The Impacts of AI, Robots, and Globalization on Labor Markets: Analysis of a Quantitative General Equilibrium Trade Model : Online Appendix

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A Data Construction

Our dataset combines several data sources, all of which can be purchased or freely downloaded. They are (1) the International Federation of Robotics (IFR) database, (2) the Bank of Japan Corporate Goods Price Index (BoJ) database, (3) the UN Comtrade database, (4) the Global Trade Analysis Project (GTAP) database version 10, (5) the International Labour Organization (ILO) stat database, (6) the Penn World Table, (7) the UNCTAD TRAINS database, (8) the CEPII GeoDist database and (9) the World Input-Output Database 2016 Release (WIOD).

Bilateral Trade and Input-Output Tables We collect data on input-output tables, bilateral trade, and final purchases from the GTAP database and aggregate the classification of industries to the ISIC classification in the IFR data. The database reports for each country n: domestic purchase by industry r of good s, X_{nnt}^{rs}; domestic final purchase (household consumption, gross capital formulation and government expenditure) of good s, X_{nnt}^{sf}; bilateral imports without usage distinction, X_{nit}^{s}; import purchases by industry r of good s in country n, $\chi_{nt}^{rs} \equiv \sum_{i\neq n} X_{nit}^{rs}$; and final imports of good s in country n, $\chi_{nt}^{sf} \equiv \sum_{i\neq n} X_{nit}^{sf}$. We obtain bilateral trade for both input usage and final usage by imposing the "proportionality" assumption, which is often assumed for

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constructing multi-region input-output tables:

$$X^{rs}_{nit} = \left(\frac{\chi^{rs}_{nt}}{\chi^{sf}_{nt} + \sum_r \chi^{rs}_{nt}} \right) X^s_{nit} \text{ and } X^{sf}_{nit} = \left(\frac{\chi^{sf}_{nt}}{\chi^{sf}_{nt} + \sum_r \chi^{rs}_{nt}} \right) X^s_{nit}.$$

Then, we obtain $X^{sm}_{nit} \equiv \sum_r X^{rs}_{nit}$.

Production Factors: Allocation and Prices For each industry, the GTAP database reports the payments for five labor occupations, which we aggregated to two skill groups, capital, and specific factors, following Weingarden and Tsigas (2010) as indicated in Table A.1.

Table A.1: Occupation categories and labor skill groups

ISCO-08 major group occupations	Occupations in GTAP	Skill types
1. Managers, 2. Professionals	Official and Managers	High-skilled
3. Technicians and Associate Professionals	Technicians	High-skilled
4. Clerical Support Worker	Clerks	Low-skilled
5. Service and Sales Workers	Service/Shop Workers	Low-skilled
6,7,8,9*	Agricultural and Low-skilled	Low-skilled

*Note: 6. Skilled Agricultural, Forestry and Fishery Workers; 7. Craft and Related Trades Workers; 8. Plant and Machine Operators and Assemblers; 9. Elementary Occupations. We removed category 0. Armed Forces Occupations from data.

Using total high-skilled and low-skilled employment in each country reported in the ILO database, we obtain country-level wage rates as the wage payment per worker. Then, we divide the industry-level wage payment by the wage rate to calculate industry-level employment.

We obtain non-robot capital rental rates and allocations as follows. Because the capital income in GTAP includes payments for robots, we subtract robot income that we have estimated to get country-industry-level non-robot capital income $w_{Knt}K^s_{nt}$. Then, we aggregate them to the country-level and divide it by real capital stocks from the Penn World Table to obtain non-robot capital rental rate w_{Knt}. Finally, we calculate industry-level capital stocks by dividing the country-industry-level non-robot capital income by the estimated capital rental rate.

Tariffs and Gravity Variables The data for tariffs come from the simple averages of the MFN tariffs and simple averages of preferential tariffs from the UNCTAD TRAINS database (via the

World Trade Integrated System). Tariffs reported at the Harmonized System 6-digit level are aggregated to the IFR industry level, with the weights of import volumes in 2000, which are from the UN Comtrade. Missing values are imputed for up to +/- 3 years. Variables used in the gravity equation, such as geographic distances, are from the CEPII GeoDist database.

Parameters for the Robot Producing Industry Neither the IFR database nor the GTAP database treats the robot-producing industry separately from other industries. We construct data for the robot-producing industry as follows. First, we assume that the robot producing industry shares the same production function parameters and tariffs with the IFR industry 10, "Electrical, electronics, and machinery", which includes robot production. Second, we calculate the share of robot sales $\sum_{i=1}^{N} X_{int}^{R}$ that is estimated from the robot gravity equation (12) in the main text, in the total sales of the IFR industry 10 by country n. Then, by multiplying the share, we separate the robot industry's trade volume and factor inputs from those of the IFR industry 10.

Parameters for AI To construct data for countries' expenditure on AI, we collect expenditure data from the GTAP database on the communication sector and multiply them by individual countries' share of "Computer programming, consultancy, and the related activities; information service activities" in the communication sector, calculated from the World Input-Output Database (WIOD). We further adjust the resulting shares by multiplying them by 0.015 to make the world average share of AI in the most AI installing industry, "All other non-manufacturing branches" (IFR industry 14), equals 0.002, the world average share of robots in the most robot-installing industry. We use the Service Producer Price Index data on "Information and communications" provided by the Bank of Japan to construct the price data for AI.

B Equilibrium Conditions and Numerical Solution Algorithm

B.1 Equilibrium Conditions for Change

It follows from

$$w_{Tnst} = \frac{(w_{Rnt})^{v_{nst}} (w_{Lnt})^{1-v_{nst}}}{\Gamma_{st}(v_{nst})}. \tag{A1}$$

that a change in unit costs of low-skilled tasks is expressed as

$$\hat{w}_{Tnst} = (\hat{w}_{Rnt})^{\upsilon_{nst}} (\hat{w}_{Lnt})^{1-\upsilon_{nst}} \Omega_{nst}, \tag{A2}$$

where

$$\Omega_{nst} \equiv \exp\left(\int_{\frac{w_{nRt}}{w_{nLt}}}^{\frac{w_{nRt}}{w_{nLt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}} \frac{\upsilon_{st}(x)}{x} dx\right) \left(\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)^{-\upsilon_{nst}} \lambda_{st}{}^{-\upsilon_{nst}\hat{\upsilon}_{nst}}$$

represents the productivity effect of automation. Under the logistic formulation of υ_{nst}, $\hat{\upsilon}_{nst}$ and Ω_{nst} are further simplified as

$$\begin{aligned}
\hat{\upsilon}_{nst} &= \frac{\left(\hat{w}_{Rnt}/\left(\lambda_{st}\hat{w}_{Lnt}\right)\right)^{1-\sigma_s}}{1+\upsilon_{nst}\left\{\left(\hat{w}_{Rnt}/\left(\lambda_{st}\hat{w}_{Lnt}\right)\right)^{1-\sigma_s}-1\right\}}, \\
\Omega_{nst} &= \left[1+\upsilon_{nst}\left\{\left(\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)^{(1-\sigma_s)}-1\right\}\right]^{\frac{1}{\sigma_s-1}} \left(\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)^{-\upsilon_{nst}} \lambda_{st}{}^{-\upsilon_{nst}\hat{\upsilon}_{nst}}.
\end{aligned} \tag{A3}$$

The derivations of $\hat{\upsilon}_{nst}$ and Ω_{nst} are given in section B.3 below. By estimating the robot demand function υ_{st} from the data, we obtain $\hat{\upsilon}_{nst}$, Ω_{nst} and $\hat{w}_{Tnst}$ as functions of $\hat{w}_{Rnt}$ and $\hat{w}_{Lnt}$.

It follows from equations (9) and (17) in the main text that changes in unit costs and prices are expressed as

$$\hat{c}_{it}^{s} = \hat{w}_{Git}^{\beta_{Git}^{s}} \hat{w}_{Hit}^{\beta_{Hit}^{s}} \hat{w}_{Kit}^{\beta_{Kit}^{s}} \hat{w}_{Tist}^{\beta_{Tit}^{s}} \prod_{k=1}^{S} \left(\hat{P}_{it}^{km}\right)^{\beta_{it}^{sk}}, \tag{A4}$$

$$\left(\hat{P}_{nt}^{su}\right)^{-\theta^s} = \sum_{h=1}^{N} \pi_{nht}^{su} \left(\hat{c}_{ht}^{s}\hat{d}_{nht}^{su}\right)^{-\theta^s}, \tag{A5}$$

for $s = 1, ..., S$. The Euler equations (21) in the main text imply the changes in rental rates as follows:

$$\hat{w}_{Knt} = \hat{P}_{nt}^{f} = \prod_{s=1}^{S-1} \left(\hat{P}_{nt}^{sf}\right)^{\alpha_s} \text{ and } \hat{w}_{Rnt} = \hat{P}_{nt}^{R}. \tag{A6}$$

It follows from equation (8) in the main text that the change in trade shares can be expressed as

$$\hat{\pi}_{nit}^{su} = \frac{\hat{A}_{it}^{s}\left(\hat{c}_{it}^{s}\hat{d}_{nit}^{su}\right)^{-\theta^s}}{\left(\hat{P}_{nt}^{su}\right)^{-\theta^s}}. \tag{A7}$$

We see from equations (19) in the main text that the expenditures in the counterfactual equilibrium satisfy

$$
\begin{aligned}
X_{nt}^{sf\prime} &= \alpha_n^s \left(V_{nt}^{\prime} + \sum_{s=1}^{S} \sum_{i=1}^{N} \frac{\tau_{nit}^{s\prime}}{1+\tau_{nit}^{s\prime}} (\pi_{nit}^{sf\prime} X_{nt}^{sf\prime} + \pi_{nit}^{sm\prime} X_{nt}^{sm\prime}) + TD_{nt}^{\prime} - X_{nt}^{Sf\prime} \right), \\
X_{nt}^{Sf} &= X_{nt}^{Sf} \hat{w}_{Rnt} \hat{R}_{nt}, \\
X_{nt}^{sm\prime} &= \sum_{k=1}^{S} \beta_{nt}^{ks} \left(\sum_{i=1}^{N} \frac{\pi_{int}^{kf\prime}}{1+\tau_{int}^{k\prime}} X_{it}^{kf\prime} + \sum_{i=1}^{N} \frac{\pi_{int}^{km\prime}}{1+\tau_{int}^{k\prime}} X_{it}^{km\prime} \right),
\end{aligned} \tag{A8}
$$

where $V_{nt}^{\prime}$ is the factor income in the counterfactual equilibrium:

$$
\begin{aligned}
V_{nt}^{\prime} &= \sum_{s} (\beta_{Tnt}^{s} \hat{v}_{snt} v_{snt} + \beta_{Knt}^{s}) \left(\sum_{i=1}^{N} \frac{\pi_{int}^{kf\prime}}{1+\tau_{int}^{k\prime}} X_{it}^{kf\prime} + \sum_{i=1}^{N} \frac{\pi_{int}^{km\prime}}{1+\tau_{int}^{k\prime}} X_{it}^{km\prime} \right) \\
&\quad + \hat{w}_{Hnt} w_{Hnt} H_{nt} + \hat{w}_{Lnt} w_{Lnt} L_{nt} + \sum_{s} \hat{w}_{Gnst} w_{Gnst} G_{nst}.
\end{aligned} \tag{A9}
$$

It follows from equations (20) in the main text that changes in factor incomes are expressed as

$$
\begin{aligned}
\hat{w}_{Hnt} &= \left(\frac{1}{w_{Hnt} H_{nt}} \right) \sum_{s=1}^{S} \beta_{Hnt}^{s} Y_{nt}^{s\prime}, \\
\hat{w}_{Lnt} &= \left(\frac{1}{w_{Lnt} L_{nt}} \right) \sum_{s=1}^{S} \beta_{Lnt}^{s} v_{snt}^{L} \hat{v}_{snt}^{L} Y_{nt}^{s\prime}, \\
\hat{w}_{Gnst} &= \left(\frac{1}{w_{Hnt} G_{nt}} \right) \beta_{Gnt}^{s} Y_{nt}^{s\prime},
\end{aligned} \tag{A10}
$$

where $v_{snt}^{L} \equiv 1 - v_{snt}$ and $Y_{nt}^{s\prime} \equiv \sum_{i=1}^{N} \frac{\pi_{int}^{kf\prime}}{1+\tau_{int}^{k\prime}} X_{it}^{kf\prime} + \sum_{i=1}^{N} \frac{\pi_{int}^{km\prime}}{1+\tau_{int}^{k\prime}} X_{it}^{km\prime}$. Finally, we impose an exogenous constraint on trade deficit in real terms, namely the restriction that the trade deficit relative to the world labor income remains the same between the two equilibria.

$$
\begin{aligned}
&\frac{TD_{nt}^{\prime}}{\sum_{i=1}^{N} (\hat{w}_{Hit} w_{Hit} H_{it} + \hat{w}_{Lit} w_{Lit} L_{it} + \sum_{s} \hat{w}_{Gist} w_{Gist} G_{ist})} \\
&= \frac{TD_{nt}}{\sum_{i=1}^{N} (w_{Lit} L_{it} + w_{Hit} H_{it} + \sum_{s} w_{Gist} G_{ist})}
\end{aligned} \tag{A11}
$$

B.2 Solution Algorithm

Extending the algorithms in Dekle et al. (2008) and Caliendo and Parro (2015), we solve the above system for changes in the factor prices $\{\hat{w}_{Hnt}, \hat{w}_{Lnt}, \hat{w}_{Gnst}\}$.

1. First, we choose initial values of $\{\hat{w}_{Hnt}, \hat{w}_{Lnt}, \hat{w}_{Gnst}\}$.

2. Second, we solve the system of equations (A2), (A4), (A5), and (A6) for changes in goods prices $\left\{\hat{P}^{sf}_{nt}, \hat{P}^{su}_{nt}\right\}$ and rental prices $\{\hat{w}_{Knt}, \hat{w}_{Rnt}\}$.

3. Third, with changes in goods and factor prices, we obtain changes in trade shares $\hat{\pi}^{su}_{nit}$ from (A7).

4. Forth, substituting (A9) and (A11) into (A8), we have a system of linear equations that determines expenditures $\{X^{sf\prime}_{nt}, X^{sm\prime}_{nt}\}$ in the counterfactual equilibrium. We solve the system for $\{X^{sf\prime}_{nt}, X^{sm\prime}_{nt}\}$.

5. Finally, we obtain changes in the factor prices $\{\hat{w}_{Hnt}, \hat{w}_{Lnt}, \hat{w}_{Gnst}\}$ from (A10).

Step 1 to Step 5 can be considered as a function from $\{\hat{w}_{Hnt}, \hat{w}_{Lnt}, \hat{w}_{Gnst}\}$ to $\{\hat{w}_{Hnt}, \hat{w}_{Lnt}, \hat{w}_{Gnst}\}$. We repeat these steps until $\{\hat{w}_{Hnt}, \hat{w}_{Lnt}, \hat{w}_{Gnst}\}$ converge. Walras's law implies that only $3N-1$ equations out of $3N$ equations in (A11) are independent. Therefore, we normalize $\hat{w}_{H,US,t}=1$ for the US.

B.3 Derivation of (A3)

Suppose the robot productivity changes uniformly across tasks, i.e., $\hat{\gamma}_{st}(x) = \lambda_{st}$ for all x. The change in $\Gamma_{st}(x) \equiv \exp\left(\int_0^x \ln\gamma_{st}(v)\,dv\right)$ is expressed as

$$\begin{aligned}
\hat{\Gamma}_{st} &= \frac{\Gamma_{st}(v_{nst})}{\Gamma_{st}(\hat{v}_{nst}v_{nst})} \\
&= \exp\left(\int_0^{v_{nst}} \ln\gamma_{st}(x)\,dx - \int_0^{v_{nst}\hat{v}_{nst}} \ln\left[\lambda_{st}\gamma_{st}(x)\right]dx\right) \\
&= \exp\left(-\int_{v_{nst}}^{v_{nst}\hat{v}_{nstt}} \ln\gamma_{st}(x)\,dx - v_{nst}\hat{v}_{nst}\ln\lambda_{st}\right).
\end{aligned}$$

From this, a change in w_{Tnst} can be written as

$$\begin{aligned}
\hat{w}_{Tnst} &= \frac{\left(w_{Rnt}\hat{w}_{Rnt}\right)^{v_{nst}\hat{v}_{nst}}\left(w_{Lnt}\hat{w}_{Lnt}\right)^{1-v_{nst}\hat{v}_{nst}}}{\left(w_{Rnt}\right)^{v_{nst}}\left(w_{Lnt}\right)^{1-v_{nst}}}\frac{\Gamma_{st}(v_{nst})}{\Gamma_{st}(\hat{v}_{nst}v_{nst})} \\
&= \left(\hat{w}_{Rnt}\right)^{v_{nst}}\left(\hat{w}_{Lnt}\right)^{1-v_{nst}}\left(\frac{w_{Rnt}}{w_{Lnt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)^{v_{nst}\hat{v}_{nst}-v_{nst}}\frac{\Gamma_{st}(v_{nst})}{\Gamma_{st}(\hat{v}_{nst}v_{nst})} \\
&= \left(\hat{w}_{Rnt}\right)^{v_{nst}}\left(\hat{w}_{Lnt}\right)^{1-v_{nst}} \\
&\times \exp\left[\left(v_{nst}\hat{v}_{nst}-v_{nst}\right)\ln\left(\frac{w_{Rnt}}{w_{Lnt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)-\int_{v_{nst}}^{v_{nst}\hat{v}_{nstt}}\ln\gamma_{st}\left(x\right)dx-v_{nst}\hat{v}_{nst}\ln\lambda_{st}\right]. \quad \text{(A12)}
\end{aligned}$$

We simplify the terms inside the exponent in (A12) by applying the integration by substitution and the integration by parts. Define $z \equiv \gamma_{st}(x)$. The definition of $v_{st}(\cdot) \equiv \gamma_{st}^{-1}(\cdot)$ implies $v_{st}\left(z\right) = x$ and $v'_{st}\left(z\right)dz = dx$. From $v_{nst} = \frac{w_{Rnt}}{w_{Lnt}}$ and $\hat{v}_{nst} = \frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}$, we have

$$\begin{aligned}
\int_{v_{nst}}^{v_{nst}\hat{v}_{nst}}\ln\gamma_{st}\left(x\right)dx &= \int_{\frac{w_{Rnt}}{w_{Lnt}}}^{\frac{w_{Rnt}}{w_{Lnt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}}\ln z\left(v'_{st}\left(z\right)dz\right) \quad \text{(integratnon by substitution)} \\
&= \int_{\frac{w_{Rnt}}{w_{Lnt}}}^{\frac{w_{Rnt}}{w_{Lnt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}}\left[v_{st}\left(z\right)\left(\ln z\right)\right]'dz-\int_{\frac{w_{Rnt}}{w_{Lnt}}}^{\frac{w_{Rnt}}{w_{Lnt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}}\frac{v_{st}\left(z\right)}{z}dz \quad \text{(integration by parts)} \\
&= v_{nst}\hat{v}_{nst}\ln\frac{w_{Rnt}}{w_{Lnt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}-v_{nst}\ln\frac{w_{Rnt}}{w_{Lnt}}-\int_{\frac{w_{Rnt}}{w_{Lnt}}}^{\frac{w_{Rnt}}{w_{Lnt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}}\frac{v_{st}\left(z\right)}{z}dz. \\
&= \left(v_{nst}\hat{v}_{nst}-v_{nst}\right)\ln\frac{w_{Rnt}}{w_{Lnt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}+v_{nst}\ln\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}-\int_{\frac{w_{Rnt}}{w_{Lnt}}}^{\frac{w_{Rnt}}{w_{Lnt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}}\frac{v_{st}\left(z\right)}{z}dz.
\end{aligned}$$

From (A12), we obtain

$$\begin{aligned}
\hat{w}_{Tnst} &= \left(\hat{w}_{Rnt}\right)^{v_{nst}}\left(\hat{w}_{Lnt}\right)^{1-v_{nst}}\Omega_{nst}, \\
\Omega_{nst} &\equiv \exp\left(\int_{\frac{w_{nRt}}{w_{nLt}}}^{\frac{w_{nRt}}{w_{nLt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}}\frac{v_{st}\left(x\right)}{x}dx\right)\left(\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)^{-v_{nst}}\lambda_{st}{}^{-v_{nst}\hat{v}_{nst}}.
\end{aligned}$$

With the logistic formulation, namely

$$v_{st}\left(\frac{w_{Rnt}}{w_{Lnt}}\right) = \frac{\exp\left(\iota_{st} - (\sigma_s - 1)\ln\frac{w_{Rnt}}{w_{Lnt}} + \epsilon_{nst}\right)}{1 + \exp\left(\iota_{st} - (\sigma_s - 1)\ln\frac{w_{Rnt}}{w_{Lnt}} + \epsilon_{nst}\right)}$$
$$= \frac{\exp\left(\iota_{st} + \epsilon_{nst}\right)\left(\frac{w_{Rnt}}{w_{Lnt}}\right)^{\sigma_s - 1}}{1 + \exp\left(\iota_{st} + \epsilon_{nst}\right)\left(\frac{w_{Rnt}}{w_{Lnt}}\right)^{\sigma_s - 1}},$$

we can calculate $\hat{v}_{nst}$ and Ω_{ist} explicitly. Noting that

$$\frac{v_{nst}}{1 - v_{nst}} = \exp\left(\iota_{st} - (\sigma_s - 1)\ln\frac{w_{Rnt}}{w_{Lnt}} + \epsilon_{nst}\right)$$
$$= \exp\left(\iota_{st} + \epsilon_{nst}\right)\left(\frac{w_{Rnt}}{w_{Lnt}}\right)^{\sigma_s - 1},$$

we obtain $\hat{v}_{nst}$ as follows:

$$\hat{v}_{nst} = \frac{v_{st}\left(\frac{1}{\lambda_{st}}\frac{w_{nRt}}{w_{nLt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)}{v_{st}\left(\frac{w_{nRt}}{w_{nLt}}\right)}$$
$$= \left(\frac{\exp\left(\iota_{st} + \epsilon_{nst}\right)\left(\frac{\hat{w}_{Rnt}}{\lambda_{st}\hat{w}_{Lnt}}\frac{w_{Rnt}}{w_{Lnt}}\right)^{-(\sigma_s - 1)}}{1 + \exp\left(\iota_{st} + \epsilon_{nst}\right)\left(\frac{\hat{w}_{Rnt}}{\lambda_{st}\hat{w}_{Lnt}}\frac{w_{Rnt}}{w_{Lnt}}\right)^{-(\sigma_s - 1)}}\right)\left(\frac{1 + \exp\left(\iota_{st} + \epsilon_{nst}\right)\left(\frac{w_{Rnt}}{w_{Lnt}}\right)^{-(\sigma_s - 1)}}{\exp\left(\iota_{st} + \epsilon_{nst}\right)\left(\frac{w_{Rnt}}{w_{Lnt}}\right)^{-(\sigma_s - 1)}}\right)$$
$$= \left(\frac{\hat{w}_{Rnt}}{\lambda_{st}\hat{w}_{Lnt}}\right)^{-(\sigma_s - 1)}\left(\frac{1 + \exp\left(\iota_{st} + \epsilon_{nst}\right)\left(\frac{w_{Rnt}}{w_{Lnt}}\right)^{-(\sigma_s - 1)}}{1 + \exp\left(\iota_{st} + \epsilon_{nst}\right)\left(\frac{w_{Rnt}}{w_{Lnt}}\right)^{-(\sigma_s - 1)}\left(\frac{\hat{w}_{Rnt}}{\lambda_{st}\hat{w}_{Lnt}}\right)^{-(\sigma_s - 1)}}\right)$$
$$= \left(\frac{\hat{w}_{Rnt}}{\lambda_{st}\hat{w}_{Lnt}}\right)^{-(\sigma_s - 1)}\left(\frac{1 + \frac{v_{nst}}{1 - v_{snt}}}{1 + \left(\frac{v_{nst}}{1 - v_{nst}}\right)\left(\frac{\hat{w}_{Rnt}}{\lambda_{st}\hat{w}_{Lnt}}\right)^{-(\sigma_s - 1)}}\right)$$
$$= \frac{\left(\hat{w}_{Rnt}/\left(\lambda_{st}\hat{w}_{Lnt}\right)\right)^{1 - \sigma_s}}{1 + v_{nst}\left\{\left(\hat{w}_{Rnt}/\left(\lambda_{st}\hat{w}_{Lnt}\right)\right)^{1 - \sigma_s} - 1\right\}}.$$

Second, we obtain Ω_{nst}. Since

$$\frac{v_{st}(x)}{x} = \frac{\exp\left(\iota_{st} + \epsilon_{nst}\right)x^{-\sigma_s}}{1 + \exp\left(\iota_{st} + \epsilon_{nst}\right)(x)^{1 - \sigma_s}}$$
$$= \frac{d}{dx}\left[\frac{1}{(1 - \sigma_s)}\ln\left(1 + \exp\left(\iota_{st} + \epsilon_{nst}\right)x^{1 - \sigma_s}\right)\right],$$

we have

$$\begin{aligned}
\int_{\frac{w_{nRt}}{w_{nLt}}}^{\frac{w_{nRt}}{w_{nLt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}} \frac{v_{st}(x)}{x}dx &= \frac{1}{(1-\sigma_s)} \ln\left(\frac{1+\exp(\iota_{st}+\epsilon_{nst})\left(\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\frac{w_{Rnt}}{w_{Lnt}}\right)^{-(\sigma_s-1)}}{1+\exp(\iota_{st}+\epsilon_{nst})\left(\frac{w_{Rnt}}{w_{Lnt}}\right)^{-(\sigma_s-1)}}\right) \\
&= \frac{1}{(\sigma_s-1)} \ln\left(\frac{1+\frac{v_{nst}}{1-v_{nst}}\left(\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)^{-(\sigma_s-1)}}{1+\frac{v_{nst}}{1-v_{nst}}}\right) \\
&= \frac{1}{(\sigma_s-1)} \ln\left(1+v_{nst}\left\{\left(\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)^{(1-\sigma_s)}-1\right\}\right).
\end{aligned}$$

Therefore, we can simplify Ω_{nst} as

$$\begin{aligned}
\Omega_{nst} &= \exp\left(\int_{\frac{w_{nRt}}{w_{nLt}}}^{\frac{w_{nRt}}{w_{nLt}}\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}} \frac{v_{st}(x)}{x}dx\right)\left(\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)^{-v_{nst}} \lambda_{st}{}^{-v_{nst}\hat{v}_{nst}} \\
&= \left[1+v_{nst}\left\{\left(\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)^{(1-\sigma_s)}-1\right\}\right]^{\frac{1}{\sigma_s-1}} \left(\frac{\hat{w}_{Rnt}}{\hat{w}_{Lnt}}\right)^{-v_{nst}} \lambda_{st}{}^{-v_{nst}\hat{v}_{nst}}.
\end{aligned}$$

C Results for All Countries

The main text presents the results only for the selected countries. This section shows the results for all countries in our sample.

C.1 Results shown in Table 3

Table A.2: Robot income shares in low-skilled tasks in 2014

	Industry-level shares			Aggregate share
	median	min	max	
Country	(1)	(2)	(3)	(4)
Argentina	0.00%	0.00%	0.45%	0.01%
Australia	0.02%	0.00%	0.71%	0.02%
Austria	0.09%	0.00%	3.39%	0.10%
Belgium	0.14%	0.00%	5.82%	0.23%
Brazil	0.02%	0.00%	4.05%	0.05%
Bulgaria	0.00%	0.00%	0.51%	0.02%
Canada	0.00%	0.00%	0.74%	0.01%
Chile	0.00%	0.00%	0.04%	0.00%
China	0.01%	0.00%	0.89%	0.04%
Croatia	0.00%	0.00%	0.30%	0.01%
Czech Republic	0.05%	0.00%	5.32%	0.35%
Denmark	0.07%	0.00%	0.71%	0.04%
Estonia	0.02%	0.00%	0.24%	0.01%
Finland	0.14%	0.00%	1.01%	0.07%
France	0.06%	0.00%	4.71%	0.07%
Germany	0.09%	0.00%	3.26%	0.21%
Greece	0.04%	0.00%	0.34%	0.02%
Hong Kong	0.00%	0.00%	0.63%	0.01%
Hungary	0.05%	0.00%	3.01%	0.17%
India	0.00%	0.00%	1.40%	0.02%
Indonesia	0.00%	0.00%	0.33%	0.02%
Ireland	0.00%	0.00%	0.50%	0.01%
Israel	0.01%	0.00%	0.08%	0.01%
Italy	0.13%	0.00%	6.01%	0.22%
Japan	0.17%	0.00%	2.78%	0.29%

Table A.3: Robot cost shares in low-skilled tasks in 2014 (continued)

	Industry-level shares			Aggregate share
	median	min	max	
Country	(1)	(2)	(3)	(4)
Korea	0.04%	0.00%	3.43%	0.31%
Latvia	0.00%	0.00%	0.58%	0.01%
Lithuania	0.00%	0.00%	0.12%	0.00%
Mexico	0.00%	0.00%	0.58%	0.03%
Netherlands	0.06%	0.00%	1.80%	0.08%
New Zealand	0.01%	0.00%	0.35%	0.02%
Norway	0.02%	0.00%	0.21%	0.01%
Philippines	0.00%	0.00%	0.73%	0.01%
Poland	0.02%	0.00%	1.86%	0.07%
Portugal	0.04%	0.00%	2.41%	0.08%
Romania	0.00%	0.00%	0.90%	0.04%
Russia	0.01%	0.00%	1.87%	0.04%
Singapore	0.19%	0.00%	5.20%	0.30%
Slovakia	0.02%	0.00%	4.40%	0.26%
Slovenia	0.15%	0.00%	10.34%	0.24%
South Africa	0.00%	0.00%	1.65%	0.04%
Spain	0.06%	0.00%	3.81%	0.09%
Sweden	0.07%	0.00%	2.04%	0.07%
Switzerland	0.04%	0.00%	1.92%	0.03%
Taiwan	0.12%	0.00%	2.37%	0.17%
Thailand	0.02%	0.00%	5.21%	0.24%
Turkey	0.03%	0.00%	1.92%	0.05%
United Kingdom	0.03%	0.00%	1.47%	0.03%
United States	0.01%	0.00%	1.13%	0.03%
Vietnam	0.00%	0.00%	0.52%	0.03%

C.2 Results shown in Table 5

Table A.4: The impacts of robotics and trade Liberalization: robot price and robot density

	Robot rental / Low-skilled wage		Robot density (per 1000 workers)		
	Robot	Trade	2014	Robot	Trade
Country	(1)	(2)	(3)	(4)	(5)
Argentina	+47.1%	+9.7%	0.066	-68.6%	-21.5%
Australia	+47.1%	+2.6%	0.645	-69.4%	+2.1%
Austria	+47.1%	+14.3%	1.824	-68.6%	-42.1%
Belgium	+47.0%	+42.4%	2.069	-68.2%	-64.5%
Brazil	+47.1%	-2.7%	0.096	-66.8%	+9.0%
Bulgaria	+47.1%	+9.5%	0.044	-69.3%	-11.2%
Canada	+47.1%	+12.8%	0.417	-68.3%	-37.8%
Chile	+47.1%	+9.8%	0.007	-67.8%	-23.4%
China	+47.1%	+5.0%	0.221	-69.0%	-7.3%
Croatia	+47.1%	+2.5%	0.049	-69.3%	-4.4%
Czech Republic	+46.9%	+91.9%	1.660	-67.0%	-76.6%
Denmark	+47.1%	+7.8%	1.882	-72.9%	-11.1%
Estonia	+47.1%	+26.9%	0.087	-69.3%	-50.7%
European Union	+47.0%	+26.3%	2.036	-68.6%	-21.3%
Finland	+47.1%	-6.0%	1.965	-71.2%	+12.4%
France	+47.1%	+4.8%	1.419	-67.9%	-0.9%
Germany	+47.0%	+11.4%	4.793	-68.3%	-29.1%
Greece	+47.1%	+11.6%	0.079	-61.2%	-18.7%
Hong Kong	+47.1%	-49.3%	0.183	-66.1%	+465.6%
Hungary	+47.0%	+48.0%	0.924	-67.3%	-69.7%
India	+47.1%	+13.5%	0.022	-67.0%	-25.1%
Indonesia	+47.1%	-15.8%	0.039	-65.8%	+51.2%
Ireland	+47.1%	+1.8%	0.232	-68.5%	-17.0%
Israel	+47.1%	+7.4%	0.201	-68.8%	-19.6%
Italy	+47.0%	+1.7%	3.174	-69.3%	-1.0%
Japan	+47.1%	+2.2%	8.386	-69.5%	-8.3%

Note: Robot density is the number of industrial robots per 1000 workers (including both high-skilled and low-skilled workers). The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

Table A.5: The impacts of robotics and trade Liberalization: robot price and robot density (continued)

	Robot rental/Low-skilled wage		Robot density (per 1000 workers)		
	Robot	Trade	2014	Robot	Trade
Country	(1)	(2)	(3)	(4)	(5)
Korea	+47.1%	+8.2%	6.331	-69.8%	-22.0%
Latvia	+47.1%	+96.1%	0.014	-68.7%	-77.5%
Lithuania	+47.1%	+75.3%	0.022	-66.6%	-68.4%
Mexico	+47.0%	+15.7%	0.173	-67.0%	-48.5%
Netherlands	+47.1%	+5.0%	0.990	-71.1%	+24.4%
New Zealand	+47.1%	+5.7%	0.269	-69.9%	-14.4%
Norway	+47.1%	-0.2%	0.460	-73.5%	-2.0%
Philippines	+47.1%	-13.0%	0.014	-65.1%	+36.7%
Poland	+47.0%	+33.0%	0.345	-67.6%	-54.7%
Portugal	+47.1%	+12.9%	0.627	-69.2%	-33.5%
Romania	+47.1%	+44.6%	0.137	-66.8%	-57.6%
Russia	+47.1%	+4.3%	0.175	-68.4%	+2.0%
Singapore	+46.9%	-63.5%	2.759	-70.4%	+4314.5%
Slovakia	+47.0%	+77.9%	1.560	-66.5%	-63.0%
Slovenia	+47.0%	+27.8%	1.642	-66.8%	-61.7%
South Africa	+47.1%	+15.5%	0.186	-67.5%	-21.1%
Spain	+47.1%	+7.6%	1.732	-68.4%	-27.4%
Sweden	+47.1%	-2.3%	2.604	-70.5%	+12.4%
Switzerland	+47.1%	+9.5%	1.449	-70.4%	-30.0%
Taiwan	+47.1%	+3.3%	3.298	-71.7%	-16.4%
Thailand	+47.1%	-21.0%	0.521	-66.3%	+10.7%
Turkey	+47.1%	+23.5%	0.212	-68.7%	-41.7%
United Kingdom	+47.0%	+5.1%	0.682	-67.7%	-15.3%
United States	+47.1%	-3.0%	1.525	-68.6%	+12.5%
Vietnam	+47.1%	+19.9%	0.031	-65.6%	-7.7%
World	+47.1%	+13.0%	0.740	-69.1%	+13.1%

Note: Robot density is the number of industrial robots per 1000 workers (including both high-skilled and low-skilled workers). The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

C.3 Results shown in Table 6

Table A.6: The impacts of robotics and globalization from 1993 to 2014: wages

	Real wage for low-skilled		Real wage for high-skilled		Skill wage premium	
	Robot	Trade	Robot	Trade	Robot	Trade
Country	(1)	(2)	(3)	(4)	(5)	(6)
Argentina	-0.00%	-2.90%	-0.01%	-2.08%	-0.01%	+0.84%
Australia	-0.00%	-0.17%	-0.02%	-0.15%	-0.01%	+0.01%
Austria	-0.00%	-9.76%	-0.05%	-9.70%	-0.05%	+0.06%
Belgium	+0.05%	-23.46%	-0.07%	-22.72%	-0.12%	+0.97%
Brazil	+0.00%	-1.82%	-0.02%	-0.78%	-0.03%	+1.06%
Bulgaria	-0.02%	-4.76%	-0.03%	-2.19%	-0.00%	+2.70%
Canada	-0.00%	-4.34%	-0.01%	-3.94%	-0.01%	+0.42%
Chile	-0.01%	-4.29%	-0.01%	-3.30%	+0.00%	+1.04%
China	-0.01%	-4.96%	-0.03%	-5.37%	-0.02%	-0.43%
Croatia	-0.00%	+0.54%	-0.01%	+0.79%	-0.00%	+0.25%
Czech Republic	+0.08%	-34.44%	-0.09%	-34.07%	-0.17%	+0.56%
Denmark	+0.00%	-3.73%	-0.02%	-2.64%	-0.02%	+1.13%
Estonia	-0.01%	-9.04%	-0.01%	-8.12%	-0.01%	+1.01%
European Union	+0.01%	-10.56%	-0.04%	-9.80%	-0.05%	+1.02%
Finland	+0.01%	+0.48%	-0.04%	+0.73%	-0.04%	+0.26%
France	+0.01%	-2.63%	-0.03%	-2.43%	-0.04%	+0.20%
Germany	+0.03%	-5.89%	-0.07%	-5.00%	-0.10%	+0.95%
Greece	-0.00%	-0.12%	-0.01%	-0.49%	-0.01%	-0.37%
Hong Kong	-0.00%	+59.74%	-0.01%	+65.01%	-0.01%	+3.30%
Hungary	+0.03%	-18.47%	-0.05%	-17.91%	-0.08%	+0.70%
India	-0.00%	-6.37%	-0.01%	-2.37%	-0.01%	+4.28%
Indonesia	-0.01%	+0.64%	-0.02%	+0.64%	-0.01%	-0.00%
Ireland	-0.00%	+0.14%	-0.01%	+0.10%	-0.01%	-0.04%
Israel	-0.01%	-2.72%	-0.01%	-1.47%	+0.00%	+1.29%
Italy	+0.03%	-1.09%	-0.08%	-1.33%	-0.11%	-0.25%
Japan	-0.01%	-2.14%	-0.11%	-1.50%	-0.10%	+0.66%

Note: The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

Table A.7: The impacts of robotics and globalization from 1993 to 2014: wages (continued)

	Real wage for low-skilled		Real wage for high-skilled		Skill wage premium	
	Robot	Trade	Robot	Trade	Robot	Trade
Country	(1)	(2)	(3)	(4)	(5)	(6)
Korea	+0.00%	-4.59%	-0.16%	-4.88%	-0.17%	-0.30%
Latvia	-0.01%	-35.06%	-0.01%	-32.25%	-0.00%	+4.34%
Lithuania	-0.01%	-28.32%	-0.01%	-22.80%	+0.00%	+7.71%
Mexico	+0.01%	-8.31%	-0.01%	-7.65%	-0.02%	+0.72%
Netherlands	+0.00%	+1.85%	-0.01%	+0.98%	-0.02%	-0.85%
New Zealand	-0.00%	-1.82%	-0.02%	-1.21%	-0.01%	+0.62%
Norway	-0.00%	-1.01%	-0.01%	-1.08%	-0.01%	-0.07%
Philippines	-0.01%	+2.62%	-0.01%	+3.23%	-0.00%	+0.60%
Poland	+0.01%	-14.31%	-0.03%	-13.60%	-0.03%	+0.83%
Portugal	-0.00%	-6.94%	-0.03%	-6.67%	-0.03%	+0.29%
Romania	-0.00%	-18.39%	-0.02%	-16.82%	-0.02%	+1.92%
Russia	+0.00%	+0.25%	-0.02%	-0.37%	-0.02%	-0.62%
Singapore	+0.11%	+64.63%	-0.06%	+86.31%	-0.18%	+13.17%
Slovakia	+0.06%	-30.77%	-0.06%	-28.25%	-0.12%	+3.64%
Slovenia	+0.05%	-9.92%	-0.08%	-10.58%	-0.12%	-0.73%
South Africa	-0.00%	-4.28%	-0.02%	-3.73%	-0.02%	+0.57%
Spain	+0.01%	-4.23%	-0.04%	-4.05%	-0.05%	+0.19%
Sweden	-0.00%	-1.14%	-0.04%	-1.03%	-0.04%	+0.11%
Switzerland	-0.00%	-6.95%	-0.02%	-6.31%	-0.01%	+0.68%
Taiwan	-0.01%	-0.22%	-0.10%	-0.71%	-0.10%	-0.48%
Thailand	+0.00%	+7.28%	-0.11%	+9.99%	-0.11%	+2.53%
Turkey	-0.00%	-11.54%	-0.03%	-10.99%	-0.03%	+0.61%
United Kingdom	+0.01%	-1.29%	-0.01%	-1.31%	-0.02%	-0.02%
United States	+0.00%	-0.47%	-0.02%	-0.74%	-0.02%	-0.27%
Vietnam	-0.02%	-12.97%	-0.03%	-11.06%	-0.01%	+2.20%
World	+0.01%	-4.15%	-0.04%	-2.92%	-0.04%	+1.16%

Note: The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

C.4 Results shown in Table 7

Table A.8: The impacts of robotics and globalization from 1993 to 2014: robot-worker replacement

	The most robot installing industry			
	Industry name	Robot change	Change in low-skilled labor	
			Robot	Trade
Country	(1)	(2)	(3)	(4)
Argentina	Automotive	-546	926	-8,592
Australia	Food and beverages	-1,897	215	3,250
Austria	Automotive	-2,071	421	-7,863
Belgium	Automotive	-4,510	1,409	-18,628
Brazil	Automotive	-3,738	10,818	15,155
Bulgaria	Metal	-41	83	-8,722
Canada	Automotive	-3,811	772	-47,648
Chile	Food and beverages	-11	5	-17,749
China	Automotive	-50,933	65,934	1,752,039
Croatia	Metal	-20	4	-6,244
Czech Republic	Automotive	-4,834	3,244	-36,900
Denmark	Metal	-1,455	26	625
Estonia	Plastic and chemical products	-14	4	873
European Union	Automotive	-159,652	33,857	-290,725
Finland	Metal	-1,138	122	-3,772
France	Automotive	-13,150	2,625	20,174
Germany	Automotive	-85,275	11,362	-149,281
Greece	Plastic and chemical products	-33	48	2,777
Hong Kong	Food and beverages	-9	-4	-13,023
Hungary	Automotive	-1,825	1,220	-57,080
India	Automotive	-5,394	26,952	-138,858
Indonesia	Plastic and chemical products	-1,629	1,488	600,476
Ireland	Plastic and chemical products	-149	23	2,165
Israel	Plastic and chemical products	-241	16	-18,753
Italy	Automotive	-15,220	3,825	6,494
Japan	Electrical, electronics, and machinery	-130,283	10,572	-526,303

Note: The most robot-installing industry is an industry with the largest increase in robot stocks from the counterfactual equilibrium (where both robot and trade costs are set at their 1993 levels) to the 2014 equilibrium. The robot change is the change in the number of industrial robots in the most robot-installing industry. Columns (3) and (4) show the effects of changes in robot technology and trade costs on the number of low-skilled workers in the most robot-installing industry. The values for the European Union and the World are the total net values of EU countries and all countries in the sample, respectively.

Table A.9: The impacts of robotics and globalization from 1993 to 2014: robot-worker replacement (continued)

	The most robot installing industry			
	Industry name	Robot change	Change in low-skilled labor: Robot	Change in low-skilled labor: Trade
Country	(1)	(2)	(3)	(4)
Korea	Electrical, electronics, and machinery	-68,512	8,872	-169,508
Latvia	Food and beverages	-5	-1	-1,979
Lithuania	Plastic and chemical products	-9	15	-14,607
Mexico	Automotive	-5,453	8,264	-652,539
Netherlands	Metal	-2,055	241	-35,279
New Zealand	Food and beverages	-256	44	-20,509
Norway	Metal	-375	20	-2,084
Philippines	Plastic and chemical products	-296	1,443	37,541
Poland	Automotive	-2,428	2,269	-75,904
Portugal	Automotive	-1,063	446	-11,745
Romania	Automotive	-638	1,584	-53,230
Russia	Automotive	-3,531	4,167	80,596
Singapore	Plastic and chemical products	-482	307	-12,483
Slovakia	Automotive	-2,640	1,667	8,352
Slovenia	Automotive	-696	278	-3,315
South Africa	Automotive	-1,566	2,010	9,863
Spain	Automotive	-13,821	2,373	-38,880
Sweden	Metal	-3,356	225	-2,018
Switzerland	Metal	-1,906	85	-61,638
Taiwan	Electrical, electronics, and machinery	-21,346	2,989	-215,518
Thailand	Automotive	-6,972	17,055	-256,422
Turkey	Automotive	-2,133	2,859	-52,371
United Kingdom	Automotive	-9,397	1,667	-18,685
United States	Automotive	-73,910	7,147	127,833
Vietnam	Plastic and chemical products	-1,031	-173	899,010
World	Automotive	-488,763	213,092	504,859

Note: The most robot-installing industry is an industry with the largest increase in robot stocks from the counterfactual equilibrium (where both robot and trade costs are set at their 1993 levels) to the 2014 equilibrium. The robot change is the change in the number of industrial robots in the most robot-installing industry. Columns (3) and (4) show the effects of changes in robot technology and trade costs on the number of low-skilled workers in the most robot-installing industry. The values for the European Union and the World are the total net values of EU countries and all countries in the sample, respectively.

C.5 Results shown in Table 8

Table A.10: Tenfold increases in robot productivity: robot usage

	Robot task share (v_{nst}) in the most robot installing industry			Country-level robot density (per 1000 workers)	
	IFR	2014	CF	2014	CF
Country	(1)	(2)	(3)	(4)	(5)
Argentina	11	0.004	0.029	0.07	0.58
Australia	3	0.003	0.040	0.64	6.73
Austria	9	0.007	0.092	1.82	17.00
Belgium	11	0.058	0.294	2.07	16.95
Brazil	11	0.040	0.221	0.10	0.67
Bulgaria	9	0.002	0.035	0.04	0.46
Canada	11	0.007	0.048	0.42	3.44
Chile	3	0.000	0.001	0.01	0.08
China	10	0.001	0.012	0.22	2.03
Croatia	9	0.001	0.020	0.05	0.47
Czech Republic	11	0.053	0.274	1.66	11.75
Denmark	9	0.007	0.098	1.88	36.51
Estonia	9	0.001	0.008	0.09	0.94
European Union	11	0.027	0.145	2.04	19.60
Finland	9	0.009	0.125	1.97	24.37
France	11	0.047	0.250	1.42	11.73
Germany	11	0.033	0.186	4.79	45.53
Greece	3	0.000	0.007	0.08	0.61
Hong Kong	7	0.006	0.036	0.18	1.34
Hungary	11	0.030	0.173	0.92	6.90
India	11	0.014	0.087	0.02	0.16
Indonesia	7	0.003	0.015	0.04	0.26
Ireland	10	0.001	0.013	0.23	2.03
Israel	7	0.001	0.003	0.20	2.07
Italy	9	0.013	0.173	3.17	33.10
Japan	10	0.010	0.111	8.39	90.93

Note: The most robot-installing industry is an industry with the largest increase in robot stocks from 2014 to the counterfactual equilibrium. Their IFR industry codes are shown in column (1). The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

Table A.11: Tenfold increases in robot productivity: robot usage (continued)

	Robot task share (v_{nst}) in the most robot installing industry			Country-level robot density (per 1000 workers)	
	IFR	2014	CF	2014	CF
Country	(1)	(2)	(3)	(4)	(5)
Korea	10	0.018	0.181	6.33	64.43
Latvia	3	0.001	0.008	0.01	0.13
Lithuania	9	0.000	0.006	0.02	0.17
Mexico	11	0.006	0.038	0.17	1.21
Netherlands	9	0.006	0.087	0.99	11.73
New Zealand	3	0.002	0.022	0.27	2.85
Norway	5	0.002	0.137	0.46	8.93
Philippines	7	0.007	0.043	0.01	0.09
Poland	11	0.019	0.113	0.35	2.88
Portugal	9	0.007	0.100	0.63	6.65
Romania	11	0.009	0.058	0.14	0.96
Russia	9	0.002	0.035	0.18	1.52
Singapore	10	0.052	0.388	2.76	23.04
Slovakia	11	0.044	0.236	1.56	10.57
Slovenia	9	0.008	0.113	1.64	12.07
South Africa	11	0.016	0.101	0.19	1.40
Spain	11	0.038	0.211	1.73	16.40
Sweden	9	0.011	0.150	2.60	30.56
Switzerland	9	0.003	0.037	1.45	16.73
Taiwan	10	0.009	0.101	3.30	40.98
Thailand	11	0.052	0.273	0.52	3.68
Turkey	9	0.005	0.076	0.21	1.98
United Kingdom	11	0.015	0.091	0.68	6.07
United States	11	0.011	0.072	1.52	13.46
Vietnam	7	0.005	0.031	0.03	0.21
World	10	0.002	0.021	0.74	7.31

Note: The most robot-installing industry is an industry with the largest increase in robot stocks from 2014 to the counterfactual equilibrium. Their IFR industry codes are shown in column (1). The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

C.6 Results shown in Table 9

Table A.12: Ten-fold increases in robot productivity: labor market impacts

Country	Real wage for low-skilled (1)	Real wage for high-skilled (2)	Skill wage premium (3)	Aggregate low-skilled labor relocation (4)
Argentina	+0.13%	+0.21%	+0.08%	0.17%
Australia	+0.24%	+0.49%	+0.25%	0.26%
Austria	+0.57%	+1.42%	+0.84%	0.58%
Belgium	+0.36%	+1.97%	+1.61%	1.30%
Brazil	+0.28%	+0.56%	+0.27%	0.28%
Bulgaria	+0.55%	+0.53%	-0.02%	0.51%
Canada	+0.18%	+0.31%	+0.12%	0.28%
Chile	+0.28%	+0.19%	-0.09%	0.20%
China	+0.55%	+0.90%	+0.35%	0.32%
Croatia	+0.21%	+0.30%	+0.09%	0.22%
Czech Republic	+0.07%	+2.13%	+2.05%	1.37%
Denmark	+0.44%	+0.86%	+0.42%	0.63%
Estonia	+0.07%	+0.25%	+0.17%	0.42%
European Union	+0.34%	+1.09%	+0.74%	0.65%
Finland	+0.33%	+1.22%	+0.89%	0.57%
France	+0.33%	+0.83%	+0.50%	0.44%
Germany	+0.60%	+2.04%	+1.44%	0.94%
Greece	+0.17%	+0.43%	+0.26%	0.29%
Hong Kong	+0.17%	+0.29%	+0.12%	0.33%
Hungary	+0.31%	+1.33%	+1.02%	0.64%
India	+0.17%	+0.07%	-0.10%	0.19%
Indonesia	+0.30%	+0.47%	+0.17%	0.30%
Ireland	+0.13%	+0.09%	-0.04%	0.19%
Israel	+0.17%	+0.19%	+0.02%	0.40%
Italy	+0.84%	+2.58%	+1.72%	0.83%
Japan	+2.12%	+3.30%	+1.16%	1.01%

Note: The skill wage premium is the ratio of the high-skilled wage rate to low-skilled wage rate. The aggregate low-skilled labor relocation is calculated by $\sum_{s=1}^{S} \left| L_{i2014}^{s\prime} - L_{i2014}^{s} \right| / 2L_{i2014}^{s}$ and shown as a percentage, where L_{i2014}^{s} and $L_{i2014}^{s\prime}$ denote the actual and counterfactual numbers of low-skilled workers employed in industry s in 2014, respectively. We divide the sum of changes in employment over the industries by 2 to avoid double counting. Note: The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively..

Table A.13: Tenfold increases in robot productivity: labor market impacts (continued)

Country	Real wage for low-skilled (1)	Real wage for high-skilled (2)	Skill wage premium (3)	Aggregate low-skilled labor relocation (4)
Argentina	+1.74%	+4.41%	+2.62%	1.38%
Australia	-0.26%	-0.06%	+0.21%	0.71%
Austria	+0.32%	+0.18%	-0.13%	0.46%
Belgium	+0.06%	+0.40%	+0.34%	0.42%
Brazil	+0.58%	+0.86%	+0.28%	0.57%
Bulgaria	+0.19%	+0.44%	+0.25%	0.33%
Canada	+0.19%	+0.42%	+0.24%	0.22%
Chile	+0.32%	+0.23%	-0.09%	0.21%
China	+0.32%	+0.85%	+0.53%	0.54%
Croatia	+0.76%	+1.19%	+0.43%	0.46%
Czech Republic	+0.26%	+0.51%	+0.25%	0.58%
Denmark	-0.22%	+0.44%	+0.66%	0.67%
Estonia	-1.06%	+1.38%	+2.46%	1.24%
European Union	+0.06%	+1.51%	+1.45%	1.36%
Finland	+0.36%	+1.96%	+1.59%	0.94%
France	+0.30%	+0.55%	+0.25%	0.39%
Germany	+0.42%	+1.19%	+0.77%	0.37%
Greece	+0.51%	+1.35%	+0.84%	0.55%
Hong Kong	+0.38%	+0.66%	+0.28%	0.19%
Hungary	+1.51%	+3.18%	+1.65%	0.97%
India	+1.22%	+2.22%	+0.99%	0.59%
Indonesia	+0.60%	+1.04%	+0.44%	0.30%
Ireland	+0.09%	+0.34%	+0.25%	0.23%
Israel	+0.19%	+0.47%	+0.28%	0.20%
Italy	+0.86%	+0.96%	+0.09%	0.39%
Japan	+0.39%	+0.99%	+0.60%	0.54%

Note: The skill wage premium is the ratio of the high-skilled wage rate to low-skilled wage rate. The aggregate low-skilled labor relocation is calculated by $\sum_{s=1}^{S} |L_{i2014}^{s\prime} - L_{i2014}^{s}| / 2L_{i2014}^{s}$ and shown as a percentage, where L_{i2014}^{s} and $L_{i2014}^{s\prime}$ denote the actual and counterfactual numbers of low-skilled workers employed in industry s in 2014, respectively. We divide the sum of changes in employment over the industries by 2 to avoid double counting. Note: The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

C.7 Results shown in Table 11

Table A.14: Tenfold increases in AI productivity: AI shares

	AI task share in the most AI subscribing industry		
	IFR	2014	CF
Country	(1)	(2)	(3)
Argentina	17	0.0002	0.0004
Australia	14	0.0012	0.0018
Austria	14	0.0035	0.0054
Belgium	14	0.0082	0.0128
Brazil	14	0.0018	0.0028
Bulgaria	14	0.0035	0.0055
Canada	14	0.0010	0.0016
Chile	14	0.0005	0.0008
China	14	0.0007	0.0011
Croatia	14	0.0012	0.0019
Czech Republic	14	0.0059	0.0092
Denmark	17	0.0011	0.0019
Estonia	14	0.0024	0.0038
European Union	14	0.0032	0.0049
Finland	14	0.0026	0.0041
France	14	0.0025	0.0038
Germany	14	0.0031	0.0048
Greece	14	0.0011	0.0017
Hong Kong	14	0.0004	0.0006
Hungary	14	0.0028	0.0043
India	17	0.0003	0.0005
Indonesia	14	0.0006	0.0009
Ireland	17	0.0028	0.0050
Israel	17	0.0003	0.0006
Italy	14	0.0033	0.0052
Japan	14	0.0020	0.0032

Note: The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

Table A.15: Tenfold increases in AI productivity: AI shares (continued)

	AI task share in the most AI subscribing industry		
	IFR	2014	CF
Country	(1)	(2)	(3)
Korea	14	0.0011	0.0017
Latvia	14	0.0055	0.0085
Lithuania	14	0.0014	0.0022
Mexico	14	0.0002	0.0002
Netherlands	14	0.0065	0.0101
New Zealand	14	0.0007	0.0011
Norway	14	0.0011	0.0018
Philippines	14	0.0003	0.0005
Poland	14	0.0021	0.0032
Portugal	14	0.0021	0.0033
Romania	17	0.0020	0.0035
Russia	14	0.0003	0.0005
Singapore	14	0.0007	0.0011
Slovakia	14	0.0043	0.0067
Slovenia	14	0.0022	0.0035
South Africa	14	0.0007	0.0011
Spain	14	0.0014	0.0023
Sweden	14	0.0034	0.0053
Switzerland	14	0.0009	0.0014
Taiwan	14	0.0005	0.0008
Thailand	14	0.0004	0.0006
Turkey	14	0.0008	0.0013
United Kingdom	14	0.0025	0.0039
United States	14	0.0007	0.0011
Vietnam	14	0.0005	0.0007
World	14	0.0020	0.0031

Note: The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

C.8 Results shown in Table 12

Table A.16: Tenfold increases in AI productivity: labor market impacts

	Real wage for low-skilled	Real wage for high-skilled	Skill wage premium
Country	(1)	(2)	(3)
Argentina	+0.07%	-0.05%	-0.12%
Australia	+0.29%	+0.18%	-0.11%
Austria	+0.64%	+0.49%	-0.15%
Belgium	+1.23%	+0.90%	-0.32%
Brazil	+0.35%	+0.21%	-0.14%
Bulgaria	+0.49%	+0.32%	-0.16%
Canada	+0.24%	+0.13%	-0.11%
Chile	+0.13%	+0.04%	-0.09%
China	+0.07%	-0.04%	-0.11%
Croatia	+0.20%	+0.06%	-0.13%
Czech Republic	+0.80%	+0.64%	-0.16%
Denmark	+0.37%	+0.19%	-0.17%
Estonia	+0.41%	+0.28%	-0.14%
European Union	+0.58%	+0.40%	-0.17%
Finland	+0.50%	+0.36%	-0.15%
France	+0.49%	+0.35%	-0.14%
Germany	+0.56%	+0.45%	-0.11%
Greece	+0.23%	+0.09%	-0.14%
Hong Kong	+0.03%	-0.08%	-0.11%
Hungary	+0.55%	+0.44%	-0.11%
India	+0.07%	-0.04%	-0.11%
Indonesia	+0.07%	-0.08%	-0.15%
Ireland	+0.73%	+0.44%	-0.29%
Israel	+0.11%	-0.05%	-0.16%
Italy	+0.64%	+0.51%	-0.13%
Japan	+0.37%	+0.26%	-0.11%

Note: The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

Table A.17: Ten-fold increases in AI productivity: labor market impacts (continued)

Country	Real wage for low-skilled (1)	Real wage for high-skilled (2)	Skill wage premium (3)
Korea	+0.14%	+0.02%	-0.12%
Latvia	+0.89%	+0.69%	-0.19%
Lithuania	+0.25%	+0.07%	-0.18%
Mexico	+0.07%	-0.03%	-0.10%
Netherlands	+1.24%	+0.95%	-0.29%
New Zealand	+0.19%	+0.07%	-0.12%
Norway	+0.27%	+0.15%	-0.12%
Philippines	+0.07%	-0.06%	-0.13%
Poland	+0.38%	+0.29%	-0.09%
Portugal	+0.41%	+0.27%	-0.15%
Romania	+0.43%	+0.32%	-0.11%
Russia	+0.10%	-0.00%	-0.11%
Singapore	+0.17%	+0.04%	-0.12%
Slovakia	+0.75%	+0.55%	-0.19%
Slovenia	+0.43%	+0.30%	-0.13%
South Africa	+0.18%	+0.07%	-0.11%
Spain	+0.30%	+0.18%	-0.12%
Sweden	+0.59%	+0.40%	-0.20%
Switzerland	+0.23%	+0.11%	-0.13%
Taiwan	+0.10%	-0.01%	-0.11%
Thailand	+0.02%	-0.08%	-0.11%
Turkey	+0.14%	+0.01%	-0.12%
United Kingdom	+0.48%	+0.31%	-0.17%
United States	+0.18%	+0.07%	-0.11%
Vietnam	+0.05%	-0.11%	-0.16%
World	+0.35%	+0.20%	-0.14%

Note: The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

C.9 Tenfold increases in AI and robot productivities: labor market impacts

Tables A.18 and A.19 report the results of a counterfactual analysis where both AI and robot increased their task productivities by tenfold. We see that both low-skilled and high-skilled labor would benefit in almost all countries.

Table A.18: Tenfold increases in AI and robot productivities: labor market impacts

	Real wage for low-skilled	Real wage for high-skilled	Skill wage premium
Country	(1)	(2)	(3)
Argentina	+0.23%	+0.17%	-0.05%
Australia	+0.54%	+0.69%	+0.15%
Austria	+1.20%	+1.85%	+0.64%
Belgium	+1.46%	+2.85%	+1.36%
Brazil	+0.61%	+0.76%	+0.14%
Bulgaria	+1.04%	+1.12%	+0.08%
Canada	+0.42%	+0.48%	+0.06%
Chile	+0.58%	+0.24%	-0.33%
China	+0.60%	+0.94%	+0.34%
Croatia	+0.54%	+0.57%	+0.03%
Czech Republic	+0.95%	+2.62%	+1.66%
Denmark	+0.82%	+0.59%	-0.23%
Estonia	+0.73%	+0.76%	+0.03%
European Union	+0.92%	+1.45%	+0.56%
Finland	+0.81%	+1.44%	+0.63%
France	+0.76%	+1.16%	+0.39%
Germany	+1.12%	+2.32%	+1.19%
Greece	+0.46%	+0.72%	+0.26%
Hong Kong	+0.53%	+0.46%	-0.06%
Hungary	+0.81%	+1.73%	+0.91%
India	+0.23%	+0.31%	+0.08%
Indonesia	+0.38%	+0.43%	+0.05%
Ireland	+0.62%	+0.47%	-0.15%
Israel	+0.25%	+0.24%	-0.01%
Italy	+1.38%	+2.98%	+1.58%
Japan	+2.59%	+3.46%	+0.85%

Note: The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

Table A.19: Tenfold increases in AI and robot productivities: labor market impacts (continued)

Country	Real wage for low-skilled (1)	Real wage for high-skilled (2)	Skill wage premium (3)
Korea	+1.80%	+3.70%	+1.87%
Latvia	+0.97%	+1.51%	+0.54%
Lithuania	+0.71%	+0.77%	+0.06%
Mexico	+0.12%	+0.52%	+0.40%
Netherlands	+1.67%	+1.84%	+0.17%
New Zealand	+0.45%	+0.53%	+0.08%
Norway	+0.42%	+0.63%	+0.21%
Philippines	+0.49%	+0.42%	-0.07%
Poland	+0.69%	+1.27%	+0.58%
Portugal	+1.19%	+1.40%	+0.21%
Romania	+0.67%	+1.23%	+0.56%
Russian Federation	-0.19%	+0.49%	+0.68%
Singapore	-0.13%	+0.64%	+0.77%
Slovakia	+0.79%	+2.07%	+1.27%
Slovenia	+0.77%	+2.02%	+1.24%
South Africa	+0.47%	+0.69%	+0.21%
Spain	+0.69%	+1.21%	+0.53%
Sweden	+1.02%	+1.61%	+0.58%
Switzerland	+0.62%	+0.65%	+0.02%
Taiwan	+1.77%	+2.54%	+0.76%
Thailand	+1.23%	+1.52%	+0.29%
Turkey	+0.74%	+1.08%	+0.34%
United Kingdom	+0.63%	+0.74%	+0.11%
United States	+0.36%	+0.54%	+0.17%
Vietnam	+0.89%	+0.65%	-0.23%
World	+0.76%	+1.14%	+0.40%

Note: The values for the European Union and the World are the mean values of EU countries and all countries in the sample, respectively.

D Alternative Trade Elasticity Estimates

D.1 Subsample Estimation

Following Caliendo and Parro (2015), we investigate the robustness of our trade elasticity estimates by using only subsamples that remove observations with small trade shares. We find that all estimates are stable across subsamples.

Table A.20: Trade Elasticity Estimates with Subsamples

	Full Sample			99% Sample			97.5% Sample		
IFR	θ	SE	n.obs	θ	SE	n.obs	θ	Robust SE	n.obs
1	4.456	(1.341)	15,940	4.500	(1.325)	15,786	4.786	(1.314)	15,544
2	18.685	(5.029)	15,890	18.066	(4.695)	15,770	18.560	(4.512)	15,566
3	8.429	(0.759)	15,952	8.319	(0.743)	15,826	8.153	(0.730)	15,605
4	6.799	(0.721)	15,960	6.405	(0.707)	15,809	6.079	(0.698)	15,582
5	11.535	(1.663)	15,950	10.961	(1.584)	15,888	10.680	(1.567)	15,666
6	17.533	(1.743)	15,948	17.160	(1.711)	15,793	16.621	(1.700)	15,573
7	11.142	(1.087)	15,962	10.993	(1.067)	15,836	10.668	(1.030)	15,651
8	8.913	(1.172)	15,958	8.807	(1.167)	15,836	8.520	(1.157)	15,618
9	14.522	(1.459)	15,962	13.726	(1.355)	15,797	13.246	(1.303)	15,569
10	11.228	(1.212)	15,962	10.670	(1.190)	15,804	10.336	(1.191)	15,616
11	10.582	(0.883)	15,950	10.581	(0.876)	15,820	10.459	(0.865)	15,637
12	9.198	(1.621)	15,934	8.934	(1.612)	15,790	8.821	(1.594)	15,602
13	6.545	(1.017)	15,950	6.257	(1.022)	15,806	6.068	(1.024)	15,581

Note: Standard errors (SE) are clustered at the exporter-importer-year level. All estimates are statistically significant at 1% level.

D.2 Counterfactual Analysis with Trade Elasticity Estimates from Other Studies

D.2.1 Estimates from Other Studies

In Table A.21, we collect trade elasticity estimates at the ISIC 2 digit industry level from previous studies, Caliendo and Parro (CP) (2015, Table 1 column (4)), Shapiro (2016, Table 2 column (4)) and Giri, Yi, and Yilmazkuday (GYY) (2012, Table 2 column(3)). The columns “Mean” and “Max” report the mean and maximum of the three estimates for each industry by these authors. Our estimates tend to be greater than mean estimates, but comparable to the maximum of the three.

Table A.21: Trade Elasticity Estimates from Other Studies

IFR	Our estimates	CP	Shapiro (2016)	GYY	Mean	Max
1	4.46	9.11	3.34	NA	6.22	9.11
2	18.69	13.53	3.45	NA	8.49	13.53
3	8.43	2.62	5.26	3.57	3.82	5.26
4	6.80	8.10	14.25	4.32	8.89	14.25
5	11.55	11.50	5.90	4.32	7.24	11.50
6	17.53	16.52	5.77	2.97	8.42	16.52
7	11.14	2.40	1.55	4.00	2.65	4.00
8	8.92	2.41	8.95	5.14	5.50	8.95
9	14.53	6.99	12.94	7.01	8.98	12.94
10	11.23	1.45	10.84	3.27	5.19	10.84
11	10.58	1.84	6.87	4.47	4.39	6.87
12	9.20	0.39	6.87	4.47	3.91	6.87
13	6.56	3.98	12.76	NA	8.37	12.76
	10.74	6.22	7.60	4.35	6.31	10.26

Note: CP reports trade elasticities from Caliendo and Parro (2015, Table 1 column (4)); Shapiro (2016) reports those from Shapiro (2016, Table 2 column (4)) and GYY reports those from Giri, Yi, and Yilmazkuday (2012, Table 2 column(3)). The columns "Mean" and "Max" report the mean and maximum of these three estimates for each industry.

D.2.2 Robot prices, robot income shares and elasticities of substitution

With the mean estimates of trade elasticities from previous studies in Table A.21, we recalculate robot prices, robot income shares, and elasticities of substitution between robots and low skilled labor. The mean trade elasticity for robots (IFR industry 10) is 5.19, which is much smaller than our estimate of 11.23. As a consequence, the variation in the derived robot prices across countries become greater, as we can infer from (13) in the main text. Figure A.1, which compares estimated robot prices with the unit prices from data, shows this greater variation in the estimated robot prices, compared with the variation shown in Figure 3 in the main text. Table A.22 reports robot income shares. Even though the estimated robot prices are greater in some countries, the aggregate income shares of robots are still very small and not very different from the ones that are reported in Table 3 in the main text.

Figure A.1: Estimated and actual robot prices

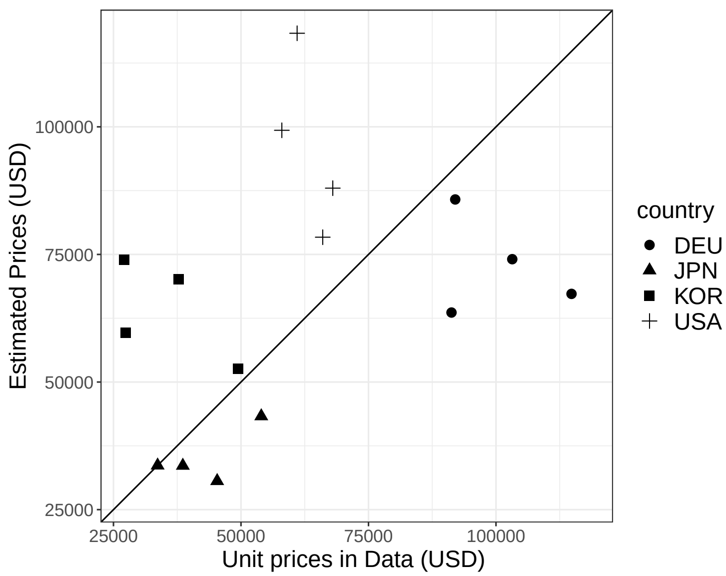

Table A.22: Robot cost shares in low-skilled tasks in 2014

	Industry-level shares			Aggregate
	median	min	max	share
Country	(1)	(2)	(3)	(4)
China	0.01%	0.00%	1.37%	0.06%
Germany	0.14%	0.00%	4.66%	0.31%
India	0.01%	0.00%	2.60%	0.03%
Indonesia	0.00%	0.00%	0.85%	0.06%
Japan	0.17%	0.00%	2.78%	0.29%
Korea	0.05%	0.00%	4.61%	0.42%
Singapore	0.02%	0.00%	0.82%	0.05%
Thailand	0.04%	0.00%	11.03%	0.54%
United States	0.01%	0.00%	2.00%	0.06%

Table A.23 reports estimated elasticities of substitution between robots and low-skilled labor. Since the variation in robot prices become greater, the estimated elasticities of substitution are slightly smaller. The elasticities are estimated smaller than one in industry 14 and industry 16. We replace those elasticities with one in the following counterfactual simulation.

Table A.23: Elasticities of substitution between robots and low-skilled Labor

IFR	Description	σ_s	Robust SE	1st Stage F	n.obs
1	Agriculture, forestry, and fishing	1.551	(0.164)	28.5	118
2	Mining and quarrying	1.037	(0.276)	26.5	82
3	Food and beverages	1.596	(0.128)	37.0	182
4	Textiles	2.243	(0.171)	20.1	120
5	Wood and furniture	2.175	(0.208)	34.0	140
6	Paper	1.375	(0.132)	28.1	133
7	Plastic and chemical products	1.313	(0.113)	38.2	189
8	Glass, ceramics, stone, and mineral products	1.505	(0.124)	40.8	170
9	Metal	1.606	(0.116)	38.4	189
10	Electrical, electronics, and machinery	1.544	(0.145)	30.9	176
11	Automotive	1.367	(0.136)	30.7	175
12	Other vehicles	1.412	(0.130)	43.1	170
13	All other manufacturing branches	1.409	(0.117)	35.8	178
14	All other non-manufacturing branches	0.938	(0.160)	35.3	132
15	Electricity, gas, and water supply	1.445	(0.127)	33.0	99
16	Construction	0.832	(0.151)	30.6	145
17	Education, research, and development	1.276	(0.135)	33.5	175

Note: Standard errors are heteroscedasticity robust standard errors. The first stage F values differ across industries because of the difference in the sample sizes.

D.2.3 Counterfactual Analysis

In order to see how robust the results of our counterfactual analysis in Section 4 is to a choice of trade elasticities, we conduct a counterfactual analysis in section 4.1.2 about the past impacts of robots and globalization with the mean estimates of trade elasticities taken from the other studies, which are shown in Table A.21. We calibrate the change in robot technology as $\hat{\gamma}_{s2014}(v) = \lambda_{s2014} = 0.21$ and $\hat{A}^R_{2014} = \hat{A}^R_{n2014} = 0.71$ ($\lambda_{s2014} = 0.65$ and $\hat{A}^R_{2014} = 0.685$ in our main analysis). Note that with the smaller estimates of the elasticities of substitution, the robot task-productivity should have been much smaller in 1993 to explain the changes in the robot price and robot density in the period of 1993-2014.

With the smaller trade elasticities and elasticities of substitution, changes in prices tend to be greater, to explain the trade data. This can be seen from the comparison of the impacts of robots and trade on the real wage rates depicted in Table A.25 with those shown in Table 6 in the main text. Changes in real wage rates are generally greater in magnitude in the counterfactual analysis with the mean estimates of the three trade elasticities in the other studies than in the analysis with our own estimates. Most importantly, the labor market impact of robots continues to be much smaller than that of globalization.

Counterpart of Table 5

Table A.24: The impacts of robotics and trade Liberalization: robot price and robot density

	Robot rental/Low-skilled wage		Robot density (per 1000 workers)		
	Robot	Trade	2014	Robot	Trade
Country	(1)	(2)	(3)	(4)	(5)
China	+40.9%	-1.2%	0.221	-68.6%	+2.5%
Germany	+40.9%	+21.0%	4.793	-67.2%	-33.4%
India	+40.9%	+19.6%	0.022	-65.2%	-25.7%
Indonesia	+41.0%	-35.2%	0.039	-62.5%	+98.4%
Japan	+41.0%	+2.0%	8.386	-69.3%	-7.3%
Korea	+41.1%	+12.5%	6.331	-70.0%	-24.6%
Thailand	+40.9%	+11.0%	0.521	-69.2%	-17.1%
United States	+40.9%	-43.9%	1.525	-63.6%	+63.4%
World	+40.9%	-8.5%	0.740	-67.9%	+20.3%

Note: Robot density is the number of industrial robots per 1000 workers (including both high-skilled and low-skilled workers). The value of "robot rental/low-skilled wage" in the world is the mean value of the countries in the sample.

Counterpart of Table 6

Table A.25: The impacts of robotics and globalization from 1993 to 2014: wages

	Real wage for low-skilled		Real wage for high-skilled		Skill wage premium	
	Robot	Trade	Robot	Trade	Robot	Trade
Country	(1)	(2)	(3)	(4)	(5)	(6)
China	-0.04%	-7.06%	-0.07%	-7.71%	-0.03%	-0.70%
Germany	+0.02%	-9.52%	-0.14%	-8.65%	-0.15%	+0.97%
India	-0.02%	-8.88%	-0.02%	-4.61%	-0.00%	+4.68%
Indonesia	-0.04%	+1.11%	-0.06%	+1.18%	-0.03%	+0.07%
Japan	-0.03%	-2.80%	-0.15%	-2.10%	-0.11%	+0.72%
Korea	-0.03%	-6.99%	-0.27%	-7.46%	-0.24%	-0.51%
Thailand	-0.02%	-3.13%	-0.05%	-2.54%	-0.03%	+0.61%
United States	-0.03%	+18.70%	-0.28%	+22.22%	-0.25%	+2.96%
World	-0.01%	-0.88%	-0.04%	-1.16%	-0.03%	-0.28%

Note: The values for the World are the mean values of the countries in the sample.

Counterpart of Table 7

Table A.26: The impacts of robotics and globalization from 1993 to 2014: robot-worker replacement

	The most robot installing industry			
	Industry name	Robot change	Change in low-skilled labor	
			Robot	Trade
Country	(1)	(2)	(3)	(4)
China	Automotive	-46,376	97,088	1,687,371
Germany	Automotive	-85,295	16,809	-145,935
India	Automotive	-5,289	47,455	-96,748
Indonesia	Plastic and chemical products	-851	9,933	569,198
Japan	Electrical, electronics, and machinery	-134,045	13,529	-648,124
Korea	Electrical, electronics, and machinery	-70,660	14,217	-207,558
Thailand	Food and beverages	-262	135	-17,827
United States	Automotive	-4,696	35,403	-243,037
World	Automotive	-67,634	11,608	133,899

Note: The most robot-installing industry is an industry with the largest increase in robot stocks from the counterfactual equilibrium (where both robot and trade costs are set at their 1993 levels) to the 2014 equilibrium. The robot change is the change in the number of industrial robots in the most robot-installing industry. Columns (3) and (4) show the effects of changes in robot technology and trade costs on the number of low-skilled workers in the most robot-installing industry.

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