Robots and Jobs: Evidence from US Labor Markets.*

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Abstract

As robots and automation technologies take over tasks performed by labor, there is increasing concern about the future of jobs and wages. We analyze the effect of the increase in industrial robot usage between 1990 and 2007 on US labor markets. Using a model in which robots compete against human labor in the production of tasks, we show that advances in robotics technology may reduce employment and wages, and that the local labor market impacts of robots can be estimated by regressing the change in employment and wages on the exposure to robots in each local labor market—defined from advances in robotics technology in each industry and the local distribution of employment across industries. Using this approach, we estimate robust negative effects of robots on employment and wages across commuting zones. We bolster this evidence by showing that the commuting zones most exposed to robots in the post-1990 era do not exhibit any differential trends before 1990. The impact of robots is distinct from the effects of overall productivity increases, other types of IT capital and the total capital stock. According to our estimates, one more robot per thousand workers reduces the employment to population ratio by about 0.2 percentage points and wages by 0.37 percent.

Keywords: automation, industrial robots, employment, jobs, labor, wages.

JEL Classification: J23, J24.

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1 Introduction

In 1929 John Maynard Keynes famously predicted that the rapid spread of automation technologies would bring "technological unemployment" (Keynes, 1930). Two decades later, Wassily Leontief would foretell similar problems for workers, writing "Labor will become less and less important... More and more workers will be replaced by machines. I do not see that new industries can employ everybody who wants a job" (Leontief, 1952). Though these predictions did not come to pass in the decades that followed, there is renewed concern that with the impressive advances in robotics and artificial intelligence we are on the verge of seeing them realized (e.g., Brynjolfsson and McAfee, 2014; Ford, 2015). The mounting evidence that the automation of a range of low- and medium-skill occupations has contributed to wage inequality and employment polarization (e.g., Autor, Levy and Murnane, 2003; Goos and Manning, 2007; Michaels, Natraj and Van Reenen, 2014) adds to these worries. These concerns notwithstanding, we have little systematic evidence on the *equilibrium impact* of automation technologies, and especially of robots, on employment and wages.[1]

In this paper we estimate the equilibrium impact of a leading automation technology, *industrial robots*, on local US labor markets. The International Federation of Robotics—IFR for short—defines an industrial robot as "an automatically controlled, reprogrammable, and multipurpose [machine]" (IFR, 2014). That is, industrial robots are fully autonomous machines that do not need a human operator and that can be programmed to perform several manual tasks such as welding, painting, assembly, handling materials, or packaging. Textile looms, elevators, cranes, or transportation bands are not industrial robots as they have a unique purpose, cannot be reprogrammed to perform other tasks, and/or require a human operator. This definition excludes other types of equipment, and enables an internationally and temporally comparable measurement of a class of technologies—industrial robots—that are capable of replacing human labor in a range of tasks.

Robotics technology advanced significantly in the 1990s and 2000s, leading to a fourfold rise in the stock of robots in the United States and Western Europe between 1993 and 2007. As Figure 1 shows, in the United States the increase amounted to one new industrial robot per thousand workers, and in Western Europe to 1.6 new industrial robots per thousand workers. The automotive industry employs 38 percent of existing industrial robots, followed by the electronics industry (15 percent), plastic and chemicals (10 percent), and metal products (7 percent).

To motivate our approach, we start with a model where robots and workers compete in the production of different tasks. Our model builds on Acemoglu and Autor (2011), Acemoglu and Restrepo (2018a) and Zeira (1998), but extends these frameworks so that the share of tasks performed by robots varies across sectors and there is trade between labor markets specializ-

[1] Frey and Osborne (2013), World Development Report (2016) and McKinsey (2017) estimate which types of jobs will be susceptible to automation based on various technological projections. Such approaches are not informative about the equilibrium impact of automation since they do not take into account how other sectors and occupations will respond to these changes. See also Arntz, Gregory and Zierahn (2016) on other problems with these methodologies.

ing in different industries. Greater penetration of robots into the economy affects wages and employment negatively owing to a *displacement effect* (as they directly displace workers from tasks they were previously performing), but also positively because of a *productivity effect* (as other industries and/or tasks increase their demand for labor). Our framework clarifies that, because of the displacement effect, robots can have very different implications for labor demand than capital deepening or factor-augmenting technologies. It further shows that the impact of robots on employment and wages in a labor market can be estimated by regressing the change in these variables on *exposure to robots*. Exposure to robots is a Bartik-style measure (Bartik, 1991), exploiting baseline industry shares in a local labor market and technological possibilities for the introduction of robots across industries.

We first document that there is considerable variation in the adoption of robots across industries (even within manufacturing), and that industries rapidly adopting robots in the United States are the same ones doing so in Europe. We further show that at the industry level, the adoption of robots is uncorrelated or only weakly correlated with several other major trends, including increased import competition from China, competition from Mexico, offshoring, the decline of routine tasks, investments in IT capital and overall capital deepening. Moreover, consistent with theory, the adoption of robots at the industry level is associated with lower labor share and employment, and greater value added and labor productivity.

After presenting these industry-level correlations, we investigate the equilibrium impact of robots in local labor markets, proxied by commuting zones in the United States.[2] We construct our measure of *exposure to robots* using data from the IFR on the increase in robot usage across 19 industries (roughly at the two-digit level outside manufacturing and at the three-digit level within manufacturing) and their baseline employment shares from the Census before the onset of recent robotic advances. In order to focus on the component of investment in robots driven by technological advances, we exploit adoption trends in European economies that are ahead of the United States in robotics.[3]

Using this source of variation, we estimate a strong relationship between a commuting zone's exposure to robots and its post-1990 labor market outcomes. Our estimates imply that between 1990 and 2007 the increase in the stock of robots (approximately one additional robot per thousand workers from 1993 to 2007) reduced the employment to population ratio in a commuting

[2]Not all equilibrium responses take place within commuting zones—the most important omitted ones being trade with other local labor markets, which we model explicitly below; migration, which we investigate empirically; and the response of technology and new tasks to changes in factor prices emphasized in Acemoglu and Restrepo (2018a). All the same, recent research suggests that much of the adjustment to shocks, both in the short run and the medium run, takes place locally (e.g., Acemoglu, Autor and Lyle, 2005, Moretti, 2011, Autor, Dorn and Hanson, 2013).

[3]This strategy is similar to that used by Autor, Dorn and Hanson (2013) and Bloom, Draca and Van Reenen (2015) to estimate the impact of Chinese imports. Though not a panacea against all sources of omitted variable bias, it allows us to filter out variation in robot adoption coming from idiosyncratic US factors (e.g., US-specific declines or worsening labor relations in some industries). This strategy would be compromised if changes in robot usage in other advanced economies are correlated with adverse shocks to US industries. For instance, there may be common shocks affecting the same industries across advanced economies, such as import competition or rising wages, and these shocks could induce the same industries everywhere to adopt robots; or the decline of an industry in the United States may encourage both US domestic producers and their foreign competitors to adopt robots. We provide evidence suggesting that these concerns are not responsible for our results.

zone with the average US change in robots by 0.38 percentage points, and average wages by 0.71 percent (relative to a commuting zone with no exposure to robots). These numbers are sizable but not implausible. For example, they imply that one more robot in a commuting zone reduces employment by about 6 workers; this estimate includes both direct and indirect effects, the latter being caused by the decline in the demand for nontradables as a result of reduced employment and wages in the local economy.

To understand the aggregate implications of these estimates, we need to make additional assumptions about how different commuting zones interact. Greater use of robots in a commuting zone is likely to generate benefits for the rest of the US economy by reducing the prices of tradable goods now produced using robots and by creating shared capital gains. Our model enables us to quantify these positive spillovers across commuting zones, and leads to somewhat smaller but still uniformly negative aggregate effects. With our preferred choice of parameters, our estimates imply that one more robot per thousand workers reduces aggregate employment to population ratio by about 0.2 percentage points or equivalently one new robot reduces employment by about 3.3 workers and wages by about 0.37 percent (as opposed to 0.37 percentage points and 0.71 percent, respectively, without trade).

We verify that our measure of exposure to robots is unrelated to past trends in employment and wages from 1970 to 1990, a period that preceded the onset of rapid advances in robotics technology. Several robustness checks further support our interpretation. First, our results are robust to including differential trends by various baseline characteristics, linear commuting zone trends, and controls for other changes affecting demand or productivity in various industries. Second, we show that the automotive industry, which is the most robots-intensive sector, is not driving our results. Third, consistent with our theoretical emphasis that automation technologies, such as robots, have very different labor market effects than other types of machinery and overall capital deepening, we find no similar negative impact from capital, other measures of IT and overall productivity increases.

We also document that the employment effects of robots are most pronounced in manufacturing, and in particular, in industries most exposed to robots; in routine manual, blue collar, assembly and related occupations. Consistent with the presence of spillovers on nontradables, we estimate negative effects on construction and retail and personal services.

Besides the papers that we have already mentioned, our work is related to the empirical literature on the effects of technology on wage inequality (Katz and Murphy, 1992), employment polarization (Autor, Levy and Murnane, 2003; Goos and Manning, 2007; Autor and Dorn, 2013; Michaels, Natraj and Van Reenen, 2014), aggregate employment (Autor, Dorn and Hanson, 2015; Gregory, Salomons and Zierahn, 2016), the demand for labor across cities (Beaudry, Doms and Lewis, 2006), and firms' organization and demand for workers with different skills (Caroli and Van Reenen, 2001, Bartel, Ichniowski, and Shaw, 2007, and Acemoglu et al., 2007).

Most closely related to our work is the pioneering paper by Graetz and Michaels (2018). Focusing on the variation in robot usage across industries in different countries, Graetz and Michaels estimate that industrial robots increase productivity and wages, but reduce the employment of low-skill workers. Although we rely on the same IFR data, we utilize a different empirical strategy, which enables us to go beyond cross-country, cross-industry comparisons, exploit plausibly exogenous changes in the spread of robots, and estimate the equilibrium impact of robots on local labor markets. Our micro data also allow us to control for detailed demographic and compositional variables when focusing on commuting zones, check the validity of our exclusion restrictions with placebo exercises, and study the impact of robots on industry and occupation-level outcomes, bolstering the plausibility of our estimates.

The rest of the paper is organized as follows. Section 2 presents a simple model of the effects of robots on employment and wages, which both clarifies the main economic forces and enables us to derive our estimating equations. Section 3 introduces our data sources. Section 4 presents the correlation between robot adoption at the industry level and employment, the labor share and productivity. Section 5 presents our main empirical results and various robustness checks. Section 6 looks at the differential effects of robots on workers in different industries, occupations and skill groups. Section 7 concludes, while the Appendix presents proofs, additional theoretical results especially useful in interpreting our empirical findings when there are trade links between commuting zones, and a large number of further robustness checks.

2 Robots, Employment and Wages: A Model

This section presents a model building on Acemoglu and Restrepo (2018a) to exposit the potential effects of robots on employment and wages, and derives our estimating equations. To develop intuition, we start with a model without trade between commuting zones.

2.1 Robots in Autarky Equilibrium

The economy consists of $|\mathcal{C}|$ commuting zones. Each commuting zone $c \in \mathcal{C}$ has preferences defined over an aggregate of the consumption of the output of $|\mathcal{I}|$ industries, given by

$$Y_c = \left(\sum_{i \in \mathcal{I}} \nu_i^{\frac{1}{\sigma}} Y_{ci}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where $\sigma > 0$ denotes the elasticity of substitution across goods produced by different industries, while the ν_i's are share parameters that designate the importance of industry i in the consumption aggregate (with $\sum_{i \in \mathcal{I}} \nu_i = 1$).

In the autarky equilibrium, a commuting zone consumes its own production of each good, denoted by X_{ci}. Hence, for all $i \in \mathcal{I}$ and $c \in \mathcal{C}$, we have $Y_{ci} = X_{ci}$. We choose the consumption aggregate in each commuting zone as a numeraire (with price normalized to 1) and denote the price of the output of industry i in commuting zone c by P_{ci}^X.

Each industry produces output by combining capital with a continuum of tasks indexed by $s \in [0, 1]$, each of which can be produced using industrial robots or human labor. We denote by $x_{ci}(s)$ the quantity of task s utilized in the production of X_{ci}. These tasks must be combined in fixed proportions so that

$$X_{ci} = \alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)} A_{ci}[\min_{s\in[0,1]} \{x_{ci}(s)\}]^{\alpha} K_{ci}^{1-\alpha}, \tag{2}$$

where K_{ci} denotes the non-robot capital used in industry i, $1-\alpha$ is its share in the production process, A_{ci} is the productivity of industry i, and the term $\alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}$ is included as a convenient normalization. Differences in the A_{ci}'s will translate into different industrial compositions of employment across commuting zones.

We model industrial robots as replacing labor in some of the tasks it was performing. Specifically, in industry i tasks $[0, \theta_i]$ are *technologically automated* and can be performed by robots. We assume that all commuting zones have access to the same technology, i.e., the same θ_i in industry i. Denoting the productivity of labor by γ_L and the productivity of robots by $\gamma_M > 0$, we have

$$x_{ci}(s) = \begin{cases} \gamma_M M_{ci}(s) + \gamma_L L_{ci}(s) & \text{if } s \leq \theta_i \\ \gamma_L L_{ci}(s) & \text{if } s > \theta_i, \end{cases}$$

where $L_{ci}(s)$ and $M_{ci}(s)$ are, respectively, the numbers of workers and robots used in the production of task s. Because tasks above θ_i have not yet been technologically automated, they have to be produced by labor.

In each commuting zone c labor is supplied by a representative household with preferences

$$\frac{C_c^{1-\psi} - 1}{1-\psi} - \frac{B}{1+\varepsilon} L_c^{1+\varepsilon},$$

where C_c denotes this household's consumption and L_c is its labor supply. Its budget constraint is $C_c \leq W_c L_c + \Pi_c$, where Π_c is non-labor (capital and profit) income. In this specification, ψ is the income elasticity of labor supply, and ε is the Frisch elasticity of labor supply. These preferences are consistent with balanced growth when $\psi \to 1$ (in which case the first term becomes $\log C_c$).

Robots are produced using investment (in units of the final good), denoted by I_c, with the production function $M_c = D(1+\eta) I_c^{\frac{1}{1+\eta}}$, and have a rental price of R_c^M. This formulation, with $\eta > 0$, allows the supply of robot services to a commuting zone to be upward sloping. This is reasonable in the medium term, since about two thirds of the costs of robots are for services supplied by local, specialized robot integrators that install, program and maintain this equipment (Leigh and Kraft, 2018). Finally, in the autarky model we take the supply of capital in commuting zone c to be fixed at K_c, and denote its price by R_c^K.

An equilibrium is a tuple of prices $\{W_c, R_c^M, R_c^K\}_{c\in \mathcal{C}}$ and quantities $\{L_c, M_c\}_{c\in\mathcal{C}}$ such that in all commuting zones, firms maximize profits, households maximize their utility, and the markets for capital, labor, robots and final goods clear:

$$\sum_{i\in\mathcal{I}} \int_{[0,1]} L_{ci}(s) = L_c, \qquad \sum_{i\in\mathcal{I}} \int_{[0,1]} M_{ci}(s) = M_c, \qquad \sum_{i\in\mathcal{I}} K_{ci}(s) = K_c, \qquad C_c = Y_c - I_c.$$

We prove in the Appendix that an equilibrium exists and is unique.

To analyze the equilibrium impact of robots, let us first define cost savings from the use of robots in commuting zone c as

$$\pi_c = 1 - \frac{\gamma_L R_c^M}{\gamma_M W_c}.$$

Robots will not be adopted when $\pi_c < 0$, and in what follows we focus on the case where $\pi_c > 0$ in all commuting zones. The next proposition characterizes the partial equilibrium impact of an advance in automation/robotics technology for industry i, denoted by $d\theta_i$.

PROPOSITION 1 *Suppose that $\pi_c > 0$. Then*

$$d\ln L_{ci} = -\frac{d\theta_i}{1-\theta_i} + \frac{1}{\alpha}d\ln Y_c - \left(\sigma + \frac{1}{\alpha} - 1\right) d\ln P_{ci}^X, \tag{3}$$

where L_{ci} denotes the employment in industry i in commuting zone c.

Like all other results in this section, the proof of this proposition is provided in the Appendix.

Equation (3) highlights three different forces shaping labor demand of industry i, represented by L_{ci}. First there is a negative *displacement effect*: an increase in θ_i will lead to the use of robots in tasks otherwise performed by labor, displacing workers employed in these tasks. This displacement effect always reduces the labor share in the industry undergoing automation, and may also reduce its overall labor demand.[4] The reason why labor demand does not necessarily decline following automation is because of the countervailing (positive) *productivity effect*, which is represented by the second term. Intuitively, automation lowers the cost of production (thus increases "productivity"), and via this channel, raises the demand for labor in non-automated tasks in *all* industries. Finally, there is a *composition effect*, represented by the third term: industries undergoing automation expand at the expense of others, and this raises the demand for labor coming from their non-automated tasks.

The industry-level implications of Proposition 1 can be aggregated to derive the impact of robots on local labor demand as follows:

$$d\ln L_c = -\sum_{i\in\mathcal{I}} \ell_{ci}\frac{d\theta_i}{1-\theta_i} + \frac{1}{\alpha}d\ln Y_c - \left(\sigma + \frac{1}{\alpha} - 1\right)\sum_{i\in\mathcal{I}}(\ell_{ci} - \chi_{ci}) d\ln P_{ci}^X, \tag{4}$$

where ℓ_{ci} is the share of industry i in total employment in commuting zone c, while χ_{ci} is this industry's share of value added. The first two terms are direct analogues of the displacement and productivity effects in (3). The third term shows that the implications of the composition effect for labor demand depends on whether automation is reallocating output towards sectors

[4] The negative impact on the labor share can be seen by computing the total task production in industry i as $X_{ci} = A_{ci}\alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}\left[\min\left\{\frac{\gamma_M M_{ci}}{\theta_i}, \frac{\gamma_L L_{ci}}{1-\theta_i}\right\}\right]^{\alpha} K_{ci}^{1-\alpha}$, which shows that an increase in θ_i always makes production less labor intensive (see Acemoglu and Restrepo, 2018a). We establish in the Appendix that a sufficient condition for the displacement effect to dominate the other forces and reduce (relative) industry employment is $\frac{1/\alpha}{1/\alpha+\sigma-1} > \pi_c s_{ic}^L$, where s_{ic}^L is this industry's labor share. This condition always holds if σ is not too much greater than 1.

that are more labor intensive than average (those for which $\ell_{ci} > \chi_{ci}$). This composition effect disappears when all industries have the same labor share.

Equation (4) provides a partial equilibrium characterization of how the demand for labor changes following automation. The next proposition links changes in prices and total output to automation technologies and thus derives the full equilibrium impact of automation.

Proposition 2 *Suppose that $\pi_c > 0$ for all $c \in \mathcal{C}$ and $\theta_i = 0$ for all $i \in \mathcal{I}$. Then*

$$d \ln L_c = [-\zeta^{disp} + \zeta^{prod}\pi_c - \zeta^{inc}_{c,L}\psi] \cdot \sum_{i \in \mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i} \frac{\gamma_L}{\gamma_M}, \quad (5)$$

$$d \ln W_c = [-\zeta^{disp}\varepsilon + \zeta^{prod}\varepsilon\pi_c + \zeta^{inc}_{c,W}\psi] \cdot \sum_{i \in \mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i} \frac{\gamma_L}{\gamma_M}, \quad (6)$$

where $\zeta^{disp} = (1-\alpha+\eta)/\Lambda$, $\zeta^{prod} = (1+\eta)/\Lambda$, $\zeta^{inc}_{c,L} = \alpha\pi_c/\Lambda_c$, $\zeta^{inc}_{c,W} = \alpha(\pi_c - (1-\pi_c)(1-\alpha+\eta))/\Lambda$, and $\Lambda = \frac{\gamma_L}{\gamma_M}(1-\alpha+\alpha\psi+\varepsilon) > 0$.

This proposition is stated under the assumption that $\theta_i = 0$ for all i, which simplifies the relevant expressions by removing the composition effect. The economic effects are similar when this assumption is relaxed as shown in the Appendix.[5]

This proposition shows that the response of both employment and wages to automation is shaped by the term $\sum_{i \in \mathcal{I}} \ell_{ci} \frac{d\theta_i}{1-\theta_i} \frac{\gamma_L}{\gamma_M}$, which will be the basis of our *exposure to robots* measure. In addition, the coefficient of this variable in both equations comprises three distinct terms. The first one, $-\zeta^{\text{disp}}$, represents the displacement effect. The second one, ζ^{prod}, represents the productivity effect, generated by cost savings, π_c. When cost savings from automation are limited, the impact of automation on employment will be negative. Conversely, when π_c is large, automation will increase labor demand, employment and wages. Finally, the third term in both equations incorporates the negative income effect of automation on labor supply.

It is worth noting that the impacts of robots highlighted in Proposition 2 are very different than those of overall capital deepening (which would result from an increase in the supply of capital, K_c), or from other technological changes that increase the productivity of labor, γ_L, in the model. Capital deepening—or an increase in the productivity of robots, γ_M—that does not displace workers from the tasks they are performing always raises wages and employment, and labor-augmenting technological change does so as well since the elasticity of substitution between capital and labor is one (see, e.g., Acemoglu and Restrepo, 2018b). This observation clarifies that the displacement effect created by automation is responsible for its potentially negative impact on labor demand.

[5]In any case, the composition effects are likely to be small in practice; there were few robots in any industry in the early 1990s, and moreover, the source of composition effects—the correlation between $\ell_{ci} - \chi_{ci}$ (or equivalently the labor share) in equation (4) and the introduction of robots across industries—is not present in the data. For example, the correlation between the labor share of an industry in 1992 subsequent robots usage is 0.13 across all industries (and -0.09 within manufacturing).

2.2 Robots When Commuting Zones Trade

The autarky model transparently illustrates the displacement and productivity effects of automation, but ignores how its economic consequences may spill over across local labor markets, for example, due to trade in goods and services between commuting zones. Such linkages change both the sensitivity of employment and wages to the adoption of robots and their aggregate implications. We now incorporate automation/robots into a simple model of trade between commuting zones building on the work of Armington (1969) and Anderson (1979). Specifically, we modify our model in two related ways. First, we assume that the representative household's utility depends on a tradable good, C_c, and a nontradable (service) good, S_c:

$$\frac{(C_c^{\phi} S_c^{(1-\phi)})^{1-\psi} - 1}{1-\psi} - \frac{B}{1+\varepsilon} L_c^{1+\varepsilon}. \tag{7}$$

This Cobb-Douglas specification implies that a constant share $\phi \in (0,1)$ of spending will be on the tradable good. We assume that this nontradable good is produced with labor, that is, $S_c = L_c^S$, and we denote its price in commuting zone c by P_c. The remaining labor, $L_c - L_c^S$, is used in the labor-intensive tasks in the production of tradable goods.

The second modification is to assume that the tradable good is produced as in (1), but now with inputs sourced from all commuting zones so that

$$Y_{ci} = \left(\sum_{s \in \mathcal{C}} \upsilon_{si}^{\frac{1}{\lambda}} X_{sci}^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}} \text{ (for all } c \text{ and } i\text{)}, \tag{8}$$

where λ is the elasticity of substitution between varieties sourced from different commuting zones, and the share parameters, the υ_{si}'s, indicate the desirability of varieties from different sources. We assume that there are no trade costs, so that the price of the tradable good is equalized across commuting zones and we choose it as the numeraire. Denoting the amount of good i exported from commuting zone c to destination d by X_{cdi} (including $d = c$), market clearing imposes

$$X_{ci} = \sum_{d \in \mathcal{C}} X_{cdi} \text{ (for all } c \text{ and } i\text{)}.$$

We also assume that the initial stock of capital of the economy, K, is perfectly mobile across commuting zones, and we modify the budget constraint of households to $C_c + P_c S_c \leq W_c L_c + \chi_c^{\Pi} \Pi$, where Π is the national non-labor income and a share χ_c^{Π} of this income is allocated to commuting zone c (with $\sum_{c \in \mathcal{C}} \chi_c^{\Pi} = 1$). The main result of this section is presented in the next proposition, which parallels Proposition 2.

PROPOSITION 3 *Suppose that $\pi_c = \pi_0$ for all $c \in \mathcal{C}$ and $\theta_i = 0$ for all $i \in \mathcal{I}$. Then*

$$d\ln L_c = [-\bar{\zeta}^{disp}\phi + \bar{\zeta}^{prod}\phi\pi_0 - \bar{\zeta}_L^{inc}\psi]\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M} + \bar{\zeta}_L^{Y} d\ln Y + \bar{\zeta}_L^{\Pi} d\ln \Pi + \bar{\zeta}_{cL}^{price} \tag{9}$$

$$d\ln W_c = [-\bar{\zeta}^{disp}\varepsilon + \bar{\zeta}^{prod}\varepsilon\pi_0 + \bar{\zeta}_W^{inc}\psi]\sum_{i\in\mathcal{I}}\ell_{ci}\frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M} + \bar{\zeta}_W^{Y} d\ln Y + \bar{\zeta}_W^{\Pi} d\ln \Pi + \bar{\zeta}_{cW}^{price}, \tag{10}$$

where the $\bar{\zeta}$'s are functions of the underlying parameters of the model.

This proposition is stated under the assumption that π_c is the same across commuting zones as well as $\theta_i = 0$ for all i, and we provide a more general version in the Appendix.

As before, the $\bar{\zeta}$'s summarize the local impact of robots on employment and wages. In addition, trade between commuting zones implies that productivity gains and price changes in one area will be shared with others. The productivity spillovers, generated by the change in national income $d\ln Y$, are captured by the $\bar{\zeta}^Y$ terms, while spillovers from changes in prices are summarized by the $\bar{\zeta}^{\text{price}}$ terms. Finally, the $\bar{\zeta}^{\Pi}$ terms represent the income effects and the demand for nontradables resulting from non-labor income, $d\ln\Pi$. These general equilibrium effects are not functions of exposure to robots in the commuting zone, and thus we obtain the same reduced-form relationship between robots and local labor demand as in the autarky model. The aggregate implications of robots, however, depend on the extent of trade across commuting zones because of the additional spillover terms and because the $\bar{\zeta}$'s in this proposition differ from their autarky counterparts in Proposition 2. We take these differences into account in our quantitative evaluation below.

2.3 Empirical Specification

Proposition 2 and 3 summarize the effects of changes in the robotics technology on local employment and wages. The key equations, (9) and (10), show that the equilibrium impact of robots depends on the same object, which we will call a commuting zone's *(US) exposure to robots*,

$$\text{US exposure to robots}_c = \sum_{i\in\mathcal{I}}\ell_{ci}\cdot APR_i, \tag{11}$$

where recall that ℓ_{ci} is the *baseline employment share* of industry i in commuting zone c, and

$$APR_i = \frac{d\theta_i}{1-\theta_i}\frac{\gamma_L}{\gamma_M} = \frac{dM_i}{L_i} - \frac{dY_i}{Y_i}\frac{M_i}{L_i} \tag{12}$$

is the *(US) adjusted penetration of robots* in industry i. Exposure to robots is thus a Bartik-style measure combining industry-level variation in the usage of robots and baseline employment shares. Our model implies a specific form for this relationship, including an adjustment for the overall expansion of each industry's output as given by the last term in (12).

With this measure of exposure to robots, we can estimate

$$d \ln L_c = \beta_L \cdot \text{US exposure to robots}_c + \epsilon_c^L; \quad d \ln W_c = \beta_W \cdot \text{US exposure to robots}_c + \epsilon_c^W, \quad (13)$$

regardless of whether or not there is trade between commuting zones, though the coefficients β_L and β_W have different interpretations in these two cases. In these equations, ϵ_c^L and ϵ_c^W represent other factors affecting labor supply and demand, and in our empirical work, we will model them as functions of various baseline characteristics and observed economic changes.

The models in equation (13) can be readily estimated using OLS with the US exposure to robots variable computed from US data on the adjusted penetration of robots across industries. However, there are two related reasons why the US exposure to robots could be correlated with the error terms, ϵ_c^L and ϵ_c^W, leading to biased estimates. First, some industries may be adopting robots in response to other changes that they are undergoing, which could directly impact their labor demand. Second, any shock to labor demand in a commuting zone affects the decisions of the industries located in that commuting zone, including their decisions concerning the adoption of robots.[6] Ideally, we would only want to use changes in robot penetration driven by exogenous improvements in technology, $d\theta_i$.

To identify the component of robot penetration driven by changes in technology, we instrument the US exposure to robots using an analogous measure constructed from the penetration of robots in European countries that are ahead of the United States in robotics, given by

$$\text{Exposure to robots}_c = \sum_{i \in \mathcal{I}} \ell_{ci} \cdot \overline{APR}_i, \quad (14)$$

where $\overline{APR}_i$ is the adjusted penetration of robots computed from European countries. We describe and motivate this choice in greater detail in the next section.

3 Data

In this section we describe our main data sources.

3.1 Robots

Our main data consist of counts of the stock of robots by industry, country and year from the IFR. The IFR data are based on yearly surveys of robot suppliers and cover 50 countries from 1993 to 2014, corresponding to about 90 percent of the industrial robots market. The stock of industrial robots by industry going back to the 90s is only available for Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom, which together ac-

[6] An example for the first concern would be the automotive industry adopting more robots in the United States because of higher wage push from its unions. An example for the second would be a local recession in Detroit, MI that impacts the automotive industry that has a large footprint there.

count for 41 percent of the world industrial robot market.[7] Outside of manufacturing, we have consistent data for the use of robots in six broad industries: agriculture, forestry and fishing; mining; utilities; construction; education, research and development; and services. Within manufacturing, we have consistent data on the use of robots for 13 more disaggregated industries: food and beverages; textiles (including apparel); wood and furniture; paper and printing; plastic and chemicals; minerals, glass, and ceramics; basic metals; metal products; industrial machinery; electronics; automotive; shipbuilding and aerospace; and miscellaneous manufacturing (e.g., production of jewelry and toys). We use this industry classification throughout, and refer to it as the IFR industries.

Table A1 in the Appendix and Figure 1 depict the evolution of robots stocks for different subsets of these countries and for the United States. In Figure 1 we show separately the evolution of the stock of robots for Germany, the average for Denmark, Finland, France, Italy and Sweden, the average for Norway, Spain and the UK, and the United States. The trends for Denmark, Finland, France, Germany, Italy and Sweden are particularly interesting, because these are the countries that are technologically more advanced than the United States in robotics.[8] US robot usage starts near 0.4 robots per thousand workers in the early 1990s, increases to 0.7 in 2000, and then rises rapidly to 1.4 robots per thousand workers in the late 2000s; this closely tracks but is about 20 percent lower than the average of Denmark, Finland, France, Italy and Sweden.[9]

The IFR data have some shortcomings worth noting. First, not all robots are classified into one of the 19 IFR industries. About 30 percent of robots are unclassified, and this fraction has declined throughout our sample. We allocate these unclassified robots to industries in the same proportions as in the classified data. Second, although the IFR reports data on the total stock of industrial robots in the United States from 1993 onwards, it does not provide industry breakdowns until 2004. This does not affect the exposure to robots measure computed from European data, and we describe how we use US data in our IV strategy in Section 5.9. Finally, the IFR only reports the overall stock of robots for North America. Though this aggregation introduces noise in our measures of US exposure to robots, this is not a major concern, since the United States accounts for more than 90 percent of the North American market, and our IV procedure should purge the US exposure to robots from this type of measurement error.[10]

[7]Though the IFR also reports data by industry for Japan, these data underwent a major reclassification. We follow the recommendations of the IFR and exclude Japan from our analysis.

[8]This can be seen from their level of robot adoption at the beginning of the sample, in 1993, or from their rate of investments in robotics during our sample. It can also be seen from their "robot exports" (measured as exports of intermediates related to robotics from the Comtrade dataset, see Acemoglu and Restrepo, 2018c, for details). For example, robot exports per worker are three to four times as large in Italy, France and Denmark as in the United States, and more than six times as large in Germany, Finland and Sweden. Norway and the UK are behind the United States in all of these metrics. Spain has adopted robots rapidly in the automotive industry since 1993, but is behind or comparable to the United States in other sectors, and its robot exports are at the same level as the United States.

[9]We show in Acemoglu and Restrepo (2018c) that demographic factors account for a large fraction of this cross-country variation and for why European countries are ahead of the United States in robotics. The relative shortage of middle-aged (production) workers in countries aging rapidly, such as Germany, France, Italy, Japan and South Korea, encourages the development and adoption of robotics technology, which is then exported to other countries, including the United States, experiencing less rapid demographic change.

[10]Although in principle robots in different sectors may have different capabilities and values, in practice there

We combine the IFR data with employment counts and output produced by country and industry from the EUKLEMS dataset (see Jägger, 2016),[11] which allows us to construct adjusted penetration of robots, APR_i and $\overline{APR}_i$, for different time periods. Following equation (12), our baseline measure of the adjusted penetration of robots between two dates, t_0 and t_1, is given by

$$\overline{APR}_{i,(t_0,t_1)} = \frac{1}{5} \sum_{j \in EURO5} \left[\frac{M^j_{i,t_1} - M^j_{i,t_0}}{L^j_{i,1990}} - g^j_{i,(t_0,t_1)} \frac{M_{i,t_0}}{L^j_{i,1990}} \right] \tag{15}$$

where $M^j_{i,t}$ is the number of robots in industry i in country j at time t (from the IFR data), $g^j_{i,(t_0,t_1)}$ is the growth rate of output of industry i in country j between t_0 and t_1 (also from the EUKLEMS), and $L^j_{i,1990}$ is the baseline employment level in industry i and country j (from the EUKLEMS).[12] In our long-differences models, we take $t_0 = 1993$ and $t_1 = 2007$, though we also present models where we focus on other periods.

For our baseline measure we use the average penetration in $EURO5$, comprising Denmark, Finland, France, Italy, and Sweden, that is, countries ahead of the United States in robotics excluding Germany. Focusing on countries that are ahead of the United States helps us isolate the source of variation coming from technological advances (rather than idiosyncratic US factors). We exclude Germany from our baseline measure because, as Figure 1 shows, it is so far ahead of the other countries that its adoption trends may be less relevant for US patterns than those of the countries in $EURO5$.[13]

We also measure the US adjusted penetration of robots as

$$APR^{US}_{i,(t_0,t_1)} = \frac{M^{US}_{i,t_1} - M^{US}_{i,t_0}}{L^{US}_{i,1990}} - g^{US}_{i,(t_0,t_1)} \frac{M_{i,t_0}}{L^{US}_{i,1990}}. \tag{16}$$

is little variation in these dimensions. Industrial robots belong to one of a handful of standardized types—articulated robots, SCARA (selective compliance assembly robot arm) robots, Cartesian robots, and parallel robots. Consistent with this, robot prices are fairly similar across sectors (ranging from about $44,000 per robot to about $88,000), and our results in Table 5 suggest that the quantitative effects of robots in different sectors are similar. In Tables A21 and A22 in the Appendix, we investigate the role of robot prices further.

[11] To obtain comparable data, we first use information on hours worked to obtain a count of equivalent US workers by industry in 1990. We then compute the number of robots by industry, country and year divided by US equivalent workers in 1990. Because the data for Norway are missing from the EUKLEMS, we use the distribution of employment in the remaining Scandinavian countries in our sample (Denmark, Finland, and Sweden) to impute the Norwegian distribution. In addition, we were able to match most of the industries used in the EUKLEMS dataset to the 19 IFR industries. One exception is wood and furniture, since employment in furniture products is pooled with miscellaneous manufacturing. To address this issue, we allocated 40% of the employment in miscellaneous manufacturing to the wood and furniture sector based on the proportions of employment in the US in these detailed industries (obtained from the NBER-CES dataset described below). Finally, because the IFR data for Denmark are not classified by industry before 1996, we construct estimates for 1993-1995 by deflating the 1996 stocks by industry using the total growth in its stock of robots.

[12] Because the level of robot adoption was low in 1993, the adjustment term $g^j_{i,(t_0,t_1)} M_{i,t_0}/L^j_{i,1990}$ is not quantitatively important; 96 percent of the variation in the adjusted penetration of robots across industries between 1993 and 2007 is driven by the increase in robot density, the term $(M^j_{i,t_1} - M^j_{i,t_0})/L^j_{i,1990}$ in equation (15). The exception is the electronics industry, which had a high stock of robots in 1993 and experienced rapid growth.

[13] The Appendix presents versions of our main results for different constructions of the $\overline{APR}_i$ measure, including a specification where we use all European countries, one where we use both Germany and the $EURO5$, one where we use the observed increase in robot density without the $g^j_{i,(t_0,t_1)} M_{i,t_0}/L^j_{i,1990}$ term, and a complementary measure where we include an adjustment for variation in the average price of a robot in an industry.

Given the coverage of the IFR data for US industries, this variable only goes back to $t_0 = 2004$.

3.2 Industry Data

To investigate the industry-level correlates of robot adoption, we use data on US industry employment, wage bill, value added, and labor share. The employment and wage bill data come from the County Business Patterns (CBP). We supplement the CBP with the NBER-CES dataset, which covers the manufacturing sector and reports data on employment and wage bills for all workers and for production workers (see Acemoglu et al., 2016). We also use data on value added and labor share from the Bureau of Economic Analysis (BEA), on IT capital and overall capital stock from the Bureau of Labor Statistics (BLS), and on productivity (TFP) from the NBER-CES. These data are available for a detailed set of industries which we aggregated to the 19 IFR industries. Industry-level imports from China and Mexico and total exports from Germany, Japan and South Korea are computed from Comtrade data (following Acemoglu et al., 2016; see also Autor, Dorn and Hanson, 2013). Finally, we use the index of offshoring (share of imported intermediates) from Feenstra and Hanson (1999) and Wright (2014).

3.3 Commuting Zone Data and Exposure to Robots

In our main analysis, we focus on the 722 commuting zones covering the US continental territory (Tolbert and Sizer, 1996). Following equations (11) and (14), we measure US exposure to robots in a commuting zone as

$$\text{US exposure to robots}_{c,(t_0,t_1)} = \sum_{i \in \mathcal{I}} \ell_{ci}^{1990} \cdot APR_{i,(t_0,t_1)}, \tag{17}$$

where ℓ_{ci}^{1990} is the share of industry i in the total employment of commuting zone c and APR_i is as defined in (16). Exposure to robots is defined analogously, exploiting variation in industry-level adoption of robots in the $EURO5$ countries,

$$\text{Exposure to robots}_{c,(t_0,t_1)} = \sum_{i \in \mathcal{I}} \ell_{ci}^{1970} \cdot \overline{APR}_{i,(t_0,t_1)}, \tag{18}$$

where $\overline{APR}_{i,(t_0,t_1)}$ is given in (15). We now use the 1970 employment shares, ℓ_{ci}^{1970}, as the baseline in order to focus on historical, persistent differences in the industrial specialization of commuting zones that predated robotics technology. This choice avoids any mechanical correlation or mean reversion associated with changes in industry employment in the 1980s that were temporary or in anticipation of the subsequent introduction of industrial robots. It is also worth noting that even when we consider changes in subperiods (e.g., in our models where differences for multiple periods are stacked together), we keep the baseline employment shares constant, and thus avoid the introduction of endogenous and serially correlated changes in our exposure variable.

We use the public use data from the 1970, 1990, and 2000 Censuses and the American Community Survey (see Ruggles et al., 2010) to construct measures of population, employment,

employment by industry and occupation, and demographics for each commuting zone. To increase sample size, we follow Autor, Dorn and Hanson (2013) and measure the 2007 outcomes using the ACS for the years 2006-2008. Similarly, we measure the 2014 outcomes from the ACS for 2012-2016. We complement these data with employment counts from the CBP for 1990, 2000 and 2007, which we again aggregate to the commuting zone level. We also use the Census and ACS to compute the average hourly and weekly wage within 500 demographic $\times$ commuting zone cells, which corrects for the changes in the observed characteristics of employed workers. Our demographic cells are defined by gender, education, ten-year age bins, race and birthplace (American or foreign born). All top coded wage income observations are set equal to 1.5 times the value of the top code as in Acemoglu and Autor (2011). We supplement these with data from the BEA on wage and non-wage income and from the IRS on wage income and net migration.

To control for potentially confounding changes in trade patterns, we rely on data on the exposure to Chinese imports from Autor, Dorn and Hanson (2013), and data on the fraction of employment in a commuting zone in routine occupations (as defined in Autor and Dorn, 2013). To distinguish the role of robots from that of capital accumulation, investments in IT, and other technologies raising productivity, we also construct Bartik-style measures of increases in capital stock, IT capital, value added and productivity across the 19 IFR industries.

Finally, we use data compiled by Leigh and Kraft (2018), who scraped the web to obtain the location and employment of robot integrators—which are companies that install, program and maintain robots for different industrial applications. Using these data, we construct estimates of robot integrator activity in each commuting zone.

4 Industry Correlations

We start by documenting industry trends. Figure 2 depicts the relationship between $\overline{APR}_{i,(1993,2007)}$ (computed from $EURO5$) and $APR_{i,(2004,2007)}$ (computed from the US data and scaled to a 14-year equivalent change). Both variables are given in terms of robots per thousand workers. Consistent with the notion that US industry trends in robotics are driven by technological factors, there is a strong correlation between adoption of robots in the $EURO5$ countries and in the United States (see also Table A2 in the Appendix). The figure also reveals significant heterogeneity across industries, even within manufacturing. While some industries, such as automotive, plastics and chemicals, and metal products, exhibit increases in robot penetration of more than 7.5 robots per thousand workers, others like paper and printing, textiles, and industrial machinery have experienced only modest increases both in Europe and the US.

In the rest of this section, we focus on the variation in $\overline{APR}_i$, which we interpret as a proxy for improvements in robotics technologies available to US firms.[14] Figure 3 shows that this measure of robotics technology does not mimic other industry-level trends. Together with our $\overline{APR}_{i,(1993,2007)}$ variable, the figure plots the concurrent increase in the capital stock and IT

[14]This interpretation is bolstered by Figure A1 in the Appendix, which shows a close association between $\overline{APR}_i$ and Graetz and Michaels's (2018) replaceability index, which measures the fraction of occupations in an industry involving tasks that can be automated.

capital stock, increases in Chinese and Mexican imports (relative to US consumption), increase in offshoring, and increase in total exports from Germany, Japan and South Korea (also relative to US consumption).[15] The figure reveals that the industries that are adopting more industrial robots are not the ones affected by Chinese or Mexican import competition or offshoring. Nor are they the same ones experiencing rapid growth in total capital or IT capital. This strengthens our presumption that the use of industrial robots is a technological phenomenon that is largely unrelated to other industry trends.[16]

As emphasized in our model, we expect the adoption of robots to be associated with declines in an industry's labor demand and labor share. Table 1 reports regressions of various industry-level changes on $\overline{APR}_i$ for different time periods. Panel A uses wage bill as a proxy for labor demand, while Panel B looks at employment. The first four columns present long-differences specifications where we regress the change in log wage bill from 1993 to 2007 on our baseline measure of adjusted robot penetration for the same period, $\overline{APR}_{i,(1993,2007)}$. In column 1 of Panel A we first show the raw correlation between $\overline{APR}_i$ and log wage bill, which is negative, indicating that industries experiencing greater penetration of robots have also seen significant (relative) declines in labor demand. To control for other changes over this time period, column 2 includes several key industry-level covariates that we use in our baseline commuting zone models as well: change in imports from China and dummies for manufacturing and light manufacturing (which covers paper and printing and textiles, industries that have been on a steep downward trend in the United States for a number of reasons other than automation). These controls allow for differential trends in these industries unrelated to robots. The inclusion of these controls reduces the magnitude of the coefficient on $\overline{APR}_i$, but also makes it more precisely estimated (-0.843, standard error = 0.408). Quantitatively, this number implies that an industry adopting one more robot per thousand workers according to our $EURO5$ measure has had a 0.84 percent relative decline in wage bill.[17] Columns 3 and 4 show similar patterns for the wage bill of all workers and production workers in manufacturing using the NBER-CES dataset.

Columns 5-9 present stacked-differences models for two periods of seven years, 1993-2000 and 2000-2007, with analogues of our $\overline{APR}_i$ variable computed for these two subperiods (in this case we have two observations per industry). These models have the advantage that they exploit more accurately the timing of the adoption of robots. For instance, robot penetration in the automotive industry accelerated in the 2000s, whereas in shipbuilding and aerospace it decelerated in the 2000s. We now see a more precisely estimated relationship than the one shown in columns 1-4. For example, the equivalent of the estimate in column 2 is now -1.037 (standard

[15] For ease of comparison, we normalize these measures relative to the industry with the largest increase for each variable.

[16] Within manufacturing, the correlation between our measure of adjusted penetration of robots, $\overline{APR}_i$, and change in imports from China is -0.43 (the overall correlation is 0.081). The correlation with the change in imports from Mexico and with offshoring is, respectively, -0.01 and -0.008 within manufacturing (and 0.3 and 0.27 overall). The correlation with the increase in capital is 0.14 within manufacturing (and -0.35 overall), and the correlation with the increase in IT capital is 0.17 within manufacturing (and -0.16 overall).

[17] Equivalently, an increase of 5 robots per thousand workers in $\overline{APR}_i$, which corresponds to the interquartile range of the distribution of this variable (between food manufacturing and agriculture), leads to a 4 percent decline in wage bill.

error = 0.195), which implies that one more robot per thousand workers (in $EURO5$) is associated with over a one percent decline in labor demand. Stacked-differences models also enable us to include linear industry trends, thus controlling more flexibly for the possibility that our industries have been on differential trends for other reasons. Although specifications controlling for industry trends are demanding, in column 7 we estimate a similar negative relationship between the adoption of robots and labor demand. Finally, columns 8 and 9 depict the estimates for all workers and production workers in manufacturing, which are again very similar. Panel B shows similar results for employment.

We also use the BEA data to estimate the relationship between robot penetration and the labor share and value added between 1992 and 2007. Column 10 in Panel A shows that, consistent with robots increasing productivity, value added is increasing in industries adopting more robots—even though their employment is contracting.[18] This result suggests that industries adopting robots are not just becoming more productive but also less labor intensive, and this is confirmed by our estimate in column 10 in Panel B, which shows a large decline in the labor share. This estimate implies that one more robot per thousand workers is associated with a 0.7 percentage point decline in the labor share between 1992 and 2007.

Figure 4 shows the relationship between $\overline{APR}_i$ and log wage bill, log employment, the labor share and log value added visually. For wage bill and employment, we show the stacked-differences specifications from column 6 after partialing out the covariates, while for the labor share and value added we focus on long-differences specifications from column 10. Notably, Figure A2 in the Appendix verifies that there are no significant pre-trends for log wage bill and log employment for all workers and for production workers in the NBER-CES data (the CBP dataset does not go back far enough for such an exercise). Tables A3 and A4 in the Appendix further confirm that the patterns shown in Table 1 are similar when we use different constructions for the $\overline{APR}_i$ variable and when we explore more recent time periods.

Although we view the industry correlations mostly as descriptive, the patterns are consistent with our theoretical expectations and show that industries where robotics technology has made greater advances have been experiencing expanding output and declining labor demand, employment and labor share. We next turn to an investigation of the implications of robots for employment and wages in local labor markets.

[18] Within manufacturing, automotive, plastics and chemicals, and metal products—the industries that adopted the greatest number of robots—experienced the fastest growth of value added between 1992 and 2007, ranging between 2 percent and 4 percent per year. In contrast, textiles and paper and printing—which did not adopt many robots and are the industries we classified as light manufacturing—have the lowest growth. In Table A5 in the Appendix, we also document the significant positive effect of robots on labor productivity, which confirms one of the main findings of Graetz and Michaels (2018) from cross-industry, cross-country data.

Because of data availability for value added, labor productivity and labor share, we cannot construct comparable stacked differences, and thus focus on long differences for these variables.

5 Main Results

In this section we first describe our measure of exposure to robots and document its variation. We then present reduced-form results for employment and wages, and investigate their robustness. We finally present IV estimates and discuss their quantitative implications.

5.1 Exposure to Robots and Robot-Related Activities

We focus on the exposure measure defined in equation (18) and constructed from European data on robot penetration by industry. We will use this variable as an instrument to uncover the impact of improvement in robotics technologies on US labor markets.

Panel A of Figure 5 depicts the geographic distribution of exposure to robots between 1993 and 2007. In many parts of the United States there is only a small increase of about 0.27-0.67 robots per thousand workers. In others, including parts of Kentucky, Louisiana, Missouri, Tennessee, Texas, Virginia and West Virginia, our measure of exposure ranges between 2 and 5 robots per thousand workers. More strikingly, in some parts of the Rust Belt and Texas, robot penetration increases by 5-10 per thousand workers. Figures 2 and 3 above already highlighted that there is greater penetration of robots in the automotive industry than in other sectors (both in the United States and Europe). Panel B of Figure 5 verifies that even after this industry is left out, there is still considerable geographic variation in exposure to robots.

It is also useful to remark that, consistent with the industry-level patterns shown in Figure 3, there is very little correlation between our exposure to robots measure and other major economic trends affecting US labor markets, such as the exposure to imports from China, the replacement of routine jobs, overall capital deepening and investments in IT capital. This is reassuring for the interpretation of the results we present in the next subsection.

Are commuting zones with a high exposure to robots adopting more industrial robots as our model predicts? Though data on robots adoption at the commuting zone are not available, in Figure 6 we provide evidence of greater robot-related activities in exposed commuting zones using the data on integrators from Leigh and Kraft (2018). The figure shows the residual plot of the log of one plus the number of integrators in a commuting zone against exposure to robots (as in most figures that follow, we partial out the covariates from our main specification in column 4 of Table 2, which we describe below). The blue dashed line corresponds to the regression relationship after the top one percent of commuting zones with the highest exposure to robots are excluded.[19] In both cases we see a positive association between exposure to robots and the number of integrators in a commuting zone. Table A6 shows that this relationship is robust to alternative specifications and to different ways of measuring robot integrator activity.

[19] These are Alpena, MI; Defiance, OH; Detroit, MI; Houghton Lake, MI; Lansing, MI; Lorain, OH; Mount Pleasant, MI; Saginaw, MI; Sault Ste. Marie, MI; Wilmington, DE.

5.2 Reduced-form Results for Employment and Wages

Table A7 in the Appendix provides a first look at how commuting zones with different exposure to robots differ. Columns 2-5 present the mean for various outcomes and covariates by quartiles of exposure to robots. Three patterns are notable. First, among the covariates, the only four variables that show significant differences between high and low exposure commuting zones are the shares of manufacturing employment and light manufacturing employment, the share of female workers in manufacturing employment, and imports from China, and we control for these variables in our base specification (the positive correlation with imports from China disappears once we condition on manufacturing employment). Second, across commuting zones at different quartiles of exposure to robots, there are no differences in hourly wages in 1990 and only small differences in our main employment variable, private employment to population ratio in 1990 (which excludes public employment and self-employment). Finally and most notably, from 1990 to 2007, more exposed commuting zones experienced more negative labor market trends.

To explore these patterns in detail, we estimate reduced-form specifications similar to equation (13). We regress changes in employment to population ratio and log wages on our measure of exposure to robots computed from the European data. The identifying assumption is that the commuting zones that house industries with significant improvements in robotics technologies are not experiencing other shocks or trends affecting their labor markets. We discuss threats to the validity of this identifying assumption and report IV specifications later in this section.

Table 2 presents results for a long-differences specification for 1990-2007, where we regress the change in employment to population ratio or log hourly wage between 1990 and 2007 on the exposure to robots variable for the same period. We end our sample in 2007 to avoid the potentially confounding effects of the Great Recession, and present results for a longer time window in the Appendix.[20] The table focuses on our two main outcome variables: the (private) employment to population ratio in Panel A and log hourly wage in Panel B.[21] Our baseline specifications are weighted by population in 1990 and report standard errors that are robust against arbitrary heteroscedasticity and correlation within US states in parentheses.

Column 1 presents a parsimonious specification that only includes Census division dummies as covariates. In Panel A we estimate a strong negative relationship between exposure to robots and employment changes in a commuting zone with a coefficient of -0.38 (standard error = 0.08). This estimate implies that an increase of one robot per thousand workers in our exposure to robots measure is associated with a relative decline in employment of 0.38 percentage points.[22]

[20]To match the time window over which we measure the adjusted penetration of robots, we rescale the outcomes to a 14-year equivalent change. In particular, for each variable, we define long differences as $(y_{2007} - y_{2000}) + 0.7 \times (y_{2000} - y_{1990})$.

[21]Equation (13) has change in log employment on the left-hand side. We estimate this relationship in Table A12 in the Appendix, but opt for employment to population ratio as our baseline because it is the standard specification in the literature.

[22]A difference in exposure of one robot per thousand workers between 1993 and 2007 (from $EURO5$) is approximately the increase in US exposure to robots over the same time period. It also corresponds to the interquartile range of this variable (between Pittsburgh, PA at the 75th percentile and Omaha, NE at the 25th percentile). The difference in exposure between the 1st percentile (West Palm Beach, FL) and the 99th percentile (Detroit, MI) is much larger—about 9 robots per thousand workers.

In column 2 we control for demographic characteristics in 1990, specifically, the log of population; the share of males; the share of population above 65 years; the shares of population with high school, some college, college (including professional degrees) and post-graduate (masters and doctoral) degrees; and the shares of Whites, Blacks, Hispanics and Asians in the population. Since our regression specification is in changes, these controls allow for differential trends by these baseline demographic characteristics. Their inclusion reduces our estimate of the impact of exposure to robots on employment to population ratio slightly to -0.36.

In column 3, we control for the baseline shares of employment in manufacturing, light manufacturing, mining and construction, as well as the share of female workers in manufacturing employment.[23] These controls allow for differential trends by the baseline industrial structure of a commuting zone and ensure that our exposure variable does not proxy for other trends affecting manufacturing employment. These controls have little impact on our coefficient of interest, which now stands at -0.41 in Panel A, and is more precisely estimated with a standard error of 0.05 (the coefficient estimates for these controls are shown in Table A9).

In column 4 we control for other changes that have impacted labor market outcomes during our period of analysis: imports from China between 1990 and 2007 and the decline of routine occupations proxied by their baseline shares in employment (see Autor, Dorn and Hanson, 2015). Consistent with the patterns shown in Figure 3, these controls have little impact on our estimates. The point estimate remains at -0.41 (standard error = 0.05).

Figure 7 provides a residual regression plot for our specification from column 4 in Panel A, with the regression estimate depicted with the solid line. The presence of a number of commuting zones with very large exposure to robots is apparent. Column 5 demonstrates that the negative relationship between exposure to robots and employment is not due to these commuting zones by reestimating the specification in column 4 after excluding the top one percent commuting zones with the greatest exposure. The coefficient estimate in Panel A increases to -0.52 (standard error = 0.14). The blue dashed line in Figure 7 shows this estimate visually.

Finally, column 6 shows that the results are similar with unweighted regressions. In a specification as in column 4, we now estimate a coefficient of -0.42 (standard error = 0.09).

Panel B presents results for log hourly wage for the same specifications. Because wages are only available for employed workers, and our evidence in Panel A suggests that employment declines in more exposed commuting zones, we present estimates adjusted for changes in the composition of wage earners. Specifically, we now use change in average log wage between 1990 and 2007 for each of the 500 demographic cells in a commuting zone as our left-hand side variable (we simultaneously control for a full set of cell dummies).[24] Because in this case we have

[23]As shown in Table A7 and discussed above, the shares of employment in manufacturing and light manufacturing and the share of female workers in manufacturing employment differ between high and low exposure commuting zones. In addition, Table A8 in the Appendix shows that these variables, as well as the share of employment in mining, remain correlated with either exposure to robots, exposure to robots in the automotive industry (which we use in Table 5 below) or exposure to robots in the remaining industries. Following the recommendation in Goldsmith-Pinkham, Sorkin and Swift (2018), we include these variables as covariates.

[24]For each demographic group g in commuting zone c, we compute the long difference of average log hourly wage $\Delta \ln W_{cg}$ as explained in footnote 20. We then regress $\Delta \ln W_{cg}$ on the exposure measure for commuting zone c and control for a full set of group fixed effects.

multiple observations for each commuting zone—one for each demographic group—we weight each observation by the size of the demographic group in the commuting zone in 1990. The estimates show negative effects on wages. In column 4, when we control for all of our baseline covariates, the coefficient estimate is -0.77 (standard error = 0.11). This implies that an increase in exposure to robots equivalent to one more robot per thousand workers is associated with a relative decline in hourly wages of 0.77 percent. Figure 7 depicts this estimate as well.

We next turn to stacked-differences models where we exploit variation over two periods: 1990-2000 and 2000-2007 (the former converted to a seven-year change for consistency). Panel A is for employment and Panel B is for log hourly wage. The first six columns have the same structure as those of Table 2. In both panels, the estimates are more negative than before and remain precisely estimated. For example, in column 4 of Panel A the coefficient of interest is -0.51 (standard error = 0.05), while in Panel B the estimate for log hourly wage increases to -1.3 (standard error = 0.16). The bottom panels of Figure 7 present these stacked-differences estimates visually, separately marking observations from the two periods and showing that the negative relationship is present for both periods.

The stacked-differences model focuses on the differential changes in exposure to robots between these two time periods and also enables us to control for linear commuting zone trends. Although this specification is demanding and exploits a different source of variation than long differences, we still estimate a similar negative impact of the exposure to robots on both employment and wages. In column 7, for example, the estimates for employment and wages are, respectively, -0.4 (standard error = 0.07) and -1.27 (standard error = 0.24). These findings bolster our confidence that exposed commuting zones are not simply on a differential trend unrelated to advances in robotics technology.

We obtain similar patterns when we use more recent data as shown in Table A10 in the Apendix, which presents results for the entire period 1990-2014 as well as for 2000-2007 and 2000-2014 (periods for which we estimate IV models below).

5.3 Other Labor Market Outcomes

In the Appendix, we investigate the impact of exposure to robots on a range of other labor market outcomes. Table A11 shows robust negative effects on employment in manufacturing, which is relevant since robots are adopted mostly in manufacturing and substitute directly for production workers in this industry (see also Acemoglu and Restrepo, 2018d).

Tables A12 and A13 look at alternative measures of employment and wages. These include private employment to population ratio including self-employment, the total employment to population ratio including public employment and self-employment, employment counts from the CBP and the NHGIS divided by population, the log of employment, the log of weekly and yearly wages, and the log of wage bill from the CBP. Both in the long-differences and stacked-differences specifications, the results are broadly similar with all of these measures.

Table A12 also explores what happens to the nonemployed by looking at the participation and unemployment margins. We estimate a positive impact of exposure to robots on the nonparticipation and unemployment rates. Quantitatively, our estimates imply that about three quarters of the additional nonemployed drop out of the labor force, while a quarter remain unemployed. In line with the rise in nonparticipation, in Table A14 we estimate increased use of SSA retirement and disability benefits and other government transfers. Table A15 explores the response of migration. Some of our estimates show a negative impact on population and net migration (computed from the IRS data), though these effects are neither consistent across specifications nor precisely estimated. Quantitatively, they imply that the migration responses are about one fifth of the size of the employment responses.[25]

Finally, we also use data from the BEA and the IRS to estimate the impact of robots on wage and non-wage income separately. Our estimates in Table A16 in the Appendix show precise and large negative effects on wage income, and no significant impact on non-wage income, which is consistent with the notion that owners of robot integrators and firms introducing robotics technology are not necessarily located in exposed commuting zones.

5.4 Pre-trends

There are two main threats to the identifying assumption behind our estimates. First, the industries that have been adopting more robots over the last two decades (in the United States and Europe) could have already been on a downward trend because of declining demand, international competition, other technological changes or worsening labor relations. Second, the commuting zones that house the industries that are adopting more robots may be affected by other negative shocks. In either case, our estimates might confound the impact of robots with these pre-existing industry and commuting zone trends.[26]

Our analysis in Section 4, which demonstrates that the penetration of robots in $EURO5$ is not correlated with industry pre-trends or with other major sources of changes in labor demand, is reassuring for the first threat. Moreover, the fact that value added has expanded in industries with the greatest penetration of robots suggests that our measure is not correlated with negative demand shocks to industries. Regarding the second threat, our stacked-differences analysis, which controlled for commuting zone trends, already established that exposed commuting zones are not on a differential trend unrelated to robotics technology. These results notwithstanding, we next investigate these issues directly by checking for pre-trends (which could result from both types of concerns) and by controlling for other trends at the industry or commuting zone level.

Panel A of Table 4 shows that there are no significant pre-trends. Specifically, we estimate the relationship between exposure to robots and the change in the employment to population ratio (columns 1-4) and the change in log hourly wage (columns 5-8) between 1970 and 1990. Our base specification, in columns 2 and 6, shows that there is no quantitatively or statistically

[25]For example, using our baseline specification from column 4 of Table 2 and comparing this to the equivalent specification in column 4 of Table A15 in the Appendix, we see that an increase of one robot per thousand workers in our exposure measure reduces *total* employment by 1.4 percent, of which 0.3 percent is explained by the decline in population and 1.1 percent is explained by the decline in the employment to population ratio.

[26]We provide evidence against possible violations of our identifying assumption coming from international factors that may impact both US and European robots adoption in Table 6 below.

significant association between exposure to robots and pre-1990 changes in employment or wages. The picture is similar when we exclude highly-exposed commuting zones in columns 3 and 7 or when we report unweighted specifications in columns 4 and 8. These results are summarized in Figure 8, which presents residual plots for employment and wages from the specifications in columns 2, 3, 6 and 7. In Table A17 in the Appendix, we confirm that there are also no pre-trends in other key labor market variables for which we can extend the sample back in time—in particular, for manufacturing employment, the employment rate including self-employment and the public sector, the non-participation rate, the unemployment rate and log weekly wages.

Panel B of Table 4 investigates potentially confounding industry trends. Specifically, we present estimates that control for predicted employment declines based on a Bartik-style measure of past industry trends. To construct this measure, we use the 19 IFR industries and interact their national log employment decline between 1970 and 1990 with their baseline employment share in 1970 in each commuting zone. Though the coefficient of this Bartik measure of industry decline is negative, and significant in a few specifications, the point estimates for exposure to robots remain unaffected. These results are encouraging for our interpretation that the exposure to robots variable is not proxying for declining industries.[27]

Finally, Panel C goes one step further and directly controls for the 1970-1990 change in employment to population ratio or hourly wages on the right-hand side of our baseline specifications. This control has no effect on our parameter estimates from Table 2.

5.5 The Role of the Automotive Industry

As shown in Figure 3, from 1993 to 2007 the automotive industry adopted more robots than any other sector.[28] This raises the concern that our estimates may be confounded with other changes affecting this sector.

To address this concern, in Table 5 we decompose our measure of exposure to robots in two parts; one exploiting the penetration of robots in the automotive industry and the other one exploiting the penetration of robots across all other industries. We then include both of these measures on the right-hand side of our employment and wage regressions. The table presents both long-differences (columns 1-3) and stacked-differences (columns 4-6) specifications. Panel A is for employment, while Panel B is for wages. In both panels, we find that the effects of exposure to robots in the automotive industry is very similar to those of exposure to robots in other sectors (and we never reject the hypothesis that the coefficients of these two variables are equal). These results are reassuring both because they indicate that our results are not solely

[27] One could also construct a similar Bartik-like measure from contemporaneous declines in employment. But to the extent that, as we have already shown in Table 1, robot adoption is associated with industry-level employment declines, this variable would be a "bad control."Nevertheless, in Table A18 in the Appendix, we continue to estimate relatively precise negative impacts of exposure to robots on employment and wages when we control for this variable, though the point estimates are smaller than our baseline estimates.

[28] In the raw data, the share of employment in the automotive industry explains 67 percent of the cross-commuting zone variation in exposure robots. Table A19 in the Appendix shows that the automotive industry has the highest Rotemberg weight, which ranges from 50 to 90 percent in the specifications presented in Table 2 (see Goldsmith-Pinkham, Sorkin and Swift, 2018). In our stacked-differences specifications in Table 3, this industry also receives a large weight, but only during the 2000-2007 period when its robot penetration accelerated.

driven by the automotive industry and also because they suggest that the effects of robots in different sectors are similar.

5.6 Robots, Capital and Other Technologies

Our model demonstrates that capital deepening and technological changes that do not involve automation of tasks previously performed by labor should have very different impacts on the labor demand because they do not generate a displacement effect. We now investigate the effects of capital deepening, IT capital and general increases in value added and productivity on employment and wages both to see how these differ from the effects of robots and to verify that controlling for these trends does not change our key estimates (which we expect to be the case since we have already shown in Figure 3 that these other trends are uncorrelated with robots).

Table 6 presents the results from this exercise. We again report both long-differences and stacked-differences specifications. The first four columns are for employment while the next four are for wages. In Panel A, we control for a Bartik-style measure of the percent increase in the capital stock across industries. In Panel B, we control for a Bartik measure of the percent increase in IT capital, while in Panels C and D, we control for similar Bartik measures for increases in value added and TFP by industry.

The inclusion of these variables has little effect on our estimates of the impact of robots. More importantly, and in line with our theoretical emphasis that automation is conceptually different from overall productivity increases, capital deepening and other types of technological changes, these variables themselves are either not significant or when they are significant, they have a positive effect, which suggests that other types of capital equipment and even IT capital tend to increase the demand for labor (see Table A20 in the Appendix for similar results with other measures of computer technology). This result underscores the possibility that industrial robots might have a very different impact on labor demand than other (non-automation) technologies.

5.7 International Competition

A direct threat to our IV strategy is that, as noted in footnote 3, international competition may affect robot adoption decisions both in the United States and Europe, or investments in robots in the countries that are most advanced in robotics technology, Germany, Japan and South Korea, may increase international competition for US industries. Panel D of Table 6 investigates this issue and shows that our estimates of the effects of robots are very similar when we control for exposure to imports from Mexico, offshoring and total exports from Germany, Japan and South Korea. Moreover, none of these variables appear to be significant determinants of employment or wages across US commuting zones.

5.8 Other Robustness Checks

The Appendix reports additional robustness checks. First, Tables A21 and A22 show that the exact construction of exposure to robots does not affect our results. We report estimates where this measure is computed from the average of all European countries and from the average of $EURO5$ plus Germany, and a specification where we use the 1990, rather than the 1970, employment distribution. In addition, we also report estimates using a Bartik measure using raw penetration of robots (rather than our theory-derived measure based on adjusted penetration of robots) and from a specification where we weight each industry's adjusted penetration of robots by the average cost of robots in that industry. In all cases, the reduced-form estimates using these alternative measures of exposure are negative and significant, and the IV estimates reported in column 7 of Tables A21 and A22 are similar to those in Table 7 below.

Table A23 explores the role of outliers. Our results are robust when we exclude Detroit (the commuting zone with the highest exposure to robots), when we exclude observations with residuals above or below 1.95 standard deviations, when we estimate Li's (1985) robust regression which downweights influential observations, and when we estimate median regressions.

Table A24 shows that our results are also robust to controlling for a full set of state fixed effects, to allowing for mean-reverting dynamics in employment and wages by including the baseline value of the dependent variable, and to controlling for contemporaneous changes in all of our baseline demographic variables.

Finally, Table A25 in the Appendix reports results with alternative exposure measures constructed from Graetz and Michaels's (2018) replaceability index, which measures the fraction of tasks in an industry that can be automated, and BCG's classification of industries that provide greatest opportunities for automation. It is reassuring that these alternative measures still yield uniformly negative and significant estimates.[29]

5.9 IV Estimates

We next use our measure of the US exposure to robots to compute two-stage least squares (2SLS) estimates of β^L and β^W in equation (13). Figure 2 already showed the close association between the industry-level spread of robots in the United States, $APR_{i,(2004,2007)}$, and in Europe as captured by $\overline{APR}_{i,(1993,2007)}$. Figure A3 in the Appendix depicts our first-stage relationship by plotting US exposure to robots at the commuting zone level computed using $APR_{i,(2004,2007)}$ against exposure to robots computed using $\overline{APR}_{i,(1993,2007)}$.

Table 7 reports our IV estimates for the long-differences specifications analogous to those in Table 2 and also reports the corresponding first-stage coefficients and F-statistics (Table A26 in the Appendix reports the OLS estimates). Because we will use the IV estimates to quantify the aggregate implications of robot adoption, we focus on the population-weighted specifications. Columns 1-3 are for employment to population ratio and columns 4-6 are for the log hourly wages. The first two columns in each block are the analogues of the specifications in columns 1 and 4 in Table 2, while columns 3 and 6 estimate models in which baseline industry shares are used as instruments following Goldsmith-Pinkham, Sorkin and Swift (2018); these columns also report overidentification tests for the validity of the source of variation coming from each

[29] We do not report IV estimates using these variables because the implied identification restriction is less plausible; for example, replaceable tasks may be automated by other, non-robot technologies.

one of these industries. The identifying assumption behind these models now requires that *all industry* shares in 1970 are exogenous (and is thus much more demanding than the identifying assumption in our baseline IV specification, which simply requires that commuting zones with higher exposure to robots are not experiencing differential labor market trends for other reasons).

Panel A covers our baseline period, 1990-2007. Panel B also focuses on 1990-2007, but constructs the US exposure to robots by imputing US industry data using the aggregate US change between 1993 and 2004 rather than rescaling the 2004-2007 industry data. Panel C is for 1990-2014, while Panels D and E focus on time windows for which there is a close overlap with US robots data, 2000-2007 and 2000-2014. In all cases, the 2SLS estimates are negative and precise for both employment and wages. Our base estimates in columns 2 and 5, Panel A, which we will use in our quantitative evaluation in the next subsection, are -0.38 (standard error = 0.08) for employment and -0.71 (standard error = 0.14) for log hourly wage.[30]

The estimates using all baseline industry shares as instruments are similar, -0.29 (standard error = 0.046) for employment and -0.55 (standard error = 0.08) for wages in Panel A. The overidentification tests do not reject the hypothesis that all baseline shares are valid instruments at 5 percent except for employment in 1990-2007 and marginally for wages for 1990-2014.

5.10 Quantitative Magnitudes

The IV estimates in the previous subsection quantify the impact of one additional robot per thousand workers on employment and wages of a commuting zone *relative* to other regions. Our estimates in columns 2 and 5 in Panel A, for example, imply that the adoption of one additional robot per thousand workers in a commuting zone reduces its employment to population ratio by 0.38 percentage points (or by one percent) and hourly wages by 0.71 percent relative to other regions. Equivalently, these numbers imply that one more robot reduces employment by about 6 workers in the affected commuting zone relative to others.[31] These are sizable magnitudes, but not implausible since they include both the direct effects of robots on employment and wages in a commuting zone and any indirect effects resulting from the decline in local demand following the loss of local employment and wage income.[32]

[30]The IV estimate for employment is about 40 percent smaller and the estimate for wages is about 40 percent larger for 1990-2014 in Panel C. This might reflect the fact that as wages have continued to adjust in the affected commuting zones, some of the initial employment response may have been reversed.

[31]The increase of one more robot per thousand workers between 1993 and 2007 is equivalent to an increase of 0.6 robots per thousand people or a total increase of 120,000 robots. Consequently, our estimates imply that this increase led to a 0.38 percentage points lower employment to population ratio, which is equivalent to one robot reducing employment by 6 ($\approx 0.0038/(0.6/1000)$) workers. Equivalently, the increase of 120,000 in the stock of robots during this period is predicted to have reduced employment by 756,000 jobs. We obtain a reduction in employment of 720,000 jobs (or about 4 jobs per robot) if we use the estimate for 1990-2014 from Panel C together with the larger increase of 180,000 in the stock of robots over this longer time period.

[32]These magnitudes can be compared to the size of the effects from exposure to imports from China using the stacked-differences estimates from Table A9 in the Appendix, which correspond to the specification used in Autor, Dorn and Hanson (2013). The implied quantitative magnitude from the national rise in Chinese imports for a commuting zone with the average exposure to Chinese imports (compared to a no exposure commuting zone) is a decline of about one percentage point in the employment to population ratio, almost three times the 0.38 percentage points implied decline from the adoption of robots.

The more challenging question is how much (and whether) *employment* and *wages in the aggregate* decline in response to the adoption of industrial robots. As emphasized in Proposition 3, when commuting zones interact through trade and capital markets, our local IV estimates do not directly translate into aggregate effects because robot adoption in one commuting zone reduces the costs of goods consumed in other areas and generates capital gains shared by households in these areas. To explore these aggregate implications, we need to make further assumptions on cross-commuting zone spillovers (and this suggests greater caution in interpreting these aggregate estimates than the local effects discussed in the previous paragraph).

We assume that Proposition 3 provides a reliable approximation to these cross-commuting zone interactions and then use our regression evidence and external information to discipline the key parameters of the model. Specifically, we use equations (9) and (10) in Proposition 3, which provide expressions for β_L and β_W in terms of the underlying parameters of the model as well as the labor share. We then use information on the labor share and the parameters σ, λ, α, π_0 and γ_M/γ_L, and solve for the values of the inverse of the Frish elasticity of labor supply, ε, and the inverse of the elasticity of the robot supply, η, that are consistent with our IV estimates, $\widehat{\beta}_L$ and $\widehat{\beta}_W$. Using these estimates, we then compute the aggregate implications of robots using our model. Proposition A7 in the Appendix provides formulas for the aggregate effects of robots on employment and wages as a function of η and ε.

Our parameter choices are as follows: (1) $\sigma = 1$ as the elasticity of substitution between different industries (e.g., Oberfield and Raval, 2014); (2) $\lambda = 5$ for the elasticity of substitution between traded varieties, which follows the trade literature (e.g., Simonovska and Waugh, 2014; and Head and Meyer, 2015); (3) $s^L = 0.9916$ as the baseline share of labor in task production, which is implied by the number of robots in US industries in 1993;[33] (4) $\alpha = 0.67$, which together with the estimate for s^L implies an initial labor share of approximately 2/3 in all commuting zones; (5) $\phi = 0.25$, which matches the share of employment in the tradable or manufacturing sector, which is 18 percent; (6) $\pi_0 = 0.3$, which, in line with the evidence surveyed in BCG (2015), implies that robot adoption reduces costs by about 30 percent; (7) $\gamma_M/\gamma_L = 3$, which implies that in automated tasks a robot performs, on average, the work of three workers (an estimate supported by the engineering literature surveyed in Groover et al. 1986); and (8) $\psi = 0.02$, which is consistent with a marginal propensity to consume leisure of 10 percent (see Imbens, Rubin and Sacerdote, 2001).

Given these parameter values, equations (9) and (10) yield $\eta = 0.72$ and $\varepsilon = 0.16$. The estimate for η implies a fairly inelastic supply of robots to the local economy, which limits the productivity gains from the adoption of robots, and instead generates rents for robot integrators. If we suppose that local robot services are provided by combining (elastically supplied) robotics equipment and (mostly inelastically) supplied services of robot integrators, this estimate is equivalent to the share of the inelastic component of the services of integrators in the total cost of robots being about $\eta/(1+\eta) = 0.42$. Since the share of local robot integrators in total costs

[33] In Propositions 2 and 3 we simplified the exposition by focusing on the case where $\theta_0 = 0$, which implied a share of labor in task production equal to $s^L = 1$. Our more general expressions in Proposition A2 and A6 show the role of this share.

is about 0.66 (Leigh and Kraft, 2018), this number implies that about two thirds of the services they provide are inelastically supplied to the local economy. The estimate for ε, on the other hand, implies an elastic response of labor supply. This estimate is in line with the "macro" Frisch elasticities that are consistent with the observed relationship between employment and wages in the aggregate (see Table 1 in Chetty et al., 2011).

Using these parameter estimates, we compute the aggregate effects of robots. One more robot per thousand workers is predicted to reduce *aggregate employment to population ratio* by 0.2 percentage points (or 400,000 jobs), which is equivalent to one more robot reducing employment by 3.3 workers, and *aggregate wages* by 0.37 percent.[34] At these parameter values, about two thirds of the decline in the demand for labor in an exposed commuting zone is driven by the contraction of the nontradable sector (which is consistent with the significant decline in construction, retail and personal services that we document in the next section). Our model also implies a 0.33 percent increase in the productivity of the tradable sector, a sizable capital gain of 1.74 percent, and a 136 percent increase in industrial robot utilization, which roughly matches the 139 percent increase in the stock of robots observed during this period.

Table A28 in the Appendix considers variations in the values of the key parameters, σ, λ, π_0, γ_M/γ_L and ψ, and shows that both the implied values of η and ε and the resulting aggregate effects are not sensitive to reasonable variations.

6 Effects by Industry, Occupation, Gender and Skill

This section investigates how exposure to robots has impacted employment in different industries and occupations as well as the employment and wages of workers with different characteristics.

The top panel in Figure 9 presents estimates of the effects of exposure to robots on employment in different industries. We present point estimates and confidence intervals for the long-differences specifications analogous to columns 4, 5 and 6 in Table 2 (Figure A4 in the Appendix presents estimates from analogous stacked-difference models). The figure shows that the effects of robots concentrate in manufacturing (as shown as well in Table A11), and especially in heavily-robotized industries, which include automotive, plastic and chemicals, metal products, basic metals, and electronics. There are no significant effects on the remaining manufacturing industries. Consistent with the indirect effects on nontradables discussed in Section 2.2 and the previous section, we find negative effects on construction and retail and personal services. The only two sectors that show positive effects in some specifications are agriculture and education, health care and the public sector (although these estimates are neither precise nor robust).

The bottom panel in Figure 9 presents analogous results for employment by occupation. In line with our expectations, the negative employment effects of robots are mostly in routine

[34] The aggregate effects are broadly similar if we use the IV estimate for 1990-2014 from Panel C of Table 7. In this case, the same procedure leads to $\eta = 0.88$ and $\varepsilon = 0.35$, which imply that one additional robot per thousand workers reduces employment by 0.14 percentage points and hourly wages by 0.56 percent. Thus, the increase of 180,000 robots during this period is estimated to have reduced aggregate employment by 414,000 jobs and hourly wages by 0.84 percent.

manual occupations, and in particular, in blue collar occupations such as machinists, assemblers, material handlers, and welders. Workers in these occupations engage in tasks that are being automated by industrial robots, so it is natural for them to experience the bulk of the displacement effect created by this technology. We do not estimate positive employment effects in other occupations, suggesting that, at least locally, the productivity gains from the use of industrial robots have not resulted in an expansion of employment in non-automated tasks.

Figure 10 in the main text and Table A27 in the Appendix investigate the employment and wage effects by gender. We estimate negative effects both for men and women. Quantitatively, the effects are larger for men. For example, with our baseline specification in long differences, reported in Figure 10 and in column 1 of Table A27, the effect of exposure to robots for the employment to population ratio of men is -0.53, while for women it is -0.3. Table A27 also shows that the decline for male employment is concentrated in manufacturing, while the decline in female employment is more pronounced in nonmanufacturing.

Figure 10 also shows the impact of robots on employment and wages for workers in different education groups. We present estimates for all workers, for men and for women separately. We see negative employment and wage effects for workers with less than high school, with a high school degree, with some college and with a college degree (including professional degrees), both for men and women. We find it surprising that there is no positive effect on workers with postgraduate (masters or doctoral) degrees. One interpretation is that this result reflects a combination of reduced demand for the nontradable sector where many of these workers are employed and the fact that, in contrast to other computer-assisted technologies, industrial robots are not complementing any well-defined group of workers.

Finally, Figure 11 investigates the impact of robots on the wage distribution by estimating quantile regressions (using our baseline specification from column 4 of Table 2). For all workers, we estimate negative and significant effects below the 35th percentile of the wage distribution. When we focus on workers with less than college, the negative and significant effects extend all the way up to the 85th percentile, while for workers with a college degree, the negative effects concentrate below the 15th percentile. Overall, these results confirm that the negative wage effects of robots are mostly at the bottom and the middle of the distribution.

7 Concluding Remarks

The spread of robots, artificial intelligence and other automation technologies has raised concerns about the future of jobs and wages. Nevertheless, there is relatively little work on the equilibrium effects of new automation technologies and especially of robots. In this paper, we estimate the impact of industrial robots between 1990 and 2007 on US local labor markets. We start with a simple task-based model in which robots compete against human labor in the production of different tasks. This model clarifies why robots, and automation technologies more generally, which displace workers from tasks they were performing, have very different labor market effects than other types of technological changes and overall capital deepening. It also demonstrates that both with and without trade between local labor markets, advances in robotics may have a positive or negative impact on employment and wages. Their positive impact comes from the productivity effect, while their negative impact is a consequence of the direct displacement of workers by robots. Moreover, in this class of models, the local labor market effects of robots can be estimated by regressing the change in employment and wages on the exposure to robots in each local labor market—where the exposure to robots is defined from industry advances in robotics technology and the distribution of industrial employment across local labor markets.

In our empirical work, we focus on variation in robot adoption coming from the technological frontier (proxied by trends in other advanced economies). This enables us to purge exposure to robots from potentially endogenous trends in US industries. Using this methodology and approximating local labor markets with commuting zones, we estimate large and robust negative effects of robots on employment and wages. We show that commuting zones most affected by robots in the post-1990 era were on similar trends to others before 1990, and that the impact of robots is distinct and only weakly correlated with the prevalence of routine jobs, the impact of imports from China, imports from Mexico, offshoring, IT capital, and capital deepening. Moreover, consistent with our theoretical emphasis, robots are estimated to have very different effects than IT technologies and overall capital deepening. Our estimates imply that each additional robot per thousand workers reduces local employment to population ratio by 0.38 percentage points and wages by about 0.71 percent. Because of the benefits of robots adoption for other commuting zones resulting from trade, the implied aggregate effects are somewhat smaller—one additional robot per thousand workers reduces aggregate employment to population ratio by 0.2 percentage points and aggregate wages by 0.38 percent.

Because there are relatively few robots in the US economy, the number of jobs lost due to robots has been limited so far (a 0.2 percentage point decline in the employment to population ratio or equivalently about 400,000 jobs). However, if the spread of robots proceeds as expected by experts over the next two decades (e.g., Brynjolfsson and McAfee, 2014, especially pp. 27-32, and Ford, 2015), the future aggregate implications of the spread of robots could be larger. For example, BCG (2015) offers two scenarios for the spread of robots over the next decade. In their aggressive scenario, the world stock of robots will quadruple by 2025. This would correspond to 5.25 more robots per thousand workers in the United States, and with our estimates, it would lead to a one percentage point lower employment to population ratio and two percent lower wage growth between 2015 and 2025. Their more conservative scenario involves a less than threefold increase in the stock of robots, and would correspondingly have a more modest impact (a reduction of 0.6 percentage point decline in the employment to population ratio and one percent lower wage growth). Crucially, however, any extrapolation about the future effects of robots should acknowledge not only the usual uncertainty associated with such exercises but also the possibility that some of the general equilibrium effects working through technology might emerge only slowly (Acemoglu and Restrepo, 2018a), and the response of employment and wages may be different once robots become sufficiently widespread

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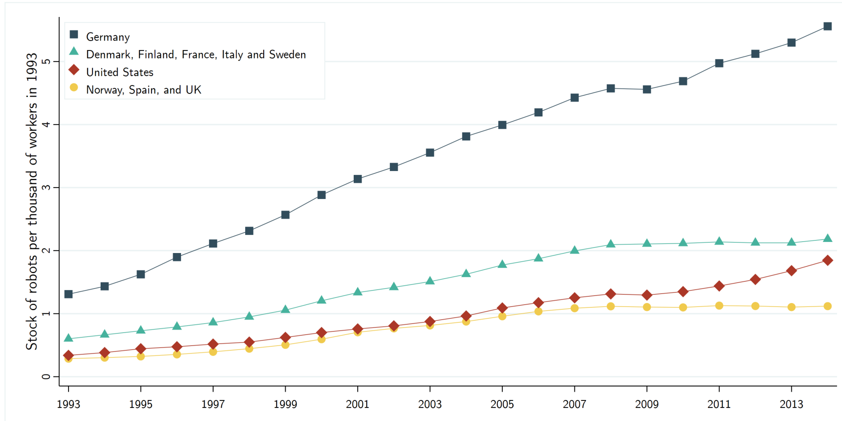

FIGURE 1: INDUSTRIAL ROBOTS IN THE UNITED STATES AND EUROPE.
Industrial robots per thousand workers in the United States and Europe.

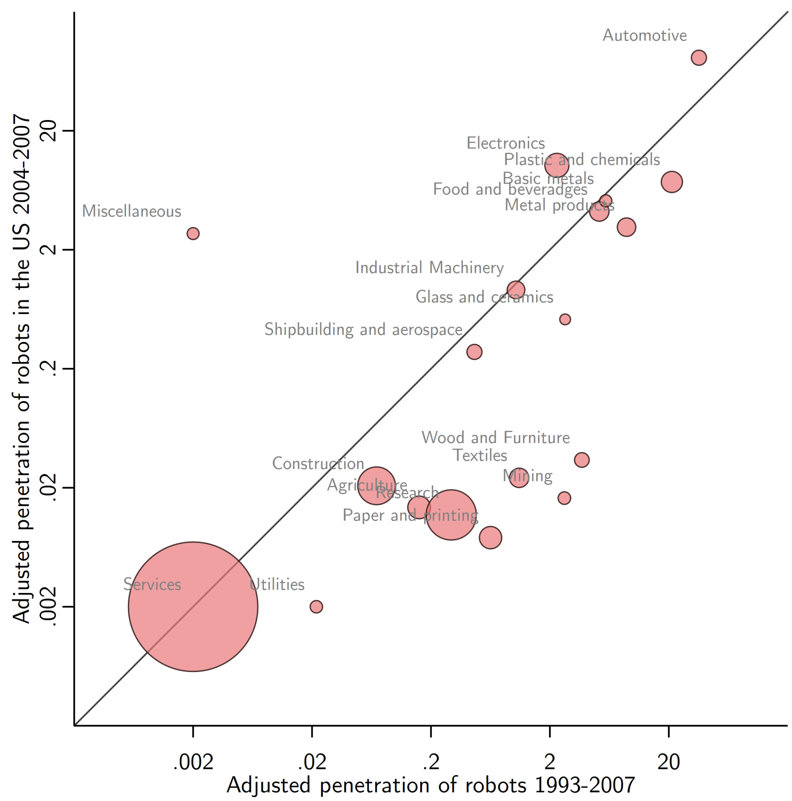

FIGURE 2: ADJUSTED ROBOT PENETRATION IN EUROPE AND THE UNITED STATES.
Plot of the adjusted penetration of robots between 1993 and 2007 ($\overline{APR_i}$) and the adjusted penetration of robots in the United States between 2004 and 2007 (APR_i rescaled to a 14-year equivalent change). The solid line corresponds to the 45^o line. Marker size indicates the baseline US employment in the corresponding industry.

FIGURE 3: INDUSTRY-LEVEL CHANGES IN ROBOTS, CAPITAL, IT CAPITAL AND TRADE PATTERNS.
For each of the 19 industries used in our analysis, the figure plots the adjusted penetration of robots between 1993 and 2007 ($\overline{APR_i}$); the percent increase in capital and IT capital; the increase in the dollar value of Chinese imports, Mexican imports, and imports from Germany, Japan and Korea between 1990 and 2007 relative to US consumption; and the increase in offshoring (the share of intermediates that are imported). See the text for a description of the data and sources.

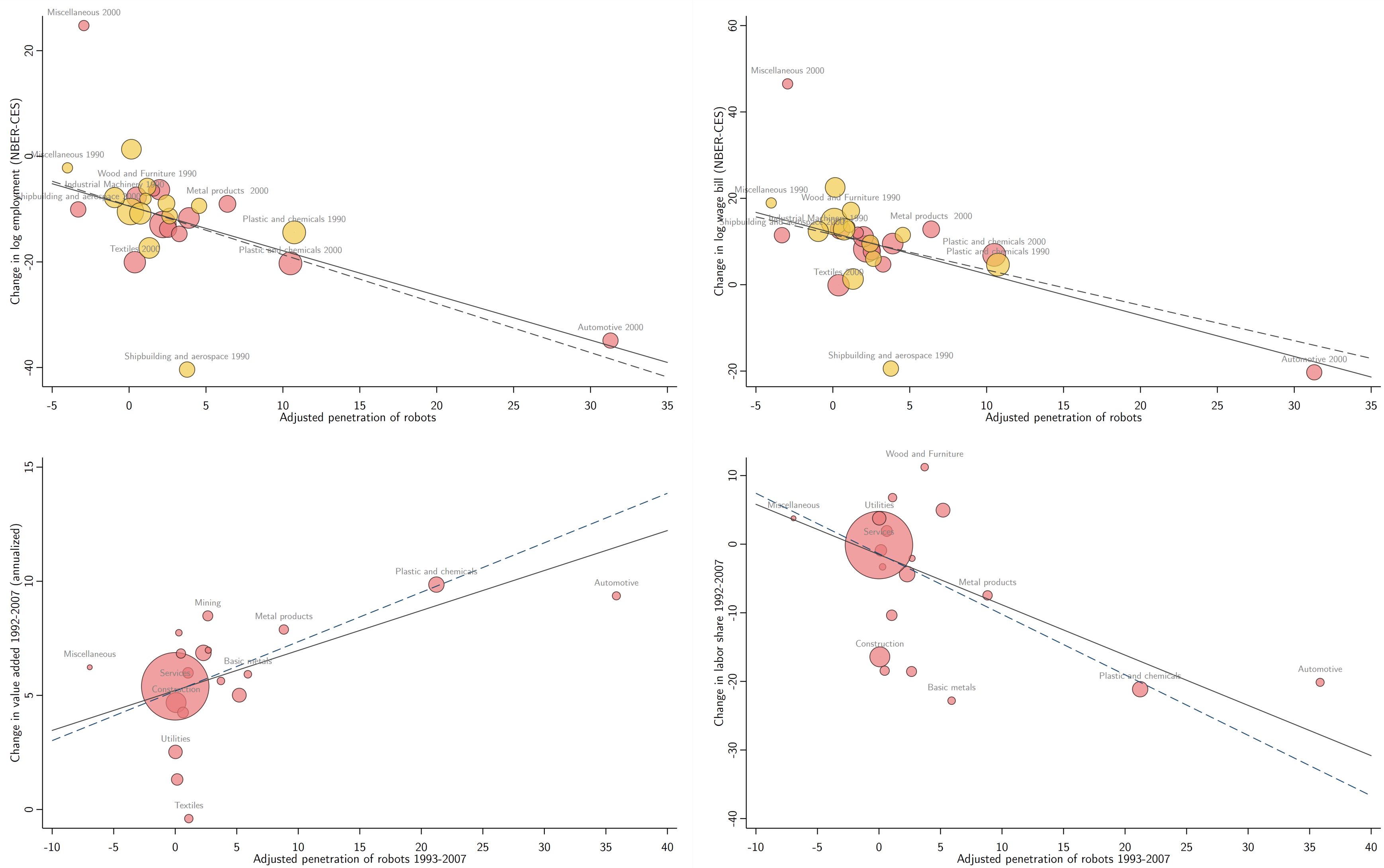

FIGURE 4: INDUSTRY-LEVEL RELATIONSHIP BETWEEN ROBOTS AND LABOR DEMAND, LABOR SHARE AND VALUE ADDED.
The figure presents residual plots of the estimates of the relationship between the adjusted penetration of robots between 1993 and 2007 ($\overline{APR}_i$) and changes in log wage bill (top left panel), log employment (top right panel), log value added (bottom left panel), and labor share (bottom right panel). The top panel presents estimates from stacked-differences models for 1993-2000 (in yellow) and 2000-2007 (in red). The bottom panel presents estimates from long-differences models for 1992-2007. The solid line corresponds to the estimates in column 8 of Panel A, column 8 of Panel B, column 10 of Panel A, and column 10 of Panel B of Table 1, respectively. The blue dashed line is for a regression excluding the automotive industry. Marker size indicates the baseline US employment in the corresponding industry.

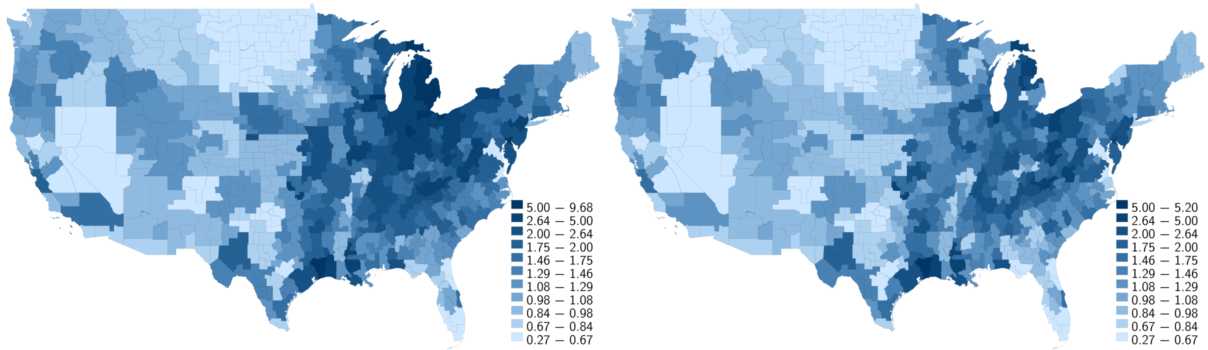

FIGURE 5: GEOGRAPHIC DISTRIBUTION OF THE EXPOSURE TO ROBOTS
The left panel shows the distribution of the exposure to robots, and the right panel shows the distribution of the exposure to robots excluding the automotive industry.

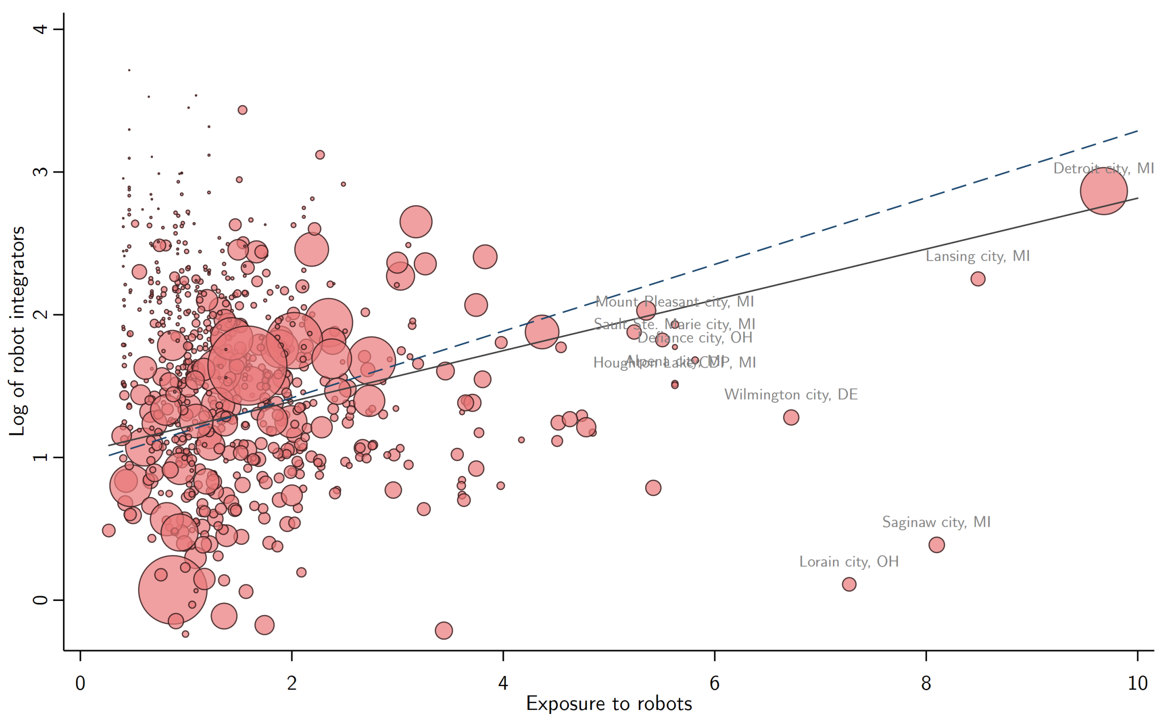

FIGURE 6: EXPOSURE TO ROBOTS AND THE LOCATION OF ROBOT INTEGRATORS.
The figure presents the residual plot of the log of one plus the number of integrators in a commuting zone against the exposure to robots between 1993 and 2007 after the covariates in column 4 of Table 2 have been partialled out. The data on the location of robot integrators, which install, program and maintain robots, are from Leigh and Kraft (2018). The solid line corresponds to a weighted regression with commuting zone population in 1990 as weights. The blue dashed line is for a regression excluding the top one percent commuting zones with the highest exposure to robots. Marker size indicates the 1990 population in the corresponding commuting zone.

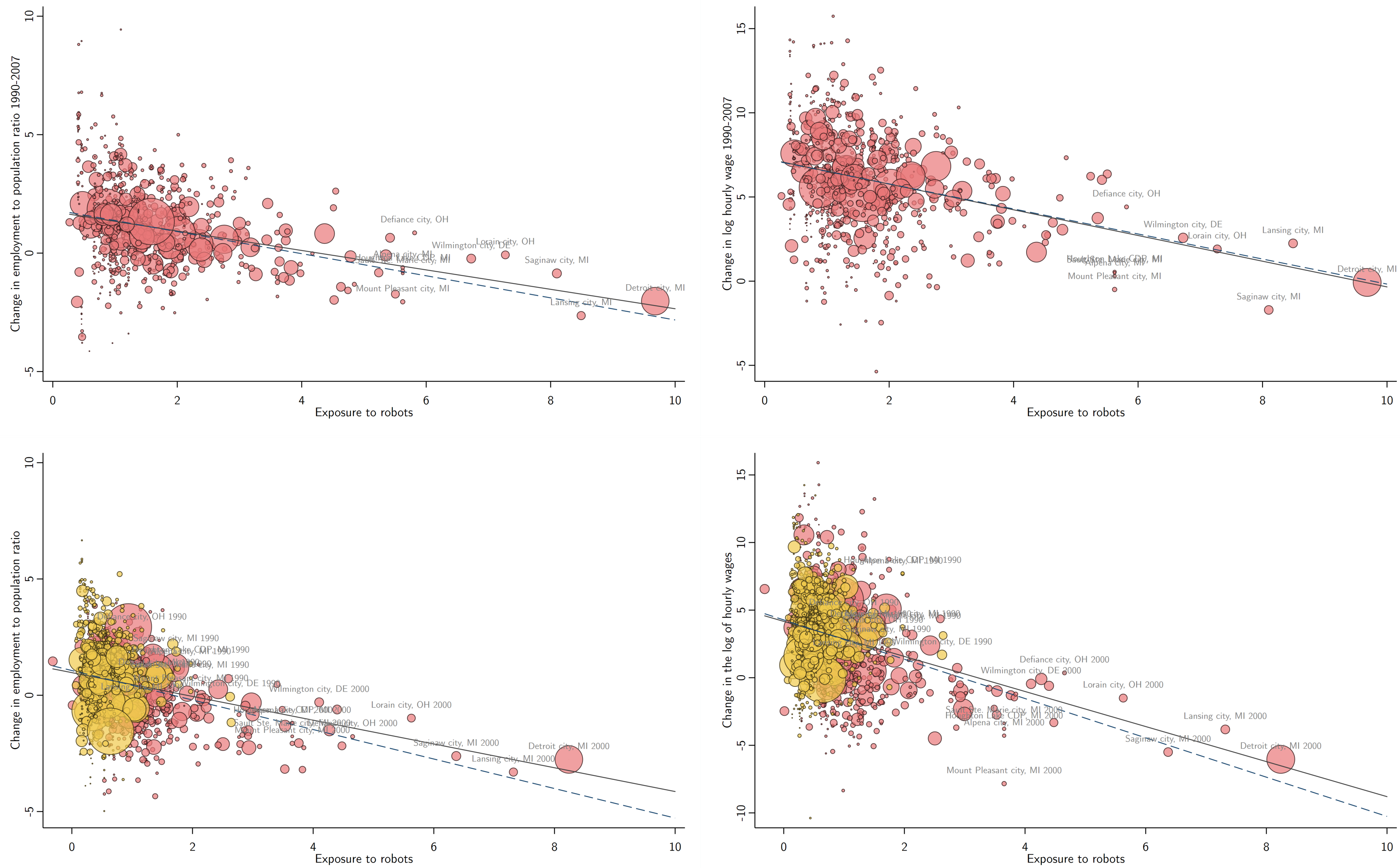

FIGURE 7: THE EFFECTS OF ROBOTS ON EMPLOYMENT AND WAGES.

The top panel of the figure presents the long-differences relationship between the exposure to robots and changes in employment to population ratio 1990-2007 (top left panel) and log hourly wage 1990-2007 (top right panel) after the covariates in column 4 of Table 2 have been partialled out. The bottom panel of the figure presents the stacked-differences relationship between the exposure to robots and changes in employment to population ratio (bottom left panel) and log hourly wage (bottom right panel) after the covariates in column 4 of Table 3 have been partialled out. In the bottom panel, the observations for 1990-2000 are depicted in yellow and the observations for 2000-2007 are depicted in red. The solid line corresponds to a regression with commuting zone population in 1990 as weights. The blue dashed line is for a regression excluding the top one percent commuting zones with the highest exposure to robots. Marker size indicates the 1990 population in the corresponding commuting zone.

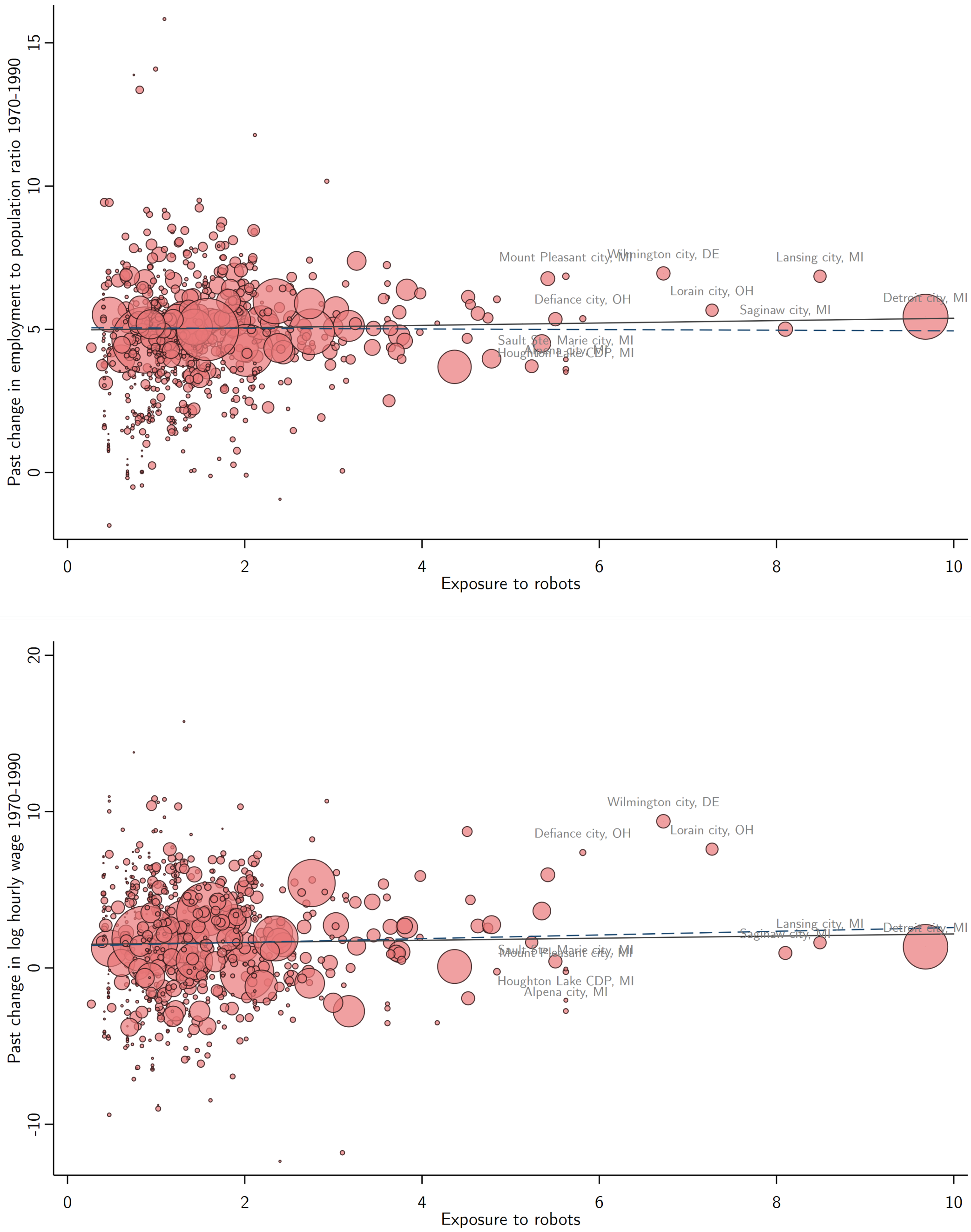

Figure 8: Pre-trends in employment and wages.
The figure presents residual plots of the estimates of the relationship between the exposure to robots and past changes in employment to population ratio 1970-1990 (top panel) and log hourly wage 1970-1990 (bottom panel) after the covariates in column 2 of Table 4 have been partialled out. The solid line shows the regression line from a weighted regression with commuting zone population in 1990 as weights. The blue dashed line is for a regression excluding the top one percent commuting zones with the highest exposure to robots. Marker size indicates the 1970 population in the corresponding commuting zone.

FIGURE 9: THE EFFECTS OF ROBOTS ON INDUSTRIES AND OCCUPATIONS.
The figure presents long-differences estimates of exposure to robots on the employment to population ratio by industry (top panel) and occupation (bottom panel). The green bars correspond to estimates equivalent to our baseline specification in column 4 of Table 2; the red bars to column 5 of Table 2 (where we remove the top one percent commuting zones with the highest exposure to robots); and the blue bars to column 6 of Table 2 (unweighted specifications).

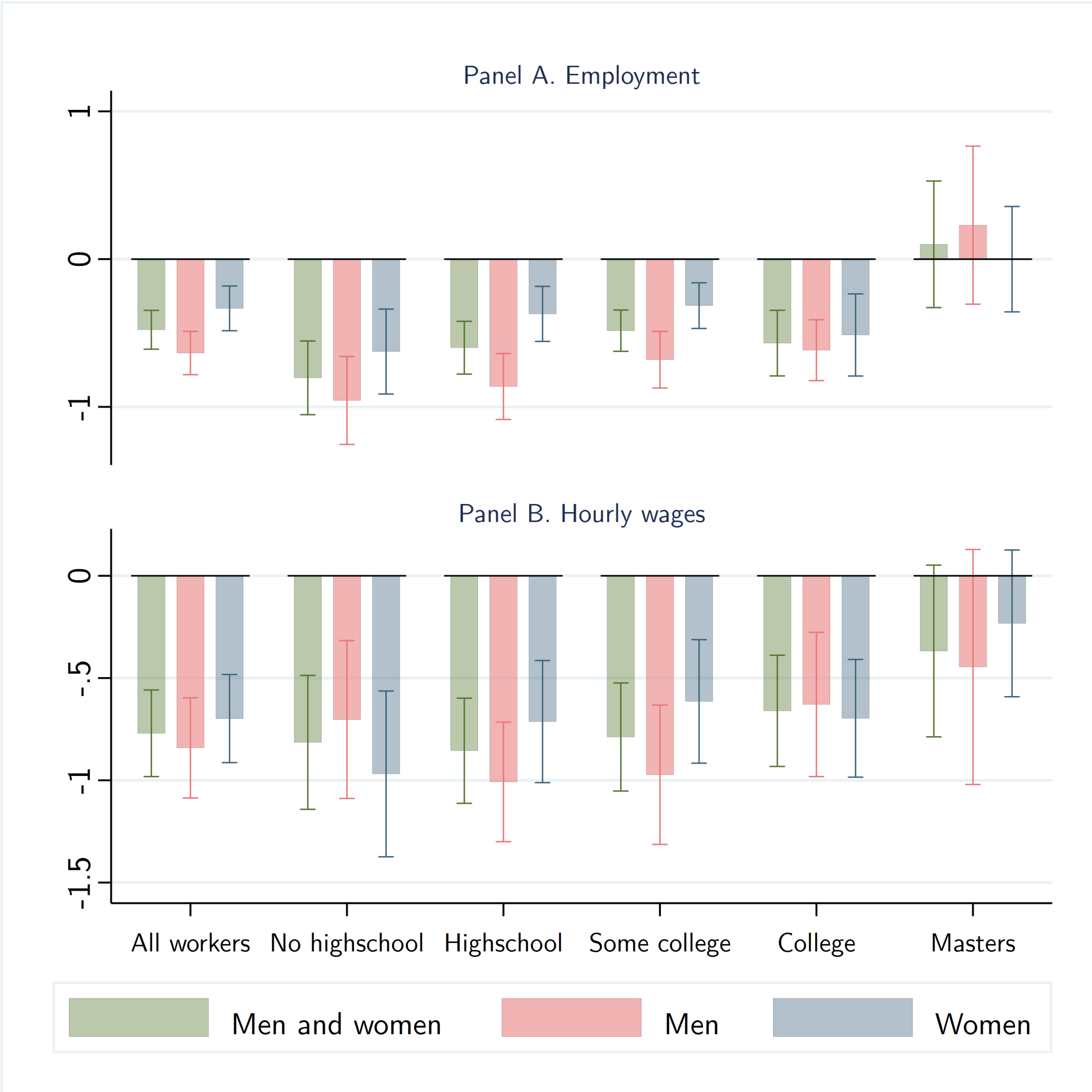

Figure 10: Effects of robots on employment and wages by education and gender. The figure presents estimates of exposure to robots (from the specification of column 4 in Table 2) for changes in employment to population ratio (top panel) and log hourly wage (bottom panel).

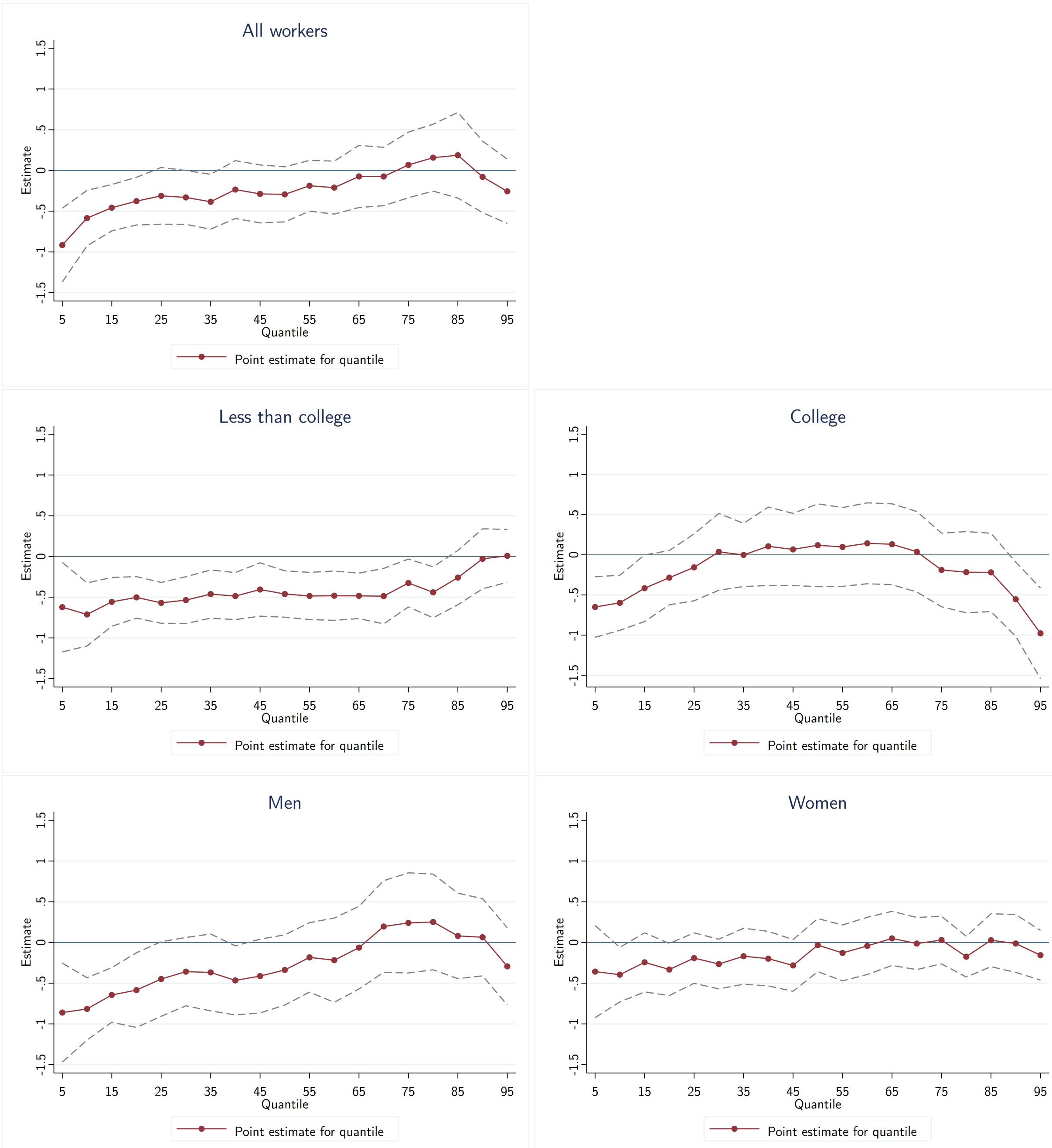

FIGURE 11: THE EFFECTS OF ROBOTS ON THE WAGE DISTRIBUTION.
The figure presents estimates of the effects of the exposure to robots on different quantiles of the wage distribution for a specification equivalent to column 4 in Table 2 following the methodology of Chetverikov, Larsen and Palmer (2016). Estimates for the 5th, 10th, . . . , and 95th quantiles together with their 95% confidence intervals are depicted. The different panels are for all workers, workers with less than a college degree, workers with a college degree, male and female workers.

TABLE 1: ROBOTS, LABOR DEMAND, LABOR SHARE AND VALUE ADDED: INDUSTRY-LEVEL RESULTS

	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 workers	All workers	All workers	Production workers	All workers	All workers	All workers	All workers	Production workers	All workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A. Change in log wage bill									Value added
Adjusted penetration of robots, $\overline{APR}_i$	-2.451	-0.843	-0.719	-0.883	-1.827	-1.037	-1.411	-0.953	-1.029	0.117
	(0.627)	(0.408)	(0.368)	(0.295)	(0.254)	(0.195)	(0.545)	(0.137)	(0.165)	(0.061)
Observations	19	19	13	13	38	38	38	26	26	19
R-squared	0.17	0.92	0.85	0.92	0.80	0.91	0.95	0.87	0.92	0.71
	Panel B. Change in log employment									Labor share
Adjusted penetration of robots, $\overline{APR}_i$	-1.730	-0.659	-0.728	-0.878	-1.270	-0.829	-1.280	-0.846	-0.917	-0.704
	(0.563)	(0.365)	(0.346)	(0.269)	(0.215)	(0.124)	(0.398)	(0.102)	(0.128)	(0.289)
Observations	19	19	13	13	38	38	38	26	26	19
R-squared	0.10	0.90	0.88	0.93	0.74	0.86	0.93	0.89	0.94	0.36
Covariates:										
Broad industry shares		✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-specific trends							✓			

The table presents estimates of the relationship between the adjusted penetration of robots and labor demand, value added and labor share across US industries. Columns 1 to 4 present long-differences estimates for log wage bill, 1993-2007 (Panel A) and log employment, 1993-2007 (Panel B). Columns 5 to 9 present stacked-differences estimates for log wage bill, 1993-2000 and 2000-2007 (Panel A), and log employment, 1993-2000 and 2000-2007 (Panel B). Column 10 presents long-differences estimates for log value added, 1992-2007 (Panel A) and labor share, 1992-2007 (Panel B). The sources of data and their coverage are indicated in the top row, and the set of covariates is indicated at the bottom row. Column 1 does not include covariates, and column 5 only includes time period dummies. Columns 2-4, 5-6, and 10 control for dummies for manufacturing and light manufacturing, and exposure to Chinese imports by industry from Acemoglu et al. (2016). Column 7 includes a full set of industry fixed effects. The regressions in columns 1-9 are weighted by baseline industry employment in 1993, and the regressions in column 10 are weighted by baseline value added by industry in 1992. Standard errors robust against heteroskedasticity and correlation within industries in parentheses.

Table 2: The effects of robots on employment and wages: long differences

	Long differences 1990-2007					
	Weighted by population				Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Change in employment to population ratio, 1990-2007					
Exposure to robots	-0.385	-0.362	-0.411	-0.410	-0.524	-0.416
	(0.082)	(0.068)	(0.055)	(0.053)	(0.136)	(0.092)
Observations	722	722	722	722	712	722
R-squared	0.26	0.46	0.66	0.68	0.67	0.63
	Panel B. Change in log hourly wage, 1990-2007					
Exposure to robots	-1.122	-0.926	-0.778	-0.770	-0.729	-0.898
	(0.141)	(0.111)	(0.122)	(0.109)	(0.223)	(0.177)
Observations	109906	109906	109906	109906	108157	109906
R-squared	0.28	0.29	0.29	0.29	0.29	0.08
Covariates:						
Census division dummies	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade and routinization				✓	✓	✓

The table presents estimates of the impact of the exposure to robots on employment and wages. Panel A presents long-differences estimates for employment to population ratio, 1990-2007. Panel B presents long-differences estimates for log hourly wage, 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, race, and birthplace. Columns 1-5 present regressions weighted by population in 1990. Column 5 presents results excluding the top one percent commuting zones with the highest exposure to robots. Column 6 presents unweighted regressions. The covariates included in each model are indicated at the bottom rows. Column 1 only includes Census division dummies. Column 2 adds demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians). Column 3 adds shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990. Columns 4-6 add the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table 3: The effects of robots on employment and wages: stacked differences

	Stacked differences 1990-2000 and 2000-2007							
							Commuting zone trends	
	Weighted by population				Excludes zones with high exposure	Unweighted	Weighted by population	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Change in employment to population ratio, 1990-2000 and 2000-2007							
Exposure to robots	-0.578	-0.550	-0.484	-0.511	-0.709	-0.680	-0.397	-0.862
	(0.097)	(0.085)	(0.060)	(0.052)	(0.155)	(0.084)	(0.072)	(0.104)
Observations	1444	1444	1444	1444	1424	1444	1444	1444
R-squared	0.24	0.33	0.41	0.43	0.42	0.40	0.72	0.44
	Panel B. Change in log hourly wage, 1990-2000 and 2000-2007							
Exposure to robots	-1.435	-1.409	-1.246	-1.300	-1.577	-1.601	-1.268	-2.457
	(0.219)	(0.204)	(0.167)	(0.157)	(0.523)	(0.264)	(0.241)	(0.379)
Observations	236008	236008	236008	236008	232243	257583	236008	257583
R-squared	0.24	0.24	0.24	0.25	0.24	0.08	0.27	0.09
Covariates:								
Census division dummies	✓	✓	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓	✓
Trade and routinization				✓	✓	✓	✓	✓
Commuting zone trends							✓	✓

The table presents estimates of the impact of the exposure to robots on employment and wages. Panel A presents stacked-differences estimates for employment to population ratio, 1990-2000 and 2000-2007. Panel B presents stacked-differences estimates for log hourly wage, 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, race, and birthplace. Columns 1-5 and 7 present regressions weighted by population in 1990. Column 5 presents results excluding the top one percent commuting zones with the highest exposure to robots. Columns 6 and 8 present unweighted regressions. The covariates included in each model are indicated at the bottom rows. Column 1 only includes Census division dummies and period dummies. Column 2 adds demographic characteristics of commuting zones in 1990 (log of population, share of males, the share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians). Column 3 adds shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990. Columns 4-6 add the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and share of employment in routine jobs. In addition, columns 7 and 8 include a full set of commuting zone fixed effects. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table 4: Pre-trends

	Change in employment to population ratio				Change in log hourly wage			
	Weighted by population		Excludes zones with high exposure	Unweighted	Weighted by population		Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Past change in labor market outcomes, 1970-1990							
Exposure to robots	0.024	0.042	-0.121	-0.244	0.085	0.122	0.269	-0.249
	(0.061)	(0.061)	(0.170)	(0.155)	(0.209)	(0.202)	(0.421)	(0.301)
Observations	722	722	712	722	68495	68495	67474	68495
R-squared	0.47	0.48	0.48	0.31	0.50	0.50	0.49	0.30
	Panel B. Estimates controlling for a Bartik-measure of industry decline between 1970-1990							
Exposure to robots	-0.372	-0.381	-0.460	-0.383	-0.736	-0.742	-0.661	-0.784
	(0.041)	(0.043)	(0.137)	(0.094)	(0.118)	(0.119)	(0.258)	(0.185)
Bartik for industries in decline 1970-1990	-0.054	-0.050	-0.046	-0.062	-0.059	-0.056	-0.061	-0.086
	(0.021)	(0.020)	(0.021)	(0.021)	(0.036)	(0.037)	(0.037)	(0.033)
Observations	722	722	712	722	109906	109906	108157	109906
R-squared	0.67	0.67	0.66	0.62	0.29	0.29	0.29	0.08
	Panel C. Estimates controlling for the change in labor market outcomes between 1970-1990							
Exposure to robots	-0.410	-0.420	-0.568	-0.519	-0.803	-0.811	-0.822	-1.112
	(0.056)	(0.057)	(0.133)	(0.114)	(0.127)	(0.128)	(0.275)	(0.191)
Observations	722	722	712	722	62714	62714	61771	62714
R-squared	0.66	0.66	0.66	0.62	0.38	0.38	0.37	0.16
Covariates:								
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓
Trade and routinization		✓	✓	✓		✓	✓	✓

The table presents estimates of the impact of the exposure to robots on past employment and wages, as well as estimates controlling for past changes in employment and wages. Panel A presents estimates for past changes in employment to population ratio (columns 1 to 4) and log hourly wage (columns 5 to 8) between 1970 and 1990. For comparison with our main results, these outcomes are scaled to a 14-year equivalent change. Panel B presents long-differences estimates for employment to population ratio (columns 1 to 4) and log hourly wage (columns 5 to 8) between 1990 and 2007 controlling for a Bartik-style measure of exposure to industries that were in decline from 1970 to 1990 (see the main text for details on this variable). Panel C presents long-differences estimates for employment to population ratio (columns 1 to 4) and log hourly wage (columns 5 to 8) between 1990 and 2007 controlling for the change in each outcome between 1970 and 1990. The specifications for log hourly wage are estimated at the demographic cell $\times$ commuting zone level, where demographic cells are defined by age, gender, education, race, and birthplace. Columns 1-3 and 5-7 present regressions weighted by population in 1990. Columns 3 and 7 present results excluding the top one percent commuting zones with the highest exposure to robots. Columns 4 and 8 present unweighted regressions. The covariates included in each model are indicated at the bottom rows. Columns 1 and 5 include Census division dummies; demographic characteristics of commuting zones (log of population, share of males, the share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians); and shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990. In Panel A, the baseline covariates are from 1970, and in Panels B and C they are from 1990. Columns 2-4 and 6-8 add the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table 5: The role of the automotive industry

	Long differences 1990-2007			Stacked differences 1990-2000 and 2000-2007		
	Weighted by population		Unweighted	Weighted by population		Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Change in employment to population ratio			
Exposure to robots in automotives	-0.385	-0.413	-0.444	-0.563	-0.513	-0.714
	(0.074)	(0.055)	(0.121)	(0.082)	(0.051)	(0.120)
Exposure in other industries	-0.385	-0.388	-0.378	-0.668	-0.499	-0.612
	(0.208)	(0.111)	(0.125)	(0.290)	(0.224)	(0.150)
Test for equality of coefficients (p-value)	[1.00]	[0.82]	[0.69]	[0.71]	[0.95]	[0.62]
Observations	722	722	722	1444	1444	1444
R-squared	0.26	0.68	0.63	0.25	0.43	0.40
			Panel B. Change in log hourly wage			
Exposure to robots in automotives	-1.092	-0.776	-0.842	-1.363	-1.322	-1.598
	(0.098)	(0.104)	(0.177)	(0.151)	(0.123)	(0.243)
Exposure in other industries	-1.269	-0.726	-0.979	-1.888	-1.123	-1.609
	(0.502)	(0.288)	(0.343)	(0.791)	(0.795)	(0.579)
Test for equality of coefficients (p-value)	[0.71]	[0.85]	[0.71]	[0.49]	[0.80]	[0.98]
Observations	109906	109906	109906	236008	236008	257583
R-squared	0.28	0.29	0.08	0.24	0.25	0.08
Covariates:						
Division dummies	✓	✓	✓	✓	✓	✓
Baseline covariates		✓	✓		✓	✓

The table presents estimates of the impact of the exposure to robots separately for the automotive industry and the remaining industries. Columns 1 to 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 employment to population ratio. Panel B presents results for log hourly wage. The specifications in Panel B are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education, race, and birthplace. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 3 and 6 present unweighted regressions. The covariates in each model are reported at the bottom of the table. Columns 1 and 4 only includes Census division dummies. Columns 2-3 and 5-6 add demographic characteristics of commuting zones in 1990 (log of population, share of males, the share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians); shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990; and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and share of employment in routine jobs. Also, for each model, we present the p-value for a test of equality between the coefficients of exposure to robots in automotive manufacturing and in other industries. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table 6: The effects of capital, other technologies and trade

	Change in employment to population ratio				Change in log hourly wage			
	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. Estimates controlling for exposure to capital							
Exposure to robots	-0.392	-0.388	-0.468	-0.557	-0.728	-0.817	-1.183	-0.916
	(0.048)	(0.091)	(0.049)	(0.076)	(0.109)	(0.187)	(0.135)	(0.232)
Exposure to capital	0.037	0.034	0.071	0.110	0.087	0.098	0.202	0.144
	(0.018)	(0.024)	(0.033)	(0.028)	(0.031)	(0.030)	(0.086)	(0.114)
Observations	722	722	1444	1444	109906	109906	236008	257596
R-squared	0.68	0.64	0.44	0.41	0.29	0.08	0.25	0.03
	Panel B. Estimates controlling for exposure to IT capital							
Exposure to robots	-0.406	-0.413	-0.472	-0.674	-0.744	-0.876	-1.216	-1.010
	(0.051)	(0.090)	(0.050)	(0.084)	(0.109)	(0.179)	(0.176)	(0.286)
Exposure to IT capital	0.008	0.006	0.053	0.010	0.050	0.044	0.116	0.071
	(0.009)	(0.011)	(0.031)	(0.014)	(0.016)	(0.015)	(0.054)	(0.042)
Observations	722	722	1444	1444	109906	109906	236008	257596
R-squared	0.68	0.63	0.44	0.40	0.29	0.08	0.25	0.03
	Panel C. Estimates controlling for exposure to value added							
Exposure to robots	-0.438	-0.471	-0.543	-0.722	-0.785	-0.931	-1.335	-1.062
	(0.055)	(0.091)	(0.056)	(0.080)	(0.112)	(0.174)	(0.162)	(0.284)
Exposure to value added increases	0.055	0.055	0.081	0.081	0.031	0.033	0.087	0.008
	(0.012)	(0.014)	(0.026)	(0.019)	(0.021)	(0.016)	(0.051)	(0.062)
Observations	722	722	1444	1444	109906	109906	236008	257596
R-squared	0.69	0.65	0.44	0.41	0.29	0.08	0.25	0.03
	Panel D. Estimates controlling for exposure to TFP							
Exposure to robots	-0.412	-0.415	-0.509	-0.678	-0.771	-0.890	-1.297	-1.050
	(0.054)	(0.092)	(0.049)	(0.083)	(0.107)	(0.177)	(0.155)	(0.281)
Exposure to productivity increases	-0.026	0.004	0.048	0.030	-0.023	0.032	0.086	0.102
	(0.019)	(0.024)	(0.034)	(0.024)	(0.074)	(0.049)	(0.082)	(0.082)
Observations	722	722	1444	1444	109906	109906	236008	257596
R-squared	0.68	0.63	0.43	0.40	0.29	0.08	0.25	0.03
	Panel E. Estimates controlling for exposure to trade and offshoring							
Exposure to robots	-0.400	-0.406	-0.499	-0.649	-0.762	-0.889	-1.268	-1.018
	(0.052)	(0.088)	(0.050)	(0.083)	(0.105)	(0.176)	(0.153)	(0.259)
Observations	722	722	1444	1444	109906	109906	236008	257596
R-squared	0.68	0.64	0.44	0.40	0.29	0.08	0.25	0.03
Covariates:								
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots, capital accumulation, and increases in value-added on employment and wages. Columns 1-2 and 5-6 present long-differences estimates for 1990-2007. Columns 3-4 and 7-8 present stacked-differences estimates for 1990-2000 and 2000-2007. Columns 1-4 present results for employment to population ratio. Columns 5-8 present results for log hourly wage. The specifications in columns 5-8 for log hourly wage are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education, race, and birthplace. 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 capital, constructed by interacting the increase in log capital by industry with the baseline employment share of that industry in the commuting zone. In Panel B we control for a measure of exposure to IT capital, constructed by interacting the increase in log IT capital by industry with the baseline employment share of that industry in the commuting zone. In Panel C we control for a measure of exposure to productivity increases, constructed by interacting the increase in log value added by industry (between 1992 and 2007 in all models) with the baseline employment share of that industry in the commuting zone. In Panel D we control for a measure of exposure to productivity increases, constructed by interacting the increase in TFP among manufacturing industries (from the NBER-CES) with the baseline employment share of that industry in the commuting zone. In Panel E we control for measures of exposure to offshoring, Mexican imports, and imports from countries experiencing mayor advances in automation (Germany, Japan, and Korea). The main text describes the construction of these additional covariates. All models include Census division dummies; demographic characteristics of commuting zones in 1990 (log of population, share of males, the share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians); shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990; and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table 7: The effects of robots on employment and wages: IV estimates

	Change in employment to population ratio			Change in log hourly wage		
	Instrumented using exposure to robots		IV using industry shares	Instrumented using exposure to robots		IV using industry shares
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Long-differences, 1990-2007			
US exposure to robots	-0.347	-0.380	-0.291	-1.005	-0.714	-0.549
	(0.102)	(0.083)	(0.046)	(0.209)	(0.138)	(0.082)
Observations	722	722	722	109906	109906	109906
First-stage coefficient	1.11	1.08		1.12	1.08	
	(0.15)	(0.16)		(0.15)	(0.15)	
First-stage F-statistic	52.5	47.4	1414.2	54.9	49.0	1459.7
Overid test p-value			[0.029]			[0.119]
			Panel B. Alternative imputation of US data			
US exposure to robots	-0.485	-0.531	-0.407	-1.421	-1.010	-0.776
	(0.143)	(0.116)	(0.064)	(0.296)	(0.195)	(0.116)
Observations	722	722	722	109906	109906	109906
First-stage coefficient	0.79	0.77		0.79	0.76	
	(0.11)	(0.11)		(0.11)	(0.11)	
First-stage F-statistic	52.5	47.4	1414.2	54.9	49.0	1459.7
Overid test p-value			[0.029]			[0.119]
			Panel C. Long-differences, 1990-2014			
US exposure to robots	-0.269	-0.239	-0.203	-1.243	-1.086	-1.000
	(0.107)	(0.072)	(0.059)	(0.142)	(0.157)	(0.123)
Observations	722	722	722	115180	115180	115180
First-stage coefficient	1.05	1.00		1.06	1.00	
	(0.08)	(0.09)		(0.08)	(0.09)	
First-stage F-statistic	180.0	116.2	1718.9	189.8	120.3	1779.0
Overid test p-value			[0.239]			[0.046]
			Panel D. Long-differences, 2000-2007			
US exposure to robots	-0.613	-0.647	-0.667	-1.380	-1.287	-1.224
	(0.132)	(0.076)	(0.083)	(0.229)	(0.181)	(0.153)
Observations	722	722	722	131494	131494	131494
First-stage coefficient	0.71	0.68		0.71	0.67	
	(0.04)	(0.05)		(0.04)	(0.05)	
First-stage F-statistic	323.0	166.4	1016.6	337.6	176.1	1048.1
Overid test p-value			[0.116]			[0.218]
			Panel E. Long-differences, 2000-2014			
US exposure to robots	-0.426	-0.350	-0.353	-1.569	-1.605	-1.578
	(0.177)	(0.067)	(0.069)	(0.142)	(0.193)	(0.181)
Observations	722	722	722	143502	143502	143502
First-stage coefficient	0.83	0.77		0.83	0.77	
	(0.02)	(0.04)		(0.02)	(0.04)	
First-stage F-statistic	1543.6	366.6	1122.1	1650.8	386.5	1174.9
Overid test p-value			[0.574]			[0.329]
Covariates:						
Division dummies	✓	✓	✓	✓	✓	✓
Baseline covariates		✓	✓		✓	✓

The table presents IV estimates of the impact of the 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 C presents results for 2000-2007. Panel D presents results for 2000-2014. In all models, we instrument the US exposure to robots using the 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 employment to population ratio. Columns 4-6 present results for log hourly wage. The specifications for log hourly wage are estimated at the demographic cell $\times$ commuting zone level, where demographic cells are defined by age, gender, education, race, and birthplace. All IV estimates are from regressions weighted by population in 1990. The covariates included in each model are indicated at the bottom rows. Columns 1 and 4 only include Census division dummies. Columns 2-3 and 5-6 add demographic characteristics of commuting zones in 1990 (log of population, share of males, the share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians); shares of employment in manufacturing, light manufacturing and construction in 1990, and the share of female workers in manufacturing employment in 1990; and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and share of employment in routine jobs. We also report the first-stage coefficients in columns 1-2 and 4-5, the first-stage F-statistic in all models, and the p-value for Hansen's overidentification test in columns 3 and 6. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Online Appendix (Not for Publication)

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

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

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

$$s_{ci}^L = \frac{W_c L_{ci}}{\alpha P_{ci}^X X_{ci}} = \frac{(1-\theta_i)\frac{W_c}{\gamma_L}}{\theta_i \frac{R_M^K}{\gamma_M} + (1-\theta_i)\frac{W_c}{\gamma_L}}. \tag{A6}$$

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.*

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

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

Using the formulas for s_{ci}^L and P_{ci}^X in equations (A5) and (A6), we obtain

$$\begin{aligned}
W_c L_{ci} =& \frac{(1-\theta_i)\frac{W_c}{\gamma_L}}{\theta_i \frac{R_M^K}{\gamma_M} + (1-\theta_i)\frac{W_c}{\gamma_L}} \alpha \nu_i P_{ci}^{X\,1-\sigma} Y_c \\
=& \frac{(1-\theta_i)\frac{W}{\gamma_L}}{(A_{ci}P_{ci}^X)^{\frac{1}{\alpha}}} R_c^{K\,\frac{1-\alpha}{\alpha}} \alpha \nu_i P_{ci}^{X\,1-\sigma} Y_c \\
=& \frac{(1-\theta_i)\frac{W}{\gamma_L}}{(A_{ci}P_{ci}^X)^{\frac{1}{\alpha}}} \left((1-\alpha)\frac{Y_c}{K_c}\right)^{\frac{1-\alpha}{\alpha}} \alpha \nu_i P_{ci}^{X\,1-\sigma} Y_c,
\end{aligned}$$

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

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

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, $\frac{1/\alpha}{1/\alpha+\sigma-1} > \pi_c s_{ic}^L$. 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

$$\begin{aligned}\frac{d\theta_i}{1-\theta_i} &> \left(\sigma + \frac{1}{\alpha} - 1\right) d\ln P_{ci}^X \\ &= \left(\sigma + \frac{1}{\alpha} - 1\right) \alpha s_{ic}^L \pi_c \frac{d\theta_i}{1-\theta_i}.\end{aligned}$$

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*

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

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

where $\zeta_c^{disp} = (1-\alpha+\eta)/\Lambda_c$, $\zeta_c^{prod} = s_c^L(1+\eta)/\Lambda_c$, $\zeta_c^{L,inc} = \alpha(s_c^L)^2\pi_c/\Lambda_c$, $\zeta_c^{W,inc} = \alpha s_c^L(\pi_c + \pi_c(\eta-\alpha)(1-s_c^L) - (1-s_c^L\pi_c)(1-\alpha+\eta))/\Lambda_c$, *and*

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

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

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

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

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

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

$$d\ln R_c^K = d\ln Y_c. \quad \text{(A20)}$$

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. ■

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

$$C_c^L \leq W_c L_c + \omega_c \Pi_c,$$

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

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

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 non-tradable "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

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

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 $d\ln W_c$. ■

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

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

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

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

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

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

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

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

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

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

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

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

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).*

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*

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

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

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

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

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

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, when $\theta_0 = 0$, these simplified to the expressions given above. ■

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*

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

where the ζ*'s coincide with those given in Proposition A4 for* $\pi_c = \pi_0$, *and* $s_c^L = s^L$.

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

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

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 $\Pi + \sum_c W_c L_c = \frac{1}{\phi}(Y - I)$, 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

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

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 $Y_i P_i^Y = \sum_c X_{ci}P_{ci}^X$, and we also used $\ell_{ci} = \varrho\chi_{ci}$, which follows from the fact that all tradable sectors have the same labor intensity.

Likewise,

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

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

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

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

$$d\ln R^K=d\ln Y \tag{A46}$$

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. ■

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

$$W_c \frac{dL_c}{dC_c} = -\frac{\psi}{\varepsilon}\frac{W_c L_c}{C_c} = -\frac{\psi}{\varepsilon}\omega^L,$$

where we used the fact that, in our model, $\frac{W_c L_c}{C_c} = \omega^L$—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

$$\begin{aligned}\varepsilon =& \frac{\phi\beta_W}{0.1(\hat{\beta}_W + \hat{\beta}_L) - \frac{0.1(1-\phi)}{\omega^L}\hat{\beta}_W + \hat{\beta}_L} = 0.16\\ \psi =& \frac{0.1}{\omega^L}\frac{\phi\hat{\beta}_W}{0.1(\hat{\beta}_W + \hat{\beta}_L) - \frac{0.1(1-\phi)}{\omega^L}\hat{\beta}_W + \hat{\beta}_L} = 0.02.\end{aligned}$$

Given the values of ψ and ε , η is chosen to match our IV estimate $\hat{\beta}_L$ (or $\hat{\beta}_W$). This yields $\eta = 0.72$.

A4 Additional Figures and Tables

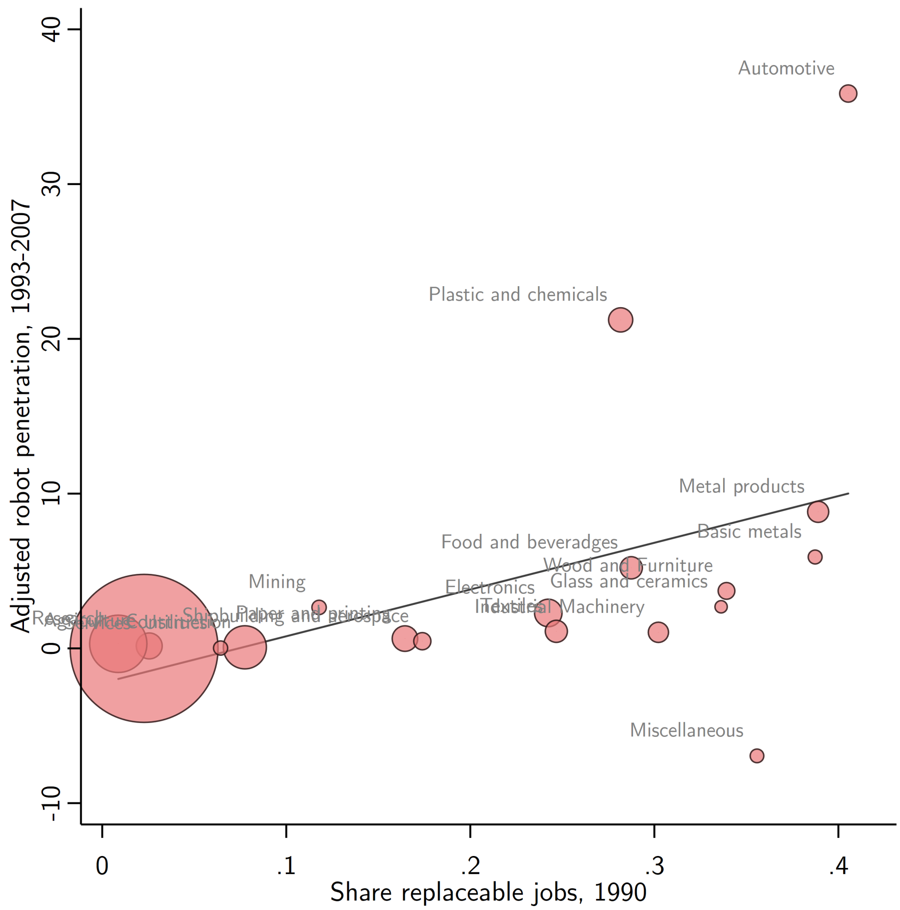

FIGURE A1: ADJUSTED ROBOT PENETRATION AND SHARE REPLACEABLE JOBS.
Plot of the adjusted penetration of robots between 1993 and 2007 ($\overline{APR_i}$) and the share of replaceable jobs by industry in 1990. The data on replaceable jobs are from Graetz and Michaels (2018). Marker size indicates the baseline US employment in the corresponding industry.

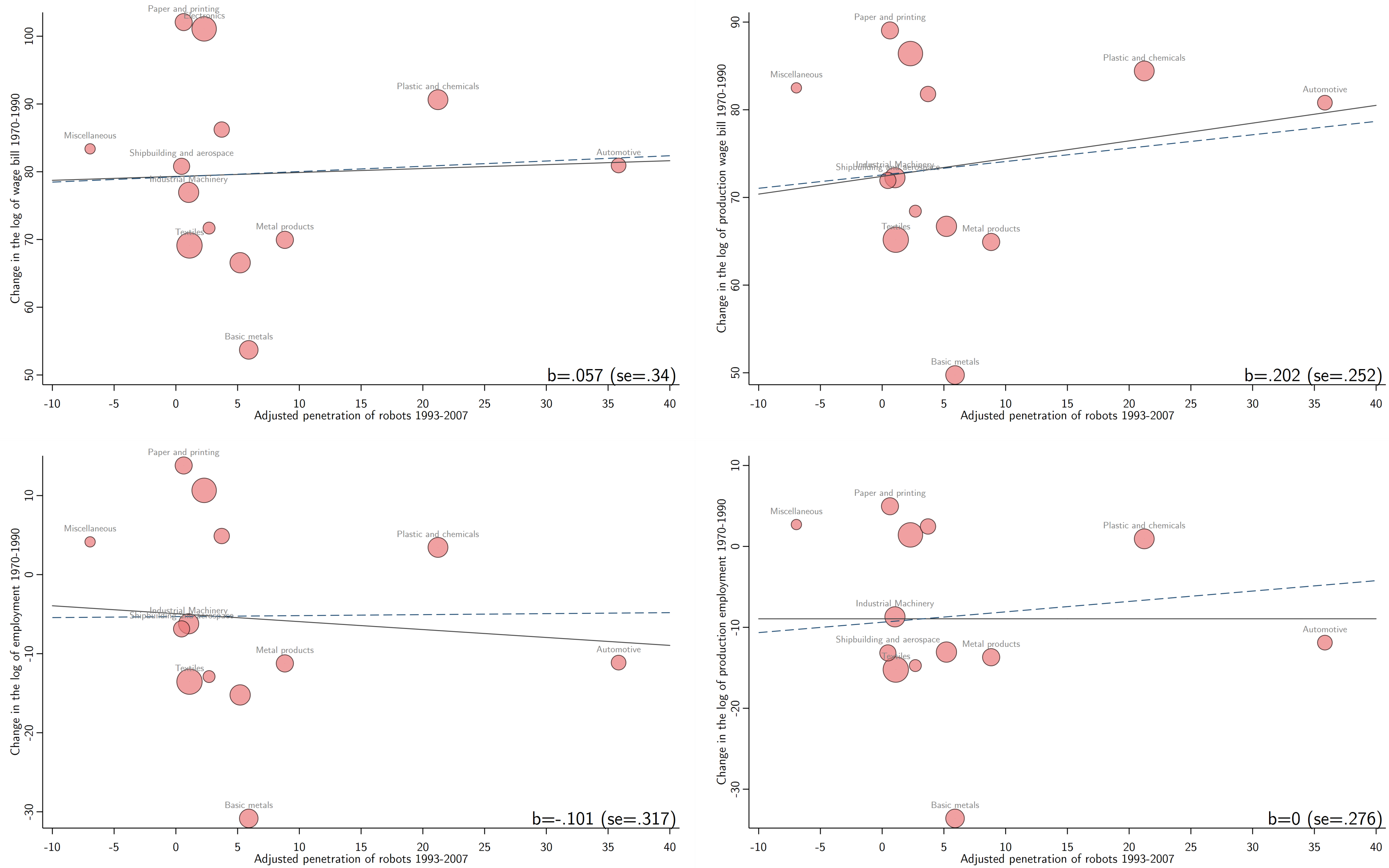

FIGURE A2: INDUSTRY-LEVEL PRE-TRENDS.
The figure presents residual plots of the estimates of the relationship between the adjusted penetration of robots between 1993 and 2007 ($\overline{APR}_i$) and past changes between 1970 and 1990 in log wage bill (top left panel), log wage bill for production workers (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 column 8 of Panels A and B of Table 1. The coefficients for these models and their standard errors are reported next to each plot. The blue dashed line is for a regression excluding the automotive industry. Marker size indicates the baseline US employment in the corresponding industry.

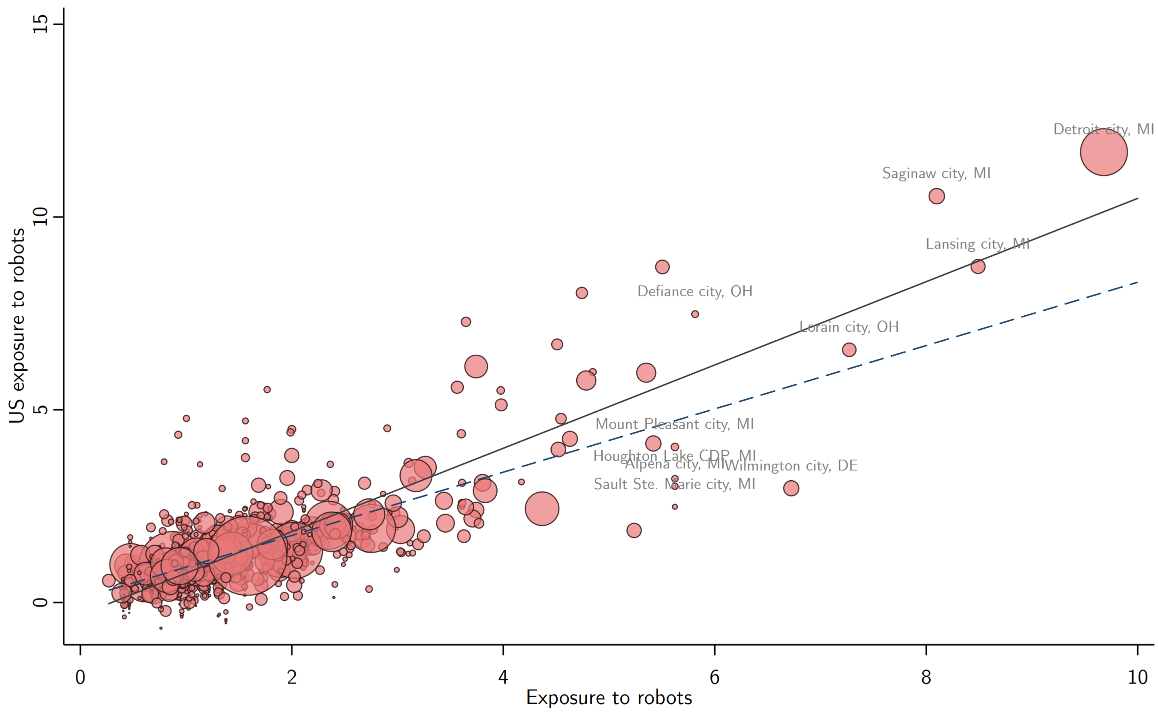

Figure A3: First-stage relationship for commuting zones.
The figure presents the residual plot of the US exposure to robots, 2004-2007 (rescaled to a 14-year equivalent change), and the exposure to robots between 1993 and 2007 after the covariates in column 2 and 5 of Table 7 have been partialled out. The solid line corresponds to a weighted regression with commuting zone population in 1990 as weights. The blue dashed line is for a regression excluding the top one percent commuting zones with the highest exposure to robots. Marker size indicates the 1990 population in the corresponding commuting zone.

FIGURE A4: THE EFFECTS OF ROBOTS ON INDUSTRIES AND OCCUPATIONS, STACKED DIFFERENCES.
The figure presents stacked-differences estimates of exposure to robots on the employment to population ratio by industry (top panel) and occupation (bottom panel). The green bars correspond to estimates equivalent to our baseline specification in column 4 of Table 3; the red bars to column 5 of Table 3 (where we remove the top one percent commuting zones with the highest exposure to robots); and the blue bars to column 6 of Table 3 (unweighted specifications).

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	(millions)
Manufacturing:								
Automotive	19.96	37.87	69.30	76.70	69.01	85.72	117.72	1,111
Plastics, chemicals and pharmaceuticals	3.25	15.23	26.07	22.93	5.12	6.95	9.91	2,205
Metal products	8.32	14.04	21.81	21.24	4.60	5.84	8.29	1,689
Industrial machinery	4.10	4.46	7.41	11.74	1.32	1.67	2.37	1,541
Food and beveradges	0.47	1.80	5.75	10.83	2.91	3.92	6.17	1,862
Basic metals	1.24	3.92	7.05	10.31	3.98	5.05	7.17	712
Miscellaneous manufacturing	6.84	5.83	3.40	7.78	1.40	1.96	13.81	690
Electronics	2.88	5.94	9.85	7.11	5.71	8.66	13.11	2,868
Clay, glass, and minerals	0.77	2.01	3.78	4.99	0.12	0.23	0.67	558
Wood and funriture	0.66	2.04	4.64	4.83	0.01	0.01	0.14	1,048
Shibbuilding and aerospace	3.87	7.36	4.05	2.37	0.05	0.12	0.54	1,111
Apparel and Textiles	0.33	1.03	1.27	1.53	0.00	0.01	0.05	1,848
Paper and publishing	0.27	0.46	0.95	1.36	0.00	0.00	0.11	2,467
Nonmanufacturing:								
Mining	0.32	2.00	3.16	2.14	0.00	0.01	0.06	763
Research and education	0.04	0.21	0.35	0.40	0.01	0.01	0.06	12,636
Agriculture	0.00	0.00	0.16	0.24	0.00	0.00	0.04	2,552
Utilities	0.00	0.02	0.02	0.18	0.00	0.00	0.03	745
Construction	0.00	0.03	0.07	0.14	0.00	0.01	0.02	7,108
Services	0.00	0.00	0.00	0.00	0.00	0.00	0.00	84,776

The table presents statistics on the number 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.

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

	Estimates for adjusted penetration of robots, US			Estimates for penetration of robots, US		
	Weighted by baseline US employment		Unweighted	Weighted by baseline US employment		Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. 1993-2007			
Adjusted penetration of robots,	1.412	1.475	1.703	1.388	1.400	1.621
$\overline{APR}_i$	(0.654)	(0.730)	(0.618)	(0.594)	(0.672)	(0.565)
Observations	19	19	19	19	19	19
R-squared	0.65	0.66	0.72	0.67	0.67	0.73
			Panel B. 2000-2007			
Adjusted penetration of robots,	1.076	1.125	1.176	1.050	1.067	1.117
$\overline{APR}_i$	(0.230)	(0.232)	(0.181)	(0.194)	(0.205)	(0.158)
Observations	19	19	19	19	19	19
R-squared	0.84	0.85	0.88	0.85	0.85	0.88
			Panel C. 2004-2007			
Adjusted penetration of robots,	0.953	0.966	1.092	0.934	0.917	1.040
$\overline{APR}_i$	(0.408)	(0.457)	(0.407)	(0.367)	(0.420)	(0.371)
Observations	19	19	19	19	19	19
R-squared	0.64	0.64	0.69	0.66	0.66	0.71
			Panel D. 2000-2014			
Adjusted penetration of robots,	1.296	1.241	1.323	1.496	1.449	1.550
$\overline{APR}_i$	(0.209)	(0.281)	(0.204)	(0.253)	(0.331)	(0.238)
Observations	19	19	19	19	19	19
R-squared	0.78	0.79	0.80	0.79	0.79	0.82
Covariates:						
Manufacturing dummy		✓	✓		✓	✓

The table presents estimates of the relationship between the adjusted penetration of robots, $\overline{APR}_i$, and the penetration of robots in the US. Columns 1 to 3 present estimates using the adjusted penetration of robots in the US as outcome. Columns 4 to 6 present estimates using the raw penetration of robots in the US as outcome. Each panel presents results for a different time period, and when necessary we rescale the penetration of robots in the US to match its length. Column 1 and 4 do not include 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 robust against heteroskedasticity in parentheses.

Table A3: 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,	-0.843	-0.719	-0.883	-1.037	-1.411	-0.953	-1.029	0.117	-0.704
$\overline{APR}_i$	(0.408)	(0.368)	(0.295)	(0.195)	(0.545)	(0.137)	(0.165)	(0.061)	(0.289)
Observations	19	13	13	38	38	26	26	19	19
Panel B. Including Germany in the construction of the instrument									
Adjusted penetration of robots,	-0.681	-0.589	-0.724	-0.885	-1.563	-0.802	-0.887	0.082	-0.533
$\overline{APR}_i$	(0.258)	(0.230)	(0.165)	(0.140)	(0.580)	(0.075)	(0.147)	(0.057)	(0.254)
Observations	19	13	13	38	38	26	26	19	19
Panel C. using all European countries in the construction of the instrument									
Adjusted penetration of robots,	-0.718	-0.618	-0.755	-0.929	-2.000	-0.831	-0.936	0.073	-0.520
$\overline{APR}_i$	(0.247)	(0.217)	(0.156)	(0.152)	(0.714)	(0.081)	(0.221)	(0.056)	(0.255)
Observations	19	13	13	38	38	26	26	19	19
Panel D. Ignoring adjustment term in the construction of the instrument									
Adjusted penetration of robots,	-0.570	-0.509	-0.649	-0.814	-2.758	-0.723	-0.805	0.090	-0.526
$\overline{APR}_i$	(0.283)	(0.258)	(0.190)	(0.177)	(1.091)	(0.131)	(0.280)	(0.055)	(0.252)
Observations	19	13	13	38	38	26	26	19	19
Panel E. Adjusting penetration using robot prices									
Adjusted penetration of robots,	-0.992	-0.816	-0.987	-1.141	-1.364	-1.032	-1.043	0.108	-0.717
$\overline{APR}_i$	(0.408)	(0.369)	(0.274)	(0.163)	(0.499)	(0.083)	(0.179)	(0.070)	(0.335)
Observations	19	13	13	38	38	26	26	19	19
Covariates:									
Broad industry shares	✓	✓	✓	✓	✓	✓	✓	✓	✓
Import competition	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-specific trends					✓				

The table presents estimates of the relationship between the adjusted penetration of robots and labor demand, value added and labor share across US industries. Columns 1 to 3 present long-differences estimates for log wage bill, 1993-2007 Columns 4 to 7 present stacked-differences estimates for log wage bill, 1993-2000 and 2000-2007. Columns 8-9 present long-differences estimates for log value added, 1992-2007 and labor share, 1992-2007. The sources of data and their coverage are indicated in the top row, and the set of covariates is indicated at the bottom row. 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 period 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 robust against heteroskedasticity and correlation within industries in parentheses.

Table A4: 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,	-1.354	-1.205	-1.435	-1.121	-0.979	-1.104
$\overline{APR}_i$	(0.589)	(0.562)	(0.559)	(0.448)	(0.401)	(0.425)
Observations	19	13	13	19	13	13
R-squared	0.93	0.86	0.88	0.94	0.89	0.89
			Panel B. 2000- 2010			
Adjusted penetration of robots,	-1.782	-1.765	-1.933	-1.473	-1.274	-1.314
$\overline{APR}_i$	(0.378)	(0.350)	(0.408)	(0.301)	(0.243)	(0.338)
Observations	19	13	13	19	13	13
R-squared	0.82	0.75	0.74	0.84	0.79	0.77
			Panel C. 2004-2010			
Adjusted penetration of robots,	-3.063	-2.995	-3.339	-2.379	-1.984	-1.978
$\overline{APR}_i$	(1.211)	(1.289)	(1.446)	(0.969)	(0.956)	(1.263)
Observations	19	13	13	19	13	13
R-squared	0.64	0.46	0.43	0.65	0.45	0.38
			Panel D. 2000-2007			
Adjusted penetration of robots,	-1.056	-1.026	-1.162	-0.821	-0.908	-1.006
$\overline{APR}_i$	(0.152)	(0.134)	(0.143)	(0.138)	(0.133)	(0.143)
Observations	19	13	13	19	13	13
R-squared	0.90	0.87	0.88	0.91	0.89	0.90
			Panel E. 2004-2007			
Adjusted penetration of robots,	-1.924	-1.722	-2.102	-1.416	-1.484	-1.787
$\overline{APR}_i$	(0.482)	(0.675)	(0.665)	(0.215)	(0.473)	(0.530)
Observations	19	13	13	19	13	13
R-squared	0.79	0.62	0.66	0.64	0.64	0.65
Covariates:						
Broad industry shares	✓	✓	✓	✓	✓	✓
Import competition	✓	✓	✓	✓	✓	✓

The table presents estimates of the relationship between the adjusted penetration of robots and labor demand across US industries. Columns 1 to 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 to 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 indicated in the top row, and the set of covariates is indicated at the bottom row. 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 in 1993. Standard errors robust against heteroskedasticity and correlation within industries in parentheses.

Table A5: 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)	(5)
			Panel A. Change in labor share		
Adjusted penetration of robots, $\overline{APR}_i$	-0.784	-0.764	-0.704	-0.866	-0.557
	(0.144)	(0.182)	(0.289)	(0.355)	(0.216)
Observations	19	19	19	18	19
R-squared	0.35	0.35	0.36	0.31	0.33
			Panel B. Change in log value added (annualized)		
Adjusted penetration of robots, $\overline{APR}_i$	-0.010	0.160	0.117	0.183	0.074
	(0.044)	(0.060)	(0.061)	(0.046)	(0.039)
Observations	19	19	19	18	19
R-squared	0.00	0.60	0.71	0.74	0.67
			Panel C. Change in log value added per worker (annualized)		
Adjusted penetration of robots, $\overline{APR}_i$	0.101	0.109	0.137	0.208	0.098
	(0.041)	(0.056)	(0.070)	(0.064)	(0.051)
Observations	19	19	19	18	19
R-squared	0.20	0.20	0.34	0.39	0.21
Covariates:					
Manufacturing		✓	✓	✓	✓
Light manufacturing and Import competition			✓	✓	✓

The table presents estimates of the relationship between the adjusted penetration of robots and the labor share and value added across US industries. Panel A presents long-differences estimates for share value added, 1992-2007. Panel B presents long-differences estimates for log value added, 1992-2007. Panel C presents long-differences estimates for log value added per worker, 1992-2007. Column 1 presents the raw data. Column 2 controls for a dummy for manufacturing. Column 3 controls for dummies for light manufacturing and exposure to Chinese imports by industry from Acemoglu et al. (2016). Column 4 excludes the automotive industry from the sample. The regressions in columns 1-4 are weighted by baseline industry value added in 1992, and the regression in column 5 is unweighted. Standard errors robust against heteroskedasticity and correlation within industries in parentheses.

Table A6: Exposure to robots and the location of integrators

	Location of robot integrators					
	Weighted by population				Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. log one plus number of integrators					
Exposure to robots	0.236	0.222	0.184	0.178	0.291	0.087
	(0.070)	(0.057)	(0.033)	(0.035)	(0.104)	(0.017)
Observations	722	722	722	722	712	722
R-squared	0.27	0.74	0.75	0.75	0.74	0.57
	Panel B. log one plus employment in integrators					
Exposure to robots	0.437	0.403	0.264	0.249	0.745	0.227
	(0.155)	(0.153)	(0.101)	(0.106)	(0.235)	(0.062)
Observations	722	722	722	722	712	722
R-squared	0.24	0.68	0.70	0.70	0.71	0.52
	Panel C. log one plus number of integrators, separating automotive manufacturing					
Exposure to robots	0.228	0.202	0.176	0.168	0.226	0.128
in automotive	(0.064)	(0.037)	(0.025)	(0.027)	(0.132)	(0.020)
Exposure to robots	0.273	0.314	0.249	0.256	0.342	0.029
in other industries	(0.166)	(0.140)	(0.098)	(0.099)	(0.103)	(0.030)
Observations	722	722	722	722	712	722
R-squared	0.27	0.74	0.75	0.75	0.74	0.57
	Panel D. Dummy for location of integrators					
Exposure to robots	0.056	0.052	0.024	0.022	0.134	0.034
	(0.029)	(0.034)	(0.026)	(0.027)	(0.039)	(0.017)
Observations	722	722	722	722	712	722
R-squared	0.12	0.51	0.54	0.54	0.56	0.47
Covariates:						
Census division dummies	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade and routinization				✓	✓	✓

The table presents estimates of the relationship between exposure to robots and the location of integrators. Panel A presents estimates for log of one plus the number of integrators. Panels B and C presents estimates for log of one plus employment by integrators. Panel D presents estimates for a dummy for the presence of integrators. Columns 1-5 present regressions weighted by population in 1990. Column 5 presents results excluding the top one percent commuting zones with the highest exposure to robots. Column 6 presents unweighted regressions. The covariates included in each model are indicated at the bottom rows. Column 1 only includes Census division dummies. Column 2 adds demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians). Column 3 adds shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990. Columns 4-6 add the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A7: Summary statistics: commuting zone data

	All commuting zones	By quartiles of exposure to robots: First quartile	Second quartile	Third quartile	Fourth quartile
	(1)	(2)	(3)	(4)	(5)
Outcomes:					
Change in employment to population ratio, 1990-2007 (p.p.)	0.96	1.77	1.68	0.32	0.71
Change in log hourly wage, 1990-2007 (log points, adjusted for composition)	5.84	8.14	8.83	5.35	3.47
Baseline characteristics:					
Employment to population ratio, 1990	0.35	0.32	0.34	0.36	0.37
log hourly wage, 1990	2.59	2.61	2.52	2.61	2.60
Covariates:					
Share male	0.49	0.49	0.49	0.49	0.48
Share Hispanic	0.09	0.17	0.06	0.10	0.04
Share White	0.85	0.83	0.86	0.84	0.85
Share Black	0.12	0.13	0.11	0.11	0.13
Share Asian	0.03	0.03	0.02	0.04	0.01
Share with a highschool degree	0.56	0.54	0.53	0.55	0.59
Share with a college degree	0.18	0.19	0.18	0.18	0.17
Share with a masters degree	0.05	0.05	0.04	0.05	0.04
Share above 65 years of age	0.12	0.13	0.11	0.12	0.12
log population	13.97	14.18	13.34	14.15	14.01
Share employment in manufacturing	0.24	0.15	0.22	0.26	0.27
Share female workers (within manufacturing)	0.33	0.36	0.31	0.34	0.31
Share light manufacturing (within manufacturing)	0.22	0.29	0.21	0.23	0.19
Share employment in mining	0.01	0.01	0.01	0.01	0.01
Share employment in construction	0.08	0.09	0.09	0.08	0.08
Exposure to Chinese imports	3.35	2.22	2.80	4.18	3.54
Share employment in routine jobs	0.34	0.33	0.32	0.34	0.34

Sample means for the entire sample of commuting zones and by quartiles of the exposure to robots measure. See text for variable definitions and sources

Table A8: 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 male	-0.200^L	-0.260	-0.089	-0.144	-0.111^L	-0.116
	(0.086)	(0.080)	(0.073)	(0.063)	(0.056)	(0.055)
Share Hispanic	-0.153	-0.072	-0.081	-0.003	-0.072	-0.069
	(0.079)	(0.099)	(0.082)	(0.102)	(0.030)	(0.037)
Share White	0.115	-0.002	0.020	-0.093	0.096	0.091
	(0.129)	(0.148)	(0.136)	(0.151)	(0.046)	(0.049)
Share Black	0.269	0.055	0.236	0.056	0.033	-0.001
	(0.160)	(0.132)	(0.171)	(0.129)	(0.061)	(0.065)
Share Asian	-0.099	0.121	-0.156	-0.002	0.057	0.123
	(0.175)	(0.133)	(0.183)	(0.141)	(0.048)	(0.072)
Share with a highschool degree	-0.075	-0.274	-0.571	-0.710	0.495^L	0.436
	(0.444)	(0.498)	(0.472)	(0.550)	(0.121)	(0.118)
Share with a college degree	-1.102	-1.019	-1.631	-1.568	0.529	0.549
	(0.905)	(0.904)	(0.953)	(0.962)	(0.211)	(0.237)
Share with a masters' degree	-0.401	-0.471	-0.767	-0.821	0.366	0.350
	(0.461)	(0.512)	(0.467)	(0.539)	(0.163)	(0.171)
Share above 65 years of age	-0.174	-0.182	-0.080	-0.104	-0.094	-0.077
	(0.082)	(0.079)	(0.114)	(0.102)	(0.064)	(0.069)
Log population	0.353^L	0.434	0.247	0.307	0.106^L	0.127
	(0.222)	(0.225)	(0.237)	(0.260)	(0.058)	(0.065)
Share employment in manufacturing	1.621^L	1.589^L	0.984^L	0.924^L	0.637^L	0.665^L
	(0.474)	(0.454)	(0.516)	(0.514)	(0.142)	(0.153)
Share female manufacturing employment	-0.847^L	-0.843^L	-0.473	-0.454	-0.375^L	-0.388^L
	(0.344)	(0.327)	(0.364)	(0.356)	(0.139)	(0.144)
Share light manufacturing employment	-0.562^L	-0.424^L	-0.435^L	-0.328^L	-0.126	-0.096
	(0.112)	(0.117)	(0.099)	(0.093)	(0.056)	(0.064)
Share employment in mining	0.079	0.135	-0.003	0.055	0.082^L	0.080
	(0.051)	(0.073)	(0.061)	(0.081)	(0.035)	(0.036)
Share employment in construction	-0.008	0.131	-0.089	0.006	0.081	0.125
	(0.092)	(0.073)	(0.091)	(0.070)	(0.053)	(0.059)
Exposure to Chinese imports	-0.201	-0.136	-0.243	-0.181	0.042	0.046
	(0.116)	(0.097)	(0.122)	(0.104)	(0.039)	(0.036)
Share employment in routine jobs	0.281	0.091	0.320^L	0.156	-0.039	-0.065
	(0.135)	(0.103)	(0.124)	(0.082)	(0.050)	(0.054)
Observations	722	722	722	722	722	722
R-squared	0.56	0.61	0.44	0.49	0.43	0.45
F-statistic	17.99	27.57	8.14	13.63	19.57	21.94
Additional covariates:						
Division dummies		✓		✓		✓

The table presents the relation between the covariates used in our analysis and the exposure to robots (columns 1-2), the exposure to robots in automotive manufacturing (columns 3-4), and the exposure to robots in the remaining industries (columns 5-6). Each column presents a regression of the exposure to robots measure against the full set of covariates used in our analysis. All covariates are standardized to ease the interpretation. Even-numbered columns also control for a full set of Census division dummies. The covariates with a superscript L were chosen by a LASSO procedure conditioning on the share of employment in manufacturing. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A9: Coefficients for the main covariates in Tables 2 and 3

	Estimates for employment			Estimates for log hourly wage		
	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Long-differences, 1990-2007			
Exposure to robots	-0.410	-0.524	-0.416	-0.770	-0.729	-0.898
	(0.053)	(0.136)	(0.092)	(0.109)	(0.223)	(0.177)
Share manufacturing employment	3.680	4.436	0.576	-20.257	-20.344	-33.547
	(3.548)	(3.457)	(3.252)	(6.034)	(6.011)	(6.161)
Share manufacturing female employment	-24.290	-25.281	-16.779	34.749	33.933	53.635
	(6.514)	(6.564)	(7.789)	(11.192)	(11.352)	(12.536)
Share light manufacturing employment	-4.923	-5.283	-5.629	-10.220	-9.508	-11.068
	(3.432)	(3.325)	(3.143)	(6.460)	(6.612)	(5.049)
Exposure to Chinese imports	-0.083	-0.079	-0.040	-0.081	-0.080	-0.103
	(0.044)	(0.044)	(0.031)	(0.074)	(0.076)	(0.047)
Share routine jobs employment	-10.160	-9.955	-15.380	-16.903	-17.509	-7.121
	(2.549)	(2.516)	(2.949)	(4.915)	(4.860)	(4.597)
Observations	722	712	722	109906	108157	109906
R-squared	0.68	0.67	0.63	0.29	0.29	0.08
			Panel B. Stacked differences, 1990-2000 and 2000-2007			
Exposure to robots	-0.511	-0.709	-0.680	-1.300	-1.577	-1.601
	(0.052)	(0.155)	(0.084)	(0.157)	(0.523)	(0.264)
Share manufacturing employment	0.470	-0.135	-2.735	-12.043	-13.313	-23.386
	(2.831)	(2.762)	(1.804)	(5.417)	(5.514)	(3.976)
Share manufacturing female employment	-14.714	-12.707	-1.557	16.370	20.271	40.146
	(6.232)	(5.596)	(4.794)	(13.584)	(13.374)	(8.018)
Share light manufacturing employment	-0.106	-0.412	-3.276	0.273	-0.448	-1.244
	(2.213)	(2.140)	(2.112)	(4.192)	(4.604)	(3.161)
Exposure to Chinese imports	-0.196	-0.180	-0.133	-0.402	-0.381	-0.259
	(0.027)	(0.030)	(0.030)	(0.105)	(0.102)	(0.083)
Share routine jobs employment	-10.454	-10.576	-9.775	-19.786	-19.890	-4.055
	(4.433)	(4.699)	(3.431)	(8.082)	(8.536)	(6.862)
Observations	1444	1424	1444	236008	232243	257583
R-squared	0.43	0.42	0.40	0.25	0.24	0.08
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots on employment and wages. Panel A presents long differences for 1990-2007. Panel B presents stacked differences for 1990-2000 and 2000-2007. Columns 1-3 present estimates for employment to population ratio. Columns 4-6 present estimates for log hourly wage. 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, race, and birthplace. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent commuting zones with the highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A10: The effects of robots on employment and wages: recent periods

	Estimates for employment			Estimates for log hourly wage		
	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Long-differences, 1990-2014			
Exposure to robots	-0.239	-0.387	-0.328	-1.082	-1.059	-0.965
	(0.059)	(0.147)	(0.084)	(0.123)	(0.351)	(0.219)
Observations	722	712	722	115180	113349	115180
R-squared	0.57	0.56	0.60	0.41	0.40	0.16
			Panel B. Long-differences, 1990-2010			
Exposure to robots	-0.442	-0.528	-0.444	-1.050	-1.142	-1.131
	(0.059)	(0.136)	(0.097)	(0.126)	(0.271)	(0.178)
Observations	722	712	722	110215	108476	110215
R-squared	0.65	0.64	0.70	0.33	0.32	0.11
			Panel C. Long-differences, 2000-2014			
Exposure to robots	-0.270	-0.389	-0.181	-1.234	-1.275	-1.111
	(0.047)	(0.140)	(0.077)	(0.131)	(0.386)	(0.243)
Observations	722	712	722	143502	141321	143502
R-squared	0.68	0.67	0.48	0.30	0.28	0.08
			Panel D. Long-differences, 2000-2007			
Exposure to robots	-0.437	-0.426	-0.357	-0.868	-0.512	-0.934
	(0.054)	(0.136)	(0.099)	(0.130)	(0.327)	(0.242)
Observations	722	712	722	131494	129475	131494
R-squared	0.69	0.66	0.59	0.18	0.18	0.05
			Panel E. Long-differences, 2000-2010			
Exposure to robots	-0.480	-0.503	-0.410	-1.191	-1.146	-1.227
	(0.049)	(0.135)	(0.105)	(0.131)	(0.342)	(0.211)
Observations	722	712	722	133259	131247	133259
R-squared	0.71	0.69	0.68	0.22	0.21	0.06
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots on employment and wages. Panel A presents long differences for 1990-2014. Panel B presents long differences for 1990-2010. Panel C presents long differences for 2000-2014. Panel D presents long differences for 2000-2007. Panel E presents long differences for 2000-2010. Columns 1-3 present estimates for employment to population ratio. Columns 4-6 present estimates for log hourly wage. 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, race, and birthplace. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent commuting zones with the highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A11: The effects of robots on manufacturing employment

	Long differences, 1990-2007				Stacked differences, 1990-2000 and 2000-2007			
	Weighted by population	Excludes zones with high exposure	Unweighted	Control for automotive manufacturing	Weighted by population	Excludes zones with high exposure	Unweighted	Control for automotive manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Employment to population ratio, all workers in manufacturing								
Exposure to robots	-0.139	-0.218	-0.289	-0.251	-0.206	-0.328	-0.388	-0.362
	(0.038)	(0.084)	(0.072)	(0.078)	(0.031)	(0.068)	(0.081)	(0.095)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.78	0.78	0.77	0.78	0.58	0.57	0.60	0.58
Panel B. Employment to population ratio, male workers in manufacturing								
Exposure to robots	-0.109	-0.173	-0.191	-0.168	-0.143	-0.213	-0.235	-0.231
	(0.027)	(0.061)	(0.048)	(0.057)	(0.018)	(0.043)	(0.053)	(0.064)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.70	0.69	0.68	0.70	0.49	0.48	0.52	0.50
Panel C. Employment to population ratio, female workers in manufacturing								
Exposure to robots	-0.030	-0.044	-0.098	-0.083	-0.063	-0.115	-0.153	-0.131
	(0.013)	(0.028)	(0.025)	(0.029)	(0.014)	(0.029)	(0.028)	(0.039)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.86	0.86	0.84	0.86	0.69	0.69	0.68	0.69
Panel D. Employment to population ratio, workers with less than college in manufacturing								
Exposure to robots	-0.168	-0.214	-0.247	-0.213	-0.184	-0.308	-0.359	-0.282
	(0.024)	(0.068)	(0.062)	(0.054)	(0.032)	(0.059)	(0.071)	(0.064)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.80	0.80	0.79	0.80	0.60	0.60	0.62	0.60
Panel E. Employment to population ratio, workers with more than college in manufacturing								
Exposure to robots	0.030	-0.004	-0.042	-0.038	-0.022	-0.019	-0.029	-0.080
	(0.020)	(0.022)	(0.023)	(0.042)	(0.010)	(0.019)	(0.018)	(0.047)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.46	0.46	0.28	0.48	0.28	0.28	0.16	0.28
Covariates:								
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓
Automotive manufacturing				✓				✓

The table presents estimates of the impact of the exposure to robots on manufacturing employment to population ratio. Columns 1-4 present long differences for 1990-2007. Columns 5-8 present stacked differences for 1990-2000 and 2000-2007. Panel A present results for the manufacturing employment to population ratio. Panels B-C decompose manufacturing employment in employment by males (Panel B) and females (Panel C). Panels D-E decompose manufacturing employment in employment by workers with less than a college degree (Panel D) and workers with more than a college degree (Panel E). 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 commuting zones with the highest exposure to robots. Columns 3 and 7 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. In addition, Columns 4 and 8 control for the exposure to robots in automotive manufacturing. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A12: 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 high exposure	Unweighted	Control for automotive manufacturing	Weighted by population	Excludes zones with high exposure	Unweighted	Control for automotive manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Log of employment to population ratio								
Exposure to robots	-1.099	-1.462	-1.086	-1.115	-1.402	-1.989	-1.884	-1.483
	(0.154)	(0.381)	(0.262)	(0.331)	(0.157)	(0.437)	(0.251)	(0.650)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.69	0.68	0.63	0.69	0.43	0.43	0.39	0.43
Panel B. Employment to population ratio, including self employment								
Exposure to robots	-0.383	-0.474	-0.315	-0.393	-0.539	-0.759	-0.637	-0.587
	(0.053)	(0.139)	(0.088)	(0.116)	(0.063)	(0.171)	(0.074)	(0.257)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.63	0.62	0.56	0.63	0.41	0.41	0.32	0.41
Panel C. Employment to population ratio, including self employment and public employment								
Exposure to robots	-0.343	-0.361	-0.251	-0.233	-0.554	-0.773	-0.674	-0.563
	(0.048)	(0.139)	(0.100)	(0.106)	(0.063)	(0.175)	(0.087)	(0.271)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.72	0.71	0.67	0.72	0.52	0.52	0.44	0.52
Panel D. Employment to population ratio from the NHGIS								
Exposure to robots	-0.435	-0.502	-0.389	-0.389	-0.572	-0.809	-0.766	-0.591
	(0.051)	(0.130)	(0.093)	(0.135)	(0.062)	(0.158)	(0.091)	(0.235)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.66	0.65	0.53	0.66	0.47	0.47	0.32	0.47
Panel E. Employment to population ratio from the CBP								
Exposure to robots	-0.512	-0.704	-0.452	-0.682	-0.794	-1.034	-0.940	-0.730
	(0.115)	(0.332)	(0.139)	(0.379)	(0.114)	(0.272)	(0.119)	(0.447)
Observations	719	709	719	719	1438	1418	1438	1438
R-squared	0.50	0.49	0.47	0.50	0.50	0.47	0.41	0.50
Panel F. Non-participation rate								
Exposure to robots	0.242	0.207	0.277	0.125	0.430	0.747	0.541	0.666
	(0.033)	(0.117)	(0.107)	(0.091)	(0.084)	(0.190)	(0.080)	(0.278)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.65	0.65	0.54	0.65	0.50	0.51	0.31	0.50
Panel G. Unemployment rate								
Exposure to robots	0.211	0.194	0.133	0.069	0.556	0.546	0.604	0.349
	(0.034)	(0.067)	(0.050)	(0.075)	(0.054)	(0.129)	(0.073)	(0.196)
Observations	722	712	722	722	1444	1424	1444	1444
R-squared	0.65	0.63	0.51	0.66	0.50	0.42	0.31	0.50
Covariates:								
Covariates:								
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓
Automotive manufacturing				✓				✓

The table presents estimates of the impact of the exposure to robots on the outcomes indicated in each panel. Columns 1-4 present long differences for 1990-2007. Columns 5-8 present stacked differences for 1990-2000 and 2000-2007. Panel A present estimates for log employment to popualtion ratio. Panel B present estimates for employment (including self employment) to popualtion ratio. Panel C present estimates for employment (including self employment and public-sector employment) to popualtion ratio. Panel D present estimates for employment to popualtion ratio computed from the NHGIS. Panel E present estimates for employment to popualtion ratio computed from the CBP. Panel F present estimates for the nonparticipation rate, defined as the share of people above 16 years of age who are not in the labor force. Panel G present estimates for the unemployment rate, defined as the share of people in the labor force who are not employed. 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 commuting zones with the highest exposure to robots. Columns 3 and 7 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. In addition, Columns 4 and 8 control for the exposure to robots in automotive manufacturing. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A13: 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 high exposure	Unweighted	Control for automotive manufacturing	Weighted by population	Excludes zones with high exposure	Unweighted	Control for automotive manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Log of weekly wage				
Exposure to robots	-1.167	-0.940	-1.164	-0.898	-1.968	-2.358	-2.407	-1.699
	(0.122)	(0.220)	(0.233)	(0.314)	(0.160)	(0.571)	(0.291)	(0.905)
Observations	109906	108157	109906	109906	236008	232243	257583	236008
R-squared	0.39	0.38	0.12	0.39	0.31	0.30	0.10	0.31
				Panel B. Log of yearly wage				
Exposure to robots	-1.428	-1.220	-1.406	-1.168	-2.434	-3.024	-3.121	-2.238
	(0.128)	(0.284)	(0.240)	(0.396)	(0.209)	(0.726)	(0.352)	(1.153)
Observations	109906	108157	109906	109906	236008	232243	257583	236008
R-squared	0.40	0.39	0.13	0.40	0.34	0.33	0.11	0.34
				Panel C. Hourly wage, 2007 dollars				
Exposure to robots	-0.112	-0.126	-0.146	-0.103	-0.217	-0.245	-0.251	-0.158
	(0.024)	(0.052)	(0.034)	(0.064)	(0.029)	(0.087)	(0.045)	(0.134)
Observations	109906	108157	109906	109906	236008	232243	257583	236008
R-squared	0.37	0.37	0.08	0.37	0.21	0.21	0.04	0.21
				Panel D. Log of wage bill from the CBP				
Exposure to robots	-1.946	-4.201	-2.308	-4.613	-3.290	-3.959	-4.209	-3.735
	(0.599)	(0.938)	(0.888)	(1.103)	(0.441)	(1.055)	(0.589)	(1.892)
Observations	719	709	719	719	1438	1418	1438	1438
R-squared	0.71	0.70	0.43	0.72	0.63	0.60	0.39	0.63
Covariates:								
Covariates:								
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓
Automotive manufacturing				✓				✓

The table presents estimates of the impact of the exposure to robots on the outcomes indicated in each panel. Columns 1-4 present long differences for 1990-2007. Columns 5-8 present stacked differences for 1990-2000 and 2000-2007. The specifications in panels A-C are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education, race, and birthplace. 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 commuting zones with the highest exposure to robots. Columns 3 and 7 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. In addition, Columns 4 and 8 control for the exposure to robots in automotive manufacturing. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A14: The effects of robots on government transfers

	Long differences, 1990-2007			Stacked differences, 1990-2000 and 2000-2007		
	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Dollar value of total transfers per capita					
Exposure to robots	23.339	69.215	93.330	51.904	91.010	98.510
	(17.377)	(37.655)	(29.912)	(11.899)	(28.140)	(23.202)
Observations	722	712	722	1444	1424	1444
R-squared	0.69	0.70	0.50	0.80	0.79	0.68
	Panel B. Dollar value of SSA retirement benefits per capita					
Exposure to robots	28.944	27.525	37.078	17.323	21.248	31.895
	(4.766)	(10.098)	(13.709)	(3.209)	(9.923)	(10.306)
Observations	722	712	722	1444	1424	1444
R-squared	0.62	0.62	0.30	0.55	0.54	0.29
	Panel C. Dollar value of SSA disability benefits per capita					
Exposure to robots	6.728	4.805	12.217	5.459	7.183	10.586
	(2.163)	(5.230)	(4.374)	(1.670)	(4.755)	(3.427)
Observations	722	712	722	1444	1424	1444
R-squared	0.72	0.72	0.59	0.67	0.67	0.56
	Panel D. Dollar value of TAA benefits per capita					
Exposure to robots	0.740	0.234	0.603	1.230	0.776	1.405
	(0.191)	(0.239)	(0.381)	(0.273)	(0.475)	(0.479)
Observations	722	712	722	1444	1424	1444
R-squared	0.59	0.57	0.50	0.45	0.34	0.35
	Panel E. Dollar value of Unemployment benefits per capita					
Exposure to robots	1.141	9.917	-2.636	15.053	21.248	15.329
	(2.723)	(5.225)	(1.863)	(2.074)	(6.228)	(2.854)
Observations	722	712	722	1444	1424	1444
R-squared	0.34	0.36	0.28	0.50	0.47	0.22
	Panel F. Dollar value of education and training assistance per capita					
Exposure to robots	0.922	10.187	3.289	7.200	11.140	9.173
	(2.892)	(4.102)	(3.441)	(1.409)	(3.154)	(2.060)
Observations	722	712	722	1444	1424	1444
R-squared	0.29	0.31	0.28	0.42	0.41	0.25
	Panel G. Dollar value of Medical benefits per capita					
Exposure to robots	11.889	22.295	53.493	10.306	26.403	19.750
	(13.096)	(31.482)	(20.387)	(10.723)	(26.954)	(17.268)
Observations	722	712	722	1444	1424	1444
R-squared	0.67	0.68	0.50	0.73	0.73	0.63
	Panel H. Dollar value of Federal income assistance per capita					
Exposure to robots	-12.895	-11.896	0.796	3.784	8.523	14.544
	(3.269)	(7.358)	(5.211)	(2.353)	(7.521)	(3.422)
Observations	722	712	722	1444	1424	1444
R-squared	0.52	0.52	0.26	0.56	0.56	0.50
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots on transfers, as indicated in each panel. Columns 1-3 present long differences for 1990-2007. Columns 4-6 present stacked differences for 1990-2000 and 2000-2007. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent commuting zones with the highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A15: The effects of robots on migration

				Control for baseline population		
	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Migration rate, long differences 1990-2007.					
Exposure to robots	0.031	0.025	-0.013	-0.007	-0.030	-0.058
	(0.023)	(0.059)	(0.039)	(0.026)	(0.058)	(0.031)
Log of baseline population				0.312	0.313	0.459
				(0.094)	(0.098)	(0.069)
Observations	722	712	722	722	712	722
R-squared	0.61	0.61	0.34	0.66	0.65	0.46
	Panel B. Migration rate, stacked differences 1990-2000 and 2000-2007.					
Exposure to robots	-0.023	-0.049	0.028	-0.074	-0.129	-0.048
	(0.022)	(0.065)	(0.045)	(0.020)	(0.057)	(0.034)
Log of baseline population				0.307	0.310	0.405
				(0.063)	(0.068)	(0.047)
Observations	1444	1424	1444	1444	1424	1444
R-squared	0.53	0.52	0.35	0.58	0.58	0.46
	Panel C. Log population, long differences 1990-2007					
Exposure to robots	0.092	-0.797	-0.586	-0.295	-1.358	-1.023
	(0.364)	(0.898)	(0.528)	(0.366)	(0.899)	(0.516)
Log of baseline population				3.142	3.167	4.418
				(0.924)	(0.980)	(0.618)
Observations	722	712	722	722	712	722
R-squared	0.63	0.62	0.50	0.65	0.65	0.60
	Panel D: Log population, stacked differences 1990-2000 and 2000-2007					
Exposure to robots	-0.082	-0.562	-0.346	-0.368	-1.008	-0.725
	(0.158)	(0.439)	(0.287)	(0.165)	(0.428)	(0.290)
Log of baseline population				1.696	1.718	2.030
				(0.424)	(0.457)	(0.300)
Observations	1444	1424	1444	1444	1424	1444
R-squared	0.60	0.60	0.48	0.63	0.62	0.54
Covariates:						
Baseline covariates (except population)	✓	✓	✓	✓	✓	✓
Log population in 1990				✓	✓	✓

The table presents estimates of the impact of the exposure to robots on migration rates (obtained from the IRS) and log population. Panel A presents long-differences estimates for the net migration rate, 1990-2007. Panel B presents stacked-differences estimates for the net migration rate, 1990-2000 and 2000-2007. Panel C presents long-differences estimates for log population, 1990-2007. Panel D presents stacked-differences estimates for log population, 1990-2000 and 2000-2007. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent commuting zones with the highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. In addition, columns 4-6 control for the log population in 1990. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A16: 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 high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. log wage income per capita, BEA			
Exposure to robots	-1.413	-1.998	-1.261	-2.865	-3.474	-3.985
	(0.271)	(0.694)	(0.609)	(0.261)	(0.800)	(0.436)
Observations	722	712	722	1444	1424	1444
R-squared	0.54	0.50	0.48	0.47	0.42	0.32
			Panel B. log wage income per capita, IRS			
Exposure to robots	-1.212	-1.665	-1.458	-2.373	-2.907	-3.749
	(0.172)	(0.345)	(0.415)	(0.203)	(0.598)	(0.402)
Observations	722	712	722	1444	1424	1444
R-squared	0.57	0.53	0.61	0.52	0.48	0.40
			Panel C. log total income per capita, BEA			
Exposure to robots	-1.101	-1.157	-0.691	-2.182	-2.481	-2.608
	(0.162)	(0.388)	(0.442)	(0.205)	(0.572)	(0.350)
Observations	722	712	722	1444	1424	1444
R-squared	0.58	0.53	0.31	0.40	0.33	0.19
			Panel D. log nonwage income per capita, BEA			
Exposure to robots	0.084	0.029	0.733	-0.340	-0.593	-0.085
	(0.307)	(1.002)	(0.488)	(0.428)	(1.010)	(0.394)
Observations	721	711	721	1443	1423	1443
R-squared	0.50	0.50	0.22	0.23	0.23	0.11
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots on income. Columns 1-3 present long differences for 1990-2007. Columns 4-6 present stacked differences for 1990-2000 and 2000-2007. Panel A presents results for log wage income per capita from the BEA. Panel B presents results for log wage income per capita from the IRS. Panel C presents results for log total income per capita from the BEA. Panel D presents results for log nonwage 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 commuting zones with the highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A17: Pre-trends 1970-1990: additional outcomes

	Long differences, 1970-1990					
	Weighted by population				Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Manufacturing employment to population ratio					
Exposure to robots	-0.162	-0.092	0.019	0.048	-0.108	-0.166
	(0.082)	(0.058)	(0.054)	(0.054)	(0.110)	(0.104)
Observations	722	722	722	722	712	722
R-squared	0.44	0.54	0.57	0.61	0.61	0.31
	Panel B. Employment to population ratio, including public sector and self employment					
Exposure to robots	-0.047	-0.036	-0.012	0.001	-0.192	-0.219
	(0.066)	(0.060)	(0.065)	(0.065)	(0.168)	(0.139)
Observations	722	722	722	722	712	722
R-squared	0.12	0.38	0.43	0.44	0.44	0.27
	Panel C. Non-participation rate					
Exposure to robots	0.197	0.150	0.027	0.023	0.042	0.131
	(0.049)	(0.038)	(0.046)	(0.046)	(0.145)	(0.104)
Observations	722	722	722	722	712	722
R-squared	0.18	0.37	0.43	0.43	0.42	0.35
	Panel D. Unemployment rate					
Exposure to robots	0.031	0.031	0.041	0.045	0.048	0.050
	(0.063)	(0.036)	(0.036)	(0.038)	(0.112)	(0.068)
Observations	722	722	722	722	712	722
R-squared	0.35	0.55	0.61	0.61	0.60	0.42
	Panel E. Log weekly wages					
Exposure to robots	-0.422	-0.285	0.278	0.313	0.345	-0.137
	(0.191)	(0.186)	(0.224)	(0.211)	(0.492)	(0.318)
Observations	68495	68495	68495	68495	67474	68495
R-squared	0.52	0.52	0.53	0.53	0.53	0.28
	Panel F. Log population					
Exposure to robots	-1.221	-0.636	-0.201	-0.184	-1.558	-1.285
	(0.503)	(0.437)	(0.512)	(0.514)	(1.136)	(0.885)
Observations	722	722	722	722	712	722
R-squared	0.48	0.56	0.63	0.63	0.63	0.34
Covariates:						
Census division dummies	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade and routinization				✓	✓	✓

The table presents estimates of the impact of the exposure to robots on past outcomes, as indicated on each panel. Panel A presents results for manufacturing employment to population ratio. Panel B presents results for employment (including self employment and public-sector employment) to population ratio. Panel C presents results for the nonparticipation rate, defined as the share of people above 16 years of age who are not in the labor force. Panel D presents results for the unemployment rate, defined as the share of people in the labor force who do not have a job. Panel E present results for log weekly wage. Panel F present results for log population. For comparison with our main results, all changes in past outcomes are rescaled to a 14-year equivalent change. The specifications for log weekly wage in Panel E are estimated at the demographic cell $\times$ commuting zone level, where demographic cells are defined by age, gender, education, race, and birthplace. Column 1 only includes Census division dummies. Column 2 adds demographic characteristics of commuting zones in 1970 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians). Column 3 adds shares of employment in manufacturing, light manufacturing, construction and mining in 1970, and the share of female workers in manufacturing employment in 1970. Columns 4-6 add the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A18: The effect of robots on employment and wages: Controlling for contemporary industry decline

	Long differences, 1990-2007					
	Weighted by population				Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Employment to population ratio					
Exposure to robots	-0.269	-0.299	-0.374	-0.382	-0.459	-0.354
	(0.072)	(0.044)	(0.043)	(0.045)	(0.133)	(0.091)
Bartik of industries in decline	-0.094	-0.122	-0.073	-0.057	-0.055	-0.058
	(0.012)	(0.010)	(0.015)	(0.014)	(0.014)	(0.019)
Observations	722	722	722	722	712	722
R-squared	0.41	0.64	0.68	0.69	0.68	0.64
	Panel B. Log hourly wage					
Exposure to robots	-0.978	-0.868	-0.735	-0.742	-0.664	-0.840
	(0.115)	(0.103)	(0.118)	(0.108)	(0.223)	(0.174)
Bartik of industries in decline	-0.120	-0.115	-0.087	-0.058	-0.057	-0.057
	(0.019)	(0.021)	(0.024)	(0.024)	(0.024)	(0.022)
Observations	109906	109906	109906	109906	108157	109906
R-squared	0.29	0.29	0.29	0.29	0.29	0.08
Covariates:						
Census division dummies	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade and routinization				✓	✓	✓

The table presents estimates of the impact of the exposure to robots on employment and wages. Panel A presents long-differences estimates for employment to population ratio, 1990-2007. Panel B presents long-differences estimates for log hourly wage, 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, race, and birthplace. Columns 1-5 present regressions weighted by population in 1990. Column 5 presents results excluding the top one percent commuting zones with the highest exposure to robots. Column 6 presents unweighted regressions. The covariates included in each model are indicated at the bottom rows. Column 1 only includes Census division dummies. Column 2 adds demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians). Column 3 adds shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990. Columns 4-6 add the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A19: Rotemberg weights

	Weighted by population				Unweighted	
	Raw data	Baseline covariates	Excludes zones with high exposure	Excludes automotive manufacturing	Baseline covariates	Excludes automotive manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Long differences, 1990-2007						
Metal products	.034	-.001	.041	.059	.027	.061
Basic metals	.035	-.011	.026	.053	.023	.049
Plastic and chemicals	.137	.15	.503	.894	.395	.873
Automotive	.802	.888	.439	-.001	.579	-.001
Panel B. Stacked differences, 1990-2000 and 2000-2007						
Food and beveradges 2000-2007	-.005	-.007	.001	.009	.001	.021
Wood and Furniture 2000-2007	-.004	-.007	-.01	-.001	-.003	.018
Industrial Machinery 1990-2000	-.002	.006	.012	.011	.008	.009
Mining 1990-2000	0	.002	.006	.006	.008	.019
Ships and plains 1990-2000	.002	.002	.015	.033	.004	.019
Basic metals 1990-2000	.005	-.009	-.015	-.002	-.007	.01
Electronics 2000-2007	.005	.001	.032	.029	.016	.021
Ships and plains 2000-2007	.011	.015	.033	.073	.006	.027
Industrial Machinery 2000-2007	.015	.009	.027	.022	.016	.018
Automotive 1990-2000	.016	-.033	-.026	0	-.018	0
Basic metals 2000-2007	.019	.011	.04	.054	.026	.038
Metal products 2000-2007	.026	.019	.058	.067	.045	.073
Plastic and chemicals 1990-2000	.04	.024	.085	.313	.082	.372
Plastic and chemicals 2000-2007	.05	.049	.168	.377	.14	.356
Automotive 2000-2007	.817	.919	.576	0	.687	0

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% in one of our specifications. Column 1 presents Rotemberg weights for an specification with no covariates. Columns 2 and 5 present Rotemberg weights for an specification with our baseline covariates (from column 4 in table 2). Column 3 presents Rotemberg weights for an specification that excludes the top one percent commuting zones with the highest exposure to robots. Columns 4 and 6 present Rotemberg weights for an specification that controls for the exposure to robots in automotive manufacturing. Columns 1-4 are for regression models weighted by population. Columns 5-6 are for unweighted models.

Table A20: The effect of robots on employment and wages: controls for IT and computer adoption

	Estimates for employment				Estimates for log hourly wage			
	Long differences, 1990-2007		Stacked differences, 1990-2000 and 2000-2007		Long differences, 1990-2007		Stacked differences, 1990-2000 and 2000-2007	
	Weighted (1)	Unweighted (2)	Weighted (3)	Unweighted (4)	Weighted (5)	Unweighted (6)	Weighted (7)	Unweighted (8)
Panel A. Controls for observed increase in computer use.								
Exposure to robots	-0.410	-0.415	-0.510	-0.661	-0.773	-0.899	-1.299	-1.064
	(0.053)	(0.091)	(0.052)	(0.082)	(0.107)	(0.172)	(0.157)	(0.277)
Increase in computer use	-0.267	0.781	-0.179	1.017	-4.786	-4.230	-3.519	2.116
	(0.660)	(0.579)	(1.096)	(0.662)	(0.753)	(0.901)	(1.203)	(1.252)
Observations	696	696	1392	1392	107288	107288	230289	251348
R-squared	0.68	0.64	0.43	0.40	0.29	0.08	0.25	0.03
Panel B. Controls for exposure to IT-intensive industries								
Exposure to robots	-0.418	-0.420	-0.480	-0.679	-0.740	-0.897	-1.231	-1.039
	(0.057)	(0.091)	(0.044)	(0.083)	(0.108)	(0.170)	(0.140)	(0.275)
Exposure to IT-intensive industries	-0.072	-0.041	0.246	0.011	0.263	0.008	0.532	0.150
	(0.108)	(0.098)	(0.160)	(0.048)	(0.298)	(0.157)	(0.249)	(0.133)
Observations	722	722	1444	1444	109906	109906	236008	257596
R-squared	0.68	0.63	0.43	0.40	0.29	0.08	0.25	0.03
Covariates:								
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots, capital accumulation, and increases in value-added on employment and wages. Columns 1-2 and 5-6 present long-differences estimates for 1990-2007. Columns 3-4 and 7-8 present stacked-differences estimates for 1990-2000 and 2000-2007. Columns 1-4 present results for employment to population ratio. Columns 5-8 present results for log hourly wage. The specifications in columns 5-8 for log hourly wage are estimated at the demographic cell $\times$ commuting zone level, where demographic cells are defined by age, gender, education, race, and birthplace. Odd-numbered columns present regressions weighted by population in 1990. Even-numbered columns present unweighted regressions. In Panel A we control for the observed increase in computer use by commuting zone between 1992 and 2006. In Panel B we control for a measure of exposure to IT-intensive industries, constructed by interacting the share of IT capital investment by industry in 1992 with the baseline employment share of that industry in the commuting zone. All models include Census division dummies; demographic characteristics of commuting zones in 1990 (log of population, share of males, the share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians); shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990; and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A21: The effect of robots on employment: alternative constructions of exposure to robots

	Estimates for 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 high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Baseline construction of the instrument							
Exposure to robots	-0.410	-0.524	-0.416	-0.511	-0.709	-0.680	
	(0.053)	(0.136)	(0.092)	(0.052)	(0.155)	(0.084)	
US robot adoption							-0.380
							(0.083)
Observations	722	712	722	1444	1424	1444	722
R-squared	0.68	0.67	0.63	0.43	0.42	0.40	0.65
First-stage F-statistic							47.4
Panel B. Exposure computed using employment shares in 1990							
Exposure to robots	-0.659	-0.678	-0.588	-1.020	-1.426	-1.124	
	(0.092)	(0.179)	(0.162)	(0.141)	(0.269)	(0.104)	
US robot adoption							-0.322
							(0.058)
Observations	722	712	722	1444	1424	1444	722
R-squared	0.67	0.66	0.63	0.46	0.45	0.41	0.66
First-stage F-statistic							77.3
Panel C. Including penetration of robots in Germany							
Exposure to robots	-0.317	-0.495	-0.357	-0.428	-0.659	-0.596	
	(0.047)	(0.134)	(0.080)	(0.041)	(0.145)	(0.086)	
US robot adoption							-0.352
							(0.069)
Observations	722	712	722	1444	1424	1444	722
R-squared	0.68	0.67	0.63	0.42	0.42	0.39	0.66
First-stage F-statistic							173.5
Panel D. Including penetration of robots in 9 European countries							
Exposure to robots	-0.325	-0.548	-0.381	-0.439	-0.718	-0.660	
	(0.051)	(0.157)	(0.089)	(0.042)	(0.152)	(0.105)	
US robot adoption							-0.338
							(0.062)
Observations	722	712	722	1444	1424	1444	722
R-squared	0.68	0.67	0.63	0.41	0.41	0.39	0.66
First-stage F-statistic							405.6
Panel E. Using the raw penetration of robots							
Exposure to robots	-0.313	-0.437	-0.317	-0.417	-0.575	-0.526	
	(0.045)	(0.113)	(0.076)	(0.042)	(0.135)	(0.084)	
US robot adoption							-0.367
							(0.077)
Observations	722	712	722	1444	1424	1444	722
R-squared	0.68	0.67	0.63	0.41	0.41	0.38	0.66
First-stage F-statistic							91.9
Panel F. Adjusting robot quantities using relative robot prices							
Exposure to robots	-0.420	-0.577	-0.436	-0.526	-0.744	-0.695	
	(0.057)	(0.154)	(0.101)	(0.072)	(0.206)	(0.080)	
US robot adoption							-0.365
							(0.076)
Observations	722	712	722	1444	1424	1444	722
R-squared	0.68	0.67	0.63	0.44	0.43	0.40	0.66
First-stage F-statistic							78.5
Covariates:							
Baseline covariates	✓	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots on the employment to population ratio. Columns 1-3 present long differences for 1990-2007. Columns 4-6 present stacked differences for 1990-2000 and 2000-2007. Column 7 presents IV estimates for 1990-2007. Panel A presents results for the baseline construction of the exposure to robots measure. Panel B computes the exposure to robots measure using the 1990 employment shares. Panel C includes Germany in the construction of the exposure to robots measure. Panel D uses the 9 European countries for which the IFR carries data to construct the exposure to robots measure. Panel E computes the exposure to robots measure using the raw robot penetration by industry. Panel F computes the exposure to robots adjusting for differences in robot prices across industries. 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 commuting zones with the highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A22: The effect of robots on wages: alternative constructions of exposure to robots

	Estimates for log hourly wage						
	Long differences, 1990-2007			Stacked differences, 1990-2000 and 2000-2007			IV estimates, 1990-2007
	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Baseline construction of the instrument							
Exposure to robots	-0.770	-0.729	-0.898	-1.300	-1.577	-1.601	
	(0.109)	(0.223)	(0.177)	(0.157)	(0.523)	(0.264)	
US robot adoption							-0.727
							(0.150)
Observations	109906	108157	109906	236008	232243	257583	109906
R-squared	0.29	0.29	0.08	0.25	0.24	0.08	0.29
First-stage F-statistic							49.8
Panel B. Exposure computed using employment shares in 1990							
Exposure to robots	-1.218	-0.851	-1.139	-2.482	-3.067	-2.731	
	(0.207)	(0.334)	(0.273)	(0.310)	(0.673)	(0.363)	
US robot adoption							-0.616
							(0.108)
Observations	109906	108157	109906	236008	232243	257583	109906
R-squared	0.29	0.29	0.08	0.25	0.24	0.08	0.29
First-stage F-statistic							83.7
Panel C. Including penetration of robots in Germany							
Exposure to robots	-0.592	-0.640	-0.735	-1.100	-1.404	-1.341	
	(0.082)	(0.176)	(0.129)	(0.115)	(0.455)	(0.216)	
US robot adoption							-0.676
							(0.123)
Observations	109906	108157	109906	236008	232243	257583	109906
R-squared	0.29	0.29	0.08	0.24	0.23	0.08	0.29
First-stage F-statistic							182.0
Panel D. Including penetration of robots in nine European countries							
Exposure to robots	-0.608	-0.689	-0.773	-1.148	-1.530	-1.454	
	(0.085)	(0.180)	(0.131)	(0.111)	(0.461)	(0.232)	
US robot adoption							-0.652
							(0.113)
Observations	109906	108157	109906	236008	232243	257583	109906
R-squared	0.29	0.29	0.08	0.24	0.23	0.08	0.29
First-stage F-statistic							425.3
Panel E. Using the raw penetration of robots							
Exposure to robots	-0.570	-0.545	-0.667	-1.047	-1.104	-1.140	
	(0.079)	(0.170)	(0.129)	(0.141)	(0.453)	(0.208)	
US robot adoption							-0.691
							(0.132)
Observations	109906	108157	109906	236008	232243	257583	109906
R-squared	0.29	0.29	0.08	0.24	0.23	0.08	0.29
First-stage F-statistic							97.6
Panel F. Adjusting robot quantities using relative robot prices							
Exposure to robots	-0.793	-0.809	-0.959	-1.340	-1.706	-1.662	
	(0.110)	(0.224)	(0.166)	(0.187)	(0.556)	(0.268)	
US robot adoption							-0.706
							(0.140)
Observations	109906	108157	109906	236008	232243	257583	109906
R-squared	0.29	0.29	0.08	0.25	0.24	0.08	0.29
First-stage F-statistic							83.3
Covariates:							
Baseline covariates	✓	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots on the log hourly wage. Columns 1-3 present long differences for 1990-2007. Columns 4-6 present stacked differences for 1990-2000 and 2000-2007. Column 7 presents IV estimates for 1990-2007. The specifications are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education, race, and birthplace. Panel A presents results for the baseline construction of the exposure to robots measure. Panel B computes the exposure to robots measure using the 1990 employment shares. Panel C includes Germany in the construction of the exposure to robots measure. Panel D uses the 9 European countries for which the IFR carries data to construct the exposure to robots measure. Panel E computes the exposure to robots measure using the raw robot penetration by industry. Panel F computes the exposure to robots adjusting for differences in robot prices across industries. 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 commuting zones with the highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A23: 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	-0.410	-0.460	-0.414	-0.435	-0.426
	(0.053)	(0.095)	(0.049)	(0.084)	(0.112)
Observations	722	721	681	722	722
R-squared	0.68	0.67	0.72	0.70	
	Panel B. Stacked differences for employment to population ratio, 1990-2000 and 2000-2007				
Exposure to robots	-0.511	-0.632	-0.521	-0.682	-0.644
	(0.052)	(0.111)	(0.049)	(0.075)	(0.101)
Observations	1444	1442	1358	1444	1444
R-squared	0.43	0.42	0.47	0.39	
	Panel C. Long differences for log hourly wage, 1990-2007				
Exposure to robots	-0.770	-0.767	-0.755	-0.755	-0.829
	(0.109)	(0.153)	(0.107)	(0.125)	(0.118)
Observations	109906	109504	102675	109909	109909
R-squared	0.29	0.28	0.34	0.01	
	Panel D. Stacked differences for log hourly wage, 1990-2000 and 2000-2007				
Exposure to robots	-1.300	-1.435	-1.299	-1.088	-1.120
	(0.157)	(0.362)	(0.156)	(0.115)	(0.102)
Observations	236008	235189	220719	257600	257600
R-squared	0.25	0.24	0.30	0.02	
Covariates:					
Baseline covariates	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots on employment and wages. Panel A presents long differences for employment to population ratio, 1990-2007. Panel B presents stacked differences for employment to population ratio, 1990-2000 and 2000-2007. Panel C presents long differences for log hourly wage, 1990-2007. Panel D presents stacked differences for log hourly wage, 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, race, and birthplace. 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, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A24: The effect of robots on employment and wages: additional covariates

	Estimates for employment			Estimates for log hourly wage		
	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Long differences 1990-2007, controlling for state fixed effects					
Exposure to robots	-0.263	-0.386	-0.258	-0.449	-0.515	-0.611
	(0.068)	(0.124)	(0.087)	(0.133)	(0.190)	(0.157)
Observations	722	712	722	109906	108157	109906
R-squared	0.80	0.80	0.74	0.30	0.29	0.08
	Panel B. Stacked differences 1990-2000 and 2000-2007, controlling for state fixed effects					
Exposure to robots	-0.529	-0.666	-0.670	-1.348	-1.656	-1.548
	(0.066)	(0.174)	(0.085)	(0.209)	(0.561)	(0.287)
Observations	1444	1424	1444	236008	232243	257583
R-squared	0.47	0.46	0.47	0.25	0.24	0.08
	Panel C. Long differences 1990-2007, controlling for lagged-dependent variable					
Exposure to robots	-0.361	-0.352	-0.351	-0.621	-0.588	-0.739
	(0.048)	(0.098)	(0.113)	(0.121)	(0.248)	(0.190)
Observations	722	712	722	109906	108157	109906
R-squared	0.75	0.75	0.68	0.42	0.41	0.28
	Panel D. Stacked differences 1990-2000 and 2000-2007, controlling for lagged dependent variable					
Exposure to robots	-0.433	-0.476	-0.610	-1.116	-1.376	-1.407
	(0.056)	(0.138)	(0.089)	(0.164)	(0.510)	(0.265)
Observations	1444	1424	1444	236008	232243	257583
R-squared	0.57	0.56	0.45	0.45	0.44	0.43
	Panel E. Long differences 1990-2007, controlling for change in demographics					
Exposure to robots	-0.402	-0.518	-0.360	-0.813	-0.726	-0.808
	(0.048)	(0.129)	(0.087)	(0.099)	(0.200)	(0.172)
Observations	722	712	722	109906	108157	109906
R-squared	0.76	0.75	0.75	0.29	0.29	0.08
	Panel F. Stacked differences 1990-2000 and 2000-2007, controlling for change in demographics					
Exposure to robots	-0.476	-0.598	-0.617	-1.185	-1.325	-1.425
	(0.046)	(0.153)	(0.079)	(0.157)	(0.503)	(0.256)
Observations	1444	1424	1444	236008	232243	257583
R-squared	0.57	0.56	0.52	0.25	0.24	0.08
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots on employment and wages. Panel A presents long differences for 1990-2007 controlling for state fixed effects. Panel B presents stacked differences for 1990-2000 and 2000-2007 controlling for state fixed effects. Panel C presents long differences for 1990-2007 controlling for lagged-dependent variables. Panel D presents stacked differences for 1990-2000 and 2000-2007 controlling for lagged-dependent variables. Panel A presents long differences for 1990-2007 controlling for the change in demographic characteristics included as covariates. Panel B presents stacked differences for 1990-2000 and 2000-2007 controlling for the change in demographic characteristics included as covariates. Columns 1-3 present estimates for employment to population ratio. Columns 4-6 present estimates for log hourly wage. The specifications in columns 4-6 are estimated at the demographic cell × commuting zone level, where demographic cells are defined by age, gender, education, race, and birthplace. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent commuting zones with the highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A25: Reduced-form estimates using other proxies for automation technologies

	Long differences 1990-2007					
	Estimates for employment			Estimates for log hourly wage		
	Weighted by population	Excludes zones with high exposure to robots	Unweighted	Weighted by population	Excludes zones with high exposure to robots	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Exposure to industries with replaceable jobs					
Exposure to replaceable jobs	-0.277	-0.244	-0.228	-0.301	-0.210	-0.330
	(0.068)	(0.062)	(0.059)	(0.127)	(0.111)	(0.086)
Observations	722	712	722	109906	108157	109906
R-squared	0.66	0.67	0.64	0.29	0.29	0.08
	Panel B. Exposure to industries with greatest potential for robots, BCG					
Exposure to industries with greatest	-0.076	-0.060	-0.058	-0.122	-0.078	-0.106
potential for robots, BCG	(0.019)	(0.019)	(0.020)	(0.041)	(0.038)	(0.038)
Observations	722	712	722	109906	108157	109906
R-squared	0.66	0.66	0.63	0.29	0.29	0.08
Covariates:						
Baseline covariates	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to several proxies of automation on employment and wages. Panel A present results for the exposure to industries with replaceable jobs, constructed by interacting the share of replaceable jobs by industry in 1990 with the baseline employment share of that industry in the commuting zone. Panel B present results for the exposure to industries with the greatest potential for the use of robots, constructed as the baseline share of employment in automotive manufacturing, electronics, plastics and chemicals, and metal-working industries. Columns 1-3 present long-differences estimates for employment to population ratio, 1990-2007. Columns 4-6 present long-differences estimates for log hourly wage, 1990-2007. 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, race, and birthplace. Columns 1-2 and 4-5 present regressions weighted by population in 1990. Columns 2 and 5 present results excluding the top one percent commuting zones with the highest exposure to robots. Columns 3 and 6 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A26: OLS estimates of the relationship between US exposure to robots and employment and wages

	Estimates for employment		Estimates for log hourly wage	
	(1)	(2)	(3)	(4)
	Panel A. Long-differences between 1990 and 2007			
US robot adoption	-0.283	-0.267	-0.772	-0.512
	(0.063)	(0.043)	(0.085)	(0.089)
Observations	722	722	109906	109906
R-squared	0.26	0.65	0.28	0.29
	Panel B. Long-differences between 1990 and 2014			
US robot adoption	-0.297	-0.170	-1.092	-0.891
	(0.103)	(0.052)	(0.118)	(0.107)
Observations	722	722	115180	115180
R-squared	0.29	0.55	0.38	0.41
	Panel C. Long-differences between 2000 and 2007			
US robot adoption	-0.640	-0.599	-1.321	-1.103
	(0.123)	(0.073)	(0.183)	(0.140)
Observations	722	722	131494	131494
R-squared	0.36	0.69	0.18	0.18
	Panel D. Long-differences between 2000 and 2014			
US robot adoption	-0.470	-0.288	-1.509	-1.363
	(0.164)	(0.052)	(0.141)	(0.143)
Observations	722	722	143502	143502
R-squared	0.37	0.68	0.28	0.30
Covariates:				
Division dummies	✓	✓	✓	✓
Baseline covariates		✓		✓

The table presents OLS estimates corresponding to the IV models in columns 1-2 and 4-5 of Table 7. Each panel presents long-differences estimates for a different time period, and we rescale the US exposure measure to match the length of that period. Columns 1-3 present long-differences estimates for employment to population ratio, 1990-2007. Columns 4-6 present long-differences estimates for log hourly wage, 1990-2007. 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, race, and birthplace. All regressions are weighted by population in 1990. All models include Census division dummies. In addition, columns 2 and 4 control for demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A27: Effect of robots on employment and wages by gender

	Long differences						Stacked differences					
	Men			Women			Men			Women		
	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted	Weighted by population	Excludes zones with high exposure	Unweighted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Employment to population ratio												
Exposure to robots	-0.528	-0.651	-0.557	-0.301	-0.405	-0.282	-0.632	-0.814	-0.882	-0.391	-0.597	-0.480
	(0.059)	(0.144)	(0.114)	(0.054)	(0.142)	(0.098)	(0.059)	(0.179)	(0.124)	(0.051)	(0.138)	(0.069)
Observations	722	712	722	722	712	722	1444	1424	1444	1444	1424	1444
R-squared	0.63	0.60	0.61	0.72	0.72	0.58	0.39	0.37	0.37	0.47	0.47	0.37
Panel B. Manufacturing employment to population ratio												
Exposure to robots	-0.227	-0.360	-0.389	-0.058	-0.088	-0.194	-0.289	-0.428	-0.470	-0.124	-0.228	-0.304
	(0.057)	(0.127)	(0.097)	(0.026)	(0.055)	(0.051)	(0.037)	(0.085)	(0.105)	(0.027)	(0.058)	(0.057)
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	0.50	0.49	0.53	0.68	0.68	0.67
Panel C. Log of hourly wages												
Exposure to robots	-0.842	-0.882	-0.895	-0.698	-0.585	-0.902	-1.730	-2.199	-2.180	-1.178	-1.393	-1.320
	(0.126)	(0.250)	(0.248)	(0.110)	(0.260)	(0.159)	(0.222)	(0.716)	(0.450)	(0.141)	(0.413)	(0.166)
Observations	55330	54449	55330	54576	53708	54576	62900	61901	67888	56056	55159	61798
R-squared	0.26	0.24	0.07	0.30	0.29	0.08	0.25	0.24	0.08	0.17	0.16	0.04
Panel D. Nonparticipation rate												
Exposure to robots	0.310	0.225	0.361	0.178	0.176	0.187	0.579	0.903	0.750	0.283	0.574	0.331
	(0.054)	(0.115)	(0.124)	(0.030)	(0.138)	(0.115)	(0.091)	(0.207)	(0.104)	(0.079)	(0.180)	(0.083)
Observations	722	712	722	722	712	722	1444	1424	1444	1444	1424	1444
R-squared	0.52	0.50	0.41	0.71	0.71	0.57	0.56	0.56	0.36	0.43	0.44	0.34
Covariates:												
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

The table presents estimates of the impact of the exposure to robots on employment, wages and other outcomes by gender. Columns 1-6 present long differences for 1990-2007. Columns 7-12 present stacked differences for 1990-2000 and 2000-2007. 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 employment to population ratios. Panel B presents results for employment to population ratios in manufacturing. Panel C presents results for log hourly wages. Panel D presents results for the nonparticipation rate (defined as the share of the population above 16 years of age who are not in the labor market). 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 commuting zones with the highest exposure to robots. Columns 3, 6, 9 and 12 present unweighted regressions. All models include Census division dummies, demographic characteristics of commuting zones in 1990 (log of population, share of males, share of population above 65 years, shares of population with high school, some college, college and postgraduate education, and shares of Whites, Blacks, Hispanics and Asians), shares of employment in manufacturing, light manufacturing, construction and mining in 1990, and the share of female workers in manufacturing employment in 1990, and the exposure to Chinese imports from Autor, Dorn and Hanson (2013) and the share of employment in routine jobs. Standard errors robust against heteroskedasticity and correlation within states in parentheses.

Table A28: 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 ψ, σ, λ	$\eta = 0.50$ $\varepsilon = 0.16$ $d\ln L =$ -0.77 $d\ln W =$ -0.53	$\eta = 0.72$ $\varepsilon = 0.16$ $d\ln L =$ -0.55 $d\ln W =$ -0.37	$\eta = 1.12$ $\varepsilon = 0.16$ $d\ln L =$ -0.32 $d\ln W =$ -0.21	$\eta = 1.23$ $\varepsilon = 0.16$ $d\ln L =$ -0.64 $d\ln W =$ -0.44	$\eta = 0.72$ $\varepsilon = 0.16$ $d\ln L =$ -0.55 $d\ln W =$ -0.37	$\eta = 0.47$ $\varepsilon = 0.16$ $d\ln L =$ -0.46 $d\ln W =$ -0.31
Changing ψ:						
$\psi = 0$	$\eta = 0.50$ $\varepsilon = 0.18$ $d\ln L =$ -0.76 $d\ln W =$ -0.53	$\eta = 0.72$ $\varepsilon = 0.18$ $d\ln L =$ -0.54 $d\ln W =$ -0.38	$\eta = 1.12$ $\varepsilon = 0.18$ $d\ln L =$ -0.31 $d\ln W =$ -0.22	$\eta = 1.23$ $\varepsilon = 0.18$ $d\ln L =$ -0.63 $d\ln W =$ -0.44	$\eta = 0.72$ $\varepsilon = 0.18$ $d\ln L =$ -0.54 $d\ln W =$ -0.38	$\eta = 0.47$ $\varepsilon = 0.18$ $d\ln L =$ -0.45 $d\ln W =$ -0.31
$\psi = 0.1$	$\eta = 0.50$ $\varepsilon = 0.07$ $d\ln L =$ -0.81 $d\ln W =$ -0.52	$\eta = 0.72$ $\varepsilon = 0.07$ $d\ln L =$ -0.60 $d\ln W =$ -0.36	$\eta = 1.12$ $\varepsilon = 0.07$ $d\ln L =$ -0.38 $d\ln W =$ -0.19	$\eta = 1.23$ $\varepsilon = 0.07$ $d\ln L =$ -0.68 $d\ln W =$ -0.42	$\eta = 0.72$ $\varepsilon = 0.07$ $d\ln L =$ -0.60 $d\ln W =$ -0.36	$\eta = 0.47$ $\varepsilon = 0.07$ $d\ln L =$ -0.51 $d\ln W =$ -0.29
$\psi = 0.15$	$\eta = 0.50$ $\varepsilon = 0.02$ $d\ln L =$ -0.84 $d\ln W =$ -0.51	$\eta = 0.72$ $\varepsilon = 0.02$ $d\ln L =$ -0.63 $d\ln W =$ -0.34	$\eta = 1.12$ $\varepsilon = 0.02$ $d\ln L =$ -0.42 $d\ln W =$ -0.18	$\eta = 1.23$ $\varepsilon = 0.02$ $d\ln L =$ -0.71 $d\ln W =$ -0.41	$\eta = 0.72$ $\varepsilon = 0.02$ $d\ln L =$ -0.63 $d\ln W =$ -0.34	$\eta = 0.47$ $\varepsilon = 0.02$ $d\ln L =$ -0.55 $d\ln W =$ -0.28
Changing σ:						
$\sigma = 0.5$	$\eta = 0.49$ $\varepsilon = 0.16$ $d\ln L =$ -0.76 $d\ln W =$ -0.52	$\eta = 0.68$ $\varepsilon = 0.16$ $d\ln L =$ -0.51 $d\ln W =$ -0.35	$\eta = 1.03$ $\varepsilon = 0.16$ $d\ln L =$ -0.27 $d\ln W =$ -0.18	$\eta = 1.19$ $\varepsilon = 0.16$ $d\ln L =$ -0.61 $d\ln W =$ -0.42	$\eta = 0.68$ $\varepsilon = 0.16$ $d\ln L =$ -0.51 $d\ln W =$ -0.35	$\eta = 0.43$ $\varepsilon = 0.16$ $d\ln L =$ -0.41 $d\ln W =$ -0.28
$\sigma = 1.5$	$\eta = 0.51$ $\varepsilon = 0.16$ $d\ln L =$ -0.78 $d\ln W =$ -0.54	$\eta = 0.76$ $\varepsilon = 0.16$ $d\ln L =$ -0.58 $d\ln W =$ -0.39	$\eta = 1.21$ $\varepsilon = 0.16$ $d\ln L =$ -0.38 $d\ln W =$ -0.25	$\eta = 1.27$ $\varepsilon = 0.16$ $d\ln L =$ -0.66 $d\ln W =$ -0.45	$\eta = 0.76$ $\varepsilon = 0.16$ $d\ln L =$ -0.58 $d\ln W =$ -0.39	$\eta = 0.51$ $\varepsilon = 0.16$ $d\ln L =$ -0.50 $d\ln W =$ -0.34
Changing λ:						
$\lambda = 2.5$	$\eta = 0.52$ $\varepsilon = 0.16$ $d\ln L =$ -0.79 $d\ln W =$ -0.55	$\eta = 0.82$ $\varepsilon = 0.16$ $d\ln L =$ -0.62 $d\ln W =$ -0.42	$\eta = 1.34$ $\varepsilon = 0.16$ $d\ln L =$ -0.45 $d\ln W =$ -0.30	$\eta = 1.48$ $\varepsilon = 0.16$ $d\ln L =$ -0.77 $d\ln W =$ -0.53	$\eta = 0.82$ $\varepsilon = 0.16$ $d\ln L =$ -0.62 $d\ln W =$ -0.42	$\eta = 0.48$ $\varepsilon = 0.16$ $d\ln L =$ -0.47 $d\ln W =$ -0.32
$\lambda = 7.5$	$\eta = 0.49$ $\varepsilon = 0.16$ $d\ln L =$ -0.76 $d\ln W =$ -0.52	$\eta = 0.69$ $\varepsilon = 0.16$ $d\ln L =$ -0.52 $d\ln W =$ -0.35	$\eta = 1.04$ $\varepsilon = 0.16$ $d\ln L =$ -0.28 $d\ln W =$ -0.18	$\eta = 1.13$ $\varepsilon = 0.16$ $d\ln L =$ -0.58 $d\ln W =$ -0.40	$\eta = 0.69$ $\varepsilon = 0.16$ $d\ln L =$ -0.52 $d\ln W =$ -0.35	$\eta = 0.47$ $\varepsilon = 0.16$ $d\ln L =$ -0.45 $d\ln W =$ -0.30

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 indicated in the top row. Rows vary the values of ψ, σ and λ used, as indicated in the left column.