# Exploiting or Augmenting Labor?

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*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.*
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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 and 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

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in China, as SOEs were privatized and foreign firms entered the market.[1] Similar liberalizations have been implemented outside of China (Brown, Earle and 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 and Mongey, 2022). This requires a model that allows separate identification of these variables. Rather than estimating the productivity and markdown effects of ownership changes within firms over time, we compare firms with different ownership structures using both cross-sectional and time-series variation. Therefore, we do not attempt to disentangle selection of firms into different ownership types from treatment effects.

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 and Zilibotti, 2011; Hsieh and Song, 2015; Chen et al., 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 offer higher non-wage amenities (Zhao, 2002). Similarly, multinational enterprises may set different wage markdowns as they provide different nonwage amenities due to different management practices and cultural norms (González and Kong, 2025). The few studies that have compared wage markdowns by firm ownership have typically relied on Hicks-neutral production functions, thereby imposing that labor-augmenting productivity does not depend on ownership (Lu, Sugita and 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. On the other hand, assuming competitive factor mar-

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

kets leads to underestimating the productivity disadvantage of SOEs by 18% and overestimating the productivity advantage of foreign firms by 27%.

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 smaller markdowns, which contrasts with prior work that relied on Hicks-neutral estimates (Lu, Sugita and Zhu, 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, Sugita and Zhu, 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, whereas this does not apply to FDI liberalization policies.

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 and Macaluso, 2022; Mertens, 2019; Kroft et al., 2020; Brooks et al., 2021; Rubens, 2023), and to the literature that estimated directed technological change under the assumption of competitive factor markets (Doraszelski and 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, Navarro and Rivers (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 and Klenow, 2009; Doraszelski and 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 I, we discuss the main identification challenge in a general setup, and present our proposed identification strategy. In Section II, we empirically implement this approach in the context of the Chinese NFM sector. Section III concludes.

## I. Theoretical Framework

### A. 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 $\Omega_{ft}$ 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 $\varepsilon_{ft}$ 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 elasticities $\psi^l_{ft} - 1$ 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 $\lambda_{ft}$, the cost minimization problem is given by Equation (3):

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

### B. 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:

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

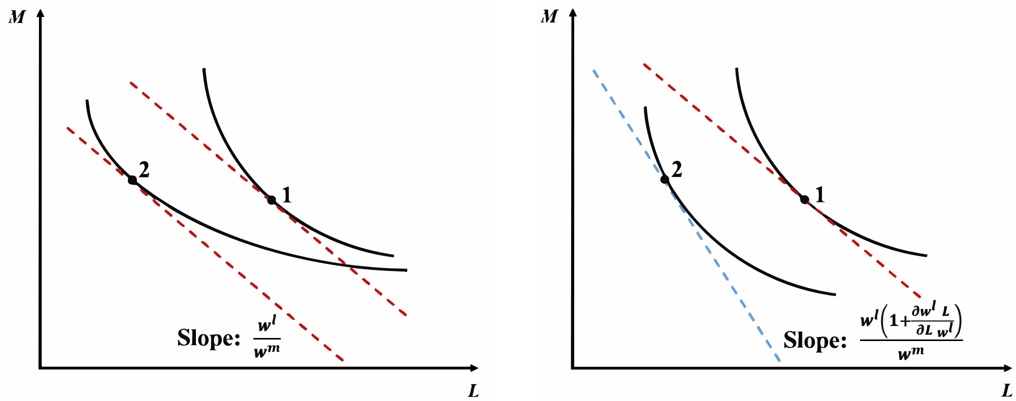
[2]This can be relaxed by imposing a supply model for materials as well.

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 and 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, Hershbein and Macaluso, 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-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 and Tuttle, 2022; Kusaka et al., 2022; Miller et al., 2022; Delabastita and 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. 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 rev-




(a) Directed Technological Change (b) Change in Monopsony Power

Figure 1. Non-Identification Using Only Cost Share Variation

*Note:* 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).

enue products. This could, for instance, be more difficult in industries that rely on intangible inputs or that feature high sunk costs.

## II. Empirical Application

### *A. 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) (National Bureau of Statistics , NBS). Second, the NBS also reports production quantities at the product-year level for a subset of the sample, which we aggregate to the firm level (National Bureau of Statistics , NBS). Third, we use China's Population Census data to compute county-level employment in the year 2000 (China Data Lab, 2020). Fourth, annual international market prices of various NFMs are from the Bloomberg Industrial Metals Subindex (Bloomberg, 2022). Finally, we obtain monthly minimum wages for full-time employees at the county-year level from official county publications (Wang, 2022). Appendix Table A.1 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."

### B. 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 et al., 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, Hustrulid and Bullock, 2001; Loow, Abrahamsson and Johansson, 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 and Hunt, 2005). These new smelters have been introduced in China during the 1990s and 2000s, mostly as imported technologies (Wang and Chandler, 2010; Wu et al., 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 and Hunt, 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, Sugita and Zhu, 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 and 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.[3]

#### 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

[3] We compute these numbers based on the 2004 industry census (National Bureau of Statistics, 2004).

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 and Song, 2015) and relaxations on foreign ownership restrictions after 1997 (Lu, Sugita and Zhu, 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, Sugita and Zhu (2019) found that both SOEs and foreign-owned private firms set higher markdowns compared to domestic private firms, Dobbelaere and Kiyota (2018) found smaller markdowns at foreign-owned firms, whereas Aisbett et al. (2019) argue that multinational and domestic firms do not differ in terms of ‘worker exploitation.’

### C. *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 I 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 $\sigma$ and a returns-to-scale parameter $\nu$:

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

The common parameters $\beta^m$ and $\beta^k$ govern how much material and capital contribute to output relative to labor.[4] We denote $\omega_{ft}$, $a_{ft}$, and $p_{ft}$ as the logarithms of Hicks-neutral and labor-augmenting productivity and of the output

[4]In Appendix B.1, we allow $\beta^k$ to change over time.

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 et al. (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, including a function of output prices in the production function can address this bias under additional strong assumptions, such as vertical product differentiation, which is a result of De Loecker et al. (2016). Therefore, we control for log prices in the production function:

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

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 $\rho^\omega$ and $\rho^a$, and idiosyncratic productivity shocks $\upsilon^\omega$ and $\upsilon^a$, as shown in Equation (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 and 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, Berry and Marinescu, 2022; Berger, Herkenhoff and Mongey, 2022). Workers $i$ choose between a set of firms in a labor market $\ell$, defined as prefectural cities, which are further divided into county-by-4-digit-industry nests $n$. The nesting parameter $\varsigma$ 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 $\xi_{ft}$. The shocks $\zeta_{jn}$ capture random taste variation for nest $n$, whereas $e_{jft}$ is a type-I distributed firm-worker utility shock. The coefficient $\gamma_t$ 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: $\gamma_t = \gamma_0 + \gamma_1 t$.[5]

[5] Alternatively, a loglinear labor supply model is in Appendix B.2.

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

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:

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

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

$$s_{ft} - s_{0t} = \gamma_t W^l_{ft} + \varsigma s^n_{ft} + \boldsymbol{\gamma}^X \mathbf{X}_{ft} + \xi_{ft} \tag{8}$$

where $s^n_{ft}$ 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 $\upsilon^a_{ft}$ and $\upsilon^\omega_{ft}$, but that capital investment is decided before these shocks arrive. We assume that firms minimize variable costs:[6]

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

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

$$\psi^l_{ft} = 1 + \frac{1-\varsigma}{\gamma_t W^l_{ft}(1 - \varsigma S^n_{ft} - (1-\varsigma)S_{ft})} \tag{10}$$

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

[6] In Appendix B.3, we discuss other sources of labor wedges between SOEs and other firms.

inverse 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 $\mu^w_{ft}$ 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.[7]

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 $\alpha^j_{ft}$ 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 $\theta^j_{ft}$ 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:

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

### D. *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 $\xi_{ft}$. 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 final product produced by manufacturers affect labor demand at Chinese firms, but not their amenities. This assumption also requires that individual firms cannot affect the world price of

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

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.[8]

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. 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 $\xi_{ft}$. 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).[9] Using the estimated labor supply parameters $\varsigma$ and $\gamma_t$, we can estimate the inverse labor supply elasticity $\psi^l_{ft}$ 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 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.[10] 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

[8] We test this in Appendix B.4.

[9] We let wage coefficients differ by ownership in Appendix B.2.

[10] As wages are measured in 1000RMBs, we obtain very small $\gamma$ estimates so we rescale and report $\gamma$*100 in Table 1(a).

28.1%, which is more than typically found for U.S. labor markets (Azar, Berry and Marinescu, 2022) but substantially below prior 'cost-side' markdown estimates in Brooks et al. (2021) and Yeh, Hershbein and Macaluso (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 $\upsilon^a$, which was defined in Equation (6), by taking $\rho^a$ differences of Equation (14), similarly to Blundell and Bond (2000), but for labor-augmenting productivity rather than for TFP:

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

We estimate $(\sigma, \rho^a, c)$ 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 $\upsilon^a_{ft}$ arrives.[11] 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.[12] 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.[13]

[11] 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.

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

[13] A possible concern is that minimum wage variation might induce labor quality differences between firms. However, in Appendix A.7, we find no meaningful correlation between minimum wage bindingness

From Equation (14), the log factor-augmenting productivity residual $a_{ft}$ can be written as a function of the parameters $\sigma$ and $\psi^l_{ft}$, which we have already estimated, and the parameter $\beta^m$, 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 $\rho^\omega$ differences to isolate the Hicks-neutral productivity shock $\upsilon^\omega_{ft}(\beta^m, \beta^k, \beta^p, \rho, \nu)$:

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

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

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

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 $\upsilon^\omega$, 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,[14] which allows estimating markdowns and markups from Equations (11) and (12).

and labor-augmenting productivity.

[14]See Appendix B.1.

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.

In Figure 2, we plot the evolution of the annual average wage markdown, weighted by 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 model.[15] This difference arises because the Hicks-neutral model interprets factor-augmenting productivity growth as a growing markdown.

### *E. 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.

Turning to monopsony power, Table 2c compares wage markdowns by ownership type. The first column uses the markdown estimates from the Hicks-neutral

[15] Appendix B.1. contains the estimation details for this model.

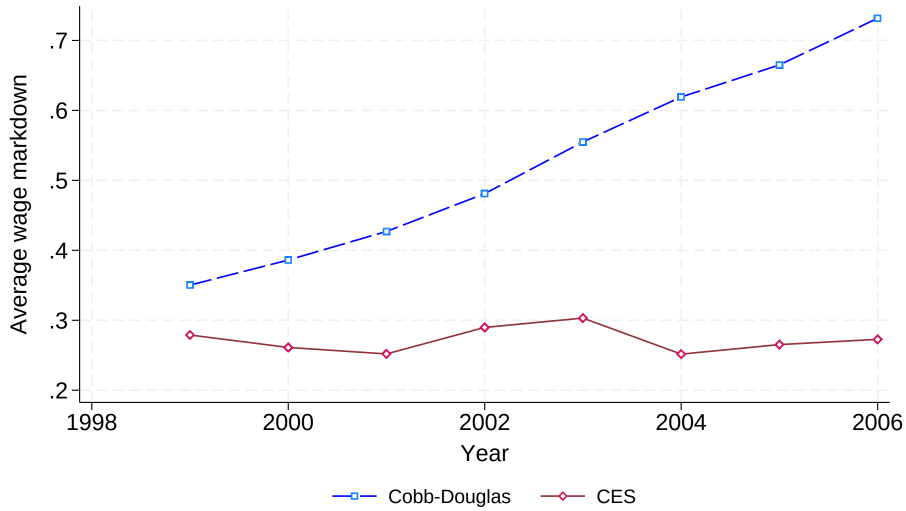



Figure 2. Wage Markdowns

*Note:* 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.

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. This is in line with prior evidence of SOEs as offering nonwage amenities (Chen et al., 2021) but different from prior evidence of MNEs as offering lower nonwage amenities (González and Kong, 2025). In contrast, the Hicks-neutral model fails to pick up smaller markdowns at foreign firms and overestimates the markdown gap with SOEs, by misinterpreting high labor-augmenting productivity as high markdowns. The specification that allows for labor-augmenting productivity differences while assuming competitive labor markets underestimates the productivity disadvantage of SOEs by 18%, and overestimates the productivity advantage of foreign firms by 27%. This difference is both due to the bias introduced in estimating the production function without controlling for markdown variation in the first stage, and due to markdown variation being interpreted as labor-augmenting productivity residuals.

In sum, our estimates reveal that although SOEs are less productive than private firms, they also set smaller 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 smaller markdowns than other firms.

## III. 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 smaller 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.

Table 1—Labor Supply and Demand Estimates

| *(a) Labor supply* | | OLS | | IV | | IV | |
|---|---|---|---|---|---|---|---|
| | | Est. | S.E. | Est. | S.E. | Est. | S.E. |
| Wage coefficient | $\gamma$ | 0.002 | 0.0005 | 0.182 | 0.026 | 0.240 | 0.051 |
| Nesting parameter | $\varsigma$ | 0.196 | 0.004 | -0.001 | 0.012 | -0.019 | 0.019 |
| Constant factor | $\gamma_0$ | | | | | 64.939 | 31.650 |
| Time-varying factor | $\gamma_1$ | | | | | -0.032 | 0.016 |
| 1st stage F-stat: $W^L_{ft}$ | | | | 10.596 | | 11.722 | |
| 1st stage F-stat: $s_{ft}$ | | | | 12160.018 | | 12268.141 | |
| 1st stage F-stat: $W^L_{ft} \times year$ | | | | | | 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 | $\sigma$ | 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 | $\beta^l$ | 0.076 | 0.218 | . | . | . | . |
| Material coefficient | $\beta^m$ | 0.756 | 0.349 | 1.596 | 138.985 | 0.211 | 16.614 |
| Capital coefficient | $\beta^k$ | 0.048 | 0.061 | $< 0.001$ | 0.008 | 0.001 | 0.075 |
| Serial correlation | $\rho$ | 1.046 | 0.057 | 0.983 | 0.370 | 0.749 | 0.158 |
| Returns to scale | $\nu$ | . | . | 1.042 | 0.039 | 0.984 | 0.036 |
| Observations | | 10433 | | 10433 | | 9867 | |
| Output elas. of labor | $\theta^l_{ft}$ | 0.076 | 0.218 | 0.073 | 0.004 | 0.086 | 0.010 |
| Output elas. of materials | $\theta^m_{ft}$ | 0.756 | 0.349 | 0.958 | 0.409 | 0.797 | 0.072 |
| Output elas. of capital | $\theta^k_{ft}$ | 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 | |

*Note:* 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 | |

*Note:* '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.

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