Robots and Wage Polarization:

The Effects of Robot Capital across Occupations

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Motivation

- Robotization has changed production environments and affected workers
  - Imports of industrial robots are growing at 12% per year in the world
  - Robots replace workers to different degrees in different occupations
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  - Substitutability of robots for workers governs the change of labor demand
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  - Substitutability of robots for workers governs the change of labor demand
  - International trade in robots and their capital accumulation affect the policy efficacy
- I study the distributional effect of robotization, considering these points

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- Provides new data on robot prices and stylized facts
  - Combining the price and quantity suggests robot-labor substitutability
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  - I develop a model-implied optimal instrumental variable (MOIV)
- Counterfactually examines the effect of robotization
  - Occupational wage growths caused by robotization
  - The effect of robot taxes on aggregate real income

Contributions

- Introducing the robot price data
    - Robot prices are observed by “application,” or the specified task for robots
    - I match the codes of robot application and occupations
    - I then obtain the measure of robot cost reduction, called “Japan robot shock”

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- Elaborating on “robotization,” which comprise two shocks:
  - The reduction of the cost of robots
  - Automation: Robots can perform a wider range of tasks (Acemoglu Restrepo ’20)
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- Showing that its real-wage effect is negatively related to the EoS
- Using the MOIV to estimate the model
  - The correlation of robotization shocks make the identification challenging
  - I derive the moment conditions based on the model's structural residual
  - The MOIV increases the estimator precision

Main Findings

- The data show two stylized facts about the Japan robot shock
  - Robot cost declines and exhibit sizable occupational dispersion
  - A 10% drop of the robot costs decreases wage by 1.2% by occupation
  - This pattern is especially seen in some routine occupations (production and material-moving)

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  - This pattern is especially seen in some routine occupations (production and material-moving)
- The robot-labor EoS is heterogeneous across occupations:
  - ≈ 3 in production and material-moving,
    - Higher than assumed in the robot literature (Acemoglu Restrepo ’20; Humlum ’19)
    - Higher than general capital-labor EoS (Chirinko ’08; Karabarbounis Neiman ’14)
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  - much lower in other occupations (e.g., manual, abstract), close to 1
- The counterfactual reveals low wage growths for middle-wage occupations
  - Robots are in the middle-wage distribution, and the robot-labor EoS is high in these occupations
  - This explains 6.4% of the rise of 90-50th percentile wage ratio

Related Literature

- Labor market effects of automation
    - Robots: Dauth et al. ('18); Graetz Michaels ('18); Dinlersoz ('18); Bessen et al. ('19); Koch Manuylof Smolka ('19); Humlum ('19); Acemoglu Restrepo ('20); Acemoglu Lelarge Restrepo ('20); Bonfiglioli et al. ('20); Dixon Hong Wu ('20)
    - Other automation: Doms et al. ('97); Zeira ('98); Autor et al. ('03); Autor Dorn ('13); Agrawal et al. ('19); Eeckhout et al. ('20); Jaimovich et al. ('20)

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- Estimating capital-labor substitution: Arrow et al. ('61); Chirinko ('08); Karabarbounis Neiman ('14); Oberfield Raval ('20); ...

  $\rightarrow$ I find high EoS for robots (special capital goods) in some occupations

Roadmap

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- Other conventional data: IPUMS (US labor), BACI and WIOD (trade)

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  - Both are the set of tasks where each factor of production is applied. E.g.:

O*NET SOC Code	Occupation Title		Robot Application
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- Formally, I allocate a-level measure $x^R_{i,a,t}$ to the o level:

$$x^R_{i,o,t} = \sum_a \omega_{oa} x^R_{i,a,t} \text{ where } \omega_{oa} \equiv \frac{m_{oa}}{\sum_a m_{oa}},$$

  - m_{oa} is the match score, used as the weight
  - x is either quantity q or sales pq

Measuring the Japan Robot Shock

- Take average price $p^R_{i,o,t} = (pq)^R_{i,o,t} / q^R_{i,o,t}$. Issues of average prices:
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  - Prices are also affected by non-cost components (e.g., demand shock) $e_{i,o,t}$
    $\rightarrow$ Use other countries' robot prices
    - An underlying assumption: $e_{i,o,t}$ are independent across i (cf. Hausman '96)

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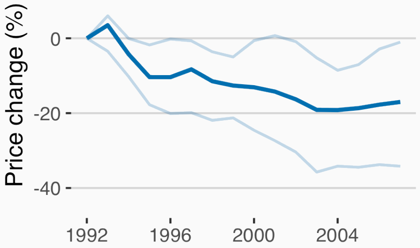
- Compute Japan robot shock (JRS) $\psi^J_{o,t}$ in the US by

$$\ln\left(p^R_{i,o,t}\right) - \ln\left(p^R_{i,o,t_0}\right) = \psi_{i,t} + \psi^J_{o,t} + e_{i,o,t}, \; i \neq USA$$

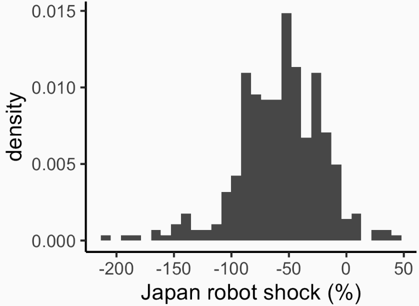
  - I drop the US to remove the effect of the US demand shock (Acemoglu Restrepo, '20)

Fact 1: Trend and Variation of the Japan Robot Shock

Stock trends



Robot Price in US, $p^R_{US,o,t}$



15-year Robot Cost Shock, $\psi^J_{o,2007}$

Note: The author's calculation based on JARA and O*NET. The left shows the trend of robot price in the US. The dark line shows the median price and two light lines are the 10th and 90th percentiles by occupations. Three-year moving averages are taken to smooth noise.

- The median JRS is 5.0% annually over 1992-2007
- JRS heterogeneity: $[2.7\%, 11.4\%]$ for $[10, 90]$-th percentile

Fact 2: The Japan Robot Shock Regression Quality Pretrend

$$\Delta \ln \left(Y_o \right) = \alpha_0 + \alpha_1 \times \left(-\psi^J_{o,2007} \right) + \alpha_2 \times IPW_{o,2007} + \boldsymbol{X}_o \cdot \boldsymbol{\alpha} + \varepsilon_o,$$

$IPW_{o,2007}$ is the China trade shock at the occupation level (Autor Dorn Hanson, '13)

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VARIABLES	(1) $\Delta \ln(w)$	(2) $\Delta \ln(w)$	(3) $\Delta \ln(L)$	(4) $\Delta \ln(L)$
Japan Robot Shock, $-\psi^J$	-0.116**	-0.118**	-0.358**	-0.371***
	(0.0570)	(0.0569)	(0.148)	(0.142)
Exposure to China Trade		-0.582		-3.868**
		(0.763)		(1.495)
Observations	324	324	324	324
R-squared	0.275	0.279	0.074	0.096
Demographic controls	✓	✓	✓	✓

Note: Observations are 4-digit level occupations, and the sample is all occupations that existed throughout 1970 and 2007. ψ^J is the Japan robot shock and IPW stands for the occupation-level China import penetration measure (in USD 1,000). All time differences (Δ) are taken with a long difference between 1990 and 2007. Demographic controls are shares of female, college-graduates, ages, and foreign-born in 1990 and their changes from 1990-2007. Robust standard errors are in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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- I focus on novel elements in the following:
  - Labor and robots perform occupation o with EoS θ_o
    - This production function is called “occupation performance function”
    - The EoS negatively affects the size of the effect of automation on real wages
  - The adjustment cost of robot adoption
    - Policy effects can vary in the short-run and in the long-run
  - Robots are traded in an Armington fashion
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- I omit the following model elements in today's presentation
  - Worker's occupation choice
  - Intermediate good trade and non-robot capital

Occupation Performance Function and Automation

- Fix an industry i and year t
- Producers aggregate occupational outputs T_o with EoS β
- T_o is produced with the occupation performance function:

$$T_o = \left[(a_o)^{\frac{1}{\theta_o}} \left(K_o^R\right)^{\frac{\theta_o - 1}{\theta_o}} + (1 - a_o)^{\frac{1}{\theta_o}} \left(L_o\right)^{\frac{\theta_o - 1}{\theta_o}} \right]^{\frac{\theta_o - 1}{\theta_o}} \tag{1}$$

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  - This problem is called the “task-based approach” in the automation literature (Acemoglu Autor ’11)

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  - Adding a distributional assumption yields eq. (1) (McFadden, '78)

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  - Relative quality of robots to labor Graphical representation

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- The parameter $\theta_o > 0$ is the EoS between robots and labor
  - For general capital goods, $[0.4, 1.6]$ (cf., Chirinko '08; Karabarbounis Neiman '14)
    - But no estimates exist for robots
  - A key parameter for the occupational wage effect of robots Detail

Dynamic Decision: Robot Capital Accumulation

- Investment requires a per-unit convex adjustment cost $\gamma Q^R_{i,o,t}/K^R_{i,o,t}$
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- The country-i producer's problem is

$$\max_{\left\{Q^R_{i,o,t}\right\}_{o,t}} \sum_{t=0}^{\infty} \left(\frac{1}{1+\iota}\right)^t \left[\pi_{i,t}\left(\left\{K^R_{i,o,t}\right\}_o\right) - P^R_{i,o,t} Q^R_{i,o,t} \left(1 + \gamma \frac{Q^R_{i,o,t}}{K^R_{i,o,t}}\right)\right]$$

  - s.t. robot capital accumulation $K^R_{i,o,t+1} = (1-\delta) K^R_{i,o,t} + Q^R_{i,o,t}$
  - $\pi_{i,t}$ is the profit derived from the occupation aggregate function
  - The FOC implies a standard Euler equations Detail

Robotization Shock 1: Automation Shock

- Fix a country i and drop the subscript in this slide
- Relative robot demand in occupation o:

$$\frac{c_o^R K_o^R}{w_o L_o} = \frac{a_o}{1 - a_o} \left(\frac{c_o^R}{w_o} \right)^{1-\theta_o} \tag{2}$$

  - c_o^R: User cost of robots
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  - $a_o \in [0, 1]$: Parameter that represents the robot task share (Acemoglu Restrepo, '20)

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- Use hat notation to denote log change from steady state: $\hat{x} \equiv d \ln x \equiv \ln x' - \ln x_0$
- The automation shock is $\hat{a}_o > 0$ that automates labor tasks to robots'

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- Relating robot user cost $c_{j,o}^{R}$ (model) and Japan robot shock ψ_o^J (data):
  - Gravity trade equation for robots: Detail

$$X_{ij,o}^{R} = \left(\frac{p_{ij,o}^{R}}{P_{j,o}^{R}}\right)^{1-\varepsilon^{R}} X_{j,o}^{R},$$

    - $X_{ij,o}^{R}$: Trade value of occupation-o robot from country i to j
    - ε^{R}: Robot trade elasticity
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    - Thus the Japan robot shock can be represented by $\psi^J_o = -\hat{A}^R_{JP,o}$
- In sum, writing robot trade share as $x^R_{ij,o}$,

$$\hat{c}^R_{j,o} = \hat{P}^R_{j,o} = x^R_{JPj,o}\left(\hat{P}_{JP} + \psi^J_o\right) + \sum_{i \neq JP} x^R_{ij,o}\left(\hat{P}_i - \hat{A}^R_{i,o}\right) \tag{3}$$

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  - Long vectors of endogenous variables including occupational wages Detail
- First-order approximation to solve the model
  - E.g., Consider the effect of automation shock $\widehat{\boldsymbol{a}}_t$ on $\widehat{\boldsymbol{y}}_t$ and $\widehat{\boldsymbol{y}}$
  - Characterized by SS matrix $\overline{\boldsymbol{E}}$ and transition dynamics matrix $\overline{\boldsymbol{F}_t}$ with:

$$\widehat{\boldsymbol{y}} = \overline{\boldsymbol{E}}\widehat{\boldsymbol{a}} \text{ and } \widehat{\boldsymbol{y}}_t = \overline{\boldsymbol{F}_t}\widehat{\boldsymbol{a}}$$

and $\overline{\boldsymbol{F}_t} \to \overline{\boldsymbol{E}}$ as $t \to \infty$ (Blanchard Kahn '80) Detail

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- The estimation targets are substitution elasticity θ_g and β
  - The remaining parameters are fixed as follows:

Notation	Description	Value
ι	Annual disc. rate	0.05
δ	Depreciation rate	0.1
γ	Robot capital adj. cost	0.22

Notation	Description	Value
ε	Good trade elasticity	4
ε^R	Robot trade elasticity	1.2 Detail
ϕ	Occupation switch elast.	0.8

Identification Challenge

- To identify θ_g, factor demand function (2) and robot cost eq. (3) imply

$$\left(\frac{c^R_{US,o}\hat{K}^R_{US,o}}{w_{US,o}L_{US,o}}\right) = \left(\frac{\hat{a}_o}{1-a_o}\right) + (1-\theta_g)\, x^R_{JP,US}\psi^J_o + \epsilon_o \tag{4}$$

where ϵ_o is an error term Detail

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- Approach: Use the labor market clearing restriction about $\hat{w}_{US,o}$
  - I can then write $\hat{w}_{US,o}$ (observed) in terms of ψ^J_o (observed) and $\hat{a}_o$ (unobserved)

The 3-step Recipe for the Structural Residual

- Technically, I obtain the unobserved component as the structural residual:

1. Measure implied automation shock $\widehat{a_o^{\mathbf{imp}}}$ by SS relative demand:

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  - $\widehat{\boldsymbol{\nu}^w}$ is variation *after controlling for* the wage effect of the automation shock
  - In addition to $\widehat{\mathbf{w}}$, it also applies for variables $\widehat{\boldsymbol{L}}$, $\widehat{\boldsymbol{p}^R}$, and $\widehat{\boldsymbol{Q}^R}$

Moment Condition and Model-implied Optimal IV

- I assume the structural residual $\widehat{\nu}_o$ is mean independent of the JRS:

$$\mathbb{E}\left(\widehat{\nu}_o | \boldsymbol{\psi}^J\right) = 0 \tag{5}$$

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  - The optimal IV minimizes the asymptotic variance (Chamberlain '87)

$$H^*_o\left(\boldsymbol{\psi}^J; \boldsymbol{\Theta}\right) \equiv \mathbb{E}\left[\nabla_{\boldsymbol{\Theta}} \widehat{\nu_o}\left(\boldsymbol{\Theta}\right) | \boldsymbol{\psi}^J\right] \left(\mathbb{E}\left[\widehat{\nu_o}\left(\boldsymbol{\Theta}\right) \left(\widehat{\nu_o}\left(\boldsymbol{\Theta}\right)\right)^\top | \boldsymbol{\psi}^J\right]\right)^{-1}.$$

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  - The IV can be implemented with the two-step method (Adao et al '19) Detail

Estimation Results

- The elasticity of substitution between occupations: $\beta = 0.73$ (0.06)

g	Routine			Manual	Abstract
	Production	Transportation	Others		
θ_g	2.95	2.90	1.16	1.23	0.64
	(0.42)	(0.48)	(0.32)	(0.55)	(1.24)

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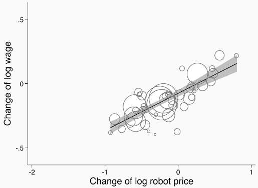
- Estimates reveal heterogeneous θ_g Model Fit
  - Robots are substitutable in production/transportation ($\theta_g \approx 3$)
  - Estimates are much lower in other occupations (e.g., Manual and Abstract)
- The robot cost-wage positive correlation drives the results, as follows:

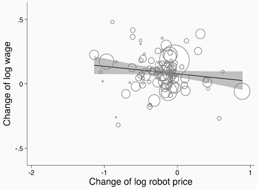
Source of Identification: Wage-Japan Robot Schok Correlation



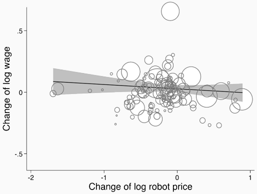
Routine, Production

Routine, Transportation

Routine, Others



Manual



Abstract

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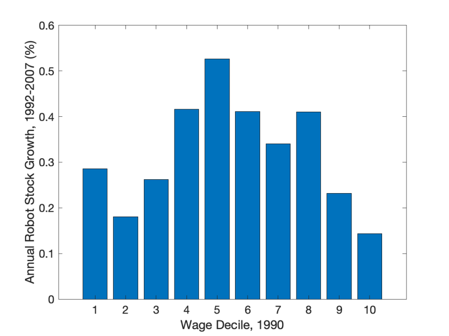
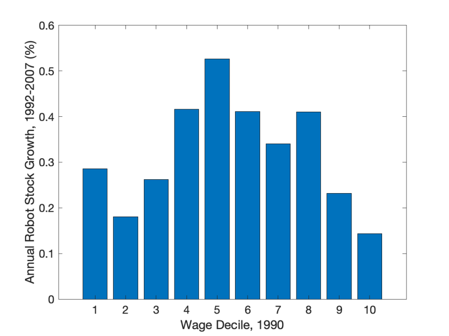
Wage Polarization



US Robot Stock Growth

Wage Polarization



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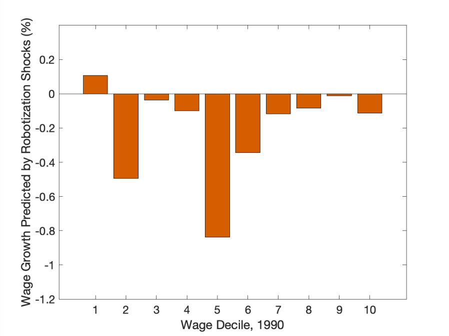
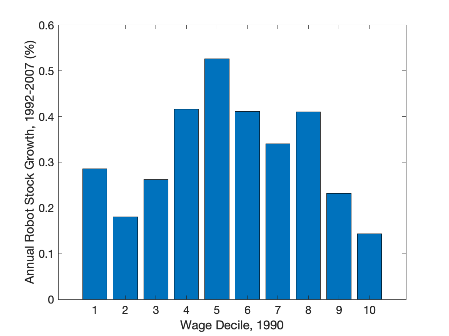


The Effects on US Real Wage

- Robotization shocks compressed wage growths in the middle of wage dist’n

Wage Polarization



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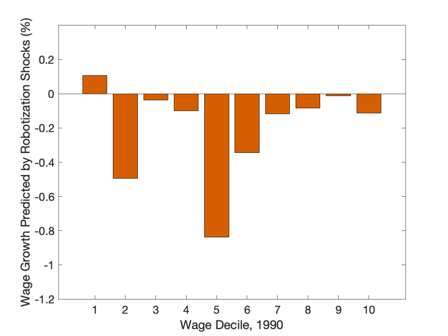
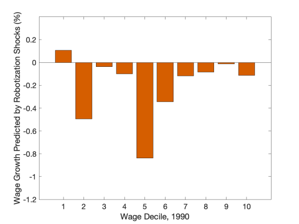


The Effects on US Real Wage

- Robotization shocks compressed wage growths in the middle of wage dist'n
  - It contributes to the wage polarization The role of high theta
  - It raises 90-50th percentile wage ratio by 0.9 percentage point, or 6.4%

Decomposing the Effect of the Robotization Shocks

- The model allows to decompose the wage effects into two sources:



Both Shocks

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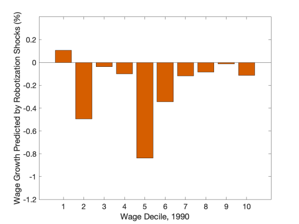

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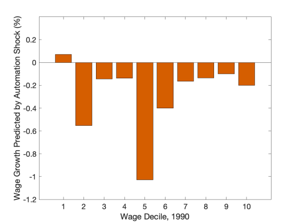

Automation Shock

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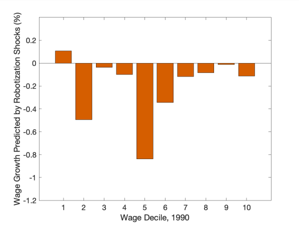

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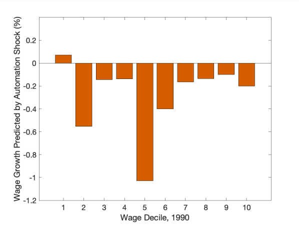

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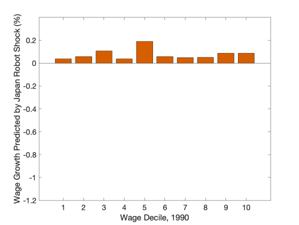

Japan Robot Shock

- The Japan robot shock increases real wage for all occupations
  - It reduces the cost of robot capital, and thus increases MPL
- The automation shock reduces the real wage for middle-wage occupations
  - Tasks in middle-wage occupations (e.g., production) are automated to robots

Robot Taxes and Total Real Income

- Can a robot tax increase aggregate income? Consider two scenarios:
  1. US taxes on general robot purchase at 6% (cf. Humlum, '19: 30% in Denmark)
  2. US taxes on robot imports at 34% (same revenue as in scenario 1)

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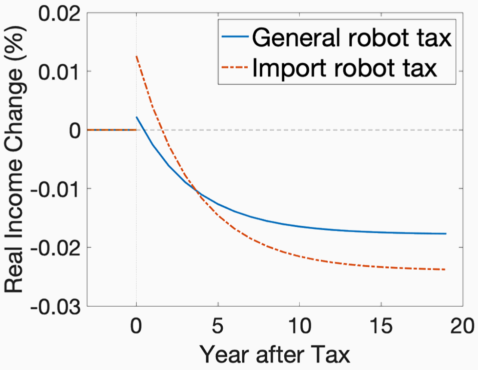

Effects of the Import Robot Tax on Imported Robots

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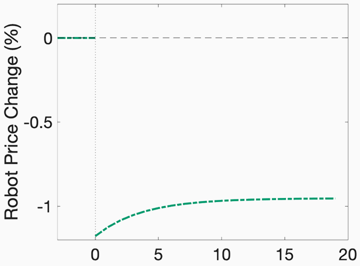

Import robot price

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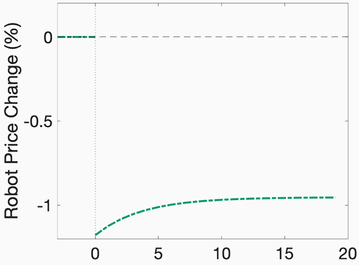

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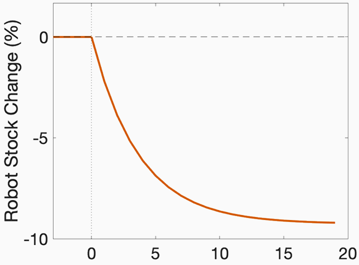

US Robot stock

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- In the long-run, robot stock de-accumulates. Income ↓ as firm profit ↓

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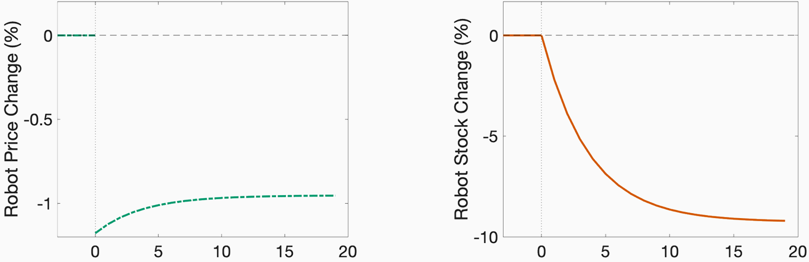

Import robot price — US Robot stock

  - Importer has monopsony power, thus reduces imported robot price (cf. Broda, Limao, Weinstein '08)
  - In the long-run, robot stock de-accumulates. Income ↓ as firm profit ↓

- The results highlights the role of trade and accumulation of robots

Roadmap

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- New theory and measurement to study robotization and wage polarization:
  - A new dataset of robot costs and their substitution for labor by occupations
  - A model with robot costs and automation (robot task expansion)
  - An estimation method to deal with robot task expansion

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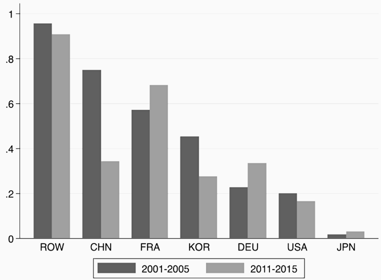
- Key takeaways
  - Japanese robot costs are decreasing and driving down US wages
  - The robot-labor EoS is heterogeneous by occupations, as high as 3
  - The estimated model explains 6.4% of US wage polarization 1990-2007

Roadmap

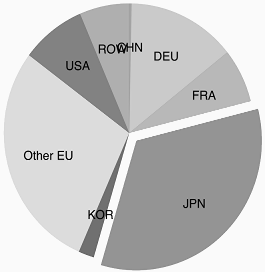
Backup

Trade of Robots Back

- In IFR data, robot definition is based on ISO 8373:2012 (“Industrial Robots”)
- In trade data, robot HS code 847950 (“Industrial Robots For Multiple Uses”)



Robot Import-Absorption Ratio



World Robot Export Share, 2001-2005

Notes: The author’s calculation from IFR and BACI.

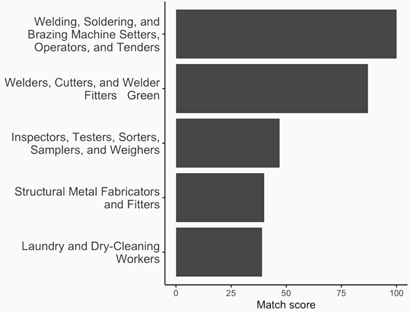
List of JARA Application Codes

Back

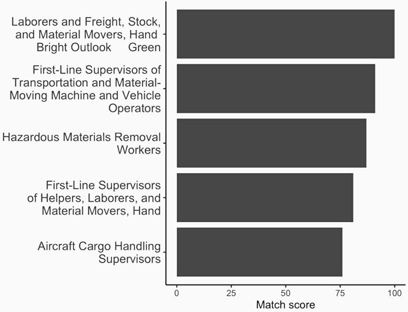
Die casting	Water jet cutting
Forging	General assembly
Resin molding	Inserting
Pressing	Mounting
Arc welding	Bonding
Spot welding	Soldering
Laser welding	Sealing and gluing
Painting	Screw tightening
Loading and unloading	Picking alignment and packaging
Mechanical cutting	Palletizing
Polishing and deburring	Measuring, inspecting, and testing
Gas cutting	Material handling
Laser cutting	

Example Match Scores

Back to data



Spot Welding



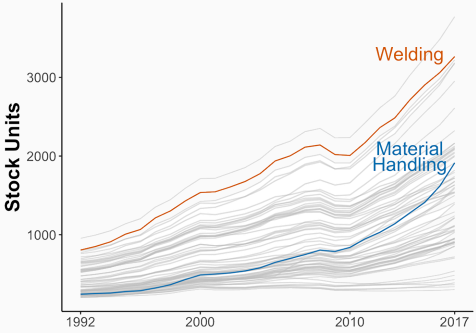
Material Handling

Notes: Authors calculation based on the O*NET Code Connector (https://www.onetcodeconnector.org). The left panel shows the occupation distribution of match scores for Spot welding robots, and the right one shows the distribution for Material handling robots. The match score is defined by Morris (2019) and implemented by O*NET Code Connector. Occupations codes are 2010 O*NET SOC codes. In each panel, the occupations are sorted descendingly with the relative relevance scores. The top 5 occupations are shown.

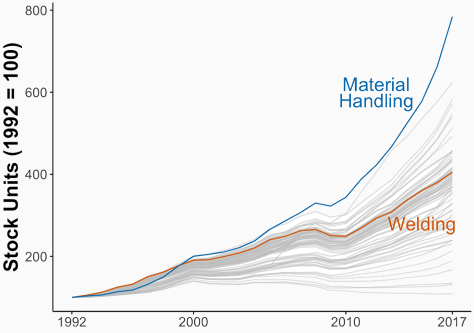
Growth of Robot Stocks by Occupation

Back

- US robot stocks grow at different rates across occupations in 1992-2017



Level



Normalized

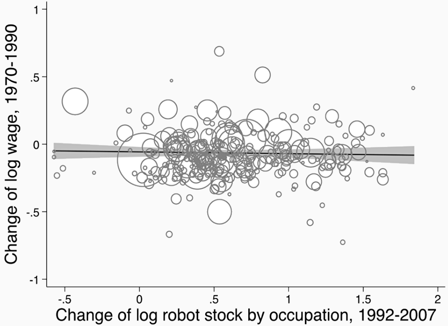
Quality-adjusted Price Back

- Measure quality and remove it (Khandelwal Schott Wei '13)

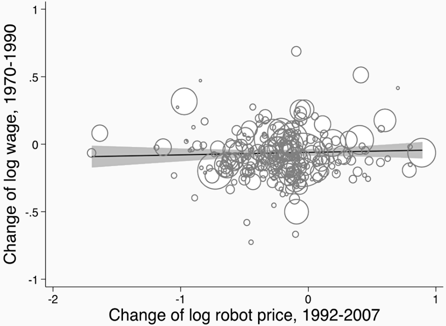
$$\ln\left((pq)^R_{i,o,t}\right) = -\varsigma \ln\left(p^R_{i,o,t}\right) + \underbrace{a^R_{o,t}}_{\text{quality}} + e^R_{i,o,t}$$

Note: The author's calculation based on JARA, O*NET Code Connector, and IPUMS data. Each observation represents an occupation and is weighted by the initial employment size. The sample is all occupations that existed throughout 1970 Census to 2007 ACS. Standard errors are heteroskedasticity-robust.

Pretrend Back



Wage vs Stock



Wage vs Price

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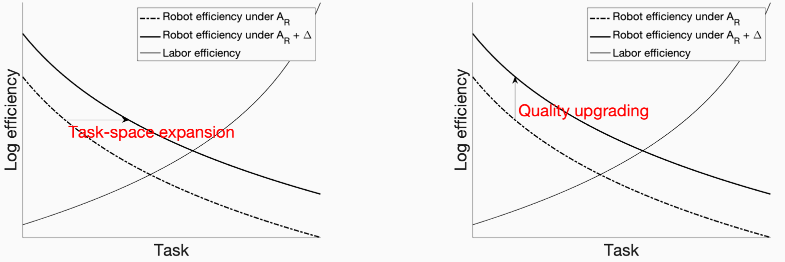
Task Space a_o as Relative Quality of Robots Back

- Quality is a non-price factor that increases the demand (E.g., Khandelwal, '10)
- Fréchet $\Rightarrow$ Share parameter a_o is both robots' task space and quality

Figure 1: Graphical representation à la Dornbusch-Fisher-Samuelson ('77)



Note: Task space is reordered descendingly by relative robot efficiency

Steady-state Real-wage Formula Back

- In the SS, the change of real wage satisfies:

$$\widehat{\left(\frac{w_{i,o}}{P_i^G}\right)} = \frac{1}{1-\theta_o}\hat{x}_{i,o}^L + \frac{1}{1-\varepsilon}\hat{x}_i^G$$

  - $\hat{x}_{i,o}^L \equiv \widehat{\frac{w_{i,o}L_{i,o}}{P_{i,o}^O T_{i,o}^O}}$, $\hat{x}_i^G \equiv \widehat{\frac{p_i^G Q_{ii}^G}{P_i^G Y_i^G}}$
  - $P_{i,o}^O$ is steady-state cost of occ. o: $\left(P_{i,o}^O\right)^{1-\theta_o} = (1-a_o)\left(w_{i,o}\right)^{1-\theta_o} + a_o\left(c_{i,o}^R\right)^{1-\theta_o}$

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  - The first term reveals the robot cost reduction relative to labor cost
  - The second term reveals the relative sectoral cost reduction
- Without robots, the first term disappears and the formula reduces to the ACR

International Trade of Robots

Back

- Demand (investment) for robots, $Q^R_{i,o,t}$

- Supply of robots: $Y^R_{i,o,t}$

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    - Hardware is origin l-specific, $\{q^R_{li,o,t}\}_l$
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  - Specify: (cf. Anderson et al. '19)

$$Q^R_{i,o,t} \equiv \left[\sum_l \left(q^R_{li,o,t}\right)^{\frac{\varepsilon^R-1}{\varepsilon^R}}\right]^{\frac{\varepsilon^R}{\varepsilon^R-1}\alpha^R} \left(I_{i,o,t}\right)^{1-\alpha^R}$$

$\Rightarrow$ Robot trade gravity equation $q^R_{li,o,t} = \left(\frac{p^R_{li,o,t}(1+u_{li,t})}{P^R_{i,o,t}}\right)^{-\varepsilon^R} Q^R_{i,o,t}$. Price index P^R

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  - $A^R_{i,o,t}$ is also a negative cost shock $\Rightarrow A^R_{JP,o,t} = -\psi^J_{o,t}$

Estimating Robot Trade Elasticity Back

- The "trilateral" method given the robot gravity equation (Caliendo Parro '14, CP)

$$\ln\left(\frac{X^R_{li}X^R_{ij}X^R_{jl}}{X^R_{lj}X^R_{ji}X^R_{il}}\right) = \left(1-\varepsilon^R\right)\ln\left(\frac{\tau^R_{li}\tau^R_{ij}\tau^R_{jl}}{\tau^R_{lj}\tau^R_{ji}\tau^R_{il}}\right), \quad (6)$$

  with X^R_{li} the bilateral sales of robots from l to i
  - CP find the regression coefficient of -0.52 for "Machinery n.e.c," roughly HS 84

- Robots are HS 847950 (Humlum '19). Data from BACI 1998-2014

	(1) HS 847950	(2) HS 847950	(3) HS 8479	(4) HS 8479
Tariff	-0.272***	-0.236***	-0.146***	-0.157***
	(0.0718)	(0.0807)	(0.0127)	(0.0131)
Constant	-0.917***	-0.893***	-1.170***	-1.170***
	(0.0415)	(0.0381)	(0.00905)	(0.00853)
FEs	h-i-j-t	ht-it-jt	h-i-j-t	ht-it-jt
N	4610	4521	88520	88441
r2	0.494	0.662	0.602	0.658

Error Term in Detail Back

- The relative demand equation is

$$\left(\frac{c_{US,o}^{R}\hat{K}_{US,o}^{R}}{w_{US,o}L_{US,o}}\right) = \left(\frac{\hat{a}_o}{1-a_o}\right) + (\theta_g - 1)\,\alpha^R x_{JP,US}^{R}\psi_o^J + \epsilon_o,$$

$$\epsilon_o = \underbrace{(1-\theta_g)\left[\alpha^R \sum_l x_{l,US}^{R}\hat{P}_l + \left(1-\alpha^R\right)\hat{P}_{US}\right]}_{\text{fixed effect}} + (1-\theta_g)\left[\alpha^R \sum_{l\neq JP} x_{l,US}^{R}\hat{A}_{l,o}^{R} - \hat{w}_{US,o}\right]$$

  - The second term depends on o:
    - US wage changes $\hat{w}_{US,o}$ can be controlled
    - For the other countries productivity growth $\hat{A}^R_{-JP,o} \equiv \sum_{l\neq JP} x_{l,US}^{R}\hat{A}_{l,o}^{R}$, I assume orthogonality with the Japan Robot Shock

The Two-step Estimator Back

- Since H_o^* depends on parameters, we need a two-step method to compute it
  1. With an arbitrary initial value $\boldsymbol{\Theta}_0$, construct optimal IV and estimate first-step $\boldsymbol{\Theta}_1$
  2. By moment condition (5), $\boldsymbol{\Theta}_1$ is consistent. Use it to obtain second-step $\boldsymbol{\Theta}_2$

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  $\rightarrow$ $\boldsymbol{\Theta}_2$ is consistent and asymptotically efficient (Adao et al '19)

The Performance of the Estimated Model–Method Back

- I consider two exercises to check the estimation performance
  1. Write the wage change predicted by Japan robot shock $\boldsymbol{\psi}^J$ and observed automation shock $\widehat{\boldsymbol{a}^{\text{obs}}}$ as $\hat{\mathbf{w}}_{\psi^J \hat{\mathbf{a}}^{obs}}$
     - Regression using this wage change answers if the estimated model reproduce the stylized fact 2
  2. Write the wage change predicted by Japan robot shock $\boldsymbol{\psi}^J$
     - Regression using this wage change answers how severe the bias of not taking into account the automation shock

The Performance of the Estimated Model–Result

VARIABLES	(1) $\widehat{\boldsymbol{w}}_{data}$	(2) $\widehat{\boldsymbol{w}}_{\psi^J \widehat{\mathbf{a}^{obs}}}$	(3) $\widehat{\boldsymbol{w}}_{\psi^J}$
ψ^J	0.118	0.107	0.536
	(0.0569)	(0.0711)	(0.175)
Observations	324	324	324

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  - This negative "bias" is included in coefficient in column (2)
  - By taking into account the observed automation shock, I could estimate the EoS even when the reduced-form estimation contains the bias

Robotization and Income

- At the initial equilibrium, hit Japan robot shock and/or automation shock
    - Define "Robotization" as both of Japan robot shock and automation shock

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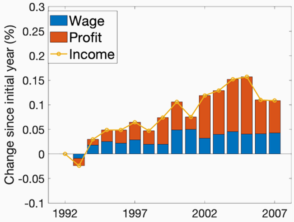

Japan Robot Shock

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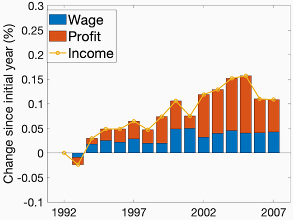
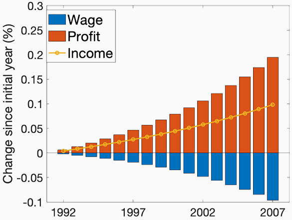
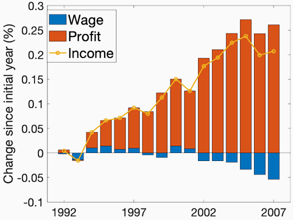


Japan Robot Shock



Automation Shock



Robotization (Both)

- In all scenarios, profits rise
- Workers gain by Japan robot shock, but lose by automation shock

Equilibrium Definition Back

- In period t, a *temporary equilibrium* (TE) is, given state variables $\boldsymbol{S}_t \equiv \{\boldsymbol{K}_t^R, \boldsymbol{\lambda}_t^R, \boldsymbol{L}_t, \boldsymbol{V}_t\}$, prices and flow quantities $\boldsymbol{x}_t \equiv \left\{\boldsymbol{p}_t^G, \boldsymbol{p}_t^R, \boldsymbol{w}_t, \boldsymbol{Q}_t^G, \boldsymbol{Q}_t^R, \boldsymbol{\mu}_t\right\}$ that satisfies TE conditions

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  1. SE conditions, and
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- A *steady state* (SS) is a SE $\boldsymbol{y}$ that does not change over time

Temporary Equilibrium Conditions Back

1. Good supply: $\forall i$

$$\sum_j \frac{Q^G_{ij,t}}{1+\tau^G_{ij,t}} = A^G_{i,t}\left[\sum_o \left(Q_{i,o,t}\right)^{\frac{\beta-1}{\beta}}\right]^{\frac{\beta}{\beta-1}\alpha_L} \left(M_{i,t}\right)^{\alpha_M}\left(K_{i,t}\right)^{1-\alpha_L-\alpha_M}$$

2. Robot supply: $\forall i, o$

$$p_{i,o,t} = \frac{P_{i,t}}{A_{i,o,t}}$$

3. Labor supply (or transition probability): $\forall i, o, o'$

$$\mu_{i,oo',t} = \frac{\left[\left(1-\chi_{i,oo',t}\right)\left(V_{i,o',t+1}\right)^{(1+\iota)^{-1}}\right]^{\phi}}{\sum_{o''}\left[\left(1-\chi_{i,oo'',t}\right)\left(V_{i,o'',t+1}\right)^{(1+\iota)^{-1}}\right]^{\phi}}$$

(Cont'd) Temporary Equilibrium Conditions Back

4. Good demand (or budget constraint, or trade balance): $\forall i, j$ Further Detail

$$p^G_{ij,t} Q^G_{ij,t} = \left(\frac{p^G_{ij,t}}{P^G_{j,t}} \right)^{1-\varepsilon^G} \left(\sum_k p^G_{jk,t} Q^G_{jk,t} + \sum_{k,o} p^R_{jk,o,t} Q^R_{jk,o,t} - \sum_{i,o} p^R_{ij,o,t} Q^R_{ij,o,t} \right).$$

5. Robot demand (or investment function): $\forall i, j, o$

$$p^R_{ij,o,t} (1 + u_{ij,t}) + 2\gamma P^R_{j,o,t} \left(\frac{Q^R_{j,o,t}}{K^R_{j,o,t}} \right) \frac{\partial Q^R_{j,o,t}}{\partial Q^R_{ij,o,t}} = \lambda^R_{j,o,t} \frac{\partial Q^R_{j,o,t}}{\partial Q^R_{ij,o,t}}$$

6. Labor demand: $\forall i, o$

$$p^G_{i,t} \alpha_L \frac{Y^G_{i,t}}{Q^O_{i,t}} \left(b_{i,o,t} \frac{Q^O_{i,t}}{Q^O_{i,o,t}} \right)^{\frac{1}{\beta}} \left((1 - a_{o,t}) \frac{Q^O_{i,o,t}}{L_{i,o,t}} \right)^{\frac{1}{\theta}} = w_{i,o,t}$$

Good Trade and Trade Balance Back

- Good G is intermediate goods as well as final consumption good
- Intermediate goods are differentiated by origin:

$$M_{i,t} = \sum_{l} \left(M_{li,t}\right)^{\frac{\varepsilon^G - 1}{\varepsilon^G}} .$$

- Thus the trade demand is

$$p^G_{li,t} Q^G_{li,t} = \left(\frac{p^G_{li,t}}{P^G_{i,t}}\right)^{1-\varepsilon^G} P^G_{i,t} X^G_{i,t}$$

(Cont'd) Good Trade and Trade Balance Back

- The total expenditure $P^G_{i,t}X^G_{i,t}$ satisfies

$$P^G_{i,t}X^G_{i,t} = \underbrace{P^G_{i,t}C_{i,t}}_{\text{final consumption}} + \underbrace{\alpha_M p^G_{i,t}Y^G_{j,t}}_{\text{intermediate goods}} + \underbrace{\sum_{j,o} p^R_{ij,o,t}Q^R_{ij,o,t}}_{\text{robot production}} + \underbrace{\left(1-\alpha^R\right)\sum_{o} P^R_{i,o,t}Q^R_{i,o,t}}_{\text{robot integration}}$$

$$= \sum_k p^G_{jk,t}Q^G_{jk,t} + \sum_{k,o} p^R_{jk,o,t}Q^R_{jk,o,t} - \sum_{i,o} p^R_{ij,o,t}Q^R_{ij,o,t}$$

Sequential Equilibrium Conditions

Back

1. Capital accumulation: $\forall i$, o,

$$K^R_{i,o,t+1} = (1-\delta)\,K^R_{i,o,t} + Q^R_{i,o,t}$$

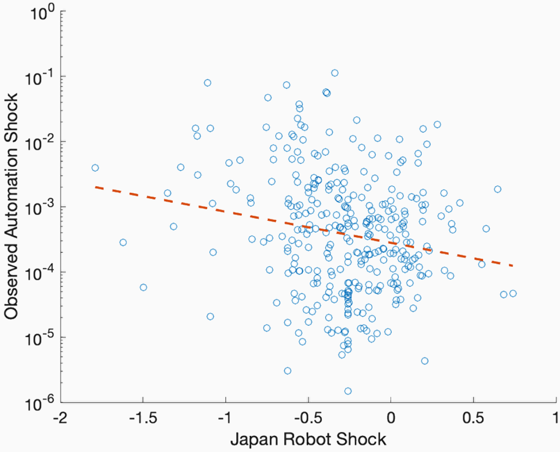
2. Robot demand Euler equation: $\forall i$, o

$$(1+\iota)\,\lambda^R_{i,o,t} = (1-\delta)\,\lambda^R_{i,o,t+1} + \frac{\partial}{\partial K^R_{i,o,t}}\pi_{i,t+1}\left(\left\{K^R_{i,o,t+1}\right\}\right) + \gamma p^R_{i,o,t+1}\left(\frac{Q^R_{i,o,t+1}}{K^R_{i,o,t+1}}\right)^2.$$

3. Labor transition: $\forall i$, o

$$\underbrace{p^G_{i,t}\alpha_L\frac{Y^G_{i,t}}{Q^O_{i,t}}\left(b_{i,o,t}\frac{Q^O_{i,t}}{Q^O_{i,o,t}}\right)^{\frac{1}{\beta}}\left((1-a_{o,t})\,\frac{Q^O_{i,o,t}}{L_{i,o,t}}\right)^{\frac{1}{\theta}}}_{MPL_{i,o,t}} = w_{i,o,t}$$

Correlation between Japan robot shock ψ_o^J and automation shock $\widehat{a_o^{obs}}$ Back



Note: The author's calculation based on JARA, O*NET, and US Census/ACS. The observed automation shock is backed out from the relative robot demand equation with the estimated parameters. Each circle is 4-digit occupation and dashed line is the fitted line.

Other Values of the Elasticity of Substitution θ_g Back

- What if the EoS θ_g is low as assumed in the literature?
  - cf. Acemoglu-Restrepo's ('20) production function is equivalent to $\theta = 0$

    Formal statement

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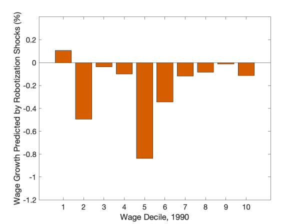
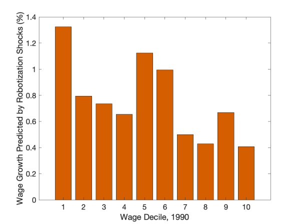
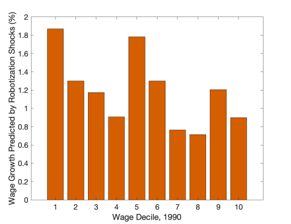
Formal statement



Baseline Estimates



$\theta_o = 1$



$\theta_o = 0$

$\rightarrow$ The polarizing effect of robots comes from high θ_g's

Effects of the General Robot Tax on Workers and Firms Back

- Impose a counterfactual 30% tax on robots in 2017:

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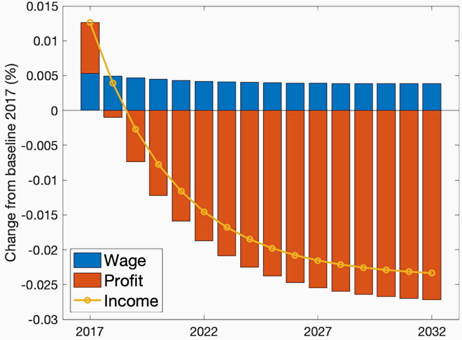

- Workers benefit overall from the robot tax
- This benefit is overturned by profit loss over time as robots de-accumulate