The Future of Labor: Automation and the Labor Share in the Second Machine Age

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- Recent developments make economists rethink the impact of automation:
  - labor share is falling globally since 1980s
  - employment in many sectors trails productivity (manufacturing)
  - routine well-paying jobs replaced by machines, leading to job polarization
  - rapid spread of advanced automation technology does not bode well for the future
    - quality-adjusted real price of industrial robots fell by a factor of five between 1990 and 2005
    - global stock of industrial robots rose fivefold between 1993 and 2015

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- Needed: More measurement, better understanding of GE vs technology

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Key idea:

- Exploit unique and rich dataset on Chinese manufacturers' and use variation in government subsidies for automation as an instrument to:

    1. Identify direct impact of automation on the labor share (largely free from GE) and
    2. Structurally estimate the elasticity between automation capital and labor withing the canonical model of automation (Acemoglu and Restreppo, 2018)

Preview of Findings

- Find average elasticity of 3.8 on the intensive margin (among automating firms)
- Show high elasticity squares well with aggregate data
- Extensive margin holds the key to impact of automation

Related literature

- "Causal" estimates largely based on shift-share identification, focus on GE impact, and only a few papers analyze the labor share:
  - Acemoglu and Restreppo (2018); Dauthy, Findeisenz, Suedekum and Woessner (2019): use variation in geographic exposure to automation (the latter paper looks at labor share)
  - Graetz and Michaels (2018): look at exposure by occupation, do not study labor share
  - Autor and Salomons (2018): document long-run correlation between labor share and productivity growth (indirectly linked to automation)
- This paper: Impact of automation attributed to technology
- Both approaches useful for different purposes (ours for modeling)

Data – First Look

Data: China Enterprise General Survey (CEGS)

- Longitudinal survey of manufacturing firms between 2015 and 2017
  - Effective sample size: 1618 firms
  - conducted and hosted by Wuhan University, in cooperation with HKUST, Stanford and the Chinese Academy of Social Science
- Covers vast array firms' operations, including purchases of automation equipment and subsidies received:
  - Industrial robots (Machine-1): "an automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications."
  - Semi-automated machinery (Machine-2): "numerically controlled production-line machinery that may involve human operator(s) but performs most of the work autonomously"
- High-quality: response rate above 80%, economists travel to site
- Caveats regarding internal "data cleaning procedures"

Data: China Enterprise General Survey (CEGS)

- Survey coverage coincident with unrolling of "Made in China 2025" in 2015
  - A vast national government program subsidizing automation

    > "...increase the adoption rate of automation from 33 percent of in 2015 to 64 percent in 2025..."

    > "...pilot the construction of smart factories/digital workshops in key areas, accelerate the application of technologies and equipment such as human-machine intelligent interaction, industrial robots, smart logistics management..."

  - Implementation and budgeting left to local municipalities, resulting in significant policy dispersion
  - Arguably intentional design to foster experimentation and identify the "winners"

MIC Implementation Examples

Foshan (Guangdong Province): "assign 130 million RMB per year to support automation and robotic machinery [...] the government provides subsidies on robots purchases — 12% of machines value if the robots are made in Foshan (the maximum subsidy cannot be larger than 3 million RMB per year); 8% of machines value if the robots are made elsewhere (the maximum subsidy cannot be larger than 2 million per year) [...] every year, the government awards 8 million RMB per firm to 10 selected firms as the automation demonstration based on the following criterions..." '

Huzhou (Zhejiang Province): "to encourage automation, the government provides subsidies based on the following three categories: a) 6% of machines value (one time claim cannot be larger than 10 million RMB) for four industries — metal material, furniture, modern textile, and fashion products; b) 8% of machines value (one time claim cannot be larger than 15 million RMB) for three industries — information technology, advanced machinery, and biomedicine. c) 10% of machines value (one time claim cannot be larger than 20 million RMB) for the industrial areas of integrated circuit, new energy (including adoption to electronic vehicles, battery, and machinery), logistics equipment, aerospace and aviation equipment, new medical technology.

Wuhan (Hubei Province): "the government provides subsidies at the rate 12% of machines value (one time claim cannot be larger than 3 million)."

Sample structure

- Automating firms: invest in automation in any of the three years
- Subsidized firms: receive subsidy for automation in any of the three years

Statistic	All firms	Automating firms	Subsidized firms
Number of cities	60	44	18
Number of industries	31	23	14
Number of city-industry pairs	666	117	31
Number of observations	4602	491	106
Number of (unique) firms	1618	171	37
Share in total employment (in %)	100%	23%	5.6%
Share in total value added (in %)	100%	24%	5.9%

Summary Statistics

Variable	W.Mean	Mean	Median
All firms			
Employment	-	307	100
Automation investment/output	.07	.07	0
LS 2017 − LS 2015	-.026	-.024	-.012
Automating firms			
Employment	656	656	357
Automation investment/output	.1	.1	.02
LS 2017 − LS 2015	-.022	-.036	-.19
Subsidy rate	.036	.037	0
Subsidized firms			
Employment	791	791	660
Automation investment/output	.17	.14	.06
LS 2017 − LS 2015	-.035	-.083	-.02
Subsidy rate	.12	.11	.10

- In subsidized groupings 80 percent of automating firms receive a subsidy

Is Automation Correlated with Labor Share Declines?

- Consider OLS regression of the form

$$\Delta LS_{\omega,t,t-1} = \alpha \log(Z_{\omega,t-1}) + \delta_\omega + \varepsilon_t,$$

	Dependent Variable: ΔLS_ω	
Explanatory variables	Full Sample	
	(1)	(2)
Automation: $\log\left(\frac{I_A}{VA}\right)_{-1}$	-0.0320*	
	(.0186)	
Other equipment: $\log\left(\frac{I_O}{VA}\right)_{-1}$		-.007*
		(0.036)
Firm fixed effect	Yes	Yes
R-squared	0.81	0.59
Observations	186	233

Model

Basic Structure

- Consistent with Graetz and Michaels (2018) and Acemoglu and Restreppo (2018)
- Add GE with heterogeneity and firm-level shocks

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- Small open economy
  - global final good $P = 1$
  - fixed cost of funds r
  - immobile labor supply (fixed, one market)

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- Three distinct types of capital subject to linear depreciation rule
  - support k_s: obtained from $p_s = 1$ units of final good
  - equipment k_e: obtained from $p_e = 1$ units of final good
  - automation k_m: obtained from $p_m(t)$ units of final good

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    Investment in automation subsidized from period τ onward at rate s

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- Goods produced by monopolistic producers from labor and capital, then aggregated
- Implies exogenous user cost of capital
  - support k_s: $r_s = (1 + r) - (1 - \delta_s) = r + \delta_s$
  - equipment k_e: $r_e = (1 + r) - (1 - \delta_e) = r + \delta_e$
  - automation k_m (gross): $r_e = (1 + r)p_m(\tau) - (1 - \delta_e)p_m(\tau + 1)$
  - automation k_m (net): $r_e(1 - s) = (1 + r)p_m(\tau)(1 - s) - (1 - \delta_e)p_m(\tau + 1)(1 - s)$

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Aggregation and Demand Structure

- Two layers of aggregation:
  - In city-industry (c, i), firm $\omega \in \Omega_{ij}$ produces goods $q(\omega)$ sold at price $p(\omega)$

$$\Downarrow$$

  - Competitive regional producers aggregate goods $q(\omega)$ into composite good Q_{ci}

$$\Downarrow$$

  - Competitive final producers aggregate goods Q_{ci} from all (c, i) into final good Y

Aggregation and Demand Structure

- Final good producers maximize

$$\max_{Y,Q_{ci}} Y - \sum_{c=1}^{n} \sum_{i=1}^{m} P_{ci}(t) Q_{ci}$$

subject

$$Y = \left(\sum_{c=1}^{n} \sum_{i=1}^{m} D_{ci}^{\frac{1}{\rho}} Q_{ci}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}$$

where Q_{ci} is city-industry (c, i) composite good and D_{ci} is ci-share.

- Implied demand for (c, i) good is

$$Q_{ci}(t) = D_{ci} (P_{ci})^{-\rho} Y$$

Aggregation and Demand Structure

- Regional producers maximize

$$\max_{q(\omega)} P_{ci}(t)\, Q_{ci} - \sum_{j=1}^{k} \int_{\Omega_{cij}} p(t,\omega)\, q(t,\omega)\, d\omega,$$

subject to

$$Q_{ci} = \prod_{j=1}^{k} \left(\int_{\Omega_{cij}} d(t,\omega)^{\frac{1}{\theta_j}}\, q(t,\omega)^{\frac{\theta_j - 1}{\theta_j}}\, d\omega \right)^{\phi_j \frac{\theta_j}{\theta_j - 1}}$$

where $p(t,\omega)$ and $q(t,\omega)$ denote the price and quantity of good ω;

θ_j and ϕ_j ($\sum_j \phi_j = 1$) are markup shocks and $d(t,\omega)$ is demand shock

- Implies demand for goods produced by monopolistic producers (next slide)

Demand Faced by Monopolistic Producers

- Demand faced by firm ω in city c and industry i

$$q(t,\omega) = d(t,\omega)\left(\frac{p(t,\omega)}{P_{cij(t,\omega)}(t)}\right)^{-\theta_{j(t,\omega)}}\left(\frac{P_{ci}(t)}{P_{cij(t,\omega)}(t)}\right)\phi_{j(t,\omega)}Q_{ci}(t)$$

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- Elasticity of demand $\theta_{j(t,\omega)}$ and demand $\phi_{j(t,\omega)}$ may covary
    - may imply “spurious” correlation between automation investment and labor share

Production Function of Monopolistic Producers

- Production function of firm ω in city c and industry i

$$A_\omega(t)\left(\underbrace{k_s^{\gamma_\omega} l_s^{1-\gamma_\omega}}_{(1)}\right)^{\eta_\omega}\left(\underbrace{a_\omega^{\frac{1}{\sigma_\omega}}\left(k_e^{\alpha_\omega} l^{1-\alpha_\omega}\right)^{\frac{\sigma_\omega-1}{\sigma_\omega}}+(1-a_\omega)^{\frac{1}{\sigma_\omega}}\, m^{\frac{\sigma_\omega-1}{\sigma_\omega}}}_{(2)}\right)^{(1-\eta_\omega)\frac{\sigma_\omega}{\sigma_\omega-1}}$$

(1) Support activities: CD labor-support capital bundle $k_s^{\gamma_\omega} l_s^{1-\gamma_\omega}$

(2) Production activities: CD labor-equipment capital bundle $k_e^{\alpha_\omega} l^{1-\alpha_\omega}$ and robots m

Example: Nailing two pieces of material together can be done by using a worker l with a hammer k_e or an industrial robot m.

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  - $\sigma_\omega > 1$: Cheaper robots leads to smaller labor share
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- Goal: estimate "average" σ_ω across automating firms between $\tau - 1$ and τ

Production Function Consistent With Kaldor's Fact

- When automation is unavailable ($p_m \to \infty$) the firm's labor share collapses to

$$LSO\left(t,\omega\right) := \left(\underbrace{\frac{\theta_{j(t,\omega)}-1}{\theta_{j(t,\omega)}}\left(1-\eta_{\omega}\right)\left(1-\alpha_{\omega}\right)}_{LSOP(t,\omega)} + \underbrace{\frac{\theta_{j(t,\omega)}-1}{\theta_{j(t,\omega)}}\eta_{\omega}\left(1-\gamma_{\omega}\right)}_{LSON(t,\omega)} \right)$$

- Key property: Automation $m > 0$ affects the labor share via term in red

$$LSO\left(t,\omega\right) - LS\left(t,\omega\right) = LSOP\left(t,\omega\right) - LSP\left(t,\omega\right)$$

where $LSP\left(t,\omega\right)$ is labor share of production workers

- Implies one has to give enough m for firm to drive down LS from assumed LSO

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Firm problem

- Firm's maximize profits

$$\pi(t,\omega) := \max_q \left(p(t,\omega) - \lambda(t,\omega)\right) q$$

subject to their demand curve and where λ is the marginal cost of production:

$$\lambda(t,\omega) := \min_{l,k_e,k_s,m} r_i^s(t)\,k_s + r_i^e(t)\,k_e + r_i^m(t)\,(1 - s(t,\omega))\,m + w(t)\,(l_s + l),$$

subject to $F_i(k_s, l_s, k_e, l, m) \geq 1$.

- Notice the presence of a subsidy $s(t,\omega)$ to automation investment
  - Provides incentives to automate (useful to construct instrument)

- Solution implies constant markup pricing:

$$p(t,\omega) = \frac{\theta_{j(t,\omega)}}{\theta_{j(t,\omega)} - 1}\lambda(t,\omega)$$

Labor Share Dynamics

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Lemma 1

The automation to labor ratio $m(t,\omega)/l(t,\omega)$ is given by

$$\log \frac{m(t,\omega)}{l(t,\omega)} = \Theta(t,\omega) - \sigma_\omega \log(1 - s(t,\omega)),$$

where $\Theta(t,\omega)$ only involves parameters and factor prices.

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Lemma 2

The labor share $LS(t,\omega)$ depends on $m(t,\omega)/l(t,\omega)$ as

$$\log \frac{LSO(t,\omega) - LS(t,\omega)}{LS(t,\omega) - LSN(t,\omega)} = \Psi(t,\omega) + \frac{\sigma_\omega - 1}{\sigma_\omega} \log \frac{m(t,\omega)}{l(t,\omega)},$$

where LSN is the labor share of support workers and $\Psi(t,\omega)$ only involves parameters and factor prices.

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where LSN is the labor share of support workers and $\Psi(t,\omega)$ only involves parameters and factor prices.

- Result useful to understand model but not for estimation:
  - LSO not measurable
  - Data on stock of robots m not available and likely inaccurate

Identification

Identification Assumptions

Let τ be the year subsidies are introduced.

Assumption 1

The subsidy $s(\tau, \omega)$ follows

$$s(\tau, \omega) = s_i(\tau) + s_c(\tau) + \varepsilon^s(\tau, \omega)$$

where s_i and s_c are industry and city-specific and $\varepsilon^s(\tau, \omega)$ is a firm-specific mean-zero i.i.d random variable.

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Assumption 2

The random variable $\varepsilon^s(\tau, \omega)$ is orthogonal to any parameter, shock or factor price (or their combination) $z(t, \omega)$ in the sense that

$$\mathbb{E}\left[z(t, \omega) \,|\varepsilon^s(\tau, \omega)\right] = \mathbb{E}\left[z(t, \omega)\right]$$

for all t.

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Intuition for identification

1. Subsidies can vary systematically by cities and industries (absorbed by dummies)
2. What's left (ε^s) cannot be correlated with other exogenous quantities

Key Steps to Get More Useful Expression

- Define investment intensity in automation capital as:

$$\frac{x(\tau,\omega)}{l(\tau,\omega)} := p_m(\tau)\frac{m(\tau,\omega)}{l(\tau,\omega)} - (1-\delta_i^m)\, p_m(\tau-1)\frac{m(\tau-1,\omega)}{l(\tau-1,\omega)}\frac{l(\tau-1,\omega)}{l(\tau,\omega)}$$

- Apply Lemma 1 to right hand side to obtain difference equation on RHS

- Approximate linearly policy function with respect to subsidy s on RHS to "remove" labor growth term

- Approximate LHS around some $\overline{s}$, $\overline{LS}$, $\overline{LSN}$, $\overline{LSO}$.

$$\log\frac{LSO(\tau,\omega)-LS(\tau,\omega)}{LS(\tau,\omega)-LSN(\tau,\omega)} - \frac{LSO(\tau-1,\omega)-LS(\tau-1,\omega)}{LS(\tau-1,\omega)-LSN(\tau-1,\omega)}$$

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where LSN is the labor share of support workers and $\Psi(t,\omega)$ only involves parameters and factor prices.

Main Result

Proposition 1

Up to a linear approximation, the following holds

$$LS(\tau,\omega) - LS(\tau-1,\omega) \approx cte + \mathcal{B}\frac{x(\tau,\omega)}{l(\tau,\omega)} + FE_i + FE_c + e(\omega),$$

$$\frac{x(\tau,\omega)}{l(\tau,\omega)} \approx cte + \mathcal{L}s_\omega + FE_i + FE_c + u(\omega),$$

where e and s_ω are uncorrelated, u is an iid error term,

$$\mathcal{B} = -\frac{1}{1-\bar{s}}\frac{1}{\mathcal{L}}\left(\frac{1}{\overline{LS}-\overline{LSN}} + \frac{1}{\overline{LSO}-\overline{LS}}\right)^{-1}\mathbb{E}\left[\sigma_\omega - 1\right],$$

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These equations

1. allow us to estimate (2SLS) the causal impact of automation on the labor share
2. lead to a structural estimate of the average elasticity $\mathbb{E}\left[\sigma_\omega\right]$
3. involve automation investment $x(\tau,\omega)$ (instead of the stock)

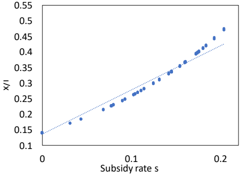
Approximation Point

To get structural estimate for $\mathbb{E}[\sigma_\omega]$ we need to pick approximation point:

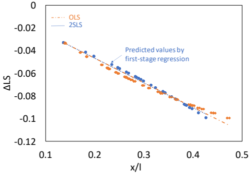
- Use mean values from data for automating firms ($x > 0$, any year)
  - $\overline{s} = 0.109$ (average subsidy rate)
  - $\overline{LS} = 0.485$ (average labor share in 2017)
  - $\overline{LSN} = 0.345$ (average labor share of nonproduction workers)
- Results under two options for $\overline{LSO}$ (labor share before automation)
  - $\overline{LSO} = 0.6$ (best fit of quantitative model)
  - $\overline{LSO} = 0.66$ (textbook labor share, also US manufacturing share in 1960s)

Validation on Model-Generated Data

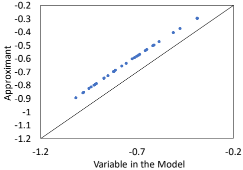
A. No dispersion in parameters and no shocks:



(a) First-stage regression

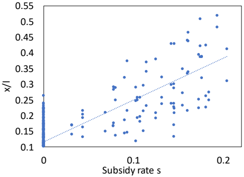


(b) Second-stage regression

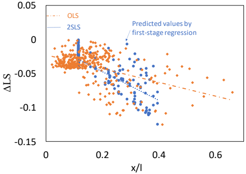


(c) Fit of linear approximation

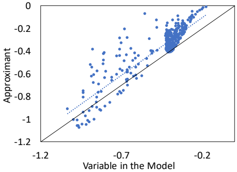
B. Baseline calibration:



(a) First-stage regression



(b) Second-stage regression



(c) Fit of linear approximation

Validation on Model-Generated Data

Statistic	Model	
	No heterogeneity	Baseline
Assumed σ	3.76	3.76
Estimated σ	3.80	3.72
S.E.	—	(0.27)
Estimated σ w/ no GE feedback	3.80	3.74
S.E.	—	(0.24)
Observations (out of 342)	143	143

Estimation Results

2SLS Regression Setup

- Instrument: average subsidy rate for each city-industry grouping:

$$s_{\omega}^{\Omega_{ci}} = \frac{\sum_{t=2015}^{2017} \sum_{\omega \in \Omega'_{ci}} S_{ci}(t,\omega)}{\sum_{t=2015}^{2017} \sum_{\omega \in \Omega'_{ci}} x_{ci}(t,\omega)}$$

- Consider two specifications for explanatory variable (x/l):
  - The most recent year (2017): $x_{17}(\omega)$
  - Cumulative investment 2015-2017:

$$x_{15-17}(\omega) := \frac{\sum_{t=15,\ldots,17} x(\omega,t)\left(\frac{1-\delta_m}{1+\pi_t}\right)^{17-t}}{3}$$

Estimation results (A)

	Second stage dependent variable $\Delta LS_\omega = LS_\omega\,(2017) - LS_\omega\,(2015)$		
Automation investment (x_{17}/l_{17})	$-.0382$*** (0.014)	$-.0458$* (0.026)	$-.0377$*** (0.012)
	First stage dependent variable Automation investment (x_{17}/l_{17})		
Subsidy rate average $(s_\omega^{\Omega ci})$	7.772*** (2.15)	6.401** (2.65)	7.092*** (2.76)
FEs: Industry / city / size	No/Yes	Yes/No	Yes/Yes
# observations	143	143	143
F-statistic	20.8	5.6	14.9
$\bar{\sigma}$ $(\overline{LSO} = 0.565)$	4.1	4.0	3.8
$\bar{\sigma}$ $(\overline{LSO} = .66)$	3.3	3.3	3.1

Two-stage least squares estimation (2SLS). *** indicates significance at 1 %, ** at 5% and * at 10% level of confidence. Robust standard errors in parenthesis. Sample is restricted to observations with positive automation investment.

Estimation results (B)

	Second stage dependent variable $\Delta LS_\omega = LS_\omega(2017) - LS_\omega(2015)$		
Automation investment (x_{17}/l_{17})	-0.0928*	-0.0815*	-0.0734*
	(0.051)	(0.045)	(0.045)
	First stage dependent variable Automation investment (x_{17}/l_{17})		
Subsidy rate average $(s_\omega^{\Omega_{ci}})$	3.584	4.319**	3.838*
	(2.26)	(2.13)	(2.36)
FEs: Industry / city / size	No/Yes	Yes/No	Yes/Yes
# observations	143	143	143
F-statistic	3.5	3.5	2.9
$\bar{\sigma}$ $(\overline{LSO} = 0.6)$	4.4	4.6	3.9
$\bar{\sigma}$ $(\overline{LSO} = .66)$	3.6	3.7	3.2

Two-stage least squares estimation (2SLS). *** indicates significance at 1 %, ** at 5% and * at 10% level of confidence. Robust standard errors in parenthesis. Sample is restricted to observations with positive automation investment.

Back-of-the-envelope calculation

A one percent decline in real price of robots leads to a 0.26% decline in LS

- Partial equilibrium effect (need GE)
- Pertains to automating firms only

For comparison, the US labor share fell 12 percentage points since the early 1990s

Quantitative Analysis (incomplete)

Plan

- Model with parameter heterogeneity and shocks: see paper
- Explain why $\overline{LSO = .6}$ best fits the data using model without parameter heterogeneity and two types of firms:
    - nonautomating firms $a = 1$
    - automating firms $a < 1$
    - (subsidized firms $s = 0$ gone)
- Show final results from calibrated model

Calibration Mean Values of Parameters

- $\overline{LSO}$ is unobservable but can tie all parameters to it:
  - $\alpha = \gamma$ (neutral for correlation of LS with production intensity)
  - markup $= 33\%$ (mean operating income in data)
  - $\overline{\alpha} = \overline{\gamma} = 1 - \frac{\theta}{\theta - 1}\overline{LSO} = 1 - 1.33\overline{LSO}$
  - $\overline{\eta} = 1 - \frac{\overline{LSOP}}{\overline{LSO}} = 1 - \frac{.345 + \overline{LSO} - .485}{\overline{LSO}} = \frac{.155}{\overline{LSO}}$.
- Growth of A s.t. model fits 13% growth of real manufacturing wages in China
- $p_m(\tau - 1)$ fits average labor share $LS = .5$ of automating firms in 2015
- $p_m(\tau)/p_m(\tau - 1)$ s.t. stock of automation capital doubles (estimates by IFR)

Why $\overline{LSO} = .6$ Fits Data Best?

- Higher $\overline{LSO}$ requires more m initially to fit $LS = .5$
- This consequence and does not fit data well

Parameterization	$LS_{\tau-1}$	ΔLS_τ	$\Delta_{\%} L_\tau$	$y_{\tau-1}$	$\Delta_{\%} y_\tau$	$m_{\tau-1}$	$\Delta_{\%} m_\tau$
A. Baseline ($\overline{LSO} = .6$, $\sigma = 3.76$)							
Automating firm	.50	**-.04**	1%	1.33	**25%**	**.19**	98%
Nonautomating firm	.60	0.	0%	.62	13%	0.	-
B. "Lower σ" ($\overline{LSO} = .66$, $\sigma = 3.05$)							
Automating firm	.50	**-.05**	5%	1.28	**32%**	**.28**	97%
Nonautomating firm	.61	0.	0%	.63	.28	0.	-

Baseline Model's Aggregate Implications

Statistic	Firm type					
	Automating		Subsidized		All	
	Data	Model	Data	Model	Data	Model
$LS(\omega, \tau-1)$ w.m.	.500	.500	.502	.505	.496	.573
ΔLS_ω w.m.	-.022	-.041	-.035	-.070	-.026	-.010
ΔLS_ω m.	-.036	-.039	-.083	-.065	-.024	-0.004
$\sum_\omega p_m x_\omega / \sum_\omega y_\omega$	15.2%	15.2%	22.6%	24.6%	3.6%	3.6%

Conclusions

- Developed a new methodology to estimate the impact of automation on the labor share and have used it on micro data from China
- Found large impact of automation on the labor share of automating firms
- Estimated an elasticity of substitution of 3.8
- Showed estimate consistent with aggregate data
- Made progress disentangling GE from effect of technology