Appendix B: Supplemental Material for "Tasks, Automation, and the Rise in US Wage Inequality"

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February 15, 2022

Appendix B-1 Additional Theory Results

Derivation of Threshold $\bar{q}$

This section proves the existence of the threshold $\bar{q}$ introduced in Assumption 1.

Proposition B-1 (Existence of $\bar{q}$) *Suppose that workers can only produce non-overlapping sets of tasks (i.e., $\psi_g(x) > 0$ only if $\psi_{g'}(x) = 0$ for all $g' \neq g$). Consider the set of tasks where capital has positive productivity, $\mathcal{S} = \{x : \psi_k(x) > 0\}$. Suppose that there exists $\underline{\psi} > 0$, such that for all $x \in \mathcal{S}$ we have $\psi_k(x) > \underline{\psi}$. Then there exists a threshold $\bar{q}$ such that, if $q(x) > \bar{q}$ for all $x \in \mathcal{S}$, all the tasks in $\mathcal{S}$ are allocated to capital.*

Proof. Consider an allocation with $\mathcal{T}_k = \mathcal{S}$ and where $\mathcal{T}_g = \{x : \psi_g(x) > 0, x \notin \mathcal{S}\}$. This allocation is the unique equilibrium of the economy if and only if

$$\frac{w_g}{A_g \cdot \psi_g(x)} \geq \frac{1}{q(x) \cdot A_k \cdot \psi_k(x)} \text{ for all } x \in \mathcal{S} \text{ and } g \in \mathcal{G}.$$

Using the formula for wages in equation (2) and the fact that $\psi_k(x) > \underline{\psi}$, it follows that a sufficient condition for this inequality is that

$$\text{(B-1)} \qquad \frac{\left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\frac{1}{M}\int_{x:\psi_g(x)>0, x\notin\mathcal{S}} \psi_g(x)^{\lambda-1} dx\right)^{\frac{1}{\lambda}}}{A_g \cdot \psi_g(x)} \geq \frac{1}{q_0 \cdot A_k \cdot \underline{\psi}} \text{ for all } x \in \mathcal{S} \text{ and } g \in \mathcal{G},$$

where $q_0 = \inf_{x\in\mathcal{S}} q(x)$.

The left hand side of (B-1) is increasing in q_0 (since output increases in $q(x)$ and the candidate task allocation remains unchanged); while the right-hand side is decreasing in q_0 and converges to zero as q_0 goes to infinity. Let $\bar{q}$ denote the point at which (B-1) holds with equality. It follows that if $q_0 \geq \bar{q}$ (that is, $q(x) \geq \bar{q}$ for all $x \in \mathcal{S}$), inequality (B-1) holds and the task allocation described in Assumption 1 is the unique equilibrium. ■

Model Extensions with Markups and Endogenous Labor Supply

Proposition B-2 (Extension with markups) *Given labor-supply levels $\ell = (\ell_1, \ell_2, \ldots, \ell_G)$ and industry markups $\mu = (\mu_1, \mu_2, \ldots, \mu_I)$, and conditional on an allocation of tasks $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \ldots, \mathcal{T}_{Gi}\}$,* *equilibrium wages, industry prices, and output are a solution to the system of equations*

$$w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \mu_i^{-\lambda} \cdot \Gamma_{gi}\right)^{\frac{1}{\lambda}} \tag{B-2}$$

$$p_i = \frac{\mu_i}{A_i} \cdot \left(A_k^{\lambda-1} \cdot \Gamma_{ki} + \sum_{g\in\mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{1-\lambda}} \tag{B-3}$$

$$1 = \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}). \tag{B-4}$$

Moreover, following advances in automation or changes in markups, the change in the real wage of group g is given by

$$d\ln w_g = \Theta_g \cdot \left(\frac{1}{\lambda} d\ln y + \frac{1}{\lambda} d\ln \boldsymbol{\zeta} - \sum_{i\in\mathcal{I}} \omega_{gi} \cdot d\ln \mu_i - \frac{1}{\lambda} d\ln \boldsymbol{\Gamma}^{auto}\right) \text{ for all } g \in \mathcal{G}.$$

Proof. Let

$$\mu_i : \frac{p}{\text{mc}_i}$$

denote the markup charged in industry i, where p_i is the industry price and mc_i the marginal cost.

The demand for task $x \in \mathcal{T}_i$ can be computed as

$$\text{mc}_i = \frac{p(x)}{\frac{\partial y}{\partial y(x)}} \Rightarrow p(x) = \frac{p_i}{\mu_i} \cdot \frac{\partial y}{\partial y(x)}.$$

Using this last equation, we can solve for the quantity of task x used in sector i as

$$y(x) = \cdot \frac{1}{M_i} \cdot y \cdot \mu_i^{-\lambda} \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot p(x)^{-\lambda}, \tag{B-5}$$

where $p(x)$ is the price of task x. Following the same steps as in the proof of Proposition 3, we can therefore compute the demand for capital and labor at task x as

$$k(x)/q(x) = \begin{cases} \frac{1}{M_i} \cdot y \cdot \mu_i^{-\lambda} \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot (A_k \cdot q(x) \cdot \psi_k(x))^{\lambda-1} & \text{if } x \in \mathcal{T}_{ki} \\ 0 & \text{if } x \notin \mathcal{T}_k. \end{cases}$$

$$\ell_g(x) = \begin{cases} \frac{1}{M_i} \cdot y \cdot \mu_i^{-\lambda} \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot (A_g \cdot \psi_g(x))^{\lambda-1} \cdot w_g^{-\lambda} & \text{if } x \in \mathcal{T}_g \\ 0 & \text{if } x \notin \mathcal{T}_g. \end{cases}$$

To derive equation (B-2), we add-up the demand for labor across tasks, and rearrange the resulting expression:

$$\ell_g = \sum_{i\in\mathcal{I}} \int_{\mathcal{T}_{gi}} \frac{1}{M_i} \cdot y \cdot \mu_i^{-\lambda} \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot (A_g \cdot \psi_g(x))^{\lambda-1} \cdot w_g^{-\lambda} \cdot dx$$

$$\Rightarrow w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_{i\in\mathcal{I}} \mu_i^{-\lambda} \cdot s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \frac{1}{M_i} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} dx\right)^{\frac{1}{\lambda}}.$$

To derive the industry price index in equation (B-3), note that due to constant returns to scale and the presence of markups, we must have

$$\frac{1}{\mu_i} \cdot p_i \cdot y_i = \int_{\mathcal{T}_i} p(x) \cdot y(x) dx \Rightarrow p_i = \frac{\mu_i}{A_i} \left(\frac{1}{M_i} \int_{\mathcal{T}_i} p(x)^{1-\lambda} dx\right)^{\frac{1}{1-\lambda}}.$$

Using the allocation of tasks $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \ldots, \mathcal{T}_{Gi}\}$, this implies

$$p_i = \frac{\mu_i}{A_i} \left(A_k^{\lambda-1} \cdot \left(\frac{1}{M_i} \int_{\mathcal{T}_{ki}} (q(x) \cdot \psi_k(x))^{\lambda-1} dx\right) + \sum_{g\in\mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \left(\frac{1}{M_i} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} dx\right)\right)^{\frac{1}{1-\lambda}},$$

which yields the expression for industry prices in the proposition.

Finally, because industry shares must add up to 1, we have equation (B-3), which is equivalent to a price-index condition for industries.

The expressions for wage changes and industry shifters are derived using the same steps as in the proof of Proposition 4, but now accounting for the markup term in equation (B-2). ■

PROPOSITION B-3 (EXTENSION WITH LABOR SUPPLY) *Suppose that households choose their labor supply and consumption to maximize*

$$\max_{\ell_g, c_g} \frac{c_g^{1-\varsigma_c}}{1-\varsigma_c} - \frac{\ell_g^{1+\varsigma_\ell}}{1+\varsigma_\ell} \text{ subject to: } c_g \leq w_g \cdot \ell_g,$$

and let $\varsigma = (1-\varsigma_c)/(\varsigma_c + \varsigma_\ell)$*. Conditional on an allocation of tasks* $\{\mathcal{T}_{ki}, \mathcal{T}_{1i}, \ldots, \mathcal{T}_{Gi}\}$*, equilibrium wages, labor supply, industry prices, and output solve the system*

$$\text{(B-6)} \qquad w_g = y^{\frac{1}{\lambda+\varsigma}} \cdot A_g^{\frac{\lambda-1}{\lambda+\varsigma}} \cdot \left(\sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{\lambda+\varsigma}}$$

$$\text{(B-7)} \qquad \ell_g = y^{\frac{\varsigma}{\lambda+\varsigma}} \cdot A_g^{\frac{\varsigma\cdot(\lambda-1)}{\lambda+\varsigma}} \cdot \left(\sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{\varsigma}{\lambda+\varsigma}}$$

$$\text{(B-8)} \qquad p_i = \frac{1}{A_i} \left(A_k^{\lambda-1} \cdot \Gamma_{ki} + \sum_{g\in\mathcal{G}} w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{1-\lambda}}$$

$$\text{(B-9)} \qquad c = \left(1 - A_k^{\lambda-1} \cdot \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{ki}\right) \cdot y$$

$$\text{(B-10)} \qquad 1 = \sum_{i\in\mathcal{I}} s_i^Y(\boldsymbol{p}).$$

Moreover, the general equilibrium effect of task displacement on wages, employment, and aggregates is given by

$$
\begin{aligned}
d\ln w_g =& \Theta_g \cdot \left(\frac{1}{\lambda+\varsigma} d\ln y + \frac{1}{\lambda+\varsigma} d\ln \boldsymbol{\zeta} - \frac{1}{\lambda+\varsigma} d\ln \boldsymbol{\Gamma}^{auto} \right) \text{ for all } g \in \mathcal{G}, \\
d\ln \ell_g =& \Theta_g \cdot \left(\frac{\varsigma}{\lambda+\varsigma} d\ln y + \frac{\varsigma}{\lambda+\varsigma} d\ln \boldsymbol{\zeta} - \frac{\varsigma}{\lambda+\varsigma} d\ln \boldsymbol{\Gamma}^{auto} \right) \text{ for all } g \in \mathcal{G}, \\
d\ln \zeta_g =& \sum_{i \in \mathcal{I}} \omega_{gi} \cdot \left(\frac{\partial \ln s_i^Y(\boldsymbol{p})}{\partial \ln \boldsymbol{p}} \cdot d\ln \boldsymbol{p} + (\lambda - 1) \cdot d\ln p_i \right) \text{ for all } g \in \mathcal{G}, \\
d\ln p_i =& \sum_{g \in \mathcal{G}} s_{gi}^L \cdot \left(d\ln w_g - d\ln \Gamma_{gi}^{auto} \cdot \pi_{gi} \right) \text{ for all } i \in \mathcal{I}, \\
d\ln tfp =& \sum_{i \in \mathcal{I}} s_i^Y(\boldsymbol{p}) \sum_{g \in \mathcal{G}} s_{gi}^L \cdot d\ln \Gamma_{gi}^{auto} \cdot \pi_{gi}, \\
d\ln y =& \frac{1}{1 - s^K} \cdot \left(d\ln tfp + s^K \cdot d\ln s^K + \sum_{g \in \mathcal{G}} s_g^L \cdot d\ln \ell_g \right), \\
d\ln s^K =& -\frac{1}{s^K} \sum_{g \in \mathcal{G}} s_g^L \cdot (d\ln w_g + d\ln \ell_g - d\ln y)
\end{aligned}
$$

where the propagation matrix now becomes

$$
\Theta = \left(\mathbb{1} - \frac{1}{\lambda+\varsigma} \frac{\partial \ln \Gamma(\boldsymbol{w}, \boldsymbol{\zeta}, \Psi)}{\partial \ln \boldsymbol{w}} \right)^{-1}
$$

Proof. The household problem gives the labor-supply curve

$$
\ell_g = w_g^{\varsigma}, \tag{B-11}
$$

where ς denotes the labor supply elasticity with respect to a permanent wage change.

Plugging this labor-supply curve into the expression for wages in equation (10) yields

$$
w_g = \left(\frac{y}{w_g^{\varsigma}} \right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_{i \in \mathcal{I}} s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi} \right)^{\frac{1}{\lambda}}.
$$

Using this equation to solve for w_g yields equation (B-6). In turn, plugging (B-6) into equation (B-11) yields (B-7).

The derivations of the remaining expressions in the proposition are identical to those in the proof of proposition 3.

Turning to the effect of technologies on wage changes, and following the same steps as in the derivation of Proposition 4, we obtain

$$
d\ln w_g = \frac{1}{\lambda} d\ln y - \frac{1}{\lambda} d\ln \ell_g - \frac{1}{\lambda} d\ln \Gamma_g^{\text{auto}} + \frac{1}{\lambda} \sum_{i \in \mathcal{I}} \omega_{gi} \cdot d\ln \zeta_i + \frac{1}{\lambda} \frac{\partial \ln \Gamma_g}{\partial \ln \boldsymbol{w}} \cdot d\ln \boldsymbol{w}.
$$

Using the fact that $d\ln \ell_g = \varsigma \cdot d\ln w_g$ (from the labor-supply curve in B-11), we can rewrite this as

$$d\ln w_g = \frac{1}{\lambda+\varsigma} d\ln y - \frac{1}{\lambda+\varsigma} d\ln \Gamma_g^{\text{auto}} + \frac{1}{\lambda+\varsigma} \sum_{i\in\mathcal{I}} \omega_{gi} \cdot d\ln \zeta_i + \frac{1}{\lambda+\varsigma} \frac{\partial \ln \Gamma_g}{\partial \ln \boldsymbol{w}} \cdot d\ln \boldsymbol{w}.$$

Solving this system for wage changes gives the formula for the propagation matrix in the proposition.

The derivations of the remaining expressions in the proposition parallel those in the proof of proposition 4. ■

Propagation Matrix and Elasticities of Substitution

This section provides additional properties of the propagation matrix and relates it to traditional definitions of elasticities of substitution. In the following definitions, we use the notation $\left.\frac{\partial y}{\partial x}\right|_k$ to denote partial derivatives holding the current stock of capital constant (recall that k adjusts endogenously in our model).

First, let us recall that the *Morishima elasticity of substitution* between capital and labor of type g can be defined as

$$\sigma_{k,\ell_g} = \frac{1}{1 + \left.\frac{\partial \ln(s_g^L/s^k)}{\partial \ln A_k}\right|_k}.$$

Similarly, the *Morishima elasticity of substitution* between capital and labor can be defined as

$$\sigma_{k,\ell} = \frac{1}{1 + \left.\frac{\partial \ln(s^L/s^k)}{\partial \ln A_k}\right|_k},$$

and the *Morishima elasticity of substitution* between labor of type g' and g can be defined as

$$\sigma_{\ell_{g'},\ell_g} = \frac{1}{1 + \left.\frac{\partial \ln(s_g^L/s_{g'}^L)}{\partial \ln \ell_{g'}}\right|_k}.$$

The Morishima elasticities tell us about changes in factor shares as one factor becomes more abundant or productive. In the presence of multiple factors, these elasticities need not be symmetric, as is the case with only two factors of production.

Also, define the *q−elasticity of substitution* between capital and labor of type g by the identity

$$\sigma_{k,\ell_g}^Q = \frac{1}{\left.\frac{1}{s^k}\frac{\partial \ln w_g}{\partial \ln A_k}\right|_k},$$

and the $q-$*elasticity of substitution* between labor of type g' and g by

$$\sigma^Q_{\ell_{g'},\ell_g} = \frac{1}{\left.\frac{1}{s^L_{g'}}\frac{\partial \ln w_g}{\partial \ln \ell_{g'}}\right|_k}.$$

The $q-$elasticities of substitution tell us whether factors are $q-$complements (a positive elasticity) or $q-$substitutes (a negative elasticity), and are symmetric in a competitive economy by definition (a corollary of Young's theorem).

Proposition B-4 (Elasticities of substitution and Θ) *The Morishima elasticity of substitution between capital and labor is*

$$\sigma_{k,\ell} = \frac{1}{\frac{\bar{\varepsilon}}{\lambda} + \frac{1}{s^k}\cdot(\bar{\varepsilon}-1)} \qquad \textit{where: } \bar{\varepsilon} := \sum_{g\in\mathcal{G}} \frac{s^L_g}{s^L}\varepsilon_g \in (0,1).$$

Moreover, the Morishima elasticities of substitution between pairs of factors are

$$\sigma_{k,\ell_g} = \frac{1}{\frac{\varepsilon_g}{\lambda}s^k + \frac{\bar{\varepsilon}}{\lambda}s^L + (\varepsilon_g - 1) + \frac{s^L}{s^k}(\bar{\varepsilon}-1)} \qquad \sigma_{\ell_{g'},\ell_g} = \frac{1}{1+\frac{s^L_{g'}}{\lambda}\cdot\left(\varepsilon_g - \varepsilon_{g'} - \left(\frac{\theta_{gg'}}{s^L_{g'}} - \frac{\theta_{g'g'}}{s^L_{g'}}\right)\right)},$$

and the $q-$elasticities of substitution are

$$\sigma^Q_{k,\ell_g} = \frac{1}{\frac{\varepsilon_g}{\lambda} + \frac{1}{s^k}\cdot(\varepsilon_g - 1)} \qquad \sigma^Q_{\ell_{g'},\ell_g} = \frac{1}{\frac{1}{\lambda}\cdot\left(\varepsilon_g - \frac{\theta_{gg'}}{s^L_{g'}}\right)}.$$

Proof. The effect of an increase in A_k on the allocation of tasks is equivalent to a uniform rise in wages. That is:

$$\frac{\partial \ln \Gamma_g}{\partial \ln A_k} = \sum_{g'} \frac{\partial \ln \Gamma_g}{\partial \ln w_{g'}}.$$

Using this property, we can compute the change in wages following an increase in A_k as

$$d\ln w_g = \frac{1}{\lambda} d\ln y + \frac{1}{\lambda}\frac{\partial \ln \Gamma_g}{\partial \ln \boldsymbol{w}}\cdot d\ln \boldsymbol{w} + \frac{1}{\lambda}\frac{\partial \ln \Gamma_g}{\partial \ln \boldsymbol{w}}\cdot d\ln \boldsymbol{A_k}.$$

We can then solve for the change in wages as

$$d\ln w_g = \Theta_g \cdot \left(\frac{1}{\lambda} d\ln y + \frac{1}{\lambda}\Sigma\cdot d\ln \boldsymbol{A_k}\right).$$

The definition of Θ implies $\Theta\frac{1}{\lambda}\Sigma = \Theta - \mathbb{1}$, and plugging this into the expression for wages, we obtain

$$d \ln w_g = \frac{\varepsilon_g}{\lambda} d \ln y + (\varepsilon_g - 1) \cdot d \ln A_k.$$

Finally, holding k constant, we have that $d \ln y = s^K \cdot d \ln A_k$, which yields the formula:

$$\frac{1}{\sigma^Q_{k,\ell_g}} = \frac{1}{s^k} \frac{\partial \ln w_g}{\partial \ln A_k}\bigg|_k = \frac{\varepsilon_g}{\lambda} + \frac{1}{s^k} \cdot (\varepsilon_g - 1).$$

In addition, we also have that

$$\frac{\partial \ln s^L_g}{\partial \ln A_k}\bigg|_k = \left(\frac{\varepsilon_g}{\lambda} - 1\right) \cdot s^k + (\varepsilon_g - 1) \tag{B-12}$$

Using equation (B-12), we can compute the Morishima elasticity of substitution between capital and labor as

$$\begin{aligned}
\frac{1}{\sigma_{k,\ell}} =& 1 + \frac{\partial \ln(s^L/s^k)}{\partial \ln A_k}\bigg|_k \\
=& 1 + \frac{1}{s^k} \cdot \frac{\partial \ln s^L}{\partial \ln A_k}\bigg|_k \\
=& 1 + \frac{1}{s^k} \sum_{g \in \mathcal{G}} \frac{s^L_g}{s^L} \frac{\partial \ln s^L_g}{\partial \ln A_k}\bigg|_k \\
=& 1 + \frac{1}{s^k} \sum_{g \in \mathcal{G}} \frac{s^L_g}{s^L} \cdot \left(\left(\frac{\varepsilon_g}{\lambda} - 1\right) \cdot s^k + (\varepsilon_g - 1) \right) \\
=& 1 + \frac{1}{s^k} \left(\left(\frac{\bar{\varepsilon}}{\lambda} - 1\right) \cdot s^k + (\bar{\varepsilon} - 1) \right) \\
=& \frac{\bar{\varepsilon}}{\lambda} + \frac{1}{s^k} \cdot (\bar{\varepsilon} - 1)
\end{aligned}$$

Similarly, using equation (B-12), we can compute the Morishima elasticity of substitution between capital and labor of type g as

$$\begin{aligned}
\frac{1}{\sigma_{k,\ell_g}} =& 1 + \frac{\partial \ln(s^L_g/s^k)}{\partial \ln A_k}\bigg|_k \\
=& 1 + \frac{\partial \ln s^L_g}{\partial \ln A_k}\bigg|_k + \frac{s^L}{s^k} \frac{\partial \ln s^L}{\partial \ln A_k}\bigg|_k \\
=& 1 + \left(\frac{\varepsilon_g}{\lambda} - 1\right) \cdot s^k + (\varepsilon_g - 1) + \frac{s^L}{s^k} \left(\left(\frac{\bar{\varepsilon}}{\lambda} - 1\right) \cdot s^k + (\bar{\varepsilon} - 1) \right) \\
=& \frac{\varepsilon_g}{\lambda} s^k + \frac{\bar{\varepsilon}}{\lambda} s^L + (\varepsilon_g - 1) + \frac{s^L}{s^k} (\bar{\varepsilon} - 1).
\end{aligned}$$

We now turn to the elasticities involving chnages in $\ell_{g'}$. Following a change in $\ell_{g'}$, we have:

$$d\ln w_g = \frac{\varepsilon_g}{\lambda} d\ln y - \frac{\theta_{gg'}}{\lambda} d\ln \ell_{g'}. \tag{B-13}$$

Holding k constant, we have that $d\ln y = s^L_{g'} \cdot d\ln \ell_{g'}$, which yields the formula:

$$\frac{1}{\sigma^Q_{\ell_{g'},\ell_g}} = \frac{1}{s^L_{g'}} \frac{\partial \ln w_g}{\partial \ln \ell_{g'}}\bigg|_k = \frac{1}{\lambda} \cdot \left(\varepsilon_g - \frac{\theta_{gg'}}{s^L_{g'}}\right).$$

Finally, we can write the Morishima elasticity of substitution between labor of type g' and g as

$$\frac{1}{\sigma_{\ell_{g'},\ell_g}} = 1 + \frac{\partial \ln(s^L_g/s^L_{g'})}{\partial \ln \ell_{g'}}\bigg|_k = 1 + \frac{\partial \ln w_g}{\partial \ln \ell_{g'}}\bigg|_k - \frac{\partial \ln w_{g'}}{\partial \ln \ell_{g'}}\bigg|_k.$$

Using the formula for the change in wages in equation (B-13), we obtain

$$\frac{1}{\sigma_{\ell_{g'},\ell_g}} = 1 + \frac{s^L_{g'}}{\lambda} \cdot \left(\varepsilon_g - \varepsilon_{g'} - \left(\frac{\theta_{gg'}}{s^L_{g'}} - \frac{\theta_{g'g'}}{s^L_{g'}}\right)\right),$$

which completes proof of the proposition. ■

Proposition B-5 (Quasi-symmetry of the propagation matrix) *The propagation matrix satisfies the symmetry property*

$$\varepsilon_g - \frac{\theta_{gg'}}{s^L_{g'}} = \varepsilon_{g'} - \frac{\theta_{g'g}}{s^L_g}. \tag{B-14}$$

Proof. By definition $\sigma^Q_{\ell_{g'},\ell_g} = \sigma^Q_{\ell_g,\ell_{g'}}$, which implies the symmetry property in (B-14). ■

Appendix B-2 Measuring Task Displacement: Additional Details and Extensions

This section provides additional derivations that support our measurement of task displacement. In particular, we derive equation (A-10) and a bounding exercise for the error term ε_i.

For each type of worker g, define the elasticity σ^L_{gi} by

$$\frac{1}{\omega^g_i} \cdot \frac{\partial \ln s^L_i}{\partial \ln w_g} = s^k \cdot (1 - \sigma^L_{gi}).$$

When $\sigma^L_{gi} > 1$, an increase in w_g reduces the labor share. Instead, when $\sigma^L_{gi} < 1$, an increase in w_g increases the labor share.

Proposition B-6 (Industry labor shares) *Let s^L_i denote the labor share in industry i. Also, let $w^e_{gi} = w_g/A_{gi}$ denote the wages per efficiency unit of labor paid in industry i for workers of* *type g. Following a change in automation, factor prices (w_g, R_i), and markups μ_i, we have*

$$d\ln s_i^L = -d\ln \mu_i - \left(1 + (\lambda - 1)\cdot s_i^L \cdot \pi_i\right)\cdot \omega_i^R \cdot \vartheta_i + s_i^K \cdot (1-\sigma_i^L)\cdot d\ln w_i - s_i^K \cdot (1-\sigma_i^K)\cdot d\ln R_i,$$

where

$$\sigma_i^L := \sum_{g\in\mathcal{G}} \frac{\omega_i^g \cdot d\ln w_g}{\sum_{g'} \omega_i^{g'} \cdot d\ln w_{g'}} \cdot \sigma_{gi}^L \qquad\qquad \sigma_i^K := \sum_{g\in\mathcal{G}} \omega_i^g \cdot \sigma_{gi}^L,$$

and

$$d\ln w_i = \sum_{g\in\mathcal{G}} \omega_i^g \cdot d\ln w_{gi}.$$

Proof. Given a vector of wages and technologies, we can write the labor share as in equation (A-9), where recall that the denominator is also equal to

$$p_i^{1-\lambda} = A_k^{\lambda-1}\cdot \Gamma_{ki} + \sum_{g\in\mathcal{G}} w_{gi}^{e\;1-\lambda} \cdot \Gamma_{gi}.$$

The contribution of changes in markups is simply $-d\ln \mu_i$.

The contribution of automation was already derived in Proposition A-2, and is given by $d\ln s_i^{L,\text{auto}} = -\left(1+(\lambda-1)\cdot s_i^L \cdot \pi_i\right)\cdot \omega_i^R \cdot \vartheta_i$.

We now turn to the contribution of wages. Using the definition of σ_{gi}^L, we can compute their influence on the labor share as

$$\begin{array}{l}\text{contribution of}\\ \text{wage changes}\end{array} = \sum_{g\in\mathcal{G}} \omega_i^g \cdot (1-s_i^L)\cdot(1-\sigma_{gi}^L)\cdot d\ln w_{gi}^e.$$

Using the definition of σ_i^L and $d\ln w_i$, we obtain

$$\begin{array}{l}\text{contribution of}\\ \text{wage changes}\end{array} = (1-s_i^L)\cdot(1-\sigma_i^L)\cdot d\ln w_i.$$

Finally, to compute the effects of a uniform change in capital prices, we first provide explicit formulas for σ_{gi}^L, which we will use in our derivations below. We have that

$$\frac{1}{\omega_i^g}\cdot\frac{\partial \ln s_i^L}{\partial \ln w_g} = \frac{1}{\omega_i^g}\cdot\left(\omega_i^g\cdot(1-\lambda) + \sum_{g'}\omega_i^{g'}\cdot\frac{\partial\ln\Gamma_{g'i}}{\partial \ln w_{g'i}} - s^L\cdot\omega_i^g\cdot(1-\lambda)\right),$$

where the first two terms capture the effect of task displacement on the numerator and the third term the effect on the denominator of the labor share expression in equation (A-9). Here, we used the fact that the effect of wages on the denominator equals the direct effect holding the task allocation constant—an implication of the envelope theorem. We can rewrite this expression as

$$\frac{1}{\omega_i^g} \cdot \frac{\partial \ln s_i^L}{\partial \ln w_g} = (1 - s_i^L) \cdot (1 - \lambda) + \sum_{g'} \frac{\omega_i^{g'}}{\omega_i^g} \cdot \frac{\partial \ln \Gamma_{g'i}}{\partial \ln w_{g'i}},$$

which implies that

$$\sigma_{gi}^L = \lambda - \frac{1}{1 - s_i^L} \cdot \sum_{g'} \frac{\omega_i^{g'}}{\omega_i^g} \cdot \frac{\partial \ln \Gamma_{g'i}}{\partial \ln w_{g'i}},$$

and

$$(1 - s_i^L) \cdot (\lambda - \sigma_{gi}^L) = \sum \sum_{g'} \frac{\omega_i^{g'}}{\omega_i^g} \cdot \frac{\partial \ln \Gamma_{g'i}}{\partial \ln w_{g'i}}. \tag{B-15}$$

Consider a uniform change in the user cost of capital $d \ln R_i$. The effect of this change in the allocation of tasks is the same as a uniform reduction in wages of $-d \ln R_i$. Moreover, the effect of $d \ln R_i$ on the denominator of the labor share is just its direct effect—an application of the envelope theorem. Thus, we get

$$\text{contribution of price of capital} = -\sum_{g \in \mathcal{G}} \sum_{g'} \omega_i^{g'} \cdot \frac{\partial \ln \Gamma_{g'i}}{\partial \ln w_g} \cdot d \ln(R_i / A_{ki}) - s_i^k \cdot (1 - \lambda) \cdot d \ln(R_i / A_{ki}),$$

where the first term captures the effect of task changes on the numerator and the second term the effect on the denominator of the labor share expression in equation (A-9). Using equation (B-15), we can rewrite this expression as

$$\text{contribution of price of capital} = -\sum_{g \in \mathcal{G}} \omega_i^g \cdot (1 - s_i^L) \cdot (\lambda - \sigma_{gi}^L) \cdot d \ln(R_i / A_{ki}) - s_i^k \cdot (1 - \lambda) \cdot d \ln(R_i / A_{ki}).$$

Finally, using the definition of σ_i^K, we can rewrite this as

$$\text{contribution of price of capital} = -(1 - s_i^L) \cdot (1 - \sigma_i^K) \cdot d \ln(R_i / A_{ki}),$$

which completes the proof of the proposition. ■

Bounding Exercise: In the general case treated in Section 5 and Tables B-1 and A-4 in the appendix, our measure of task displacement is computed from the adjusted decline in the labor share:

$$-d \ln s_i^{L,\text{auto}} = -d \ln s_i^L + s_i^K \cdot \left[(1 - \sigma_i^L) \cdot d \ln w_i - (1 - \sigma_i^K) \cdot d \ln R_i \right] - \varepsilon_i,$$

where we set $\lambda = 0.5$. and $\sigma_i^L = \sigma_i^K = \sigma_i = 0.8$ or $\sigma_i^L = \sigma_i^K = \sigma_i = 1.2$.

While our formulas for the residual decline in labor shares incorporate the effects of changes in factor prices, they miss the contribution of factor-augmenting technologies, which affect the labor share when σ_i^L or σ_i^K deviate from 1, and are therefore part of the error term, $-\varepsilon_i$.

We now provide upper bounds on the effects of this type of technological change on our measures of adjusted labor share declines by industry, which reveal that these residuals are quantitatively small.

In particular, for $\sigma_i^L, \sigma_i^K < 1$, the contribution of factor-augmenting technologies to the change in the labor share is between $-s_i^K \cdot (1 - \sigma_i^L) \cdot d\ln A_{\ell i}$ (where $d\ln A_{\ell i}$ is a weighted average of $d\ln A_{gi}$ across groups) and $s_i^K \cdot (1 - \sigma_i^K) \cdot d\ln A_{ki}$. Moreover, assuming no technological regress, we have that the total increase in (gross output) TFP in industry i must exceed both $\tilde{s}_i^L \cdot d\ln A_{Li}$ and $\tilde{s}_i^K \cdot d\ln A_{ki}$, where now $\tilde{s}_i^L$ and $\tilde{s}_i^K$ denote the share of labor and capital in gross output (an application of Hulten's theorem). As a result, we can bound the contribution of factor-augmenting technologies to lie in the interval

$$\left[-\frac{s_i^K}{\tilde{s}_i^L} \cdot (1 - \sigma_i^L) \cdot d\ln \mathrm{tfp}_i, \frac{s_i^K}{\tilde{s}_i^K} \cdot (1 - \sigma_i^K) \cdot d\ln \mathrm{tfp}_i\right].$$

Likewise, for $\sigma_i^L, \sigma_i^K > 1$, the contribution of factor-augmenting technologies to the change in the labor share is between $-s_i^K \cdot (\sigma_i^K - 1) \cdot d\ln A_{ki}$ and $s_i^K \cdot (\sigma_i^L - 1) \cdot d\ln A_{\ell i}$, which we can bound by

$$\left[-\frac{s_i^K}{\tilde{s}_i^K} \cdot (\sigma_i^K - 1) \cdot d\ln \mathrm{tfp}_i, \frac{s_i^K}{\tilde{s}_i^L} \cdot (\sigma_i^L - 1) \cdot d\ln \mathrm{tfp}_i\right].$$

Figure B-2 presents our measures of the adjusted labor share decline across industries for $\sigma_i^L = \sigma_i^K = \sigma_i = 0.8$ and for $\sigma_i^L = \sigma_i^K = \sigma_i = 1.2$, depicting the bounds on the contribution of factor-augmenting technologies using the whiskers. When constructing these bounds, we assume that industries with declining TFP between 1987 and 2016, experienced no factor-augmenting improvements. Except for a handful of IT-intensive industries with vast increases in TFP (electronics, computers, and communications), our bounds exclude anything other than very small effects of factor-augmenting technologies on the decline in labor shares and our task displacement measure. This is because these technologies have limited distributional effects but generate large TFP gains. Through the lens of our model, and given the pervasive lack of productivity growth observed across industries, these technologies cannot play a key role in explaining the decline in the labor share.

Appendix B-3 Data Appendix

Industry data: Our main source of industry-level data are the BEA Integrated industry accounts for 1987–2016. These data contain information on industry value added, labor compensation, industry prices and factor prices for 61 NAICS industries. We aggregated these data to the

49 industries used in our analysis, which we could track consistently both in the BEA and the worker-level data from the 1980 US Census. Finally, when computing changes in industry's labor shares, we winsorized labor shares in value added at 20% to reduce noise in our measures of task displacement coming from industries with low and volatile labor shares.

Besides the BEA data, we also used data from the BLS multifactor productivity tables for 1987–2016. These data are also available for 61 NAICS industries which we aggregated to the 49 industries used in our analysis.

We complement the industry data with proxies for the adoption of automation technologies across industries. First, we use the measure of *adjusted penetration of robots* from Acemoglu and Restrepo (2020), which is available for 1993–2014. These measure is constructed using data from the International Federation of Robotics, and is defined for each industry i as

$$\text{APR}_i = \frac{1}{5}\sum_{e=1}^{5}\left[\frac{\text{robots}_{e,i,2014} - \text{robots}_{e,i,1993}}{\ell_{e,i,1993}} - \text{output growth}_{e,i,2004-1993} \cdot \frac{\text{robots}_{e,i,1993}}{\ell_{e,i,1993}}\right],$$

where the right-hand side is computed as an average among five European countries, e, leading the US in the adoption of industrial robots (see Acemoglu and Restrepo, 2020, for details). These measure is available for all of our manufacturing industries, but has a coarser resolution outside of manufacturing.

Finally, we also use the share of specialized software and dedicated machinery in value added from the BLS multifactor productivity tables. In particular, we use the detailed capital tables from the BLS, which provide the compensation for different assets (computed as the user cost of each asset multiplied by its stock). For software, we add custom-made software or software developed in house—which are more relevant for automation than pre-packaged software like Stata or Word. For specialized machinery, we add metalworking machinery (typically numerically controlled machines capable of automatically producing a pre-specified task), agricultural machinery other than tractors, specialized machinery used in the service sector, specialized machinery used in industry applications (which should also include industrial robots), construction machinery, and material handling machinery used in industrial applications.

For offshoring, we use a measure from Feenstra and Hanson (1999) recently updated by Wright (2014) for 1990–2007. This measure captures changes in the share of imported intermediates across industries, and is only available for the manufacturing sector. When using it, we set it to zero outside of manufacturing.

When using these proxies of automation and offshoring, we rescale the coefficients on our reduced-form estimates by the first-stage relationship between each of these variables and task displacement at the industry level reported in Panel B of Table A-1.

Turning to our proxies for changes in market structure, we use changes in sales concentration and several estimates of markups aggregated at the industry level. Our data for sales concentration comes from the Census Statistics of U.S. Businesses (SUSB) and is only available for 1997–2016.

Using these data, we computed the tail index of the sales distribution for all the industries in our sample. The SUSB data can also be used to compute tail indices for the employment distribution going back to 1992. Using this alternative proxy of concentration available over a longer period didn't alter our findings.

For markups, we provide three different estimates.

First, we compute markups in a given industry using an accounting approach, which measures markups by the ratio of output to costs:

$$\mu_i = \frac{\text{gross output}_i}{R_i K_i + \text{Variable inputs}_i}.$$

This approach requires constant returns to scale and assumes there are no adjustment costs. This approach also requires a measurement of the unobserved user cost of capital R_i. We follow Karabarbounis and Neiman (2018) and compute R_i using a user-cost formula accounting for changes in taxes. We do this using data on capital stocks and prices from NIPA's Fixed Asset Tables. We also set the internal rate of return to 6% and keep it constant over time. As shown in Karabarbounis and Neiman (2013), the alternative approach of using bond rates to proxy for firms' and investors' internal rates of return yields large, volatile, and unreasonable estimates of aggregate markups. More relevant for our exercise is the fact that different values of the internal rate of return do not affect the variation in relative trends in markups across industries.

Second, we compute the change in markups by looking at the percent decline in the share of materials in gross output. That is:

$$\Delta \ln \mu_i = -\Delta \ln \text{share materials}_i.$$

This approach assumes that the share of materials in total costs is constant, and that a decline in the share of materials thus reveals higher markups. We use the BEA data described above to measure the share of materials in gross output. Outside of manufacturing, we focus on the share of materials and intermediate services, since raw materials play a smaller role in the service sector.

Finally, we compute markups using a production function approach as in De Loecker, Eeckhout and Unger (2020). In this approach, markups are computed for firms in industry i as

$$\mu_{i,f} = \frac{\text{elasticity variable inputs}_{i,f}}{\text{share variable inputs}_{i,f}}.$$

The share of variable inputs is typically observed from the data while the elasticity of output to variable input has to be estimated. Following De Loecker, Eeckhout and Unger (2020), we estimate these markups using Compustat data, but deviate from their approach in two important aspects. First, when aggregating markups at the industry level, we use an harmonic sales-weighted mean, rather than a sales-weighted mean. As shown in Hubmer and Restrepo (2021), this is the relevant notion of an aggregate markup that matters for industry factor shares. Second, and following Hubmer and Restrepo (2021), we allow the production function to vary flexibly over time, by firm, and by firm-size quintile within each industry, which accounts for the fact that the adoption of automation technologies typically concentrates among large firms (see also Acemoglu, Lelarge and Restrepo, 2020).

Census data We use the 1980 US Census to measure group-level outcomes and specialization patterns by industry and routine occupations. In addition, we also use the 2000 US Census to measure group-level outcomes for the year 2000. Finally, and to maximize our sample size, we use data from the pooled 2014–2018 American Community Survey to measure outcomes around the year 2016.

To measure real hourly wages we follow standard cleaning procedures (see for example Acemoglu and Autor, 2011). To deal with top coding, we replace top coded observations by 1.5 times the value of the top code. Second, we convert hourly wages to 2007 dollars using the Personal Consumption Expenditure deflator from the BEA. Third, we winsorized real hourly wages from below at 2 dollars per years and from above at 180 dollars per year.

Regional variation Our estimates in Section 4.6 also exploit variation in specialization patterns across regions. In particular, we use two different groupings. First, we look at workers in 300 different demographic groups across 9 Census regions. To maintain a reasonable cell size, in this exercise we define demographic groups by gender, education, age (now defined by 16–30 years of age, 31–50 years, and 51–65 years) and race. Second, we look at workers in 54 different demographic groups across 722 commuting zones (see David, Dorn and Hanson, 2013, for a description of commuting zones). To maintain a reasonable cell size, in this exercise we define demographic groups by gender, education (completed college and less than completed college), age (now defined by 16–30 years of age, 31–50 years, and 51–65 years), and race (Whites, Blacks, and others).

Routine occupations Following Acemoglu and Autor (2011), we use $ONET$ to define routine jobs. In particular, for each Census occupation o, we compute a routine index given by

$$\text{routine index}_o = \text{routine manual input}_o + \text{routine cognitive input}_o - \text{average task input}_o.$$

Here, $\text{routine manual input}_o$ denotes the intensity of routine manual tasks in occupation o, the term $\text{routine cognitive input}_o$ denotes the intensity of routine cognitive tasks, and the term $\text{average task input}_o$ denotes the average task intensity (capturing the extent to which workers also conduct manual and analytical tasks). As is common practice in the literature, we define an occupation as routine if it is the top 33% of the routine index distribution.

Table A-5 explores the robustness of our results to using different thresholds and alternative formulations of the routine index. In particular, in Panel A we define an occupation as routine if it is the top 40% of the routine index distribution, and In Panel B we use an alternative index of the form

$$\text{routine index}_o = \text{routine manual input}_o + \text{routine cognitive input}_o.$$

Panels C–E probed the robustness of our results to using Webb (2020) indices of suitability for automation via robots and software and a combination of both of them. These measures provide a ranking of occupations depending on their suitability for automation, and we define an occupation as routine if it lies in the top 33% of each measure.

Other covariates Table 5 uses additional covariates. These include industries exposure to Chinese imports for 1990–2011, which we obtained from Acemoglu et al. (2016); the decline in the unionization rates by industry, which we computed for 1984–2016 using union membership by industry from the CPS; and industry-level changes in the quantity of capital per worker and TFP from the BEA Integrated Industry Accounts.

Appendix B-4 Additional Figures and Tables

This appendix includes additional tables discussed in footnotes in the main text:

- Figure B-1: Relationship between industry labor share declines and the percent change in routine wages, hours, and employment across industries.
- Figure B-2: Adjusted labor share declines
- Table B-1: Determinants of adjusted labor share changes across industries, 1987–2016.
- Table B-2: Relationship between industry labor share decline and the decline of routine jobs.
- Table B-3: Additional sets of standard errors for our baseline estimates in Column 3 of Table 1.
- Table B-4: Task displacement and additional employment outcomes, 1980–2016.
- Table B-5: Task displacement and changes in real hourly wages—controlling for other trends and for exposure to industry labor share declines and relative specialization in routine jobs.
- Table B-6: Task displacement and changes in real hourly wages—controlling for differential effect of markups and concentration on routine jobs.
- Table B-7: Task displacement and changes in real hourly wages—controlling for changes in markups and concentrations and for exposure to industry labor share declines and relative specialization in routine jobs.

- Table B-8: Task displacement and changes in real hourly wages, 1980–2007.

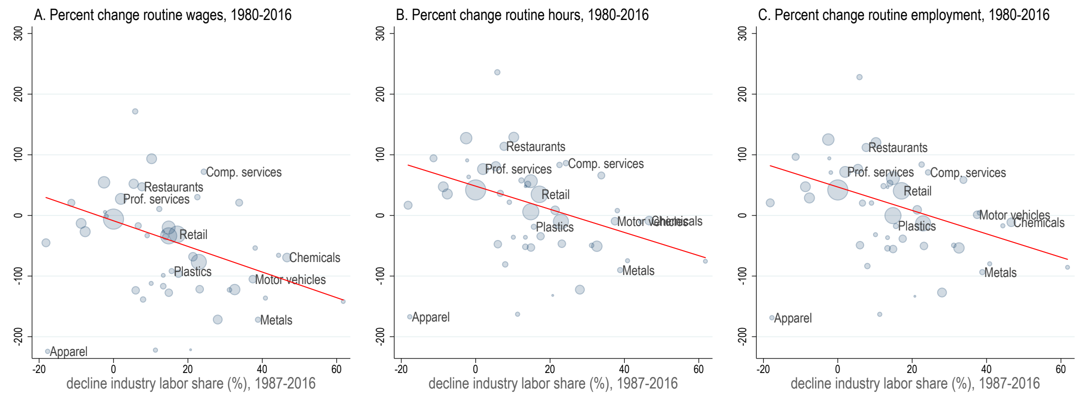

FIGURE B-1: Relationship between industry labor share declines and the percent change in routine wages, hours, and employment across industries. See text for variable definitions.

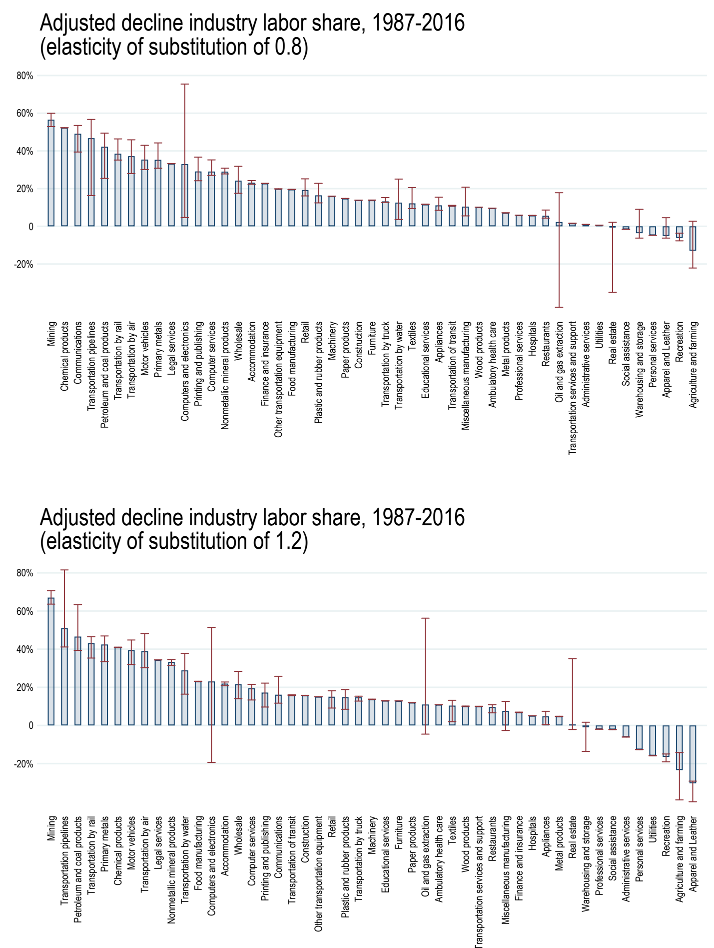

FIGURE B-2: Adjusted labor share declines. The figure provides the adjusted labor share declines for $\sigma_i = 0.8$ (top panel) and $\sigma_i = 1.2$ (bottom panel) described in Appendix A-3. The whiskers provide bounds on the decline in the adjusted labor share that cannot be explained by factor-augmenting technologies, derived in Appendix B-2.

Table B-1: Determinants of adjusted labor share changes across industries, 1987–2016.

	Dependent variable: adjusted labor share changes (in %), 1987–2016								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Adjusted labor share for $\sigma_i = 0.8$, 1987–2016								
Adjusted penetration of robots	-1.22		-0.99	-0.96	-0.99	-0.97	-1.01	-0.99	-0.59
	(0.39)		(0.47)	(0.45)	(0.46)	(0.48)	(0.48)	(0.47)	(0.63)
Change in share of dedicated machinery services		-2.57	-1.61	-1.55	-1.65	-1.64	-1.55	-1.61	-1.03
		(0.62)	(0.77)	(0.80)	(0.73)	(0.84)	(0.87)	(0.78)	(0.91)
Change in share of specialized software services	-7.89	-7.08	-8.30	-7.94	-8.40	-8.41	-8.31	-8.31	-8.07
	(1.87)	(2.16)	(1.87)	(2.03)	(2.03)	(2.10)	(1.93)	(1.93)	(1.65)
Change in share of imported intermediates				-0.71					
				(0.65)					
Change in K/Y ratio					-0.02				
					(0.03)				
Change tail index of revenue concentration						0.08			
						(0.30)			
Change in accounting markups (%)							-0.06		
							(0.35)		
Change Chinese import competition								0.01	
								(0.23)	
De-unionization rate									-0.51
									(0.34)
F-stat technology variables	11.76	12.14	12.00	10.07	11.24	10.46	9.98	11.41	8.79
Share variance explained by technology	0.35	0.27	0.40	0.38	0.40	0.40	0.40	0.40	0.31
R-squared	0.35	0.27	0.40	0.40	0.40	0.40	0.40	0.40	0.47
Observations	49	49	49	49	49	49	49	49	49
	Panel A: Adjusted labor share for $\sigma_i = 1.2$, 1987–2016								
Adjusted penetration of robots	-1.32		-0.86	-0.84	-0.86	-0.90	-0.98	-0.89	-0.86
	(0.31)		(0.37)	(0.36)	(0.38)	(0.38)	(0.37)	(0.39)	(0.44)
Change in share of dedicated machinery services		-4.07	-3.23	-3.20	-3.22	-3.15	-2.81	-3.24	-3.24
		(0.63)	(0.73)	(0.76)	(0.75)	(0.69)	(0.72)	(0.74)	(0.74)
Change in share of specialized software services	-4.78	-4.55	-5.61	-5.40	-5.58	-5.32	-5.64	-5.73	-5.61
	(1.82)	(1.71)	(1.44)	(1.60)	(1.53)	(1.54)	(1.76)	(1.53)	(1.47)
Change in share of imported intermediates				-0.41					
				(0.49)					
Change in K/Y ratio					0.00				
					(0.02)				
Change tail index of revenue concentration						-0.20			
						(0.20)			
Change in accounting markups (%)							-0.42		
							(0.39)		
Change Chinese import competition								0.24	
								(0.29)	
De-unionization rate									0.01
									(0.21)
F-stat technology variables	10.27	21.82	18.25	16.08	16.64	19.48	15.11	17.19	12.32
Share variance explained by technology	0.29	0.39	0.48	0.48	0.48	0.48	0.47	0.49	0.49
R-squared	0.29	0.39	0.48	0.49	0.49	0.49	0.54	0.49	0.48
Observations	49	49	49	49	49	49	49	49	49

Notes: This table presents estimates of the relationship between adjusted labor share changes (in %) between 1987 and 2016 at the industry level and automation technologies, offshoring, capital deepening, changes in market structure (proxied by markups or rising sales concentration), and changes in Chinese import competition for the 49 industries in our analysis. Adjusted labor share changes are computed as $d\ln s_i^L + s_i^K \cdot (1-\sigma_i) \cdot (d\ln w_i - d\ln R_i)$, where σ_i is set to 0.8 in Panel A and to 1.2 in Panel B. All regressions are weighted by industry value added in 1987. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-2: Relationship between industry labor share decline and the decline of routine jobs.

Labor share measure:	Labor share declines			Automation-driven declines		
Dependent variable:	Change in log wages in routine jobs 1980–2016	Change in log hours in routine jobs 1980–2016	Change in log employment in routine jobs 1980–2016	Change in log wages in routine jobs 1980–2016	Change in log hours in routine jobs 1980–2016	Change in log employment in routine jobs 1980–2016
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Labor share decline, 1987–2016					
Percent decline in labor share	-2.11	-1.91	-1.93	-2.85	-2.29	-2.24
	(0.54)	(0.52)	(0.52)	(0.87)	(0.80)	(0.83)
R-squared	0.21	0.20	0.20	0.17	0.13	0.12
Observations	48.00	48.00	48.00	48.00	48.00	48.00
	Panel B: Adjusted labor share decline with $\sigma_i = 0.8$, 1987–2016					
Residual decline in labor share	-2.25	-2.09	-2.13	-2.89	-2.43	-2.44
	(0.47)	(0.47)	(0.46)	(0.99)	(0.89)	(0.91)
R-squared	0.26	0.26	0.27	0.17	0.14	0.14
Observations	48	48	48	48	48	48
	Panel C: Adjusted labor share decline with $\sigma_i = 1.2$, 1987–2016					
Residual decline in labor share	-1.64	-1.42	-1.43	-2.54	-1.95	-1.87
	(0.52)	(0.50)	(0.50)	(0.70)	(0.66)	(0.69)
R-squared	0.14	0.12	0.12	0.16	0.11	0.10
Observations	48	48	48	48	48	48

Notes: This table presents estimates of the relationship between task displacement and the demand for routine jobs across industries (Transportation pipelines are excluded due to lack of ACS data). The dependent variable is indicated at the column headers. In Panel A, columns 1–3 provide estimates using the observed indutry labor share decline (in %) as explanatory variable, while columns 4–6 provide estimates using automation-driven labor share declines (in %) as explanatory variable. In Panels B and C we provide estimates using the adjusted labor share decline obtained for $\sigma_i = 0.8$ and $\sigma_i = 1.2$. All regressions are weighted by industry value added in 1987. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-3: Additional sets of standard errors for our baseline estimates from Column 3 in Table 1.

	Standard error	p−value for null $\beta = 0$	95% confidence interval
	(1)	(2)	(3)
	Panel A. Task displacement based on labor share declines, $\hat{\beta}^d = -1.31$		
Robust standard errors	(0.19)	[$p = 0.000$]	(−1.68, −0.94)
Borusyak-Hull-Jaravel	(0.18)	[$p = 0.000$]	(−1.65, −0.96)
Adao-Kolesar-Morales (correlation due to industry×routine)	(0.27)	[$p = 0.000$]	(−1.84, −0.77)
Adao-Kolesar-Morales (correlation due to industry)	(0.43)	[$p = 0.003$]	(−2.17, −0.45)
	Panel B. Task displacement based on automation-driven labor share declines, $\hat{\beta}^d = -1.36$		
Robust standard errors	(0.21)	[$p = 0.000$]	(−1.78, −0.94)
Borusyak-Hull-Jaravel	(0.17)	[$p = 0.000$]	(−1.69, −1.02)
Adao-Kolesar-Morales (correlation due to industry×routine)	(0.32)	[$p = 0.000$]	(−1.99, −0.73)
Adao-Kolesar-Morales (correlation due to industry)	(0.49)	[$p = 0.005$]	(−2.31, −0.40)
Adjusting for task displacement estimation using one-step GMM	(0.26)	[$p = 0.000$]	(−1.87, −0.84)

Notes: This table provides additional sets of standard errors and confidence intervals for the estimates in column 3 from table 1. Panel A reports results using our measure of task displacement based on the observed labor share decline. The corresponding point estimate of β is -1.31 (See Table 1 column 3, Panel A). Panel B reports results using our measure of task displacement based on automation-driven labor share declines. The corresponding point estimate of β is -1.36 (See Table 1 column 3, Panel B). The tables in the paper use robust standard errors. In addition, here we report standard errors, a p−value for testing the null that task displacement had no effect on workers, and 95% confidence intervals using other procedures. *Borusyak-Hull-Jaravel:* standard errors from Borusyak, Hull and Jaravel (2022), which are robust to unobserved industry shocks that affect workers depending on their relative specialization in routine jobs. *Adao-Kolesar-Morales:* standard errors from Adao, Kolesár and Morales (2019). We present two sets of errors. The first allows for unobserved industry shocks that affect workers depending on their relative specialization in routine jobs. The second allows for unobserved industry shocks that affect all workers in an industry. Finally, in the last row, we provide GMM estimates where we estimate the equation that predicts the labor share decline that is due to automation (at the industry level) and the equation for wages on task displacement in a single step, as in Newey (1984). This set of standard errors account for the generated regressor problem.

Table B-4: Task displacement and additional employment outcomes, 1980–2016.

	Dependent variable: Labor market outcomes 1980–2016					
	Task displacement measured from observed labor share declines			Task displacement measured from automation-driven labor share declines		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Unemployment rate					
Task displacement	0.11	0.17	0.02	0.12	0.20	0.03
	(0.02)	(0.04)	(0.10)	(0.02)	(0.05)	(0.12)
Share variance explained by:						
- task displacement	0.18	0.27	0.04	0.19	0.31	0.05
- educational dummies		0.00	-0.01		0.01	-0.02
R-squared	0.18	0.28	0.29	0.19	0.29	0.31
Observations	500	500	500	500	500	500
	Panel B. log hours per worker					
Task displacement	-0.86	-0.58	0.79	-0.92	-0.62	0.85
	(0.18)	(0.29)	(0.62)	(0.19)	(0.32)	(0.73)
Share variance explained by:						
- task displacement	0.31	0.21	-0.28	0.32	0.21	-0.29
- educational dummies		0.13	-0.01		0.16	-0.04
R-squared	0.31	0.47	0.50	0.32	0.47	0.51
Observations	500	500	500	500	500	500
Covariates:						
Industry shifters, manufacturing share, education and gender dummies		✓	✓		✓	✓
Exposure to labor share declines and relative specialization in routine jobs			✓			✓

Notes: This table presents estimates of the relationship between task displacement and labor market outcomes for 500 demographic groups, defined by gender, education, age, race, and native/immigrant status. In Panel A, the dependent variable is the change in the unemployment rate between 1980 and 2016. In Panel B, the dependent variable is the change in the log of hours per worker between 1980 and 2016. Columns 1–3 report results using our measure of task displacement based on observed labor share declines. Columns 4–6 report results using our measure of task displacement based on automation-driven labor share declines. In addition to the covariates reported in the table, columns 2–3 and 5–6 control for industry shifters, baseline wage shares in manufacturing, and dummies for education (for no high school degree, completed high school, some college, college degree and postgraduate degree) and gender. Columns 3 and 6 control for relative specialization in routine jobs and groups' exposure to industry labor share declines. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-5: Task displacement and changes in real hourly wages—controlling for other trends and for exposure to industry labor share declines and relative specialization in routine jobs.

	Dependent variable: Change in wages 1980–2016							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
Other shocks:	Rising K/Y ratio by industry	Rising TFP by industry	Chinese imports' competition	Declining unionization rates	Rising K/Y ratio by industry	Rising TFP by industry	Chinese imports' competition	Declining unionization rates
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Controlling for main effect of other shocks								
Task displacement	-1.67	-1.81	-1.60	-1.82	-1.85	-2.09	-1.55	-1.88
	(0.48)	(0.48)	(0.52)	(0.47)	(0.48)	(0.59)	(0.65)	(0.56)
Exposure to industry shock	-0.02	-0.16	0.00	1.14	0.02	-0.23	0.01	0.10
	(0.16)	(0.38)	(0.02)	(1.53)	(0.15)	(0.40)	(0.02)	(1.53)
Share variance explained by:								
- task displacement	0.70	0.76	0.67	0.76	0.72	0.82	0.60	0.73
- industry shock	-0.00	0.01	-0.00	-0.17	0.00	0.01	-0.01	-0.01
R-squared	0.84	0.84	0.84	0.84	0.83	0.83	0.83	0.83
Observations	500	500	500	500	500	500	500	500
Panel B. Controlling for effects on workers in routine jobs								
Task displacement	-1.40	-1.73	-1.19	-2.66	-1.56	-2.04	-1.06	-4.06
	(0.52)	(0.44)	(0.55)	(0.85)	(0.51)	(0.54)	(0.64)	(1.14)
Exposure to industry shock	0.31	-0.00	0.04	-1.56	0.41	-0.13	0.04	-4.77
	(0.20)	(0.45)	(0.03)	(2.17)	(0.18)	(0.49)	(0.03)	(1.95)
Exposure of routine jobs to industry shock	-0.36	-0.14	-0.03	1.69	-0.44	-0.08	-0.02	3.66
	(0.15)	(0.27)	(0.02)	(1.34)	(0.14)	(0.27)	(0.02)	(1.58)
Share variance explained by:								
- task displacement	0.59	0.72	0.50	1.11	0.61	0.79	0.41	1.58
- industry shock	0.15	0.03	0.08	-0.23	0.18	0.02	0.05	-0.29
R-squared	0.85	0.84	0.84	0.84	0.84	0.83	0.83	0.84
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in hourly wages across 500 demographic groups controlling for trade in final goods, declining unionization rates, other forms of capital investments, and other technologies leading to productivity growth in an industry. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 2016. In Panel A, we control for the main effect of these shocks on workers in exposed industries. In Panel B, we allow these shocks to have a differential impact on workers in routine jobs in exposed industries. Columns 1–4 report results using our measure of task displacement based on observed labor share declines. Columns 5–8 report results using our measure of task displacement based on automation-driven labor share declines. In addition to the covariates reported in the table, all specifications control for industry shifters, baseline wage share in manufacturing, and dummies for education (for no high school degree, completed high school, some college, college degree and postgraduate degree) and gender, relative specialization in routine jobs, and groups' exposure to industry labor share declines. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-6: Task displacement and changes in real hourly wages—controlling for differential effect of markups and concentration on routine jobs.

	Dependent variable: Change in wages 1980–2016							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
	Rising sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)	Rising sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Controlling for effects of markups and concentration on workers in routine jobs								
Task displacement	-0.69	-1.35	-1.17	-0.97	-0.58	-1.14	-1.09	-1.03
	(0.21)	(0.33)	(0.22)	(0.15)	(0.25)	(0.46)	(0.23)	(0.16)
Exposure to changes in markups or concentration	9.19	0.19	-1.95	-4.42	9.78	-0.37	-1.90	-4.69
	(2.22)	(1.52)	(0.55)	(1.01)	(2.22)	(1.68)	(0.58)	(0.98)
Exposure of routine jobs to changes in markups or concentration	-4.50	0.13	0.99	3.49	-5.02	-0.72	1.23	3.73
	(1.15)	(1.44)	(0.23)	(0.67)	(1.13)	(1.72)	(0.23)	(0.62)
Share variance explained by:								
- task displacement	0.29	0.57	0.49	0.41	0.22	0.44	0.43	0.40
- markups/concetration	0.25	-0.01	-0.12	-0.08	0.27	0.07	-0.09	-0.09
R-squared	0.86	0.84	0.85	0.88	0.86	0.83	0.84	0.87
Observations	500	500	500	500	500	500	500	500
Panel B. Net out markups from construction of task displacement								
Task displacement	-0.90	-1.35	-1.17	-0.97	-0.75	-1.30	-0.67	-0.99
	(0.25)	(0.33)	(0.22)	(0.15)	(0.39)	(0.55)	(0.14)	(0.15)
Exposure to changes in markups or concentration	9.07	0.19	-1.95	-4.42	9.91	-0.01	-1.94	-4.61
	(2.18)	(1.52)	(0.55)	(1.01)	(2.35)	(1.64)	(0.64)	(0.99)
Exposure of routine jobs to changes in markups or concentration	-4.75	-1.22	-0.18	2.52	-5.40	-1.90	1.32	3.78
	(1.05)	(1.18)	(0.37)	(0.75)	(1.06)	(1.32)	(0.27)	(0.62)
Share variance explained by:								
- task displacement	0.30	0.44	0.57	0.37	0.17	0.30	0.38	0.40
- markups/concetration	0.25	0.11	-0.19	-0.04	0.27	0.17	-0.09	-0.09
R-squared	0.87	0.84	0.85	0.88	0.86	0.83	0.83	0.87
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in hourly wages across 500 demographic groups controlling for changes in market structure and markups and any differential effect of these changes on routine jobs. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 2016. In Panel A, we control for groups' specialization in industries with changes in market structure leading to higher markups. In column 1, we proxy changes in market structure by rising sales concentration in the industry. In columns 2–4, we directly control for changes in markups. These are computed as the ratio of revenue to costs in column 2, the inverse of the materials' share in gross output in column 3, and markups estimated using a production function approach as in De Loecker, Eeckhout and Unger (2020) in column 4. In Panel B, we also subtract the percent increase in markups from the percent decline in the labor share when computing our measure of task displacement (using the accounting markup in columns 1 and 5). Columns 1–4 report results using our measure of task displacement based on observed labor share declines (net of markups in Panel B). Columns 5–8 report results using our measure of task displacement based on automation-driven labor share declines (net of markups in Panel B). In addition to the covariates reported in the table, all specifications control for industry shifters, baseline wage shares in manufacturing, and dummies for education (for no high school degree, completed high school, some college, college degree and postgraduate degree) and gender, relative specialization in routine jobs, and groups' exposure to industry labor share declines.. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-7: Task displacement and changes in real hourly wages—controlling for changes in markups and concentrations and for exposure to industry labor share declines and relative specialization in routine jobs.

	Dependent variable: Change in wages 1980–2016							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
	Rising sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)	Rising sales concentration	Markups from accounting approach	Markups from materials share	Markups from DLEU (2020)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Controlling for main effect of markups and concentration								
Task displacement	-1.39	-1.61	-2.07	-1.57	-1.58	-1.85	-2.35	-1.71
	(0.46)	(0.45)	(0.46)	(0.54)	(0.45)	(0.47)	(0.54)	(0.58)
Exposure to changes in markups or concentration	1.97	0.72	-1.29	-0.40	1.80	0.20	-1.12	-0.59
	(1.56)	(1.75)	(0.55)	(1.16)	(1.53)	(1.54)	(0.58)	(1.23)
Share variance explained by:								
- task displacement	0.58	0.68	0.87	0.66	0.62	0.72	0.91	0.67
- markups/concetration	0.04	-0.01	-0.12	0.01	0.04	-0.00	-0.10	0.01
R-squared	0.84	0.84	0.85	0.84	0.83	0.83	0.84	0.83
Observations	500	500	500	500	500	500	500	500
Panel B. Net out markups from construction of task displacement								
Task displacement	-1.22	-1.65	-1.24	-1.97	-1.77	-2.11	-0.69	-1.23
	(0.55)	(0.56)	(0.23)	(0.40)	(0.75)	(0.74)	(0.38)	(0.57)
Exposure to changes in markups or concentration	1.66	-0.64	-2.51	-2.04	0.42	-2.03	-0.59	-0.68
	(1.68)	(1.90)	(0.64)	(0.72)	(1.57)	(1.41)	(0.55)	(1.26)
Share variance explained by:								
- task displacement	0.40	0.54	0.60	0.74	0.41	0.49	0.40	0.50
- markups/concetration	0.04	0.01	-0.23	0.03	0.01	0.03	-0.05	0.01
R-squared	0.84	0.83	0.85	0.87	0.82	0.82	0.82	0.83
Observations	500	500	500	500	500	500	500	500

Notes: This table presents estimates of the relationship between task displacement and the change in hourly wages across 500 demographic groups controlling for changes in market structure and markups. These groups are defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 2016. In Panel A, we control for groups' specialization in industries with changes in market structure leading to higher markups. In column 1, we proxy changes in market structure by rising sales concentration in the industry. In columns 2–4, we directly control for changes in markups. These are computed as the ratio of revenue to costs in column 2, the inverse of the materials' share in gross output in column 3, and markups estimated using a production function approach as in De Loecker, Eeckhout and Unger (2020) in column 4. In Panel B, we also subtract the percent increase in markups from the percent decline in the labor share when computing our measure of task displacement (using the accounting markup in columns 1 and 5). Columns 1–4 report results using our measure of task displacement based on observed labor share declines (net of markups in Panel B). Columns 5–8 report results using our measure of task displacement based on automation-driven labor share declines (net of markups in Panel B). In addition to the covariates reported in the table, all specifications control for industry shifters, baseline wage shares in manufacturing, and dummies for education (for no high school degree, completed high school, some college, college degree and postgraduate degree) and gender, relative specialization in routine jobs, and groups' exposure to industry labor share declines. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.

Table B-8: Task displacement and changes in real hourly wages, 1980–2007.

	Dependent variables: Change in wages and wage declines, 1980–2007							
	Task displacement measured from observed labor share declines				Task displacement measured from automation-driven labor share declines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Change in hourly wages, 1980–2007							
Task displacement	-1.78	-1.37	-0.92	-0.33	-2.10	-1.72	-0.97	-0.24
	(0.11)	(0.14)	(0.18)	(0.56)	(0.13)	(0.22)	(0.23)	(0.66)
Share variance explained by task displacement	0.69	0.53	0.36	0.13	0.68	0.56	0.32	0.08
R-squared	0.69	0.74	0.82	0.83	0.68	0.70	0.81	0.82
Observations	500	500	500	500	500	500	500	500
	Panel B. Change in hourly wages for men, 1980–2007							
Task displacement	-1.56	-0.75	-0.57	-1.25	-1.86	-0.91	-0.70	-1.68
	(0.16)	(0.18)	(0.12)	(0.47)	(0.19)	(0.22)	(0.16)	(0.50)
Share variance explained by task displacement	0.76	0.36	0.28	0.61	0.77	0.38	0.29	0.70
R-squared	0.76	0.87	0.94	0.94	0.77	0.87	0.94	0.94
Observations	250	250	250	250	250	250	250	250
	Panel C. Change in hourly wages for women, 1980–2007							
Task displacement	-2.33	-1.99	-3.17	-1.65	-2.32	-3.31	-5.09	-1.08
	(0.34)	(0.44)	(0.60)	(0.95)	(0.35)	(0.73)	(0.87)	(1.23)
Share variance explained by task displacement	0.47	0.40	0.64	0.33	0.45	0.64	0.99	0.21
R-squared	0.47	0.50	0.66	0.72	0.45	0.48	0.64	0.71
Observations	250	250	250	250	250	250	250	250
Covariates:								
Industry shifters		✓	✓	✓		✓	✓	✓
Manufacturing share, gender and education dummies			✓	✓			✓	✓
Exposure to labor share declines and relative specialization in routine jobs				✓				✓

Notes: This table presents estimates of the relationship between task displacement and the change in hourly wages across demographic groups, defined by gender, education, age, race, and native/immigrant status. The dependent variable is the change in hourly wages for each group between 1980 and 2007. Panel A provides estimates for all demographic groups, while Panels B and C provide results for men and women respectively. Columns 1–4 report results for our measure of task displacement based on observed labor share declines. Columns 5–8 report results for our measure of task displacement based on automation-driven labor share declines. In addition to the covariates reported in the table, columns 3-4 and 7–8 control for baseline wage shares in manufacturing and dummies for education (for no high school degree, completed high school, some college, college degree and postgraduate degree) and gender, and columns 4 and 8 control for groups' exposure to industry labor share declines and groups' relative specialization in routine jobs. All regressions are weighted by total hours worked by each group in 1980. Standard errors robust to heteroskedasticity are reported in parentheses.