]

12. Cortes, G. M. (2016). Where have the middle-wage workers gone? A study of polarization using panel data. *Journal of Labor Economics*, 34(1):63–105. [Cited on page 15.]

13. Cotton, J. L. and Tuttle, J. M. (1986). Employee turnover: A meta-analysis and review with implications for research. *Academy of management Review*, 11(1):55–70. [Cited on page 4.]

14. Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2018). Adjusting to robots: Worker-level evidence. *Opportunity and Inclusive Growth Institute Working Papers*, 13. [Cited on page 2.]

15. Faber, M., Sarto, A., and Tabellini, M. (2019). The impact of technology and trade on migration: Evidence from the US. *Harvard Business School BGIE Unit Working Paper*, 20–71. [Cited on pages 2, 3, 4, and 9.]

16. Feigenbaum, J. and Gross, D. P. (2022). Answering the call of automation: How the labor market adjusted to the mechanization of telephone operation. *National Bureau of Economic Research*, No. w28061. [Cited on page 4.]

17. Felmlee, D. H. . (1982). Women's job mobility processes within and between employers. *American Sociological Review*, 47(1):142–151. [Cited on page 4.]

18. Flood, S., King, M., Rodgers, R., Ruggles, S., Warren, J. R., Backman, D., Chen, A., Cooper, G., Richards, S., Schouweiler, M., and Westberry, M. (2023). *IPUMS CPS: Version 11.0 [dataset]*. Minneapolis, MN: IPUMS. [Cited on page 8.]

19. Gabriel, P. E. (2003). An examination of occupational mobility among full-time workers. *Monthly Labor Review*, 126(9):32–36. [Cited on page 4.]

20. Ge, S. and Zhou, Y. (2020). Robots, computers, and the gender wage gap. *Journal of Economic Behavior and Organization*, 178:194–222. [Cited on page 5.]

21. Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5):753–768. [Cited on page 2.]

22. Grigoli, F., Koczan, Z., and Topalova, P. (2020). Automation and labor force participation in advanced economies: Macro and micro evidence. *European Economic Review*, 126:103443. [Cited on page 2.]

23. Lewis, G. B. and Frank, S. A. (2002). Who wants to work for the government? *Public Administration Review*, 62(4):395–404. [Cited on page 8.]

24. Markham, W. T., Macken, P. O., Bonjean, C. M., and Corder, J. (1983). A note on sex, geographic mobility, and career advancement. *Social Forces*, 61(4):1138–1146. [Cited on page 4.]

25. Muro, M., Maxim, R., and Whiton, J. (2019). Automation and Artificial Intelligence: How machines are affecting people and places. Technical report, © Brookings India. [Cited on pages 5 and 21.]

26. Ngai, L. R. and Petrongolo, B. (2017). Gender gaps and the rise of the service economy. *American Economic Journal: Macroeconomics*, 9(4):1–44. [Cited on page 5.]

27. Ranson, G. (2003). Beyond 'gender differences': A Canadian study of women's and men's careers in engineering. *Gender, Work and Organization*, 10(1):22–41. [Cited on page 4.]

28. Rendall, M. (2017). Brain versus brawn: The realization of women's comparative advantage. *University of Zurich, Institute for Empirical Research in Economics, Working Paper*, (491). [Cited on page 4.]

29. Rosenfeld, R. A. and Sorensen, A. B. (1979). Sex differences in patterns of career mobility. *Demography*, 16(1):89–101. [Cited on page 4.]

30. Royalty, A. B. (1998). Job-to-job and job-to-nonemployment turnover by gender and education level. *Journal of Labor Economics*, 16(2):392–443. [Cited on page 3.]

31. Tolbert, C. M. and Sizer, M. (1996). *US commuting zones and labor market areas: A 1990 update*. ERS Staff Paper no. AGES-9614, Econ. Res. Service, US Dept. Agriculture,, Washington, DC. [Cited on page 8.]

32. Viscusi, W. K. (1980). Sex differences in worker quitting. *The Review of Economics and Statistics*, 62(3):388–398. [Cited on page 3.]

33. Webb, M. (2019). The impact of artificial intelligence on the labor market. *SSRN Electronic Journal 3482150*. [Cited on page 3.]

34. Čapek, K. (1923). *R.U.R. (Rossum's universal robots): a fantastic melodrama in three acts and an epilogue. Translated by Paul Selver and Nigel Playfair*. S. French, New York. [Cited on page 1.]

A Appendix

Table A1: Total Employment (numbers of workers) in Manufacturing Industries by Occupational Groups
[cited on page 16]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	2757	(8975)	688	(2628)	2941	(8560)	646	(2218)	3351	(9342)	720	(2349)	3619	(9916)	926	(2884)
Business and financial operations	480	(1563)	443	(1596)	533	(1545)	520	(1541)	510	(1467)	543	(1597)	582	(1695)	618	(1866)
Computer and mathematical science	370	(1429)	160	(665)	547	(1909)	185	(653)	479	(1680)	145	(501)	522	(1756)	155	(524)
Architecture and engineering	1574	(5503)	181	(650)	1538	(4777)	215	(688)	1443	(4459)	216	(719)	1565	(4882)	262	(893)
Life, physical, and social science	626	(1868)	173	(572)	240	(746)	121	(429)	228	(743)	134	(507)	216	(715)	137	(490)
Community and social service occupation	3	(11)	3	(11)	2	(8)	2	(10)	1	(9)	1	(8)	3	(13)	3	(15)
Legal	19	(88)	12	(61)	19	(82)	17	(71)	22	(93)	22	(94)	24	(96)	26	(114)
Education, training, and library	23	(74)	19	(66)	22	(58)	16	(47)	23	(64)	14	(44)	29	(77)	17	(44)
Arts, design, entertainment, sports, and media	354	(1347)	273	(1204)	198	(693)	130	(468)	180	(660)	121	(472)	186	(657)	126	(459)
Healthcare practitioner and technical	33	(120)	41	(119)	28	(83)	32	(103)	23	(64)	22	(65)	39	(98)	33	(99)
Healthcare support	2	(8)	6	(18)	3	(14)	5	(19)	3	(12)	3	(14)	4	(15)	5	(20)
Protective service	108	(311)	19	(65)	63	(144)	19	(46)	49	(114)	19	(55)	49	(116)	19	(54)
Food preparation and serving related	32	(100)	37	(106)	26	(82)	26	(62)	20	(76)	20	(66)	34	(110)	34	(103)
Building and grounds cleaning and maintenance	383	(923)	81	(186)	265	(567)	70	(149)	256	(587)	59	(130)	249	(522)	58	(155)
Personal care and service	10	(33)	11	(36)	6	(22)	6	(20)	3	(13)	5	(18)	5	(18)	7	(25)
Sales and related	858	(2846)	371	(1298)	697	(2125)	303	(1013)	697	(2134)	316	(1079)	665	(1951)	306	(1015)
Office and administrative support	1163	(3616)	2795	(8580)	1037	(2908)	2403	(6393)	885	(2540)	2050	(5457)	846	(2277)	1677	(4402)
Farming, fishing, and forestry	121	(231)	4	(9)	33	(54)	12	(31)	25	(51)	12	(41)	21	(41)	10	(50)
Construction and extraction	7212	(19176)	209	(541)	8426	(19720)	244	(511)	10145	(26442)	268	(594)	9276	(24952)	277	(683)
Installation, maintenance, and repair	1529	(3627)	73	(190)	1802	(3728)	89	(204)	1662	(3448)	66	(146)	1650	(3439)	58	(145)
Production	8067	(21315)	4176	(10631)	7807	(18060)	3594	(8717)	6636	(15665)	2616	(6880)	6286	(13980)	2323	(5772)
Transportation and material moving	2339	(4751)	521	(1177)	2002	(3776)	411	(835)	1979	(3919)	369	(811)	1948	(3848)	379	(885)
TOTAL	28062	(75827)	10298	(29476)	28234	(67443)	9068	(23383)	28621	(71224)	7742	(20812)	27819	(68687)	7457	(19812)

Notes: This table presents unweighted averages and standard deviations of total employment (numbers of workers) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table A2: Total Employment (shares by gender) in Manufacturing Industries by Occupational Groups [cited on page 16]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	83.1	(6.1)	16.9	(6.1)	86.1	(5.4)	13.9	(5.4)	86.1	(5.6)	13.9	(5.6)	83.2	(5.0)	16.8	(5.0)
Business and financial operations	57.0	(16.4)	43.0	(16.4)	51.5	(16.5)	48.5	(16.5)	47.9	(16.1)	52.1	(16.1)	48.1	(13.3)	51.9	(13.3)
Computer and mathematical science	71.7	(24.9)	28.3	(24.9)	74.5	(22.1)	25.5	(22.1)	77.1	(20.4)	22.9	(20.4)	77.9	(17.9)	22.1	(17.9)
Architecture and engineering	89.7	(8.2)	10.3	(8.2)	88.1	(7.9)	11.9	(7.9)	87.0	(8.7)	13.0	(8.7)	86.2	(7.8)	13.8	(7.8)
Life, physical, and social science	77.2	(17.3)	22.8	(17.3)	69.6	(22.6)	30.4	(22.6)	67.4	(24.8)	32.6	(24.8)	66.0	(21.7)	34.0	(21.7)
Community and social service occupation	54.4	(46.3)	45.6	(46.3)	46.3	(46.8)	53.7	(46.8)	44.6	(48.2)	55.4	(48.2)	47.1	(45.8)	52.9	(45.8)
Legal	64.9	(39.3)	35.1	(39.3)	44.0	(40.9)	56.0	(40.9)	47.4	(41.1)	52.6	(41.1)	46.9	(41.1)	53.1	(41.1)
Education, training, and library	52.7	(38.6)	47.3	(38.6)	61.2	(38.3)	38.8	(38.3)	69.5	(36.4)	30.5	(36.4)	62.0	(37.3)	38.0	(37.3)
Arts, design, entertainment, sports, and media	53.1	(19.6)	46.9	(19.6)	54.1	(26.5)	45.9	(26.5)	57.2	(28.2)	42.8	(28.2)	60.0	(25.0)	40.0	(25.0)
Healthcare practitioner and technical	41.1	(35.5)	58.9	(35.5)	48.5	(37.8)	51.5	(37.8)	54.3	(38.4)	45.7	(38.4)	60.1	(33.0)	39.9	(33.0)
Healthcare support	24.5	(38.7)	75.5	(38.7)	36.6	(44.5)	63.4	(44.5)	42.6	(46.4)	57.4	(46.4)	46.7	(45.0)	53.3	(45.0)
Protective service	84.8	(20.7)	15.2	(20.7)	73.4	(29.1)	26.6	(29.1)	71.0	(31.8)	29.0	(31.8)	74.6	(29.2)	25.4	(29.2)
Food preparation and serving related	37.7	(34.3)	62.3	(34.3)	40.7	(35.2)	59.3	(35.2)	46.8	(39.9)	53.2	(39.9)	42.0	(36.2)	58.0	(36.2)
Building and grounds cleaning and maintenance	79.8	(15.7)	20.2	(15.7)	78.3	(16.9)	21.7	(16.9)	79.5	(16.3)	20.5	(16.3)	81.1	(14.8)	18.9	(14.8)
Personal care and service	53.1	(42.4)	46.9	(42.4)	48.9	(44.8)	51.1	(44.8)	32.8	(42.4)	67.2	(42.4)	52.5	(45.8)	47.5	(45.8)
Sales and related	68.1	(14.3)	31.9	(14.3)	71.4	(13.6)	28.6	(13.6)	71.1	(16.7)	28.9	(16.7)	71.2	(14.3)	28.8	(14.3)
Office and administrative support	28.0	(6.8)	72.0	(6.8)	28.2	(7.7)	71.8	(7.7)	28.6	(8.1)	71.4	(8.1)	31.5	(8.8)	68.5	(8.8)
Farming, fishing, and forestry	96.4	(9.9)	3.6	(9.9)	79.2	(24.5)	20.8	(24.5)	74.6	(31.5)	25.4	(31.5)	74.2	(33.1)	25.8	(33.1)
Construction and extraction	96.9	(1.4)	3.1	(1.4)	97.0	(1.3)	3.0	(1.3)	97.2	(1.3)	2.8	(1.3)	97.2	(1.4)	2.8	(1.4)
Installation, maintenance, and repair	96.1	(3.3)	3.9	(3.3)	95.8	(3.3)	4.2	(3.3)	96.5	(3.2)	3.5	(3.2)	97.0	(2.7)	3.0	(2.7)
Production	67.2	(10.7)	32.8	(10.7)	70.2	(8.3)	29.8	(8.3)	73.3	(7.2)	26.7	(7.2)	75.6	(6.7)	24.4	(6.7)
Transportation and material moving	83.9	(7.2)	16.1	(7.2)	84.2	(6.5)	15.8	(6.5)	85.6	(7.0)	14.4	(7.0)	85.3	(5.8)	14.7	(5.8)
TOTAL	75.4	(6.6)	24.6	(6.6)	77.9	(5.5)	22.1	(5.5)	80.5	(4.7)	19.5	(4.7)	80.9	(4.1)	19.1	(4.1)

Notes: This table presents unweighted averages and standard deviations of total employment (shares by gender) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table A3: Total Employment (shares by occupational groups) in Manufacturing Industries by Occupational Groups [cited on page 17]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	7.3	(2.2)	4.9	(2.8)	7.7	(2.4)	4.7	(2.7)	9.2	(2.6)	6.4	(3.4)	10.6	(2.7)	9.4	(4.0)
Business and financial operations	1.2	(0.5)	2.9	(1.8)	1.3	(0.6)	4.4	(2.1)	1.1	(0.6)	5.0	(2.4)	1.4	(0.7)	6.2	(2.7)
Computer and mathematical science	0.5	(0.7)	0.7	(1.0)	0.8	(1.0)	1.0	(1.1)	0.8	(0.8)	0.9	(1.0)	1.0	(0.8)	1.2	(1.2)
Architecture and engineering	3.4	(2.0)	1.2	(1.2)	3.4	(1.9)	1.6	(1.3)	3.2	(1.8)	1.9	(1.6)	3.7	(2.0)	2.5	(1.6)
Life, physical, and social science	1.6	(1.0)	1.5	(1.3)	0.6	(0.5)	1.0	(1.3)	0.6	(0.5)	1.2	(1.3)	0.6	(0.5)	1.4	(1.4)
Community and social service occupation	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.0	(0.1)
Legal	0.0	(0.1)	0.0	(0.2)	0.0	(0.1)	0.1	(0.2)	0.0	(0.1)	0.1	(0.3)	0.0	(0.1)	0.2	(0.4)
Education, training, and library	0.1	(0.1)	0.1	(0.3)	0.1	(0.1)	0.1	(0.3)	0.1	(0.1)	0.1	(0.4)	0.1	(0.2)	0.2	(0.4)
Arts, design, entertainment, sports, and media	0.7	(0.5)	2.2	(1.8)	0.4	(0.3)	1.2	(1.1)	0.4	(0.3)	1.1	(1.1)	0.4	(0.3)	1.3	(1.2)
Healthcare practitioner and technical	0.1	(0.1)	0.3	(0.4)	0.1	(0.1)	0.3	(0.4)	0.1	(0.1)	0.3	(0.6)	0.1	(0.2)	0.4	(0.6)
Healthcare support	0.0	(0.0)	0.1	(0.3)	0.0	(0.0)	0.1	(0.2)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.1	(0.3)
Protective service	0.4	(0.3)	0.2	(0.4)	0.2	(0.2)	0.4	(0.7)	0.2	(0.3)	0.4	(0.7)	0.2	(0.3)	0.4	(0.7)
Food preparation and serving related	0.1	(0.1)	0.5	(0.8)	0.1	(0.1)	0.4	(0.5)	0.1	(0.1)	0.2	(0.5)	0.1	(0.2)	0.5	(0.7)
Building and grounds cleaning and maintenance	1.5	(0.6)	1.1	(0.9)	1.1	(0.6)	1.1	(1.1)	1.1	(0.6)	1.2	(1.2)	1.1	(0.6)	1.1	(1.2)
Personal care and service	0.0	(0.1)	0.1	(0.3)	0.0	(0.1)	0.1	(0.2)	0.0	(0.0)	0.1	(0.5)	0.0	(0.1)	0.1	(0.5)
Sales and related	2.1	(1.1)	3.2	(2.0)	1.5	(0.8)	2.3	(1.5)	1.5	(0.8)	2.5	(1.8)	1.6	(0.7)	2.9	(2.0)
Office and administrative support	3.2	(1.1)	26.3	(8.3)	2.9	(1.1)	26.4	(7.4)	2.6	(0.9)	27.4	(8.4)	2.6	(0.9)	25.0	(7.5)
Farming, fishing, and forestry	1.0	(1.5)	0.2	(0.4)	0.3	(0.3)	0.4	(0.8)	0.2	(0.3)	0.4	(0.9)	0.1	(0.2)	0.3	(0.7)
Construction and extraction	29.9	(9.2)	3.3	(2.5)	33.9	(10.3)	4.2	(3.5)	37.4	(10.5)	5.1	(3.9)	34.7	(9.3)	4.6	(3.2)
Installation, maintenance, and repair	6.2	(1.7)	0.7	(0.6)	7.2	(1.9)	1.1	(0.9)	6.6	(1.6)	1.0	(0.9)	6.8	(1.6)	0.9	(0.9)
Production	28.8	(8.5)	43.6	(15.4)	28.9	(8.8)	42.9	(13.1)	25.5	(8.9)	38.1	(13.2)	25.3	(8.2)	34.6	(12.5)
Transportation and material moving	11.8	(3.4)	6.7	(2.9)	9.5	(2.9)	6.2	(2.8)	9.5	(3.0)	6.6	(3.6)	9.4	(3.0)	6.9	(3.5)

Notes: This table presents unweighted averages and standard deviations of total employment (shares by occupational groups) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table A4: Private Employment (numbers of workers) in Manufacturing Industries by Occupational Groups [cited on page 16]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	2142	(7122)	585	(2276)	2267	(6792)	569	(2004)	2396	(6914)	612	(2052)	2669	(7449)	799	(2547)
Business and financial operations	449	(1476)	417	(1517)	500	(1455)	497	(1480)	478	(1380)	516	(1518)	551	(1615)	589	(1786)
Computer and mathematical science	355	(1373)	153	(640)	532	(1860)	179	(636)	466	(1637)	140	(486)	509	(1714)	149	(509)
Architecture and engineering	1440	(5120)	167	(608)	1448	(4574)	205	(664)	1360	(4229)	204	(683)	1486	(4684)	249	(855)
Life, physical, and social science	592	(1783)	164	(547)	231	(727)	119	(424)	219	(722)	130	(496)	208	(698)	133	(480)
Community and social service occupation	2	(7)	1	(6)	1	(7)	1	(6)	1	(8)	1	(5)	2	(10)	3	(14)
Legal	17	(83)	11	(57)	18	(80)	16	(69)	20	(90)	21	(90)	23	(92)	25	(112)
Education, training, and library	20	(64)	16	(57)	20	(53)	14	(43)	21	(61)	13	(40)	27	(71)	16	(41)
Arts, design, entertainment, sports, and media	300	(1135)	219	(965)	173	(622)	103	(388)	158	(589)	101	(406)	167	(591)	108	(407)
Healthcare practitioner and technical	30	(106)	38	(110)	25	(77)	31	(101)	22	(60)	21	(61)	37	(93)	32	(97)
Healthcare support	2	(7)	4	(15)	3	(11)	5	(17)	3	(12)	3	(14)	4	(13)	5	(19)
Protective service	95	(276)	17	(57)	57	(133)	17	(42)	44	(103)	17	(52)	45	(104)	17	(49)
Food preparation and serving related	30	(93)	34	(95)	24	(73)	24	(58)	18	(68)	19	(64)	33	(106)	32	(96)
Building and grounds cleaning and maintenance	347	(826)	73	(165)	242	(517)	63	(135)	236	(543)	53	(116)	225	(466)	53	(142)
Personal care and service	9	(29)	9	(27)	5	(20)	5	(18)	2	(12)	5	(16)	5	(16)	6	(24)
Sales and related	765	(2536)	337	(1189)	620	(1882)	283	(949)	629	(1907)	292	(992)	612	(1787)	286	(943)
Office and administrative support	1099	(3411)	2560	(7974)	997	(2787)	2207	(5947)	843	(2412)	1847	(4981)	809	(2182)	1523	(4033)
Farming, fishing, and forestry	74	(172)	3	(8)	30	(51)	11	(30)	23	(48)	11	(41)	18	(39)	9	(48)
Construction and extraction	5432	(14940)	149	(398)	6164	(14886)	160	(353)	7417	(20000)	167	(380)	6936	(18975)	194	(509)
Installation, maintenance, and repair	1388	(3305)	69	(177)	1656	(3426)	84	(195)	1503	(3103)	62	(136)	1485	(3060)	54	(136)
Production	7650	(20079)	4003	(10082)	7467	(17210)	3464	(8378)	6299	(14812)	2480	(6540)	5995	(13300)	2200	(5493)
Transportation and material moving	2157	(4430)	499	(1121)	1879	(3581)	398	(807)	1853	(3712)	353	(779)	1837	(3649)	363	(849)
TOTAL	24395	(66377)	9528	(27208)	24359	(58653)	8456	(21924)	24011	(60089)	7067	(19140)	23680	(58282)	6846	(18327)

Notes: This table presents unweighted averages and standard deviations of private employment (numbers of workers) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table A5: Private Employment (shares by gender) in Manufacturing Industries by Occupational Groups

[cited on page 16]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	81.4	(8.2)	18.6	(8.2)	84.3	(6.8)	15.7	(6.8)	83.4	(7.7)	16.6	(7.7)	80.8	(6.6)	19.2	(6.6)
Business and financial operations	57.3	(18.1)	42.7	(18.1)	51.8	(17.2)	48.2	(17.2)	47.5	(17.0)	52.5	(17.0)	47.9	(14.1)	52.1	(14.1)
Computer and mathematical science	71.8	(25.3)	28.2	(25.3)	75.9	(21.8)	24.1	(21.8)	77.8	(20.3)	22.2	(20.3)	78.1	(18.0)	21.9	(18.0)
Architecture and engineering	89.0	(9.2)	11.0	(9.2)	87.6	(8.5)	12.4	(8.5)	87.0	(9.4)	13.0	(9.4)	86.0	(8.3)	14.0	(8.3)
Life, physical, and social science	76.5	(19.4)	23.5	(19.4)	68.9	(23.2)	31.1	(23.2)	67.3	(25.0)	32.7	(25.0)	65.6	(22.0)	34.4	(22.0)
Community and social service occupation	61.2	(46.5)	38.8	(46.5)	49.3	(47.9)	50.7	(47.9)	50.7	(48.9)	49.3	(48.9)	45.6	(46.7)	54.4	(46.7)
Legal	62.0	(40.1)	38.0	(40.1)	43.9	(40.8)	56.1	(40.8)	46.0	(40.7)	54.0	(40.7)	48.3	(42.0)	51.7	(42.0)
Education, training, and library	56.2	(39.0)	43.8	(39.0)	61.8	(39.3)	38.2	(39.3)	69.9	(36.4)	30.1	(36.4)	62.3	(38.0)	37.7	(38.0)
Arts, design, entertainment, sports, and media	53.3	(22.2)	46.7	(22.2)	60.4	(29.7)	39.6	(29.7)	58.9	(29.4)	41.1	(29.4)	62.5	(27.1)	37.5	(27.1)
Healthcare practitioner and technical	40.9	(36.4)	59.1	(36.4)	46.5	(38.0)	53.5	(38.0)	53.1	(39.0)	46.9	(39.0)	60.1	(33.4)	39.9	(33.4)
Healthcare support	22.7	(38.3)	77.3	(38.3)	34.8	(44.6)	65.2	(44.6)	43.5	(46.7)	56.5	(46.7)	50.9	(45.8)	49.1	(45.8)
Protective service	82.4	(25.7)	17.6	(25.7)	73.9	(30.1)	26.1	(30.1)	72.3	(31.9)	27.7	(31.9)	74.8	(29.7)	25.2	(29.7)
Food preparation and serving related	38.0	(35.3)	62.0	(35.3)	39.6	(35.8)	60.4	(35.8)	47.3	(40.5)	52.7	(40.5)	42.2	(36.5)	57.8	(36.5)
Building and grounds cleaning and maintenance	81.8	(13.4)	18.2	(13.4)	78.7	(16.6)	21.3	(16.6)	79.6	(17.5)	20.4	(17.5)	81.7	(15.1)	18.3	(15.1)
Personal care and service	53.5	(43.6)	46.5	(43.6)	51.7	(44.7)	48.3	(44.7)	30.4	(42.0)	69.6	(42.0)	53.9	(45.6)	46.1	(45.6)
Sales and related	68.2	(15.4)	31.8	(15.4)	70.5	(15.5)	29.5	(15.5)	71.1	(17.2)	28.9	(17.2)	70.9	(15.7)	29.1	(15.7)
Office and administrative support	29.1	(7.7)	70.9	(7.7)	29.7	(7.9)	70.3	(7.9)	30.7	(8.5)	69.3	(8.5)	33.0	(9.0)	67.0	(9.0)
Farming, fishing, and forestry	96.5	(8.1)	3.5	(8.1)	78.1	(26.4)	21.9	(26.4)	73.5	(32.6)	26.5	(32.6)	73.1	(34.0)	26.9	(34.0)
Construction and extraction	97.0	(1.8)	3.0	(1.8)	97.3	(1.4)	2.7	(1.4)	97.6	(1.5)	2.4	(1.5)	97.5	(1.5)	2.5	(1.5)
Installation, maintenance, and repair	96.0	(3.6)	4.0	(3.6)	95.8	(3.4)	4.2	(3.4)	96.4	(3.6)	3.6	(3.6)	97.0	(2.8)	3.0	(2.8)
Production	66.9	(11.0)	33.1	(11.0)	70.3	(8.6)	29.7	(8.6)	73.6	(7.5)	26.4	(7.5)	76.0	(7.0)	24.0	(7.0)
Transportation and material moving	83.1	(7.4)	16.9	(7.4)	83.8	(6.7)	16.2	(6.7)	85.1	(7.3)	14.9	(7.3)	84.9	(6.2)	15.1	(6.2)
TOTAL	73.9	(7.2)	26.1	(7.2)	76.5	(6.1)	23.5	(6.1)	79.2	(5.4)	20.8	(5.4)	79.8	(4.6)	20.2	(4.6)

Notes: This table presents unweighted averages and standard deviations of private employment (shares by gender) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table A6: Private Employment (shares by occupational groups) in Manufacturing Industries by Occupational Groups [cited on page 16]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	6.2	(2.1)	4.3	(2.7)	6.3	(2.3)	4.1	(2.6)	7.0	(2.5)	5.6	(3.6)	8.6	(2.5)	8.3	(4.0)
Business and financial operations	1.3	(0.6)	2.9	(2.0)	1.4	(0.7)	4.5	(2.3)	1.3	(0.7)	5.3	(2.6)	1.5	(0.8)	6.5	(2.9)
Computer and mathematical science	0.6	(0.8)	0.7	(1.0)	1.0	(1.1)	1.0	(1.2)	0.9	(0.9)	0.9	(1.1)	1.1	(0.9)	1.2	(1.2)
Architecture and engineering	3.4	(2.1)	1.2	(1.2)	3.5	(2.2)	1.6	(1.3)	3.6	(2.1)	2.0	(1.7)	4.1	(2.2)	2.6	(1.7)
Life, physical, and social science	1.8	(1.1)	1.5	(1.4)	0.7	(0.6)	1.1	(1.5)	0.7	(0.6)	1.3	(1.4)	0.7	(0.5)	1.6	(1.7)
Community and social service occupation	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.0	(0.1)	0.0	(0.1)	0.0	(0.1)
Legal	0.0	(0.1)	0.0	(0.2)	0.0	(0.1)	0.1	(0.2)	0.0	(0.1)	0.1	(0.4)	0.0	(0.1)	0.2	(0.5)
Education, training, and library	0.1	(0.1)	0.1	(0.2)	0.1	(0.1)	0.1	(0.3)	0.1	(0.1)	0.1	(0.4)	0.1	(0.2)	0.2	(0.5)
Arts, design, entertainment, sports, and media	0.7	(0.5)	2.0	(1.8)	0.4	(0.3)	0.8	(0.8)	0.4	(0.3)	1.0	(1.2)	0.5	(0.4)	1.1	(1.3)
Healthcare practitioner and technical	0.1	(0.2)	0.3	(0.5)	0.1	(0.1)	0.3	(0.5)	0.1	(0.2)	0.3	(0.7)	0.2	(0.2)	0.4	(0.6)
Healthcare support	0.0	(0.0)	0.1	(0.3)	0.0	(0.0)	0.1	(0.3)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.1	(0.3)
Protective service	0.4	(0.3)	0.2	(0.5)	0.2	(0.2)	0.4	(1.0)	0.2	(0.3)	0.4	(0.7)	0.2	(0.3)	0.4	(0.8)
Food preparation and serving related	0.1	(0.2)	0.5	(0.9)	0.1	(0.2)	0.4	(0.6)	0.1	(0.1)	0.2	(0.5)	0.1	(0.2)	0.6	(0.8)
Building and grounds cleaning and maintenance	1.6	(0.7)	1.1	(0.9)	1.2	(0.6)	1.1	(1.1)	1.2	(0.7)	1.2	(1.4)	1.2	(0.7)	1.1	(1.2)
Personal care and service	0.0	(0.1)	0.1	(0.3)	0.0	(0.1)	0.1	(0.2)	0.0	(0.0)	0.1	(0.6)	0.0	(0.1)	0.1	(0.6)
Sales and related	2.2	(1.2)	3.0	(2.1)	1.6	(0.9)	2.3	(1.6)	1.6	(0.9)	2.6	(1.9)	1.8	(0.9)	3.0	(2.2)
Office and administrative support	3.5	(1.2)	25.7	(8.7)	3.3	(1.2)	26.0	(7.8)	3.0	(1.1)	26.9	(9.1)	3.0	(0.9)	24.9	(8.1)
Farming, fishing, and forestry	0.8	(1.4)	0.1	(0.5)	0.3	(0.4)	0.4	(0.9)	0.2	(0.3)	0.4	(1.0)	0.2	(0.2)	0.3	(0.7)
Construction and extraction	25.7	(9.3)	2.6	(2.2)	28.6	(10.6)	3.0	(3.1)	32.4	(11.6)	3.5	(3.3)	30.3	(9.7)	3.3	(2.7)
Installation, maintenance, and repair	6.6	(1.8)	0.7	(0.7)	7.8	(2.1)	1.1	(0.9)	7.3	(1.8)	1.0	(1.0)	7.3	(1.7)	0.9	(1.0)
Production	32.2	(9.1)	45.6	(15.4)	32.7	(9.5)	44.9	(13.2)	29.3	(10.0)	39.8	(13.6)	28.7	(9.0)	35.9	(13.0)
Transportation and material moving	12.8	(3.7)	7.2	(3.1)	10.5	(3.1)	6.6	(3.1)	10.7	(3.3)	7.1	(3.8)	10.4	(3.2)	7.4	(3.8)

Notes: This table presents unweighted averages and standard deviations of private employment (shares by occupational groups) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table A7: Public Employment (numbers of workers) in Manufacturing Industries by Occupational Groups
[cited on page 16]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	64	(178)	23	(87)	41	(106)	10	(35)	61	(174)	17	(55)	73	(193)	24	(76)
Business and financial operations	16	(45)	17	(59)	8	(28)	9	(32)	10	(30)	13	(47)	12	(39)	16	(51)
Computer and mathematical science	8	(35)	6	(30)	6	(32)	4	(20)	7	(37)	4	(17)	9	(35)	4	(18)
Architecture and engineering	99	(304)	12	(43)	65	(184)	9	(32)	63	(206)	11	(39)	60	(190)	11	(41)
Life, physical, and social science	21	(56)	7	(26)	5	(16)	2	(8)	5	(17)	3	(12)	5	(17)	3	(15)
Community and social service occupation	1	(5)	1	(6)	0	(2)	1	(6)	0	(2)	0	(3)	1	(5)	0	(3)
Legal	1	(9)	1	(6)	1	(5)	0	(4)	1	(4)	1	(5)	1	(5)	1	(5)
Education, training, and library	2	(13)	2	(7)	1	(7)	1	(5)	1	(8)	1	(6)	2	(10)	1	(5)
Arts, design, entertainment, sports, and media	15	(55)	16	(78)	4	(14)	2	(8)	4	(14)	2	(11)	4	(17)	2	(11)
Healthcare practitioner and technical	2	(10)	2	(10)	1	(6)	1	(5)	1	(4)	1	(5)	1	(7)	1	(5)
Healthcare support	0	(2)	1	(6)	0	(3)	0	(3)	0	(1)	0	(1)	0	(1)	0	(4)
Protective service	12	(40)	2	(10)	5	(19)	1	(7)	5	(18)	2	(7)	4	(16)	2	(8)
Food preparation and serving related	1	(6)	2	(9)	1	(5)	1	(5)	1	(17)	0	(3)	1	(6)	1	(6)
Building and grounds cleaning and maintenance	27	(83)	5	(17)	16	(43)	3	(9)	15	(41)	3	(11)	15	(40)	3	(11)
Personal care and service	1	(4)	1	(5)	0	(3)	0	(3)	0	(2)	0	(2)	0	(2)	0	(3)
Sales and related	8	(33)	6	(22)	3	(12)	2	(10)	6	(24)	4	(19)	6	(24)	4	(17)
Office and administrative support	41	(144)	103	(330)	21	(69)	53	(146)	24	(83)	57	(164)	21	(64)	48	(137)
Farming, fishing, and forestry	2	(6)	0	(2)	2	(6)	0	(2)	1	(6)	0	(3)	1	(4)	0	(4)
Construction and extraction	418	(909)	16	(51)	368	(738)	15	(32)	447	(943)	19	(50)	421	(882)	18	(49)
Installation, maintenance, and repair	66	(183)	2	(12)	47	(115)	2	(8)	50	(120)	2	(10)	56	(138)	2	(11)
Production	191	(655)	93	(332)	103	(292)	56	(154)	135	(357)	71	(186)	124	(304)	59	(144)
Transportation and material moving	104	(202)	15	(47)	68	(124)	9	(24)	75	(138)	12	(32)	69	(135)	11	(31)
TOTAL	1101	(2812)	332	(1082)	766	(1674)	180	(468)	915	(2074)	223	(596)	886	(1971)	213	(547)

Notes: This table presents unweighted averages and standard deviations of public employment (numbers of workers) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table A8: Public Employment (shares by gender) in Manufacturing Industries by Occupational Groups
[cited on page 16]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	79.0	(26.0)	21.0	(26.0)	87.8	(22.2)	12.2	(22.2)	85.3	(23.2)	14.7	(23.2)	81.4	(23.8)	18.6	(23.8)
Business and financial operations	59.6	(40.1)	40.4	(40.1)	43.6	(42.6)	56.4	(42.6)	39.8	(41.9)	60.2	(41.9)	44.3	(41.3)	55.7	(41.3)
Computer and mathematical science	63.7	(40.2)	36.3	(40.2)	63.2	(42.8)	36.8	(42.8)	67.0	(42.1)	33.0	(42.1)	75.1	(37.7)	24.9	(37.7)
Architecture and engineering	92.2	(16.7)	7.8	(16.7)	90.2	(19.5)	9.8	(19.5)	87.6	(23.2)	12.4	(23.2)	86.9	(21.3)	13.1	(21.3)
Life, physical, and social science	77.4	(35.0)	22.6	(35.0)	78.2	(38.3)	21.8	(38.3)	60.5	(43.8)	39.5	(43.8)	70.7	(40.7)	29.3	(40.7)
Community and social service occupation	47.8	(48.7)	52.2	(48.7)	26.3	(42.1)	73.7	(42.1)	21.4	(40.7)	78.6	(40.7)	54.6	(50.0)	45.4	(50.0)
Legal	59.5	(45.0)	40.5	(45.0)	47.0	(47.9)	53.0	(47.9)	45.7	(48.7)	54.3	(48.7)	33.1	(44.7)	66.9	(44.7)
Education, training, and library	43.5	(46.8)	56.5	(46.8)	63.0	(46.5)	37.0	(46.5)	67.2	(44.4)	32.8	(44.4)	67.0	(43.4)	33.0	(43.4)
Arts, design, entertainment, sports, and media	48.8	(39.8)	51.2	(39.8)	65.5	(43.7)	34.5	(43.7)	61.4	(43.0)	38.6	(43.0)	67.8	(42.3)	32.2	(42.3)
Healthcare practitioner and technical	30.8	(43.7)	69.2	(43.7)	41.0	(48.1)	59.0	(48.1)	36.8	(47.4)	63.2	(47.4)	64.2	(46.7)	35.8	(46.7)
Healthcare support	29.2	(44.8)	70.8	(44.8)	48.4	(50.4)	51.6	(50.4)	25.0	(46.3)	75.0	(46.3)	4.4	(19.4)	95.6	(19.4)
Protective service	88.1	(28.2)	11.9	(28.2)	75.1	(40.7)	24.9	(40.7)	71.2	(41.9)	28.8	(41.9)	74.0	(40.3)	26.0	(40.3)
Food preparation and serving related	32.7	(44.0)	67.3	(44.0)	34.4	(44.8)	65.6	(44.8)	38.2	(48.6)	61.8	(48.6)	48.0	(47.5)	52.0	(47.5)
Building and grounds cleaning and maintenance	80.3	(31.1)	19.7	(31.1)	84.5	(31.1)	15.5	(31.1)	85.1	(29.7)	14.9	(29.7)	84.4	(29.6)	15.6	(29.6)
Personal care and service	46.6	(47.6)	53.4	(47.6)	52.2	(50.3)	47.8	(50.3)	37.7	(48.4)	62.3	(48.4)	46.6	(50.3)	53.4	(50.3)
Sales and related	58.7	(44.4)	41.3	(44.4)	71.6	(42.6)	28.4	(42.6)	65.1	(42.3)	34.9	(42.3)	51.4	(44.9)	48.6	(44.9)
Office and administrative support	24.7	(23.7)	75.3	(23.7)	23.9	(28.5)	76.1	(28.5)	23.1	(28.0)	76.9	(28.0)	27.3	(29.8)	72.7	(29.8)
Farming, fishing, and forestry	94.6	(18.9)	5.4	(18.9)	73.0	(42.3)	27.0	(42.3)	63.8	(48.0)	36.2	(48.0)	56.2	(49.4)	43.8	(49.4)
Construction and extraction	97.3	(3.7)	2.7	(3.7)	96.7	(4.4)	3.3	(4.4)	96.4	(5.9)	3.6	(5.9)	96.4	(5.2)	3.6	(5.2)
Installation, maintenance, and repair	98.1	(7.3)	1.9	(7.3)	96.2	(14.2)	3.8	(14.2)	97.6	(9.9)	2.4	(9.9)	96.3	(11.7)	3.7	(11.7)
Production	69.7	(20.7)	30.3	(20.7)	67.0	(24.0)	33.0	(24.0)	67.4	(24.8)	32.6	(24.8)	67.9	(22.1)	32.1	(22.1)
Transportation and material moving	90.9	(13.9)	9.1	(13.9)	90.6	(15.6)	9.4	(15.6)	91.2	(15.0)	8.8	(15.0)	90.5	(15.0)	9.5	(15.0)
TOTAL	82.0	(7.6)	18.0	(7.6)	84.7	(7.7)	15.3	(7.7)	84.1	(8.0)	15.9	(8.0)	84.4	(7.7)	15.6	(7.7)

Notes: This table presents unweighted averages and standard deviations of public employment (shares by gender) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table A9: Public Employment (shares by occupational groups) in Manufacturing Industries by Occupational Groups [cited on page 16]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	5.0	(3.4)	6.0	(9.0)	4.2	(3.9)	3.5	(7.8)	5.4	(4.2)	5.2	(9.9)	6.3	(4.4)	8.1	(11.6)
Business and financial operations	1.0	(1.6)	4.4	(9.5)	0.6	(1.4)	4.3	(9.9)	0.6	(1.3)	4.8	(10.0)	0.8	(1.5)	5.7	(9.0)
Computer and mathematical science	0.3	(0.8)	0.8	(4.5)	0.4	(1.1)	1.2	(5.0)	0.4	(1.5)	0.9	(3.9)	0.7	(1.6)	1.2	(4.4)
Architecture and engineering	6.7	(5.4)	2.7	(6.5)	6.9	(5.6)	4.2	(9.8)	5.1	(4.9)	4.3	(9.2)	5.0	(4.5)	4.2	(9.3)
Life, physical, and social science	1.6	(2.0)	1.9	(5.3)	0.6	(1.6)	0.5	(2.2)	0.4	(1.0)	0.9	(2.9)	0.5	(1.4)	1.1	(5.2)
Community and social service occupation	0.1	(0.4)	0.3	(1.9)	0.0	(0.2)	0.2	(1.3)	0.0	(0.1)	0.1	(1.2)	0.0	(0.3)	0.1	(1.0)
Legal	0.1	(0.3)	0.1	(0.6)	0.0	(0.3)	0.1	(1.0)	0.0	(0.3)	0.1	(0.6)	0.0	(0.4)	0.2	(1.3)
Education, training, and library	0.1	(0.5)	0.6	(3.0)	0.1	(0.6)	0.3	(1.4)	0.1	(0.5)	0.1	(0.8)	0.2	(1.2)	0.8	(4.9)
Arts, design, entertainment, sports, and media	0.8	(1.6)	3.2	(7.5)	0.3	(1.2)	0.7	(5.7)	0.5	(2.3)	0.7	(2.8)	0.3	(0.8)	0.7	(3.2)
Healthcare practitioner and technical	0.1	(0.4)	0.7	(3.6)	0.1	(0.4)	0.6	(4.3)	0.1	(0.5)	0.4	(2.2)	0.1	(0.6)	0.3	(2.1)
Healthcare support	0.0	(0.2)	0.2	(1.2)	0.0	(0.2)	0.1	(1.1)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.3	(2.1)
Protective service	0.9	(1.5)	0.3	(1.3)	0.6	(1.7)	1.3	(5.8)	0.6	(1.6)	1.5	(5.9)	0.5	(1.6)	0.9	(3.9)
Food preparation and serving related	0.1	(0.4)	1.2	(5.1)	0.1	(0.5)	0.3	(1.9)	0.0	(0.2)	0.2	(1.6)	0.0	(0.3)	0.3	(1.8)
Building and grounds cleaning and maintenance	2.2	(2.5)	3.2	(9.0)	2.1	(2.7)	2.5	(9.1)	1.6	(2.3)	1.3	(4.5)	1.8	(2.7)	2.5	(8.6)
Personal care and service	0.1	(0.5)	0.5	(5.1)	0.1	(0.5)	0.4	(2.4)	0.0	(0.1)	0.2	(1.4)	0.0	(0.3)	0.2	(1.1)
Sales and related	0.6	(1.3)	2.2	(6.6)	0.3	(1.0)	0.5	(2.9)	0.3	(0.9)	1.0	(3.8)	0.4	(1.1)	1.6	(7.4)
Office and administrative support	2.4	(2.5)	31.7	(20.1)	1.7	(2.5)	30.5	(24.6)	1.7	(2.4)	27.5	(20.8)	1.7	(2.7)	24.6	(20.5)
Farming, fishing, and forestry	0.3	(0.9)	0.1	(0.5)	0.5	(2.0)	0.8	(5.0)	0.3	(1.2)	0.4	(2.2)	0.1	(0.6)	0.4	(2.9)
Construction and extraction	47.6	(12.0)	6.4	(9.6)	55.5	(12.9)	11.3	(15.6)	56.0	(14.1)	11.9	(17.0)	53.9	(12.4)	11.6	(15.9)
Installation, maintenance, and repair	5.6	(3.7)	0.4	(1.7)	5.8	(4.5)	0.9	(3.8)	5.4	(4.2)	0.6	(2.9)	6.6	(5.1)	1.0	(3.1)
Production	12.9	(7.0)	27.9	(21.6)	10.3	(7.4)	29.4	(25.8)	12.2	(8.1)	32.7	(24.7)	11.3	(8.1)	29.5	(23.6)
Transportation and material moving	11.6	(6.3)	5.2	(9.2)	9.9	(6.6)	6.4	(11.9)	9.5	(7.0)	5.2	(10.4)	9.6	(6.5)	4.7	(8.1)

Notes: This table presents unweighted averages and standard deviations of public employment (shares by occupational groups) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.