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Online Appendix
Robots and Jobs: Evidence from US Labor Markets.
By: Acemoglu and Restrepo.

In this part of the Appendix, we provide proofs and generalizations of results in the text.

A1 Autarky Equilibrium

We start with the characterization of the autarky equilibrium, then establish existence and uniqueness, and prove Proposition 1 and a more general version of Proposition 2.

Characterization of Equilibrium

The first-order condition for the representative household in commuting zone c is

$$W_c = BC_c^{\psi} L_c^{\varepsilon}. \tag{A1}$$

Market clearing implies

$$\begin{aligned} C_c &= Y_c - I_c \\ &= Y_c - D^{-1-\eta}(1+\eta)^{-1-\eta} M_c^{1+\eta}, \end{aligned} \tag{A2}$$

where the second line follows by inverting the production function for robots, $M_c = D(1+\eta) I_c^{\frac{1}{1+\eta}}$, introduced in the text. Combining this with (A1), we obtain

$$W_c = B\left(Y_c - D^{-1-\eta}(1+\eta)^{-1-\eta} M_c^{1+\eta}\right)^{\psi} L_c^{\varepsilon}. \tag{A3}$$

From the production function for robots we also have

$$R_c^M = D^{-1-\eta}(1+\eta)^{-\eta} M_c^{\eta}. \tag{A4}$$

Recall as well that in the autarky model the supply of capital in commuting zone c is taken to be exogenously given at $K_c > 0$.

Under the assumption that $\pi_c > 0$ in all commuting zones, tasks below θ_i will be produced with robots at a cost $\frac{R_c^M}{\gamma_M}$ and tasks above θ_i will be produced with labor at a cost $\frac{W_c}{\gamma_L}$. Hence, the marginal cost—and thus the price—of industry i is

$$P_{ci}^X = \frac{1}{A_{ci}}\left(\theta_i \frac{R_M^K}{\gamma_M} + (1-\theta_i)\frac{W_c}{\gamma_L}\right)^{\alpha} R_c^{K\,1-\alpha}. \tag{A5}$$

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Next, define the share of labor in production tasks in industry i as

$$s^L_{ci} = \frac{W_c L_{ci}}{\alpha P^X_{ci} X_{ci}} = \frac{(1-\theta_i)\frac{W_c}{\gamma_L}}{\theta_i \frac{R^K_M}{\gamma_M} + (1-\theta_i)\frac{W_c}{\gamma_L}}. \tag{A6}$$

Here note that a fraction $1-\alpha$ of the total costs of the sector are paid to capital (given the Cobb-Douglas technology in (2)), and s^L_{ci} is the share of labor in the remainder, and thus the share of labor in the value added of industry i is simply αs^L_{ci}.

Because the final good in each commuting zone is taken as numeraire, we also have the following *ideal price index condition*,

$$1 = \sum_{i \in \mathcal{I}} \nu_i P^{X\,1-\sigma}_{ci}. \tag{A7}$$

Now combining (A5) and (A6), we can express the wage bill in commuting zone c as

$$\begin{aligned} W_c L_c &= \sum_{i\in\mathcal{I}} W_c L_{ci} \\ &= \sum_{i\in\mathcal{I}} \alpha s^L_{ci} P^X_{ci} X_{ci}. \end{aligned}$$

From equation (1), the demand for industry i in commuting zone c is $X_{ci} = \nu_i P^{X\,-\sigma}_{ci} Y_c$, and substituting for this, the previous expression can be rewritten as

$$W_c L_c = \sum_{i\in\mathcal{I}} \alpha s^L_{ci} \nu_i P^{X\,1-\sigma}_{ci} Y_c. \tag{A8}$$

Similarly, the demand for robots can be expressed as

$$R^M_c M_c = \sum_{i\in\mathcal{I}} \alpha(1-s^L_{ci}) \nu_i P^{X\,1-\sigma}_{ci} Y_c, \tag{A9}$$

and the demand for capital is

$$R^K_c K_c = (1-\alpha) Y_c. \tag{A10}$$

Definition 1 *An equilibrium of the autarky model is given by a set of factor prices* $\{W_c, R^M_c, R^K_c\}$, *factor supplies* $\{L_c, M_c\}$, *and level of output* Y_c *for each* $c \in \mathcal{C}$ *such that:*

- *factor supplies satisfy equations* (A3) *and* (A4)*;*
- *factor prices satisfy the ideal price index condition, equation* (A7)*;*
- *factor markets clear, that is, equations* (A8), (A9), *and* (A10) *hold.*

Proposition A1 *An equilibrium of the autarky model exists and is unique.*

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PROOF: The existence of equilibrium can be proved using a standard fixed point argument (as in the proof of Proposition A5 below). Here we provide a proof exploiting the second welfare theorem that establishes existence and uniqueness more directly.

Because the autarky equilibrium is a competitive equilibrium in an economy with a representative household, from the second welfare theorem any autarky equilibrium is a solution to the maximization of the utility of the representative household subject to the technology and feasibility constraints. This problem can be written as

$$\max_{\{X_{ci},L_{ci},M_{ci},K_{ci}\}_{i\in\mathcal{I}},L_c,M_c,K_c,Y_c,C_c,I_c} \frac{C_c^{1-\psi}-1}{1-\psi} - \frac{B}{1+\varepsilon}L_c^{1+\varepsilon}$$

$$\begin{aligned}
\text{subject to: } Y_c &= \left(\sum_{i\in\mathcal{I}} \nu_i^{\frac{1}{\sigma}} X_{ci}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \\
X_{ci} &= \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)} A_{ci}\left[\min\left\{\frac{\gamma_M M_{ci}}{\theta_i}, \frac{\gamma_L L_{ci}}{1-\theta_i}\right\}\right]^{\alpha} K_{ci}^{1-\alpha} \\
M_c &= D(1+\eta) I_c^{\frac{1}{1+\eta}} \\
M_c &= \sum_{i\in\mathcal{I}} M_{ci} \\
L_c &= \sum_{i\in\mathcal{I}} L_{ci} \\
K_c &= \sum_{i\in\mathcal{I}} K_{ci} \\
Y_c &= I_c + C_c.
\end{aligned}$$

The objective function is continuous and strictly concave and the constraint set is convex and compact. This ensures that this maximization problem has a unique solution, which gives us the unique equilibrium of the autarky model.■

Proposition A1 can be generalized to the case where π_c is negative in some commuting zones, in which case not all technologically automated tasks will be produced with robots as in the general framework considered in Acemoglu and Restrepo (2018a).

Proofs of Propositions from Section 2.1

PROOF OF PROPOSITION 1: Since the labor share in industry i is αs_{ci}^L and that the value added of this industry is $\nu_i {P_{ci}^X}^{1-\sigma} Y_c$, we have

$$W_c L_{ci} = s_{ci}^L \alpha \nu_i {P_{ci}^X}^{1-\sigma} Y_c.$$

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Using the formulas for s^L_{ci} and P^X_{ci} in equations (A5) and (A6), we obtain

$$\begin{aligned}
W_c L_{ci} =& \frac{(1-\theta_i)\frac{W_c}{\gamma_L}}{\theta_i \frac{R^K_M}{\gamma_M} + (1-\theta_i)\frac{W_c}{\gamma_L}} \alpha \nu_i {P^X_{ci}}^{1-\sigma} Y_c \\
=& \frac{(1-\theta_i)\frac{W}{\gamma_L}}{(A_{ci} P^X_{ci})^{\frac{1}{\alpha}}} {R^K_c}^{\frac{1-\alpha}{\alpha}} \alpha \nu_i {P^X_{ci}}^{1-\sigma} Y_c \\
=& \frac{(1-\theta_i)\frac{W}{\gamma_L}}{(A_{ci} P^X_{ci})^{\frac{1}{\alpha}}} \left((1-\alpha)\frac{Y_c}{K_c} \right)^{\frac{1-\alpha}{\alpha}} \alpha \nu_i {P^X_{ci}}^{1-\sigma} Y_c,
\end{aligned}$$

where in the last line we used the fact that $R^K_c = (1-\alpha)\frac{Y_c}{K_c}$ (equation (A10)). Simplifying this expression yields

$$L_{ci} = (1-\theta_i) \frac{\alpha(1-\alpha)^{\frac{1-\alpha}{\alpha}} \nu_i}{\gamma_L A_{ci}^{\frac{1}{\alpha}}} {P^X_{ci}}^{1-\sigma-\frac{1}{\alpha}} Y_c^{\frac{1}{\alpha}} K_c^{\frac{\alpha-1}{\alpha}}. \tag{A11}$$

Taking logs on both sides and differentiating yields (3). ■

In footnote 4, we provided a sufficient condition for (relative) labor demand in industry i to decrease following automation, $\frac{1/\alpha}{1/\alpha+\sigma-1} > \pi_c s^L_{ic}$. To prove this claim, differentiate equation (A11) and note that from equation (3) that $d\ln L_{cj} = d\ln Y_c$ for industries that are not undergoing any automation. Thus, $d\ln L_{ci} < d\ln L_{cj}$ if

$$\begin{aligned}
\frac{d\theta_i}{1-\theta_i} >& \left(\sigma + \frac{1}{\alpha} - 1\right) d\ln P^X_{ci} \\
=& \left(\sigma + \frac{1}{\alpha} - 1\right) \alpha s^L_{ic} \pi_c \frac{d\theta_i}{1-\theta_i}.
\end{aligned}$$

Rearranging this expression yields the desired condition.

We now state and prove a generalization of Proposition 2.

Proposition A2 *Suppose that $\pi_c > 0$ and $\theta_i = \theta_0 \geq 0$. Then*

$$d\ln L_c = \left[-\zeta^{disp}_c + \zeta^{prod}_c \pi_c - \zeta^{L,inc}_c \frac{\psi}{1-\frac{\alpha(1-s^L_c)}{1+\eta}} \right] \cdot \sum_{i\in\mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i} \frac{\gamma_L}{\gamma_M}, \tag{A12}$$

$$d\ln W_c = \left[-\zeta^{disp}_c \varepsilon + \zeta^{prod}_c \varepsilon \pi_c + \zeta^{W,inc}_c \frac{\psi}{1-\frac{\alpha(1-s^L_c)}{1+\eta}} \right] \cdot \sum_{i\in\mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i} \frac{\gamma_L}{\gamma_M}, \tag{A13}$$

where $\zeta^{disp}_c = (1-\alpha+\eta)/\Lambda_c$, $\zeta^{prod}_c = s^L_c(1+\eta)/\Lambda_c$, $\zeta^{L,inc}_c = \alpha (s^L_c)^2 \pi_c/\Lambda_c$, $\zeta^{W,inc}_c = \alpha s^L_c(\pi_c + \pi_c(\eta-\alpha)(1-s^L_c) - (1-s^L_c\pi_c)(1-\alpha+\eta))/\Lambda_c$, and

$$\Lambda_c = \frac{\gamma_L}{\gamma_M} \left(1-\alpha+\eta(1-s^L_c) + \alpha(s^L_c)^2 \frac{\psi}{1-\frac{\alpha(1-s^L_c)}{1+\eta}} + \varepsilon s^L_c \right) > 0.$$

PROOF: Differentiating (A2) and rearranging, we obtain

$$d\ln C_c = \frac{1}{1-\iota_c} d\ln Y_c - \frac{\iota_c}{1-\iota_c}(1+\eta) d\ln M_c,$$

where $\iota_c = I_c/Y_c$ is the share of robot investment in aggregate output of commuting zone c. Using the definition of s_c^L and equation (A4), this share is equal to $\iota_c = \frac{\alpha(1-s_c^L)}{1+\eta}$. Taking logs and differentiating equation (A1) and combining with the previous expression, we obtain

$$d\ln W_c = \frac{\psi}{1-\frac{\alpha(1-s_c^L)}{1+\eta}} \left(d\ln Y_c - \alpha(1-s_c^L) d\ln M_c \right) + \varepsilon d\ln L_c. \tag{A14}$$

Equation (A4) then yields

$$d\ln R_c^M = \eta d\ln M_c. \tag{A15}$$

Differentiating the expression for P_{ci}^X and rearranging gives

$$\begin{aligned} d\ln P_{ci}^X =& \alpha(1-s_{ci}^L) d\ln R_c^M + \alpha s_{ci}^L d\ln W_c + (1-\alpha) d\ln R_c^K - \alpha \frac{\frac{W_c}{\gamma_L} - \frac{R_c^M}{\gamma_M}}{P_{ci}^X} \\ =& \alpha(1-s_{ci}^L) d\ln R_c^M + \alpha s_{ci}^L d\ln W_c + (1-\alpha) d\ln R_c^K - \alpha \pi_c s_{ci}^L \frac{d\theta_i}{1-\theta_i} \\ =& \alpha(1-s_{ci}^L) d\ln R_c^M + \alpha s_{ci}^L d\ln W_c + (1-\alpha) d\ln R_c^K - \alpha \pi_c s_c^L \frac{\ell_{ci}}{\chi_{ci}} \frac{d\theta_i}{1-\theta_i}. \end{aligned}$$

Next taking logs and differentiating equation (A7) and combining it with the previous expression, we obtain

$$\alpha(1-s_c^L) d\ln R_c^M + \alpha s_c^L d\ln W_c + (1-\alpha) d\ln R_c^K = \alpha s_c^L \pi_c \sum_{i\in\mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i}, \tag{A16}$$

where s_c^L denotes the average labor share of production tasks in commuting zone c. When $\theta_i = \theta_0$, we have $s_{ci}^L = s_c^L$, and

$$s_c^L = \frac{(1-\theta_0)\frac{W_c}{\gamma_L}}{\theta_0 \frac{R_M^K}{\gamma_M} + (1-\theta_0)\frac{W_c}{\gamma_L}}.$$

Taking logs and differentiating equation (A8) and combining it with the previous expression, we obtain

$$\begin{aligned} d\ln W_c + d\ln L_c =& -(1-s_c^L\pi_c) \sum_{i\in\mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i} + (1-s_c^L)(d\ln W_c - d\ln R_c^M) + d\ln Y_c \\ &+ (1-\sigma) \sum_{i\in\mathcal{I}} \ell_{ci} d\ln P_{ci}^X. \end{aligned} \tag{A17}$$

Note next that

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$$(1-\sigma)\sum_{i\in\mathcal{I}}\ell_{ci}d\ln P_{ci}^X=(1-\sigma)\sum_{i\in\mathcal{I}}\chi_{ci}d\ln P_{ci}^X=0,$$

where recall that χ_{ci} is the share of industry i in value added in commuting zone c, and the first equality follows because $\alpha s_{ci}^L=\alpha s_c^L$ implies that $\ell_{ci}=\chi_{ci}$, and the second equality follows from the ideal price index condition in equation (A7). Using this expression, (A17) can be further simplified to

$$d\ln W_c+d\ln L_c=-(1-s_c^L\pi_c)\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}+(1-s_c^L)(d\ln W_c-d\ln R_c^M)+d\ln Y_c. \tag{A18}$$

Using similar steps, we obtain a simplified expression for the demand for robots in equation (A9) as

$$d\ln R_c^M+d\ln M_c=\frac{s_c^L}{1-s_c^L}(1-s_c^L\pi_c)\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}-s_c^L(d\ln W_c-d\ln R_c^M)+d\ln Y_c. \tag{A19}$$

Finally, the demand for capital in equation (A10) implies

$$d\ln R_c^K=d\ln Y_c. \tag{A20}$$

Equations (A14), (A15), (A16), (A18), (A19) and (A20) define six linear equations in six unknowns, and yield a unique solution. The solution gives the formulas for $d\ln L_c$ and $d\ln W_c$ in the proposition.

Note that as $\theta_0\downarrow 0$ and $s_c^L\uparrow 1$, we still have that equations (A14), (A15), (A16), (A18), (A19) and (A20) define six linear equations in six unknowns, but these unknowns are now given by $d\ln L_c$, $d\ln W_c$, $d\ln Y_c$, $d\ln R_c^K$ and the transformed variables $d\ln\tilde{R}_c^M=(1-s_c^L)d\ln R_c^M$ and $d\ln\tilde{M}_c=(1-s_c^L)d\ln M_c$. ■

A similar result holds when we relax the assumption that $\theta_i=\theta_0\geq 0$, except that because now s_{ci}^L varies across industries, there will be additional residual terms in the expressions (A12) and (A13).

Proof of Proposition 2: Our main result then follows immediately as a corollary of Proposition A2 by setting $\theta_0=0$, which implies that $s_c^L=1$. ■

Extension: Workers and Capitalists

We now extend Proposition A2 to account for the possibility that non-labor income generated by automation does not all accrue to workers and instead may go to "capitalists" who do not supply labor. Let us thus modify the budget constraint of the household, which supplies all labor to the commuting zone, to

$$C_c^L\leq W_cL_c+\omega_c\Pi_c,$$

where $\omega_c \in [0, 1]$ denotes the share of non-labor income owned by the household or by "workers", and C_c^L denotes their consumption of the final good. Capitalists consume the remaining resources $Y_c - I_c - C_c^L$, which ensures market clearing.

We obtain a similar set of equilibrium equations as before, but now, the labor supply in equation (A14) becomes

$$\begin{aligned} d\ln W_c =& \frac{\psi}{1-\frac{\alpha(1-s_c^L)}{1+\eta}}(1-(1-\omega_c)\delta_c)\left(d\ln Y_c - \alpha(1-s_c^L)d\ln M_c\right) + \varepsilon d\ln L_c \\ &+ \psi(1-\omega_c)\delta_c(d\ln W_c + d\ln L_c), \end{aligned} \tag{A21}$$

where δ_c denotes the share of wage income in workers total income. This equation shows that, when $\omega_c < 1$, the income effects created by capital gains are dampened. With this modification, we obtain the following generalization of Proposition A2:

PROPOSITION A3 *Suppose that $\pi_c > 0$ and $\theta_i = \theta_0$. Then*

$$d\ln L_c = \left[-\zeta_c^{disp} + \zeta_c^{prod}\pi_c - \zeta_c^{L,inc}\psi + \zeta_c^{L,\omega}\psi(1-\omega_c)\delta_c\right] \cdot \sum_{i\in\mathcal{I}} \ell_{ci}\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M},$$

$$d\ln W_c = \left[-\zeta_c^{disp}\varepsilon + \zeta_c^{prod}\varepsilon\pi_c + \zeta_c^{W,inc}\psi - \zeta_c^{W,\omega}\psi(1-\omega_c)\delta_c\right] \cdot \sum_{i\in\mathcal{I}} \ell_{ci}\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M},$$

where the ζ's are the unique solution to the system of equations given by (A15), (A16), (A18), (A19), (A20), and (A21).

PROOF: The proof is analogous to that of Proposition A2 with equation (A21) replacing equation (A14). ■

Extension: Services

In the model with trade between commuting zones, preferences are defined over a tradable "industry" good and a nontradable "service" good as shown in equation (7). In this section, we show that incorporating the same structure of preferences into the autarky model leads to very similar expressions, but this exercise will provide a better benchmark for comparison with the trade model.

Namely, we adopt the same preferences as in (7), and continue to assume that $C_c = Y_c - I_c$ and $S_c = L_c^S$. This implies that the price of the service good is equal to the wage, W_c. As in the trade model, now a fraction ϕ of income will be spent on C_c and a fraction $1-\phi$ of it on S_c so that

$$S_c = \frac{1}{W_c}\frac{1-\phi}{\phi}(Y_c - I_c).$$

We continue to take Y_c as the numeraire, which implies that the consumer price index, which incorporates the cost of the nontradable good P_c^C, is

$$P_c^C = (1-\phi)^{1-\phi}\phi^{\phi}W_c^{1-\phi}. \tag{A22}$$

Using this expression, we obtain the optimal labor supply for the representative household as

$$W_c^{\phi+(1-\phi)\psi} = (1-\phi)^{(1-\phi)}\phi^{\phi}\left(\frac{(1-\phi)}{\phi}\right)^{(1-\phi)\psi} B\left(Y_c - I_c\right)^{\psi} L_c^{\varepsilon}.$$

Naturally, when $\phi = 1$ we recover equation (A3). Taking logs, differentiating and rearranging this expression, we obtain

$$(\phi + (1-\phi)\psi)d\ln W_c = \frac{\psi}{1-\frac{\alpha(1-s_c^L)}{1+\eta}}\left(d\ln Y_c - \alpha(1-s_c^L)d\ln M_c\right) + \varepsilon d\ln L_c. \tag{A23}$$

Following similar steps to those in the proof of Proposition A2, we obtain

$$\begin{aligned} W_cL_c =& \sum_{i\in\mathcal{I}} \alpha s_{ci}^L \nu_i P_{ci}^{X\,1-\sigma} Y_c + W_c L_c^S \\ =& \sum_{i\in\mathcal{I}} \alpha s_{ci}^L \nu_i P_{ci}^{X\,1-\sigma} Y_c + \frac{1-\phi}{\phi}(Y_c - I_c), \end{aligned}$$

and therefore,

$$\begin{aligned} d\ln W_c + d\ln L_c =& -(1-s_c^L\pi_c)\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i} + \varrho(1-s_c^L)(d\ln W_c - d\ln R_c^M) \\ & + \varrho d\ln Y_c + \frac{1-\varrho}{1-\frac{\alpha(1-s_c^L)}{1+\eta}}\left(d\ln Y_c - \alpha(1-s_c^L)d\ln M_c\right), \end{aligned} \tag{A24}$$

where $\varrho = \frac{\phi\alpha}{\alpha+\phi\alpha}$ denotes the share of employment in the tradable sector, and ℓ_{ci} is now defined as the share of total employment (including the nontradable sector) in industry i. Likewise, the demand for robots can be obtained as

$$d\ln R_c^M + d\ln M_c = \frac{s_c^L}{\varrho(1-s_c^L)}(1-s_c^L\pi_c)\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i} - s_c^L(d\ln W_c - d\ln R_c^M) + d\ln Y_c. \tag{A25}$$

Once again from the ideal price index condition, we have

$$\alpha(1-s_c^L)d\ln R_c^M + \alpha s_c^L d\ln W_c + (1-\alpha)d\ln R_c^K = \frac{1}{\varrho}\alpha s_c^L\pi_c\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}. \tag{A26}$$

The supply of robots (equation (A4)) and the demand for capital (equation (A10)) remain unchanged. Combining these equations, we obtain a generalization of Proposition A2.

PROPOSITION A4 *Suppose that $\pi_c > 0$ and $\theta_i = \theta_0 \geq 0$. Then*

$$\begin{aligned} d\ln L_c =& \left[-\zeta_c^{disp}\phi + \zeta_c^{prod}\phi\pi_c - \zeta_{c,L}^{inc}\phi\psi\right]\cdot\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M}, \\ d\ln W_c =& \left[-\zeta_c^{disp}\varepsilon + \zeta_c^{prod}\varepsilon\pi_c + \zeta_{c,W}^{inc}\psi\right]\cdot\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M}, \end{aligned}$$

where the ζ's are given by the unique solution to the system of equations given by (A15), (A20), (A23), (A24), (A25) and (A26).

When $\theta_0 = 0$ as assumed in the main text, we have $\zeta_c^{disp} = \zeta^{disp} = (1+\eta-\alpha)/\Lambda$, $\zeta_c^{prod} = \zeta^{prod} = (1+\eta+(1-\phi)(1-\alpha))/\Lambda$, $\zeta_{c,L}^{inc} = (1-\phi+\phi\alpha)\pi_c/\Lambda$, $\zeta_{c,W}^{inc} = (1-\phi+\phi\alpha)(\pi_c-(1-\pi_c(1-\alpha+\eta))/\Lambda$, and $\Lambda = \frac{\gamma_L}{\gamma_M}\phi\left((1-\alpha)\phi+\psi(1-\phi+\phi\alpha)+\varepsilon\right)$.

Proof: The proof of this proposition follows by noting that now equations (A15), (A20), (A23), (A24), (A25) and (A26) can be uniquely solved for $d\ln L_c, d\ln W_c, d\ln M_c, d\ln R_c^M, d\ln Y_c$, and $d\ln R_c^K$, and yield the above expressions for $d\ln L_c$ and $d\ln W_c$.

Note that as $\theta_0 \downarrow 0$ and $s_c^L \uparrow 1$, we still have that equations (A15), (A20), (A23), (A24), (A25) and (A26) can be uniquely solved for $d\ln L_c$, $d\ln W_c$, $d\ln Y_c$, $d\ln R_c^K$ and the transformed variables $d\ln \tilde{R}_c^M = (1-s_c^L)d\ln R_c^M$ and $d\ln \tilde{M}_c = (1-s_c^L)d\ln M_c$. ■

A2 Trade Equilibrium

We next study the equilibrium of the model where there is trade between commuting zones.

First recall that in this case there is an exogenously given supply of capital for the entire economy, K. Next, we turn to the supply of labor. First, note that given the preferences in (7), a fraction ϕ of income will be spent on the tradable good C_c and a fraction $1-\phi$ on the nontradable good, which implies that

$$S_c = \frac{1}{W_c}(1-\phi)\left(W_cL_c + \chi_c^{\Pi}\Pi\right),$$

where χ_c^{Π} is the share of capital gains owned by households in commuting zone c. Because we took the tradable good Y_c as the numeraire, the consumer price index is again given by (A22), and the labor supply now satisfies

$$W_c^{\phi+(1-\phi)\psi} = (1-\phi)^{1-\phi(1+\psi)}\phi^{\phi}B\left(W_cL_c+\chi_c^{\Pi}\Pi\right)^{\psi}L_c^{\varepsilon}. \tag{A27}$$

The supply of robots continues to be given as in equation (A4).

From equation (8), the price of the (tradable) good of industry i in every commuting zone is given by

$$P_i^Y = \left(\sum_{o\in\mathcal{C}}\upsilon_{oi}{P_{oi}^X}^{1-\lambda}\right)^{\frac{1}{1-\lambda}}. \tag{A28}$$

Since the price of the tradable good aggregate is chosen as the numeraire, the ideal price index condition now becomes

$$1 = \sum_{i\in\mathcal{I}}\nu_i {P_i^Y}^{1-\sigma}. \tag{A29}$$

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With similar steps to our analysis in the autarky model, the demand for labor takes the form

$$\begin{aligned}W_cL_c =&\sum_{i\in\mathcal{I}} W_cL_{ci} + W_cL_c^S \\ =&\sum_{i\in\mathcal{I}} \alpha s_{ci}^L P_{ci}^X X_{ci} + (1-\phi)\left(W_cL_c + \chi_c^\Pi \Pi\right).\end{aligned}$$

Also, equations (1) and (8) imply that

$$\begin{aligned}X_{ci} =&\sum_{d\in\mathcal{C}} X_{cdi} \\ =&\sum_{d\in\mathcal{C}} \upsilon_{ci} Y_{di} {P_i^Y}^{\lambda} {P_{ci}^X}^{-\lambda} \\ =&\sum_{d\in\mathcal{C}} \upsilon_{ci}\nu_i Y_d {P_i^Y}^{\lambda-\sigma} {P_{ci}^X}^{-\lambda} \\ =&\upsilon_{ci}\nu_i {P_i^Y}^{\lambda-\sigma} {P_{ci}^X}^{-\lambda} \sum_{d\in\mathcal{C}} Y_d \\ =&\upsilon_{ci}\nu_i {P_i^Y}^{\lambda-\sigma} {P_{ci}^X}^{-\lambda} Y.\end{aligned}$$

Using this formula for X_{ci}, we obtain a simplified expression for labor demand in commuting zone c as

$$W_cL_c = \sum_{i\in\mathcal{I}} \alpha s_{ci}^L \upsilon_{ci}\nu_i {P_i^Y}^{\lambda-\sigma} {P_{ci}^X}^{1-\lambda} Y + (1-\phi)\left(W_cL_c + \chi_c^\Pi\Pi\right). \tag{A30}$$

Similarly, the demand for robots is

$$R_c^M M_c = \sum_{i\in\mathcal{I}} \alpha(1-s_{ci}^L)\upsilon_{ci}\nu_i {P_i^Y}^{\lambda-\sigma} {P_{ci}^X}^{1-\lambda} Y, \tag{A31}$$

and the demand for capital is given by

$$R^K K = (1-\alpha)Y. \tag{A32}$$

Finally, the national capital gains are given by

$$\Pi = Y - \sum_{c\in\mathcal{C}} W_cL_c - \sum_{c\in\mathcal{C}} D^{-1-\eta}(1+\eta)^{-1-\eta} M_c^{1+\eta}. \tag{A33}$$

Definition 2 *An equilibrium of the trade model is given by a set of factor prices $\{W_c, R_c^M\}_{c\in\mathcal{C}}$, factor supplies $\{L_c, M_c\}_{c\in\mathcal{C}}$, and national aggregates Y, R^K, and Π such that:*

- *factors supplies are given by (A4) and (A30);*
- *factor prices satisfy the ideal price index condition, equations (A28) and (A29);*
- *factor markets clear, that is, equations (A30), (A31), and (A32) hold;*
- *capital gains are given by equation (A33).*

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Proposition A5 *An equilibrium of the trade model exists.*

Proof (sketch): Existence follows from a standard fixed point argument. Our economy consists of $|\mathcal{C}|$ (representative) households, $|\mathcal{C}|$ nontradable goods, $|\mathcal{C}| \times |\mathcal{I}|$ tradable intermediates, $|\mathcal{C}|$ nontradable robot inputs, $|\mathcal{C}|$ types of labor inputs, and $|\mathcal{C}|$ final goods. The production possibilities sets of all of these goods, which use labor, capital and a subset of the other goods, are convex, and consumer preferences, defined over the $|\mathcal{C}|$ final goods and labor supply, are continuous and strictly concave, and in fact, are also homothetic. Existence of equilibrium then follows by constructing the vector of the product of excess demands and prices, verifying compactness, and then applying Brouwer's fixed point theorem. Moreover, the first welfare theorem applies and shows that equilibrium is Pareto optimal. ■

We next state and prove a generalized version of Proposition 3 in the text. To simplify the expressions, we also impose the following initial allocation of non-labor income across commuting zones $\chi_c^{\Pi} = \frac{W_c L_c}{\sum_{c' \in \mathcal{C}} W_{c'} L_{c'}}$, which ensures that the ratio of labor to non-labor income across commuting zones is constant. Note that this is only imposed for the baseline allocation.

Proposition A6 *Suppose that the initial allocation of non-labor income satisfies $\chi_c^{\Pi} = \frac{W_c L_c}{\sum_{c' \in \mathcal{C}} W_{c'} L_{c'}}$, $\pi_c = \pi_0 > 0$ and $\theta_i = \theta_0$. Then*

$$d\ln L_c = [-\bar{\zeta}^{disp}\phi + \bar{\zeta}^{prod}\phi\pi_0 - \bar{\zeta}_L^{inc}\phi\psi] \cdot \sum_{i\in\mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M} + \bar{\zeta_L}^Y d\ln Y + \bar{\zeta}_L^{\Pi} d\ln \Pi + \bar{\zeta}_L^G G_{c,US},$$

$$d\ln W_c = [-\bar{\zeta}^{disp}\varepsilon + \bar{\zeta}^{prod}\varepsilon\pi_0 + \bar{\zeta}_W^{inc}\psi] \cdot \sum_{i\in\mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M} + \bar{\zeta}_W^Y d\ln Y + \bar{\zeta}_W^{\Pi} d\ln \Pi + \bar{\zeta}_W^G G_{c,US},$$

where the $\bar{\zeta}$'s are the unique solution to the system of equations given by Equations (A15), (A36), (A37), (A38) and (A39), and

$$G_{c,US} = (\lambda - \sigma)\sum_{i\in\mathcal{I}} \ell_{ci} \sum_{o\in\mathcal{C}} \upsilon_{oi} \left(\frac{P_{oi}^X}{P_i^Y}\right)^{1-\lambda} \left(\alpha s^L d\ln W_o + \alpha(1-s^L) d\ln R_o^M\right). \tag{A34}$$

Moreover, when $\theta_0 = 0$, we have $\bar{\zeta}^{disp} = (1+\eta+(\lambda-1)\alpha\eta)/\Lambda$, $\bar{\zeta}^{prod} = (1-\alpha+\eta+(\lambda-1)\alpha\eta+\sigma\alpha)/\Lambda$, $\bar{\zeta}_L^{inc} = \alpha(\pi_0(\sigma-1)\alpha - (1-\pi_0)(1+\eta+(\lambda-1)\alpha\eta))/\Lambda$, $\bar{\zeta}_W^{inc} = (1-\phi+\phi\alpha)(\pi_0(\sigma-1)\alpha - (1-\pi_0)(1+\eta+(\lambda-1)\alpha\eta)/\Lambda$, and

$$\Lambda = \frac{\gamma_L}{\gamma_M}\phi\left(\phi + \varepsilon\left(1 + \frac{(\lambda-1)\alpha^2}{1-\phi+\phi\alpha}\right) + \psi(1-\phi+(\lambda-1)\alpha^2)\right) > 0.$$

Proof: First, note that when $\pi_c = \pi_0$ and $\theta_i = \theta_0$, we have $s_{ci}^L = s^L$ for all i and c.

Next the change in household income in a commuting zone c is given by

$$\begin{aligned} d\ln\left(W_cL_c+\chi_c^{\Pi}\Pi\right)=&\frac{W_cL_c}{W_cL_c+\chi_c^{\Pi}\Pi}(d\ln W_c+d\ln L_c)+\left(1-\frac{W_cL_c}{W_cL_c+\chi_c^{\Pi}\Pi}\right)d\ln\Pi\\ =&\frac{\sum_{c'\in\mathcal{C}}W_{c'}L_{c'}}{\sum_{c'\in\mathcal{C}}W_{c'}L_{c'}+\Pi}(d\ln W_c+d\ln L_c)+\left(1-\frac{\sum_{c'\in\mathcal{C}}W_{c'}L_{c'}}{\sum_{c'\in\mathcal{C}}W_{c'}L_{c'}+\Pi}\right)d\ln\Pi\\ =&\left(1-\phi+\phi\frac{\alpha s^L}{1-\iota}\right)(d\ln W_c+d\ln L_c)+\left(\phi-\phi\frac{\alpha s^L}{1-\iota}\right)d\ln\Pi, \end{aligned}$$

where $\iota=\sum_{c\in\mathcal{C}}I_c/Y$. Collecting terms, this expression can be rewritten as

$$d\ln\left(W_cL_c+\chi_c^{\Pi}\Pi\right)=\omega^L(d\ln W_c+d\ln L_c)+(1-\omega^L)d\ln\Pi, \tag{A35}$$

where $\omega^L=1-\phi+\phi\frac{\alpha s^L}{1-\iota}$ is the overall labor share in the economy.

Differentiating and rearranging equation (A27) and combining it with (A35), we obtain the following expression for labor demand in commuting zone c,

$$(\phi+(1-\phi)\psi)d\ln W_c=\psi\omega^L(d\ln W_c+d\ln L_c)+\psi\left(1-\omega^L\right)d\ln\Pi+\varepsilon d\ln L_c. \tag{A36}$$

The supply of robots continues to be given by equation (A15).

Moreover, again from equation (A30), we can express labor demand in commuting zone c as

$$\begin{aligned} d\ln W_c+d\ln L_c=&+\varrho d\ln Y+(1-\varrho)\left(\omega^L(d\ln W_c+d\ln L_c)+\left(1-\omega^L\right)d\ln\Pi\right)\\ &-(1-s^L\pi_0)\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}+\varrho(1-s^L)(d\ln W_c-d\ln R_c^M)\\ &+(1-\lambda)\sum_{i\in\mathcal{I}}\ell_{ci}d\ln P_{ci}^X+(\lambda-\sigma)\sum_{i\in\mathcal{I}}\ell_{ci}d\ln P_i^Y. \end{aligned}$$

where ϱ denotes the baseline share of employment in the tradable sector.

To simplify this expression, note that equation (A28) implies

$$\begin{aligned} d\ln P_i^Y=&\sum_{o\in\mathcal{C}}\upsilon_{oi}\left(\frac{P_{oi}^X}{P_i^Y}\right)^{1-\lambda}d\ln P_{oi}^X\\ =&\sum_{o\in\mathcal{C}}\upsilon_{oi}\left(\frac{P_{oi}^X}{P_i^Y}\right)^{1-\lambda}\left(\alpha s^Ld\ln W_o+\alpha(1-s^L)d\ln R_o^M+(1-\alpha)d\ln R^K-\alpha s^L\pi_0\frac{d\theta_i}{1-\theta_i}\right)\\ =&(1-\alpha)d\ln R^K-\alpha s^L\pi_0\frac{d\theta_i}{1-\theta_i}+\sum_{o\in\mathcal{C}}\upsilon_{oi}\left(\frac{P_{oi}^X}{P_i^Y}\right)^{1-\lambda}\left(\alpha s^Ld\ln W_o+\alpha(1-s^L)d\ln R_o^M\right). \end{aligned}$$

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Using this expression for $d\ln P_i^Y$, we can further simplify our labor demand expression as

$$\begin{aligned} d\ln W_c + d\ln L_c =& \varrho d\ln Y + (1-\varrho)\left(\omega^L(d\ln W_c + d\ln L_c) + \left(1-\omega^L\right)d\ln \Pi\right) \\ & - (1 - s^L\pi_0 + (1-\sigma)\alpha s^L\pi_0)\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i} + \varrho(1-s^L)(d\ln W_c - d\ln R_c^M) \\ & + \varrho(1-\lambda)\left(\alpha s^L d\ln W_c + \alpha(1-s^L)d\ln R_c^M\right) + \varrho(1-\sigma)(1-\alpha)d\ln R^K \\ & + G_{c,US}, \end{aligned} \tag{A37}$$

where $G_{c,US}$ is given in equation (A34).

Similarly, the expression for the demand for robots in equation (A31) can be rearranged to obtain

$$\begin{aligned} d\ln R_c^M + d\ln M_c =& d\ln Y \\ & + \frac{1}{\varrho}\left(\frac{(1-s^L\pi_0)s^L}{(1-s^L)} + (\sigma-1)\alpha s^L\pi_0\right)\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i} - s^L(d\ln W_c - d\ln R_c^M) \\ & + (1-\lambda)\left(\alpha s^L d\ln W_c + \alpha(1-s^L)d\ln R_c^M\right) + (1-\sigma)(1-\alpha)d\ln R^K \\ & + \frac{1}{\varrho}G_{c,US}, \end{aligned} \tag{A38}$$

while the demand for capital, equation (A10), implies

$$d\ln R^K = d\ln Y. \tag{A39}$$

Equations (A15), (A36), (A37), (A38) and (A39) define a system of five linear equations and five unknowns, $d\ln L_c, d\ln W_c, d\ln R_c^M, d\ln M_c$, and $d\ln R^K$. Solving this system of equations yields the formulas for $d\ln L_c$ and $d\ln W_c$ given in the proposition.

Moreover, as $\theta_0 \downarrow 0$ and $s_c^L \uparrow 1$, we still have that equations (A15), (A36), (A37), (A38) and (A39) can be uniquely solved for $d\ln L_c$, $d\ln W_c$, $d\ln R^K$ and the transformed variables $d\ln \tilde{R}_c^M = (1-s_c^L)d\ln R_c^M$ and $d\ln \tilde{M}_c = (1-s_c^L)d\ln M_c$. Solving this system of equations yields the formulas for $d\ln L_c$ and $d\ln W_c$ given in the proposition for $\theta_0 = 0$. ■

The next proposition shows how aggregate effects of robots can be computed in the economy with trade. We simplify the analysis by focusing on the case we use in our quantitative exercise where $\pi_c = \pi_0$ and $\theta_i = \theta_0$.

Proposition A7 *Suppose that the initial allocation of non-labor income satisfies* $\chi_c^\Pi = \frac{W_c L_c}{\sum_{c'\in\mathcal{C}} W_{c'}L_{c'}}$, $\pi_c = \pi_0 > 0$, *and* $\theta_i = \theta_0 \geq 0$. *Let* $d\ln L = \sum_{c\in\mathcal{C}}\chi_c^W d\ln L_c$ *and* $d\ln W = \sum_{c\in\mathcal{C}}\chi_c^W d\ln W_c$ *denote the average change in employment and wages across commuting zones, where* χ_c^W *denotes* *the share of the national wage bill paid in commuting zone c. Then*

$$d\ln L = \left[-\zeta^{disp}\phi + \zeta^{prod}\phi\pi - \zeta_L^{inc}\phi\psi\right] \cdot \sum_c \chi_c^W \sum_{i\in\mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M},$$
$$d\ln W = \left[-\zeta^{disp}\varepsilon + \zeta^{prod}\varepsilon\pi - \zeta_W^{inc}\psi\right] \cdot \sum_c \chi_c^W \sum_{i\in\mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M},$$

where the ζ's coincide with those given in Proposition A4 for $\pi_c = \pi_0$, and $s_c^L = s^L$. In particular, when in addition $\theta_0 = 0$, we have $\zeta^{disp} = (1+\eta-\alpha)/\Lambda$, $\zeta^{prod} = (1+\eta+(1-\phi)(1-\alpha))/\Lambda$, $\zeta_L^{inc} = (1-\phi+\phi\alpha)\pi_0/\Lambda$, $\zeta_W^{inc} = (1-\phi+\phi\alpha)(\pi_0-(1-\pi_0(1-\alpha+\eta))/\Lambda$, and $\Lambda = \frac{\gamma_L}{\gamma_M}\phi\left((1-\alpha)\phi+\psi(1-\phi+\phi\alpha)+\varepsilon\right)$

Proof: Let L_c^T denote total employment in the tradable sector. First, note that we can rewrite χ_c^W as

$$\begin{aligned}\chi_c^W =& \frac{W_cL_c}{\sum_{s\in\mathcal{C}} W_sL_s}\\ =& \frac{W_cL_c^T}{\sum_{s\in\mathcal{C}} W_sL_s^T}\\ =& \frac{\alpha s^L \sum_{i\in\mathcal{I}} X_{ci}P_{ci}^X}{\alpha s^L Y}\\ =& \frac{\sum_{i\in\mathcal{I}} X_{ci}P_{ci}^X}{Y},\end{aligned}$$

That is, because all commuting zones have the same factor intensity, χ_c^W is equal to the share of output generated by commuting zone c within the tradable sector (recall that Y denotes the aggregate output of the tradable sector).

Using the fact that $\Pi + \sum_c W_cL_c = \frac{1}{\phi}(Y-I)$, we obtain

$$\omega^L(d\ln W + d\ln L) + \left(1-\omega^L\right)d\ln\Pi = \left(\frac{1}{1-\iota_c}d\ln Y - \frac{\iota_c}{1-\iota_c}(1+\eta)d\ln M\right) \tag{A40}$$

Differentiating, rearranging and summing equation (A27) across commuting zones yields an expression for average wages in the United States,

$$(\phi+(1-\phi)\psi)d\ln W = \psi\omega^L(d\ln W + d\ln L) + \psi\left(1-\omega^L\right)d\ln\Pi + \varepsilon d\ln L,$$

which Can be simplified by substituting from equation (A40) and using the fact that $\iota = \frac{\alpha(1-s^L)}{1+\eta}$:

$$(\phi+(1-\phi)\psi)d\ln W = \frac{\psi}{1-\frac{\alpha(1-s^L)}{1+\eta}}\left(d\ln Y - \alpha(1-s^L)d\ln M\right) + \varepsilon d\ln L. \tag{A41}$$

Adding up equation (A15) across commuting zones yields

$$d\ln R^M = \eta d\ln M, \tag{A42}$$

where $d\ln R^M = \sum_{c\in\mathcal{C}} \chi_c^W d\ln R_c^M$ and $d\ln M = \sum_{c\in\mathcal{C}} \chi_c^W d\ln M_c$.

Now differentiating and rearranging (A30), and summing over commuting zones, we obtain an aggregated version of the labor demand equation demand in equation,

$$\begin{aligned} d\ln W + d\ln L =& \varrho d\ln Y + (1-\varrho)\left(\omega^L(d\ln W + d\ln L) + \left(1-\omega^L\right)d\ln\Pi\right) \\ & - (1-s^L\pi_0)\sum_{c\in\mathcal{C}}\chi_c^W\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i} + (1-s^L)(d\ln W - d\ln R^M) \\ & + (1-\lambda)\sum_{c\in\mathcal{C}}\sum_{i\in\mathcal{I}}\chi_c^W\ell_{ci}d\ln P_{ci}^X + (\lambda-\sigma)\sum_{c\in\mathcal{C}}\sum_{i\in\mathcal{I}}\chi_c^W\ell_{ci}d\ln P_i^Y. \end{aligned}$$

This equation simplifies to

$$\begin{aligned} d\ln W + d\ln L =& \varrho d\ln Y + \frac{1-\varrho}{1-\frac{\alpha(1-s^L)}{1+\eta}}\left(d\ln Y - \alpha(1-s^L)d\ln M\right) \\ & - (1-s^L\pi_0)\sum_{c\in\mathcal{C}}\chi_c^W\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i} + \varrho(1-s^L)(d\ln W - d\ln R^M) \end{aligned} \tag{A43}$$

by using equation (A40) and noting that $\sum_{c\in\mathcal{C}}\sum_{i\in\mathcal{I}}\chi_c^W\ell_{ci}d\ln P_{ci}^X = 0$ and $\sum_{c\in\mathcal{C}}\sum_{i\in\mathcal{I}}\chi_c^W\ell_{ci}d\ln P_i^Y = 0$. These last two observations follow from the price index in equation (A28) and the ideal price index condition in equation (A29). In particular, for the former, note that

$$\begin{aligned} \sum_{c\in\mathcal{C}}\sum_{i\in\mathcal{I}}\chi_c^W\ell_{ci}d\ln P_i^Y =& \varrho\sum_{i\in\mathcal{I}}\sum_{c\in\mathcal{C}}\chi_c^W\chi_{ci}d\ln P_i^Y \\ =& \varrho\sum_{i\in\mathcal{I}}\sum_{c\in\mathcal{C}}\frac{\sum_{j\in\mathcal{I}}X_{cj}P_{cj}^X}{Y}\frac{X_{ci}P_{ci}^X}{\sum_{j\in\mathcal{I}}X_{cj}P_{cj}^X}d\ln P_i^Y \\ =& \varrho\sum_{i\in\mathcal{I}}\sum_{c\in\mathcal{C}}\frac{X_{ci}P_{ci}^X}{Y}d\ln P_i^Y \\ =& \varrho\sum_{i\in\mathcal{I}}\frac{Y_iP_i^Y}{Y}d\ln P_i^Y \\ =& 0, \end{aligned}$$

which follows from equation (A29) (recall that χ_{ci} is the share of industry i in value added in commuting zone c). In this derivation, we used Y_i to denote the total output of industry i, so that $Y_iP_i^Y = \sum_c X_{ci}P_{ci}^X$, and we also used $\ell_{ci} = \varrho\chi_{ci}$, which follows from the fact that all tradable sectors have the same labor intensity.

Likewise,

$$\begin{aligned}
\sum_{c\in\mathcal{C}}\sum_{i\in\mathcal{I}}\chi_c^W \ell_{ci} d\ln P_{ci}^X =&\varrho\sum_{i\in\mathcal{I}}\sum_{c\in\mathcal{C}}\chi_c^W\chi_{ci} d\ln P_{ci}^X\\
=&\varrho\sum_{i\in\mathcal{I}}\sum_{c\in\mathcal{C}}\frac{\sum_{j\in\mathcal{I}} X_{cj}P_{cj}^X}{Y}\frac{X_{ci}P_{ci}^X}{\sum_{j\in\mathcal{I}} X_{cj}P_{cj}^X} d\ln P_{ci}^X\\
=&\varrho\sum_{i\in\mathcal{I}}\sum_{c\in\mathcal{C}}\frac{X_{ci}P_{ci}^X}{Y} d\ln P_{ci}^X\\
=&\varrho\sum_{i\in\mathcal{I}}\frac{Y_iP_i^Y}{Y}\sum_{c\in\mathcal{C}}\frac{X_{ci}P_{ci}^X}{Y_iP_i^Y} d\ln P_{ci}^X\\
=&\varrho\sum_{i\in\mathcal{I}}\frac{Y_iP_i^Y}{Y} d\ln P_i^Y\\
=&0,
\end{aligned}$$

where we have used the price index in equation (A28) and the ideal price index condition in equation (A29).

Following the same steps, we obtain aggregate robot demand from equation (A31) as

$$\begin{aligned}
d\ln R^M + d\ln M =& d\ln Y\\
&+\frac{1}{\varrho}\frac{(1-s^L\pi_0)s^L}{(1-s^L)}\sum_{c\in\mathcal{C}}\chi_c^W\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i} - s^L(d\ln W - d\ln R^M) \qquad \text{(A44)}
\end{aligned}$$

Finally, the fact that $\sum_{i\in\mathcal{I}}\sum_{c\in\mathcal{C}}\chi_c^W\chi_{ci} d\ln P_{ci}^X = 0$ also implies

$$\sum_{c\in\mathcal{C}}\chi_c^W\sum_{i\in\mathcal{I}}\chi_{ci}(\alpha s^L d\ln W_c + \alpha(1-s^L)d\ln R_c^M + (1-\alpha)d\ln R^K) = \sum_{c\in\mathcal{C}}\chi_c^W\sum_{i\in\mathcal{I}}\chi_{ci}\alpha s^L\pi_0\frac{d\theta_i}{1-\theta_i}.$$

Using the fact that $\ell_{ci} = \varrho\chi_{ci}$ and the definition of $d\ln W$ and $d\ln R^M$, we can rewrite this equation as

$$\alpha s^L d\ln W + \alpha(1-s^L)d\ln R^M + (1-\alpha)d\ln R^K = \frac{1}{\varrho}\alpha s^L\pi_0\sum_{c\in\mathcal{C}}\chi_c^W\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}. \qquad \text{(A45)}$$

Finally, taking logs and differentiating the demand for capital in equation (A32), we have

$$d\ln R^K = d\ln Y \qquad \text{(A46)}$$

Equations (A41), (A42), (A43), (A44), (A45) and (A46) define a system of six linear equations in six unknowns. Solving this system of equations yields the formulas for $d\ln L$ and $d\ln W$ in the proposition.

Moreover, as $\theta_0 \downarrow 0$ and $s_c^L \uparrow 1$, we still have that equations (A41), (A42), (A43), (A44), (A45) and (A46) can be uniquely solved for $d\ln L$, $d\ln W$, $d\ln R^K$, $d\ln Y$ and the transformed

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variables $d\ln\tilde{R}^M = (1-s^L)d\ln R^M$ and $d\ln\tilde{M} = (1-s^L)d\ln M$. Solving this system of equations yields the formulas for $d\ln L$ and $d\ln W$ given in the proposition for $\theta_0 = 0$. ■

A3 Details of the Quantitative Exercise

Propositions A6 and A7 show how to compute the local and aggregate effects of robot adoption in terms of the parameters of our model, the share of labor in production tasks, s^L, and the share of (non-robot) capital, $1-\alpha$. Here, we provide some of the details omitted from the text of how we choose parameter values to perform our quantitative exercise.

1. First, recall that $\gamma_M/\gamma_L = 3$ as explained in the text.

2. Let us next turn to the share of labor in production tasks, s^L. Our model implies that, among industries using robots, the baseline ratio of robots per thousand workers in the US is
$$1000\frac{M_i}{L_i} = 1000\frac{\theta_0}{1-\theta_0}\frac{\gamma_L}{\gamma_M}.$$
In 1993, the US had around four robots per thousand workers in industries using robots (which are almost entirely in manufacturing). Since $\gamma_M/\gamma_L = 3$, this implies $\frac{\theta_0}{1-\theta_0} = 0.012$.
We can then compute the labor share in production tasks as
$$s^L = \frac{\frac{1-\theta_0}{\theta_0}\frac{1}{1-\pi_0}}{\frac{1-\theta_0}{\theta_0}\frac{1}{1-\pi_0}+1} = 0.9916.$$
This implies that in 1993, labor accounted for 99.16 percent of the value added in tasks that can be automated using industrial robots, and robots accounted for the remaining 0.84 percent.

3. Because the overall labor share in the economy is αs^L, the previous observation implies $\alpha = 0.67$ to match the labor share of 66.6 percent.

4. We equate tradables with manufacturing, which gives a share of employment in tradables of $\varrho = 0.18$. Using the fact that $\varrho = \frac{\alpha\phi}{1-\phi+\alpha\phi}$, we obtain $\phi = 0.25$.

5. We then choose the income elasticity of labor supply ψ to match empirical estimates of the propensity to consume leisure out of additional income. In particular, our labor supply equation implies
$$W_c\frac{dL_c}{dC_c} = -\frac{\psi}{\varepsilon}\frac{W_cL_c}{C_c} = -\frac{\psi}{\varepsilon}\omega^L,$$
where we used the fact that, in our model, $\frac{W_cL_c}{C_c} = \omega^L$—where ω^L is the share of labor in total value added.
Imbens, Rubin and Sacerdote (2001) estimate that the propensity to consume leisure out

of one additional dollar is about 0.1, which implies that

$$0.1 = \frac{\psi}{\varepsilon}\omega^L. \tag{A47}$$

6. Finally, we choose the value for ε (and thus for ψ from equation (A47)) as follows. Let $\beta_L = -\zeta^{\text{disp}}\phi + \zeta^{\text{prod}}\phi\pi_0 - \zeta^{L,\text{inc}}\phi\psi$ and $\beta_W = -\zeta^{\text{disp}}\varepsilon + \zeta^{\text{prod}}\varepsilon\pi_0 + \zeta^{W,\text{inc}}\psi$. By definition, $d\ln L_c = \beta_L \cdot \sum_{i\in\mathcal{I}} \ell_{ci}\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M}$ and $d\ln W_c = \beta_W \cdot \sum_{i\in\mathcal{I}} \ell_{ci}\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M}$ solve the system of equations given by (A15), (A36), (A37), (A38) and (A39) when $d\ln Y = d\ln\Pi = G_{c,US} = 0$. Next, substituting the formulas for $d\ln L_c$ and $d\ln W_c$ into (A36), we obtain the equation

$$(\phi + (1-\phi)\psi)\beta_W = \psi\omega^L(\beta_W + \beta_L) + \varepsilon\beta_L. \tag{A48}$$

Solving equations (A47) and (A48) simultaneously and using our IV estimates $\hat{\beta}_L$ and $\hat{\beta}_W$ yields

$$\begin{aligned}
\varepsilon =& \frac{\phi\hat{\beta}_W}{0.1(\hat{\beta}_W + \hat{\beta}_L) - \frac{0.1(1-\phi)}{\omega^L}\hat{\beta}_W + \hat{\beta}_L} = 0.17 \\
\psi =& \frac{0.1}{\omega^L}\frac{\phi\hat{\beta}_W}{0.1(\hat{\beta}_W + \hat{\beta}_L) - \frac{0.1(1-\phi)}{\omega^L}\hat{\beta}_W + \hat{\beta}_L} = 0.02.
\end{aligned}$$

Given the values of ψ and ε , η is chosen to match our IV estimate $\hat{\beta}_L$ (or $\hat{\beta}_W$). This yields $\eta = 0.79$.

A4 Additional Figures and Tables

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Journal of Political Economy 128(6). DOI: https://doi.org/10.1086/705716.

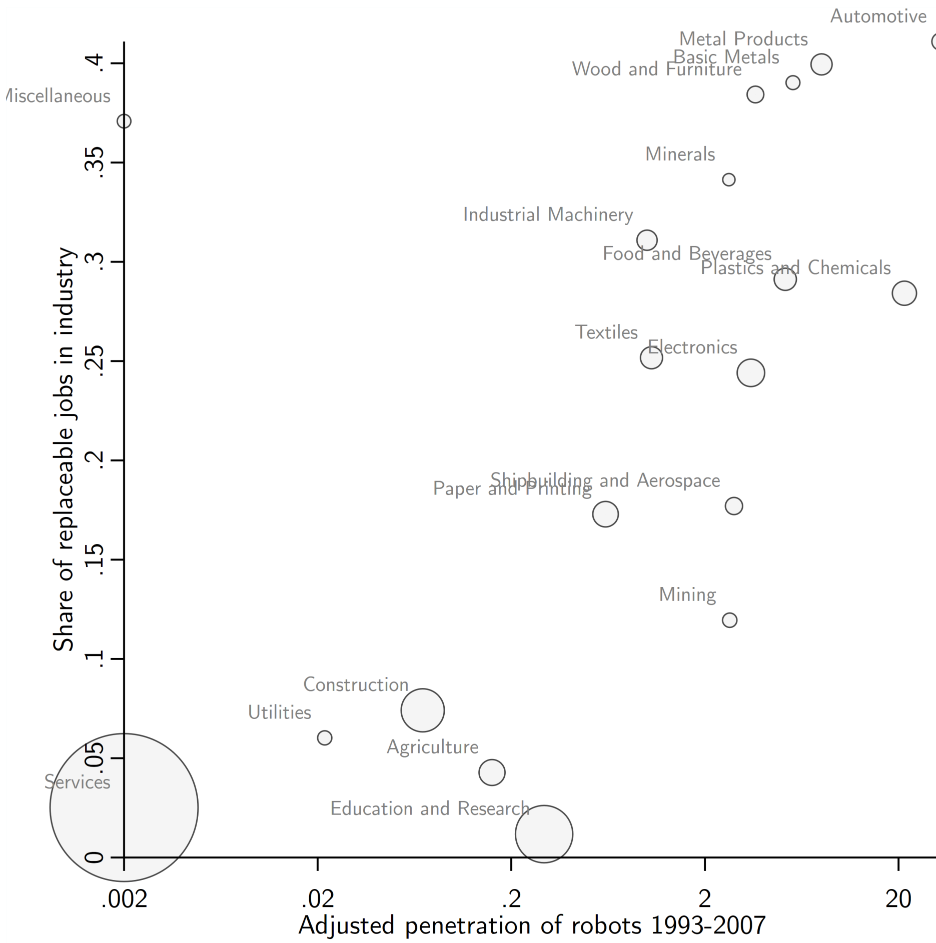

Figure A1: Adjusted robot penetration and share of replaceable jobs.
Plot of the adjusted penetration of robots between 1993 and 2007 ($\overline{APR}_i$) and the share of replaceable jobs by industry in 1990. The data on replaceable jobs are from Graetz and Michaels (2018). Marker size indicates the baseline US employment in the industry.

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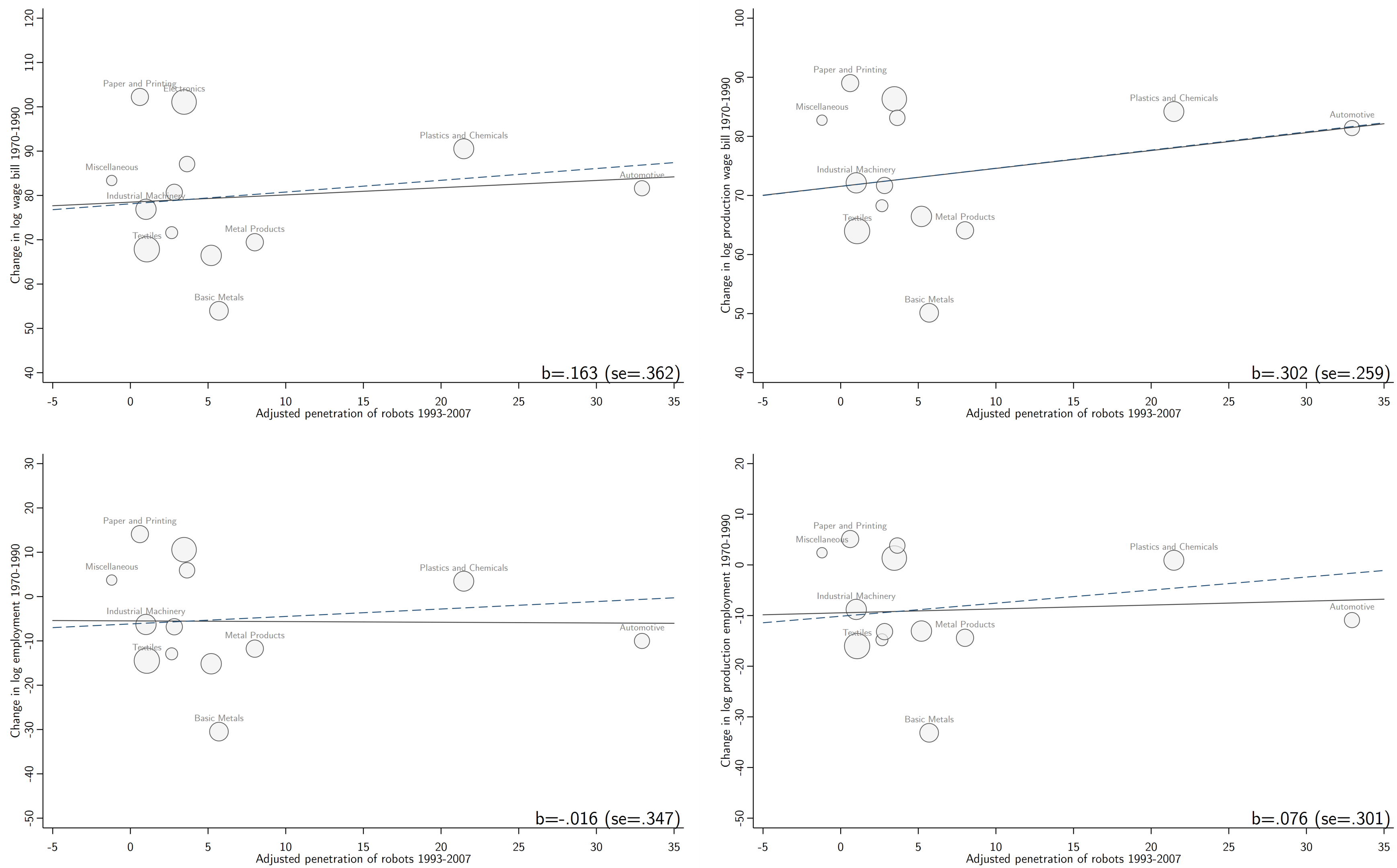

Figure A2: Industry pre-trends.

The figure presents residual plots of the relationship between the adjusted penetration of robots for 1993-2007 ($\overline{APR}_i$) and the 1970-1990 change in log wage bill (top left panel), log wage bill for production workers (top right panel), log employment (bottom left panel), and log employment for production workers (bottom right panel). The solid lines correspond to regression models analogous to those in columns 8-9 of Panels A and B of Table 1. The covariates from these models are partialled out. The coefficients for these models and their standard errors are reported next to each plot. The dashed line is for a regression which in addition excludes the automotive industry. Marker size indicates the baseline US employment in the industry.

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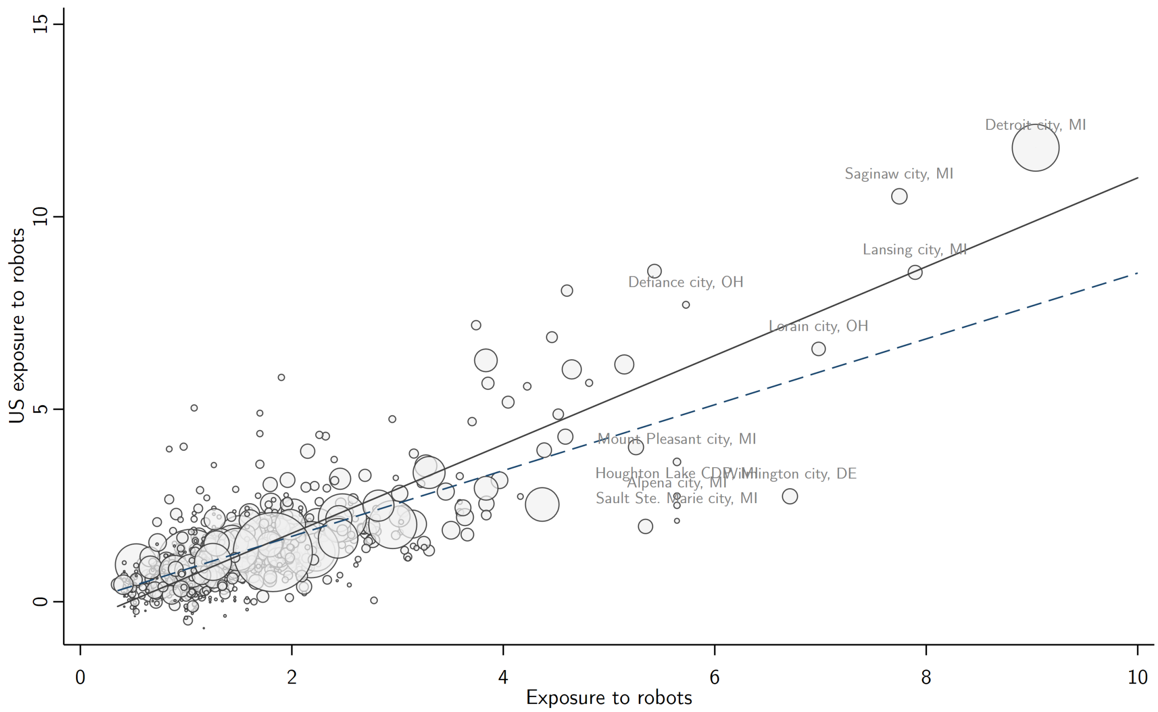

Figure A3: First-stage relationship for commuting zones.
The figure presents the relationship between exposure to robots for 1993-2007 (from $EURO5$) and US exposure to robots for 2004-2007 (rescaled to a 14-year equivalent change). The covariates from columns 3 and 6 of Table 7 are partialled out. The solid line corresponds to a regression with commuting zone population in 1990 as weights. The dashed line is for a regression which in addition excludes the top one percent of commuting zones with highest exposure to robots. Marker size indicates the 1990 population in the commuting zone.

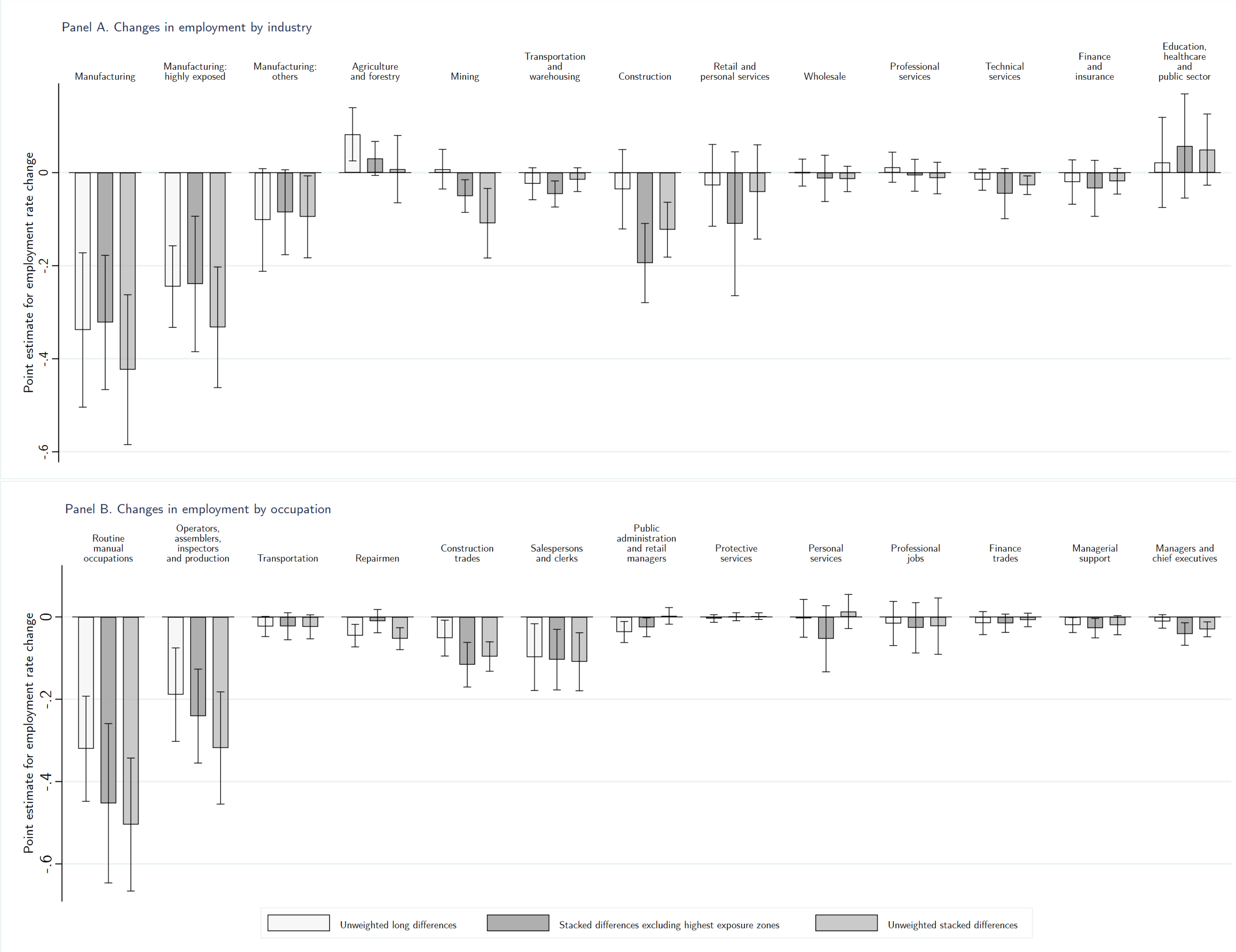

FIGURE A4: THE EFFECTS OF ROBOTS ON INDUSTRIES AND OCCUPATIONS, ADDITIONAL ESTIMATES.
The figure presents estimates of exposure to robots on the change in industry employment to population ratios (top panel) and the change in occupation employment to population ratios (bottom panel). The capped lines provide 95% confidence intervals. The first set of estimates are from long-differences specifications as in column 6 of Table 2. The second set of estimates are from stacked-differences specifications as in column 5 of Table 2 (where we remove the top one percent of commuting zones with highest exposure to robots). The third set of estimates are from stacked-differences specifications as in column 6 of Table 3 (unweighted).

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Table A1: Summary statistics: industry data

	Robots per thousand workers, *EURO5*				Robots per thousand workers, US			Baseline employment, US
IFR industry	1993	2000	2007	2014	2004	2007	2014	(thousands)
Manufacturing:								
Automotive	19.96	37.87	69.30	76.70	69.01	85.72	117.72	1110.78
Plastics and Chemicals	3.25	15.23	26.07	22.93	5.12	6.95	9.91	2205.11
Metal Products	8.51	13.70	21.81	21.24	4.60	5.84	8.29	1689.15
Industrial Machinery	3.99	4.67	7.41	11.74	1.32	1.67	2.37	1540.93
Food and Beverages	0.47	1.80	5.75	10.83	2.91	3.92	6.17	1862.25
Basic Metals	1.17	3.95	7.05	10.31	3.98	5.05	7.17	712.02
Electronics	2.88	5.94	9.85	7.11	5.71	8.66	13.11	2868.12
Miscellaneous Manufacturing	3.12	3.84	3.40	6.48	1.40	1.96	13.81	690.29
Minerals	0.77	2.01	3.78	4.99	0.12	0.23	0.67	557.74
Wood and Furniture	0.66	2.04	4.64	4.83	0.01	0.01	0.14	1047.85
Shipbuilding and Aerospace	0.83	4.56	4.05	3.09	0.05	0.12	0.54	1110.54
Textiles	0.33	1.03	1.27	1.53	0.00	0.01	0.05	1848.24
Paper and Printing	0.27	0.46	0.95	1.36	0.00	0.00	0.11	2467.12
Nonmanufacturing:								
Mining	0.32	2.00	3.16	2.14	0.00	0.01	0.06	763.19
Education and Research	0.04	0.21	0.35	0.40	0.01	0.01	0.06	12636.45
Agriculture	0.00	0.00	0.16	0.24	0.00	0.00	0.04	2551.58
Utilities	0.00	0.02	0.02	0.18	0.00	0.00	0.03	745.44
Construction	0.00	0.03	0.07	0.14	0.00	0.01	0.02	7107.59
Services	0.00	0.00	0.00	0.00	0.00	0.00	0.00	84775.62

The table shows the evolution of the stock of robots per thousand workers by industry. The number of robots is from the IFR and the number of workers in each industry is from EUKLEMS.

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Table A2: Adjusted penetration of robots in the US and in Europe

	Dependent variable: Adjusted penetration of robots, US			Dependent variable: Penetration of robots, US		
	Weighted by employment		Unweighted	Weighted by employment		Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. 1993-2007			
Adjusted penetration of	1.475	1.608	1.960	1.443	1.513	1.844
robots, $\overline{APR}_i$	(0.746)	(0.864)	(0.723)	(0.673)	(0.787)	(0.654)
Observations	19	19	19	19	19	19
R-squared	0.63	0.64	0.73	0.66	0.66	0.74
			Panel B. 2000-2007			
Adjusted penetration of	1.160	1.282	1.363	1.129	1.208	1.282
robots, $\overline{APR}_i$	(0.283)	(0.268)	(0.189)	(0.236)	(0.230)	(0.160)
Observations	19	19	19	19	19	19
R-squared	0.83	0.85	0.89	0.85	0.86	0.90
			Panel C. 2004-2007			
Adjusted penetration of	1.047	1.146	1.378	1.023	1.075	1.298
robots, $\overline{APR}_i$	(0.486)	(0.560)	(0.469)	(0.433)	(0.511)	(0.422)
Observations	19	19	19	19	19	19
R-squared	0.63	0.64	0.72	0.65	0.65	0.74
			Panel D. 2000-2014			
Adjusted penetration of	1.531	1.551	1.648	1.753	1.799	1.919
robots, $\overline{APR}_i$	(0.242)	(0.294)	(0.205)	(0.298)	(0.348)	(0.241)
Observations	19	19	19	19	19	19
R-squared	0.82	0.82	0.83	0.82	0.82	0.85
Covariates:						
Manufacturing dummy		✓	✓		✓	✓

The table presents estimates of the relationship between adjusted penetration of robots, $\overline{APR}_i$ from $EURO5$, and the penetration of robots in the US, APR_i. Columns 1-3 present estimates using the adjusted penetration of robots in the US as outcome. Columns 4-6 present estimates using the penetration of robots in the US as outcome (unadjusted for changes in output). Each panel presents results for a different time period; when necessary we rescale the penetration of robots in the US to match its length. Column 1 and 4 do not include any covariates. Columns 2-3 and 5-6 control for a dummy for manufacturing. The regressions in columns 1-2 and 2-3 are weighted by baseline industry employment in 1993, and the regressions in columns 3 and 6 are unweighted. Standard errors that are robust against heteroskedasticity are in parentheses.

Table A3: Industry-level correlations between adjusted penetration of robots and industry characteristics.

	Correlation with adjusted penetration of robots		
	Within manufacturing	Across all industries	Industry with largest value
Measures of trade competition:			
Chinese trade competition 1990-2007	-0.39	0.15	Textiles
Measures of offshoring:			
Mexican imports to the US 1990-2007	-0.03	0.31	Electronics
Share offshorable jobs in 1990	-0.41	-0.26	Textiles
Intermediate goods imports 1990-2007	-0.17	0.19	Electronics
Capital and other investments:			
Percent increase in capital stock 1990-2007	0.22	-0.37	Construction
Percent increase in IT capital stock 1990-2007	0.23	-0.17	Construction
Other industry characteristics:			
Share routine jobs in 1990	-0.24	-0.01	Paper and printing
Female share of employment in 1990	-0.30	-0.40	Textiles
Share replaceable jobs in 1990	0.41	0.64	Automotive

The table presents the correlation between adjusted penetration of robots for 1993 and 2007 ($\overline{APR}_{i,1993,2007}$) and several industry covariates. We present the correlation within manufacturing (across 13 industries) and the overall correlation (across 19 industries), with employment in 1993 as weights. The share of offshorable jobs, routine jobs, female workers, and replaceable jobs are all computed using the distribution of employment by industry in the 1990 Census. See the text for detailed definitions and sources of data.

Table A4: Industry-level results: different constructions of the adjusted penetration of robots, $\overline{APR}_i$

	Long differences, 1993-2007			Stacked differences, 1993-2000 and 2000-2007				Long differences, 1992-2007	
	CBP (all industries)	NBER-CES (within manufacturing)		CBP (all industries)		NBER-CES (within manufacturing)		BEA-IO (all industries)	
	Wage bill	Wage bill	Production workers bill	Wage bill	Wage bill	Wage bill	Production workers bill	Value added	Labor share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A. Baseline construction of the instrument					
Adjusted penetration of robots, $\overline{APR}_i$	-0.923	-0.816	-0.993	-1.096	-1.492	-1.037	-1.150	0.128	-0.797
	(0.419)	(0.378)	(0.324)	(0.235)	(0.481)	(0.177)	(0.205)	(0.061)	(0.281)
Observations	19	13	13	38	38	26	26	19	19
R-squared	0.91	0.84	0.91	0.90	0.95	0.87	0.91	0.72	0.37
				Panel B. Including penetration of robots in Germany					
Adjusted penetration of robots, $\overline{APR}_i$	-0.762	-0.678	-0.833	-0.941	-1.454	-0.881	-0.997	0.092	-0.620
	(0.273)	(0.246)	(0.184)	(0.158)	(0.414)	(0.094)	(0.136)	(0.062)	(0.267)
Observations	19	13	13	38	38	26	26	19	19
R-squared	0.91	0.84	0.91	0.90	0.95	0.86	0.91	0.70	0.34
				Panel C. Using penetration of robots among nine European countries with data					
Adjusted penetration of robots, $\overline{APR}_i$	-0.733	-0.647	-0.794	-0.914	-1.675	-0.843	-0.967	0.075	-0.562
	(0.240)	(0.218)	(0.161)	(0.149)	(0.450)	(0.094)	(0.176)	(0.057)	(0.259)
Observations	19	13	13	38	38	26	26	19	19
R-squared	0.91	0.84	0.91	0.90	0.95	0.86	0.91	0.68	0.32
				Panel D. Using penetration of robots without adjustment term					
Adjusted penetration of robots, $\overline{APR}_i$	-0.637	-0.572	-0.719	-0.836	-2.606	-0.757	-0.865	0.089	-0.569
	(0.257)	(0.235)	(0.174)	(0.177)	(1.038)	(0.132)	(0.289)	(0.057)	(0.249)
Observations	19	13	13	38	38	26	26	19	19
R-squared	0.91	0.84	0.91	0.90	0.95	0.85	0.90	0.71	0.35
				Panel E. Adjusting penetration of robots using robot prices					
Adjusted penetration of robots, $\overline{APR}_i$	-1.242	-1.061	-1.226	-1.279	-1.444	-1.214	-1.259	0.125	-0.921
	(0.379)	(0.330)	(0.249)	(0.224)	(0.568)	(0.137)	(0.164)	(0.082)	(0.364)
Observations	19	13	13	38	38	26	26	19	19
R-squared	0.92	0.86	0.92	0.91	0.95	0.88	0.92	0.70	0.36
Covariates:									
Time period dummies				✓	✓	✓	✓		
Industry shares	✓	✓	✓	✓	✓	✓	✓	✓	✓
Chinese imports	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry dummies					✓				

The table presents estimates of the relationship between adjusted penetration of robots and changes in log wage bill, log value added and labor share across US industries. Each panel presents results using a different construction of the measure for adjusted penetration of robots. Panel A presents results for our baseline construction. Panel B presents results including the penetration of robots in Germany. Panel C presents results using the data for nine European countries (Germany, Denmark, Finland, France, Italy, Sweden, Norway, Spain, and the UK) to construct the adjusted penetration of robots. Panel D presents results for the penetration of robots without the adjustment term in equation (12). Panel E present results adjusting the penetration of robots using the available data on robot prices (from Robotics Industries of America). Columns 1-3 present long-differences estimates for changes in log wage bill, 1993-2007. Columns 4-7 present stacked-differences estimates for changes in log wage bill, 1993-2000 and 2000-2007. Columns 8-9 present long-differences estimates for changes in log value added for 1992-2007 (annualized), and changes in labor share for 1992-2007. The sources of data and their coverage are reported at the top of the table, and the set of covariates is reported at the bottom of the table. All models control for dummies for manufacturing and light manufacturing, and exposure to Chinese imports by industry from Acemoglu et al. (2016). In addition, the stacked-differences models control for time period dummies, and in column 5 for industry dummies. The regressions in columns 1-7 are weighted by baseline industry employment in 1993, and the regressions in columns 8-9 are weighted by baseline value added by industry in 1992. Standard errors that are robust against heteroskedasticity and serial correlation at the industry level are in parentheses.

Table A5: Industry-level results: different time periods

	Estimates for change in log wage bill			Estimates for change in log employment		
	CBP	NBER-CES, all workers	NBER-CES, production workers	CBP	NBER-CES, all workers	NBER-CES, production workers
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. 1993-2010			
Adjusted penetration of robots, $\overline{APR_i}$	-1.509	-1.351	-1.618	-1.292	-1.147	-1.295
	(0.683)	(0.665)	(0.687)	(0.459)	(0.419)	(0.454)
Observations	19	13	13	19	13	13
R-squared	0.93	0.85	0.88	0.94	0.89	0.90
			Panel B. 2000- 2010			
Adjusted penetration of robots, $\overline{APR_i}$	-2.091	-2.076	-2.311	-1.726	-1.537	-1.616
	(0.472)	(0.441)	(0.488)	(0.358)	(0.291)	(0.378)
Observations	19	13	13	19	13	13
R-squared	0.82	0.76	0.76	0.84	0.81	0.79
			Panel C. 2004-2010			
Adjusted penetration of robots, $\overline{APR_i}$	-4.040	-3.882	-4.377	-3.117	-2.616	-2.656
	(1.770)	(1.951)	(2.149)	(1.365)	(1.420)	(1.754)
Observations	19	13	13	19	13	13
R-squared	0.64	0.45	0.43	0.65	0.46	0.40
			Panel D. 2000-2007			
Adjusted penetration of robots, $\overline{APR_i}$	-1.188	-1.169	-1.351	-0.941	-1.039	-1.165
	(0.184)	(0.151)	(0.140)	(0.155)	(0.159)	(0.157)
Observations	19	13	13	19	13	13
R-squared	0.89	0.86	0.89	0.90	0.88	0.90
			Panel E. 2004-2007			
Adjusted penetration of robots, $\overline{APR_i}$	-2.408	-2.200	-2.668	-1.751	-1.873	-2.247
	(0.565)	(0.746)	(0.768)	(0.325)	(0.507)	(0.577)
Observations	19	13	13	19	13	13
R-squared	0.79	0.65	0.68	0.64	0.68	0.68
Covariates:						
Industry shares	✓	✓	✓	✓	✓	✓
Chinese imports	✓	✓	✓	✓	✓	✓

The table presents estimates of the relationship between adjusted penetration of robots and changes in log wage bill and log employment across US industries. Columns 1-3 present estimates for changes in log wage bill for 1993-2010 (Panel A), 2000-2010 (Panel B), 2004-2010 (Panel C), 2000-2007 (Panel D), 2004-2007 (Panel E). Columns 4-6 present estimates for changes in log employment for 1993-2010 (Panel A), 2000-2010 (Panel B), 2004-2010 (Panel C), 2000-2007 (Panel D), 2004-2007 (Panel E). The sources of data and their coverage are reported at the top of the table, and the set of covariates is reported at the bottom of the table. All models control for dummies for manufacturing and light manufacturing, and exposure to Chinese imports by industry from Acemoglu et al. (2016). All regressions are weighted by baseline industry employment. Standard errors that are robust against heteroskedasticity are in parentheses.

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Table A6: Robots and labor demand: control for other industry trends

	Estimates for changes in log wage bill					
	Long differences 1993-2007			Stacked differences 1993-2000 and 2000-2007		
	CBP (all industries)	NBER-CES (within manufacturing)		CBP (all industries)	NBER-CES (within manufacturing)	
	All workers	All workers	Production workers	All workers	All workers	Production workers
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Control for trends in value added						
Adjusted penetration of robots, $\overline{APR}_i$	-1.387	-1.636	-1.799	-1.446	-1.556	-1.655
	(0.443)	(0.453)	(0.373)	(0.259)	(0.248)	(0.213)
Percent change in value added, 1992-2007	0.460	0.669	0.671	0.230	0.317	0.317
	(0.153)	(0.117)	(0.119)	(0.065)	(0.047)	(0.057)
Observations	19	13	13	38	26	26
R-squared	0.92	0.84	0.89	0.91	0.86	0.90
Panel B. Instrument trends in value added using intermediate import availability						
Adjusted penetration of robots, $\overline{APR}_i$	-1.668	-1.453	-1.583	-1.706	-1.559	-1.617
	(0.319)	(0.408)	(0.392)	(0.263)	(0.282)	(0.297)
Percent change in value added, 1992-2007	0.581	0.583	0.568	0.308	0.319	0.304
	(0.093)	(0.130)	(0.125)	(0.042)	(0.061)	(0.073)
Observations	19	13	13	38	26	26
R-squared	0.92	0.83	0.88	0.91	0.86	0.90
First-stage F	11.87	11.71	11.71	8.64	7.44	10.33
Panel C. Control for task offshorability in manufacturing industries						
Adjusted penetration of robots, $\overline{APR}_i$	-0.894	-0.771	-0.897	-1.179	-1.017	-1.096
	(0.295)	(0.273)	(0.351)	(0.243)	(0.257)	(0.279)
Share offshorable jobs in 1990	-2.299	-2.783	-2.613	-1.117	-1.331	-1.259
	(0.491)	(0.467)	(0.566)	(0.207)	(0.194)	(0.227)
Observations	19	13	13	38	26	26
R-squared	0.93	0.90	0.89	0.91	0.88	0.90
Panel D. Control for industries with significant adoption of robots						
Adjusted penetration of robots, $\overline{APR}_i$	-1.106	-1.041	-1.200	-1.168	-1.182	-1.277
	(0.415)	(0.404)	(0.405)	(0.261)	(0.280)	(0.271)
Observations	19	13	13	38	26	26
R-squared	0.91	0.71	0.78	0.90	0.80	0.85
Covariates:						
Manufacturing dummy	✓	✓	✓	✓	✓	✓
Chinese imports	✓	✓	✓	✓	✓	✓

The table presents estimates of the relationship between adjusted penetration of robots and changes in log wage bill across US industries. Column 1-3 present long-differences estimates for 1993-2007. Columns 4-6 present stacked differences estimates for 1993-2000 and 2000-2007. The sources of data are reported at the top of the table. All models include a dummy for the manufacturing industry and Chinese imports by industry from Acemoglu et al. (2016) as controls. Each panel lists additional covariates included in the models. Panel A controls for the change in industry value added between 1992 and 2007 (from the BEA input-output tables). Panel B instruments for the change in value added using intermediate imports in supplier industries (from Feenstra and Hanson, 1999). Panel C controls for the share of offshorable jobs across industries. Panel D includes a dummy for industries with significant adoption of robots (automotive, plastics and chemicals, metal products, industrial machinery, food and beverages, basic metals, electronics, miscellaneous manufacturing, and minerals). All regressions are weighted by baseline industry employment in 1993. Standard errors that are robust against heteroskedasticity and serial correlation at the industry level are in parentheses.

Table A7: Industry-level results: labor share, value added and productivity

	Long differences, 1992-2007			
	All industries, weighted by value added in 1992		Excluding automotive manufacturing	Unweighted
	(1)	(2)	(3)	(4)
	Panel A. Change in labor share (in percentage points)			
Adjusted penetration of robots, $\overline{APR}_i$	-0.864	-0.797	-0.924	-0.656
	(0.164)	(0.281)	(0.331)	(0.218)
Observations	19	19	18	19
R-squared	0.36	0.37	0.31	0.35
	Panel B. Change in log value added (percent annual change)			
Adjusted penetration of robots, $\overline{APR}_i$	0.179	0.128	0.188	0.085
	(0.059)	(0.061)	(0.043)	(0.044)
Observations	19	19	18	19
R-squared	0.62	0.72	0.74	0.67
	Panel C. Change in log value added per worker (percent annual change)			
Adjusted penetration of robots, $\overline{APR}_i$	0.123	0.153	0.220	0.111
	(0.055)	(0.069)	(0.054)	(0.055)
Observations	19	19	18	19
R-squared	0.23	0.37	0.42	0.20
Covariates:				
Manufacturing dummy	✓	✓	✓	✓
Light manufacturing dummy		✓	✓	✓
Chinese imports		✓	✓	✓

The table presents estimates of the relationship between adjusted penetration of robots and changes in labor shares and log value added across US industries. Panel A presents long-differences estimates for changes in labor share of value added, 1992-2007. Panel B presents long-differences estimates for changes in log value added, 1992-2007. Panel C presents long-differences estimates for changes in log value added per worker, 1992-2007. Column 1 controls for a manufacturing dummy. Column 2 controls for a light manufacturing dummy and exposure to Chinese imports by industry from Acemoglu et al. (2016). Column 3 excludes the automotive industry from the sample. The regressions in columns 1-3 are weighted by baseline industry value added in 1992, and the regression in column 4 is unweighted. Standard errors that are robust against heteroskedasticity are in parentheses.

Table A8: Exposure to robots and the location of integrators

	Location of robot integrators					
	Weighted by population				Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. log one plus number of integrators					
Exposure to robots	0.268	0.242	0.193	0.185	0.276	0.094
	(0.078)	(0.063)	(0.032)	(0.032)	(0.094)	(0.019)
Observations	722	722	722	722	712	722
R-squared	0.28	0.74	0.75	0.75	0.74	0.53
	Panel B. log one plus number of integrators					
Exposure to robots in	0.253	0.224	0.189	0.181	0.239	0.158
automotive industries	(0.071)	(0.042)	(0.027)	(0.028)	(0.131)	(0.022)
Exposure to robots in other	0.325	0.314	0.219	0.214	0.302	0.018
industries	(0.171)	(0.143)	(0.096)	(0.089)	(0.089)	(0.038)
Observations	722	722	722	722	712	722
R-squared	0.28	0.74	0.75	0.75	0.74	0.54
	Panel C. log one plus employment in integrators					
Exposure to robots	0.507	0.447	0.267	0.243	0.672	0.240
	(0.176)	(0.169)	(0.101)	(0.100)	(0.230)	(0.069)
Observations	722	722	722	722	712	722
R-squared	0.24	0.68	0.70	0.70	0.71	0.48
	Panel D. Dummy for the presence of integrators					
Exposure to robots	0.066	0.059	0.012	0.010	0.104	0.035
	(0.033)	(0.036)	(0.025)	(0.026)	(0.038)	(0.019)
Observations	722	722	722	722	712	722
R-squared	0.12	0.51	0.54	0.54	0.56	0.45
Covariates:						
Census divisions	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓
Industry shares			✓	✓	✓	✓
Trade, routine jobs				✓	✓	✓

The table presents estimates of the relationship between exposure to robots and the location of robot integrators. The dependent variable is log of one plus the number of integrators (Panels A and B), log of one plus employment in integrators (Panel C) and a dummy for the presence of integrators (Panel D). Columns 1-5 present regressions weighted by population in 1990. Column 5 presents results excluding the top one percent of commuting zones with highest exposure to robots. Column 6 presents unweighted regressions. The covariates included in each model are reported at the bottom of the table. Column 1 only includes Census division dummies. Column 2 adds demographic characteristics of commuting zones in 1990 (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians). Column 3 adds the shares of employment in manufacturing and light manufacturing, and the female share of manufacturing employment in 1990. Columns 4-6 add exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A9: Summary statistics: commuting zone data

		Means by quartiles of exposure to robots				Correlations with exposure to robots	
	All commuting zones	First quartile	Second quartile	Third quartile	Fourth quartile	Raw correlation	Conditional on share manufacturing and Census division
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcomes:							
Change employment to population ratio, 1990-2007 (p.p.)	0.96	1.97	1.58	0.49	0.59	-0.23	-0.23
Change log hourly wages, 1990-2007 (log points, adjusted for composition)	5.57	9.58	7.24	5.23	3.35	-0.58	-0.41
Baseline characteristics:							
Employment to population ratio, 1990	0.35	0.32	0.34	0.36	0.37	0.23	0.09
log hourly wages, 1990	2.59	2.53	2.59	2.60	2.62	0.10	0.23
Covariates:							
Share Female population in 1990	0.51	0.51	0.51	0.51	0.52	0.17	0.07
Share Hispanic in 1990	0.09	0.17	0.10	0.10	0.05	-0.25	-0.08
Share White in 1990	0.85	0.86	0.83	0.84	0.85	0.02	-0.11
Share Black in 1990	0.12	0.10	0.13	0.11	0.13	0.06	0.13
Share Asian in 1990	0.03	0.02	0.03	0.04	0.02	-0.17	0.00
Share with no college degree in 1990	0.56	0.54	0.54	0.56	0.58	0.17	-0.07
Share with college degree in 1990	0.13	0.14	0.14	0.14	0.13	-0.18	0.03
Share with masters degree in 1990	0.05	0.05	0.05	0.05	0.05	-0.10	0.07
Share above 65 years of age in 1990	0.12	0.13	0.12	0.12	0.12	-0.04	-0.10
log population in 1990	13.97	13.46	13.97	14.09	14.07	0.09	0.20
Share employment in manufacturing in 1990	0.22	0.13	0.19	0.24	0.26	0.44	.
Female share of manufacturing employment in 1990 (within manufacturing)	0.33	0.34	0.35	0.35	0.31	-0.37	-0.39
Share light manufacturing in 1990 (within manufacturing)	0.22	0.24	0.25	0.24	0.18	-0.39	-0.38
Exposure to Chinese imports between 1990 and 2007	3.35	1.87	2.86	3.97	3.73	0.06	-0.14
Share employment in routine jobs in 1990	0.36	0.35	0.36	0.36	0.37	0.20	0.00

Columns 1-5 present sample means for all commuting zones and by quartiles of exposure to robots. Columns 6 and 7 present correlations between the covariate indicated in each row and exposure to robots across commuting zones. Correlations are weighted by population, and in column 7 are conditional on the share of employment in manufacturing and Census division dummies. See text for variable definitions and sources.

Table A10: Relationship between exposure to robots and covariates

	Dependent variable:					
	Exposure to robots		Exposure to robots in automotive manufacturing		Exposure to robots in other industries	
	(1)	(2)	(3)	(4)	(5)	(6)
Share female	0.108	0.107	0.092	0.102	0.064	0.042
	(0.053)	(0.048)	(0.066)	(0.053)	(0.084)	(0.085)
Share Hispanic	-0.107	-0.055	-0.074	-0.012	-0.097	-0.101
	(0.051)	(0.055)	(0.065)	(0.069)	(0.045)	(0.056)
Share White	0.001	-0.059	-0.037	-0.108	0.074	0.078
	(0.086)	(0.102)	(0.112)	(0.125)	(0.071)	(0.072)
Share Black	0.088	-0.003	0.096	-0.003	0.011	-0.001
	(0.077)	(0.083)	(0.096)	(0.092)	(0.093)	(0.100)
Share Asian	-0.074	0.051	-0.113	0.004	0.055	0.107
	(0.098)	(0.075)	(0.132)	(0.101)	(0.074)	(0.117)
Share with no college	0.024	-0.092	-0.408	-0.510	0.852	0.789
	(0.255)	(0.285)	(0.320)	(0.374)	(0.212)	(0.206)
Share with college degree	-0.289	-0.276	-0.546	-0.536	0.415	0.423
	(0.254)	(0.259)	(0.320)	(0.327)	(0.160)	(0.183)
Share with masters degree	0.065	-0.024	-0.081	-0.167	0.304	0.274
	(0.107)	(0.130)	(0.102)	(0.141)	(0.172)	(0.180)
Share above 65 years of age	-0.120	-0.111	-0.083	-0.088	-0.110	-0.078
	(0.041)	(0.047)	(0.071)	(0.070)	(0.087)	(0.097)
Log population	0.277	0.303	0.215	0.247	0.205	0.201
	(0.127)	(0.129)	(0.182)	(0.195)	(0.111)	(0.138)
Share employment in manufacturing	1.162	1.051	0.861	0.713	0.944	0.980
	(0.309)	(0.270)	(0.413)	(0.374)	(0.202)	(0.232)
Female share of manufacturing	-0.647	-0.556	-0.490	-0.373	-0.504	-0.526
employment	(0.248)	(0.215)	(0.306)	(0.264)	(0.212)	(0.231)
Share employment in light manufacturing	-0.323	-0.276	-0.257	-0.213	-0.227	-0.207
	(0.066)	(0.076)	(0.067)	(0.066)	(0.091)	(0.101)
Exposure to Chinese imports	-0.115	-0.100	-0.160	-0.137	0.051	0.041
	(0.067)	(0.061)	(0.087)	(0.083)	(0.069)	(0.060)
Share employment in routine jobs	0.083	-0.044	0.183	0.036	-0.169	-0.170
	(0.073)	(0.052)	(0.067)	(0.054)	(0.082)	(0.095)
Observations	722	722	722	722	722	722
R-squared	0.60	0.63	0.44	0.48	0.45	0.46
Additional covariates not reported:						
Census divisions		✓		✓		✓

The table presents the relationship between the covariates used in our analysis (measured in 1990) and exposure to robots (columns 1-2), exposure to robots in the automotive industry (columns 3-4), and exposure to robots in other industries (columns 5-6) for 1993-2007. The covariates and exposure measures are standardized to ease the comparison of the point estimates. Columns 2, 4 and 6 also control for a full set of Census division dummies. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

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Table A11: The effect of robots on employment and wages: excludes the share of employment in light manufacturing and the female share of manufacturing employment from covariates.

	Long differences, 1990-2007			Stacked differences, 1990-2000 and 2000-2007		
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Change in the employment to population ratio—Excludes the share of employment in light manufacturing and the female share of employment in manufacturing from covariates.						
Exposure to robots	-0.295	-0.293	-0.356	-0.522	-0.649	-0.708
	(0.064)	(0.140)	(0.121)	(0.054)	(0.150)	(0.096)
Observations	722	712	722	1444	1424	1444
R-squared	0.64	0.63	0.60	0.40	0.39	0.39
Panel B. Change in the employment to population ratio—excludes the female share of employment in manufacturing from covariates.						
Exposure to robots	-0.411	-0.514	-0.474	-0.545	-0.691	-0.740
	(0.058)	(0.135)	(0.118)	(0.052)	(0.150)	(0.095)
Observations	722	712	722	1444	1424	1444
R-squared	0.66	0.65	0.62	0.41	0.40	0.39
Panel C. Change in log hourly wages—excludes the share of employment in light manufacturing and the female share of employment in manufacturing from covariates.						
Exposure to robots	-0.870	-0.751	-1.091	-1.457	-1.683	-1.805
	(0.124)	(0.268)	(0.181)	(0.178)	(0.522)	(0.298)
Observations	87100	85776	87100	183606	180818	183606
R-squared	0.33	0.32	0.08	0.29	0.27	0.09
Panel D. Change in log hourly wages—excludes the female share of employment in manufacturing from covariates.						
Exposure to robots	-0.928	-0.842	-1.091	-1.448	-1.657	-1.746
	(0.125)	(0.270)	(0.182)	(0.181)	(0.543)	(0.296)
Observations	87100	85776	87100	183606	180818	183606
R-squared	0.33	0.33	0.08	0.29	0.27	0.09
Covariates:						
Remaining baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on employment to population ratios (Panels A and B) and log hourly wages (Panels C and D). Columns 1-3 present long-differences estimates for the 1990-2007 period. Columns 4-6 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. All columns include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones in 1990 (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the share of employment in manufacturing, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A12: Coefficients for the main covariates in Tables 2 and 3

	Change in the employment to population ratio			Change in log hourly wages		
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Long-differences, 1990-2007			
Exposure to robots	-0.448	-0.572	-0.516	-0.884	-0.779	-0.932
	(0.059)	(0.138)	(0.118)	(0.132)	(0.274)	(0.205)
Share manufacturing	1.846	2.603	0.591	-17.649	-18.326	-32.096
employment	(3.393)	(3.376)	(3.657)	(6.246)	(6.104)	(5.398)
Female share of	-21.819	-22.380	-14.617	26.298	26.015	55.292
manufacturing employment	(7.362)	(7.444)	(9.362)	(13.705)	(13.671)	(12.221)
Share light manufacturing	-7.804	-8.260	-8.297	-13.012	-11.770	-11.985
employment	(3.474)	(3.298)	(2.902)	(6.424)	(6.510)	(4.821)
Exposure to Chinese imports	-0.082	-0.080	-0.049	-0.058	-0.057	-0.070
	(0.040)	(0.041)	(0.032)	(0.075)	(0.076)	(0.045)
Share employment in routine	-8.743	-9.677	-17.382	-7.313	-7.321	5.678
jobs	(5.206)	(5.143)	(5.441)	(11.399)	(11.367)	(10.986)
Observations	722	712	722	87100	85776	87100
R-squared	0.67	0.66	0.62	0.33	0.33	0.08
			Panel B. Stacked differences, 1990-2000 and 2000-2007			
Exposure to robots	-0.551	-0.702	-0.743	-1.431	-1.584	-1.723
	(0.052)	(0.150)	(0.092)	(0.196)	(0.586)	(0.300)
Share manufacturing	1.490	0.453	-2.062	-5.696	-8.024	-21.129
employment	(3.188)	(3.065)	(1.850)	(6.100)	(6.004)	(3.703)
Female share of	-13.630	-10.914	-1.389	12.741	18.417	37.550
manufacturing employment	(7.376)	(6.525)	(4.931)	(15.530)	(14.654)	(8.470)
Share light manufacturing	-0.895	-1.044	-3.547	0.651	0.471	-0.730
employment	(1.963)	(1.952)	(2.078)	(4.036)	(4.503)	(3.302)
Exposure to Chinese imports	-0.195	-0.180	-0.128	-0.405	-0.387	-0.249
	(0.030)	(0.034)	(0.029)	(0.105)	(0.106)	(0.082)
Share employment in routine	-6.630	-7.278	-7.201	-6.005	-7.312	14.206
jobs	(4.192)	(4.232)	(3.258)	(10.473)	(10.764)	(7.053)
Observations	1444	1424	1444	183607	180819	183607
R-squared	0.41	0.40	0.39	0.21	0.20	0.06
Covariates:						
Remaining baseline covariates	✓	✓	✓	✓	✓	✓

The table reports the coefficients for the main covariates used in our analysis for models explaining changes in employment and wages. Panel A presents long-differences estimates for the 1990-2007 period. Panel B presents stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Columns 1-3 present estimates for changes in the employment to population ratio. Columns 4-6 present estimates for changes in log hourly wages. The specifications in columns 4-6 are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education and race. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

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Table A13: The effects of robots on employment and wages: recent periods

	Change in the employment to population ratio			Change in log hourly wages		
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Long-differences estimates, 1990-2014			
Exposure to robots	-0.288	-0.484	-0.444	-1.298	-1.291	-1.279
	(0.071)	(0.163)	(0.114)	(0.142)	(0.379)	(0.282)
Observations	722	712	722	90341	88964	90341
R-squared	0.56	0.56	0.60	0.46	0.44	0.16
			Panel B. Long-differences estimates, 1990-2010			
Exposure to robots	-0.501	-0.608	-0.591	-1.204	-1.271	-1.254
	(0.068)	(0.147)	(0.128)	(0.137)	(0.291)	(0.236)
Observations	722	712	722	87417	86089	87417
R-squared	0.64	0.63	0.68	0.37	0.36	0.11
			Panel C. Long-differences estimates, 2000-2014			
Exposure to robots	-0.316	-0.476	-0.260	-1.489	-1.522	-1.447
	(0.055)	(0.158)	(0.086)	(0.158)	(0.441)	(0.320)
Observations	722	712	722	106375	104786	106375
R-squared	0.66	0.65	0.46	0.35	0.34	0.09
			Panel D. Long-differences estimates, 2000-2007			
Exposure to robots	-0.441	-0.367	-0.380	-0.897	-0.335	-0.727
	(0.062)	(0.151)	(0.123)	(0.164)	(0.353)	(0.331)
Observations	722	712	722	99319	97833	99319
R-squared	0.66	0.63	0.56	0.22	0.22	0.05
			Panel E. Long-differences estimates, 2000-2010			
Exposure to robots	-0.520	-0.480	-0.491	-1.310	-1.071	-1.309
	(0.057)	(0.164)	(0.129)	(0.151)	(0.378)	(0.303)
Observations	722	712	722	100547	99063	100547
R-squared	0.69	0.67	0.67	0.27	0.25	0.06
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on employment and wages for different periods of time. Panel A presents long-differences estimates for the 1990-2014 period. Panel B presents long-differences estimates for the 1990-2010 period. Panel C presents long-differences estimates for the 2000-2014 period. Panel D presents long-differences estimates for the 2000-2007 period. Panel E presents long-differences estimates for the 2000-2010 period. Columns 1-3 present estimates for changes in the employment to population ratio. Columns 4-6 present estimates for changes in log hourly wages. The specifications in columns 4-6 are estimated at the demographic cell $\times$ commuting zone level, where demographic cells are defined by age, gender, education and race. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A14: The effects of robots on manufacturing employment

	Long differences, 1990-2007				Stacked differences, 1990-2000 and 2000-2007			
	Weighted by population	Excludes zones with highest exposure	Unweighted	Control for automotive industry	Weighted by population	Excludes zones with highest exposure	Unweighted	Control for automotive industry
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Change in the employment to population ratio, all workers in manufacturing								
Exposure to robots	-0.158	-0.235	-0.338	-0.251	-0.225	-0.322	-0.424	-0.333
	(0.042)	(0.091)	(0.085)	(0.078)	(0.031)	(0.074)	(0.082)	(0.094)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.77	0.78	0.76	0.78	0.56	0.56	0.60	0.57
Panel B. Change in the employment to population ratio, male workers in manufacturing								
Exposure to robots	-0.123	-0.187	-0.219	-0.173	-0.155	-0.208	-0.253	-0.211
	(0.031)	(0.066)	(0.055)	(0.057)	(0.018)	(0.046)	(0.053)	(0.063)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.69	0.69	0.68	0.69	0.48	0.47	0.52	0.48
Panel C. Change in the employment to population ratio, female workers in manufacturing								
Exposure to robots	-0.035	-0.048	-0.119	-0.078	-0.070	-0.114	-0.170	-0.122
	(0.015)	(0.032)	(0.031)	(0.030)	(0.014)	(0.032)	(0.030)	(0.041)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.86	0.86	0.84	0.86	0.68	0.68	0.68	0.68
Panel D. Change in the employment to population ratio, workers with no college degree in manufacturing								
Exposure to robots	-0.185	-0.225	-0.288	-0.198	-0.200	-0.305	-0.390	-0.256
	(0.028)	(0.075)	(0.075)	(0.055)	(0.032)	(0.066)	(0.072)	(0.067)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.80	0.80	0.79	0.80	0.59	0.59	0.62	0.59
Panel E. Change in the employment to population ratio, workers with college degree or more in manufacturing								
Exposure to robots	0.027	-0.010	-0.050	-0.053	-0.025	-0.017	-0.033	-0.077
	(0.023)	(0.022)	(0.024)	(0.042)	(0.011)	(0.018)	(0.019)	(0.047)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.45	0.46	0.29	0.48	0.27	0.27	0.15	0.28
Covariates:								
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓
Automotive industry				✓				✓

The table presents estimates of the effects of exposure to robots on the manufacturing employment to population ratio. Columns 1-4 present long-differences estimates for the 1990-2007 period. Columns 5-8 present stacked-differences estimates for the 1990-2000 and 2000-2007 period. Panel A is for changes in the manufacturing employment to population ratio. Panel B is for changes in male manufacturing employment divided by population. Panel C is for changes in female manufacturing employment divided by population. Panel D is for changes in manufacturing employment of workers with no college degree divided by population. Panel E is for changes in manufacturing employment of workers with a college degree or more divided by population. Columns 1-2, 4, 5-6, and 8 present regressions weighted by population in 1990. Columns 2 and 6 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 7 present unweighted regressions. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. In addition, Columns 4 and 8 control for exposure to robots in the automotive industry. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A15: The effects of robots on employment: additional outcomes

	Long differences, 1990-2007			Stacked differences, 1990-2000 and 2000-2007		
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Change in log employment					
Exposure to robots	-1.656	-2.841	-1.629	-2.009	-3.170	-2.615
	(0.411)	(0.885)	(0.588)	(0.313)	(0.694)	(0.388)
Observations	722	712	722	1444	1424	1444
R-squared	0.62	0.61	0.38	0.46	0.45	0.29
	Panel B. Change in log manufacturing employment					
Exposure to robots	-1.238	-1.929	-2.853	-2.093	-2.904	-3.539
	(0.555)	(1.219)	(1.019)	(0.330)	(0.808)	(0.881)
Observations	722	712	722	1444	1424	1444
R-squared	0.60	0.61	0.47	0.46	0.45	0.37
	Panel C. Change in the employment to population ratio, including self employment					
Exposure to robots	-0.410	-0.504	-0.389	-0.579	-0.744	-0.688
	(0.056)	(0.134)	(0.109)	(0.064)	(0.162)	(0.083)
Observations	722	712	722	1444	1424	1444
R-squared	0.61	0.61	0.54	0.39	0.39	0.32
	Panel D. Change in the employment to population ratio, including self employment and public employment					
Exposure to robots	-0.360	-0.387	-0.337	-0.592	-0.758	-0.728
	(0.054)	(0.137)	(0.116)	(0.066)	(0.172)	(0.098)
Observations	722	712	722	1444	1424	1444
R-squared	0.70	0.69	0.67	0.50	0.50	0.44
	Panel E. Change in the employment to population ratio from the CBP					
Exposure to robots	-0.565	-0.734	-0.603	-0.911	-1.081	-1.055
	(0.152)	(0.389)	(0.174)	(0.144)	(0.344)	(0.133)
Observations	719	709	719	1438	1418	1438
R-squared	0.49	0.47	0.45	0.48	0.45	0.38
	Panel F. Change in non-participation rate					
Exposure to robots	0.281	0.251	0.334	0.486	0.773	0.612
	(0.040)	(0.121)	(0.110)	(0.087)	(0.189)	(0.091)
Observations	722	712	722	1444	1424	1444
R-squared	0.65	0.65	0.54	0.49	0.50	0.32
	Panel G. Change in unemployment rate					
Exposure to robots	0.205	0.201	0.195	0.607	0.577	0.667
	(0.039)	(0.070)	(0.049)	(0.067)	(0.135)	(0.078)
Observations	722	712	722	1444	1424	1444
R-squared	0.61	0.59	0.52	0.49	0.41	0.32
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on several labor market outcomes. Columns 1-3 present long-differences estimates for the 1990-2007 period. Columns 4-6 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Panel A presents estimates for changes in log (private) employment. Panel B presents estimates for changes in log manufacturing employment. Panel C presents estimates for changes in employment (including self employment) to population ratio. Panel D presents estimates for changes in employment (including self employment and public-sector employment) to population ratio. Panel E presents estimates for changes in the employment to population ratio computed from the County Business Patterns. Panel F presents estimates for changes in the non-participation rate (defined as the share of people above 16 years of age who are not in the labor force). Panel G presents estimates for changes in the unemployment rate (defined as the share of people in the labor force who are not employed). Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

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Table A16: The effects of robots on wages: additional outcomes

	Long differences, 1990-2007			Stacked differences, 1990-2000 and 2000-2007		
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Change in log weekly wages					
Exposure to robots	-1.299	-1.005	-1.251	-2.180	-2.471	-2.576
	(0.163)	(0.280)	(0.274)	(0.187)	(0.603)	(0.330)
Observations	87100	85776	87100	183606	180818	183606
R-squared	0.43	0.42	0.12	0.36	0.35	0.11
	Panel B. Change in log yearly wages					
Exposure to robots	-1.556	-1.306	-1.666	-2.687	-3.175	-3.413
	(0.174)	(0.338)	(0.309)	(0.238)	(0.776)	(0.404)
Observations	87100	85776	87100	183606	180818	183606
R-squared	0.44	0.43	0.13	0.39	0.37	0.13
	Panel C. Change in hourly wages (2007 dollars)					
Exposure to robots	-0.130	-0.135	-0.137	-0.242	-0.263	-0.252
	(0.029)	(0.063)	(0.037)	(0.034)	(0.093)	(0.052)
Observations	87100	85776	87100	183606	180818	183606
R-squared	0.40	0.40	0.08	0.24	0.23	0.05
	Panel D. Change in log wage bill (from the CBP)					
Exposure to robots	-2.285	-4.370	-1.731	-3.805	-4.639	-4.330
	(0.649)	(1.143)	(0.984)	(0.521)	(1.134)	(0.616)
Observations	719	709	719	1438	1418	1438
R-squared	0.67	0.65	0.38	0.62	0.60	0.37
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on several labor market outcomes. Columns 1-3 present long-differences estimates for the 1990-2007 period. Columns 4-6 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Panel A presents estimates for changes in log weekly wages. Panel B presents estimates for changes in log yearly wages. Panel C presents estimates for changes in hourly wages measured in 2007 dollars. The specifications in panels A to C are estimated at the demographic cell $\times$ commuting zone level, where demographic cells are defined by age, gender, education and race. Panel D presents estimates for changes in log wage bill by commuting zone from the County Business Patterns. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A17: The effects of robots on government transfers

	Long differences, 1990-2007			Stacked differences, 1990-2000 and 2000-2007		
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Change in total transfers per capita (2007 dollars)						
Exposure to robots	30.097	63.094	67.645	45.249	73.950	76.562
	(13.511)	(26.480)	(19.823)	(9.194)	(20.333)	(16.546)
Observations	722	712	722	1444	1424	1444
R-squared	0.68	0.69	0.50	0.79	0.78	0.67
Panel B. Change in transfers per capita, SSA retirement benefits (2007 dollars)						
Exposure to robots	23.544	22.880	32.274	13.669	16.096	25.500
	(3.701)	(7.382)	(10.347)	(2.297)	(7.057)	(8.053)
Observations	722	712	722	1444	1424	1444
R-squared	0.61	0.60	0.29	0.51	0.50	0.28
Panel C. Change in transfers per capita, SSA disability benefits (2007 dollars)						
Exposure to robots	6.774	4.577	7.732	4.969	6.162	8.256
	(1.763)	(3.578)	(3.284)	(1.313)	(3.350)	(2.342)
Observations	722	712	722	1444	1424	1444
R-squared	0.70	0.70	0.56	0.66	0.65	0.55
Panel D. Change in transfers per capita, TAA benefits (2007 dollars)						
Exposure to robots	0.580	0.197	0.467	0.935	0.548	1.025
	(0.166)	(0.158)	(0.272)	(0.235)	(0.355)	(0.362)
Observations	722	712	722	1444	1424	1444
R-squared	0.57	0.55	0.50	0.44	0.34	0.35
*Panel E.*Change in transfers per capita, Unemployment benefits (2007 dollars)						
Exposure to robots	0.507	6.469	-1.553	11.570	15.429	11.728
	(1.994)	(3.545)	(1.286)	(1.661)	(4.316)	(2.080)
Observations	722	712	722	1444	1424	1444
R-squared	0.33	0.36	0.29	0.49	0.45	0.22
*Panel F.*Change in transfers per capita, education and training assistance (2007 dollars)						
Exposure to robots	0.708	7.669	2.113	5.324	7.913	6.354
	(2.352)	(3.290)	(2.602)	(1.131)	(2.326)	(1.621)
Observations	722	712	722	1444	1424	1444
R-squared	0.28	0.31	0.27	0.41	0.40	0.25
Panel G. Change in transfers per capita, Medical benefits (2007 dollars)						
Exposure to robots	18.082	25.928	33.795	12.550	26.327	16.059
	(10.362)	(23.595)	(14.210)	(8.919)	(19.483)	(12.833)
Observations	722	712	722	1444	1424	1444
R-squared	0.65	0.66	0.48	0.72	0.71	0.63
Panel H. Change in transfers per capita, Federal income assistance (2007 dollars)						
Exposure to robots	-9.088	-7.882	0.085	2.972	5.953	10.645
	(2.744)	(5.832)	(3.925)	(1.880)	(5.421)	(2.592)
Observations	722	712	722	1444	1424	1444
R-squared	0.45	0.44	0.20	0.55	0.55	0.49
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on transfers (measured in dollars transferred per capita). Each panel presents results for transfers from a different program. Columns 1-3 present long-differences estimates for the 1990-2007 period. Columns 4-6 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A18: The effects of robots on migration, population, and housing prices and rents.

	Long differences, 1990-2007			Stacked differences, 1990-2000 and 2000-2007		
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Net migration rate—exclude baseline population from covariates.						
Exposure to robots	0.024	0.045	0.049	-0.040	-0.058	0.059
	(0.030)	(0.067)	(0.049)	(0.028)	(0.075)	(0.057)
Observations	722	712	722	1444	1424	1444
R-squared	0.55	0.55	0.30	0.48	0.48	0.32
Panel B. Net migration rate—control for baseline population.						
Exposure to robots	-0.020	-0.030	0.002	-0.097	-0.158	-0.020
	(0.029)	(0.066)	(0.035)	(0.028)	(0.069)	(0.040)
Log of baseline population	0.282	0.287	0.452	0.285	0.293	0.404
	(0.089)	(0.094)	(0.070)	(0.073)	(0.078)	(0.049)
Observations	722	712	722	1444	1424	1444
R-squared	0.59	0.59	0.41	0.54	0.53	0.43
Panel C. Change in log population—exclude baseline population from covariates.						
Exposure to robots	-0.121	-0.665	0.163	-0.231	-0.720	-0.155
	(0.390)	(0.973)	(0.630)	(0.210)	(0.543)	(0.332)
Observations	722	712	722	1444	1424	1444
R-squared	0.58	0.58	0.43	0.56	0.55	0.40
Panel D: Change in log population—control for baseline population.						
Exposure to robots	-0.487	-1.298	-0.270	-0.510	-1.218	-0.546
	(0.391)	(1.003)	(0.575)	(0.228)	(0.534)	(0.301)
Log of baseline population	2.327	2.413	4.120	1.401	1.452	2.014
	(0.935)	(0.996)	(0.685)	(0.486)	(0.521)	(0.342)
Observations	722	712	722	1444	1424	1444
R-squared	0.60	0.59	0.52	0.58	0.57	0.47
Panel E: Change in log house prices.						
Exposure to robots	-1.016	-3.859	0.142	-6.879	-9.291	-5.247
	(0.856)	(1.894)	(0.919)	(1.038)	(2.893)	(1.137)
Observations	601	591	601	1202	1182	1202
R-squared	0.72	0.72	0.55	0.51	0.52	0.31
Panel F: Change in log monthly rents.						
Exposure to robots	-0.819	-1.373	-0.369	-0.944	-2.340	-1.388
	(0.219)	(0.493)	(0.429)	(0.507)	(0.964)	(0.506)
Observations	722	712	722	1444	1424	1444
R-squared	0.42	0.42	0.19	0.57	0.57	0.37
Covariates:						
Remaining baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on migration rates (obtained from the IRS), changes in log population, and changes in house prices and rents. Columns 1-3 present long-differences estimates for the 1990-2007 period. Columns 4-6 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. Panels A and B present estimates for the net migration rate (from IRS). Panels C and D present estimates for changes in log population. Panel E presents estimates for changes in log house prices (from an index by the Federal Housing Finance Agency and available for counties covering 601 commuting zones). Panel F presents estimates for changes in log rents (computed from monthly rents in the Census and ACS, and including the cost of utilities). Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Also, the columns in Panels B and D control for baseline differences in log population. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

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Table A19: The effects of robots on wage and non-wage income

	Long differences 1990-2007			Stacked differences 1990-2000 and 2000-2007		
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Change in log wage income per capita, BEA						
Exposure to robots	-1.538	-2.176	-1.657	-3.211	-3.814	-4.381
	(0.317)	(0.724)	(0.703)	(0.283)	(0.769)	(0.466)
Observations	722	712	722	1444	1424	1444
R-squared	0.53	0.49	0.46	0.47	0.42	0.32
Panel B. Change in log wage income per capita, IRS						
Exposure to robots	-1.208	-1.389	-1.708	-2.706	-3.020	-4.248
	(0.199)	(0.442)	(0.491)	(0.252)	(0.668)	(0.430)
Observations	722	712	722	1444	1424	1444
R-squared	0.58	0.53	0.62	0.51	0.46	0.39
Panel C. Change in log income per capita, BEA						
Exposure to robots	-1.137	-1.177	-0.779	-2.371	-2.550	-2.763
	(0.221)	(0.471)	(0.479)	(0.239)	(0.575)	(0.388)
Observations	722	712	722	1444	1424	1444
R-squared	0.55	0.50	0.31	0.40	0.33	0.20
Panel D. Change in log non-wage income per capita, BEA						
Exposure to robots	0.169	-0.002	0.432	-0.203	-0.189	0.102
	(0.384)	(1.170)	(0.817)	(0.542)	(1.203)	(0.458)
Observations	722	712	722	1444	1424	1444
R-squared	0.47	0.47	0.08	0.22	0.23	0.05
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on households' income. Columns 1-3 present long-differences estimates for the 1990-2007 period. Columns 4-6 present stacked-differences estimates for the 1990-2000 and 2000-2007 period. Panel A presents results for changes in log wage income per capita (from the BEA). Panel B presents results for changes in log wage income per capita (from the IRS). Panel C presents results for changes in log income per capita (from the BEA). Panel D presents results for changes in log non-wage income per capita (from the BEA). Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

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Table A20: Pre-trends 1970-1990: additional outcomes

	Long differences, 1970-1990					
	Weighted by population				Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Change in manufacturing employment to population ratio						
Exposure to robots	-0.185	-0.103	0.019	0.055	-0.040	-0.118
	(0.088)	(0.062)	(0.059)	(0.050)	(0.105)	(0.095)
Observations	722	722	722	722	712	722
R-squared	0.44	0.54	0.57	0.63	0.63	0.36
Panel B. Change in the employment to population ratio, including public sector and self employment						
Exposure to robots	-0.045	-0.039	-0.044	-0.028	-0.188	-0.232
	(0.075)	(0.066)	(0.080)	(0.073)	(0.165)	(0.149)
Observations	722	722	722	722	712	722
R-squared	0.12	0.38	0.38	0.41	0.40	0.26
Panel C. Change in non-participation rate						
Exposure to robots	0.249	0.182	0.049	0.024	0.130	0.189
	(0.093)	(0.086)	(0.109)	(0.103)	(0.260)	(0.207)
Observations	722	722	722	722	712	722
R-squared	0.11	0.27	0.28	0.30	0.29	0.24
Panel D. Change in unemployment rate						
Exposure to robots	0.026	0.027	0.066	0.068	0.077	0.090
	(0.070)	(0.040)	(0.041)	(0.040)	(0.104)	(0.067)
Observations	722	722	722	722	712	722
R-squared	0.35	0.55	0.56	0.59	0.58	0.43
Panel E. Change in log weekly wages						
Exposure to robots	-0.477	-0.310	0.305	0.343	0.640	-0.044
	(0.188)	(0.210)	(0.256)	(0.257)	(0.532)	(0.374)
Observations	59230	59230	59230	59230	58402	59230
R-squared	0.53	0.54	0.55	0.55	0.54	0.28
Covariates:						
Census divisions	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓
Industry shares			✓	✓	✓	✓
Trade, routine jobs				✓	✓	✓

The table presents estimates of the effects of exposure to robots on past outcomes measured in the 1970-1990 period. For comparison with our main results, all changes in past outcomes are rescaled to a 14-year equivalent change. Panel A presents results for changes in manufacturing employment to population ratio 1970-1990. Panel B presents results for changes in employment (including self employment and public-sector employment) to population ratio 1970-1990. Panel C presents results for changes in the non-participation rate 1970-1990, defined as the share of people above 16 years of age who are not in the labor force. Panel D presents results for changes in the unemployment rate 1970-1990, defined as the share of people in the labor force who are not employed. Panel E present results for changes in log weekly wages 1970-1990. The specifications for log weekly wages in Panel E are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education and race. Column 1 only includes Census division dummies. Column 2 adds demographic characteristics of commuting zones in 1970 (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians). Column 3 adds the shares of employment in manufacturing and light manufacturing, and the female share of manufacturing employment in 1970. Columns 4-6 add exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A21: Rotemberg weights

	Weighted by population				Unweighted	
	Raw data	Baseline covariates	Excludes zones with highest exposure	Excludes automotive manufacturing	Baseline covariates	Excludes automotive manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Long differences, 1990-2007					
Metal products	.035	-.002	.035	.046	.029	.055
Basic Metals	.037	-.018	.008	.03	.017	.035
Plastics and Chemicals	.158	.193	.565	.949	.437	.896
Automotive	.776	.877	.417	-.001	.542	0
	Panel B. Stacked differences, 1990-2000 and 2000-2007					
Food and Beverages 00-07	-.006	-.008	-.002	.002	0	.019
Wood and Furniture 00-07	-.005	-.008	-.011	-.004	-.003	.017
Industrial Machinery 90-00	-.002	.005	.01	.01	.007	.008
Mining 90-00	0	.005	.01	.013	.011	.022
Shipbuilding and Aerospace 90-00	.002	.001	.012	.024	.004	.015
Electronics 00-07	.013	.005	.062	.068	.032	.05
Industrial Machinery 00-07	.016	.01	.026	.023	.015	.017
Automotive 90-00	.018	-.035	-.028	0	-.018	-.001
Basic Metals 00-07	.019	.01	.036	.045	.025	.032
Metal products 00-07	.032	.025	.071	.085	.053	.085
Plastics and Chemicals 90-00	.049	.034	.104	.346	.096	.381
Plastics and Chemicals 00-07	.059	.059	.184	.393	.154	.362
Automotive 00-07	.795	.906	.546	-.001	.644	-.001

The table presents Rotemberg weights for the industries (and industries by time period) used in the construction of the exposure to robots measure, as explained in Goldsmith-Pinkham, Sorkin and Swift (2018). Panel A present these weights for long-differences specifications, 1990-2007, and panel B report these weights for stacked-differences specifications, 1990-2000 and 2000-2007. In both panels, we report the Rotemberg weights only for industries with a weight above 2% (or 1% in the stacked-differences specifications) in one of our specifications. Column 1 presents Rotemberg weights for a specification with no covariates. Columns 2 and 5 present Rotemberg weights for a specification with our baseline covariates (from column 4 in table 2). Column 3 presents Rotemberg weights for a specification that excludes the top one percent of commuting zones with highest exposure to robots. Columns 4 and 6 present Rotemberg weights for a specification that controls for exposure to robots in automotive manufacturing. Columns 1-4 are for regression models weighted by population. Columns 5-6 are for unweighted models.

Table A22: The effects of robots on employment and wages controlling for trade

	Change in the employment to population ratio				Change in log hourly wages			
	Long differences		Stacked differences		Long differences		Stacked differences	
	Weighted (1)	Unweighted (2)	Weighted (3)	Unweighted (4)	Weighted (5)	Unweighted (6)	Weighted (7)	Unweighted (8)
Panel A. Controls for exposure to imports from Mexico								
Exposure to robots	-0.444	-0.508	-0.551	-0.744	-0.887	-0.937	-1.442	-1.688
	(0.059)	(0.114)	(0.052)	(0.093)	(0.131)	(0.205)	(0.181)	(0.296)
Exposure to imports from Mexico	-0.059	-0.088	0.049	0.108	0.050	0.052	0.071	0.340
	(0.056)	(0.074)	(0.111)	(0.076)	(0.153)	(0.110)	(0.230)	(0.180)
Observations	722	722	1444	1444	87100	87100	183606	183606
R-squared	0.67	0.62	0.41	0.40	0.33	0.08	0.29	0.09
Panel B. Controls for exposure to industries with offshorable jobs								
Exposure to robots	-0.505	-0.604	-0.610	-0.820	-0.965	-0.967	-1.564	-1.757
	(0.065)	(0.123)	(0.055)	(0.096)	(0.124)	(0.191)	(0.175)	(0.286)
Exposure to industries with offshorable jobs	-0.225	-0.300	-0.205	-0.196	-0.316	-0.120	-0.411	-0.183
	(0.072)	(0.083)	(0.038)	(0.047)	(0.141)	(0.118)	(0.096)	(0.067)
Observations	722	722	1444	1444	87100	87100	183606	183606
R-squared	0.68	0.63	0.42	0.41	0.33	0.08	0.29	0.09
Panel C. Controls for exposure to exports from Germany, Japan, and South Korea								
Exposure to robots	-0.450	-0.530	-0.539	-0.722	-0.867	-0.916	-1.421	-1.588
	(0.058)	(0.119)	(0.046)	(0.091)	(0.135)	(0.204)	(0.171)	(0.280)
Exposure to exports from Germany, Japan, and South Korea	0.022	0.191	-0.013	-0.016	-0.172	-0.216	-0.025	-0.075
	(0.106)	(0.103)	(0.022)	(0.012)	(0.220)	(0.175)	(0.049)	(0.041)
Observations	722	722	1444	1444	87100	87100	183606	183606
R-squared	0.67	0.62	0.41	0.39	0.33	0.08	0.29	0.09
Covariates:								
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots and changing trade patterns on employment and wages. Columns 1-2 and 5-6 present long-differences estimates for the 1990-2007 period. Columns 3-4 and 7-8 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Columns 1-4 present results for employment to population ratio. Columns 5-8 present results for log hourly wages. The specifications in columns 5-8 for log hourly wages are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education and race. Odd-numbered columns present regressions weighted by population in 1990. Even-numbered columns present unweighted regressions. In Panel A we control for exposure to imports from Mexico to the US. In Panel B we control for exposure to industries with a high share of offshorable jobs in 1990 (offshorability is measured as in Autor and Dorn, 2013). In Panel C we control for exposure to exports from Germany, Japan, and South Korea. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A23: The effects of robots, computers and IT capital on employment and wages

	Change in the employment to population ratio				Change in log hourly wages			
	Long differences		Stacked differences		Long differences		Stacked differences	
	Weighted (1)	Unweighted (2)	Weighted (3)	Unweighted (4)	Weighted (5)	Unweighted (6)	Weighted (7)	Unweighted (8)
	Panel A. Controls for exposure to IT-intensive industries (from ASM)							
Exposure to robots	-0.460	-0.519	-0.525	-0.742	-0.859	-0.932	-1.362	-1.677
	(0.061)	(0.119)	(0.050)	(0.092)	(0.130)	(0.204)	(0.175)	(0.295)
Exposure to IT-intensive industries	-0.090	-0.026	0.172	0.004	0.183	-0.002	0.536	0.064
	(0.079)	(0.073)	(0.128)	(0.035)	(0.221)	(0.128)	(0.189)	(0.073)
Observations	722	722	1444	1444	87100	87100	183606	183606
R-squared	0.67	0.62	0.41	0.39	0.33	0.08	0.29	0.09
	Panel B. Controls for exposure to computer-intensive industries (from CPS)							
Exposure to robots	-0.439	-0.552	-0.549	-0.784	-0.880	-0.975	-1.440	-1.737
	(0.061)	(0.120)	(0.051)	(0.096)	(0.131)	(0.200)	(0.180)	(0.296)
Exposure to computer-intensive	0.047	0.115	0.066	0.098	0.018	0.141	0.092	0.126
industries	(0.036)	(0.036)	(0.043)	(0.023)	(0.058)	(0.055)	(0.081)	(0.046)
Observations	722	722	1444	1444	87100	87100	183606	183606
R-squared	0.67	0.62	0.41	0.40	0.33	0.08	0.29	0.09
	Panel C. Controls for exposure to industry changes in computer use (from CPS)							
Exposure to robots	-0.474	-0.650	-0.579	-0.850	-0.895	-0.960	-1.503	-1.766
	(0.067)	(0.135)	(0.055)	(0.103)	(0.136)	(0.210)	(0.180)	(0.291)
Exposure to industry changes in	-0.226	-0.580	-0.185	-0.372	-0.105	-0.120	-0.413	-0.281
computer use	(0.143)	(0.154)	(0.097)	(0.074)	(0.253)	(0.216)	(0.221)	(0.143)
Observations	722	722	1444	1444	87100	87100	183606	183606
R-squared	0.67	0.64	0.41	0.41	0.33	0.08	0.29	0.09
Covariates:								
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots and several measures of the deployment of IT technologies and computers on employment and wages. Columns 1-2 and 5-6 present long-differences estimates for the 1990-2007 period. Columns 3-4 and 7-8 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Columns 1-4 present results for employment to population ratio. Columns 5-8 present results for log hourly wages. The specifications in columns 5-8 for log hourly wages are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education and race. Odd-numbered columns present regressions weighted by population in 1990. Even-numbered columns present unweighted regressions. In Panel A we control for a measure of exposure to IT-intensive industries, constructed by interacting the baseline share of IT investments in each industry (available for 4-digit SIC87 manufacturing industries from the American Survey of Manufacturing) with its baseline employment share in the commuting zone. In Panel B we control for a measure of exposure to computer-intensive industries, constructed by interacting the baseline share of employees using a computer in each industry (obtained from the CPS and available for the 19 IFR industries used in our analysis) with its baseline employment share in the commuting zone. In Panel C we control for a measure of exposure to changes in computer use by industry, constructed by interacting the change between 1993 and 2003 in the share of employees using a computer in each industry (obtained from the CPS and available for the 19 IFR industries used in our analysis) with its baseline employment share in the commuting zone. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

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Table A24: The effects of robots on employment: alternative constructions of exposure to robots

	Estimates for changes in employment to population ratio						
	Long differences, 1990-2007			Stacked differences, 1990-2000 and 2000-2007			IV estimates, 1990-2007
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Baseline construction of the instrument							
Exposure to robots	-0.448	-0.572	-0.516	-0.551	-0.702	-0.743	
	(0.059)	(0.138)	(0.118)	(0.052)	(0.150)	(0.092)	
US robot adoption							-0.388
							(0.091)
Observations	722	712	722	1444	1424	1444	722
Panel B. Exposure computed using employment shares in 1990							
Exposure to robots	-0.725	-0.747	-0.788	-1.138	-1.550	-1.232	
	(0.107)	(0.199)	(0.220)	(0.138)	(0.239)	(0.130)	
US robot adoption							-0.319
							(0.060)
Observations	722	712	722	1444	1424	1444	722
Panel C. Exposure computed using employment shares in 1980 from CBP							
Exposure to robots	-0.537	-0.426	-0.258	-0.804	-0.730	-0.494	
	(0.108)	(0.136)	(0.104)	(0.113)	(0.160)	(0.097)	
US robot adoption							-0.382
							(0.083)
Observations	722	712	722	1444	1424	1444	722
Panel D. Including penetration of robots in Germany							
Exposure to robots	-0.352	-0.555	-0.448	-0.459	-0.669	-0.654	
	(0.053)	(0.137)	(0.106)	(0.042)	(0.141)	(0.092)	
US robot adoption							-0.357
							(0.074)
Observations	722	712	722	1444	1424	1444	722
Panel E. Using penetration of robots among all European countries with data							
Exposure to robots	-0.327	-0.566	-0.437	-0.435	-0.681	-0.651	
	(0.052)	(0.146)	(0.108)	(0.042)	(0.146)	(0.100)	
US robot adoption							-0.342
							(0.067)
Observations	722	712	722	1444	1424	1444	722
Panel F. Using penetration of robots without the adjustment term							
Exposure to robots	-0.319	-0.475	-0.393	-0.419	-0.590	-0.543	
	(0.048)	(0.113)	(0.093)	(0.043)	(0.126)	(0.087)	
US robot adoption							-0.369
							(0.081)
Observations	722	712	722	1444	1424	1444	722
Panel G. Adjusting penetration of robots using robot prices							
Exposure to robots	-0.473	-0.663	-0.560	-0.579	-0.796	-0.773	
	(0.065)	(0.158)	(0.129)	(0.064)	(0.172)	(0.094)	
US robot adoption							-0.377
							(0.085)
Observations	722	712	722	1444	1424	1444	722
Covariates:							
Baseline covariates	✓	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on the employment to population ratio. Columns 1-3 present long-differences estimates for the 1990-2007 period. Columns 4-6 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Column 7 presents IV estimates for the 1990-2007 period. Panel A presents results for the baseline construction of the exposure to robots measure. Panel B computes exposure to robots using 1990 employment shares from Census. Panel C computes exposure to robots using 1980 employment shares from the CBP. Panel D presents results including the penetration of robots in Germany. Panel E presents results using the data for nine European countries (Germany, Denmark, Finland, France, Italy, Sweden, Norway, Spain, and the UK) to construct the adjusted penetration of robots. Panel F presents results for the penetration of robots without the adjustment term in equation (12). Panel G presents results adjusting the penetration of robots using the available data on robot prices (from Robotics Industries of America). Columns 1-2, 4-5, and 7 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

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Table A25: The effects of robots on wages: alternative constructions of exposure to robots

	Estimates for change in log hourly wages						
	Long differences, 1990-2007			Stacked differences, 1990-2000 and 2000-2007			IV estimates, 1990-2007
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Baseline construction of the instrument							
Exposure to robots	-0.884	-0.779	-0.932	-1.443	-1.643	-1.684	
	(0.132)	(0.274)	(0.205)	(0.182)	(0.551)	(0.295)	
US robot adoption							-0.768
							(0.149)
Observations	87100	85776	87100	183606	180818	183606	87100
Panel B. Exposure computed using employment shares in 1990							
Exposure to robots	-1.483	-1.077	-1.483	-2.855	-3.512	-2.991	
	(0.252)	(0.409)	(0.313)	(0.353)	(0.717)	(0.395)	
US robot adoption							-0.652
							(0.105)
Observations	87100	85776	87100	183606	180818	183606	87100
Panel C. Exposure computed using employment shares in 1980 from CBP							
Exposure to robots	-1.111	-0.794	-0.563	-2.146	-1.952	-1.220	
	(0.214)	(0.270)	(0.208)	(0.317)	(0.529)	(0.322)	
US robot adoption							-0.779
							(0.152)
Observations	87100	85776	87100	183606	180818	183606	87100
Panel D. Including penetration of robots in Germany							
Exposure to robots	-0.690	-0.692	-0.780	-1.211	-1.499	-1.440	
	(0.091)	(0.211)	(0.155)	(0.131)	(0.472)	(0.238)	
US robot adoption							-0.701
							(0.115)
Observations	87100	85776	87100	183606	180818	183606	87100
Panel E. Using penetration of robots among all European countries with data							
Exposure to robots	-0.641	-0.677	-0.746	-1.161	-1.496	-1.412	
	(0.084)	(0.193)	(0.141)	(0.118)	(0.450)	(0.226)	
US robot adoption							-0.672
							(0.102)
Observations	87100	85776	87100	183606	180818	183606	87100
Panel F. Using penetration of robots without the adjustment term							
Exposure to robots	-0.617	-0.598	-0.671	-1.096	-1.190	-1.145	
	(0.083)	(0.188)	(0.135)	(0.139)	(0.432)	(0.205)	
US robot adoption							-0.715
							(0.123)
Observations	87100	85776	87100	183606	180818	183606	87100
Panel G. Adjusting penetration of robots using robot prices							
Exposure to robots	-0.933	-0.884	-1.003	-1.522	-1.919	-1.800	
	(0.125)	(0.265)	(0.203)	(0.196)	(0.547)	(0.295)	
US robot adoption							-0.747
							(0.138)
Observations	87100	85776	87100	183606	180818	183606	87100
Covariates:							
Baseline covariates	✓	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on the log hourly wages. Columns 1-3 present long-differences estimates for the 1990-2007 period. Columns 4-6 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Column 7 presents IV estimates for the 1990-2007 period. The specifications are estimated at the demographic cell $\times$ commuting zone level, where demographic cells are defined by age, gender, education and race. Panel A presents results for the baseline construction of the exposure to robots measure. Panel B computes exposure to robots using 1990 employment shares from Census. Panel C computes exposure to robots using 1980 employment shares from the CBP. Panel D presents results including the penetration of robots in Germany. Panel E presents results using the data for nine European countries (Germany, Denmark, Finland, France, Italy, Sweden, Norway, Spain, and the UK) to construct the adjusted penetration of robots. Panel F presents results for the penetration of robots without the adjustment term in equation (12). Panel G presents results adjusting the penetration of robots using the available data on robot prices (from Robotics Industries of America). Columns 1-2, 4-5, and 7 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

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Table A26: The effects of robots on employment and wages: the role of outliers

	Weighted by population	Excludes Detroit	Excludes observations with large residuals	Robust regression	Median regression
	(1)	(2)	(3)	(4)	(5)
	Panel A. Long differences for employment to population ratio, 1990-2007				
Exposure to robots	-0.448	-0.486	-0.451	-0.493	-0.457
	(0.059)	(0.103)	(0.060)	(0.090)	(0.115)
Observations	722	721	686	722	722
R-squared	0.67	0.66	0.71	0.65	
	Panel B. Stacked differences for employment to population ratio, 1990-2000 and 2000-2007				
Exposure to robots	-0.551	-0.649	-0.567	-0.744	-0.705
	(0.052)	(0.113)	(0.050)	(0.079)	(0.106)
Observations	1444	1442	1351	1444	1444
R-squared	0.41	0.40	0.45	0.40	
	Panel C. Long differences for log hourly wages, 1990-2007				
Exposure to robots	-0.884	-0.817	-0.874	-0.829	-0.835
	(0.132)	(0.190)	(0.132)	(0.133)	(0.129)
Observations	87100	86860	81492	87101	87101
R-squared	0.33	0.32	0.38	0.01	
	Panel D. Stacked differences for log hourly wages, 1990-2000 and 2000-2007				
Exposure to robots	-1.443	-1.556	-1.444	-1.298	-1.236
	(0.182)	(0.388)	(0.180)	(0.117)	(0.108)
Observations	183606	183124	171897	183607	183607
R-squared	0.29	0.27	0.33	0.03	
Covariates:					
Baseline covariates	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on employment and wages. Panel A presents long-differences estimates for changes in the employment to population ratio, 1990-2007. Panel B presents stacked-differences estimates for changes in the employment to population ratio, 1990-2000 and 2000-2007. Panel C presents long-differences estimates for changes in log hourly wages, 1990-2007. Panel D presents stacked-differences estimates for changes in log hourly wages, 1990-2000 and 2000-2007. The specifications in panels C-D are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education and race. Columns 1-3 present regressions weighted by population in 1990. Column 2 excludes Detroit from the sample. Column 3 excludes observations with a residual above or below two estimated standard deviations in column 1 and re-estimates the model. Column 4 presents a robust regression as in Li (1985). Column 5 presents a median regression. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A27: The effects of robots on employment and wages: additional covariates

	Long differences 1990-2007			Stacked differences 1990-2000 and 2000-2007		
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Change in the employment to population ratio—controlling for state fixed effects						
Exposure to robots	-0.318	-0.441	-0.337	-0.568	-0.645	-0.726
	(0.078)	(0.130)	(0.098)	(0.067)	(0.167)	(0.094)
Observations	722	712	722	1444	1424	1444
R-squared	0.80	0.79	0.73	0.45	0.44	0.47
Panel B. Change in the employment to population ratio—controlling for baseline employment level						
Exposure to robots	-0.405	-0.404	-0.419	-0.491	-0.523	-0.668
	(0.059)	(0.106)	(0.127)	(0.067)	(0.147)	(0.098)
Observations	722	712	722	1444	1424	1444
R-squared	0.75	0.75	0.68	0.55	0.54	0.45
Panel C. Change in the employment to population ratio—controlling for changes in demographics						
Exposure to robots	-0.438	-0.550	-0.414	-0.512	-0.600	-0.670
	(0.058)	(0.137)	(0.116)	(0.049)	(0.153)	(0.086)
Observations	722	712	722	1444	1424	1444
R-squared	0.75	0.74	0.73	0.56	0.55	0.52
Panel D. Change in log hourly wages—controlling for state fixed effects						
Exposure to robots	-0.530	-0.569	-0.596	-1.478	-1.685	-1.632
	(0.154)	(0.236)	(0.161)	(0.216)	(0.558)	(0.322)
Observations	87100	85776	87100	183606	180818	183606
R-squared	0.34	0.34	0.09	0.29	0.28	0.09
Panel E. Change in log hourly wages—controlling for baseline employment level						
Exposure to robots	-0.730	-0.623	-0.699	-1.232	-1.387	-1.472
	(0.151)	(0.290)	(0.233)	(0.195)	(0.558)	(0.316)
Observations	87100	85776	87100	183606	180818	183606
R-squared	0.34	0.33	0.08	0.29	0.28	0.09
Panel F. Change in log hourly wages—controlling for changes in demographics						
Exposure to robots	-0.892	-0.717	-0.825	-1.297	-1.368	-1.515
	(0.131)	(0.267)	(0.199)	(0.186)	(0.531)	(0.287)
Observations	87100	85776	87100	183606	180818	183606
R-squared	0.34	0.33	0.08	0.29	0.28	0.09
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on employment and wages controlling for additional covariates. Columns 1-3 present long-differences estimates for the 1990-2007 period. Columns 4-6 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Panel A presents estimates for the change in employment to population ratio controlling for state fixed effects. Panel B presents estimates for the change in employment to population ratio controlling for baseline employment levels. Panel C presents estimates for the change in employment to population ratio controlling for changes in demographic characteristics of commuting zones. Panel D presents estimates for the change in log hourly wages controlling for state fixed effects. Panel E presents estimates for the change in log hourly wages controlling for baseline employment levels. Panel F presents estimates for the change in log hourly wages controlling for changes in demographic characteristics of commuting zones. The specifications in panels D-F are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education and race. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3 and 6 present unweighted regressions. Besides the covariates mentioned above, all models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A28: The effects of robots on employment and wages: covariates selected by LASSO

	Long differences, 1990-2007				Stacked differences 1990-2000 and 2000-2007			
	Covariates included in Lasso procedure:				Covariates included in Lasso procedure:			
	Baseline	Extended	Extended	Two-way Interactions	Baseline	Extended	Extended	Two-way Interactions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Change in the employment to population ratio, all workers							
Exposure to robots	-0.348	-0.342	-0.449	-0.413	-0.535	-0.580	-0.529	-0.298
	(0.059)	(0.055)	(0.148)	(0.064)	(0.074)	(0.065)	(0.196)	(0.060)
Observations	722	722	722	722	1444	1444	1444	1444
R-squared	0.62	0.66	0.64	0.64	0.36	0.39	0.41	0.65
	Panel B. Change in log hourly wages							
Exposure to robots	-0.847	-1.026	-0.888	-1.018	-1.417	-1.389	-1.945	-0.623
	(0.114)	(0.109)	(0.380)	(0.095)	(0.181)	(0.183)	(0.780)	(0.139)
Observations	87100	87100	87100	87100	183606	183606	183606	183606
R-squared	0.33	0.33	0.33	0.33	0.28	0.28	0.29	0.30
Specification details:	LASSO	LASSO	LASSO + control for automotive industry	LASSO	LASSO	LASSO	LASSO+control for automotive industry	LASSO

The table presents estimates of the effects of exposure to robots on employment and wages, where the set of covariates is selected using a LASSO procedure (see Belloni et al. 2014). Columns 1-3 present long-differences estimates for the 1990-2007 period. Columns 4-6 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Panel A presents results for changes in the employment to population ratio. Panel B presents results for changes in log hourly wages. The specifications in this panel are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education and race. The covariates included in each specification are selected using LASSO, following Belloni et al. (2014). In columns 1 and 5, we start with the baseline set of covariates from Tables 2 and 3 (demographics, industry shares, Chinese import competition and share routine jobs) and select the subset to be included in the models using LASSO. In columns 2-3 and 6-7, we include all covariates used in the main robustness checks of the paper (exposure to declining industries, trade, offshoring, and capital deepening), as well as an expanded set of industry employment shares for mining, construction, agriculture, utilities, and research and development, and select the subset to be included in the models using LASSO. In columns 3 and 7, we separate the role of exposure to robots in the automotive industry from the role of robots outside this industry. In these models, we include the covariates selected by LASSO as predictors of any of these exposure measures or the outcome. Finally, in columns 4 and 8, we include all potential two-way interactions between our baseline covariates (including Census division and time dummies) and the extended set of covariates. We then select the subset of covariates to be included in our model using LASSO. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A29: The effects of robots on employment and wages by gender

	Long differences						Stacked differences					
	Men			Women			Men			Women		
	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted	Weighted by population	Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Change in the employment to population ratio												
Exposure to robots	-0.567	-0.674	-0.652	-0.336	-0.473	-0.385	-0.684	-0.809	-0.972	-0.418	-0.590	-0.515
	(0.065)	(0.147)	(0.148)	(0.063)	(0.145)	(0.112)	(0.065)	(0.175)	(0.134)	(0.049)	(0.133)	(0.079)
Observations	722	712	722	722	712	722	1444	1424	1444	1444	1424	1444
R-squared	0.62	0.59	0.59	0.71	0.71	0.58	0.37	0.35	0.37	0.45	0.45	0.37
Panel B. Change in log of hourly wages												
Exposure to robots	-0.979	-0.973	-0.984	-0.787	-0.591	-0.879	-1.651	-1.926	-1.914	-1.216	-1.343	-1.431
	(0.148)	(0.291)	(0.241)	(0.137)	(0.306)	(0.223)	(0.211)	(0.601)	(0.320)	(0.158)	(0.512)	(0.314)
Observations	43599	42935	43599	43501	42841	43501	92008	90612	92008	91598	90206	91598
R-squared	0.29	0.28	0.07	0.34	0.33	0.08	0.25	0.24	0.08	0.31	0.30	0.11
Panel C. Change in manufacturing employment to population ratio												
Exposure to robots	-0.256	-0.386	-0.442	-0.068	-0.094	-0.238	-0.314	-0.420	-0.507	-0.137	-0.224	-0.338
	(0.064)	(0.137)	(0.112)	(0.029)	(0.061)	(0.062)	(0.037)	(0.092)	(0.105)	(0.027)	(0.064)	(0.060)
Observations	722	712	722	722	712	722	1444	1424	1444	1444	1424	1444
R-squared	0.70	0.70	0.69	0.85	0.85	0.83	0.49	0.48	0.52	0.67	0.67	0.67
Panel D. Change in non-participation rate												
Exposure to robots	0.364	0.276	0.398	0.201	0.205	0.263	0.658	0.951	0.850	0.318	0.578	0.375
	(0.063)	(0.119)	(0.129)	(0.036)	(0.144)	(0.112)	(0.096)	(0.198)	(0.117)	(0.082)	(0.188)	(0.095)
Observations	722	712	722	722	712	722	1444	1424	1444	1444	1424	1444
R-squared	0.51	0.48	0.40	0.71	0.72	0.58	0.55	0.55	0.37	0.43	0.43	0.34
Covariates:												
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

The table presents estimates of the effects of exposure to robots on employment, wages and other outcomes by gender. Columns 1-6 present long-differences estimates for the 1990-2007 period. Columns 7-12 present stacked-differences estimates for the 1990-2000 and 2000-2007 periods. Columns 1-3 and 7-9 present results for men. Columns 4-6 and 10-12 present results for women. Panel A presents results for the employment to population ratio. Panel B presents results for log hourly wages. The specifications in this panel are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education and race. Panel C presents results for manufacturing employment to population ratios. Panel D presents results for the non-participation rate (defined as the share of the population above 16 years of age who are not in the labor force). Columns 1-2, 4-5, 7-8 and 10-11 present regressions weighted by population in 1990. Columns 2, 5, 8 and 11 present results excluding the top one percent of commuting zones with highest exposure to robots. Columns 3, 6, 9 and 12 present unweighted regressions. All models include Census division dummies (and time period dummies in the stacked-differences specifications), demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, the female share of manufacturing employment, exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

Table A30: Alternative Inference following Borusyak et al. (2018): IV estimates

	Change in the employment to population ratio			Change in log hourly wages		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Long-differences, 1990-2007					
US exposure to robots	-0.375	-0.377	-0.388	-1.022	-0.762	-0.768
	(0.116)	(0.121)	(0.125)	(0.269)	(0.237)	(0.238)
Observations	19	19	19	19	19	19
	Panel B. Alternative imputation of US data, 1990-2007					
US exposure to robots	-0.388	-0.391	-0.402	-1.060	-0.790	-0.796
	(0.120)	(0.126)	(0.130)	(0.279)	(0.246)	(0.246)
Observations	19	19	19	19	19	19
	Panel C. Long-differences, 1990-2014					
US exposure to robots	-0.303	-0.241	-0.250	-1.268	-1.103	-1.128
	(0.111)	(0.055)	(0.062)	(0.129)	(0.113)	(0.127)
Observations	19	19	19	19	19	19
	Panel D. Long-differences, 2000-2007					
US exposure to robots	-0.623	-0.574	-0.585	-1.376	-1.147	-1.191
	(0.084)	(0.055)	(0.063)	(0.240)	(0.064)	(0.069)
Observations	19	19	19	19	19	19
	Panel E. Long-differences, 2000-2014					
US exposure to robots	-0.451	-0.327	-0.339	-1.590	-1.566	-1.601
	(0.147)	(0.021)	(0.023)	(0.078)	(0.052)	(0.054)
Observations	19	19	19	19	19	19
Covariates:						
Division dummies	✓	✓	✓	✓	✓	✓
Demographics and industry shares		✓	✓		✓	✓
Trade, routine jobs			✓			✓

The table presents IV estimates of the effects of exposure to robots on employment and wages for different time periods. Panels A and B present results for 1990-2007. Panel C presents results for 1990-2014. Panel D presents results for 2000-2007. Panel E presents results for 2000-2014. In all models, we instrument the US exposure to robots using exposure to robots from $EURO5$. In Panels A and C-E we rescale the US exposure to robots to match the time period used. In Panel B we use an alternative imputation strategy for US exposure to robots described in the text. Columns 1-3 present results for the employment to population ratio. Columns 4-6 present results for log hourly wages. The specifications for log hourly wages are estimated at the demographic cell $\times$ commuting zone level, where demographic cells are defined by age, gender, education and race. All IV estimates are from regressions weighted by population in 1990. The covariates included in each model are reported at the bottom of the table. Columns 1 and 4 only include Census division dummies. Columns 2 and 5 add demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, and the female share of manufacturing employment. Columns 3 and 6 add exposure to Chinese imports and the share of employment in routine jobs. Robust standard errors computed following Borusyak et al. (2018).

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Table A31: Alternative Inference following Borusyak et al. (2018): long differences

	Long differences 1990-2007					
	Weighted by population				Excludes zones with highest exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Change in the employment to population ratio, 1990-2007					
Exposure to robots	-0.445	-0.414	-0.434	-0.448	-0.572	-0.516
	(0.053)	(0.086)	(0.046)	(0.043)	(0.181)	(0.076)
Observations	19	19	19	19	19	19
R-squared	0.23	0.12	0.72	0.76	0.28	0.36
	Panel B. Change in log hourly wages, 1990-2007					
Exposure to robots	-1.220	-1.017	-0.874	-0.884	-0.779	-0.932
	(0.075)	(0.092)	(0.093)	(0.090)	(0.180)	(0.107)
Observations	19	19	19	19	19	19
R-squared	0.70	0.62	0.80	0.80	0.26	0.41
Covariates:						
Census divisions	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓
Industry shares			✓	✓	✓	✓
Trade, routine jobs				✓	✓	✓

The table presents estimates of the effects of exposure to robots on employment and wages. Panel A presents long-differences estimates for changes in the employment to population ratio, 1990-2007. Panel B presents long-differences estimates for changes in log hourly wages, 1990-2007. The specifications in Panel B are estimated at the demographic cell $\times$ commuting zone level, where demographic cells are defined by age, gender, education and race. Columns 1-5 present regressions weighted by population in 1990. Column 5 presents results excluding the top one percent of commuting zones with highest exposure to robots. Column 6 presents unweighted regressions. The covariates included in each model are reported at the bottom of the table. Column 1 only includes Census division dummies. Column 2 adds demographic characteristics of commuting zones in 1990 (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians). Column 3 adds the shares of employment in manufacturing and light manufacturing, and the female share of manufacturing employment in 1990. Columns 4-6 add exposure to Chinese imports and the share of employment in routine jobs. Robust standard errors computed following Borusyak et al. (2018).

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Table A32: Alternative Inference following Borusyak et al. (2018): stacked differences

	Stacked differences 1990-2000 and 2000-2007							
							Commuting zone trends	
	Weighted by population				Excludes zones with highest exposure	Unweighted	Weighted by population	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Change in the employment to population ratio, 1990-2000 and 2000-2007							
Exposure to robots	-0.625	-0.591	-0.525	-0.551	-0.702	-0.743	-0.508	-1.007
	(0.059)	(0.064)	(0.069)	(0.075)	(0.269)	(0.107)	(0.042)	(0.145)
Observations	38	38	38	38	38	38	38	38
R-squared	0.42	0.38	0.40	0.47	0.05	0.48	0.89	0.79
	Panel B. Change in log hourly wages, 1990-2000 and 2000-2007							
Exposure to robots	-1.544	-1.508	-1.405	-1.443	-1.643	-1.684	-1.608	-2.649
	(0.104)	(0.124)	(0.155)	(0.167)	(0.574)	(0.350)	(0.268)	(0.689)
Observations	38	38	38	38	38	38	38	38
R-squared	0.65	0.63	0.62	0.66	0.26	0.53	0.79	0.79
Covariates:								
Time period dummies	✓	✓	✓	✓	✓	✓	✓	✓
Census divisions	✓	✓	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓	✓	✓
Industry shares			✓	✓	✓	✓	✓	✓
Trade, routine jobs				✓	✓	✓	✓	✓
Commuting zone trends							✓	✓

The table presents estimates of the effects of exposure to robots on employment and wages. Panel A presents stacked-differences estimates for changes in the employment to population ratio, 1990-2000 and 2000-2007. Panel B presents stacked-differences estimates for changes in log hourly wages, 1990-2000 and 2000-2007. The specifications in Panel B are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education and race. Columns 1-5 and 7 present regressions weighted by population in 1990. Column 5 presents results excluding the top one percent of commuting zones with highest exposure to robots. Columns 6 and 8 present unweighted regressions. The covariates included in each model are reported at the bottom of the table. Column 1 only includes Census division dummies and time period dummies. Column 2 adds demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians). Column 3 adds the shares of employment in manufacturing and light manufacturing, and the female share of manufacturing employment. Columns 4-6 add exposure to Chinese imports and the share of employment in routine jobs. In addition, columns 7 and 8 include a full set of commuting zone fixed effects. Robust standard errors computed following Borusyak et al. (2018).

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Table A33: OLS estimates of the relationship between US exposure to robots and employment and wages

	Change in the employment to population ratio			Change in log hourly wages		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Long differences between 1990 and 2007					
US exposure to robots	-0.283	-0.253	-0.254	-0.752	-0.515	-0.517
	(0.064)	(0.039)	(0.042)	(0.084)	(0.085)	(0.088)
Observations	722	722	722	87100	87100	87100
R-squared	0.26	0.65	0.65	0.32	0.33	0.33
	Panel B. Long differences between 1990 and 2007, alternative imputation of US exposure					
US exposure to robots	-0.294	-0.262	-0.264	-0.780	-0.534	-0.536
	(0.066)	(0.040)	(0.044)	(0.087)	(0.088)	(0.091)
Observations	722	722	722	87100	87100	87100
R-squared	0.26	0.65	0.65	0.32	0.33	0.33
	Panel C. Long differences between 1990 and 2014					
US exposure to robots	-0.297	-0.161	-0.156	-1.072	-0.893	-0.886
	(0.103)	(0.049)	(0.052)	(0.121)	(0.102)	(0.106)
Observations	722	722	722	90341	90341	90341
R-squared	0.30	0.55	0.55	0.42	0.46	0.46
	Panel D. Long differences between 2000 and 2007					
US exposure to robots	-0.638	-0.554	-0.571	-1.296	-1.024	-1.060
	(0.123)	(0.074)	(0.074)	(0.173)	(0.137)	(0.140)
Observations	722	722	722	99319	99319	99319
R-squared	0.37	0.67	0.67	0.21	0.22	0.22
	Panel E. Long differences between 2000 and 2014					
US exposure to robots	-0.468	-0.268	-0.277	-1.493	-1.351	-1.362
	(0.163)	(0.052)	(0.052)	(0.136)	(0.144)	(0.146)
Observations	722	722	722	106375	106375	106375
R-squared	0.37	0.66	0.66	0.33	0.35	0.35
Covariates:						
Division dummies	✓	✓	✓	✓	✓	✓
Demographics and industry shares		✓	✓		✓	✓
Trade, routine jobs			✓			✓

The table presents OLS estimates corresponding to the IV models in Table 7. Different panels cover different periods, with the US exposure measure rescaled to match the relevant period. Columns 1-3 present long-differences estimates for changes in the employment to population ratio. Columns 4-6 present long-differences estimates for changes in log hourly wages. The specifications in columns 4-6 are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education and race. All regressions are weighted by population in 1990. The covariates included in each model are reported at the bottom of the table. Columns 1 and 4 only include Census division dummies. Columns 2 and 5 add demographic characteristics of commuting zones (log population; the share of females; the share of population above 65 years; the shares of population with no college, some college, college and professional degrees, and masters and doctoral degrees; and the shares of Whites, Blacks, Hispanics and Asians), the shares of employment in manufacturing and light manufacturing, and the female share of manufacturing employment. Columns 3 and 6 add exposure to Chinese imports and the share of employment in routine jobs. Standard errors that are robust against heteroskedasticity and correlation within states are in parentheses.

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Table A34: Quantitative results for different parametrizations of our model

	Changing value of π_0			Changing value of $\frac{\gamma_M}{\gamma_L}$		
	π_0=0.1	π_0=0.3	π_0=0.5	$\frac{\gamma_M}{\gamma_L}=2$	$\frac{\gamma_M}{\gamma_L}=3$	$\frac{\gamma_M}{\gamma_L}=4$
Baseline $\psi,\sigma\lambda$:	$\eta=0.55$ $\varepsilon=0.17$ $d\ln L=$ -0.77 $d\ln W=$ -0.59	$\eta=0.79$ $\varepsilon=0.17$ $d\ln L=$ -0.56 $d\ln W=$ -0.42	$\eta=1.21$ $\varepsilon=0.17$ $d\ln L=$ -0.36 $d\ln W=$ -0.26	$\eta=1.33$ $\varepsilon=0.17$ $d\ln L=$ -0.65 $d\ln W=$ -0.49	$\eta=0.79$ $\varepsilon=0.17$ $d\ln L=$ -0.56 $d\ln W=$ -0.42	$\eta=0.52$ $\varepsilon=0.17$ $d\ln L=$ -0.48 $d\ln W=$ -0.36
Changing ψ						
$\psi=0$	$\eta=0.55$ $\varepsilon=0.19$ $d\ln L=$ -0.76 $d\ln W=$ -0.59	$\eta=0.79$ $\varepsilon=0.19$ $d\ln L=$ -0.55 $d\ln W=$ -0.43	$\eta=1.21$ $\varepsilon=0.19$ $d\ln L=$ -0.34 $d\ln W=$ -0.26	$\eta=1.33$ $\varepsilon=0.19$ $d\ln L=$ -0.64 $d\ln W=$ -0.49	$\eta=0.79$ $\varepsilon=0.19$ $d\ln L=$ -0.55 $d\ln W=$ -0.43	$\eta=0.52$ $\varepsilon=0.19$ $d\ln L=$ -0.47 $d\ln W=$ -0.36
$\psi=0.1$	$\eta=0.55$ $\varepsilon=0.09$ $d\ln L=$ -0.81 $d\ln W=$ -0.57	$\eta=0.79$ $\varepsilon=0.09$ $d\ln L=$ -0.61 $d\ln W=$ -0.41	$\eta=1.21$ $\varepsilon=0.09$ $d\ln L=$ -0.41 $d\ln W=$ -0.24	$\eta=1.33$ $\varepsilon=0.09$ $d\ln L=$ -0.69 $d\ln W=$ -0.47	$\eta=0.79$ $\varepsilon=0.09$ $d\ln L=$ -0.61 $d\ln W=$ -0.41	$\eta=0.52$ $\varepsilon=0.09$ $d\ln L=$ -0.53 $d\ln W=$ -0.34
$\psi=0.15$	$\eta=0.55$ $\varepsilon=0.04$ $d\ln L=$ -0.84 $d\ln W=$ -0.56	$\eta=0.79$ $\varepsilon=0.04$ $d\ln L=$ -0.64 $d\ln W=$ -0.40	$\eta=1.21$ $\varepsilon=0.04$ $d\ln L=$ -0.45 $d\ln W=$ -0.23	$\eta=1.33$ $\varepsilon=0.04$ $d\ln L=$ -0.72 $d\ln W=$ -0.46	$\eta=0.79$ $\varepsilon=0.04$ $d\ln L=$ -0.64 $d\ln W=$ -0.40	$\eta=0.52$ $\varepsilon=0.04$ $d\ln L=$ -0.57 $d\ln W=$ -0.33
Changing σ:						
$\sigma=0.5$	$\eta=0.54$ $\varepsilon=0.17$ $d\ln L=$ -0.76 $d\ln W=$ -0.58	$\eta=0.75$ $\varepsilon=0.17$ $d\ln L=$ -0.53 $d\ln W=$ -0.40	$\eta=1.12$ $\varepsilon=0.17$ $d\ln L=$ -0.31 $d\ln W=$ -0.22	$\eta=1.29$ $\varepsilon=0.17$ $d\ln L=$ -0.63 $d\ln W=$ -0.47	$\eta=0.75$ $\varepsilon=0.17$ $d\ln L=$ -0.53 $d\ln W=$ -0.40	$\eta=0.48$ $\varepsilon=0.17$ $d\ln L=$ -0.44 $d\ln W=$ -0.33
$\sigma=1.5$	$\eta=0.56$ $\varepsilon=0.17$ $d\ln L=$ -0.78 $d\ln W=$ -0.59	$\eta=0.83$ $\varepsilon=0.17$ $d\ln L=$ -0.59 $d\ln W=$ -0.44	$\eta=1.30$ $\varepsilon=0.17$ $d\ln L=$ -0.40 $d\ln W=$ -0.30	$\eta=1.37$ $\varepsilon=0.17$ $d\ln L=$ -0.67 $d\ln W=$ -0.50	$\eta=0.83$ $\varepsilon=0.17$ $d\ln L=$ -0.59 $d\ln W=$ -0.44	$\eta=0.56$ $\varepsilon=0.17$ $d\ln L=$ -0.52 $d\ln W=$ -0.39
Changing λ:						
$\lambda=2.5$	$\eta=0.58$ $\varepsilon=0.17$ $d\ln L=$ -0.80 $d\ln W=$ -0.61	$\eta=0.89$ $\varepsilon=0.17$ $d\ln L=$ -0.64 $d\ln W=$ -0.48	$\eta=1.44$ $\varepsilon=0.17$ $d\ln L=$ -0.48 $d\ln W=$ -0.35	$\eta=1.59$ $\varepsilon=0.17$ $d\ln L=$ -0.78 $d\ln W=$ -0.59	$\eta=0.89$ $\varepsilon=0.17$ $d\ln L=$ -0.64 $d\ln W=$ -0.48	$\eta=0.54$ $\varepsilon=0.17$ $d\ln L=$ -0.50 $d\ln W=$ -0.37
$\lambda=7.5$	$\eta=0.54$ $\varepsilon=0.17$ $d\ln L=$ -0.76 $d\ln W=$ -0.58	$\eta=0.75$ $\varepsilon=0.17$ $d\ln L=$ -0.54 $d\ln W=$ -0.40	$\eta=1.13$ $\varepsilon=0.17$ $d\ln L=$ -0.31 $d\ln W=$ -0.22	$\eta=1.23$ $\varepsilon=0.17$ $d\ln L=$ -0.60 $d\ln W=$ -0.45	$\eta=0.75$ $\varepsilon=0.17$ $d\ln L=$ -0.54 $d\ln W=$ -0.40	$\eta=0.51$ $\varepsilon=0.17$ $d\ln L=$ -0.47 $d\ln W=$ -0.35

The table presents our estimates for η and ε, and the aggregate decline on employment and wages predicted by our model under different parametrizations. Columns vary the values of π_0 and $\frac{\gamma_M}{\gamma_L}$ used, as reported at the top of the table. Rows vary the values of ψ,σ and λ used, as indicated in the left column.