Factor income shares and input distortions in China

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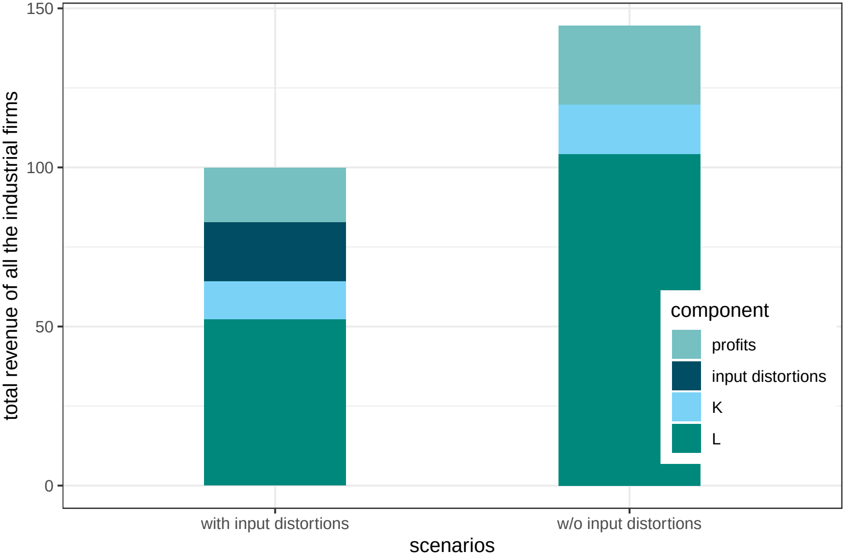
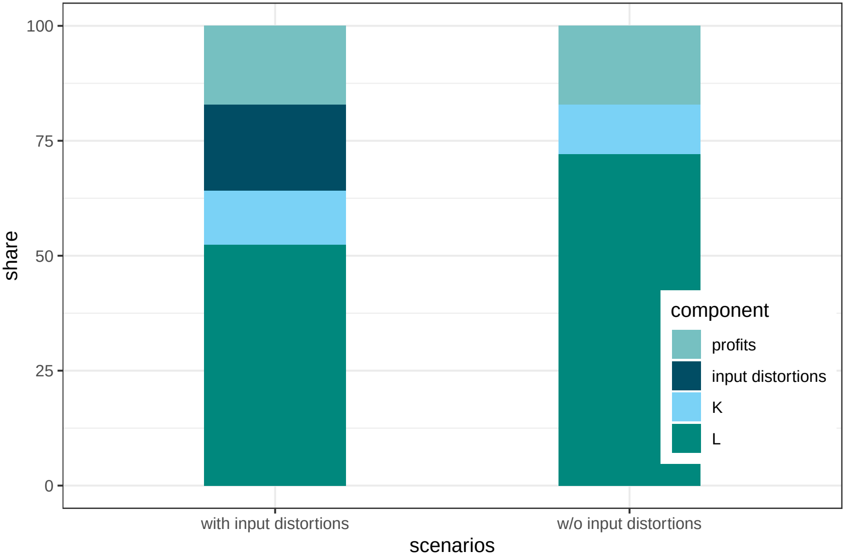
Motivation

- Capital and labor are not allocated efficiently due to input distortions such as:
  - frictions in the labor market,
  - favorable interest rates enjoyed by State-Owned Enterprises.
- Removing these input distortions can bring $30-50\%$ TFP gains (Restuccia and Rogerson (2008), Hsieh and Klenow (2009), and Zhang and Xia (2022)).
- The distributional effects of the efficiency gains are unclear.
- I estimate the changes in the factor shares in the aggregate revenue of Chinese industrial firms.

The impact from removing input distortions



The distributional impact of the efficiency gains



Key ideas

- Build on the model pioneered by Hsieh and Klenow (2009)
- but modify the framework so that:
  - industries can contain high- and low-demand-elasticities nests
  - demand elasticities differ across nests,
  - estimate production elasticities α_s^K and α_s^L from firm-level data: $Y_i = A_i K_i^{\alpha_s^K} L_i^{\alpha_s^L}$.
- Decompose the changes in aggregate factor shares.

Literature

Misallocation: Restuccia and Rogerson (2008) and Hsieh and Klenow (2009).

Decline in the US and global labor share:

- **input distortions matter:** Blanchard et al. (1997), Piketty (2014), and Karabarbounis and Neiman (2014)
- **technology differences matter:** Blanchard et al. (1997), Karabarbounis and Neiman (2014), and Autor and Salomons (2018)
- **heterogeneous demand elasticities matter:** Basu (2019), Autor et al. (2020), De Loecker et al. (2020), and Hopenhayn et al. (2022)
- **aggregation structure matters:** Elsby et al. (2013)

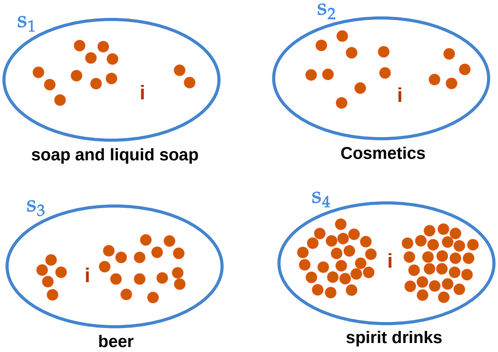
Heterogeneous demand elasticities: Atkeson and Burstein (2008) (CES with oligopolies), Klenow and Willis (2016) (Kimball preferences), etc.

Decomposition: Olley and Pakes (1996) (allocation efficiency), Edmond et al. (2019) (gains from increasing competition), and Autor et al. (2020) (changes in labor share).

Outline

Model

Figure: Demand Structure

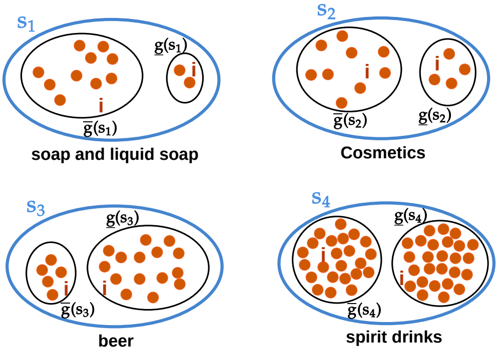


Supply:

$$Y_i = A_i K_i^{\alpha_s^K} L_i^{\alpha_s^L}$$

Model

Figure: Demand Structure



Supply:

$$Y_i = A_i K_i^{\alpha_s^K} L_i^{\alpha_s^L}$$

Demand:

$$\mathcal{Y} = \prod_{s \in \{s_1, \cdots, s_S\}} \prod_{g \in \{\bar{g}(s), \underline{g}(s)\}} Y_g^{\beta_g}$$

$$Y_g = \left(\sum_{i \in \mathcal{G}(g)} Y_i^{\frac{\epsilon_g - 1}{\epsilon_g}} \right)^{\frac{\epsilon_g}{\epsilon_g - 1}}$$

where $\epsilon_{\bar{g}(s)} > \epsilon_{\underline{g}(s)}$

The firms' problem

$$\Pi_i = P_i Y_i - (R(1+\tau_i^K)K_i + w(1+\tau_i^L)L_i)e^{\delta_i}$$

- Input distortions $\tau_i^K, \tau_i^L > -1$, normalize $\mathbb{E}[e^{\delta_i}] = 1$.
- Firms set prices, choose capital and labor before the cost shocks δ_i are realized.

$$\max_{K_i, L_i, P_i} \mathbb{E}[\Pi_i] = P_i Y_i - (R(1+\tau_i^K)K_i + w(1+\tau_i^L)L_i)$$

s.t. the nested CES demand

FOC:

$$\underbrace{\log(1+\tau_i^L)}_{\text{input distortions}} = \underbrace{\log\left(\alpha_s^L \frac{\epsilon_g - 1}{\epsilon_g}\right)}_{\substack{\text{theoretical shares} \\ \text{w/o input distortions}}} - \underbrace{\log\left(\frac{wL_i}{P_i Y_i}\right)}_{\text{observed shares}}$$

Firms' markups:

$$\mu_i = \frac{\epsilon_g}{\epsilon_g - 1} e^{-\delta_i}$$

Aggregate factor shares with τ

$$\frac{wL}{PY} = \sum_g \frac{P_g Y_g}{PY} \sum_{i \in \mathcal{G}(g)} \frac{wL_i}{P_i Y_i} \frac{P_i Y_i}{P_g Y_g}$$
$$= \sum_g \beta_g \underbrace{\alpha_g^L \frac{\epsilon_g - 1}{\epsilon_g} \cdot \frac{1}{1 + \bar{\tau}_g^L}}_{\text{nest-level labor shares}}$$

where

$$\log\left(\frac{1}{1 + \bar{\tau}_g^L}\right) \equiv \log\left(\frac{wL_g}{P_g Y_g}\right) - \log\left(\alpha_g^L \frac{\epsilon_g - 1}{\epsilon_g}\right)$$

Notation: $\mathcal{G}(g)$ the set of firms belonging to nest g, β_g expenditure share of nest g, α_g^L production elasticities of labor in nest g and $\alpha_{\bar{g}(s)}^L = \alpha_{\underline{g}(s)}^L = \alpha_s^L$, ϵ_g demand elasticities of nest g, $L_g = \sum_{i \in \mathcal{G}(g)} L_i$.

Changes in factor shares from removing τ

$$\frac{wL}{PY} = \sum_g \beta_g \alpha_g^L \frac{\epsilon_g - 1}{\epsilon_g} \cdot \frac{1}{1 + \bar{\tau}_g^L}$$

$$\frac{w^* L}{P^* Y^*} = \sum_g \beta_g \alpha_g^L \frac{\epsilon_g - 1}{\epsilon_g}$$

$$\frac{w^* L}{P^* Y^*} - \frac{wL}{PY} = \sum_g \underbrace{\beta_g \alpha_g^L \frac{\epsilon_g - 1}{\epsilon_g}}_{\text{weights}} \cdot \left[1 - \frac{1}{1 + \bar{\tau}_g^L}\right]$$

Notation: β_g expenditure share of nest g, α_g^L production elasticities of labor in nest g and $\alpha_{\bar{g}(s)}^L = \alpha_{\underline{g}(s)}^L = \alpha_s^L$, ϵ_g demand elasticities of nest g, $\bar{\tau}_g^L$ labor distortions measured for nest g.

Outline

Estimation steps

1. Calculate firm-level markups using revenue-cost ratios.
2. Use revenue-cost ratios and industry classifications to infer the nest structure and demand elasticities ϵ_g.
3. Use labor shares and capital shares to estimate production elasticities α_s^L and α_s^K.

Estimation: ϵ_g

Assumption: $\delta_i \sim \mathcal{N}(-\frac{\sigma_g^2}{2}, \sigma_g^2)$.

Firms' markups (revenue-cost ratios):

$$\mu_i = \underbrace{\frac{\epsilon_g}{\epsilon_g - 1}}_{\text{nest structure}} \cdot \underbrace{e^{-\delta_i}}_{\text{shocks}}$$

If an industry contains two nests, the distribution of markups is a mixture of two normal distributions. For $i \in \mathcal{S}(s)$:

$$\log(\mu_i) \sim p_s * \mathcal{N}\left(\log\left(\frac{\epsilon_{\bar{s}}}{\epsilon_{\bar{s}} - 1}\right) - \frac{\sigma_{\bar{s}}^2}{2}, \sigma_{\bar{s}}^2\right) + (1 - p_s) * \mathcal{N}\left(\log\left(\frac{\epsilon_{\underline{s}}}{\epsilon_{\underline{s}} - 1}\right) - \frac{\sigma_{\underline{s}}^2}{2}, \sigma_{\underline{s}}^2\right)$$

Notation: μ_i markups, $\epsilon_{\bar{s}}$ and $\epsilon_{\underline{s}}$ demand elasticities of nest $\bar{s}$ and $\underline{s}$, p_s ex-ante probability of belonging to $\bar{s}$, $\sigma_{\bar{s}}^2$ and $\sigma_{\underline{s}}^2$ variances of cost shocks in nest $\bar{s}$ and $\underline{s}$, $\mathcal{S}(s)$ the set of all the firms in industry s.

Can't use the US production parameters

$$\frac{w^*L}{P^*Y^*} - \frac{wL}{PY} = \sum_g \beta_g \alpha_g^L \frac{\epsilon_g - 1}{\epsilon_g} \cdot \left[1 - \sum_{i \in \mathcal{G}(g)} \frac{1}{1+\tau_i^L} \frac{\left(\frac{A_i}{(1+\tau_i^L)^{\alpha_g^L}} \right)^{\frac{\epsilon_g - 1}{\epsilon_g - (\epsilon_g - 1)\alpha_g^L}}}{\sum_{i \in \mathcal{G}(g)} \left(\frac{A_i}{(1+\tau_i^L)^{\alpha_g^L}} \right)^{\frac{\epsilon_g - 1}{\epsilon_g - (\epsilon_g - 1)\alpha_g^L}}} \right]$$

- Can't use US as a benchmark:
  - differences in technology between US and China will be treated as input distortions,
  - fine when talking about TFP gains,
  - but create a systematic bias for labor share change.

Notation: β_g expenditure share of nest g, α_g^L production elasticities of labor in nest g and $\alpha_{\bar{g}(s)}^L = \alpha_{\underline{g}(s)}^L = \alpha_s^L$, ϵ_g demand elasticities of nest g, $\mathcal{G}(g)$ the set of firms belonging to nest g, A_i Hicks-Neutral productivity, τ_i^L input distortions.

Estimation: α_s^K and α_s^L

Assumption: the modes of capital and labor distortions for firms in an industry are both zero:

$$\text{mode}(\tau_i^L | i \in \mathcal{S}(s)), \text{mode}(\tau_i^K | i \in \mathcal{S}(s)) = 0$$

$$\log\left(\frac{wL_i}{P_i Y_i}\right) = \log(\alpha_s^L) - \log\left(\frac{\epsilon_g}{\epsilon_g - 1}\right) - \log(1 + \tau_i^L)$$

- Allow distortions to be not mean-zero.
- Allow the possibility that all the firms inside an industry have positive (negative) input distortions.

Notation: $\mathcal{S}(s)$ the set of all the firms in industry s, α_s^L production elasticities of labor in industry s, ϵ_g demand elasticities of nest g, τ_i^L input distortions.

Outline

Data

Chinese Annual Firm-Level Survey Data (2005) from NBS:

- Includes all State-Owned Enterprises and above-scale non-state firms ($229,064$).
- Covers manufacturing, mining, and public utilities: 523 industries.
- Key variables: value added, depreciated real capital, labor expenditures, revenues, and costs.
  - Observed value added = value of output − value of intermediate inputs
  - Calculate depreciated real capital (Brandt et al. (2012))
    - infer investment from the observed sum of past investment at historical prices
    - 9% depreciation rate
    - Brandt-Rawski investment deflator

Summary statistics

Outline

Results: estimated parameters

Table: Distribution of industry-level firm counts

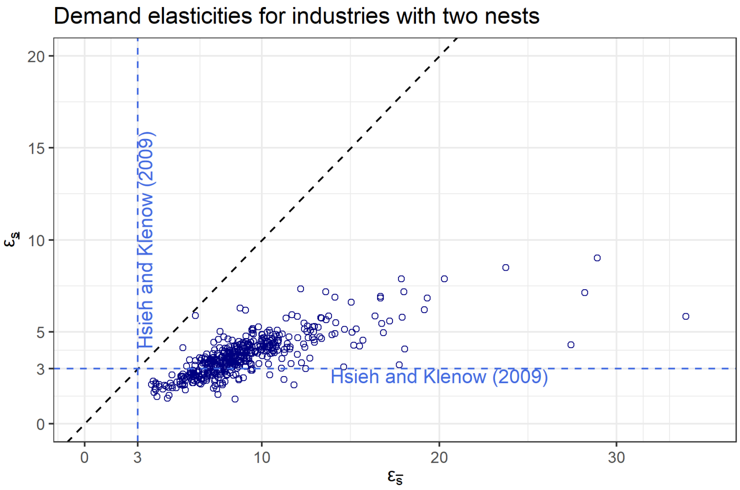
	N	Mean	Min	Pctl(25)	Median	Pctl(75)	Max
One nest	61	23	2	6	15	27	237
Two nests	462	494	12	118	256	545	9,947

Table: Summary statistics of selected estimated parameters

	Mean	St. Dev.	Pctl(10)	Pctl(25)	Median	Pctl(75)	Pctl(90)
p_s	0.73	0.16	0.54	0.66	0.75	0.83	0.89
ϵ_g	8.49	3.26	3.99	6.50	8.57	10.27	12.85
$\alpha_s^K + \alpha_s^L$	1.04	0.58	0.44	0.64	0.88	1.22	1.88

Notation: ϵ_g demand elasticities of nest g, p_s ex-ante probability of belonging to $\bar{s}$, $\alpha_s^K + \alpha_s^L$ returns to scale. Weighted Stats

Demand elasticities for industries with two nests



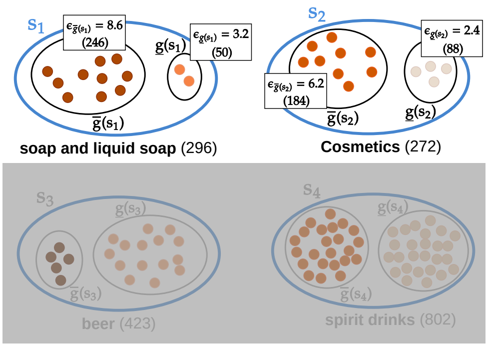
Standard deviations

Average demand elasticities at the 2-digit industry level

Industry	ϵ	**Firm counts**
Oil and gas extraction	3.22	33
Agricultural and Sideline Food Processing	9.59	12275
Tobacco	3.97	102
Textile	11.31	20197
Pharmaceutical	4.82	4233
Rubber products	7.69	2693
General Equipment Manufacturing	7.51	18088
Special-Purpose Equipment Manufacturing	6.48	8923
Recycling and processing of waste resources and materials	14.36	347

Demand elasticities of nests from different industries

Figure: Four industries as examples



- 435 out of the 462 industries: $N_{\bar{s}} > N_{\underline{s}}$.

ϵ: demand elasticities. Numbers in brackets: firm counts.

Demand elasticities of nests from different industries

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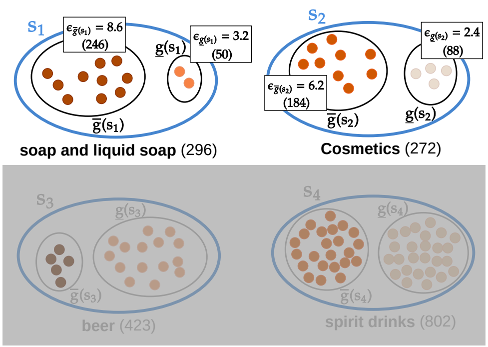

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  - Relatively fewer firms can achieve high-level of product differentiation.

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Demand elasticities of nests from different industries

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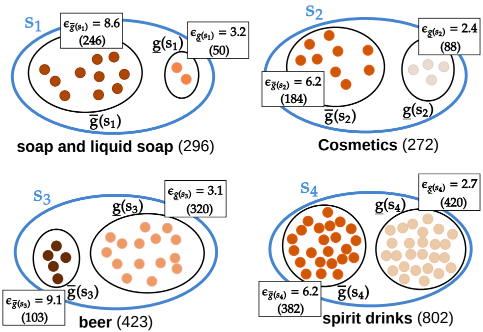
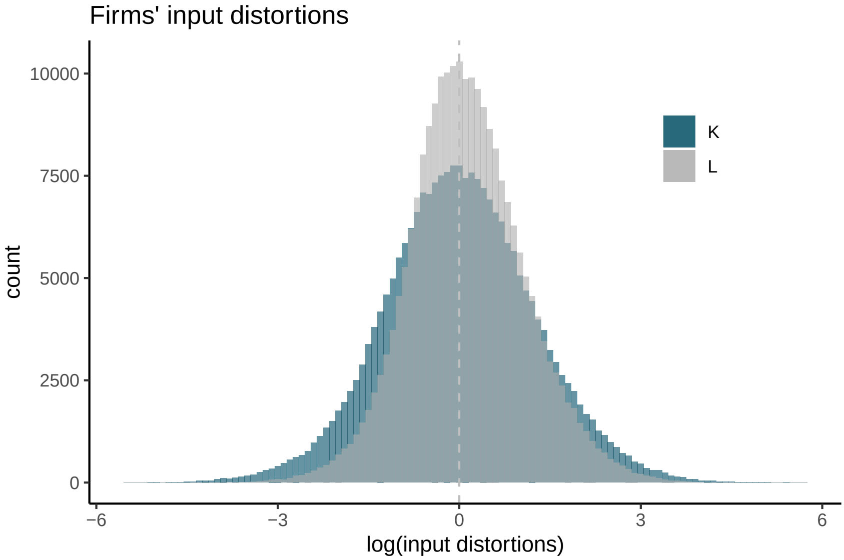


- 435 out of the 462 industries: $N_{\bar{s}} > N_{\underline{s}}$.
  - Relatively fewer firms can achieve high-level of product differentiation.
- But 27 industries e.g. beer and spirit drinks: $N_{\bar{s}} < N_{\underline{s}}$.

ϵ: demand elasticities. Numbers in brackets: firm counts.

Estimated input distortions τ_i^L and τ_i^K



Results: Labor and capital income share (%)

Table: Labor and capital income shares and their predicted changes (%)

	with input distortions	w/o input distortions	changes
L	52.37	72.10	19.73
K	11.86	10.77	-1.09

$$\frac{w^*L}{P^*Y^*} - \frac{wL}{PY} = \sum_g \underbrace{\beta_g \alpha_g^L \frac{\epsilon_g - 1}{\epsilon_g}}_{\text{weights}} \cdot \left[1 - \frac{1}{1+\bar{\tau}_g}\right]$$

Decomposition

$$\frac{w^*L}{P^*Y^*} - \frac{wL}{PY} = \sum_g \left\{ \underbrace{\text{cov}\left(\beta_g \alpha_g \frac{\epsilon_g - 1}{\epsilon_g}, 1 - \frac{1}{1+\bar{\tau}_g^L}\right)}_{\text{covariance}} + \underbrace{\left(\overline{\beta_g \alpha_g \frac{\epsilon_g - 1}{\epsilon_g}}\right)}_{\text{average}} \cdot \underbrace{\overline{\left(1 - \frac{1}{1+\bar{\tau}_g^L}\right)}}_{\text{average}} \right\}$$

- $\overline{\beta_g \alpha_g \frac{\epsilon_g - 1}{\epsilon_g}}$ the average of $\beta_g \alpha_g \frac{\epsilon_g - 1}{\epsilon_g}$, $\overline{1 - 1/(1+\bar{\tau}_g^L)}$ the average of $1 - 1/(1+\bar{\tau}_g^L)$ (averages across nests).

Notation: β_g expenditure share of nest g, ϵ_g demand elasticities of nest g, α_g^L production elasticities of labor in nest g and $\alpha_{\bar{g}(s)}^L = \alpha_{\underline{g}(s)}^L = \alpha_s^L$, $\bar{\tau}_g$ input distortions measured for nest g.

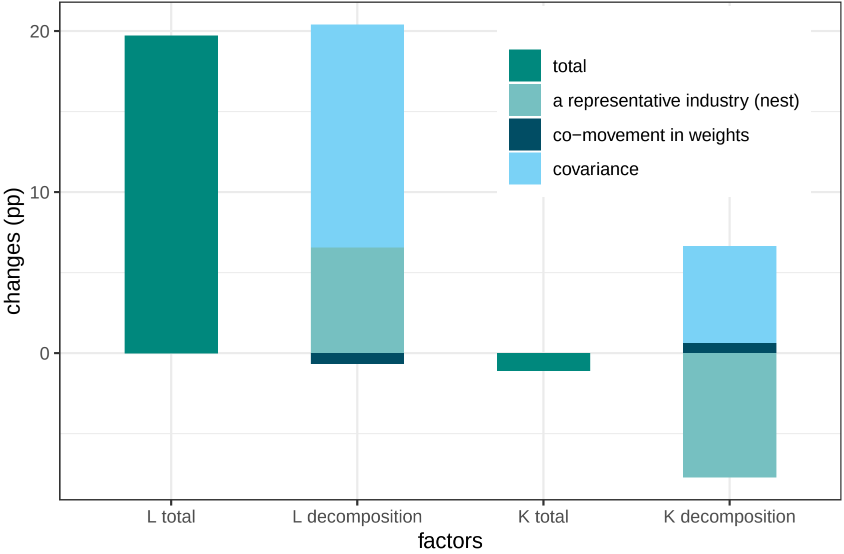
Decomposition

$$\frac{w^*L}{P^*Y^*} - \frac{wL}{PY} = \sum_g \Bigg\{ \underbrace{\text{cov}\left(\beta_g \alpha_g \frac{\epsilon_g - 1}{\epsilon_g}, 1 - \frac{1}{1+\bar{\tau}_g^L}\right)}_{\text{covariance between weights and input distortions}} + $$

$$\underbrace{\left(\overline{\beta_g \alpha_g \frac{\epsilon_g - 1}{\epsilon_g}} - \beta \alpha^L \frac{\epsilon - 1}{\epsilon}\right)}_{\text{co-movement in weights}} \overline{\left(1 - \frac{1}{1+\bar{\tau}_g^L}\right)} \Bigg\} + \underbrace{\alpha^L \frac{\epsilon - 1}{\epsilon} \cdot \overline{\left(1 - \frac{1}{1+\bar{\tau}_g^L}\right)}}_{\text{a representative industry (nest)}}$$

- $\beta = \frac{1}{N}$, α^L the average of α_g^L, $\frac{\epsilon - 1}{\epsilon}$ the average of $\frac{\epsilon_g - 1}{\epsilon_g}$ (averages across nests).
- Co-movement between the weights $\beta_g \alpha_g \frac{\epsilon_g - 1}{\epsilon_g}$ and $\bar{\tau}_g \Rightarrow$ larger factor share changes.
- Co-movement among β_g, α_g, and $\frac{\epsilon_g - 1}{\epsilon_g} \Rightarrow$ larger weights.

Decomposition



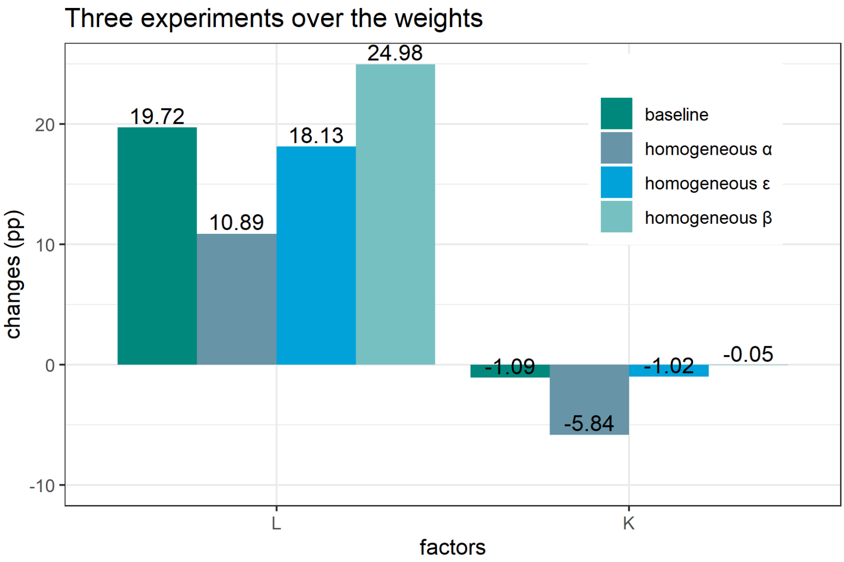
Which parameter in weights matters the most

$$\frac{w^* L}{P^* Y^*} - \frac{wL}{PY} = \sum_g \underbrace{\beta_g \alpha_g^L \frac{\epsilon_g - 1}{\epsilon_g}}_{\text{weights}} \cdot \left[1 - \frac{1}{1 + \bar{\tau}_g}\right]$$

Table: Correlations between $\bar{\tau}_g$ and weights

	$\bar{\tau}_g^L$	$\bar{\tau}_g^K$
$(\epsilon_g - 1)/\epsilon_g$	0.14	0.02
α_s	0.68	0.62
β_g	-0.10	-0.09

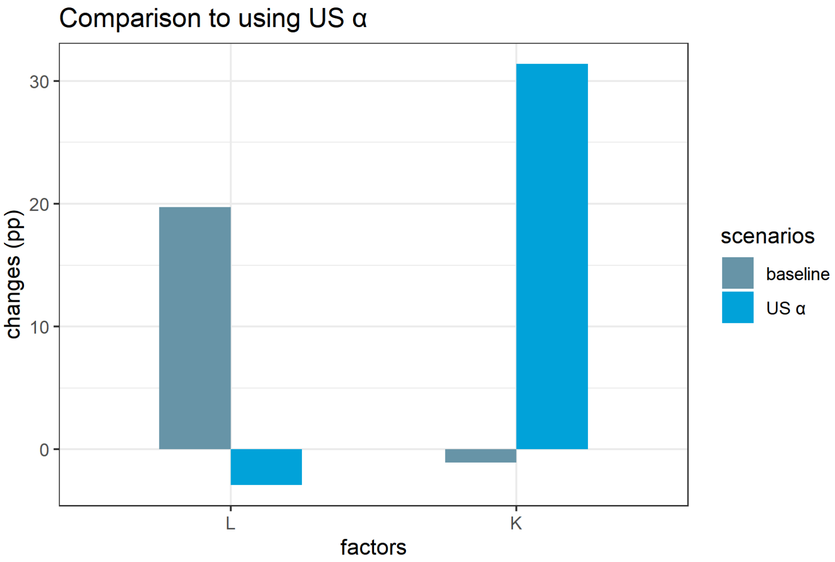
Main results: decomposition of factor share changes



Main results: summary

- Input distortions cause the overuse of capital and the underuse of labor.
- The magnitude of the factor share changes are similar if in an economy with one representative industry.
- Industry heterogeneity triples the change of the labor share but offsets that of the capital share.
- Heterogeneous technology across nests (α_s) are the most important heterogeneity.

Use production elasticities α^L and α^K of American firms



Outline

Conclusion

- The 1978 Reform and Opening-up may have caused the increase in the Chinese industrial labor share in 1978-1995.
  - The industrial labor share in industry increased from 35% in 1978 to 49% in 1995.
  - Strong restrictions prevented agricultural labor from migrating to industry.
  - The increase slowed down after major relaxation of those restrictions in the late 1990s.

Conclusion

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  - The industrial labor share in industry increased from 35% in 1978 to 49% in 1995.
  - Strong restrictions prevented agricultural labor from migrating to industry.
  - The increase slowed down after major relaxation of those restrictions in the late 1990s.
- Removing input distortions would moderate the 7.2% decrease in the Chinese labor share in 1995-2007 (NBS, Bai and Qian (2010)).
  - The decline in Chinese labor share is mainly due to structural transformation from agriculture to non-agriculture (Bai and Qian (2010)).
  - Labor share in agriculture is 85-95% and in industry is 40-50%.
  - If strict restrictions on labor mobility are restored, the labor share could increase by 5.6%.

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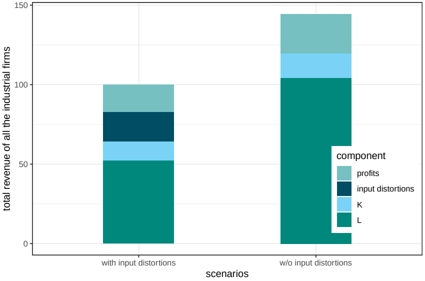
  - Labor share in agriculture is 85-95% and in industry is 40-50%.
  - If strict restrictions on labor mobility are restored, the labor share could increase by 5.6%.
- Removing input distortions in 2005 would trigger massive migration from agriculture to industry, from rural to urban areas.
  - In 1998-2005, input distortions in China declined by 15% (Hsieh and Klenow (2009))
  - Meanwhile, migrant workers from agriculture increased by 60% to 210 million, 15% out of the total population (Ministry of Agriculture).
  - Complicated social-economic issues: rural-urban income gaps, overcrowded cities, etc.

Conclusion



Is removing the input distortions always good for Chinese growth perspective?

- Take into account the 45% aggregate TFP gains (Zhang and Xia (2022)), returns to entrepreneurs can be lower without input distortions.
- returns to entrepreneurs = revenues - costs spent on capital and labor
  - 15% lower if the input distortions are all adjustment frictions or limited access to production factors;
  - 15-40% lower if parts of capital distortions are subsidies or favorable interest rates.

References

Atkeson, A. and A. Burstein (2008): "Pricing-to-Market, Trade Costs, and International Relative Prices," *The American Economic Review*, 98, 1998–2031, publisher: American Economic Association.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020): "The Fall of the Labor Share and the Rise of Superstar Firms," *The Quarterly Journal of Economics*, 135, 645–709.

Autor, D. and A. Salomons (2018): "Is Automation Labor Share–Displacing? Productivity Growth, Employment, and the Labor Share," *Brookings Papers on Economic Activity*, 1–63, publisher: Brookings Institution Press.

Bai, C.-E. and Z. Qian (2010): "The factor income distribution in China: 1978–2007," *China Economic Review*, 21, 650–670.

Basu, S. (2019): "Are Price-Cost Markups Rising in the United States? A Discussion of the Evidence," *Journal of Economic Perspectives*, 33, 3–22.

Blanchard, O. J., W. D. Nordhaus, and E. S. Phelps (1997): "The Medium Run," *Brookings Papers on Economic Activity*, 1997, 89–158, publisher: Brookings Institution Press.

Brandt, L., J. Van Biesebroeck, and Y. Zhang (2012): "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics*, 97, 339–351.

De Loecker, J., J. Eeckhout, and G. Unger (2020): "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal of Economics*, 135, 561–644.

Edmond, C., V. Midrigan, and D. Y. Xu (2019): "How Costly Are Markups," *working paper*.

Elsby, M. W. L., B. Hobijn, and A. Şahin (2013): "The Decline of the U.S. Labor Share," *Brookings Papers on Economic Activity*, 1–52, publisher: Brookings Institution Press.

Hopenhayn, H., J. Neira, and R. Singhania (2022): "From Population Growth to Firm Demographics: Implications for Concentration, Entrepreneurship and the Labor Share," *Econometrica*, 90, 1879–1914, publisher: John Wiley & Sons, Ltd.

Hsieh, C.-T. and P. J. Klenow (2009): "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 46.

Karabarbounis, L. and B. Neiman (2014): "The Global Decline of the Labor Share*," *The Quarterly Journal of Economics*, 129, 61–103.

Klenow, P. J. and J. L. Willis (2016): "Real Rigidities and Nominal Price Changes," *Economica*, 83, 443–472.

Olley, G. S. and A. Pakes (1996): "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64, 1263–1297.

Piketty, T. (2014): *Capital in the Twenty-First Century*, Harvard University Press.

Restuccia, D. and R. Rogerson (2008): "Policy Distortions and Aggregate Productivity with Heterogeneous Establishments," *Review of Economic Dynamics*, 11, 707–720.

Zhang, X. and J. Xia (2022): "Misallocation under Heterogeneous Markups," *working paper*.

Thank you!

Data

Table: Summary Statistics after data cleaning (2005)

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
value added	13,778.560	25,585.720	122	2,516	5,372	13,228	277,908
wL	7,216.359	13,415.890	212.041	1,545.247	3,146.155	7,050.356	209,273.700
K	16,334.630	41,008.100	83.761	1,619.101	4,207.121	12,127.260	515,954.200
revenue	50,065.030	112,328.500	2	9,500	19,439	45,912	11,041,153
cost	42,989.580	101,057.400	1	7,932	16,469	39,000	10,757,115
revenue/cost	1.212	0.264	0.814	1.079	1.141	1.250	4.679
wL/value added	0.850	0.844	0.033	0.310	0.621	1.108	8.338

Return

Summary Statistics of estimated parameters

Table: Revenue-based summary statistics across firms

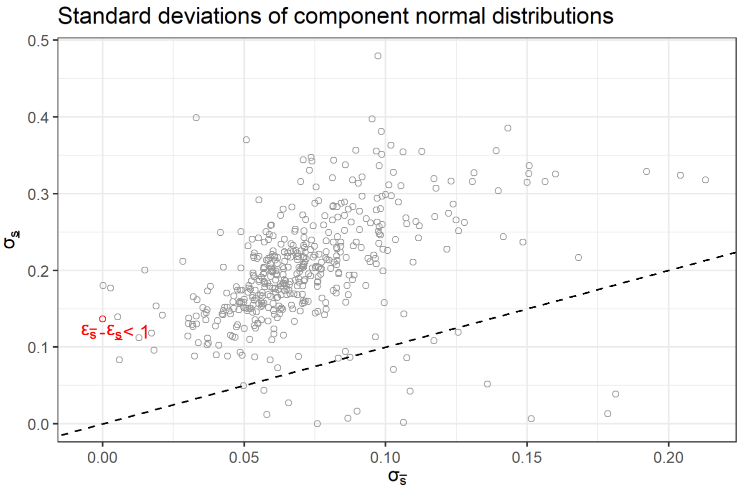
	Mean	St. Dev.	Pctl(10)	Pctl(25)	Median	Pctl(75)	Pctl(90)
ϵ_g	9.07	3.26	4.14	7.06	9.14	10.76	14.12
$\alpha_s^K + \alpha_s^L$	0.97	0.58	0.36	0.54	0.84	1.16	1.83

Table: Cost-based summary statistics across firms

	Mean	St. Dev.	Pctl(10)	Pctl(25)	Median	Pctl(75)	Pctl(90)
ϵ_g	9.37	3.26	4.50	7.44	9.20	10.91	14.16
$\alpha_s^K + \alpha_s^L$	0.96	0.58	0.36	0.53	0.82	1.16	1.83

Return

Dispersion of markups within an industry



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