Non-neutral Technological Change in Chinese Manufacturing

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NU ECONOMICS

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Abstract

This article identifies firm-level factor-augmenting productivity for capital, labor, and materials using Chinese manufacturing data from 1998 to 2008, a period of state-owned enterprise reform. We develop a novel method to estimate the parameters of a CES production function and recover the three types of factor-augmenting productivity. Results suggest technological change is strongly biased: labor-augmenting productivity grew 12% annually, capital-augmenting 5%, and material-augmenting 1.4%. Factor-augmenting productivity growth varies by sector and ownership. Productivity growth was driven primarily by incumbents, whereas entrants improved capital efficiency and exiters enhanced labor efficiency. We explain factor cost-share shifts through productivity gaps and relative input prices.

Why Non-neutral? Why Chinese Manufacturing?

Year	No. of Firms	Revenue	Capital	Labor	Materials
1998	75,949	43.732	28.001	333	32.529
2008	215,402	120.521	27.661	211	79.706

Why care about non-neutral technological change?

- Capital and Labor Share drop at firm level
- Hicks-neutral productivity cannot explain the observed input share shifts

Why choose Chinese manufacturing?

- Input/output shifts in firms: Revenue × 3; Employment ↓ 1/3; Materials × 2.
- Late-1990s SOE reforms ⇒ ideal laboratory for biased technological change

Which inputs drive economic growth?

How biased is technological change across input factors?

- Why the capital share drop significantly? What roles do entry and exit play?

This paper introduces a novel method to estimate firm-level CES production functions with factor-augmenting productivity for Capital, Labor, and Material.

What Does This Paper Contribute?

Methodologically,

- Novel method: Cost Minimization and Dynamic Panel Method
- *Robust to any product market structure* ⇒ Relax assumptions

Economically,

- New evidence on how entry&exit contribute on biased technological change
- Explains the factor-share drop: driven by biased technology and relative input price

Model: CES Production Function

$$Q_{jt} = \left\{ \left[\exp\left(\omega_{jt}^K\right) K_{jt}\right]^{-\frac{1-\sigma}{\sigma}} + \left[\exp\left(\omega_{jt}^L\right) L_{jt}\right]^{-\frac{1-\sigma}{\sigma}} + \left[\exp\left(\omega_{jt}^M\right) M_{jt}\right]^{-\frac{1-\sigma}{\sigma}} \right\}^{-\frac{\sigma}{1-\sigma}\nu}.$$

- ω_{jt}^X: firm-specific factor-augmenting productivities

Identification: Dynamic Panel GMM

1. **Cost-Minimization** FOCs give the cost share forms of the CES
2. AR(1) Productivity Process + **Pseudo Difference**
3. Estimate the system equation by **GMM** using the following moments

$$\begin{cases} y_{jt} = \rho^K y_{jt-1} + \nu(k_{jt} - \rho^K k_{jt-1}) + \nu\frac{\sigma}{1-\sigma}(s_{jt}^K - \rho^K s_{jt-1}^K) + \nu\gamma_t^K + \tilde{\xi}_{jt}^K \\ y_{jt} = \rho^L y_{jt-1} + \nu(l_{jt} - \rho^L l_{jt-1}) + \nu\frac{\sigma}{1-\sigma}(s_{jt}^L - \rho^L s_{jt-1}^L) + \nu\gamma_t^L + \tilde{\xi}_{jt}^L \\ y_{jt} = \rho^M y_{jt-1} + \nu(m_{jt} - \rho^M m_{jt-1}) + \nu\frac{\sigma}{1-\sigma}(s_{jt}^M - \rho^M s_{jt-1}^M) + \nu\gamma_t^M + \tilde{\xi}_{jt}^M \end{cases}$$

$$\begin{cases} E[(s_{jt-1}^L)'\tilde{\xi}_{jt}^L] = 0 \\ E[(s_{jt-1}^M)'\tilde{\xi}_{jt}^M] = 0 \\ E[(k_{jt-1})'\tilde{\xi}_{jt}^K] = 0 \\ E[(l_{jt-1})'\tilde{\xi}_{jt}^L] = 0 \\ E[(m_{jt-1})'\tilde{\xi}_{jt}^M] = 0 \end{cases}.$$

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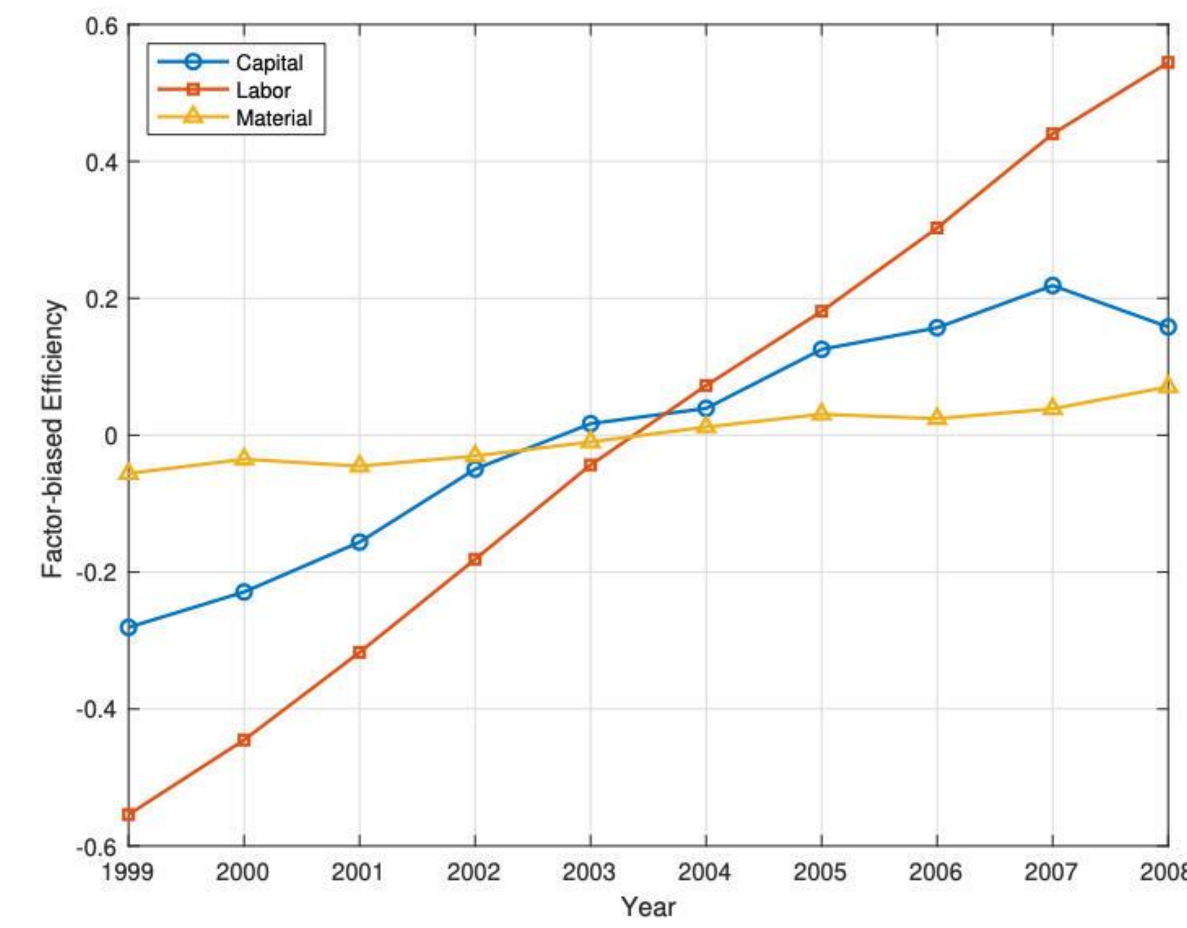
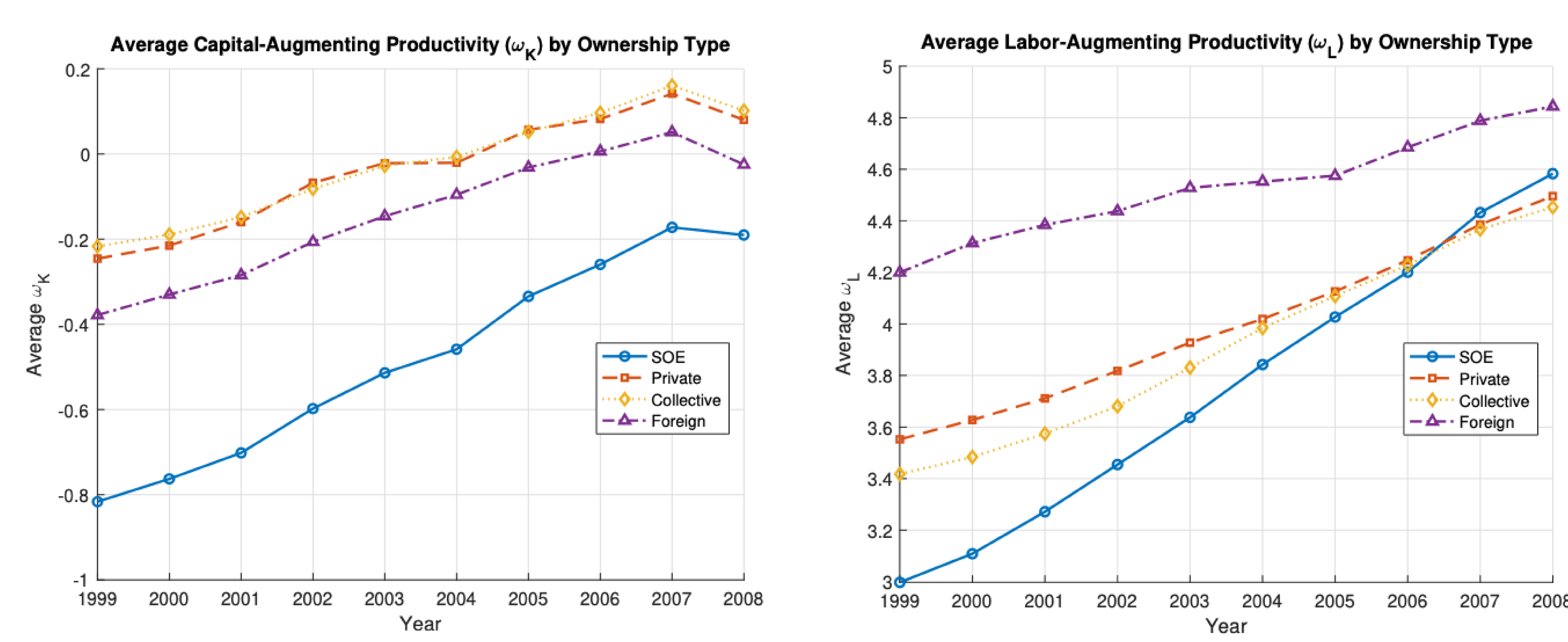
Finding: Technological Change is Biased



Annual growth rate: Labor (12.2%), Capital (4.9%), and Materials (1.4%)

During Reform: SOEs are Catching Up!



Entry ⇑ Capital ω; Exit ⇑ Labor ω

	Change in Aggregate	Decomposition				
		Survivors				
	Productivity $\Delta\phi$	Total $\Delta\phi^S$	Shift $\Delta\bar{\phi}^S$	Covariance $N^S\Delta\mathrm{Cov}(\cdot)$	Entrants $\mu_{t2}^E(\phi_{t2}^E - \phi_{t2}^S)$	Exiters $\mu_{t1}^X(\phi_{t1}^S - \phi_{t1}^X)$
Capital	0.429	0.305	0.294	0.011	0.116	0.006
Labor	1.083	0.954	0.943	0.010	-0.099	0.228
Material	0.128	0.127	0.131	-0.001	-0.024	0.020

How to Explain Capital Share Drop?

Growth of Capital Share	Decomposition					
	$\omega^K - \omega^L$	$p^L - p^K$	$\omega^K - \omega^M$	$p^M - p^K$	Realloc.	Resid.
-0.052	0.059	-0.084	-0.020	-0.024	0.006	0.012

Conclusions

- Biased technological change in Chinese manufacturing: Labor (12.2%), capital (4.9%), and materials (1.4%)
- Entrants ⇑ Capital Efficiency; Exiters ⇑ Labor Efficiency
- Factor share shift: driven by both biased tech change & relative price
- SOEs are narrowing the gap with private firms

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