Exploiting or Augmenting Labor?

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Abstract

We show that existing 'production approaches' to markdown estimation do not separately identify factor price markdowns from factor-augmenting productivity levels. We propose a method to overcome this challenge and apply it to study the effects of ownership liberalization in Chinese nonferrous metal industries. We find that private firms have much higher labor-augmenting productivity levels than state-owned enterprises (SOEs). However, we also find that private firms exert higher monopsony power over their workers than SOEs, although this only holds for domestically-owned firms. This suggests that privatization policies imply a trade-off between increased productivity and monopsony power.

Keywords: Monopsony Power, Factor-Biased Technological Change, Production Functions, Privatization, Foreign Direct Investment

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1 Introduction

Production functions are increasingly used to study market power on labor and other factor markets (Syverson, 2024). However, existing 'production approaches' to estimate wage markdowns crucially rely on Hicks neutrality. Although there exist approaches to estimate non-Hicks-neutral production functions, these assume perfectly competitive factor markets (Doraszelski & Jaumandreu, 2018; Demirer, 2019). Thus, they cannot be used to study monopsony power.

In this paper, we show that these two classes of models rely on the same variation in the data, weighted input expenditure ratios, to identify their object of interest. Hence, wage markdowns and labor-augmenting productivity levels are not separately identified. We propose a novel approach to address this identification challenge by combining a production model with a labor supply model, and jointly estimate this model using firm-level production, wage, and employment data.

We apply this approach to examine the productivity and labor market power effects of ownership liberalizations in the Chinese nonferrous metal (NFM) manufacturing and mining industries from 1999 until 2006. Ownership liberalization policies in the late 1990s led to large-scale ownership changes in these industries in China, as SOEs were privatized and foreign firms entered the market.[1] Similar liberalizations have been implemented outside of China (Brown, Earle, & Telegdy, 2006). To evaluate these policies, it is crucial to know how privatization and FDI affect both labor-augmenting productivity growth and monopsony power, as these two forces have opposite implications for aggregate economic growth (Uzawa, 1961; Berger, Herkenhoff, & Mongey, 2022). This requires a model that allows separate identification of these variables.

While prior evidence found that Chinese private firms are far more productive than SOEs, and that foreign-owned firms are more productive than domestic firms (Naughton, 1994; Song, Storesletten, & Zilibotti, 2011; Hsieh & Song, 2015; Chen, Igami, Sawada, & Xiao, 2021), these estimates generally assume competitive factor markets. Therefore, these estimates could also reflect differences in monopsony power. It is likely that SOEs set different wage markdowns than private firms because SOEs, for instance, offer higher non-wage amenities (Zhao, 2002). The few studies that have compared wage markdowns by firm ownership have typically relied on Hicks-neutral production functions, thereby imposing that

[1] These policies have been partly reversed since the late 2010s (Lardy, 2019; Fang et al., 2022).

labor-augmenting productivity does not depend on ownership (Lu, Sugita, & Zhu, 2019).

Our model builds on Doraszelski and Jaumandreu (2018), which identifies labor-augmenting productivity by comparing first-order conditions (FOCs) of a cost minimization problem across variable inputs. However, this approach assumes fully elastic residual labor supply, thereby ruling out monopsony power. We add monopsony power to this model by including residual labor supply elasticities into these FOCs. Hence, in our model, the wedge between the labor and materials FOC can be due to either labor-augmenting productivity or monopsony power. We model these labor supply elasticities using a differentiated-employers model in the spirit of Card et al. (2018), which we estimate using labor demand shifters.

Our estimates reveal that NFM industries display both strong labor-augmenting productivity growth, at 15.1% per year, and considerable monopsony power, with median wage markdowns of 27%. Using a Hicks-neutral model instead would have led to a much higher median markdown estimate of 55%, and to the conclusion that average markdowns doubled during the sample period, whereas our preferred model implies stable markdowns. Hence, our results show that markdown estimates obtained from Hicks-neutral production estimates can display a significant upward bias in terms of both levels and growth rate in industries that undergo directed technical change.

When comparing firms by ownership, we find that SOEs are significantly less productive than private firms, which is consistent with prior evidence. However, they also set lower markdowns, which contrasts with prior work that relied on Hicks-neutral estimates (Lu et al., 2019). For foreign-owned firms, we find higher labor-augmenting productivity compared to domestic private firms, although this gap closes over time. We also find that foreign-owned firms set lower wage markdowns than both SOEs and domestic private firms, which is again in contrast to prior evidence (Lu et al., 2019). Together, these patterns reveal that SOE privatization policies entail a trade-off between increased labor-augmenting productivity growth and the possibility of increased monopsony power on labor markets.

The main contribution of this paper is to propose a production function estimator that allows for both imperfect factor market competition *and* factor-biased technological change, and to apply this estimator to understand the effects of ownership liberalization policies in China. Doing so, we contribute both to the literature that uses the 'production approach' to markup estimation of De Loecker and Warzynski (2012) to estimate input price markdowns under the assumption of Hicks neutrality (Morlacco, 2017; Yeh, Hershbein, & Macaluso, 2022; Mertens, 2019; Kroft, Luo, Mogstad, & Setzler, 2020; Brooks, Kaboski, Li, & Qian, 2021; Rubens, 2023), and to the literature that estimated directed technological change under the assumption of competitive factor markets (Doraszelski & Jaumandreu, 2018; Demirer, 2019; Zhang, 2019; Raval, 2023; Miller et al., 2022). In contrast to Chan et al. (2023), who study market power in the presence of technological change building on the framework of Gandhi et al. (2020), our approach does not impose perfect goods market competition and does not rely on matched employer-employee data, which are hard to obtain in many settings, whereas their approach allows for adjustment costs and heterogeneous workers. Hence, we see our approaches as complementary.

An important caveat to our proposed approach is that while we allow for monopsony power and non-Hicks-neutral productivity differences, we still assume labor is fully variable, thereby ruling out other frictions such as labor adjustment costs, search costs, or any other 'wedges' that enter the FOC for labor in the cost minimization problem of firms (Hsieh & Klenow, 2009; Doraszelski & Jaumandreu, 2019). Although incorporating such frictions is beyond the scope of this paper, we discuss some possible ways forward to add these to our framework.

The rest of this paper is structured as follows. In Section 2, we discuss the main identification challenge in a general setup, and present our proposed identification strategy. In Section 3, we empirically implement this approach in the context of the Chinese NFM sector. Section 4 concludes.

2 Theoretical Framework

2.1 Primitives and Behavior

Consider a firm f that produces a good (Q) using labor (L), materials (M), and capital (K) at time t, according to a production function $G(.)$, as shown in Equation (1). Firms differ not only in their Hicks-neutral productivity level Ω_{ft} but also in their labor-augmenting productivity level A_{ft}. In contrast, the functional form $G(.)$ is assumed to be common. Finally, measurement error in log output is denoted ε_{ft} and is assumed to be mean independent to the inputs.

$$Q_{ft} = G(A_{ft}L_{ft}, M_{ft}, K_{ft})\Omega_{ft} \exp(\varepsilon_{ft}) \tag{1}$$

We assume $G(.)$ is twice differentiable in all inputs. Firms pay variable input prices W^l_{ft} and W^m_{ft} and face input supply curves with inverse supply elasticicities $\psi^l_{ft} - 1$ and $\psi^m_{ft} - 1$, such that:

$$\psi^l_{ft} \equiv \frac{\partial W^l_{ft}}{\partial L_{ft}} \frac{L_{ft}}{W^l_{ft}} + 1 \qquad \psi^m_{ft} \equiv \frac{\partial W^m_{ft}}{\partial M_{ft}} \frac{M_{ft}}{W^m_{ft}} + 1 \tag{2}$$

We assume that both labor and materials are variable, static inputs and that they are chosen in every period by the producer to minimize current variable costs. Denoting marginal costs as λ_{ft}, the cost minimization problem is given by Equation (3):

$$\min_{L_{ft},M_{ft}} \Big[W^m_{ft} M_{ft} + W^l_{ft} L_{ft} - \lambda_{ft} \big(Q_{ft} - G(.)\Omega_{ft} \big) \Big] \tag{3}$$

2.2 Identification Challenge

Without loss of generality, we assume that intermediate input prices are exogenous to individual firms, $\psi^m_{ft} = 1$.[2] The FOCs for the cost minimization problem are:

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

Taking the ratio of these FOCs yields:

$$\frac{W^l_{ft}(L_{ft}) + \frac{\partial W^l_{ft}(L_{ft})}{\partial L_{ft}} L_{ft}}{W^m_{ft}} = \frac{\frac{\partial G(A_{ft}L_{ft}, M_{ft}, K_{ft})}{\partial L_{ft}}}{\frac{\partial G(A_{ft}L_{ft}, M_{ft}, K_{ft})}{\partial M_{ft}}} A_{ft} \tag{4}$$

If residual labor supply is perfectly elastic, $\frac{\partial W^l_{ft}(L_{ft})}{\partial L_{ft}} = 0$, Equation (4) can be solved for labor-augmenting productivity (Doraszelski & Jaumandreu, 2018; Demirer, 2019). On the other hand, if the production function is Hicks-neutral (A_{ft} is a constant), Equation (4) can be solved for the inverse labor supply elasticity (Morlacco, 2017; Brooks et al., 2021; Yeh et al., 2022). However, if residual labor supply is not perfectly elastic and the production function is not Hicks-neutral, there are two unknowns (A_{ft} and $\frac{\partial W^l_{ft}(L_{ft})}{\partial L_{ft}}$) in a single equation, so residual labor supply and labor-augmenting productivity are not separately identified.

The intuition behind this result is visualized in Figure 1, which plots production isoquants, with the intermediate input quantity M on the y-axis and the labor quantity L on the x-

[2]This can be relaxed by imposing a supply model for both materials and labor, rather than just for labor.

axis. Panel 1a shows the effect of a labor-augmenting productivity shock to the firm with competitive factor markets. A labor-augmenting productivity shock rotates the production isoquant, because relatively less labor per unit of of materials is needed to produce a unit of output. Given that the factor prices w^l and w^m are fixed, firms adjust their input bundle from 1. to 2., substituting materials for labor. In Panel 1b, we show that the same change in input usage can be rationalized by a Hicks-neutral productivity shock and an increase in the inverse labor supply elasticity. The former causes a parallel shift in the isoquant, as the productivity effect on both inputs is identical. The latter causes an inward rotation of the isocost curve: the marginal cost of labor increases because the monopsonist internalizes that hiring more labor increases its wage, therefore it hires relatively less labor. As the same variation in input bundles can be rationalized by a labor-augmenting productivity shock and by a change in the labor supply elasticity, these two objects are not separately identified.

In general, we see two solutions to this identification challenge. First, in industries for which rich micro-data on technology usage is available, one could impose more structure on the residual A_{ft} by making it a function of this data (Foster, Haltiwanger, & Tuttle, 2022; Kusaka, Okazaki, Onishi, & Wakamori, 2022; Miller et al., 2022; Delabastita & Rubens, 2025). Second, one can impose more structure on the labor supply model so as to identify the residual inverse labor supply elasticities $\frac{\partial W^l_{ft}}{\partial L_{ft}} \frac{L_{ft}}{W^l_{ft}}$. This is the approach that we follow in this paper. We see the optimal trade-off between these different sets of assumptions as context-specific, as their attractiveness depends, among other factors, on data availability and industry characteristics.

Two important caveats apply. First, as mentioned earlier, there might exist frictions other than monopsony power that affect the wedge between the input price and marginal revenue product differently for labor and materials.[3] Using matched employer-employee data, some of these frictions, such as labor adjustment costs, could be modelled more directly (Chan et al., 2023). Second, as our approach consists on comparing *marginal* revenue products to wages, it hinges on the ability of the production function estimator to identify those marginal revenue products. This could, for instance, be more difficult in industries that rely on intangible inputs or that feature high sunk costs.

[3] We refer to Doraszelski and Jaumandreu (2019) for a discussion of potential sources of these wedges.

3 Empirical Application

3.1 Data Sources

Our empirical application focuses on the Chinese NFM manufacturing and mining industries. We match five datasets, as discussed in detail in Appendix A.1. First, we obtain firm-level balance sheet data from the Annual Survey of Industrial Production (ASIP), which is collected by the National Bureau of Statistics of China (NBS). Second, the NBS reports production quantities at the product-year level for a subset of the sample, which we aggregate to the firm level. Third, we use China's Population Census data to compute county-level employment in the year 2000. Fourth, annual international market prices of various NFMs are from the Bloomberg Industrial Metals Subindex. Finally, we obtain monthly minimum wages for full-time employees at the county-year level from official county publications. Appendix Table A1 summarizes the key characteristics of Chinese firms in the NFM manufacturing and mining sectors.

We categorize firms into three groups based on their ownership structure. We label firms as "foreign" if they are recorded as being foreign-owned or having foreign equity in the NBS statistics. Similarly, an SOE is recorded as being owned by the state or as holding state equity. If a firm has both foreign and state equity, we label it as an SOE, so the two definitions are mutually exclusive. The remaining group of firms is labeled as "domestic private."

3.2 Industry Background

Technological Change

China is the world's largest manufacturer of NFMs, such as aluminum, copper, lead, zinc, and nickel (Fa, 2009). The NFM sector consists of mining firms, which extract and crush the ores, and manufacturers, which smelt the ores into concentrated products. Both NFM mining and manufacturing underwent substantial technological change throughout the sample period. Chinese NFM mines have traditionally relied on 'shrinkage stope mining' techniques, in which ores are extracted from the bottom up (Li, Yu, Dan, Yin, & Chen, 2024). Outside of China, these techniques have been mostly replaced by 'deep-hole mining methods', in which holes are drilled from the surface down, which is much less labor-intensive (Hamrin et al., 2001; Loow et al., 2019). Although deep-hole methods have been introduced in China, shrinkage stope mining remains commonplace (Li et al., 2024).

Technological change in nonferrous metal manufacturing has mainly consisted of replacing traditional blast furnaces by new generations of smelters that inject oxygen-enriched air and fuel directly into the molten metals (Arthur, Hunt, et al., 2005). These new smelters have been introduced in China during the 1990s and 2000s, mostly as imported technologies (Wang & Chandler, 2010; Wu, Wu, Zhang, & Yang, 2007). They are both more energy-efficient and require less labor per unit of output, so its directed productivity effects are unclear ex-ante (Arthur et al., 2005). For ferrous metal industries, which share some similarities to NFM industries in terms of production processes, Zhang (2019) found strong evidence of labor-augmenting technological change in China throughout the same time period that we study.

Monopsony Power

Although we are not aware of prior work on monopsony in Chinese NFM industries specifically, prior studies have found evidence of considerable monopsony power in Chinese manufacturing industries across the board (Brooks et al., 2021; Lu et al., 2019). Institutional rigidities in Chinese labor markets, such as the Hukou registration system, likely make labor supply more inelastic and, hence, facilitate the exertion of monopsony power (Shu, Xiuzhi, & Shu, 2011; Bayari, 2014). NFM industries mostly rely on unskilled labor: in 2004, only 2% of their workers had a college degree, and 64% had not finished high school.

Ownership Change

Throughout our sample period, there has been significant ownership change in the NFM industry. As the employment share of SOEs dropped from 70% in 1999 to 35% in 2006, employment at foreign firms increased from 4% to 9% of the workforce. These changes were the consequence of centrally-imposed privatization policies under the slogan ‘’grasp the large, let go of the small," after 1995 (Hsieh & Song, 2015) and relaxations on foreign ownership restrictions after 1997 (Lu et al., 2019). Of the foreign firms in our dataset, only 35% of the capital stock is foreign-owned, as joint-ventures are often a requirement for market access. Almost all foreign firms are ‘de-novo’ entrants, only 3% of foreign firm entry happens by a change in the ownership structure of previously existing domestic firms.

As we discuss in Appendix A.2, labor cost shares are relatively higher at SOEs than at private firms and lower at foreign firms, and the overall labor cost share has declined by half over the sample period. However, as our model makes clear, cost share variation can be due to differences in either labor-augmenting productivity differences or in wage markdowns. Prior evidence has found large productivity gains from privatization across Chinese manufacturing industries and from FDI, as SOEs often rely on outdated technologies and foreign-owned firms carry out technology transfer (Chen et al., 2021; Saggi, 2002) . However, it is also likely that SOEs, domestic private firms and foreign private firms set different wage markdowns, as they offer different non-wage amenities (Zhao, 2002). The prior literature provides conflicting evidence of how monopsony differs by firm ownership. Lu et al. (2019) found that both SOEs and foreign-owned private firms set higher markdowns compared to domestic private firms, Dobbelaere and Kiyota (2018) found lower markdowns at foreign-owned firms, whereas Aisbett, Harrison, Levine, Scorse, and Silver (2019) argue that multinational and domestic firms do not differ in terms of 'worker exploitation.'

3.3 Empirical Model

To answer the question of how SOEs, domestic private firms, and foreign private firms differ in terms of both labor-augmenting productivity and monopsony power, we implement the approach from Section 2 in the context of the Chinese NFM industries.

Production

On the production side, we assume a CES specification for Equation (1) with an elasticity of substitution σ and a returns-to-scale parameter ν:

$$Q_{ft} = [(A_{ft}L_{ft})^{\frac{\sigma-1}{\sigma}} + \beta^m M_{ft}^{\frac{\sigma-1}{\sigma}} + \beta^k K_{ft}^{\frac{\sigma-1}{\sigma}}]^{\frac{\nu\sigma}{\sigma-1}} \Omega_{ft} \exp(\varepsilon_{ft}) \tag{5}$$

The common parameters β^m and β^k govern how much material and capital contribute to output relative to labor.[4] We denote ω_{ft}, a_{ft}, and p_{ft} as the logarithms of Hicks-neutral and labor-augmenting productivity and of the output price. There exists some product differentiation in NFMs as firms differ in terms of how processed and concentrated their products are. As discussed in De Loecker, Goldberg, Khandelwal, and Pavcnik (2016), this can lead to biased production estimates when using physical quantities on the left-hand side because higher-quality products require more inputs. Hence, differences in input usage are attributed to productivity rather than product quality. As higher-quality products are more expensive, a price control can bypass this issue (De Loecker et al., 2016), so we control for log prices.[5]

$$\tilde{\omega}_{ft} = \omega_{ft} - \beta^p p_{ft} + \varepsilon_{ft}$$

[4]In Appendix B.1, we conduct a robustness check in which β^k is allowed to change over time.

[5]Similarly to De Loecker et al. (2016), we find that this matters a lot when output is measured in physical quantities. Whereas De Loecker et al. (2016) finds nonsensical estimates when not including the price control, our production function estimator does not even converge in this case.

The productivity term $\tilde{\omega}_{ft}$ is Hicks-neutral productivity filtered from residual price variation and includes measurement error in output, which we cannot separately identify from true productivity. We assume an AR(1) process for both $\tilde{\omega}_{ft}$ and for a_{ft}, with serial correlation ρ^{ω} and ρ^{a}, and idiosyncratic productivity shocks υ^{ω} and υ^{a}, as shown in Equation (6).[6] We denote an ownership vector $\boldsymbol{o}_{ft}$ that indicates whether firms are SOEs, foreign-owned, or private firms. To allow for firm ownership to affect labor-augmenting productivity, we let $\boldsymbol{o}_{ft}$ enter in the transition equation for a_{ft} (Doraszelski & Jaumandreu, 2013; De Loecker, 2013). By including both quality (as measured through residual price variation) and productivity into the AR(1) process, we rule out dynamics in terms of both costs and quality, such as learning by doing (Benkard, 2000). In such cases, the AR(1) process would fail to isolate the transient productivity shock.

$$\tilde{\omega}_{ft} = \rho^{\omega}\tilde{\omega}_{ft-1} + \upsilon^{\omega}_{ft}, \qquad a_{ft}(1-\sigma) = \rho^{a}a_{ft-1}(1-\sigma) + \boldsymbol{\beta}^{o}\boldsymbol{o}_{ft} + \upsilon^{a}_{ft} \tag{6}$$

Labor Supply

To introduce labor supply decisions, we follow a discrete-choice nested logit model (Card et al., 2018; Azar et al., 2022; Berger et al., 2022). Workers i choose between a set of firms in a labor market ℓ, defined as prefectural cities, which are further divided into county-by-4-digit-industry nests n. The nesting parameter ς parametrizes how substitutable these nests are, thereby allowing for labor mobility across industries and between counties. Workers can also move out of the NFM sector by choosing the outside option $f = 0$, which is its own nest. Let the utility of a worker j be given by Equation (7), which depends on wages W_{ft}, observed firm characteristics ($\mathbf{X}_{ft}$), and unobserved amenities ξ_{ft}. The shocks ζ_{jn} capture random taste variation for nest n, whereas e_{jft} is a type-I distributed firm-worker utility shock. The coefficient γ_t measures the wage valuation in labor utility, which we allow to vary linearly over time because changes in labor market regulations might change the labor supply elasticities: $\gamma_t = \gamma_0 + \gamma_1 t$.[7]

$$U_{jft} = \underbrace{\gamma_t W^{l}_{ft} + \boldsymbol{\gamma}^{X}\mathbf{X}_{ft} + \xi_{ft}}_{\equiv \delta_{ft}} + \sum_{n}(d_{fn}\zeta_{jn}) + (1-\varsigma)e_{jft} \tag{7}$$

[6]We specify the AR(1) process for $a_{ft}(1-\sigma)$ rather than a_{ft} for notational reasons. These assumptions are equivalent, given that we simply rescale the error term with a constant.

[7]We present a loglinear labor supply model as a robustness test in Appendix B.2.

We normalize the utility of the outside option to zero such that $U_{\ell 0t} = 0$. According to the nested logit formula, we can derive the labor market share $S_{ft} = L_{ft} / \sum_f L_{ft}$ as:

$$S_{ft} = \frac{\exp(\frac{\delta_{ft}}{1-\varsigma})}{D_{nt}^{\varsigma}[\sum_g D_{gt}^{1-\varsigma}]}$$

with $D_{nt} \equiv \sum_{f \in \mathcal{F}_{it}^n} \exp\left(\delta_{ft}/(1-\varsigma)\right)$. Normalizing compared to the labor market share of the outside option results in the usual nested logit equation, Equation (8):

$$s_{ft} - s_{0t} = \gamma_t W_{ft}^l + \varsigma s_{ft}^n + \boldsymbol{\gamma}^X \mathbf{X}_{ft} + \xi_{ft} \tag{8}$$

where s_{ft}^n captures the log labor market share of firm f within nest n.

We assume intermediate input prices are exogenous to buyers, with a common input price W^m. This is consistent with both a competitive input market or with mine competition following a homogeneous goods Cournot model. Any unobserved intermediate input price heterogeneity is not separately identified from A_{ft}.

Behavior and Equilibrium

We assume that firms simultaneously choose wages and materials at time t, after firms have observed the productivity shocks υ_{ft}^a and υ_{ft}^ω, but that capital investment is decided before these shocks arrive. We assume that firms minimize variable costs:[8]

$$\min_{W_{ft}^l, M_{ft}} \Big(W^m M_{ft} + W_{ft}^l L_{ft} - \lambda_{ft}(Q_{ft} - G(.)\Omega_{ft}) \Big) \tag{9}$$

Given the assumed functional form for labor supply and the imposed assumptions, the residual inverse labor supply elasticities are:

$$\psi_{ft}^l = 1 + \frac{1-\varsigma}{\gamma_t W_{ft}^l (1 - \varsigma S_{ft}^n - (1-\varsigma) S_{ft})} \tag{10}$$

The wage 'markdown' $\mu_{ft}^w \equiv (MRPL_{ft} - W_{ft})/MRPL_{ft}$ is a function of this inverse

[8]SOEs might differ from private firms by having non-profit maximization motives (Chen et al., 2021), or other labor-specific wedges. We discuss these in Appendix B.3.

labor supply elasticity:

$$\mu^w_{ft} = \frac{\psi^l_{ft} - 1}{\psi^l_{ft}} \tag{11}$$

The one-on-one mapping between the inverse labor supply elasticity $(\psi^l_{ft} - 1)$ and the wage markdown μ^w_{ft} requires a labor market conduct assumption, in our case Nash-Bertrand oligopsony. Alternative conduct assumptions could be imposed, but would lead to a different wage markdown.[9]

As shown in De Loecker et al. (2016), the markup of the output price P_{ft} over marginal costs, $\mu^p_{ft} \equiv (P_{ft} - \lambda_{ft})/\lambda_{ft}$, is equal to Equation (12):

$$\mu^p_{ft} = \frac{\theta^j_{ft}}{\alpha^j_{ft}\psi^j_{ft}\exp(\varepsilon_{ft})} - 1 \quad \forall j = l, m \tag{12}$$

where α^j_{ft} denotes the cost of input j as a share of gross revenues of firm f in year t, such that $\alpha^j_{ft} \equiv W^j_{ft}J_{ft}/P_{ft}Q_{ft}$, and θ^j_{ft} denotes the output elasticity of input j, $\theta^j_{ft} \equiv \frac{\partial Q_{ft}}{\partial J_{ft}}\frac{J_{ft}}{Q_{ft}}$. Following De Loecker et al. (2016), the inverse supply elasticity of labor from (10) can be equally expressed as a ratio of input cost shares, weighted by the output elasticities:

$$\psi^l_{ft} = \frac{\theta^l_{ft}}{\theta^m_{ft}}\frac{\alpha^m_{ft}}{\alpha^l_{ft}} \tag{13}$$

3.4 Estimation

We estimate the model in two steps: first, we estimate the labor supply function (8), second, we estimate the production function (5). We compute standard errors by bootstrapping this entire procedure with replacement within firms, with 200 iterations.

Labor Supply: Estimation

We need instruments for wages and within-nest market shares to estimate Equation (8), because employers set wages based on their amenities ξ_{ft}. We rely on three sets of instrumental variables. First, we include the log and level of the world price of the processed metal that is manufactured in the specific industry. We assume that changes in global prices of the fi-

[9] If conduct would be unknown, $(\psi^l_{ft} - 1)$ can be consistent with a set of markdowns (Delabastita & Rubens, 2025). In this case, our model set-identifies A_{ft}.

nal product produced by manufacturers affect labor demand at Chinese firms, but not their amenities.[10] This assumption also requires that individual firms cannot affect the world price of NFMs, which is reasonable because the global market share of individual firms is above 10% for only 3% of firm-year observations, and because world prices do not change significantly in response to productivity shocks at Chinese NFM manufacturers.[11]

Second, we include the interaction term of the international metal price shock with the share of sales of each firm that comes from exports. Firms that export more experience a larger effect of international price shocks on their labor demand. Domestic prices of processed metals differ from global market prices, as the Chinese domestic market is not fully integrated with the global market.[12] In conjunction with the export share of revenue, the international price shocks induce both within- and across-nest variation in labor demand. Third, we include the number of firms in each industry-year-county pair (Verboven, 1996), as firms in more concentrated labor markets demand less labor. A limitation of this instrument is that its exclusion restriction would be violated if entry or exit of firms would occur as a function of the unobserved amenity term ξ_{ft}. However, as we do not endogeneize either market structure or firm amenities, this is already ruled out by our model.

We measure the outside option as the total working-age population minus total employment in NFM mining and manufacturing in each labor market. We compute market shares within the total market and within the nests using employee counts. The observed characteristics vector $\mathbf{X}_{ft}$ contains sector fixed effects and province fixed effects, to control for time-invariant variation in worker utility across sectors and space, ownership type indicators, because SOEs and foreign firms could offer different amenities than domestic private firms, and year fixed effects (in the constant wage coefficient specification) or a linear time trend (in the time-varying wage coefficient specification).[13] Using the estimated labor supply parameters ς and γ_t, we can estimate the inverse labor supply elasticity ψ^l_{ft} at each firm using Equation (10).

Labor Supply: Results

The labor supply estimates are in Table 1(a). We include the OLS estimates in the left column as a comparison. The middle column shows the IV estimates with a constant wage

[10]A similar approach was used in Delabastita and Rubens (2025).
[11]We test this in Appendix B.4.
[12]The correlation between global metal prices and domestic prices on the Chinese market is 0.36.
[13]In the main model we do not allow for different wage coefficients by ownership, we extend this in Appendix B.2.

coefficient, the right column shows the IV estimates with a time-varying wage coefficient, which is our preferred specification that we use for the remainder of the paper.[14] This last specification has a wage coefficient of 0.240 that decreases over time, whereas the nesting parameter is -0.019 and not significantly different from zero. Hence, different industries and counties are close to being symmetric substitutes. The resulting wage markdown moments are shown at the bottom of Table 1(a). Wages are on average marked down by 28.1%, which is more than typically found for U.S. labor markets (Azar et al., 2022) but substantially below prior 'cost-side' markdown estimates in Brooks et al. (2021) and Yeh et al. (2022).

Production Function: Estimation

Under the cost minimization assumption in (9), we derive the input ratio in Equation (14), which is similar to the expression obtained by Doraszelski and Jaumandreu (2018), but with an added term that includes the inverse labor supply elasticity:

$$m_{ft} - l_{ft} = c + \sigma\Big(w^l_{ft} + \ln(\psi^l_{ft})\Big) + (1-\sigma)a_{ft} \tag{14}$$

With $c \equiv \sigma\Big(\ln(\beta^m) - w^m\Big)$.

We isolate the labor-augmenting productivity shock υ^a, which was defined in Equation (6), by taking ρ^a differences of Equation (14), similarly to Blundell and Bond (2000), but for labor-augmenting productivity rather than for TFP:

$$\begin{aligned}\upsilon^a_{ft}(\sigma, \rho^a, c) = m_{ft} - l_{ft} - \rho^a(m_{ft-1} - l_{ft-1}) - \sigma\Big(w^l_{ft} + \ln(\psi^l_{ft}) - \rho^a(w^l_{ft-1} + \\ \ln(\psi^l_{ft-1}))\Big) - \boldsymbol{\beta}^o\boldsymbol{o}_{ft} - c(1-\rho^a)\end{aligned}$$

We estimate (σ, ρ^a, c) using the following moment conditions:

$$E\Big(\upsilon^a_{ft}(\sigma, \rho^a, c) | w^l_{ft-1}, w^{min}_{\ell(f)t}, w^{min}_{\ell(f)t-1}, c\Big) = 0$$

These moment conditions rely critically on the AR(1) process for labor-augmenting productivity, as this allows us to isolate the transient productivity shocks. As noted above, this rules out sources of more complicated productivity dynamics. We include lagged log wages as an instrument because we assumed that wages are chosen after the productivity shock

[14] Given that wages are measured in 1000RMBs, the γ estimates are very small, so we rescale and report γ*100 in Table 1(a).

υ^a_{ft} arrives.[15] Given that we have two unknowns but a single instrument (abstracting from the trivial constant), the model is underidentified. We include the minimum wage in each county-year as an additional instrument.[16] By including both current and lagged values of the minimum wage as instruments, the identifying assumption is that minimum wages are not set as a function of the transient productivity shocks. This seems warranted as minimum wages are not set by individual firms.[17]

From Equation (14), the log factor-augmenting productivity residual a_{ft} can be written as a function of the parameters σ and ψ^l_{ft}, which we have already estimated, and the parameter β^m, which remains to be estimated:

$$a_{ft} = \Big(\frac{m_{ft} - l_{ft}}{1-\sigma}\Big) - \frac{\sigma}{1-\sigma}\ln(\beta^m) + \frac{\sigma}{1-\sigma}\Big(w^m - w^l_{ft} - \ln(\psi^l_{ft})\Big)$$

Substituting the above factor-augmenting productivity term into the log production function results in the following equation:

$$q_{ft} = \frac{\nu\sigma}{\sigma-1}\ln\Bigg[\Big(L_{ft}\exp\big(\underbrace{(\frac{m_{ft}-l_{ft}}{1-\sigma}) - \frac{\sigma}{1-\sigma}(\ln(\beta^m)) + \frac{\sigma}{1-\sigma}(w^m - w^l_{ft} - \ln(\psi^l_{ft}))}_{\equiv a_{ft}}\big)\Big)^{\frac{\sigma-1}{\sigma}} + \beta^m M_{ft}^{\frac{\sigma-1}{\sigma}} + \beta^k K_{ft}^{\frac{\sigma-1}{\sigma}}\Bigg] + \beta^p p_{ft} + \tilde{\omega}_{ft}$$

We take ρ^ω differences to isolate the Hicks-neutral productivity shock $\upsilon^\omega_{ft}(\beta^m, \beta^k, \beta^p, \rho, \nu)$:

$$\upsilon^\omega_{ft}(\beta^m, \beta^k, \beta^p, \rho, \nu) = q_{ft} - \rho q_{ft-1} - \Big(h_{ft}(\beta^m, \beta^k, \nu) - \rho h_{ft-1}(\beta^m, \beta^k, \nu)\Big) - \beta^p(p_{ft} - \rho p_{ft-1})$$

[15] We verify this timing assumption by testing for overidentifying restrictions when including current wages. We obtain a Hansen J-statistic of 17.5, which strongly rejects predetermined wages.

[16] Minimum wage variation was equally used to identify production functions in a dynamic panel estimator in De Roux et al. (2021).

[17] A possible concern is that minimum wage variation might induce labor quality differences between firms. However, in Appendix A7, we find no meaningful correlation between labor-augmenting productivity, which should pick up latent worker quality variation, and the extent to which the minimum wage is binding.

where we further define the first term in the log production function as $h_{ft}(.)$:

$$h_{ft} \equiv \frac{\nu\sigma}{\sigma-1}\ln\left[\Big(L_{ft}\exp\big((\frac{m_{ft}-l_{ft}}{1-\sigma})-\frac{\sigma}{1-\sigma}(\ln(\beta^m)\big)+\frac{\sigma}{1-\sigma}(w^m-w^l_{ft}-\ln(\psi^l_{ft}))\big)\Big)^{\frac{\sigma-1}{\sigma}} + \beta^m M_{ft}^{\frac{\sigma-1}{\sigma}}+\beta^k K_{ft}^{\frac{\sigma-1}{\sigma}}\right]$$

We estimate the production function parameters $(\beta^m, \beta^k, \beta^p, \rho, \nu)$ using the following moment conditions, which correspond to the previously-made timing assumptions that capital is chosen prior to observing the Hicks-neutral productivity shock υ^ω, whereas labor, prices, and materials are chosen afterwards:

$$E\Big(\upsilon^\omega_{ft}(\beta^m, \beta^k, \beta^p, \rho, \nu)|L_{ft-1}, M_{ft-1}, K_{ft}, K_{ft-1}, p_{ft-1}\Big) = 0$$

The output elasticities of all inputs can be computed using the estimated production function coefficients,[18] which allows estimating markdowns and markups from Equations (11) and (12).

Production Function: Results

The estimated elasticity of input substitution is reported in Table 1(b). We include the OLS results and the GMM estimator that assumes competitive labor markets as a comparison in the first and second columns. Our preferred specification, which allows for non-zero wage markdowns, yields an estimate of 0.397, implying that labor and materials are gross complements.

The remaining production function parameters are reported in Table 1(c). We include Cobb-Douglas estimates as a Hicks-neutral benchmark in column 1 and the exogenous wage model in column 2, whereas column 3 contains our preferred CES estimates that allow for imperfectly competitive labor markets. We estimate the output elasticities of labor, materials, and capital at 0.086, 0.797, and 0.100 on average. Allowing for imperfect labor market competition results in markedly different production function estimates.[19]

In Figure 2, we plot the evolution of the annual average wage markdown, weighted by

[18] See Appendix B.1.

[19] Although the distributional parameters of the CES function are not statistically significant, we do not conduct inference on these parameters, but rather on the inferred labor-augmenting productivity residuals and markdowns.

employment usage. In the CES model with monopsony, markdowns remain roughly constant around 27%. In contrast, the wage markdown is estimated to increase sharply from 35% to 73% when using a Hicks-neutral (Cobb-Douglas) model.[20] This difference arises because the Hicks-neutral model interprets factor-augmenting productivity growth as a growing markdown.[21]

3.5 Ownership, Markdowns, and Technological Change

Our estimated model now permits to answer our motivating question: how do SOEs, domestic private firms, and foreign private firms differ in terms of both their monopsony power and their labor-augmenting productivity? In Table 2a, we regress log labor-augmenting productivity on the ownership indicators. We compare the model that imposes perfect labor market competition (column 2) to our preferred specification that allows for imperfect labor market competition (column 3). In both models, SOEs have significantly lower labor-augmenting productivity than other firms, the gap increases from 61% to 68% when allowing for monopsony power. In both specifications, foreign-owned firms have slightly higher labor-augmenting productivity than domestic firms, but the gap is not statistically significant.

Labor-augmenting productivity grew on average by 15.1% per year. Table 2b shows that the productivity growth was 7.2 percentage points lower at foreign-owned firms, but 5.5 percentage points higher at SOEs compared to domestic private enterprises. Hence, the technology gap between these different types of firms has narrowed over time. In sum, our results confirm the established wisdom that SOEs are less productive than both domestic and foreign firms.[22]

Turning to monopsony power, Table 2c compares wage markdowns by ownership type. The first column uses the markdown estimates from the Hicks-neutral model, whereas the third column shows the nested logit markdowns, which are also the markdowns obtained from the CES production function. In our preferred model that does not impose Hicks neutrality, markdowns are 13% lower at SOEs and 23% lower at foreign firms. In contrast, the Hicks-neutral model fails to pick up lower markdowns at foreign firms and overestimates the markdown gap with SOEs, by misinterpreting high labor-augmenting productivity as high

[20]We include the estimation details for the Cobb-Douglas model in Appendix B.1.

[21]In Appendix Figure A3, we also plot the markup and output elasticity of labor for the three models discussed in the main text.

[22]We refrain from interpreting this as a causal statement about the effects of ownership structure, as the documented differences could be due to the endogenous selection of firms into privatization or into receiving FDI, as was discussed in Chen et al. (2021).

markdowns.

In sum, our estimates reveal that although SOEs are less productive than private firms, they also charge lower markdowns than domestic private firms. Therefore, while privatization policies can increase economic growth through their productivity effects, this risks being offset by the increased exertion of monopsony power, which suppresses output. Interestingly, this side effect does not seem to apply to foreign firms, as these are both more productive *and* set lower markdowns than other firms.

4 Conclusion

In this paper, we show that prior production function estimation approaches do not separately identify factor price markdowns from factor-augmenting productivity levels, and propose a novel approach to address this identification challenge. We apply this approach to study the market power and productivity consequences of ownership liberalization policies in Chinese NFM industries during the early 2000s. Our results confirm prior evidence of privatization and FDI as a source of (factor-augmenting) productivity growth, but also reveal that domestic private firms set substantially higher wage markdowns compared to other firms. This implies that privatizations entail a trade-off between productivity gains and the exertion of labor market power. In contrast, we find that foreign-owned private firms are both more labor-productive and set lower markdowns, so the trade-off between productivity and market power only seems to apply to domestic firms. We see our approach as a way forward in using production function methodologies to study industries that are characterized by both imperfect factor market competition and directed technological change.

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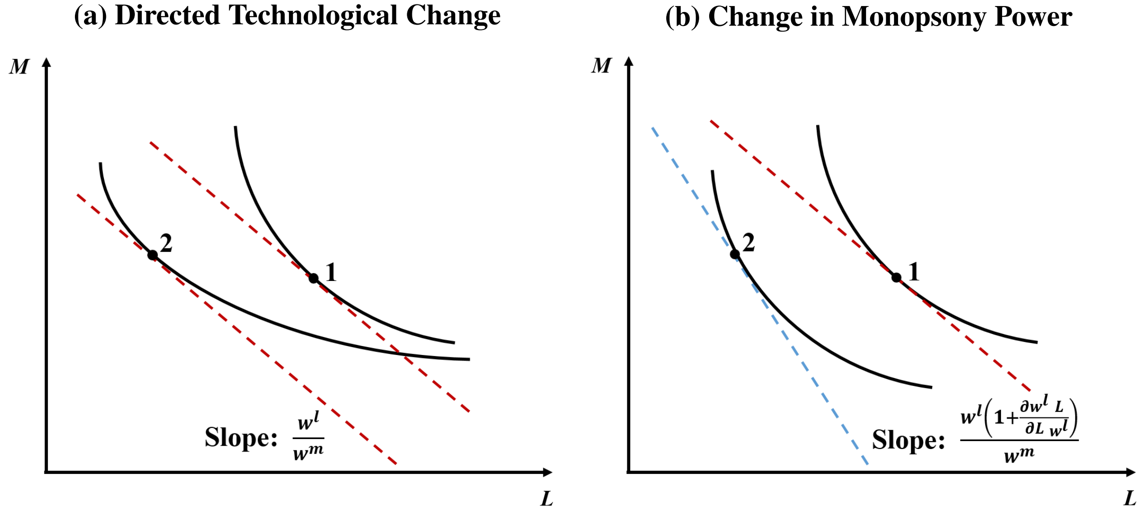
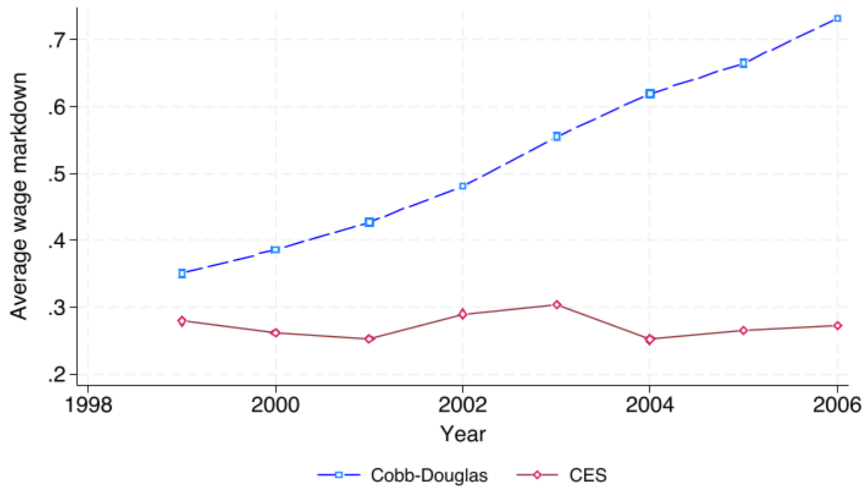
Figure 1: Non-Identification Using Only Cost Share Variation



Notes: This figure illustrates how variation in the labor-to-materials ratio can be explained either by a factor-biased technological change (Panel a) or by changes in monopsony power and Hicks-neutral shifts (Panel b).

Figure 2: Wage Markdowns



Notes: This figure compares the evolution of weighted average wage markdowns under different modeling assumptions, highlighting the divergence between Cobb-Douglas and CES models. We omit the CES specification that imposes perfect competition, as its markdown is by assumption equal to zero.

Table 1: Labor Supply and Demand Estimates

(a) Labor supply		OLS		IV		IV	
		Est.	S.E.	Est.	S.E.	Est.	S.E.
Wage coefficient	γ	0.002	0.0005	0.182	0.026	0.240	0.051
Nesting parameter	ς	0.196	0.004	-0.001	0.012	-0.019	0.019
Constant factor	γ_0					64.939	31.650
Time-varying factor	γ_1					-0.032	0.016
1st stage F-stat: W_{ft}^L				10.596		11.722	
1st stage F-stat: s_{ft}				12160.018		12268.141	
1st stage F-stat: $W_{ft}^L \times year$						11.732	
Observations		36485		24768		24768	
Average markdown		0.966		0.326		0.281	
Median markdown		0.971		0.308		0.268	
(b) Elas. of substitution		OLS		GMM exo. wage		GMM endo. wage	
		Est.	S.E.	Est.	S.E.	Est.	S.E.
Elas. of substitution	σ	1.011	0.169	0.272	0.278	0.397	0.215
Observations		36494		8677		7977	
(c) Other prod. param.		Cobb-Douglas		CES: exo. wage		CES: endo. wage	
		Est.	S.E.	Est.	S.E.	Est.	S.E.
Labor coefficient	β^l	0.076	0.218	.	.	.	.
Material coefficient	β^m	0.756	0.349	1.596	138.985	0.211	16.614
Capital coefficient	β^k	0.048	0.061	<0.001	0.008	0.001	0.075
Serial correlation	ρ	1.046	0.057	0.983	0.370	0.749	0.158
Returns to scale	ν	.	.	1.042	0.039	0.984	0.036
Observations		10433		10433		9867	
Output elas. of labor	θ_{ft}^l	0.076	0.218	0.073	0.004	0.086	0.010
Output elas. of materials	θ_{ft}^m	0.756	0.349	0.958	0.409	0.797	0.072
Output elas. of capital	θ_{ft}^k	0.048	0.061	0.010	0.408	0.100	0.064
Average markup		0.028		0.290		0.075	
Median markup		-0.031		0.242		0.065	

Notes: Panel (a) reports the nested logit labor supply model using OLS, IV with a constant wage coefficient, and IV with a time-varying wage coefficient. Panel (b) and (c) report the production estimates, with standard errors being block-bootstrapped within firms over time, with 200 draws.

Table 2: Ownership, Labor-Augmenting Productivity, and Wage Markdowns

(a) Labor-augmenting productivity	Cobb-Douglas		CES: exo. wage		CES: endo. wage	
	Est.	S.E.	Est.	S.E.	Est.	S.E.
Foreign-owned			0.066	0.086	0.052	0.054
State-owned			-0.936	0.311	-1.148	0.218
Growth rate			0.146	0.013	0.151	0.023
Observations			38186		36494	
R^2			.277		.262	
(b) Changing productivity gap over time						
Foreign-owned × time			-0.061	0.020	-0.072	0.022
State-owned × time			0.047	0.012	0.055	0.017
Observations			38186		36494	
R^2			.277		.262	
(c) Wage markdown						
Foreign-owned	-0.035	0.040			-0.256	0.024
State-owned	-0.321	0.218			-0.140	0.014
Observations	28963				36172	
R^2	.066				.262	

Notes: ’Foreign-owned’ and ’State-owned’ are dummies that equal unity if the firm has that ownership type in the current year. Standard errors are estimated from 200 bootstrap samples. Dependent variables are in logarithms. We control for industry fixed effects.

Supplemental Appendix

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. 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 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.[23] Using Chinese CPI, 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

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

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. Finally, we obtain monthly minimum wages for full-time employees at the county-year level from official county government reports.[24] 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 added.[25] 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%.

[24] These are available on https://www.51labour.com

[25] 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 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:

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

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.

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

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:

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

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.[26] 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.

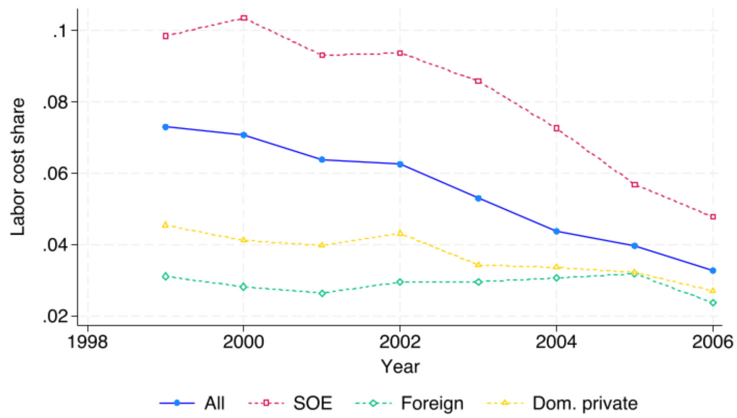
To test the exogeneity assumption of world metal prices, we regress the log world price of each industry's metal in each year on firm-level log productivity levels, including both Hicks-neutral and labor-augmenting productivity. We control for year fixed effects and firm fixed effects and cluster standard 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.

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

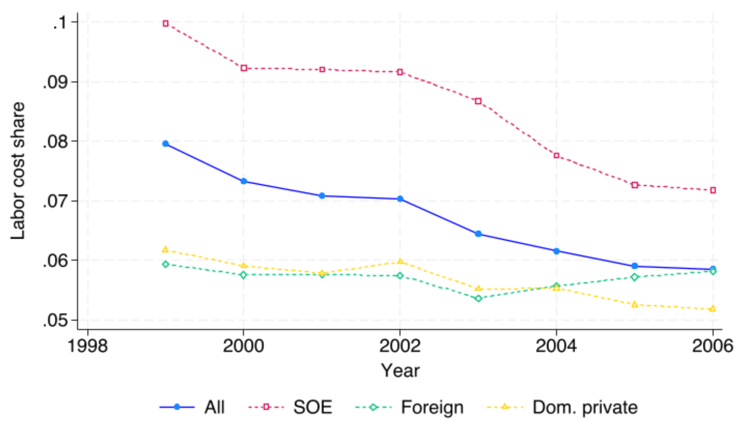
C Appendix Figures and Tables

Figure A1: Labor Share of Variable Costs

(a) NFM industries



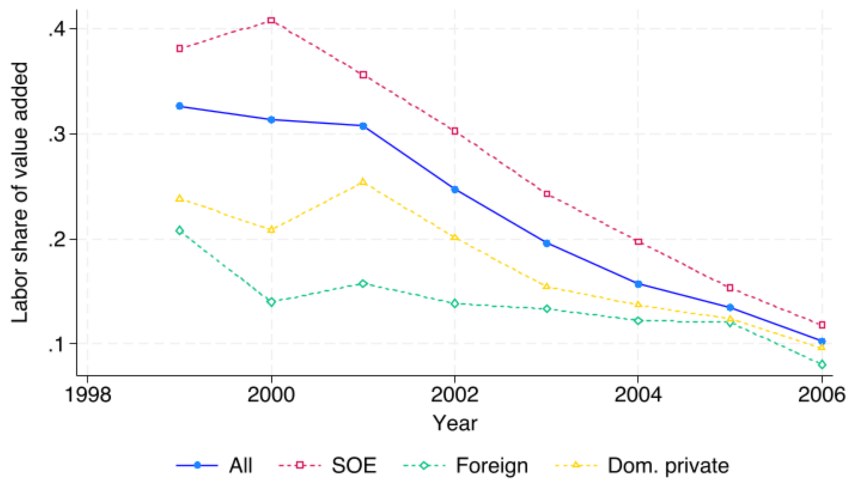
(b) All industries



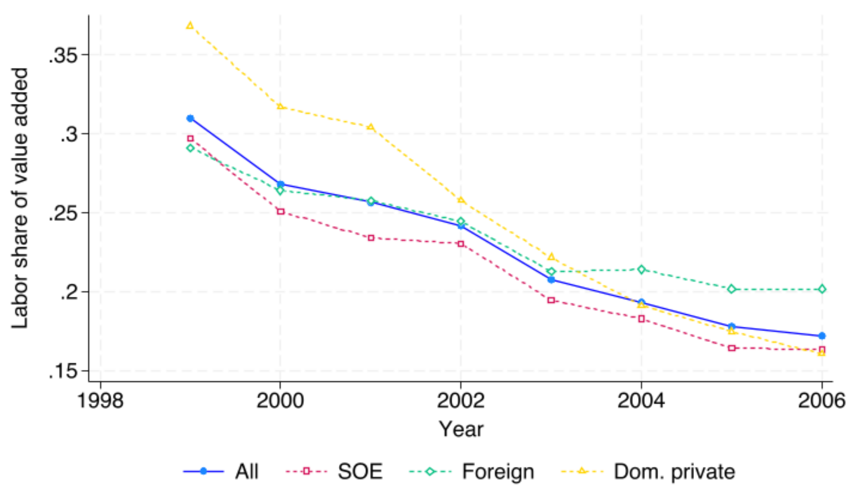
Notes: This graph plots the aggregate variable cost share of labor for NFM industries (panel a) and all manufacturing and mining industries (panel b) in China.

Figure A2: Labor Share of Value Added

(a) NFM industries



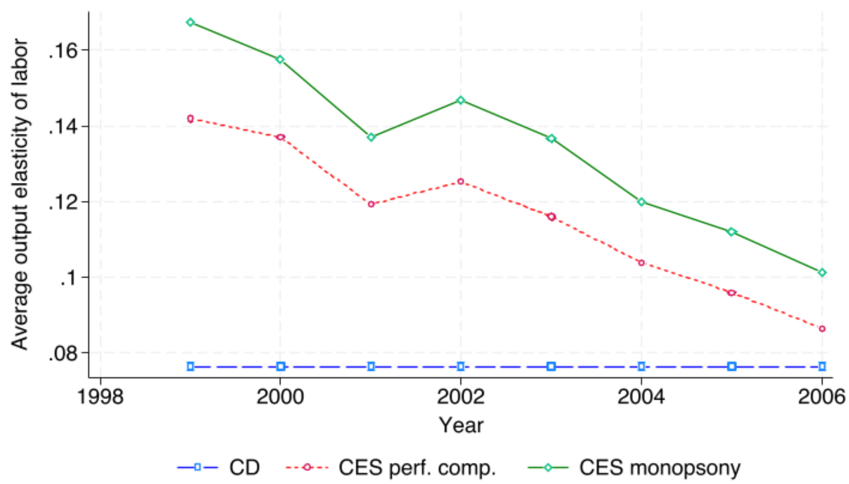
(b) All industries



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

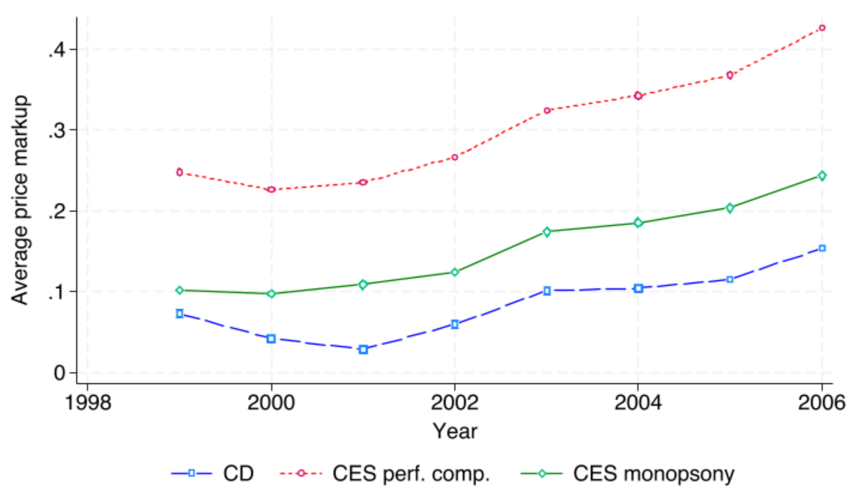
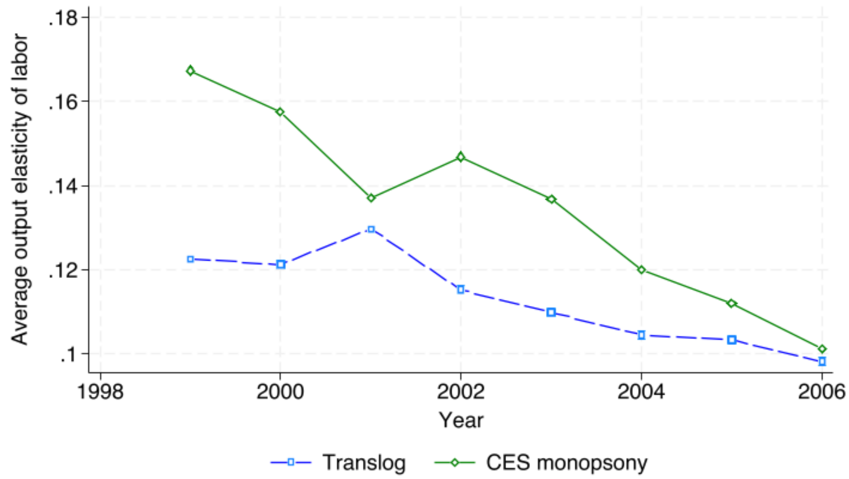


Figure A4: Translog Production Function

(a) Output Elasticity of Labor



(b) Wage Markdown

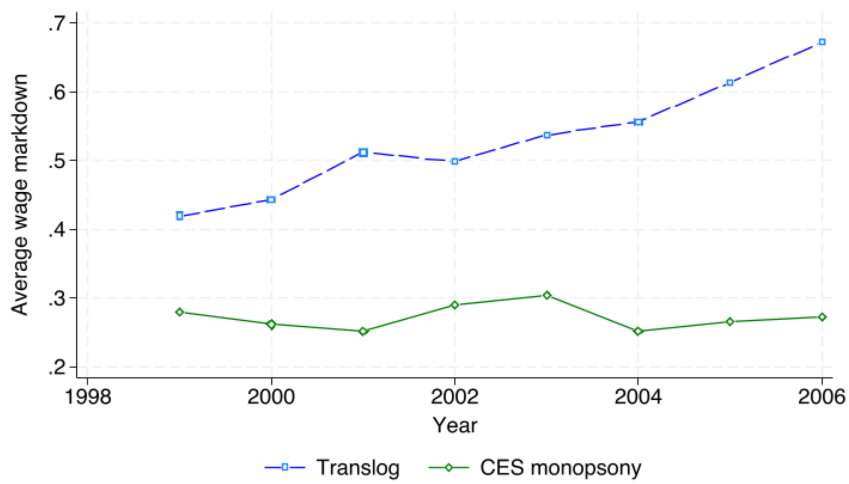
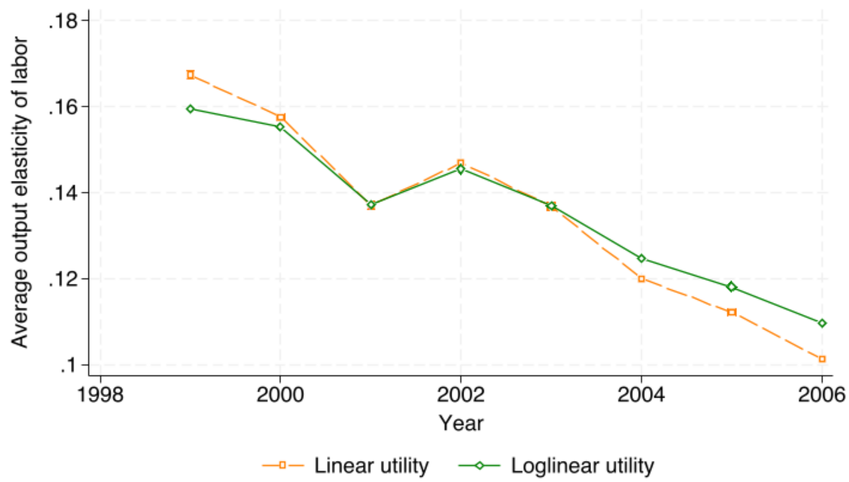


Figure A5: Loglinear Labor Supply Function

(a) Output Elasticity of Labor



(b) Wage Markdown

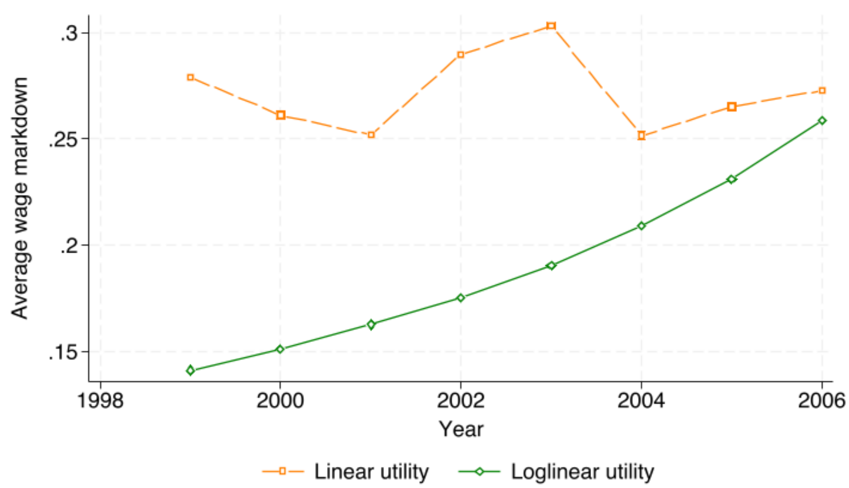


Table A1: Summary Statistics

	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_0^k		2.038	29.677
β_1^k		-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_{ft}^l	0.070	0.012
Output elas. of materials	θ_{ft}^m	0.637	0.100
Output elas. of capital	θ_{ft}^k	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.