Supplemental Appendix: Exploiting or Augmenting Labor?

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A Data Appendix

A.1 Data Cleaning

Our empirical application focuses on the Chinese NFM manufacturing and mining industries, which are classified under Code 33 of the Chinese Industry Classification (CIC) "Smelting and pressing of nonferrous metals", and under CIC Code 9,"Nonferrous metals mining and dressing."

Our main data source is the Annual Survey of Industrial Production (ASIP), which is collected by the National Bureau of Statistics of China (National Bureau of Statistics (NBS), 1999-2006). We refer to Brandt et al. (2014) for a comprehensive discussion of this dataset. The annual operation and balance sheet data are collected at the firm level, and are observed from 1998 to 2007. The dataset covers manufacturing firms with more than 5 million RMB in annual sales ($\approx$ \$700K) from 1999 to 2007. For each surveyed firm, the ASIP provides balance sheet data on revenues and input expenditure and usage at the establishment level.

For a subset of firms, we also observe product-level production quantities from 1999 to 2006. The production quantity data contains 6,699 firms, 302 product codes, and 32,114 observations in the NFM mining and manufacturing industries. The data includes a firm identifier, the product codes for each firm's production, the industry code they belong to, and the production quantity and units. For those with missing units, we assume that the unit does not change within a firm-product pair, and we replace them with another year's units

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when available. If the firm-product pair is missing for all years, we assume that the unit is tons. After standardizing the units to tons, we calculate the total production quantity for each firm-year across various products.

The ASIP panel covers all SOEs, and all other firms with annual sales of at least 5 million RMB. It provides financial data and other firm-specific information, including for each company its name, address, industry, age, and ownership structure. The ASIP dataset covers 17,411 firms and 53,130 observations in the NFM mining and manufacturing industries.[1] We obtain the Consumer Price Index (CPI) for China from Organization for Economic Cooperation and Development (2025), with which we deflate revenue, profit, wage bill, nonwage benefits, real capital, intermediate input, and export to index at 2006 RMB. Next, we change the currency unit from thousands of RMB to USD based on each year's average exchange rate. To reduce measurement error in inputs, we trim the variable input revenue shares at the 1st and 99th percentiles.

To construct a measure for the outside option, we merge the dataset with a census population dataset from 2000. We use China's Population Census data to compute county-level employment in the year 2000. Annual international market prices of various NFMs are from the Bloomberg Industrial Metals Subindex (Bloomberg, 2022). We link each nonferrous metal to a harmonized system (HS) code (?, ?), and in turn link each of these HS codes to the industry codes in the NBS dataset using the concordances provided by (Brandt et al., 2014).

Finally, we obtain monthly minimum wages for full-time employees at the county-year level from official county government reports (Wang, 2022). Appendix Table A1 summarizes the key characteristics of Chinese firms in the NFM manufacturing and mining sectors.

A.2 Cost Shares

We document the evolution of the cost share of labor and firm ownership in Chinese NFM industries. In contrast to most previous research (Karabarbounis & Neiman, 2014; Autor et al., 2020; De Loecker et al., 2020), we focus on the *variable cost* share of labor, defined as labor costs over total variable costs, rather than its *revenue* share, defined as labor costs over revenue. This allows us to abstract from markups. Throughout the sample period, the labor cost share of NFM firms plummeted: Figure A1a shows that it fell from 7% to 3% for all NFM firms. This pattern also holds for the labor expenditure share of value

[1] Table A1 has lower numbers of observations because of missing observations for different variables and our various data cleaning procedures.

added.[2] Changing ownership of firms contributed to this decline in the labor share. From 1999 to 2006, the employment share of foreign-owned private firms increased from 4% to 9%, whereas it halved from 70% to 35% for SOEs. As Figure A1 shows, the labor cost share was systematically higher at SOEs compared to domestic private firms, and lower for foreign-owned firms. Hence, the decline in the aggregate cost share of labor was partially due to the reallocation of employment from SOEs to private firms.

In terms of these descriptive facts, NFM industries mimick the overall Chinese industrial sector. In Appendix Figure A1b we replicate Figure A1a for all manufacturing and mining industries in China, rather than only the NFM sector. The labor share of variable costs, the solid blue line, fell from 8% to 5% for all industries . Similarly, the labor share of value added dropped from 33% to 17% for all industries. In terms ownership, the overall employment share of SOEs declined from 59% to 22% from 1999 to 2006. whereas the overall employment share of foreign-owned private firms doubled from 12% to 28%.

[2]See Appendix Figure A2.

B Robustness and Extensions

B.1 Production: Alternative Functional Forms

Cobb-Douglas

In the main text, we compare our model to a Cobb-Douglas production function, which we specify and estimate in this appendix. We use the Cobb-Douglas specification in Equation (A1):

$$q_{ft} = \beta^l l_{ft} + \beta^m m_{ft} + \beta^l l_{ft} + \omega_{ft} + \varepsilon_{ft} \tag{A1}$$

We maintain the AR(1) specification for Hicks-neutral productivity in Equation (6) and to the price control in the production function that was specified in the main text. Hence, we can isolate the Hicks-neutral productivity shock $\upsilon((\beta^l, \beta^m, \beta^k, \beta^p, \rho)$ as:

$$\upsilon_{ft} = q_{ft} - \rho q_{ft-1} - \beta^l(l_{ft} - \rho l_{ft-1}) - \beta^m(m_{ft} - \rho m_{ft-1}) - \beta^k(k_{ft} - \rho k_{ft-1}) - \beta^p(p_{ft} - \rho p_{ft-1})$$

Maintaining the timing assumptions imposed in the main text, we form the following moment conditions to estimate the coefficients $(\beta^l, \beta^m, \beta^k, \beta^p, \rho)$:

$$E[\upsilon_{ft}(\beta^l, \beta^m, \beta^k, \beta^p, \rho)|l_{ft-1}, m_{ft-1}, k_{ft-1}, k_{ft}, p_{ft-1}]$$

The estimates of this model are reported in the first column of Table 1(c), and are discussed in the main text.

Translog

As an additional robustness check, we estimate a translog production function:

$$\begin{aligned} q_{ft} &= \beta^l l_{ft} + \beta^m m_{ft} + \beta^k k_{ft} + \beta^{ll} l_{ft}^2 + \beta^{mm} m_{ft}^2 + \beta^{kk} k_{ft}^2 \\ &\quad + \beta^{lm} l_{ft} m_{ft} + \beta^{mk} m_{ft} k_{ft} + \beta^{lk} l_{ft} k_{ft} + \beta^{lmk} l_{ft} m_{ft} k_{ft} + \omega_{ft} + \varepsilon_{ft} \end{aligned}$$

We again maintain the AR(1) specification for Hicks-neutral productivity in Equation (6) and to the price control in the production function that was specified in the main text. Hence, we can isolate the Hicks-neutral productivity shock $\upsilon(\beta^l, \beta^m, \beta^k, \beta^p, \rho, \beta^{ll}, \beta^{mm}, \beta^{kk}, \beta^{lm}, \beta^{mk}, \beta^{lk}, \beta^{lmk})$

as:

$$
\begin{aligned}
\upsilon_{ft} = {} & q_{ft} - \rho q_{ft-1} - \beta^l (l_{ft} - \rho l_{ft-1}) - \beta^m (m_{ft} - \rho m_{ft-1}) - \beta^k (k_{ft} - \rho k_{ft-1}) - \beta^p (p_{ft} - \rho p_{ft-1}) \\
& - \beta^{ll} (l_{ft}^2 - \rho l_{ft-1}^2) - \beta^{mm} (m_{ft}^2 - \rho m_{ft-1}^2) - \beta^{kk} (k_{ft}^2 - \rho k_{ft-1}^2) \\
& - \beta^{lm} (l_{ft} m_{ft} - \rho l_{ft-1} m_{ft-1}) - \beta^{mk} (m_{ft} k_{ft} - \rho m_{ft-1} k_{ft-1}) - \beta^{lk} (l_{ft} k_{ft} - \rho l_{ft-1} k_{ft-1}) \\
& - \beta^{lmk} (l_{ft} m_{ft} k_{ft} - \rho l_{ft-1} m_{ft-1} k_{ft-1})
\end{aligned}
$$

Maintaining the timing assumptions imposed in the main text, we form the following moment conditions to estimate $(\beta^l, \beta^m, \beta^k, \beta^p, \rho, \beta^{ll}, \beta^{mm}, \beta^{kk}, \beta^{lm}, \beta^{mk}, \beta^{lk}, \beta^{lmk})$:

$$
\begin{aligned}
& E[\upsilon_{ft}(\beta^l, \beta^m, \beta^k, \beta^p, \rho, \beta^{ll}, \beta^{mm}, \beta^{kk}, \beta^{lm}, \beta^{mk}, \beta^{lk}, \beta^{lmk}) | l_{ft-1}, m_{ft-1}, k_{ft-1}, \\
& k_{ft}, p_{ft-1}, l_{ft-1}^2, m_{ft-1}^2, k_{ft-1}^2, l_{ft-1} m_{ft-1}, m_{ft-1} k_{ft-1}, l_{ft-1} k_{ft-1}, l_{ft-1} m_{ft-1} k_{ft-1}]
\end{aligned}
$$

The output elasticities are as follows. The translog model allows for heterogeneity in the output elasticities across firms and over time, but this variation is still tightly parametrized:

$$
\begin{aligned}
\theta_{ft}^l &= \beta^l + 2\beta^{ll} l_{ft} + \beta^{lm} m_{ft} + \beta^{lk} k_{ft} + \beta^{lmk} m_{ft} k_{ft} \\
\theta_{ft}^m &= \beta^m + 2\beta^{mm} m_{ft} + \beta^{lm} l_{ft} + \beta^{mk} k_{ft} + \beta^{lmk} l_{ft} k_{ft} \\
\theta_{ft}^k &= \beta^k + 2\beta^{kk} k_{ft} + \beta^{mk} m_{ft} + \beta^{lk} l_{ft} + \beta^{lmk} l_{ft} m_{ft}
\end{aligned}
$$

The translog production estimates are reported in Table A2 . The output elasticities of labor and materials are slightly lower than the estimates from Cobb-Douglas model. The markup is estimated at 4.2% on average.

In Figure A4(a), we compare the evolution of the output elasticity of labor between the translog model and our preferred specification, the CES function with imperfect labor market competition. The translog model does find a declining output elasticity of labor, from 0.12 to 0.10, but does not capture the full extent of the decline in the output elasticity of labor: the CES model finds a decline of the output elasticity of labor from 0.17 to 0.10. As a result, both the level and growth rate of wage markdowns are still overestimated in the translog model, as is shown in A4(b).

Changing capital coefficient

The capital coefficient β^k in the CES production model, Equation (5), was assumed to be time invariant. Any effects of automation are therefore loaded on variation in the labor-augmenting productivity residual A_{ft}. However, it could be that automation also changed the capital coefficient β^k. As an extension, we estimate a version of the CES production model from the main text where we allow the capital coefficient to change over time. The capital coefficient is now given by the sum of a time-invariant constant β_0^k and a linear time trend β_1^k: $\beta^k = \beta_0^k + \beta_1^k t$.

$$Q_{ft} = [(A_{ft}L_{ft})^{\frac{\sigma-1}{\sigma}} + \beta^m M_{ft}^{\frac{\sigma-1}{\sigma}} + (\beta_0^k + \beta_1^k t)K_{ft}^{\frac{\sigma-1}{\sigma}}]^{\frac{\nu\sigma}{\sigma-1}}\Omega_{ft}\exp(\varepsilon_{ft}) \tag{A2}$$

The estimates of this model are in Table A3. We find that the capital coefficient decreases by 0.001 units per year, but this trend is not significantly different from zero. We find a similar labor output elasticity as in the main model, but a lower materials and higher capital elasticity. As a result, the markup is estimated below zero, whereas it was estimated to be 7.5% on average in the main model with a constant capital coefficient.

Output Elasticities under CES

The output elasticities of labor and materials are given by:

$$\theta_{ft}^l = \nu\Big(1 + \beta^m(\frac{M_{ft}}{A_{ft}L_{ft}})^{\frac{\sigma-1}{\sigma}} + \beta^k(\frac{K_{ft}}{A_{ft}L_{ft}})^{\frac{\sigma-1}{\sigma}}\Big)^{-1}$$
$$\theta_{ft}^m = \nu\Big(1 + \frac{1}{\beta^m}(\frac{A_{ft}L_{ft}}{M_{ft}})^{\frac{\sigma-1}{\sigma}} + \frac{\beta^k}{\beta^m}(\frac{K_{ft}}{M_{ft}})^{\frac{\sigma-1}{\sigma}}\Big)^{-1}$$

B.2 Labor Supply: Alternative Functional Forms

Linear or Loglinear Labor Utility?

In the main text, we imposed a labor utility specification that is linear in wages, Equation (7). An alternative, and often-used, functional form would be a loglinear labor utility model (Card et al., 2018), which we estimate in the next section:

$$U_{jft} = \underbrace{\gamma\ln(W_{ft}) + \boldsymbol{\gamma}^X\mathbf{X}_{ft} + \xi_{ft}}_{\equiv\delta_{ft}} + \sum_n(d_{fn}\zeta_{jn}) + (1-\varsigma)e_{jft} \tag{A3}$$

The linear and the loglinear labor supply model result in different markdown levels and, especially, markdown distributions. To inform our labor supply functional form, we adapt a labor supply version of the Box-Cox demand specification of Birchall et al. (2024). Equation (A4) nests the linear and loglinear labor supply functions: under $\lambda = 1$, Equation (A4) is a linear function, in the limit of $\lim_{\lambda \to 0}$, it becomes a loglinear specification.

$$U_{jft} = \underbrace{\gamma\Big(\frac{W_{ft}^{\lambda} - 1}{\lambda}\Big) + \boldsymbol{\gamma}^{X}\mathbf{X}_{ft} + \xi_{ft}}_{\equiv \delta_{ft}} + \sum_{n}(d_{fn}\zeta_{jn}) + (1-\varsigma)e_{jft} \tag{A4}$$

We estimate Equation (A4) using the same instruments as when using the main labor supply model. We find that our estimator does not converge if we let all parameters vary freely, so we calibrate γ to be equal to our baseline estimate. The estimates of λ and σ are in Table A4. We find an estimate of λ of 0.96, which clearly rejects the loglinear specification in favor of the linear model, and which is not significantly different from the linear model used in the main text, but is significantly different from the loglinear specification.

Nested Logit with Loglinear Labor Utility

Although we provide evidence in support of the linear labor utility model, rather than the loglinear utility model, we implement the loglinear labor supply model of Equation (A3) as a comparison. The corresponding markdown expression is:

$$\psi_{ft}^{l} - 1 = \frac{1-\varsigma}{\gamma_t(1 - \varsigma S_{ft}^{n} - (1-\varsigma)S_{ft})}$$

We estimate Equation (A3) with the same instruments as those used in the main text to estimate the linear labor supply model. The resulting output elasticities and markdowns are shown in Figure A5. Figure A5a shows that the aggregate output elasticity of labor evolves very similarly in the linear and loglinear labor supply models. In contrast, Figure A5b shows that wage markdowns are estimated to increase sharply in the loglinear model whereas they are roughly stable in the linear utility model.

Different Employee Preferences by Firm Ownership

It could be that employees of SOEs, domestic private firms, and foreign-owned firms differ in terms of their valuation of wages vs. non-wage amenities. To test this, we interact the wage with indicators of foreign-owned enterprises and SOEs when estimating the labor supply model, Equation (8). The results are in Table A5. At foreign-owned firms, the wage coefficient is 0.7 points lower, and at SOEs 2.8 points lower, compared to an average wage intercent of 605 at domestic private firms. However, none of these (small) differences between firms are significant. Hence, we cannot reject that employees at these different firm types have the same wage coefficient.

B.3 Alternative Firm Objective Functions

It is often argued that SOEs differ from private firms through nonprofit motives (Chen et al., 2021). In this Appendix, we work out the implications from such nonprofit motives for our labor-augmenting productivity and markdown estimates. First, suppose SOEs have mixed objectives of achieving low costs, but also of being large. In this case, SOEs have a different shadow price λ'_{ft} than private firms.

$$\min_{L_{ft},M_{ft}} \Big[W^m M_{ft} + W^l_{ft} L_{ft} - \lambda'_{ft}\big(Q_{ft} - G(.)\Omega_{ft}\big)\Big]$$

It can be seen from Equation (12) that this results in a biased markup estimate. However, both the cost-side markdown estimate (11) and the estimate for labor-augmenting productivity are unaffected, as λ' is divided away by taking the ratios of the first-order conditions:

$$\begin{cases} W^l_{ft}(L_{ft}) + \dfrac{\partial W^l_{ft}(L_{ft})}{\partial L_{ft}} L_{ft} & = \lambda'_{ft} \frac{\partial G(A_{ft}L_{ft},M_{ft},K_{ft})}{\partial L_{ft}} \Omega_{ft} A_{ft} \\ W^m & = \lambda'_{ft} \frac{\partial G(A_{ft}L_{ft},M_{ft},K_{ft})}{\partial M_{ft}} \Omega_{ft} \end{cases}$$

Second, consider the possibility that SOEs have nonprofit objectives that are specific to one of the variable inputs, such as labor of materials. For instance, SOEs might be pressured to hire more workers in order to reduce unemployment. This would introduce a labor-specific wedge λ'_{ft} in the cost minimization equation:

$$\min_{L_{ft},M_{ft}} \Big[W^m M_{ft} + \lambda'_{ft} W^l_{ft} L_{ft} - \lambda_{ft}\big(Q_{ft} - G(.)\Omega_{ft}\big)\Big]$$

As this labor-specific wedge λ'_{ft} does not get divided away when taking ratios of the FOCs, it will show up in the labor-augmenting productivity residual A_{ft}, unless it is picked up by our labor supply elasticity estimates ψ^l_{ft}. In this case, the substantial growth that we document in A_{ft} would have to be explained by a continued change in labor-specific preferences of firms over time, rather than in labor-augmenting productivity.

Third, there might be capital-specific wedges that differ between SOEs and other firms, such as subsidized credit. As we do not rely on a capital FOC for identification of labor-augmenting productivity and wage markdowns, we do not rule out such wedges.

B.4 Testing Exogeneity of World Prices

When estimating labor supply, we use the international metal prices and firms' exposure to the international market as instruments. This implies the assumption that individual Chinese manufacturers cannot alter world prices. We compute the global production share of the firms in our dataset by multiplying their market share on their respective metal market in China with the market share of China in global production.[3] We find that global market shares of individual firms are below 10% in 97% of the observations, and that firms with global market shares above 10% generate 5% of industry revenue.

To test the exogeneity assumption of world metal prices, we regress the log world price of each industry's metal in each year on firm-level log productivity levels, including both Hicks-neutral and labor-augmenting productivity. We control for year fixed effects and firm fixed effects and cluster standard errors at the industry level. In addition, we re-estimate this regression including only firms with global market shares above 10%, which are the most likely to be able to influence global prices. The estimates in Table A6 show that none of the marginal cost measures of our firms significantly alter global prices. This suggests that world prices are indeed exogenous from individual firms' perspectives: otherwise, marginal cost shocks to individual Chinese firms should pass through to global metal prices.

[3]We use the 2006 USGS mineral summaries, U.S. Geological Service (2006), to compute global production shares of Chinese NFM industries.

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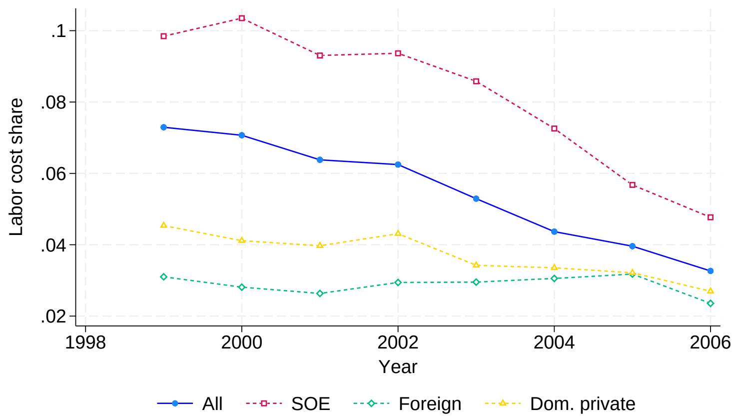
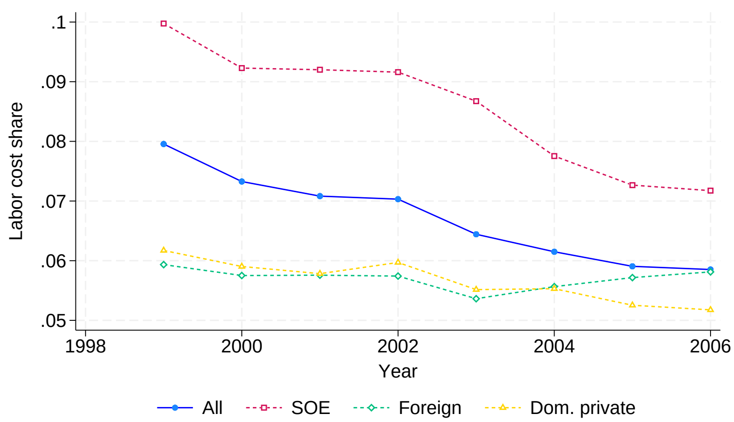
C Appendix Figures and Tables

Figure A1: Labor Share of Variable Costs

(a) NFM industries



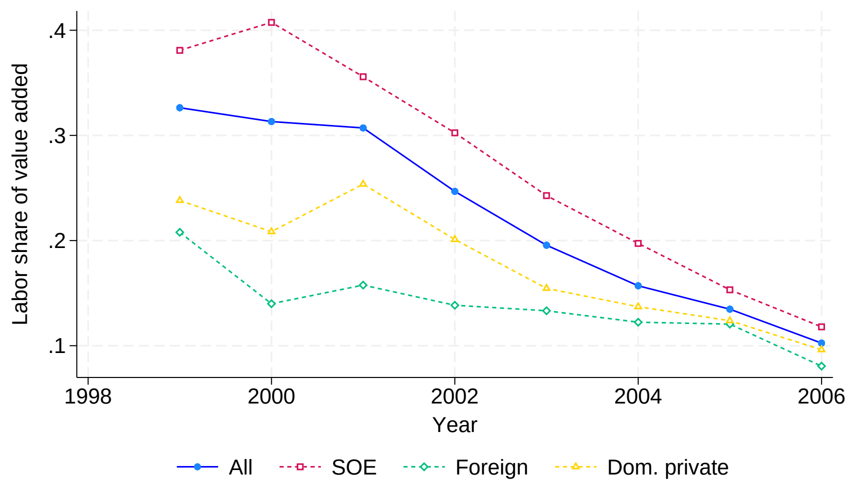
(b) All industries



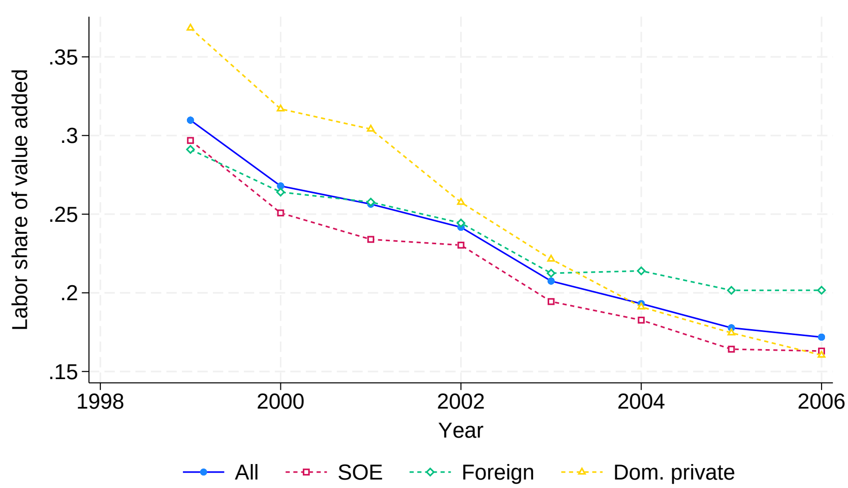
Notes: This graph plots the aggregate variable cost share of labor for NFM industries (panel a) and all manufacturing and mining industries (panel b) in China.

Figure A2: Labor Share of Value Added

(a) NFM industries



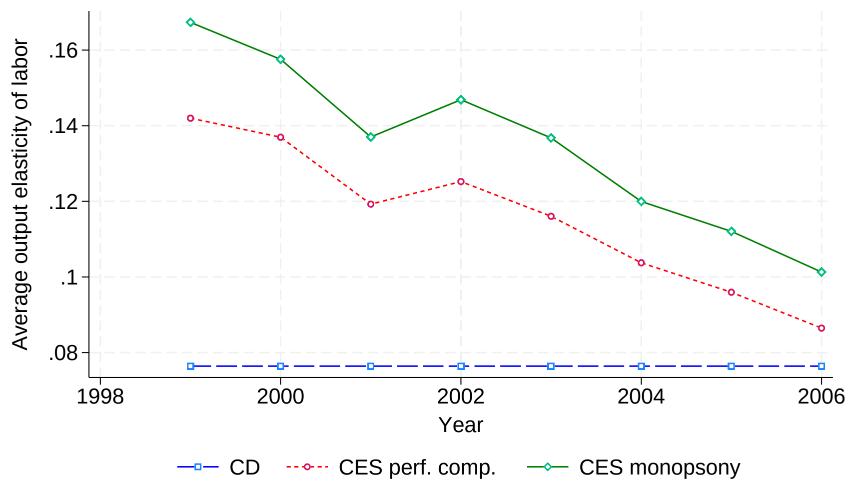
(b) All industries



Notes: Panel (a) shows the evolution of total labor expenditure over total value added in Chinese NFM industries. Panel (b) does the same for all manufacturing and mining industries.

Figure A3: Output Elasticities and Markups

(a) Output Elasticity of Labor



(b) Price Markup

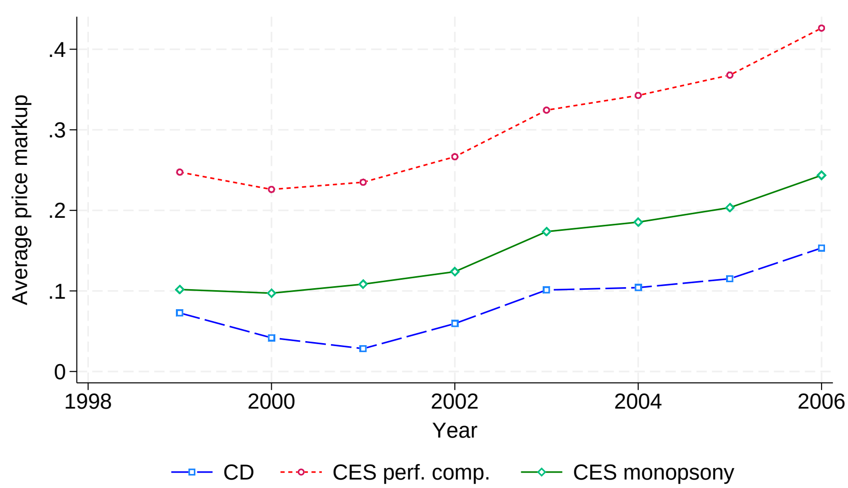
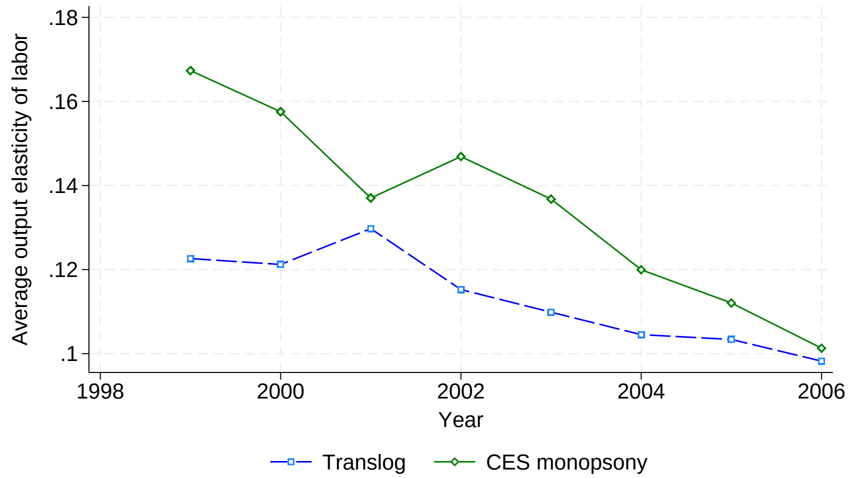


Figure A4: Translog Production Function

(a) Output Elasticity of Labor



(b) Wage Markdown

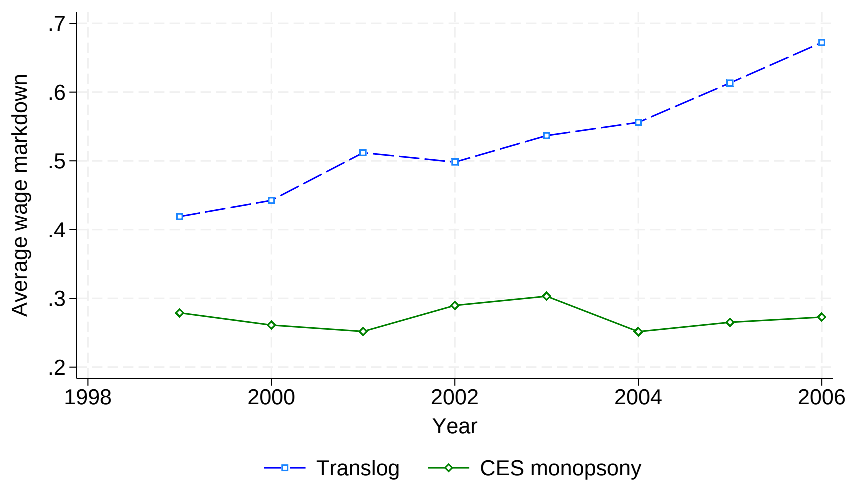
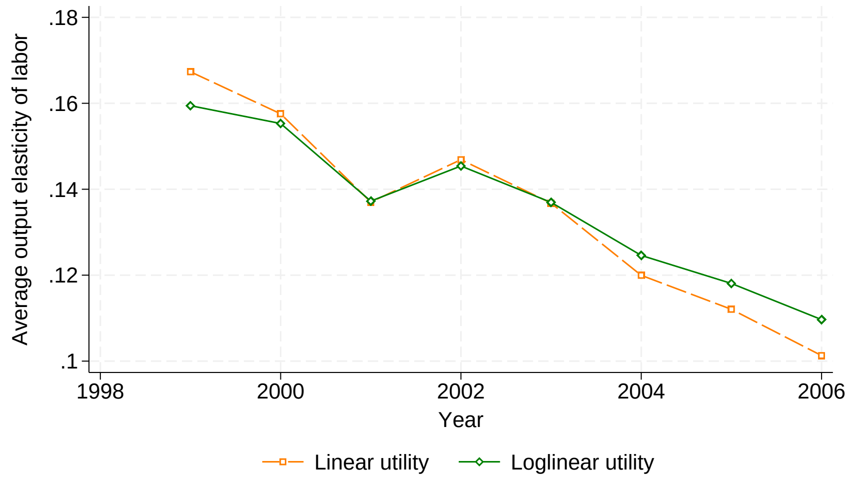


Figure A5: Loglinear Labor Supply Function

(a) Output Elasticity of Labor



(b) Wage Markdown

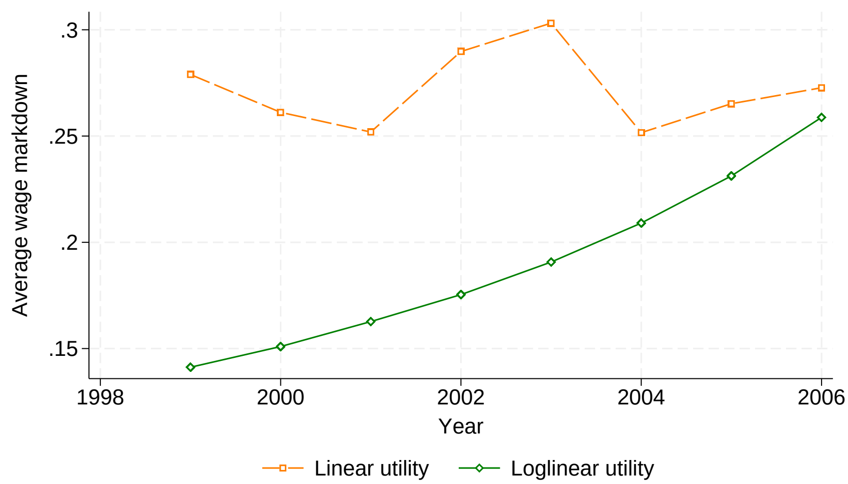


Table A1: Summary Statistics

	Observations	Mean	Std. dev.	Median	p25	p75
Revenue	38,194	14.451	69.920	3.129	1.341	8.680
Quantity	18,043	1.445	15.099	0.003	0.001	0.014
Employment	38,194	313	1,251	89	45	210
Intermediate inputs	38,194	11.158	50.850	2.400	1.030	6.740
Real capital	38,017	5.486	35.161	0.557	0.197	1.864
Wage expenditure	38,194	0.537	3.031	0.107	0.049	0.275
Wage per worker (annual)	38,186	1,482	1,326	1,238	848	1,691
Minimum wage (annual)	17,892	711	210	693	536	887
World prices	26,092	1,979	4,577	892	302	1,832
Foreign-owned	38,194	0.080	0.271	0	0	0
State-owned	38,194	0.161	0.368	0	0	0
Export dummy	38,185	0.139	0.346	0	0	0
Export share of revenue	38,185	0.050	0.180	0.000	0.000	0.000
Number of firms per market	38,194	12.179	26.552	3.000	1.000	10.000
Within-nest share (percent)	38,191	45.437	41.256	29.367	5.605	100.000
Market share (percent)	36,502	0.022	0.224	0.003	0.001	0.010

Notes: The units for revenue, intermediate inputs, real capital, and wage expenditures are millions of USD. The unit for quantity is millions of units produced. The unit for annual wage per worker and annual minimum wage is USD. World prices are the Bloomberg Industrial Metals Subindex in USD. Foreign-owned and State-owned are dummies indicating whether the firm is owned by a foreign company or by the Chinese state, respectively.

Table A2: Estimated Parameters of Translog Production Function

	Translog	
	Est.	S.E.
β^l	0.336	0.983
β^m	0.593	0.998
β^k	0.297	0.278
β^{ll}	0.009	0.030
β^{mm}	0.020	0.043
β^{kk}	0.003	0.007
β^{lm}	-0.038	0.070
β^{mk}	-0.026	0.022
β^{lk}	-0.013	0.038
β^{lmk}	0.002	0.003
Output elas. of labor θ^l_{ft}	0.037	0.086
Output elas. of materials θ^m_{ft}	0.770	0.119
Output elas. of capital θ^k_{ft}	0.052	0.033
Average markup	0.042	
Median markup	-0.009	

Notes: This table reports the estimates of the translog production model. Standard errors are block-bootstrapped with 200 draws.

Table A3: Time-Changing Capital Coefficient

		CES: endo. wage	
		Est.	S.E.
β^m		0.142	253.337
β^k_0		2.038	29.677
β^k_1		-0.001	0.015
β^k		0.004	0.048
Serial correlation	ρ	0.857	0.150
Returns to scale	ν	0.975	0.036
Observations		9867	
Output elas. of labor	θ^l_{ft}	0.070	0.012
Output elas. of materials	θ^m_{ft}	0.637	0.100
Output elas. of capital	θ^k_{ft}	0.267	0.087
Average markup		-0.125	
Median markup		-0.093	

Notes: This table reports the estimates for the CES production model with time-varying capital coefficient. Standard errors are block-bootstrapped with 200 draws.

Table A4: Box-Cox Estimation

	Est.	S.E.
Box-Cox parameter λ	0.955	0.342
Nesting parameter ς	0.046	0.026
Observations	24768	

Notes: We report the estimates of the Box-Cox labor supply function, estimated using GMM. Standard errors are block-bootstrapped with 200 draws.

Table A5: Wage Coefficient Differs by Firm Ownership

		Est.	S.E.
Wage coefficient	γ	1.800	4.243
Nesting parameter	ς	-0.232	0.747
Constant factor	γ_0	604.709	1342.975
Time-varying factor	γ_t	-0.301	0.668
Dummy: Foreign-owned		8.446	67.616
Dummy: Foreign-owned $\times$ wage		-0.726	3.826
Dummy: SOE		41.321	76.487
Dummy: SOE $\times$ wage		-2.836	5.514
1st stage F-stat: W_{ft}^L		11.722	
1st stage F-stat: s_{ft}		12268.141	
1st stage F-stat: $W_{ft}^L \times year$		11.732	
Observations		24768	
Average markdown		0.062	
Median markdown		0.053	

Notes: We interact the time-invariant part of the wage coefficient in the labor supply equation with indicators of foreign and SOEs, in the time-varying wage coefficient labor supply model.

Table A6: Test Exogeneity of World Prices

	Log(world price)			
	Est.	S.E.	Est.	S.E.
Log(labor-augmenting productivity)	0.005	0.011	-0.001	0.015
Log(Hicks-neutral productivity)	-0.026	0.015	0.010	0.017
Industries	All		Market Share $>$ 10%	
R-squared	.972		.993	
Observations	11521		375	

Notes: We regress the world price of each industry's metal on firms' labor-augmenting and Hicks-neutral productivity levels. Year fixed effects are included. Standard errors are clustered at the industry level. The second column restricts the sample to industries in which China has a global market share above 10%.

Table A7: Minimum Wage and Productivity

	Log(labor-augmenting productivity)	
	Est.	S.E.
Log(relative minimum wage)	0.012	0.034
R-squared	<0.001	
Observations	16638	

Notes: We regress log labor-augmenting productivity on the logarithm of the ratio of the minimum wage over the wage. The latter is proportional to the probability that the minimum wage is binding.