Online Appendix:
From Blue to Steel-Collar Jobs:
The Decline in Employment Gaps?

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A1 Data

This section discusses the data sources and the construction of the variables.

A1.1 Current Population Survey

Figure 1 illustrates employment rates and gaps across demographic groups using data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey between 1980 and 2019 (Flood et al., 2020). These data are publicly available at IPUMS and include monthly repeated cross-sectional surveys. The frequency with which these data are collected comes at the expense of the scale of the survey, making it representative at the national level, but not at the CZ level. I use these data in Figure 1 to trace the development of employment across demographic groups in the US on a yearly basis. In the empirical analysis, I use data from the US Census and the ACS.

A1.2 Industrial robots

IFR data on industrial robots are praised for their reliability, but they include also some limitations. First, a fraction of the stock of industrial robots is not attributed to any industry and is referred to as "unclassified". I attribute unclassified robots proportionally to an industry's share of total classified robots for each year (Graetz and Michaels, 2018). Second, up to 2011, the IFR provides data on the operational stock of robots only for North America as a whole, which includes the United States, Canada and Mexico. This aggregation introduces noise, but is not a major concern for the identification of US robot adoption, since the Unites States account for more than 90 percent of the North American market and the IV strategy purges this type of measurement error (Acemoglu and Restrepo, 2020). Third, the stock of robots by industry going back to the 1990s is only available for a subset of European countries: Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom. The IFR provides data on the total stock of robots in North America from 1993, but it does not provide industry breakdowns until 2004. For these years, I attribute the aggregate number of robots to industries proportionally to their shares of the total stock in 2004. I use the same procedure to impute the stock of robots for Denmark, for which the industry breakdown starts in 1996.

A1.3 Import exposure

China – I follow Autor et al. (2013) in using a shift-share approach to measure the exposure of local labor markets to imports from China. I interact CZs' industry employment shares in the manufacturing sector prior to the admission of China to the World Trade Organization in 2001 with the growth in product trade flows from China to the US. Since US imports from China may also be endogenous to demand shocks, I use a similar identification strategy to Equation 4.4 and exploit plausibly exogenous variation in the trade shock by instrumenting the shift component with trade flows from China to other industrialized countries with a similar trade development as the US:

$$\text{Import exposure}_{c,(t_0,t_1)} = \sum_{j \in J} \frac{1}{8} \sum_{i \in OT8} \ell^{90}_{c,j} \Delta IM^i_{j,(t_0,t_1)} \tag{A1.1}$$

where $\Delta IM^i_{j,(t_0,t_1)}$ is the change in industry $j \in J$ imports from China in thousand dollars per worker of country $i \in OT8$, which includes Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. I keep the baseline employment shares constant to avoid endogeneity and serial correlation concerns.

To build this measure, I collect product-level data at the six-digit Harmonized System (HS) on Chinese imports from the UN Comtrade Database (UN Comtrade, 2019) which I match with industry employment shares from the 1991 County Business Patterns (CBP, 2019). The CBP classifies industry employment according to the Standard Classification System (SIC) until 1997 and according to the North American Industry Classification System (NAICS) afterwards. These systems are more detailed than the industrial classification system used in the IPUMS. I use crosswalks from Autor et al. (2013) to convert SIC and NAICS manufacturing industries and six-digit HS product-level trade data to 392 four-digit SIC industries. I construct the import penetration measure by matching local employment shares with converted product-level trade data on imports from China. For confidentiality reasons, county-industry observations with few cases are reported as ranges. In reconstructing these data, I follow Acemoglu et al. (2016).

Europe – I build a measure of international product market competition from Europe using a shift-share approach as described in the previous section. The share component is the same as in Equation A1.1, while the shift component does not account for imports from China, but for average trade flows from Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom (EU7 countries) to the US from UN Comtrade. Since US imports are again subject to endogeneity concerns, I instrument imports to the US with trade flows from Europe to Canada, an industrialized country with a comparable trade engagement with European countries as the US, but whose import intensity is less likely to be affected by US domestic shocks than the US itself.

A1.4 Technology shocks

I account for technology shocks other than industrial robots using shift-share measures of the adoption of PCs and IT capital intensity, and a measure of routine task-intensity at the CZ level in

1990.

Exposure to PCs – I measure PC adoption at the CZ level following Acemoglu and Restrepo (2020). The measure is computed by interacting the share of workers using a computer in each industry from the 1993 Current Population Survey (shift component) with CZ baseline employment shares from the Census (share component). Ge and Zhou (2020) show that computer capital in the 1990s is a strong predictor of subsequent computer adoption.

IT capital intensity – I use a measure of IT capital intensity from Acemoglu and Restrepo (2020). The measure is computed by interacting the industry share of IT investments in 1992 from the Annual Survey of Manufactures (ASM, 2020) (shift component) with baseline CZ employment shares from the Census (share component). Industry data are available for 4-digit SIC87 manufacturing industries.

Routine-biased technological change – I build a measure of RBTC using the share of routine task-intensive employment in a local labor market in 1990. For this purpose, I match the classification of occupational routine task-intensity from Autor and Dorn (2013) with employment data from the Census and compute the corresponding employment shares at the CZ level.

A1.5 CZ characteristics

I construct time-invariant controls for CZ characteristics from the 1990 Census, which include demographic characteristics, the industrial and occupational composition of employment, and the demographic-specific composition of workers within industries and occupations.

Demographics of the population – These controls include the population share of women, Blacks, Hispanics, college-educated individuals, and three age groups (25-34, 35-44 and 45-54 years), as well as the log-population in 1990. Shares are computed in terms of the total population in the CZ.

Industry and occupation – These controls include the employment share in the construction, education and research, manufacturing, mining, services, and utilities industry, as well as the share of offshorable, skill-intensive, white-collar, blue-collar and low-skill occupations in 1990. I use a measure of offshorability of occupations from Autor and Dorn (2013). Shares are computed in terms of total employment in the CZ.

Demographics of employment – These covariates control for the initial composition of employment of women and racial/ethnic minorities within industries (high robot-intensive manufacturing and low-robot intensive manufacturing) and occupations (skill-intensive, white-collar and blue-collar). I compute these measures as the number of women (non-whites) who are employed in industry or occupation j divided by total employment in j. This measure is also used to represent the industrial and occupational segregation of the US labor market in Figure 3.

A2 Comparison with Acemoglu and Restrepo (2020)

The results of this paper account for partial equilibrium effects of robot adoption and do not consider aggregate effects resulting from cross-CZ spillovers that could influence the gender- or race/ethnicity-specific demand for labor in other areas. A parametric model to quantify the general equilibrium effects of robots on employment is presented in Acemoglu and Restrepo (2020), although it does not allow to differentiate for demographic-specific cross-CZ effects either.

It is worth noting that the magnitude of the employment estimates of this paper are larger than those reported in Acemoglu and Restrepo (2020), since the authors are not exploring variation in US robot exposure within states, but within census divisions. However, as demographic-specific labor market outcomes are highly heterogeneous across US states, it is critical to account for systematic differences across these areas in this type of analysis.

To compare the consistency of my results with Acemoglu and Restrepo (2020), Table A12 reports estimates of the effect of robots on employment rates and gaps, controlling only for time-varying division fixed effects, the vector of time-invariant regional characteristics and economic variables, pre-trends and structural labor market shocks contemporaneous to the introduction of robots from Equations 4.1 and 4.2. This specification does not include state fixed effects.

Results show that the relative size of the effects by gender and race/ethnicity is similar to that in Table 3, even when excluding state fixed effects (despite changes in the absolute size). Using this specification, the results on the overall population (Column 1) are similar to the finding of Acemoglu and Restrepo (2020), i.e. that each industrial robot reduces local employment by six workers (3.3 workers when accounting for general equilibrium effects across CZs).

Based on this result, my findings suggest that each robot displaces four men and two women or, when looking at differences by race/ethnicity, 3.6 whites and 2.4 non-whites. These values are illustrated in Table A13, which reports estimates of the impact of robots on employment by demographic groups as shares of the total local population.

A3 Robustness checks

This section performs a set of robustness checks in support of the identification strategy and of my preferred specification. I report results for the overall population and the population without a college degree, which is driving my results.

A3.1 Product market competition

A concern that I need to address is that the adoption of robots in Europe is influencing US labor market conditions through increased product market competition, violating the exclusion restriction of my IV strategy. Although I cannot rule out this possibility, I can show that it is rather unlikely that my results are driven by this causal link.

In Table A14, I estimate the labor market impact of robots on the employment gaps when controlling for international competition on the product market using a shift-share measure of US imports from Europe à la Autor et al. (2013), as defined in Appendix A1. Between the mid-1990s and 2014, trade flows from Europe to the US have increased substantially. This increase is mainly driven by a rise in imports of manufacturing goods that is positively related to the introduction of robots in Europe (Figure A5, Panel A). Since US imports could be subject to domestic shocks that affect also local labor demand (demand shocks), I account for endogeneity of imports by using trade flows from Europe to Canada, a country with a comparable trade engagement with European countries as the US (Figure A5, Panel B). My estimates are not significantly affected by the inclusion of these additional controls.

In a second approach, I omit from the instrument the European countries with the largest trade engagement with the US, namely the UK, Italy and France. By including only countries that are less likely to impact US labor market conditions through product market competition because of their national adoption of robots, the results lose some precision (because of the heavier exposure of the instrument to labor market shocks in Nordic countries and in Spain), but remain statistically significant at conventional levels. These findings suggest that my estimates are unlikely to be driven by higher product market competition through the heavier utilization of robots in Europe.

A3.2 Pre-trends

The secular decline in the gender and the race/ethnicity employment gap raises the concern that changes in the employment gaps and the adoption of industrial robots are driven by some common factors. For instance, changes in the employment gaps and the adoption of robots could both stem from a labor market's industrial composition of employment. In this case, my estimates could confound the impact of robot exposure with pre-existing local labor market trends. I account for this concern in my preferred specification by controlling for past changes in the employment gaps between 1970 and 1990 and the employment composition of industries and occupations by gender and race/ethnicity in 1990.

I report estimates of pre-trends in employment of men, women, whites and non-whites between 1970 and 1990 in Table A15. There is no evidence of pre-trends affecting subsequent employment by gender. However, I do find that increases in employment of whites between 1970 and 1990 decrease the race/ethnicity employment gap between 1990 and 2014, and that increases in employment of non-whites widen it (although to a smaller extent). Nevertheless, Table A5 shows that there is no evidence of these pre-trends confounding the estimated effect of industrial robots on the employment gaps (see sequential inclusion of controls).

A3.3 Weights

Figure A2 in the Appendix shows that there is substantial variation in the distribution of racial and ethnic minorities in the US, with the largest concentration in states of the Sun Belt because of their proximity to Mexico and the Caribbean islands. Table A16 examines the role of population weights and the geographic distribution of non-whites for the determination of the effect of robots on changes in the race/ethnicity employment gap.

I start by estimating Equations 4.1 and 4.2 using as regression weights the initial population of non-whites in the CZ. The size of the estimates is larger than in my preferred specification, suggesting that the effect is likely to emerge from labor markets with a larger population of racial and ethnic minorities. Column 2 estimates the effect of robots on the employment gaps without any weights. The results are not economically nor statistically significant, since CZs with a small population of non-whites receive too much weight. Column 3 restricts the sample to CZs with a large population of racial and ethnic minorities (see Panel B of Figure A2) and repeats the exercise of the previous column, showing that the results specific to these CZs are similar to my preferred specification's estimates in Table 3.[39] This finding suggests that my main results are indeed driven by CZs with a sufficiently large population of racial and ethnic minorities, and that this effect is captured by the population weight of my preferred specification.

The homogeneous distribution of men and women across labor markets does not expose my results to the above mentioned concerns. As illustrated in Panel B of Table A16, the estimates of the labor market effect of robots on the gender employment gap are economically and statistically significant across all specifications, independently of the regression weights.

A3.4 Shift-share measure

Table A17 shows that the exact construction of the shift-share measure is not affecting my results. Panels A1, A2, B1 and B2 report estimates with a different mix of European countries used in the construction of the instrument. Panels A3 and B3 report estimates using an instrument with baseline employment shares from 1990, $\ell^{90}_{c,j}$, rather than those from 1970. Panels A4 and B4 report estimates using measures that omit the adjustment for industry growth, $g_{j,(t_0,t_1)} \frac{R_{j,t_0}}{L_{j,90}}$. The estimates are not significantly different from my preferred specification's results.

A3.5 Exclusion of CZs

Table A18 excludes a set of outlying CZs with the heaviest adoption of robots. Panels A1 and B1 report estimates when excluding the area around Detroit (MI), which is the CZ with the largest exposure to robots, while Panels A2 and B2 exclude CZs in the top 1 percentile of the distribution of robot exposure during my sample period. The results lose some precision, because most of the identification is coming from CZs in the Rust Belt (see Figure 4), but they are not significantly different from my baseline results, especially for individuals without a college degree. These findings suggest that my results are not solely driven by the subset of CZs with the largest adoption of robots.

[39] I perform a double median split and select the 275 CZs with a population of non-whites and a share of the non-white population above the US local labor market median, as shown in Figure A2.

A3.6 Covariates and CZ trends

Table A19 shows that unobserved heterogeneity does not alter my results. Panels A1 and B1 include covariates of CZ characteristics at the beginning of each subperiod (1990, 2000 and 2007) instead of covariates from 1990. Panels A2 and B2 use a more demanding specification and include CZ fixed effects (CZ trends). Using both specifications, the results are quantitatively and qualitatively significant at conventional levels.

A4 Conceptual framework: Proofs

In this part of the Appendix, I provide proofs and further results of the equilibrium labor market impact of robots on the demand for human skills and the employment gaps.

The model presents a basic production function which combines labor (brawn labor, L_A, and brain labor, L_B) and robot capital, R, to produce an output good Y (Equation 6.1). The perfectly competitive environment implies that input factors are paid their marginal productivity (Equations 6.2 and 6.3). Robot capital is produced and competitively supplied each period using the following technology, $R_t = Y_{R,t}\frac{e^{\delta t}}{\theta}$, where $Y_{R,t}$ is the amount of the final output allocated to produce robots and $e^{\delta(t-1)}$ is the total factor productivity (Autor and Dorn, 2013). That is, firms can sell their output good Y at the normalized price of 1 or they can invest a share of their production, Y_R, in the production of robot capital at price p:

$$\pi_t = Y_{R,t} - p_t R_t \tag{A4.1}$$

Taking the first order condition of Equation A4.1 with respect to $Y_{R,t}$ gives:

$$\frac{\partial \pi_t}{\partial Y_{R,t}} = 1 - p_t \frac{e^{\delta t}}{\theta} = 0 \tag{A4.2}$$

which solves to $p_t = \theta e^{-\delta t}$.

Labor is supplied by a unit continuum of individuals who are endowed with independently and identically distributed skills on two input tasks, $f(x_{A,i}, x_{B,i})$ with support $x_{j,i} \in [\varepsilon_j, 1 + \varepsilon_j]$, where $j = \{A, B\}$, $\varepsilon_A \in [0, \overline{x}_A)$ and $\varepsilon_B \in (\overline{x}_B - 1, 0]$.

Workers want to maximize their income and may supply labor by choosing between brawn labor, brain labor or any convex combination of the two, or they may choose not to supply any labor and consume one unit of leisure. These assumptions imply that workers choose tasks according to their comparative advantage, given their skills and equilibrium wages. The share of individuals who supply labor is determined by Equations 6.6 and 6.7, while the share of individuals who is not employed is given by Equation 6.8. Labor supplies are determined by Equations 6.9 and 6.10. In equilibrium, wages adjust such that labor demand and labor supply are equal.

Figure A6 illustrates the distribution of individuals in N_A, N_B and N_N graphically in a two-dimensional space in which every point designates the endowment of brawn and brain skills $(x_{A,i}, x_{B,i})$

of an individual i. The yellow area denotes the share of individuals who are employed in brawn labor, the green area those who are employed in brain labor and the blue area those who are not employed.

According to Proposition 1, the comparative advantage of men in brawn skills implies that they are employed more often in brawn labor and that women opt more often for non-employment. Moreover, whites are employed more often in brain labor, given their comparative advantage in brain skills, and racial/ethnic minorities opt more often for non-employment. Therefore, the gender employment gap and the race/ethnicity employment gap are both positive.

I prove the first part of the proposition by supposing that men have a comparative advantage in brawn skills, $\varepsilon_A^M > 0$, $\varepsilon_A^W = 0$ and $\varepsilon_B = 0$. The gender employment gap, expressed as the difference between the employment rate of men and the employment rate of women, can be computed using gender-specific forms of Equation 6.8:

$$EG^{(M,W)} = (1 - N_N^M) - (1 - N_N^W) = \int_0^{\varepsilon_A^M} \int_0^{\overline{x}_B} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} > 0 \qquad \text{(A4.3)}$$

The positive sign of this expression suggests that the employment rate of men is higher than the employment rate of women. Panel A of Figure A6 shows that men have the same support over the distribution of brain skills as women ($\varepsilon_B = 0$), but on average they hold more brawn skills ($\varepsilon_A^M > \varepsilon_A^W$), such that in equilibrium women opt more often for non-employment.[40] Note that Equation A4.3 denotes the density of the population in the bottom left rectangle (light blue area) of Figure A6. The comparative advantage implies also that in equilibrium men are employed more often in brawn task-intensive jobs:

$$EG_A^{(M,W)} = N_A^M - N_A^W = \int_0^{\varepsilon_A^M} \int_0^{x_{B,i}^*} f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} > 0 \qquad \text{(A4.4)}$$

To compute the employment gap by race and ethnicity, I assume that non-whites have a comparative disadvantage in brain skills, i.e. $\varepsilon_B^{NW} < 0$, $\varepsilon_B^{WH} = 0$ and $\varepsilon_A = 0$. The comparative advantage of whites in brain skills implies that a higher proportion of them supplies brain labor in equilibrium:

$$EG_B^{(WH,NW)} = N_B^{WH} - N_B^{NW} = \int_0^1 \int_{\varepsilon_B^{NW}}^0 f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} > 0 \qquad \text{(A4.5)}$$

Using Equation 6.8, the computation of the race and ethnicity employment gap is straightforward:

$$EG^{(WH,NW)} = (1 - N_N^{WH}) - (1 - N_N^{NW}) = \int_0^{\overline{x}_A} \int_{\varepsilon_B^{NW}}^0 f(x_{A,i}, x_{B,i}) dx_{B,i} dx_{A,i} > 0 \qquad \text{(A4.6)}$$

Panel B of Figure A6 shows that if non-whites have the same support over the distribution of brawn

[40] The claim that fewer men opt for non-employment works with any skill distribution function which assumes that men have a comparative advantage in brawn skills, conditional on men and women having the same skill density between $[\varepsilon_A, 1]$.

skills ($\varepsilon_A = 0$), but on average they hold less brain skills ($\varepsilon_B^{NW} < \varepsilon_B^{WH}$), they are employed less often in brain task-intensive jobs, and in equilibrium they have a lower employment rate than whites.

To sum up, as stated in Proposition 1, Equations A4.3 and A4.4 show that the comparative advantage of men in brawn skills implies that in equilibrium they are employed more often in brawn labor and that the gender employment gap is positive. Moreover, Equations A4.5 and A4.6 show that the comparative advantage of whites in brain skills implies that they are employed more often in brain labor and that the race/ethnicity employment gap is positive, too. ■

From Equation A4.2, we know that the price of robots decreases over time due to exogenous technological progress, increasing robot capital in the production of output good Y. An increase in the adoption of robots has adverse effects on the demand for labor and, through changes in wages, also on labor supply.

To understand the mechanism through which the adoption of robots influences the demand of labor in the economy, I compute the components of the following equations, showing the partial derivatives of brawn and brain labor with respect to the price of robots:

$$\frac{\partial L_A}{\partial p} = \frac{\partial L_A}{\partial \omega_A}\frac{\partial \omega_A}{\partial p} + \frac{\partial L_A}{\partial \omega_B}\frac{\partial \omega_B}{\partial p} \tag{A4.7}$$

$$\frac{\partial L_B}{\partial p} = \frac{\partial L_B}{\partial \omega_A}\frac{\partial \omega_A}{\partial p} + \frac{\partial L_B}{\partial \omega_B}\frac{\partial \omega_B}{\partial p} \tag{A4.8}$$

I start with the computation of the partial derivatives of L_A and L_B with respect to labor wages:

$$\begin{aligned}\frac{\partial L_A}{\partial \omega_A} =& -\left[\frac{\partial}{\partial \overline{x}_A}\int_{\overline{x}_A}^{1+\varepsilon_A}\left(\int_{\varepsilon_B}^{x^*_{B,i}} x_{A,i} f(x_{A,i}, x_{B,i}) dx_{B,i}\right) dx_{A,i}\right]\frac{\overline{x}_A}{\omega_A} + \\ &+ \int_{\overline{x}_A}^{1+\varepsilon_A} (x_{A,i})^2 f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{1}{\omega_B} dx_{A,i} > 0\end{aligned} \tag{A4.9}$$

where $\overline{\omega} = \frac{\omega_A}{\omega_B}$ such that $x^*_{B,i} = \overline{\omega} x_{A,i}$.

$$\frac{\partial L_A}{\partial \omega_B} = -\int_{\overline{x}_A}^{1+\varepsilon_A} (x_{A,i})^2 f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{\overline{\omega}}{\omega_B} dx_{A,i} < 0 \tag{A4.10}$$

$$\begin{aligned}\frac{\partial L_B}{\partial \omega_A} =& -\int_{\overline{x}_B}^{1+\varepsilon_B} x_{B,i} f(\overline{x}_A, x_{B,i}) \frac{\overline{x}_A}{\omega_A} dx_{B,i} - \\ &- \left[\frac{\partial}{\partial \overline{x}_A}\int_{\overline{x}_A}^{1+\varepsilon_A}\left(\int_{x^*_{B,i}}^{1+\varepsilon_B} x_{B,i} f(x_{A,i} x_{B,i}) dx_{B,i}\right) dx_{A,i}\right]\frac{\overline{x}_A}{\omega_A} - \\ &- \int_{\overline{x}_A}^{1+\varepsilon_A} (x_{A,i})^2 f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{\overline{\omega}}{\omega_B} dx_{A,i} < 0\end{aligned} \tag{A4.11}$$

The positive term in the second line of Equation A4.11 is outweighed by the other terms.

$$\frac{\partial L_B}{\partial \omega_B} = \int_{\varepsilon_A}^{\overline{x}_A} f(x_{A,i}, \overline{x}_B) \frac{(\overline{x}_B)^2}{\omega_B} dx_{A,i} + \\ + \int_{\overline{x}_A}^{1+\varepsilon_A} (x_{A,i})^2 f(x_{A,i} \overline{\omega} x_{A,i}) \frac{\overline{\omega}^2}{\omega_B} dx_{A,i} > 0 \tag{A4.12}$$

These equations show that the supply of brawn (brain) labor increases as brawn (brain) wages increase and decreases if brain (brawn) wages increase.

Next, I compute changes in equilibrium wages in response to an increase in the price of robots. Taking total differentials of Equations 6.2 and 6.3, I obtain that:

$$\frac{\partial \omega_A}{\partial p} = -\frac{\left(\frac{\beta}{\rho} - 1\right) \rho R^{\rho-1} L_B}{\left(R^\rho + L_A^\rho\right)\left[\left(\frac{\beta}{\rho} - 1\right) \frac{\rho L_A^{\rho-1} L_B}{R^\rho + L_A^\rho} \frac{\partial L_A}{\partial \omega_A} + (\rho - 1) \frac{L_B}{L_A} \frac{\partial L_A}{\partial \omega_A} + (1 - \beta) \frac{\partial L_B}{\partial \omega_A} - \frac{L_B}{\omega_A}\right]} \frac{\partial R}{\partial p} > 0 \tag{A4.13}$$

$$\frac{\partial \omega_B}{\partial p} = -\frac{\beta R^{\rho-1}}{\left(R^\rho + L_A^\rho\right)\left[\frac{\beta L_A^{\rho-1}}{R^\rho + L_A^\rho} \frac{\partial L_A}{\partial \omega_B} - \frac{\beta}{L_B} \frac{\partial L_B}{\partial \omega_B} - \frac{1}{\omega_B}\right]} \frac{\partial R}{\partial p} < 0 \tag{A4.14}$$

because of $0 < \beta < \rho < 1$, $\frac{\partial R}{\partial p} < 0$ and Equations A4.9 to A4.12. Inserting Equations A4.9 to A4.14 in Equations A4.7 and A4.8 already shows that, as the price of robots falls, in equilibrium, the demand for brawn labor decreases and the demand for brain labor increases:

$$\frac{\partial L_A}{\partial p} = -\left[\frac{\partial}{\partial \overline{x}_A} \int_{\overline{x}_A}^{1+\varepsilon_A} \left(\int_{\varepsilon_B}^{x_{B,i}^*} x_{A,i} f(x_{A,i}, x_{B,i}) dx_{B,i}\right) dx_{A,i}\right] \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} + \\ + \int_{\overline{x}_A}^{1+\varepsilon_A} (x_{A,i})^2 f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{1}{\omega_B} \left[\frac{\partial \omega_A}{\partial p} - \overline{\omega} \frac{\partial \omega_B}{\partial p}\right] dx_{A,i} > 0 \tag{A4.15}$$

$$\frac{\partial L_B}{\partial p} = \int_{\varepsilon_A}^{\overline{x}_A} f(x_{A,i}, \overline{x}_B) \frac{(\overline{x}_B)^2}{\omega_B} \frac{\partial \omega_B}{\partial p} dx_{A,i} - \\ - \int_{\overline{x}_B}^{1+\varepsilon_B} x_{B,i} f(\overline{x}_A, x_{B,i}) \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} dx_{B,i} - \\ - \int_{\overline{x}_A}^{1+\varepsilon_A} (x_{A,i})^2 f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{\overline{\omega}}{\omega_B} \left[\frac{\partial \omega_A}{\partial p} - \overline{\omega} \frac{\partial \omega_B}{\partial p}\right] dx_{A,i} - \\ - \left[\frac{\partial}{\partial \overline{x}_A} \int_{\overline{x}_A}^{1+\varepsilon_A} \left(\int_{x_{B,i}^*}^{1+\varepsilon_B} x_{B,i} f(x_{A,i}, x_{B,i}) dx_{B,i}\right) dx_{A,i}\right] \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} < 0 \tag{A4.16}$$

since the positive term in the fourth line of Equation A4.16 is outweighed by the other terms. This result follows from the fact that there is a more than offsetting increase in the demand for manual tasks in the form of robot capital (since it becomes relatively cheaper) which increases the productivity of brain labor (and therefore its wage), raising its equilibrium level.

Following the procedure outlined above, we can show that the share of workers who supply brawn labor decreases. These workers are either reallocating their labor supply towards brain labor, as the relative wage $\frac{\omega_B}{\omega_A}$ increases, or they opt for non-employment, as also $\frac{\omega_N}{\omega_A}$ increases.

$$\begin{aligned} \frac{\partial N_A}{\partial p} = & - \left[\frac{\partial}{\partial \overline{x}_A} \int_{\overline{x}_A}^{1+\varepsilon_A} \left(\int_{\varepsilon_B}^{x^*_{B,i}} f(x_{A,i}, x_{B,i}) dx_{B,i} \right) dx_{A,i} \right] \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} + \\ & + \int_{\overline{x}_A}^{1+\varepsilon_A} x_{A,i} f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{1}{\omega_B} \left[\frac{\partial \omega_A}{\partial p} - \overline{\omega} \frac{\partial \omega_B}{\partial p} \right] dx_{A,i} > 0 \end{aligned} \tag{A4.17}$$

Note again that $\frac{\partial R}{\partial p} < 0$. Panels A2 and B2 of Figure A6 show how the decrease in brawn wages makes brain labor and non-labor income relatively more attractive to workers, who respond by moving away from brawn task-intensive jobs.

The share of brain workers increases, since a fraction of workers who were previously employed in brawn labor reallocates towards brain task-intensive jobs (see previous equation) and some non-employed individuals enter the workforce to supply brain labor, as $\frac{\omega_N}{\omega_B}$ decreases.

$$\begin{aligned} \frac{\partial N_B}{\partial p} = & \int_{\varepsilon_A}^{\overline{x}_A} f(x_{A,i}, \overline{x}_B) \frac{\overline{x}_B}{\omega_B} \frac{\partial \omega_B}{\partial p} dx_{A,i} - \\ & - \int_{\overline{x}_B}^{1+\varepsilon_B} f(\overline{x}_A, x_{B,i}) \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} dx_{B,i} - \\ & - \int_{\overline{x}_A}^{1+\varepsilon_A} x_{A,i} f(x_{A,i}, \overline{\omega} x_{A,i}) \frac{1}{\omega_B} \left[\frac{\partial \omega_A}{\partial p} - \overline{\omega} \frac{\partial \omega_B}{\partial p} \right] dx_{A,i} - \\ & - \left[\frac{\partial}{\partial \overline{x}_A} \int_{\overline{x}_A}^{1+\varepsilon_A} \left(\int_{x^*_{B,i}}^{1+\varepsilon_B} f(x_{A,i}, x_{B,i}) dx_{B,i} \right) dx_{A,i} \right] \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} < 0 \end{aligned} \tag{A4.18}$$

The positive term in the fourth line of Equation A4.18 is outweighed by the other terms.[41]

Altogether, robots could increase or decrease aggregate employment depending on whether the displacement effect or the productivity effect prevails:

$$\begin{aligned} \frac{\partial N_N}{\partial p} = & - \int_{\varepsilon_B}^{\overline{x}_B} f(\overline{x}_A, x_{B,i}) \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} dx_{B,i} - \\ & - \int_{\varepsilon_A}^{\overline{x}_A} f(x_{A,i}, \overline{x}_B) \frac{\overline{x}_B}{\omega_B} \frac{\partial \omega_B}{\partial p} dx_{A,i} \lesseqgtr 0 \end{aligned} \tag{A4.19}$$

[41] This result is visible from changes in the areas of the shapes in Figure A6, where the share of brain workers, N_B, is formed by a rectangle and a trapezoid. The shift of $\overline{x}_A$ to the left decreases the rectangle (second term) and at the same time increases the trapezoid (fourth term), without affecting the area of N_B. This, however, is going to change with shifts in $x^*_{B,i}$ and $\overline{x}_B$.

or simply:

$$\frac{\partial N_N}{\partial p} = 1 - \frac{\partial N_A}{\partial p} - \frac{\partial N_B}{\partial p} \lesseqgtr 0 \tag{A4.20}$$

Despite the ambiguous effect of robot adoption on employment, robots clearly reduce the gender employment gap:

$$\frac{\partial EG^{(M,W)}}{\partial p} = -\int_0^{\varepsilon_A^M} f(x_{A,i}, \overline{x}_B)\frac{\overline{x}_B}{\omega_B}\frac{\partial \omega_B}{\partial p} dx_{A,i} > 0 \tag{A4.21}$$

Analogously, using Equation A4.6, it can be shown that the adoption of robots is widening the race and ethnicity employment gap:

$$\frac{\partial EG^{(WH,NW)}}{\partial p} = -\int_{\varepsilon_B^{NW}}^0 f(\overline{x}_A, x_{B,i})\frac{\overline{x}_A}{\omega_A}\frac{\partial \omega_A}{\partial p} dx_{B,i} < 0. \tag{A4.22}$$

These results emerge from one of three scenarios. First, robots reduce male (non-white) employment more than female (white) employment. Second, robots increase male (non-white) employment less than female (white) employment. Third, robots reduce male (non-white) employment and increase female (white) employment. The empirical analysis shows that US labor markets experience the first scenario.

One could also investigate which scenario occurs theoretically by assuming a closed form solution for the skill distribution, $f(x_{A,i}, x_{B,i})$, as well as values for the exogenous parameters ω_N, ρ, β and ε_j^g with $j \in \{A, B\}$ and $g \in \{(M, W), (WH, NW)\}$.

To sum up, as stated in Proposition 2, Equations A4.21 and A4.22 show that an increase in the adoption of robots in the production of output Y decreases the gender employment gap and increases the race/ethnicity employment gap. ■

These findings come along with a decrease (increase) in the gender (race/ethnicity) employment gap in brawn labor as robot capital increases:

$$\frac{\partial EG_A^{(M,W)}}{\partial p} = \int_0^{\varepsilon_A^M} x_{A,i} f(x_{A,i}, \overline{\omega} x_{A,i})\frac{1}{\omega_B}\left[\frac{\partial \omega_A}{\partial p} - \overline{\omega}\frac{\partial \omega_B}{\partial p}\right] dx_{A,i} > 0 \tag{A4.23}$$

$$\frac{\partial EG_A^{(WH,NW)}}{\partial p} = -\int_{\varepsilon_B^{NW}}^0 f(\overline{x}_A, x_{B,i})\frac{\overline{x}_A}{\omega_A}\frac{\partial \omega_A}{\partial p} dx_{A,i} < 0 \tag{A4.24}$$

where $EG_A^{(M,W)} = N_A^M - N_A^W$. Conversely, the adoption of robots generates an ambiguous effect on the gender employment gap in brain labor:

$$\begin{aligned} \frac{\partial EG_B^{(M,W)}}{\partial p} = &-\int_0^{\varepsilon_A^M} f(x_{A,i}, \overline{x}_B)\frac{\overline{x}_B}{\omega_B}\frac{\partial \omega_B}{\partial p} dx_{A,i} - \\ &-\int_0^{\varepsilon_A^M} x_{A,i} f(x_{A,i}, \overline{\omega} x_{A,i})\frac{1}{\omega_B}\left[\frac{\partial \omega_A}{\partial p} - \overline{\omega}\frac{\partial \omega_B}{\partial p}\right] dx_{A,i} \lesseqgtr 0 \end{aligned} \tag{A4.25}$$

where $EG_B^{(M,W)} = N_B^M - N_B^W$ and does not influence the race and ethnicity employment gap in brain labor (Equation A4.5):

$$\frac{\partial EG_B^{(WH,NW)}}{\partial p} = 0 \tag{A4.26}$$

Example using a uniform skill distribution – I provide an illustrative example of the impact of robots on the employment gaps using a uniform skill distribution, $f(x_{A,i}, x_{B,i}) = 1$. To keep the notation simple, I focus on the gender case and assume that $\varepsilon_B = 0$. The shares of workers (Equations 6.6 and 6.7) and of non-employed individuals (Equation 6.8) simplify to:

$$N_A = \frac{1}{2}\varpi\Big[(1+\varepsilon_A)^2 - (\overline{x}_A)^2\Big] \tag{A4.27}$$

$$N_B = 1 - \overline{x}_B(\overline{x}_A - \varepsilon_A) - \frac{1}{2}\varpi\Big[(1+\varepsilon_A)^2 - (\overline{x}_A)^2\Big] \tag{A4.28}$$

$$N_N = \overline{x}_B(\overline{x}_A - \varepsilon_A) \tag{A4.29}$$

with $\varepsilon_A < \overline{x}_A$ and $\omega_B > \omega_N + \frac{1}{2}\omega_A$ to ensure that $N_B > 0$ and $N_N > 0$. Using Equation A4.29, we can again compute the gender employment gap (Equation 6.12):

$$EG^{(M,W)} = N_N^W - N_N^M = \varepsilon_A^M \overline{x}_B > 0 \tag{A4.30}$$

Analogously, the employment rates of whites and non-whites are equal to $1 - \overline{x}_A(\overline{x}_B - \varepsilon_B)$ and the race/ethnicity employment gap is given by:

$$EG^{(WH,NW)} = -\varepsilon_B^{NW} \overline{x}_A > 0 \tag{A4.31}$$

where $\varepsilon_B = 0$ for whites and $\varepsilon_B < 0$ for non-whites.

To compute the effect of the adoption of robots on employment, I need to define again all components of Equations A4.7 and A4.8. Let's start with the computation of the brawn and brain labor supply (Equations 6.9 and 6.10):

$$L_A = \frac{1}{3}\varpi\Big[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\Big] \tag{A4.32}$$

$$L_B = \frac{1}{2}\Big[1 - (\overline{x}_A - \varepsilon_A)(\overline{x}_B)^2 - \frac{1}{3}\varpi^2\big[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\big]\Big] \tag{A4.33}$$

Next, we take first derivatives of the labor supplies with respect to wages (as in Equations A4.9

to A4.12):

$$\frac{\partial L_A}{\partial \omega_A} = \frac{1}{3\omega_B}\left[(1+\varepsilon_A)^3 + 2(\overline{x}_A)^3\right] > 0 \tag{A4.34}$$

$$\frac{\partial L_A}{\partial \omega_B} = -\frac{1}{3}\frac{\overline{\omega}}{\omega_B}\left[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\right] < 0 \tag{A4.35}$$

$$\frac{\partial L_B}{\partial \omega_A} = \frac{1}{2}\left[\frac{\overline{x}_A(\overline{x}_B)^2}{\omega_A} - \frac{1}{3}\frac{\overline{\omega}}{\omega_B}\big[2(1+\varepsilon_A)^3 + (\overline{x}_A)^3\big]\right] < 0 \tag{A4.36}$$

$$\frac{\partial L_B}{\partial \omega_B} = \left[\frac{(\overline{x}_B)^2}{\omega_B}(\overline{x}_A - \varepsilon_A) + \frac{1}{3}\frac{\overline{\omega}^2}{\omega_B}\big[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\big]\right] > 0 \tag{A4.37}$$

where Equations A4.35 and A4.37 hold since $\varepsilon_A < \overline{x}_A$ and Equation A4.36 holds since $\omega_A > \omega_N$. The partial derivatives of wages with respect to the price of robot capital are the same as in Equations A4.13 and A4.14, since they depend on the distribution of skills only through Equations A4.34 to A4.37.

Using these equations, it is possible to compute the impact of an exogenous decline in the price of robots on the equilibrium levels of labor and employment:

$$\frac{\partial L_A}{\partial p} = \frac{\partial \omega_A}{\partial p}\left[(1+\varepsilon_A)^3 + 2(\overline{x}_A)^3\right]\frac{1}{3\omega_B} - \frac{\partial \omega_B}{\partial p}\left[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\right]\frac{\overline{\omega}}{3\omega_B} > 0 \tag{A4.38}$$

$$\begin{aligned}\frac{\partial L_B}{\partial p} &= \frac{\partial \omega_A}{\partial p}\left[(\overline{x}_A)^2\overline{x}_B - \frac{1}{3}\overline{\omega}\big[2(1+\varepsilon_A)^3 + (\overline{x}_A)^3\big]\right]\frac{1}{2\omega_B} + \\ &+ \frac{\partial \omega_B}{\partial p}\left[\overline{x}_B(\overline{x}_A - \varepsilon_A) + \frac{1}{3}\overline{\omega}^2\big[(1+\varepsilon_A)^3 - (\overline{x}_A)^3\big]\right]\frac{1}{\omega_B} < 0\end{aligned} \tag{A4.39}$$

$$\frac{\partial N_A}{\partial p} = \frac{\partial \omega_A}{\partial p}\left[(1+\varepsilon_A)^2 + (\overline{x}_A)^2\right]\frac{1}{2\omega_B} - \frac{\partial \omega_B}{\partial p}\left[(1+\varepsilon_A)^2 - (\overline{x}_A)^2\right]\frac{\overline{\omega}}{2\omega_B} > 0 \tag{A4.40}$$

$$\begin{aligned}\frac{\partial N_B}{\partial p} &= -\frac{\partial \omega_A}{\partial p}\left[(1+\varepsilon_A)^2 - (\overline{x}_A)^2\right]\frac{1}{2\omega_B} + \\ &+ \frac{\partial \omega_B}{\partial p}\left[(1+\varepsilon_A)^2 - (\overline{x}_A)^2 + 2\frac{\overline{x}_B(\overline{x}_A - \varepsilon_A)}{\overline{\omega}}\right]\frac{\overline{\omega}}{2\omega_B} < 0\end{aligned} \tag{A4.41}$$

$$\frac{\partial N_N}{\partial p} = \frac{\partial \omega_A}{\partial p}\left[-\overline{x}_A\overline{x}_B\right]\frac{1}{\omega_A} + \frac{\partial \omega_B}{\partial p}\left[(-\overline{x}_A + \varepsilon_A)\overline{x}_B\right]\frac{1}{\omega_B} \lesseqgtr 0 \tag{A4.42}$$

where the signs of the equations hold as long as $\omega_N < \omega_A$ and $\varepsilon_A < \overline{x}_A$. Again, an increase in the stock of robots unambiguously reduces the gender employment gap:

$$\frac{\partial EG^{(M,W)}}{\partial p} = -\varepsilon_A^M \frac{\overline{x}_B}{\omega_B} \frac{\partial \omega_B}{\partial p} > 0 \tag{A4.43}$$

and increases the race/ethnicity employment gap:

$$\frac{\partial EG^{(WH,NW)}}{\partial p} = \varepsilon_B^{NW} \frac{\overline{x}_A}{\omega_A} \frac{\partial \omega_A}{\partial p} < 0. \tag{A4.44}$$

Results by gender are represented visually in Figure A7 in a 3-dimensional space, showing the impact of changes of robot capital and ρ on wages, labor quantities, employment and the employment gap.

Wages – The previous results focus on the mechanism through which an increase in robot capital affects the employment gaps. Interestingly, the effect of robots on employment depends on how it influences labor wages, raising the question of whether an increase in robot capital affects also the wage gap. The gender wage gap can be simply computed using Equations 6.2, 6.3, 6.9 and 6.10:

$$WG^{M,W} = \frac{\omega^M}{\omega^W} = \frac{\omega_A L_A^M + \omega_B L_B^M}{\omega_A L_A^W + \omega_B L_B^W} \tag{A4.45}$$

where the gender-specific wage is determined by gender-specific labor supplies and marginal products of labor. Analogously, the race and ethnicity employment gap can be computed substituting men (M) with whites and women (W) with non-whites. Note that the wage gap considers only wages of employed individuals (ω_N is excluded, since it includes unemployment benefits, Social Security income, welfare assistance, etc.). To compute the effect of a decrease in the price of robot capital on Equation A4.45, one could use the results from Equations A4.13, A4.14, A4.15 and A4.16.

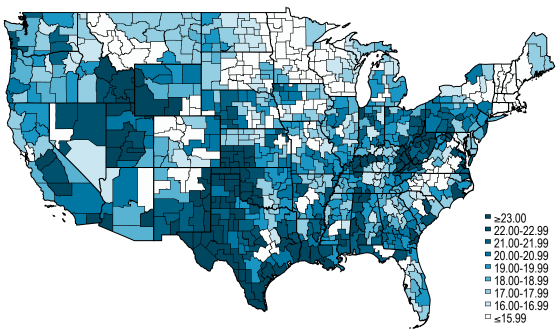
An increase in robot capital has an ambiguous effect on both ω^M and ω^W, since robots decrease the wage of brawn labor, ω_A, and increase the wage of brain labor, ω_B (and respectively affect labor supplies). I provide insights on how the adoption of robots affects wages across demographic groups in the empirical analysis. For a detailed theoretical illustration of the mechanism through which robot adoption affects the gender wage gap, see Ge and Zhou (2020).

A5 Additional figures and tables

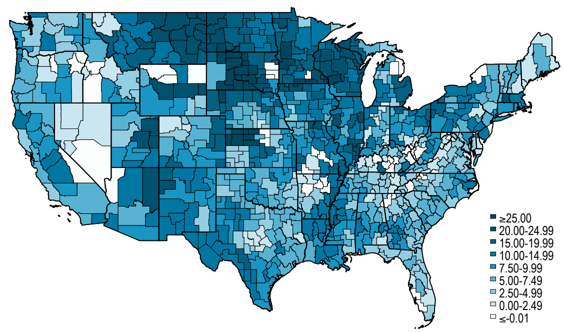
Figure A1: Employment gaps at the commuting zone level

Panel A: Employment gaps in 1990

Gender

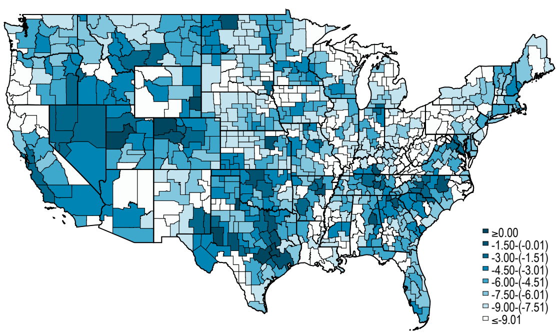


Race and ethnicity

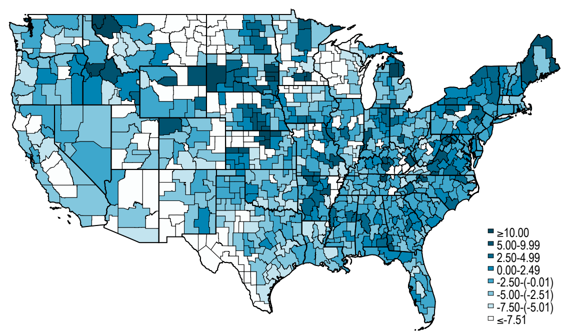


Panel B: Change in employment gaps between 1990 and 2014

Gender



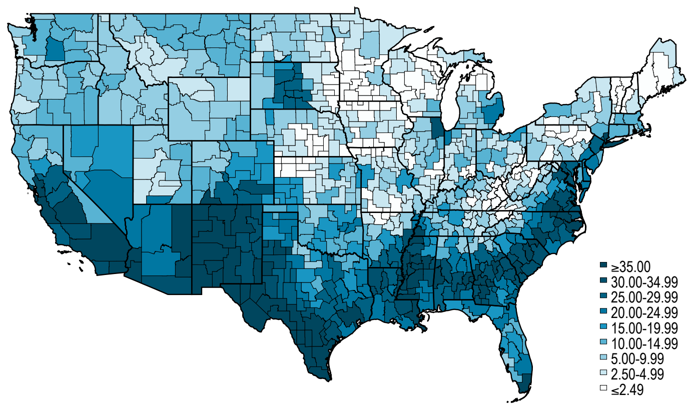
Race and ethnicity



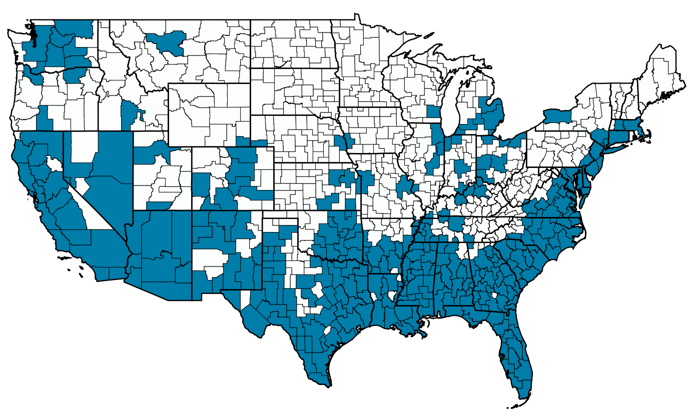
Notes: This figure illustrates the geographic distribution of the gender and race/ethnicity employment gap in 1990 and their changes between 1990 and 2014 at the CZ level, all multiplied by 100.

Figure A2: Racial and ethnic minorities at the commuting zone level in 1990

Panel A: Share of non-whites

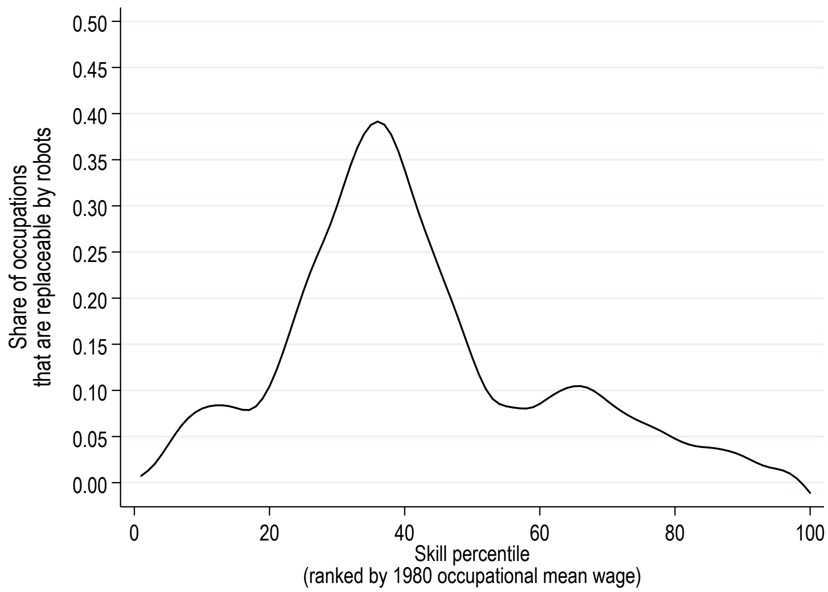


Panel B: Commuting zones with a large population of non-whites



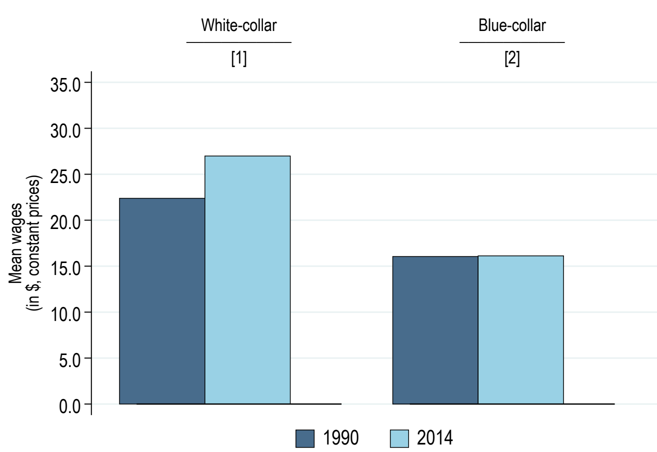
Notes: This figure illustrates the geographic distribution of non-whites in the US in 1990. Panel A shows the CZ share of non-whites multiplied by 100. Panel B shows the CZs with a population of non-whites and a share of non-whites both above the US local labor market median.

Figure A3: Robots along the skill distribution



Notes: This figure illustrates the share of occupations that are replaceable by robots, as defined in Graetz and Michaels (2018), by occupational skill percentile. This is a modified version of Figure 4 in Autor and Dorn (2013).

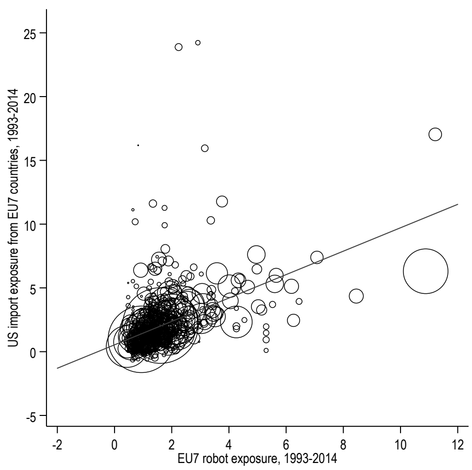
Figure A4: Wages in white-collar and blue-collar occupations



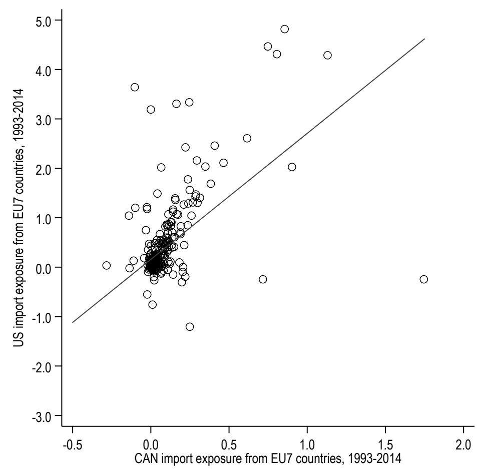
Notes: This figure illustrates the average hourly wages in white-collar and in blue-collar occupations in 1990 and 2014, expressed in 2007 prices. Occupation groups are computed from a median split of the standardized measures of the brawn and brain task content of jobs. White-collar jobs include occupations that are brain task intensive and require only few brawn skills. Blue-collar jobs include occupations that are brawn task intensive and require only few brain skills.

Figure A5: Robot exposure in Europe and imports to the US and Canada

Panel A: Robot exposure in Europe and imports to the US



Panel B: Industry trade flows from Europe to the US and Canada

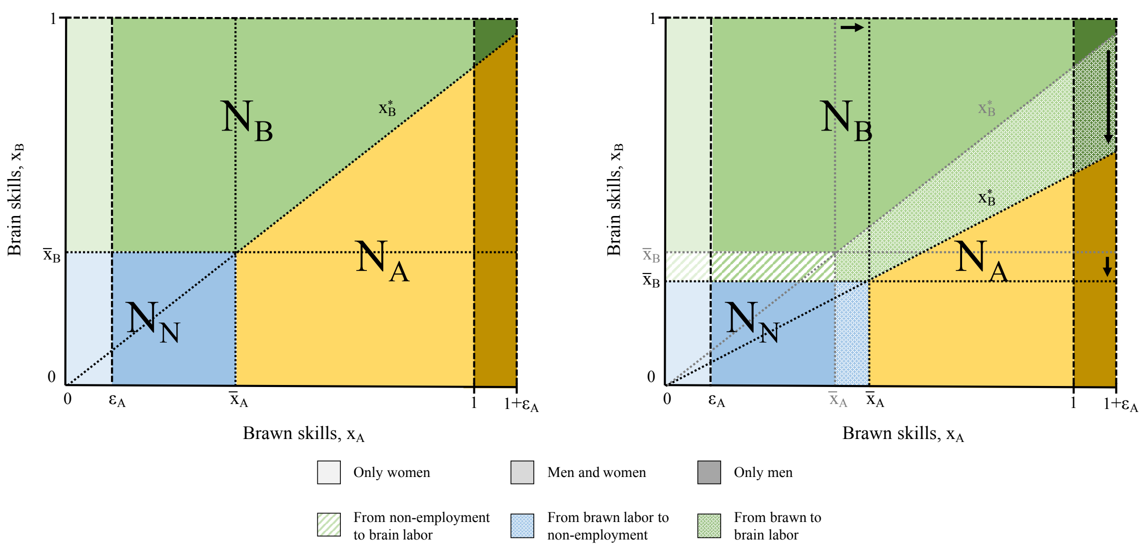


Notes: Panel A of this figure presents the unweighted correlation between robot exposure in seven European countries (Denmark, Finland, France, Italy, Spain, Sweden and the United Kingdom), as presented in Equation 4.4, and a shift-share measure of imports from these countries to the US. The size of the circles represent a labor market's size in terms of population in 1990. The solid line represents a prediction for US import exposure from European countries from a linear regression on robot exposure in Europe. Panel B presents the unweighted correlation between imports from the seven European countries to the US and Canada. Imports are represented by 392 SIC industry of the manufacturing sector in billions of US dollars in 2017 prices. For visual purposes, I omitt outlying industries with imports that exceed five billion US dollars in the US or three billion US dollars in Canada. These industries are ice cream and frozen desserts (2024), food preparations, nec (2099), hardwood dimension and flooring mills (2426), millwork (2431), pharmaceutical preparations (2834), petroleum refining (2911), women's handbags and purses (3171), primary nonferrous metals, nec (3339), electronic connectors (3678), motor vehicles and car bodies (3711), motor vehicle parts and accessories (3714), aircraft (3721), aircraft engines and engine parts (3724). The solid line represents a prediction for US import exposure from European countries from a linear regression on Canadian import exposure from European countries based on all 392 SIC industries of the manufacturing sector.

Figure A6: Robots and labor

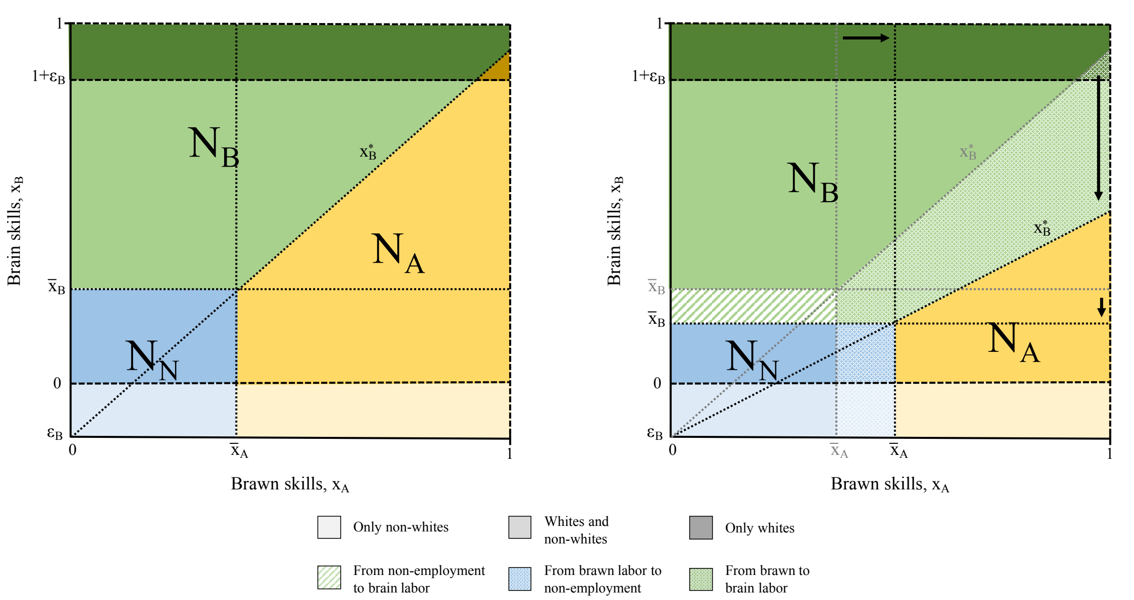
Panel A: Gender

Panel A1: Employment rates — Panel A2: The effect of robots



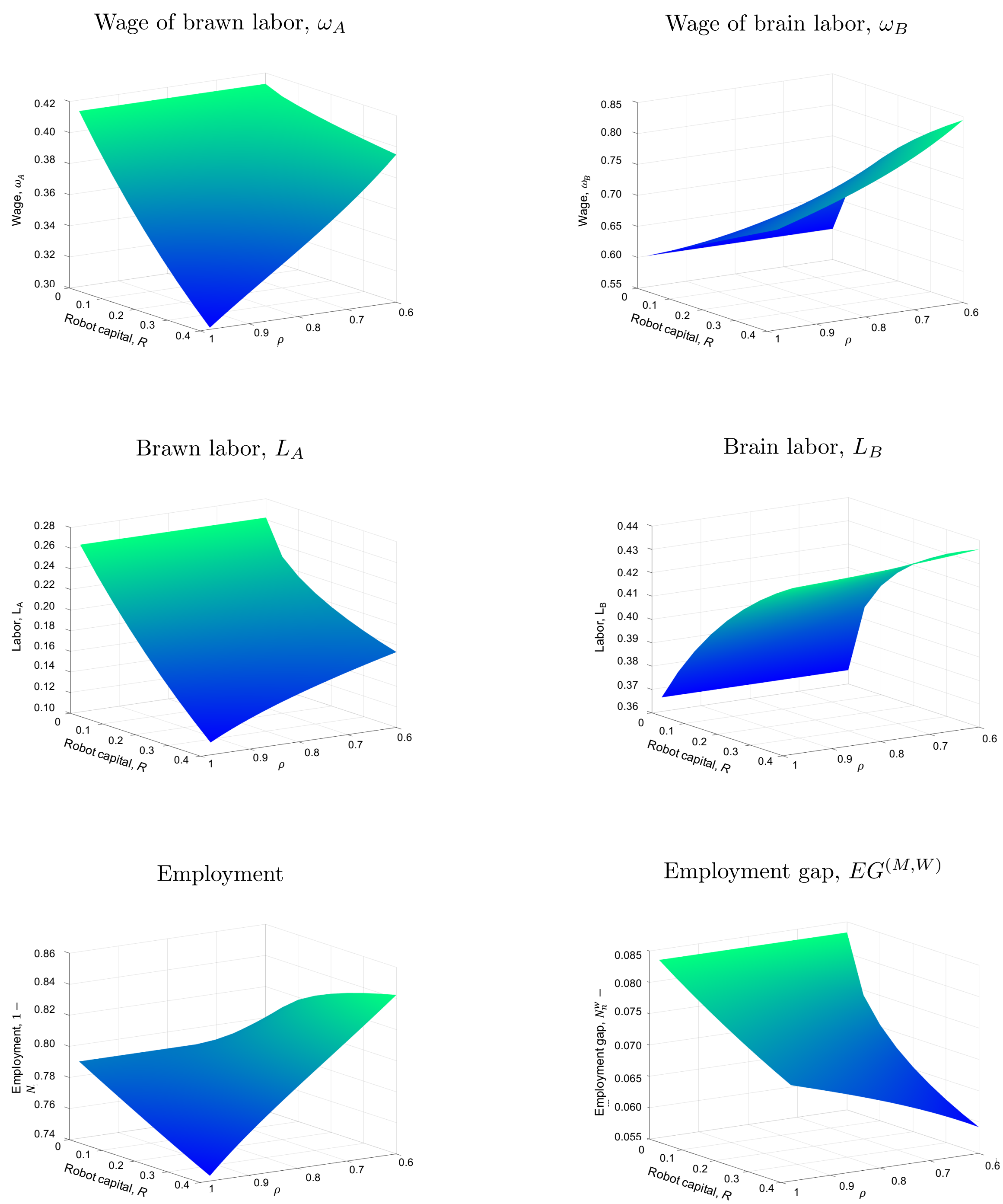
Panel B: Race and ethnicity

Panel B1: Employment rates — Panel B2: The effect of robots



Notes: This figure illustrates theoretically the impact of robots on employment outcomes across demographic groups. Panel A shows the results by gender and Panel B by race/ethnicity. Panels A1 and B1 illustrate the employment allocation by gender and race/ethnicity in equilibrium. N_A, N_B and N_N represent the share of individuals that supply brawn labor, brain labor and no labor. $\varepsilon_A > 0$ accounts for the comparative advantage of men in brawn skills, $\varepsilon_B < 0$ accounts for the comparative disadvantage of non-whites in brain skills, $\overline{x}_A = \frac{\omega_N}{\omega_A}$, $\overline{x}_B = \frac{\omega_N}{\omega_B}$ and $x^*_{B,i} = \frac{\omega_A}{\omega_B} x_{A,i}$. Panels A2 and B2 illustrate the effect of an exogenous decrease in the price of robot capital on relative wages and the equilibrium allocation of labor across these demographic groups.

Figure A7: Robots, elasticity of substitution and the gender employment gap



Notes: This figure illustrates the impact of changes in R (through changes in p) and ρ on equilibrium wages, labor, employment rates and gaps by solving for Equations 6.2, 6.3, 6.9 and 6.10. The model is calibrated using a uniform skill distribution with the following parameters: $\beta = 0.33$ (based on employment in blue-collar jobs in 1970), $\omega_N = 0.25$, $\varepsilon_A^M = 0.2$.

Table A1: Summary statistics: Racial and ethnic minorities

	Population rates		Employment rates					
	All	Minorities	All		1st quartile		4th quartile	
	1990	1990	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Blacks	11.4	37.6	69.1	-1.8	72.6	-2.2	66.8	-0.9
Hispanics	12.6	41.8	71.2	1.4	72.3	1.2	70.3	1.5
Asians	4.4	14.6	71.6	1.7	71.4	2.1	72.0	1.0
American Indian or Alaska Natives	0.6	2.1	68.0	-5.3	68.8	-6.0	67.5	-4.2
Other	1.2	3.9	68.2	1.5	72.1	-0.8	66.3	1.5
Observations	722	722	722	722	181	181	180	180

Notes: This table illustrates average population and employment rates for Blacks, Hispanics, Asians, American Indian or Alaska Natives, and other not elsewhere classified races. Columns 1, 2, 3, 5 and 7 show values in 1990, and Columns 4, 6 and 8 show changes between 1990 and 2014 weighted by CZ population in 1990. Columns 1 reports the share of each subgroup in the population, while Columns 2 reports the share among racial and ethnic minorities. Columns 1 to 4 reports averages over all 722 CZs in the sample. Columns 5 to 8 split the sample into quartiles according to the CZ's exposure to robots between 1993 and 2014, reporting averages for the first and the fourth quartile.

Table A2: Occupations with the largest and smallest shares of non-whites and women

Racial and ethnic minorities					Women				
	%	Type	Brawn	Brain		%	Type	Brawn	Brain
	[1]	[2]	[3]	[4]		[5]	[6]	[7]	[8]
Panel A: Top 15 occupations					Panel A: Top 15 occupations				
Private household cleaners and servants	62.03	Low skill	32	5	Secretaries	98.98	White collar	48	88
Parking lot attendants	59.38	Low skill	1	13	Dental hygenists	98.33	White collar	20	53
Housekeepers, maids, butlers and related	53.58	Low skill	42	5	Kindergarten and earlier school teachers	98.21	White collar	45	64
Elevator operators	50.34	Blue collar	63	24	Dental assistants	97.52	White collar	3	60
Baggage porters	47.50	Low skill	36	28	Receptionists	96.96	Low skill	22	41
Materials movers	47.10	Low skill	41	6	Child care workers	96.58	Low skill	3	37
Garbage and recyclable material collectors	45.56	Low skill	23	1	Typists	95.38	Low skill	35	39
Textile sewing machine operators	45.53	Blue collar	83	7	Private household cleaners and servants	94.80	Low skill	32	5
Laundry workers	45.19	Low skill	49	1	Teacher's aides	94.62	White collar	4	59
Waiter's assistant	45.05	Low skill	1	13	Home economics instructors	94.52	White collar	38	100
Taxi cab drivers and chauffeurs	44.74	Skill intensive	87	55	Registered nurses	94.50	Skill intensive	65	84
Farm workers	44.21	Blue collar	50	18	Licensed practical nurses	93.85	Skill intensive	65	50
Tailors	44.04	Blue collar	92	37	Dressmakers and seamstresses	93.66	Blue collar	83	28
Graders and sorters in manufacturing	43.40	Blue collar	50	2	Bank tellers	93.54	Skill intensive	98	65
Vehicle washers and equipment cleaners	42.96	Low skill	21	2	Health record tech specialists	93.40	White collar	1	84
Panel B: Bottom 15 occupations					Panel B: Bottom 15 occupations				
Tool and die markers and die setters	7.71	Skill intensive	86	53	Automobile mechanics	1.87	Skill intensive	80	56
Psychology instructors	7.61	White collar	1	100	Structural metal workers	1.82	Blue collar	67	25
Lawyers	7.53	White collar	2	96	Excavating and loading machine operators	1.82	Blue collar	64	11
Other health and therapy	7.22	Skill intensive	87	94	Materials movers	1.71	Low skill	41	6
Veterinarians	7.17	Skill intensive	97	75	Operating engineers of construction equipm.	1.70	Blue collar	84	33
Optometrists	7.04	Skill intensive	91	69	Carpenters	1.64	Blue collar	89	45
Writers and authors	6.79	White collar	10	83	Mason, tilers, and carpet installers	1.59	Blue collar	81	31
Podiatrists	6.65	White collar	36	88	Roofers and slaters	1.44	Blue collar	91	27
Foresters and conservation scientists	6.52	Low skill	46	47	Electric power installers and repairers	1.44	Skill intensive	92	48
Dental hygenists	6.00	White collar	20	53	Plumbers, pipe fitters, and steamfitters	1.38	Blue collar	90	46
Geologists	5.44	Skill intensive	63	95	Railroad brake, coupler, and switch operators	1.36	Blue collar	65	23
History instructors	4.74	White collar	1	100	Concrete and cement workers	1.35	Blue collar	80	25
Sales engineers	4.62	White collar	39	94	Heating, air cond., and refrig. mechanics	1.22	Blue collar	67	42
Airplane pilots and navigators	4.60	Skill intensive	97	66	Paving, surfacing, tamping equipm. operators	1.07	Blue collar	91	23
Farmers (owners and tenants)	2.88	White collar	22	58	Heavy equipm. and farm equipm. mechanics	0.86	Blue collar	92	43

Notes: This table presents a set of occupations with the corresponding share of non-white and female workers, the percentile of the standardized brawn and brain task content in the distribution of occupations and the respective occupation group. Occupation groups are computed from a median split of the standardized measures of the brawn and brain task content of jobs. Skill-intensive jobs include occupations that are both brawn and brain task intensive. White-collar jobs include occupations that are brain task intensive and require only few brawn skills. Blue-collar jobs include occupations that are brawn task intensive and require only few brain skills. Low-skill jobs include occupations that do not require particular brawn or brain skills. Panel A shows the 15 occupations with the highest share of non-whites and women. Panel B shows the 15 occupations with the highest share of whites and men.

Table A3: Summary statistics: Employment by occupation and industry

	Occupation								Industry					
	Skill-intensive		White-collar		Blue-collar		Low-skill		High robot-int.		Low robot-int.		Non-manuf.	
	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}	1990	Δ_{14-90}
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Panel A: Gender														
Men	13.3	-1.60	31.4	-0.12	24.1	-3.70	8.22	0.95	9.78	-2.70	9.39	-3.90	65.0	1.71
Women	9.86	2.55	30.9	1.34	12.2	-3.70	9.06	0.76	4.07	-1.20	4.99	-2.80	56.9	5.94
Gender gap	3.47	-4.20	0.53	-1.40	11.8	-0.00	-0.84	0.19	5.70	-1.50	4.40	-1.10	8.03	-4.20
Panel B: Race and ethnicity														
Whites	12.2	0.36	34.8	2.11	16.4	-4.30	7.38	-0.23	6.70	-2.00	7.05	-3.10	62.8	3.61
Non-whites	9.49	1.35	19.8	3.55	21.9	-4.50	12.2	0.75	7.64	-2.10	6.89	-3.40	54.2	6.78
Race and ethnicity gap	2.71	-0.99	15.0	-1.40	-5.40	0.23	-4.90	-0.98	-0.94	0.13	0.15	0.30	8.67	-3.10
Observations	722	722	722	722	722	722	722	722	722	722	722	722	722	722

Notes: This table illustrates employment rates and gaps of demographic groups by occupation and industry groups in 1990 and their changes between 1990 and 2014. Averages are weighted by the CZ population in 1990. Occupation groups are computed from a median split of the standardized measures of the brawn and brain task content of jobs. Skill-intensive jobs include occupations that are both brawn and brain task intensive. White-collar jobs include occupations that are brain task intensive and require only few brawn skills. Blue-collar jobs include occupations that are brawn task intensive and require only few brain skills. Low-skill jobs include occupations that do not require particular brawn or brain skills. As shown in Table 1, industry groups are created according to the relative adoption of industrial robots of industries. High robot-intensive manufacturing industries include the industries with the heaviest adoption of industrial robots. Low robot-intensive manufacturing industries include the remaining manufacturing industries, while non-manufacturing industries include all industries outside of the manufacturing sector.

Table A4: Summary statistics: Covariates

		US robot exposure 1993-2014			
	All	Q1	Q2	Q3	Q4
	[1]	[2]	[3]	[4]	[5]
Pre-trends					
Employment men	-5.09	-3.98	-5.0	-3.93	-6.25
Employment women	19.8	20.3	19.7	19.2	19.9
Employment whites	9.43	10.4	9.41	9.62	8.94
Employment non-whites	3.16	5.51	5.04	4.14	0.54
Labor market shocks					
Import exposure	3.61	1.70	3.34	4.34	5.06
PC exposure	44.8	44.5	44.8	44.2	45.3
IT capital	2.02	1.40	1.92	2.32	2.15
Routine task-intensity	35.0	33.6	35.1	35.1	35.4
Offshorable	37.2	37.2	38.0	37.4	36.6
Demographics					
Black	10.9	9.33	12.1	9.82	11.5
Hispanic	7.94	15.8	7.92	10.2	3.62
Women	51.1	50.9	51.3	50.7	51.4
Less educated	77.1	76.6	75.4	77.7	78.0
Log population	13.3	12.8	13.4	13.4	13.4
25-34 years	33.9	34.1	34.2	34.5	33.2
35-44 years	29.4	29.4	29.7	29.5	29.3
45-54 years	20.0	19.7	19.8	19.9	20.3
Industries					
Construction	6.24	7.72	6.17	6.24	5.73
Manufacturing	24.4	14.8	21.3	27.3	28.3
Mining	0.99	1.45	1.05	0.96	0.81
Research and education	1.91	1.89	1.98	1.76	1.96
Services	63.0	69.4	65.9	60.1	60.5
Utilities	1.49	1.59	1.46	1.40	1.52
Occupations					
Skill-intensive	16.1	17.0	16.2	15.5	16.2
White-collar	41.4	42.1	42.6	40.2	41.0
Blue-collar	28.3	26.1	27.1	30.1	29.0
Employment composition					
Women in high robot-intensive industries	30.8	31.9	32.3	32.2	28.7
Women in low robot-intensive industries	35.3	35.1	36.8	36.8	33.6
Non-whites in high robot-intensive industries	23.8	30.7	24.9	29.3	17.3
Non-whites in low robot-intensive industries	22.7	30.0	25.4	28.1	15.3
Women in skill-intensive occupations	47.3	47.5	47.3	46.2	47.8
Women in white-collar occupations	50.8	51.4	51.0	50.0	50.8
Women in blue-collar occupations	35.3	34.0	36.0	36.1	35.0
Non-whites in skill-intensive occupations	17.9	24.1	19.1	20.9	13.0
Non-whites in white-collar occupations	13.3	19.1	13.6	15.6	9.64
Non-whites in blue-collar occupations	29.2	38.1	31.2	35.2	21.0
Observations	722	181	180	181	180

Notes: This table illustrates averages of the covariates used in the main analysis. Column 1 reports averages over all 722 CZs in the sample. Columns 2 to 5 split the sample into four quartiles, accounting for a labor market's exposure to robots between 1993 and 2014. Pre-trends account for changes in employment of men, women, whites and non-whites between 1970 and 1990. Labor market shocks include the China trade shock, a measure of exposure to PCs, IT capital intensity and the share of workers who are employed in routine task-intensive and offshorable occupations. Demographics, industries and occupations include measures of the population composition in 1990. The remaining variables report the employment composition by demographic group within industries and occupations in 1990.

Table A5: The effect of robots on the employment gaps and first-stage estimates

	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A: Gender employment gap					
US robot exposure	-0.508***	-0.497***	-0.519***	-0.519***	-0.618***	-0.644***
	(0.141)	(0.143)	(0.144)	(0.144)	(0.158)	(0.166)
	Panel B: Race/ethnicity employment gap					
US robot exposure	0.640***	0.685***	0.687***	0.687***	0.804***	0.846***
	(0.232)	(0.221)	(0.225)	(0.225)	(0.268)	(0.276)
	Panel C: First-stage					
EU7 robot exposure	0.568***	0.565***	0.555***	0.555***	0.497***	0.478***
	(0.047)	(0.042)	(0.051)	(0.053)	(0.049)	(0.036)
Kleibergen-Paap F stat	146.98	177.31	119.76	107.91	103.18	180.31
Observations	2166	2166	2166	2166	2166	2166
Covariates:						
Region	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Pre-trends		✓	✓	✓	✓	✓
Computer & IT			✓	✓	✓	✓
Chinese imports				✓	✓	✓
Demographics					✓	✓
Occupations					✓	✓
Industries					✓	✓
Composition						✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment gaps by gender and race/ethnicity and first-stage estimates at the CZ level adding covariates sequentially. Changes in Panel A and B are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. Panel C standardizes also the dependent variable. There are three time periods and 722 CZs. Column 1 includes only state fixed effects and time-varying division fixed effects. Column 2 includes also pre-trends in employment of men, women, whites and non-whites between 1970 and 1990. Column 3 controls for the adoption of PCs, IT capital intensity and RBTC. Column 4 includes the exposure to Chinese imports. Column 5 controls also for demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990. Column 6 controls also for the initial composition of industry and occupation employment by gender and race/ethnicity in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A6: Robots and employment: Exclusion of the Great Recession period (2007-14)

	Panel A: Gender		
	Men	Women	Gap
	[1]	[2]	[3]
US robot exposure	-0.695***	-0.357***	-0.343***
	(0.137)	(0.121)	(0.072)
Observations	1444	1444	1444
	Panel B: Race and ethnicity		
	Whites	Non-whites	Gap
	[1]	[2]	[3]
US robot exposure	-0.375***	-0.958***	0.583***
	(0.050)	(0.194)	(0.155)
Observations	1444	1444	1444
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are two time periods and 722 CZs. Time periods are 1990-2000 and 2000-07. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A7: Robots and labor force participation

	Panel A: Gender		
	Men	Women	Gap
	[1]	[2]	[3]
US robot exposure	-0.632***	-0.111	-0.521***
	(0.183)	(0.150)	(0.136)
Observations	2166	2166	2166
	Panel B: Race and ethnicity		
	Whites	Non-whites	Gap
	[1]	[2]	[3]
US robot exposure	-0.164*	-0.807***	0.643***
	(0.091)	(0.229)	(0.232)
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on labor force participation rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A8: The effect of labor market shocks on employment

	Panel A: Gender					
	Full sample			Exclude Great Recession		
	Men	Women	Gap	Men	Women	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
EU7 robot exposure	-0.553***	-0.245***	-0.308***	-0.583***	-0.263*	-0.321***
	(0.104)	(0.079)	(0.085)	(0.154)	(0.133)	(0.065)
Import exposure	-0.328***	-0.141	-0.187***	-0.403***	-0.328**	-0.075
	(0.112)	(0.129)	(0.067)	(0.125)	(0.133)	(0.094)
PC exposure	0.002	0.057	-0.055	0.065	-0.020	0.085
	(0.081)	(0.059)	(0.050)	(0.070)	(0.084)	(0.069)
IT capital intensity	-0.022	-0.016	-0.006	0.034	-0.011	0.045
	(0.095)	(0.094)	(0.068)	(0.114)	(0.097)	(0.077)
Routine task-intensity	0.137	-0.072	0.209***	0.101	-0.047	0.148
	(0.083)	(0.092)	(0.061)	(0.097)	(0.112)	(0.096)
Observations	2166	2166	2166	1444	1444	1444
	Panel B: Race and ethnicity					
	Full sample			Exclude Great Recession		
	Whites	Non-whites	Gap	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
EU7 robot exposure	-0.272***	-0.676***	0.404***	-0.266***	-0.713***	0.447***
	(0.039)	(0.135)	(0.126)	(0.059)	(0.210)	(0.164)
Import exposure	-0.147*	-0.298*	0.150	-0.291***	-0.352*	0.062
	(0.079)	(0.166)	(0.161)	(0.098)	(0.188)	(0.206)
PC exposure	0.084	-0.264***	0.348***	0.085	-0.486***	0.571***
	(0.064)	(0.093)	(0.075)	(0.061)	(0.148)	(0.151)
IT capital intensity	-0.022	-0.078	0.056	-0.037	0.088	-0.125
	(0.073)	(0.145)	(0.096)	(0.074)	(0.197)	(0.161)
Routine task-intensity	0.027	-0.015	0.042	-0.014	-0.097	0.083
	(0.072)	(0.137)	(0.105)	(0.080)	(0.187)	(0.179)
Observations	2166	2166	2166	1444	1444	1444
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents reduced form estimates of the effect of robot exposure, import exposure, PC adoption, IT capital intensity and routine task-intensity on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A9: Robots and race/ethnicity employment gaps in non-manufacturing industries

	Agriculture	Construction	Mining	Research and Education	Services	Utilities
	[1]	[2]	[3]	[4]	[5]	[6]
US robot exposure	0.068*	-0.003	-0.015	-0.043*	0.662***	0.029*
	(0.040)	(0.052)	(0.013)	(0.025)	(0.200)	(0.016)
Observations	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on the employment gap by race/ethnicity at the CZ level. Columns decompose the outcomes by sectors outside of manufacturing. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A10: Robots and industry employment by race/ethnicity as a share of total population

	High robot-intensive		Low robot-intensive		Non-manufacturing	
	White	Non-white	White	Non-white	White	Non-white
	[1]	[2]	[3]	[4]	[5]	[6]
US robot exposure	-0.271***	-0.109***	0.042	0.002	-0.275***	-0.220*
	(0.056)	(0.029)	(0.045)	(0.017)	(0.094)	(0.121)
Observations	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates by race/ethnicity at the CZ level. Columns decompose the outcomes between industry groups. Changes are expressed in percentage points of the overall working-age population and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A11: Robots and race/ethnicity employment gap by industry

	High robot-intensive	Low robot-intensive	Non manufacturing
	[1]	[2]	[3]
Robots in high robot-intensive	0.070	0.012	0.327***
	(0.083)	(0.034)	(0.116)
Robots in low robot-intensive	0.066	-0.050	0.423***
	(0.056)	(0.045)	(0.155)
Robots in non-manufacturing	0.014	0.105*	0.197
	(0.077)	(0.054)	(0.226)
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure by industry group on the employment gap by race/ethnicity at the CZ level. Columns decompose the outcomes (employment) by industry group. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A12: Robots and employment: No state fixed effects

	Panel A: Gender			
	All	Men	Women	Gap
	[1]	[2]	[3]	[4]
US robot exposure	-0.588***	-0.794***	-0.392***	-0.408***
	(0.112)	(0.138)	(0.108)	(0.113)
Observations	2166	2166	2166	2166
	Panel B: Race and ethnicity			
	All	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]
US robot exposure	-0.588***	-0.439***	-1.026***	0.587***
	(0.112)	(0.060)	(0.188)	(0.174)
Observations	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include time-varying division fixed effects (but no state fixed effects), pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A13: Robots and employment: Shares of total population

	Panel A: Gender		
	All	Men	Women
	[1]	[2]	[3]
US robot exposure	-0.826***	-0.559***	-0.267***
	(0.202)	(0.132)	(0.096)
Relative contribution	100.0	67.7	32.3
Observations	2166	2166	2166
	Panel B: Race and ethnicity		
	All	Whites	Non-whites
	[1]	[2]	[3]
US robot exposure	-0.826***	-0.494***	-0.332**
	(0.202)	(0.144)	(0.165)
Relative contribution	100.0	59.8	40.2
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates by gender and race/ethnicity at the CZ level and the relative contribution of each demographic group to the aggregate effect (in percent). Changes are expressed in percentage points of the total working-age population in the CZ and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. All regressions include time-varying division fixed effects (but no state fixed effects), pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A14: Robots and employment: Product market competition from Europe

	Panel A: Gender					
	All			Less than college		
	Men	Women	Gap	Men	Women	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A1: Import competition in the US					
US robot exposure	-1.180***	-0.523**	-0.657***	-1.468***	-0.541**	-0.927***
	(0.246)	(0.195)	(0.164)	(0.319)	(0.226)	(0.188)
US imports from EU7	0.299***	0.135***	0.164*	0.289**	0.136**	0.153
	(0.100)	(0.047)	(0.090)	(0.130)	(0.062)	(0.114)
	Panel A2: Import competition in Canada					
US robot exposure	-1.157***	-0.513***	-0.644***	-1.445***	-0.531**	-0.915***
	(0.243)	(0.190)	(0.166)	(0.318)	(0.222)	(0.190)
CAN imports from EU7	0.134	0.157	-0.024	0.085	0.126	-0.041
	(0.116)	(0.152)	(0.097)	(0.122)	(0.160)	(0.113)
	Panel A3: Include only countries with least trade with the US					
US robot exposure	-0.916***	-0.596*	-0.320**	-1.141***	-0.678*	-0.463***
	(0.318)	(0.328)	(0.130)	(0.417)	(0.380)	(0.165)
Observations	2166	2166	2166	2166	2166	2166
	Panel B: Race and ethnicity					
	All			Less than college		
	Whites	Non-whites	Gap	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel B1: Import competition in the US					
US robot exposure	-0.584***	-1.436***	0.852***	-0.636***	-1.633***	0.997***
	(0.104)	(0.316)	(0.274)	(0.112)	(0.365)	(0.297)
US imports from EU7	0.192***	0.270**	-0.078	0.169***	0.266*	-0.097
	(0.053)	(0.119)	(0.093)	(0.059)	(0.146)	(0.105)
	Panel B2: Import competition in Canada					
US robot exposure	-0.570***	-1.416***	0.846***	-0.623***	-1.612***	0.989***
	(0.098)	(0.316)	(0.276)	(0.108)	(0.366)	(0.300)
CAN imports from EU7	0.207	0.201	0.006	0.160	0.152	0.008
	(0.127)	(0.201)	(0.151)	(0.125)	(0.229)	(0.216)
	Panel B3: Include only countries with least trade with the US					
US robot exposure	-0.537**	-1.132***	0.596*	-0.652***	-1.304***	0.653*
	(0.202)	(0.393)	(0.338)	(0.230)	(0.467)	(0.369)
Observations	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. Panels A1 and B1 include a shift-share measure of US imports from the seven European countries included in the instrument. Panels A2 and B2 include a shift-share measure of Canadian imports from the seven European countries included in the instrument. Panels A3 and B3 report IV estimates using an instrument that includes only the four European countries with the lowest trade engagement with the US (Denmark, Finland, Spain and Sweden). Columns 1 to 3 report results for all individuals, while Columns 4 to 6 report results for individuals without a college degree. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A15: Robots and employment: Pre-trends

	Panel A: Gender		
	Men	Women	Gap
	[1]	[2]	[3]
US robot exposure	-1.148***	-0.507**	-0.644***
	(0.243)	(0.189)	(0.166)
Employment of men, 1970-1990	-0.041	-0.029	-0.009
	(0.041)	(0.030)	(0.024)
Employment of women, 1970-1990	0.037	0.006	0.032
	(0.040)	(0.032)	(0.030)
Employment of whites, 1970-1990	-0.024	0.026	-0.054
	(0.070)	(0.052)	(0.052)
Employment of non-whites, 1970-1990	0.001	0.006	-0.006
	(0.007)	(0.005)	(0.005)
Observations	2166	2166	2166
	Panel B: Race and ethnicity		
	Whites	Non-whites	Gap
	[1]	[2]	[3]
US robot exposure	-0.569***	-1.415***	0.846***
	(0.097)	(0.315)	(0.276)
Employment of men, 1970-1990	-0.001	-0.091	0.090*
	(0.024)	(0.059)	(0.048)
Employment of women, 1970-1990	0.050**	-0.010	0.060
	(0.025)	(0.050)	(0.042)
Employment of whites, 1970-1990	-0.054	0.117	-0.171**
	(0.042)	(0.094)	(0.078)
Employment of non-whites, 1970-1990	0.006	-0.025*	0.032**
	(0.005)	(0.015)	(0.012)
Observations	2166	2166	2166
Covariates:	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. US robot exposure has been standardized to have mean zero and standard deviation of one. Changes in the employment rates between 1970 and 1990 are demographic specific and are multiplied by 100. There are three time periods and 722 CZs. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A16: Robots and employment: Weights

	Panel A: Gender					
	All	Less than college	All	Less than college	All	Less than college
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A1: Employment rate of men					
US robot exposure	-1.662***	-2.091***	-1.015***	-1.216***	-1.309***	-1.370***
	(0.307)	(0.400)	(0.300)	(0.342)	(0.371)	(0.358)
	Panel A2: Employment rate of women					
US robot exposure	-0.753***	-0.812***	-0.124	-0.037	-0.767**	-0.730**
	(0.262)	(0.264)	(0.132)	(0.164)	(0.283)	(0.271)
	Panel A3: Employment gap					
US robot exposure	-0.909***	-1.279***	-0.890***	-1.179***	-0.542**	-0.640**
	(0.202)	(0.256)	(0.320)	(0.393)	(0.244)	(0.282)
Observations	2166	2166	2166	2166	825	825
	Panel B: Race and ethnicity					
	All	Less than college	All	Less than college	All	Less than college
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel B1: Employment rate of whites					
US robot exposure	-0.658***	-0.750***	-0.516***	-0.528***	-0.691***	-0.606***
	(0.154)	(0.138)	(0.152)	(0.174)	(0.213)	(0.221)
	Panel B2: Employment rate of non-whites					
US robot exposure	-1.888***	-2.164***	-0.469	-0.640	-1.476***	-1.614***
	(0.365)	(0.435)	(0.382)	(0.457)	(0.395)	(0.425)
	Panel B3: Employment gap					
US robot exposure	1.230***	1.414***	-0.047	0.111	0.785**	1.008**
	(0.355)	(0.402)	(0.403)	(0.509)	(0.319)	(0.400)
Observations	2166	2166	2166	2166	825	825
Covariates:						
Division	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Computer & IT	✓	✓	✓	✓	✓	✓
Chinese imports	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Occupations	✓	✓	✓	✓	✓	✓
Industries	✓	✓	✓	✓	✓	✓
Non-white population weights	✓			✓		
Unweighted		✓	✓		✓	✓
Non-white CZs			✓			✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs in the first four columns and three time periods and 275 CZs in the last pair of columns. The latter restrict the sample to CZs with a population of non-whites and a share of non-whites above the respective local labor market median in 1990. Columns 1 to 3 report results for all individuals, while Columns 4 to 6 report results for individuals without a college degree. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions in Columns 1 and 4 are weighted by the population of non-whites in the CZ in 1990. Regressions in the remaining columns are unweighted. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A17: Robots and employment: Alternative construction of the instrument

	Panel A: Gender					
	All			Less than college		
	Men	Women	Gap	Men	Women	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A1: EU7 countries and Germany					
US robot exposure	-0.975***	-0.408***	-0.568***	-1.223***	-0.422**	-0.801***
	(0.212)	(0.141)	(0.148)	(0.280)	(0.170)	(0.172)
	Panel A2: EU5 countries (Acemoglu and Restrepo, 2020)					
US robot exposure	-1.254***	-0.627**	-0.627***	-1.567***	-0.682**	-0.885***
	(0.309)	(0.269)	(0.164)	(0.403)	(0.306)	(0.197)
	Panel A3: EU7 countries with $\ell^{90}_{j,c}$					
US robot exposure	-1.161***	-0.573***	-0.588***	-1.464***	-0.672***	-0.793***
	(0.250)	(0.198)	(0.161)	(0.334)	(0.242)	(0.203)
	Panel A4: EU7 countries without $g_{j,(t_0,t_1)}\frac{R_{j,t_0}}{L_{j,90}}$					
US robot exposure	-0.918***	-0.404**	-0.514***	-1.143***	-0.375**	-0.768***
	(0.179)	(0.151)	(0.166)	(0.226)	(0.166)	(0.184)
Observations	2166	2166	2166	2166	2166	2166
	Panel B: Race and ethnicity					
	All			Less than college		
	Whites	Non-whites	Gap	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel B1: EU7 countries and Germany					
US robot exposure	-0.477***	-1.205***	0.728***	-0.528***	-1.368***	0.840***
	(0.074)	(0.279)	(0.245)	(0.087)	(0.322)	(0.265)
	Panel B2: EU5 countries (Acemoglu and Restrepo, 2020)					
US robot exposure	-0.631***	-1.566***	0.935***	-0.712***	-1.784***	1.073***
	(0.144)	(0.383)	(0.313)	(0.156)	(0.444)	(0.342)
	Panel B3: EU7 countries with $\ell^{90}_{j,c}$					
US robot exposure	-0.497***	-1.446***	0.950***	-0.597***	-1.627***	1.030***
	(0.107)	(0.319)	(0.276)	(0.122)	(0.381)	(0.310)
	Panel B4: EU7 countries without $g_{j,(t_0,t_1)}\frac{R_{j,t_0}}{L_{j,90}}$					
US robot exposure	-0.461***	-1.115***	0.654***	-0.468***	-1.272***	0.804***
	(0.097)	(0.260)	(0.231)	(0.097)	(0.293)	(0.250)
Observations	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. Panels A1 and B1 report estimates using an instrument which includes seven European countries and Germany. Panels A2 and B2 report estimates using an instrument that includes only five European countries. I exclude Spain and the United Kingdom as in Acemoglu and Restrepo (2020). Panels A3 and B3 report estimates using an instrument with seven European countries, but US employment shares of 1990 instead of 1970. Panels A4 and B4 report estimates using an endogenous variable and an instrument of robot density without the adjustment term of industry growth. Columns 1 to 3 report results for all individuals, while Columns 4 to 6 report results for individuals without a college degree. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A18: Robots and employment: Exclude CZs with highest robot exposure

	Panel A: Gender					
	All			Less than college		
	Men	Women	Gap	Men	Women	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A1: Exclusion of Detroit area					
US robot exposure	-1.292***	-0.764*	-0.528*	-1.570**	-0.815	-0.755**
	(0.460)	(0.450)	(0.283)	(0.595)	(0.511)	(0.355)
Observations	2163	2163	2163	2163	2163	2163
	Panel A2: Exclusion of CZs in top 1 percentile					
US robot exposure	-1.561**	-1.019	-0.542	-1.888**	-1.009	-0.879*
	(0.646)	(0.746)	(0.390)	(0.828)	(0.853)	(0.454)
Observations	2142	2142	2142	2142	2142	2142
	Panel B: Race and ethnicity					
	All			Less than college		
	Whites	Non-whites	Gap	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel B1: Exclusion of Detroit area					
US robot exposure	-0.614**	-1.688***	1.074**	-0.649**	-1.974***	1.325**
	(0.269)	(0.546)	(0.456)	(0.286)	(0.648)	(0.500)
Observations	2163	2163	2163	2163	2163	2163
	Panel B2: Exclusion of CZs in top 1 percentile					
US robot exposure	-0.781*	-1.772**	0.990	-0.771	-2.149**	1.378*
	(0.454)	(0.792)	(0.654)	(0.483)	(0.974)	(0.739)
Observations	2142	2142	2142	2142	2142	2142
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. Panels A1 and B1 exclude Detroit from the sample. Panels A2 and B2 exclude the CZs in the top 1 percentile of US robot exposure between 1993 and 2014. Columns 1 to 3 report results for all individuals, while Columns 4 to 6 report results for individuals without a college degree. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.

Table A19: Robots and employment: Unobserved heterogeneity

	Panel A: Gender					
	All			Less than college		
	Men	Women	Gap	Men	Women	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel A1: CZ characteristics at $t-1$					
US robot exposure	-0.863***	-0.345**	-0.519***	-1.104***	-0.404**	-0.700***
	(0.196)	(0.140)	(0.112)	(0.260)	(0.175)	(0.151)
	Panel A2: CZ fixed effects					
US robot exposure	-1.839***	-0.877***	-0.962***	-2.416***	-1.196***	-1.219***
	(0.177)	(0.098)	(0.172)	(0.232)	(0.128)	(0.225)
Observations	2166	2166	2166	2166	2166	2166
	Panel B: Race and ethnicity					
	All			Less than college		
	Whites	Non-whites	Gap	Whites	Non-whites	Gap
	[1]	[2]	[3]	[4]	[5]	[6]
	Panel B1: CZ characteristics at $t-1$					
US robot exposure	-0.390***	-1.016***	0.626***	-0.483***	-1.191***	0.707***
	(0.072)	(0.251)	(0.203)	(0.093)	(0.288)	(0.223)
	Panel B2: CZ fixed effects					
US robot exposure	-0.817***	-2.083***	1.266***	-1.059***	-2.523***	1.464***
	(0.074)	(0.224)	(0.203)	(0.091)	(0.260)	(0.222)
Observations	2166	2166	2166	2166	2166	2166
Covariates:	✓	✓	✓	✓	✓	✓

Notes: This table presents IV estimates of the effect of US robot exposure on employment rates and gaps by gender and race/ethnicity at the CZ level. Changes are expressed in percentage points of the working-age population of the respective demographic group and are multiplied by 100. Independent variables are standardized to have mean zero and standard deviation of one. There are three time periods and 722 CZs. Panels A1 and B1 use time-varying covariates. Panels A2 and B2 include CZ fixed effects. Columns 1 to 3 report results for all individuals, while Columns 4 to 6 report results for individuals without a college degree. All regressions include state fixed effects, time-varying division fixed effects, pre-trends in employment of men, women, whites and non-whites between 1970 and 1990, controls for the adoption of PCs, IT capital intensity and RBTC, exposure to Chinese imports, demographic characteristics (share of Blacks, Hispanics, women, population with less than a college degree, three age groups (25-34, 35-44 and 45-54 years), and the logarithmic population), the industry (employment share in construction, manufacturing, mining, research, service and utilities) and occupation composition of employment (employment share in offshorable, skill-intensive, white-collar, blue-collar and low-skill jobs) of CZs in 1990, and the composition of industry and occupation employment by gender and race/ethnicity of CZs in 1990. Standard errors are robust against heteroskedasticity and allow for clustering at the state level. Regressions are weighted by CZ population in 1990. Coefficients with ***, ** and * are significant at the 1%, 5% and 10% confidence level.