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 differences. We propose a method to overcome this challenge and apply it to study the labor market effects of ownership liberalization in Chinese nonferrous metal industries. We find that state-owned enterprises (SOEs) set lower markdowns than domestic private firms, but higher markdowns than foreign-owned enterprises. However, SOEs also have much lower labor-augmenting productivity levels compared to both foreign-owned and domestic private firms, although the productivity gap diminishes over time.

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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-based' markdown estimators crucially rely on Hicks neutrality. Although there are 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 solve 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. In an empirical application, we apply our model to study how the privatization and internationalization of the Chinese nonferrous metal (NFM) manufacturing and mining industries contributed to both labor market power and labor-augmenting productivity growth.

We motivate our empirical analysis by three stylized facts on the Chinese NFM industry, which hold for the entire Chinese industrial sector as well. First, the aggregate cost share of labor declined substantially between 1999 and 2006. Second, the ownership structure of Chinese industries changed drastically over this period due to privatization and FDI inflows. Third, labor cost shares differ substantially by firm ownership type, with SOEs having the highest labor cost shares, followed by domestic and foreign firms.

To assess whether this cost share variation is due to changes in wage markdowns or to directed technological change, we build and estimate a model of production and labor supply in the Chinese NFM industry. On the production side, we rely on the approach proposed by Doraszelski and Jaumandreu (2018), which we extend to allow for endogenous factor prices. On the labor supply side, we impose a nested logit model with differentiated employers, following a recent class of oligopsony models (Card et al., 2018; Azar et al., 2019; Berger et al., 2022). We rely on price shocks on international metal exchanges as demand shifters to identify the labor supply model, and combine the usual timing assumptions on input decisions with minimum wage variation to identify the production model.

We find strong evidence for labor-augmenting technological change in our set of industries, with labor-augmenting productivity growing at 15.5% per year on average. We also find that labor markets are imperfectly competitive, with wage markdowns of 28% on average, and that markdowns were stable over time. Using a Hicks-neutral model instead would have led to much higher markdown estimates, at 57% on average, and to the conclusion that markdowns doubled during the sample period. The reason for these diverging markdown estimates is that a Hicks-neutral model interprets the low labor cost shares associated with unobserved high labor-augmenting productivity levels as high wage markdowns. Compared to existing approaches that do not allow for imperfect labor market competition, our model also leads to substantially different estimates of key production parameters, such as the elasticity of factor substitution, and to lower price-cost markups.

Comparing firms by ownership, we find that wage markdowns are the highest at domestic private firms, relatively lower at SOEs, and the lowest at foreign-owned enterprises. In contrast, labor-augmenting productivity is 4% higher at foreign firms and 71% lower at SOEs compared to domestic private firms. These differences in labor-augmenting productivity diminish over time as domestic Chinese firms grow closer to the international technology frontier. Overall, these patterns suggest that both privatization and foreign capital inflows were associated with strong growth in labor-augmenting productivity, but not in increased labor market power.

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. 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 et al., 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 & 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.

We also contribute to the literature on the effects of ownership changes on firm performance. The productivity effects of privatizations and of foreign direct investment are well-documented (Javorcik, 2004; Brown et al., 2006; Song et al., 2011; Hsieh & Song, 2015;

Sun, 2020; Leblebicioğlu & Weinberger, 2021; Chen et al., 2021), but SOEs and foreign-owned firms have also been found to differ from other firms in terms of monopsony power (Dobbelaere & Kiyota, 2018; Lu et al., 2019; Méndez & Van Patten, 2022; Rubens, 2023). To distinguish these different mechanisms, a model is needed that allows for both imperfect factor market competition and factor-biased technological change. Doing so is especially policy-relevant in the Chinese setting, given that both the privatization of China SOEs and FDI liberalization have been increasingly reversed in recent years (Lardy, 2019; Fang et al., 2022).

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

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 production function coefficients $\boldsymbol{\beta}$ are assumed to be common across firms:

$$Q_{ft} = G(A_{ft}L_{ft}, M_{ft}, K_{ft}; \boldsymbol{\beta})\Omega_{ft} \tag{1}$$

We assume $G(.)$ is twice differentiable in all inputs, and we denote the output elasticity of labor and materials as θ^l_{ft} and θ^m_{ft}:

$$\theta^l_{ft} \equiv \frac{\partial G(.)}{\partial L_{ft}} \frac{L_{ft}}{G(.)} \qquad \theta^m_{ft} \equiv \frac{\partial G(.)}{\partial M_{ft}} \frac{M_{ft}}{G(.)} \tag{2}$$

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:

$$\psi^l_{ft} \equiv \frac{\partial W^l_{ft}}{\partial L_{ft}} \frac{L_{ft}}{W^l_{ft}} + 1 \qquad \psi^m_{ft} \equiv \frac{\partial W^m_{ft}}{\partial M_{ft}} \frac{M_{ft}}{W^m_{ft}} + 1 \tag{3}$$

2.2 Firm Behavior

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. We denote marginal costs as λ_{ft}, and the cost minimization problem is given by Equation (4):

$$\min_{L_{ft},M_{ft}} \Big[W^m_{ft}M_{ft} + W^l_{ft}L_{ft} - \lambda_{ft}\big(Q_{ft} - G(.)\big)\Big] \tag{4}$$

As shown in De Loecker et al. (2016), the markup of the final goods P_{ft} over marginal costs, $\mu^p_{ft} \equiv (P_{ft} - \lambda_{ft})/\lambda_{ft}$, is equal to Equation (5):

$$\mu^p_{ft} = \frac{\theta^j_{ft}}{\alpha^j_{ft}\psi^j_{ft}} - 1 \quad \forall j = l, m \tag{5}$$

where α^j_{ft} denotes the cost of input j as a share of gross revenues of firm f in year t, such that $\alpha^l_{ft} \equiv W^l_{ft}L_{ft}/P_{ft}Q_{ft}$ and $\alpha^m_{ft} \equiv W^m_{ft}L_{ft}/P_{ft}Q_{ft}$. Following Morlacco (2017) and Yeh et al. (2022), the inverse supply elasticity of labor can be expressed relatively to the inverse supply elasticity of materials by weighting the ratio of input expenditures by the respective output elasticities of both inputs:

$$\psi^l_{ft} = \frac{\theta^l_{ft}}{\theta^m_{ft}}\frac{\alpha^m_{ft}}{\alpha^l_{ft}}\psi^m_{ft} \tag{6}$$

The wage markdown $\mu^w_{ft} \equiv (MRPL_{ft} - W_{ft})/MRPL_{ft}$ can be expressed in function of this inverse labor supply elasticity:

$$\mu^w_{ft} = \frac{\psi^l_{ft} - 1}{\psi^l_{ft}} \tag{7}$$

The more inelastic the labor supply curve, the greater a firm's ability to exercise monopsony power and suppress wages.

2.3 Identification Challenge

Without loss of generality, we assume that intermediate input prices are exogenous to individual firms, $\psi^m_{ft} = 1$.[1] If the production function is Cobb-Douglas, there is no heterogeneity in the output elasticities across firms: $\theta^j_{ft} = \theta^j$. In this case, the inverse labor supply elas-

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

ticity ψ^l_{ft} is identified by weighted relative variable input expenditure, using Equations (6) and (7). In general, if firms vary only in their Hicks-neutral productivity shifter Ω_f but not in the labor-augmenting parameter A_{ft}, the relative markdown can be identified as long as the common production function coefficients $\boldsymbol{\beta}$, and hence the output elasticities $\boldsymbol{\theta}_{ft}$, are identified. For instance, a translog production function allows for variation in the output elasticities θ_{ft}, but its variation is fully parametrized by the common coefficients $\boldsymbol{\beta}$.[2]

However, as soon as the labor-augmenting productivity level A_{ft} varies, this introduces unobserved variation in output elasticities across firms and time, as the output elasticities $\boldsymbol{\theta}_{ft}$ are a function of A_{ft}.[3] In this case, Equation (7) has unknown variables on both its left- and right-hand sides, even if the common production function coefficients $\boldsymbol{\beta}$ have been identified: both the output elasticities θ^j_{ft} and the inverse input supply elasticity ψ^l_{ft} are unknown. The intuition behind this result is visualized in Figure 1. Panel 1a shows a firm that faces exogenous labor wages and experiences a labor-augmenting productivity shock, which flattens the isoquant curve and makes the firm decrease its relative labor usage from bundle 1 to 2. 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, which rotates the isocost curve inward. Although bundles 1 and 2 have same labor-to-material ratios, one cannot know whether this variation in relative input usage is due to factor-biased technological change or a change in the labor supply elasticity.

The above identification challenge differs from those raised in the factor-biased identification literature. For instance, Raval (2023); Foster et al. (2022); Doraszelski and Jaumandreu (2018); Demirer (2019) all make the point that *revenue share* variation $V^j_f W^j_f / P_f Q_f$ can be due to either markups or factor-augmenting productivity. However, they rely on the assumption of exogenous input prices, which allows the *cost share* variation $V^j_f W^j_f / \sum_j (V^j_f W^j_f)$ to be used to separately identify markups from factor-augmenting productivity differences. Our approach focuses on the *cost share* variation, which can be driven by a change in either markdowns or factor-augmenting productivity.

In general, we see two solutions to this identification challenge. First, one can rely on observed technology usage or technological innovations to measure technological heterogeneity $\boldsymbol{\theta}_{ft}$ (Foster et al., 2022; Kusaka et al., 2022; Miller et al., 2022; Delabastita & Rubens, 2022). Alternatively, one can impose more structure on the supply market of each

[2]We illustrate this in Appendix B.1.

[3]For instance, for the CES production function, a change in factor-biased technological parameters A_{ft} affects the output elasticities of inputs, which we discuss in detail in Section 3.3.

input j so as to identify the factor price markdowns ψ^j_{ft}, which is the approach we follow in our empirical application below. 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.

3 Empirical Application

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". This set of industries provides an interesting case study to answer the questions raised, for three reasons. First, there is evidence of both imperfect labor market competition and of labor-augmenting technological change in these industries, which makes the answer to our question nontrivial. Second, these industries mimick the aggregate Chinese industrial sector in terms of both the trend in the labor cost share and of its ownership correlations. Third, these industries permit estimating production functions with well-defined production quantities in physical units.

3.1 Data Sources

Our main dataset consists of the Annual Survey of Industrial Production (ASIP), which is collected by the National Bureau of Statistics (NBS) of China (Brandt et al., 2014). 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. In addition, the NBS reports production quantities at the product-year level for a subset of establishments.

We merge our main dataset to multiple additional data sources. We use data on exports and imports at the HS eight-digit code-firm-destination-year level for all international transactions from China, which ranges from 2000 to 2006. We also use China's Population Census data from 2000 to compute county-level employment. We use international market prices of various NFMs from the Bloomberg Industrial Metals Subindex, at the annual level. Finally, we obtain monthly minimum wages for full-time employees at the county-year level from official county government reports.[4] Appendix Table A1 summarizes the key characteristics of Chinese firms in the NFM manufacturing and mining sectors.

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

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 Key Facts on Chinese NFM Industries

Industry Background

In 2001, China became the world’s largest manufacturer of NFMs, such as aluminum, copper, lead, zinc, and nickel (Wang & Chandler, 2010). In 2008, right after our sample period, NFM industries achieved an industrial-added value of 576.6 billion yuan, 1.9% of China’s GDP, and employed more than 3 million workers (Fa, 2009). The sector has seen fast-paced technological change during the 1990s and 2000s (Wang & Chandler, 2010). Given the technology gap with foreign industries, part of this technological upgrading has occured through imports of foreign capital and through foreign direct investment. On average 8% of capital investment of Chinese NFM manufacturers was imported capital throughout our sample period, and in mining industries, nearly 60% of mining equipment is imported from overseas (Wu et al., 2007). This technological change is likely not Hicks-neutral (Loow et al., 2019; Loow, 2022). For ferrous metal industries, which share some similaries 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.

Falling Aggregate Cost Shares of Labor

We present three stylized facts on the evolution of the cost share of labor and firm ownership in Chinese NFM industries, which mimick the entire Chinese industrial sector.[5] Throughout the sample period, the labor cost share of NFM firms plummeted: Figure 2 shows that it fell from 7% to 3% for all NFM firms. This pattern also holds for the labor expenditure share of value added.[6] 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 2 shows, the labor cost

[5]We show this in Appendix C. 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 rather than its *revenue* share, which allows us to abstract from markups and from measurement issues regarding the capital stock.
[6]See Appendix Figure A2.

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.

As Equation (6) showed, this variation in relative labor expenditure can be due to both labor-augmenting technological change or to variation in wage markdowns. Neither of these competing hypotheses can be dismissed a priori: in addition to the already presented evidence of labor-augmenting technological change, Brooks et al. (2021); Lu et al. (2019), find evidence for considerable monopsony power in Chinese manufacturing industries. Also, Chinese labor markets have institutional rigidities, such as the Hukou registration system, which may lead to inelastic labor supply and, hence, the exertion of monopsony power (Shu et al., 2011; Bayari, 2014).

3.3 Empirical Model

In order to separately identify wage markdowns from labor-augmenting productivity differences, we implement an empirical model of Chinese NFM industries that follows the general structure as proposed in Section 2.

Production

On the production side, we assume a CES production function where the elasticity of input substitution between labor (L_{ft}), material (M_{ft}), and capital (K_{ft}) is σ, and the returns-to-scale parameter is ν, as shown in Equation (8):[7]

$$Q_{ft} = [(A_{ft}\, L_{ft})^{\frac{\sigma-1}{\sigma}} + \beta^m M_{ft}^{\frac{\sigma-1}{\sigma}} + \beta^k K_{ft}^{\frac{\sigma-1}{\sigma}}]^{\frac{\nu\sigma}{\sigma-1}} \Omega_{ft} \tag{8}$$

The common parameters β^m and β^k govern how much material and capital contribute to output relative to labor.[8] We denote ω_{ft} and a_{ft} as the logarithms of Hicks-neutral and labor-augmenting productivity. To allow for product differentiation, we add a linear control function in log prices to the production function, following De Loecker et al. (2016):

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

We assume an AR(1) process for both $\tilde{\omega}_{ft}$ and a_{ft} with serial correlation ρ^ω and ρ^a, and idiosyncratic productivity shocks υ^ω and υ^a, which are determined by the following law of

[7]We abstract from land use as a separate input as it is not observed in the dataset.
[8]In Appendix B.1, we conduct a robustness check in which β^k is allowed to change over time.

motion:

$$\tilde{\omega}_{ft} = \rho^{\omega}\tilde{\omega}_{ft-1} + \upsilon^{\omega}_{ft}, \qquad a_{ft}(1-\sigma) = \rho^{a} a_{ft-1}(1-\sigma) + \upsilon^{a}_{ft} \tag{9}$$

In particular, 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.

Labor Supply

To introduce labor supply decisions, we follow a discrete-choice nested logit model of labor supply in the tradition of Berry (1994), which has been implemented in labor market settings by, among others, Azar et al. (2019) and Berger et al. (2022). Manufacturing workers i in labor markets ℓ choose between a set of firms in that market. We follow a nested logit structure with nesting parameter ς, where we define labor markets at the prefectural city level, and the nests n at the county-by-4-digit-industry level. This nested structure allows for labor mobility across industries and between counties, which are usually used to define labor markets in China (Erten & Leight, 2021). Workers can also move out of the NFM sector, in which case they move to the outside option $f = 0$, which forms a separate nest on its own. Let the utility function of a worker j be given by Equation (10), which depends on wages W_{ft}, observed firm characteristics ($\mathbf{X}_{ft}$), and unobserved firm "amenities" ξ_{ft}. Workers face random utility shocks ζ_{jn}, which captures random taste variation for nest n, and ϵ_{jft}, which is a type-I distributed firm-worker utility shock. The coefficient γ_t measures the wage valuation in labor utility. We allow this parameter to change over time to allow for varying labor supply elasticities throughout the panel, given that labor market regulations have varied over time. We implement this time variation as a linear trend: $\gamma_t = \gamma_0 + \gamma_1 t$.[9]

$$U_{jft} = \underbrace{\gamma_t W^{l}_{ft} + \boldsymbol{\gamma}^{X}\mathbf{X}_{ft} + \xi_{ft}}_{\equiv \delta_{ft}} + \sum_{n}(d_{fn}\zeta_{jn}) + (1-\varsigma)\epsilon_{jft} \tag{10}$$

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

[9] In contrast to Card et al. (2018), Berger et al. (2022), and Azar et al. (2019), we let wages enter labor utility linearly, rather than loglinearly. We include the loglinear model as a robustness test in Appendix B.2.

following equation:

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

where the parameter $D_{nt} \equiv \sum_{f \in \mathcal{F}_{it}^n} \exp\left(\delta_{ft}/(1-\varsigma)\right)$. The nesting parameter ς measures the extent to which the different nests are substitutable. Normalizing compared to the labor market share of the outside option results in the usual nested logit equation, Equation (11):

$$s_{ft} - s_{0t} = \gamma_t W_{ft}^l + \varsigma s_{ft}^n + \boldsymbol{\gamma}^X \mathbf{X}_{ft} + \xi_{ft} \tag{11}$$

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.[10] Although we cannot verify this assumption in general due to a lack of firm-specific intermediate input prices, it is possible to test the exogenous input price assumption for NFM smelters as we observe their suppliers, the mining industries.[11]

Behavior and Equilibrium

We assume that firms simultaneously choose wages, which pin down employment given the labor supply curve, and materials at time t, after firms have observed the productivity shocks υ_{ft}^a and υ_{ft}^ω. Capital investment decisions are assumed to be made before observing these productivity shocks at time $t-1$. In addition, we assume that intermediate inputs and wages are chosen to minimize current variable costs:

$$\min_{W_{ft}, M_{ft}} \left(W_{ft}^m M_{ft} + W_{ft}^l L_{ft} - \lambda_{ft}(Q_{ft} - Q(.)) \right) \tag{12}$$

Under the functional form assumption for labor supply and under the behavioral assumptions made, the inverse labor supply elasticity faced by each firm, $\psi_{ft}^l - 1$, is equal to:

$$\psi_{ft}^l = 1 + \frac{1-\varsigma}{\gamma_t W_{ft}^l (1 - \varsigma s_{ft}^n - (1-\varsigma) s_{ft})} \tag{13}$$

[10] This is consistent with both a competitive input market or with mine competition following a homogeneous goods Cournot model.

[11] We refer to Appendix B.4 for this test, which validates our assumption of price-taking buyers on intermediate input markets.

3.4 Estimation

We estimate the model in two steps: first, we estimate the labor supply function (11), second, we estimate the production function (8). 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 the labor supply model in Equation (11), because employers set wages in the function of their amenities ξ_{ft}. We rely on three instrumental variables. First, we include the log world price of the processed metal that is manufactured in the specific industry. The identifying assumption is that changes in global prices of the final product produced by manufacturers affect labor demand of Chinese firms, but not their amenity value. This assumption 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.[12]

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 processed metal prices are not identical to global market prices, as the Chinese domestic market is not fully integrated with the global market.[13] Third, we include the number of firms in each industry-year-county pair, providing variation that is useful for identifying the nesting parameter.

We measure the outside option as the total prefectural city population minus total employment in NFM mining and manufacturing. We compute labor market shares within the total market and within the nests using employee counts. The observed characteristics vector $\mathbf{X}_{ft}$ contains the following three variables: 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.[14] 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 (13).

[12] We provide this test in Appendix B.3.

[13] The correlation between global metal prices and domestic prices on the Chinese market is 0.36.

[14] In the main model we do not allow for different wage coefficients by firm ownership type, we extend this in Appendix B.2.

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. The time-invariant model yields a wage coefficient of 0.187, the preferred model has a wage coefficient of 0.245 that decreases over time. The nesting parameter is -0.026 in the preferred specification, but 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). At the average firm, wages are marked down by 27.7%; at the median firm, they are marked down by 26.4%. Although these wage markdowns are larger than typically found for U.S. labor markets using labor supply approaches, such as in Azar et al. (2019), they are substantially below the 'cost-side' markdown estimates of Brooks et al. (2021) and Yeh et al. (2022).

Production Function: Estimation

Under the cost minimization assumption in (12), we derive the input ratio in Equation (14a), which is similar to the expression obtained by Doraszelski and Jaumandreu (2018) but with an added term that includes the inverse labor supply elasticity:

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

We define a constant $c \equiv \sigma\Big(\ln(\beta^m) - w^m\Big)$ and rearrange terms to obtain Equation (14b), which is the regression equation to be estimated:

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

We isolate the labor-augmenting productivity shock υ^a, which was defined in Equation (9), by taking ρ^a differences of Equation (14b), similarly to Blundell and Bond (2000), but for labor-augmenting productivity rather than for TFP:

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

We estimate (σ, ρ^a, c) using the following moment conditions. We include lagged log wages as an instrument for the labor-augmenting productivity shock, which reflects the timing assumption that wages are chosen after the productivity shock υ^a_{ft} is observed. In addition, we include the current and lagged values of the minimum wage in each firm's county ℓ in year t as an additional instrument.[15] The identifying restriction here is that variation in minimum wages leads to substitution between materials and labor by making labor more expensive, but not by increasing the transient labor-augmenting productivity shocks.

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

From Equation (14a), 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:

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

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

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

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

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

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

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

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

Using the estimated production function coefficients, the output elasticities of labor and materials can be computed as:

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

The markup can now be estimated using Equation (5), for any of the variable inputs. Markdowns can be estimated using Equation (7), which delivers the identical value as the markdown formula derived from the labor supply model, Equation (13).

Production Function: Results

The estimated elasticity of input substitution is reported in Table 1(b). We include the OLS results as a comparison in the first column. Using the GMM estimator but assuming competitive labor markets, the second column, results in an elasticity of substitution of 0.303. In contrast, our preferred estimator that allows for non-zero wage markdowns yields an estimate of 0.440. Both of these estimates imply that labor and materials are gross complements, but allowing for imperfect labor market competition increases the substitution elasticity estimate by 45%.

The remaining production function parameters are reported in Table 1(c). The first column reports the Cobb-Douglas estimates, as a Hicks-neutral benchmark. This model delivers output elasticities of labor and materials of 0.074 and 0.727, respectively. The second column shows the CES estimates assuming competitive labor markets, in which ψ_{ft} is set equal to one. The output elasticity of labor is nearly identical to the Cobb-Douglas estimate, although the CES model allows for heterogeneity in output elasticities across firms, the output elasticity of materials is quite higher at 0.958. The third column shows our preferred CES estimates that allow for imperfectly competitive labor markets, which we use throughout the rest of the paper. The output elasticities of labor and materials are now estimated at 0.086 and 0.798 on average, respectively, whereas the output elasticity of capital is estimated at 0.098. Allowing for imperfect labor market competition again results in markedly different production estimates.

In Figure 3, 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 36% to 73% when using a (Hicks-neutral) Cobb-Douglas model.[16] This difference arises because the Hicks-neutral model interprets all cost share variation as markdown variation: the declining labor cost share is entirely attributed to increasing wage markdowns in that model.[17]

3.5 Ownership, Markdowns, and Technological Change

Are the differences in costs shares between foreign, domestic private firms, and SOEs from Section 3.2 due to differences in labor market power, or due to technological change? We examine this question by comparing labor-augmenting productivity and wage markdowns by ownership type. We refrain from making causal statements about the effects of ownership structure on either markdowns or labor-augmenting productivity; 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).

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 63% to 71% when allowing for monopsony power. In both specifications, foreign-owned firms have slightly higher labor-augmenting productivity than domestic firms,

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

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

but the gap is not statistically significant.

Labor-augmenting productivity grew on average by 15.5% per year. Table 2b shows that the productivity growth was 7.7 percentage points lower at foreign-owned firms, but 5.8 percentage points higher at SOEs compared to domestic private enterprises. Hence, the technology gap between these different types of firms has narrowed over time.

Table 2c compares wage markdowns by ownership. The first column uses the markdown estimates from the Hicks-neutral model, whereas the third column shows the nested logit markdowns. The Hicks-neutral model finds that SOEs set markdowns that are 28% lower than private domestic firms, whereas foreign-owned firms set markdowns that are 3% lower. In contrast, using our preferred model that does not impose Hicks neutrality, markdowns are merely 13% lower at SOEs and 23% lower at foreign firms. This stark difference in findings is, again, due to latent variation in labor-augmenting productivity that is interpreted as markdown variation in the Hicks-neutral model.

3.6 Caveats

We end with two caveats to our approach. First, throughout the paper, we have imposed a conduct assumption on the labor market, Nash-Bertrand wage setting. Alternative models of conduct could be imposed, and would lead to a different labor supply elasticity estimate. However, imposing a conduct assumption is important, as this guarantees a one-on-one mapping between the inverse labor supply elasticity $(\psi^l_{ft} - 1)$ and the wage markdown μ^w_{ft}, hence, permits to point-identify the labor-augmenting productivity level A_{ft}. If conduct is unknown, as shown in Delabastita and Rubens (2022), the firm-level inverse labor supply elasticity $(\psi^l_{ft} - 1)$ can be consistent with a set of markdowns. In this case, our model no longer point-identifies A_{ft}, but can still set-identify A_{ft} using the markdown bounds. Second, our approach relies on the assumption that both inputs used for the cost minimization first order conditions are static, variable inputs. The presence of frictions that violate this assumption, such as adjustment or search costs, would enter the factor-augmenting residual A_{ft}. With matched employer-employee data, these frictions could be modelled more directly, as in Chan et al. (2023), and can be incorporated into our framework.

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 solve this identification challenge. We apply this approach to study monopsony power and technological change in Chinese NFM industries, and find that allowing for non-Hicks-neutral production functions substantially decreases both the implied levels, growth rate, and cross-ownership differences of wage markdowns. We find that private and foreign-owned firms have substantially higher labor-augmenting productivity differences than SOEs, but that this gap almost closed by the late 2000s. We see our approach as a way forward in using production function methodologies in industries that are characterized by both imperfect factor market competition and directed technological change.

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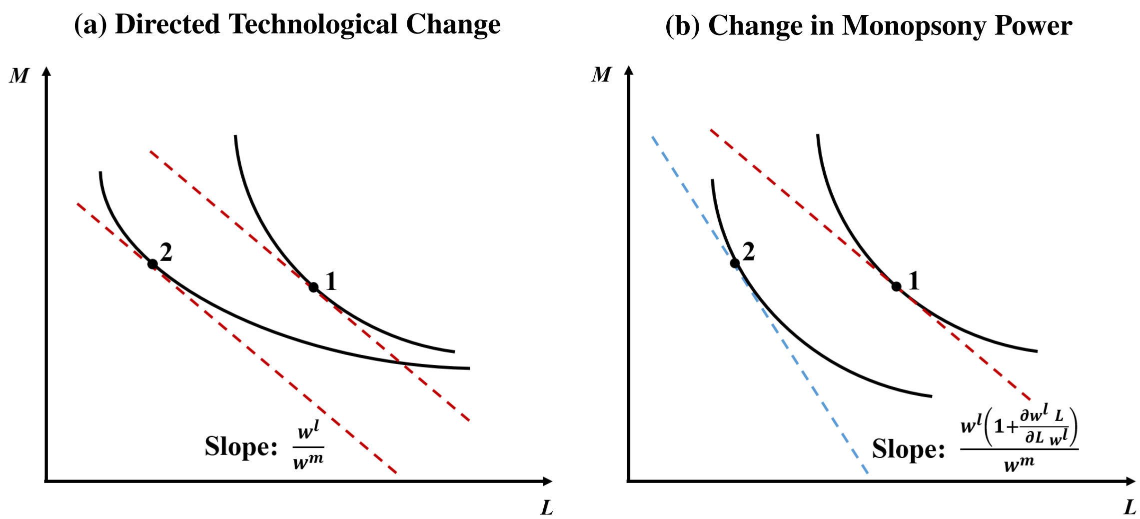
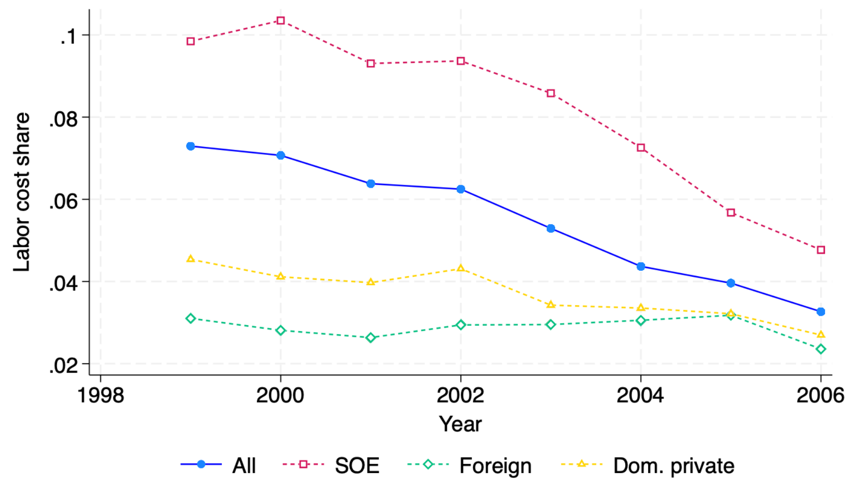
Figure 1: Non-Identification Using Only Cost Share Variation



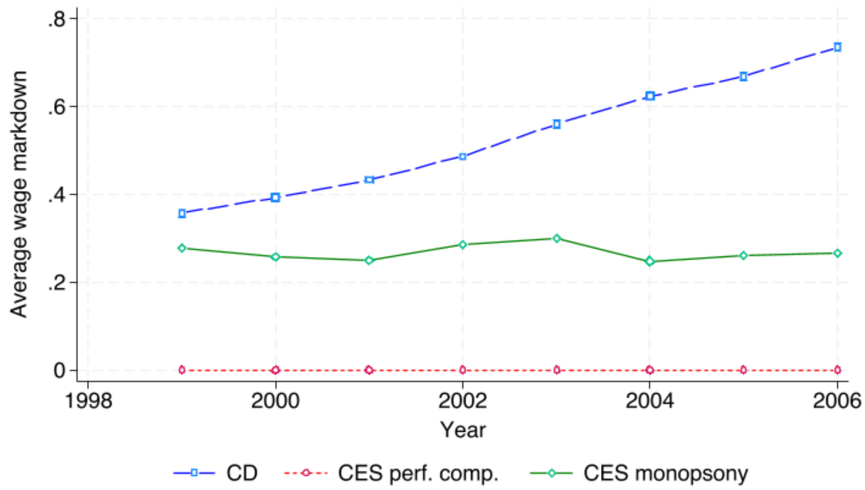
Notes: Panel (a) rationalizes variation in the labor-to-materials ratio by a (factor-biased) rotation of the isoquant, holding relative prices fixed. Panel (b) shows that the same labor-to-materials variation can be explained by a (Hicks-neutral) parallel shift in the isoquant, but increase in the inverse labor supply elasticity, again holding relative prices constant.

Figure 2: Labor Share of Variable Costs



Notes: This figure shows the evolution of total labor expenditure over total variable input expenditure in Chinese NFM industries, and disaggregates this evolution by firm ownership.

Figure 3: Wage Markdowns



Notes: This figure compares the evolution of the weighted average wage markdown between the (Hicks-neutral) Cobb-Douglas model ('CD'), the CES model that assumes competitive labor markets ('CES perf. comp.'), and the CES model that allows for monopsony power ('CES monopsony').

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	0.0003	0.187	0.026	0.245	0.052
Nesting parameter	ς	0.235	0.004	-0.009	0.012	-0.026	0.019
Constant factor	γ_0					64.978	32.254
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		0.962		0.321		0.277	
Median markdown		0.968		0.303		0.264	
(b) Elas. of substitution		OLS		GMM exo. wage		GMM endo. wage	
		Est.	S.E.	Est.	S.E.	Est.	S.E.
Elas. of substitution	σ	1.009	0.088	0.303	0.326	0.440	0.078
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	0.074	0.105	.	.	.	.
Material coefficient	β^m	0.727	0.170	1.590	225.769	0.243	2.433
Capital coefficient	β^k	0.054	0.029	0.000	0.237	0.001	0.016
Serial correlation	ρ	1.028	0.026	0.981	0.272	0.762	0.122
Returns to scale	ν	.	.	1.040	0.077	0.981	0.059
Observations		10433		10433		9867	
Output elas. of labor	θ_{ft}^l	0.074	0.105	0.073	0.009	0.086	0.010
Output elas. of materials	θ_{ft}^m	0.727	0.170	0.958	0.147	0.798	0.073
Output elas. of capital	θ_{ft}^k	0.054	0.029	0.009	0.114	0.098	0.060
Average markup		-0.011		0.290		0.075	
Median markup		-0.068		0.240		0.058	

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			0.055	0.359	0.036	0.070
State-owned			-0.985	1.533	-1.247	0.213
Growth rate			0.148	0.051	0.155	0.041
Observations			38186		36494	
R^2			.275		.259	
(b) Changing productivity gap over time						
Foreign-owned × time			-0.063	0.107	-0.077	0.026
State-owned × time			0.048	0.060	0.058	0.017
Observations			38186		36494	
R^2			.275		.259	
(c) Wage markdown						
Foreign-owned	-0.032	0.031			-0.257	0.024
State-owned	-0.324	0.134			-0.142	0.014
Growth rate	0.014	0.009			0.022	0.058
Observations	29058				36172	
R^2	.068				.259	

Notes: 'Foreign-owned' and 'State-owned' are dummies that equal unity if the firm has the 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 Cleaning

Our main data source is the Annual Survey of Industrial Production (ASIP), which is collected by the National Bureau of Statistics of China. The annual operation and balance sheet data are collected at the firm level, and are observed from 1998 to 2007. 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 28,016 firms and 89,647 observations in the NFM mining and manufacturing industries. 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 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 follow the conventional method to match firms from the China Customs Data to the ASIP (Feenstra et al., 2014; Yu, 2015; Manova & Yu, 2016); we use the firms' name, location, postal code, and telephone number to match firms between the two datasets, and we are able to match 30% to 40% of exporters to the ASIP dataset. We match each NFM in the Bloomberg dataset to the ASIP using the corresponding four-digit CIC codes of each industry.

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):

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

We maintain the AR(1) specification for Hicks-neutral productivity in Equation (9) 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:

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

We maintain the AR(1) specification for Hicks-neutral productivity in Equation (9) and to the price control in the production function that was specified in the main text. Hence, we can isolate the Hicks-neutral productivity shock $\upsilon(\beta^l, \beta^m, \beta^k, \beta^p, \rho, \beta^{ll}, \beta^{mm}, \beta^{kk}, \beta^{lm}, \beta^{mk}, \beta^{lk}, \beta^{lmk})$

as:

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

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

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

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

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

The translog production estimates are reported in Table A2 . The output elasticities of materials and capital 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 (8), 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: $\beta^k = \beta_0^k + \beta_1^k t$.

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

The estimates of this model are in Table A3. We find that the capital coefficient decreases by 0.002 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.

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 (10). An alternative, and often-used, functional form would be a loglinear labor utility model, which we estimate in the next section:

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

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.

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

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 with a standard error close to 0, 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.

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:

$$\psi^{l}_{ft} - 1 = \frac{1-\varsigma}{\gamma_t(1-\varsigma s^{n}_{ft} - (1-\varsigma)s_{ft})}$$

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 (11). The results are in Table A5. At foreign-owned firms, the wage coefficient is 1 point lower, and at SOEs 3 points lower, compared to an average wage coefficient of 626 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 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.[18] 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 A7 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.

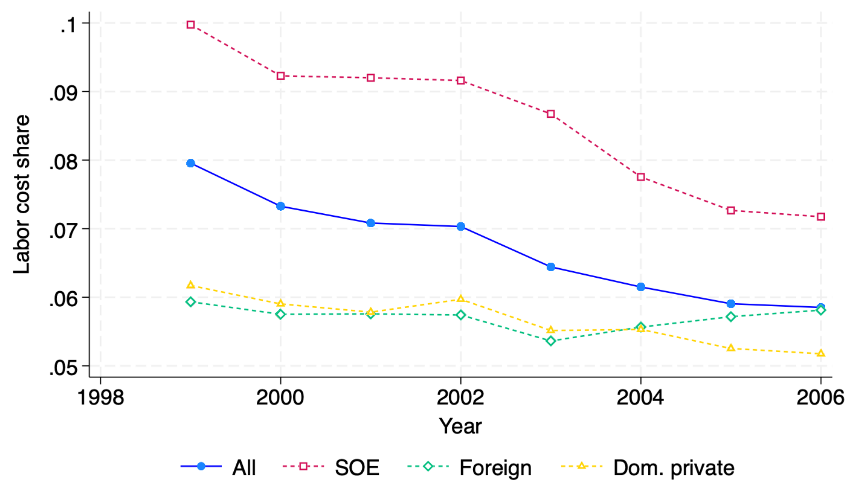
B.4 Exogenous Intermediate Input Prices Assumption

In the main model, we assumed that intermediate input prices are exogenous to each firm: firms do not exert monopsony power on their intermediate input markets. Although we cannot test this model in general, as we do not observe firm-level intermediate input prices, we can construct information on input prices for NFM manufacturers based on the output prices of NFM mines. For each county, we compute the average metal price for each metal type by taking the average output price of the mines in a certain four-digit industry code. For instance, for copper mining this is the CIC code 0911. Next, we compute the number of firms in the corresponding smelting industry in that same county. In the copper example, this is 3311. In Table A6, we regress the log average metal price received by the mines, for each county-year observation, on the number of smelters in the same industry in that county-year. We control for industry fixed effects and year fixed effects. If monopsony power would exist, we would find a negative relationship between raw metal prices and the number of raw metal buyers. However, we do not find statistically significant negative coefficients.

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

C Appendix Figures and Tables

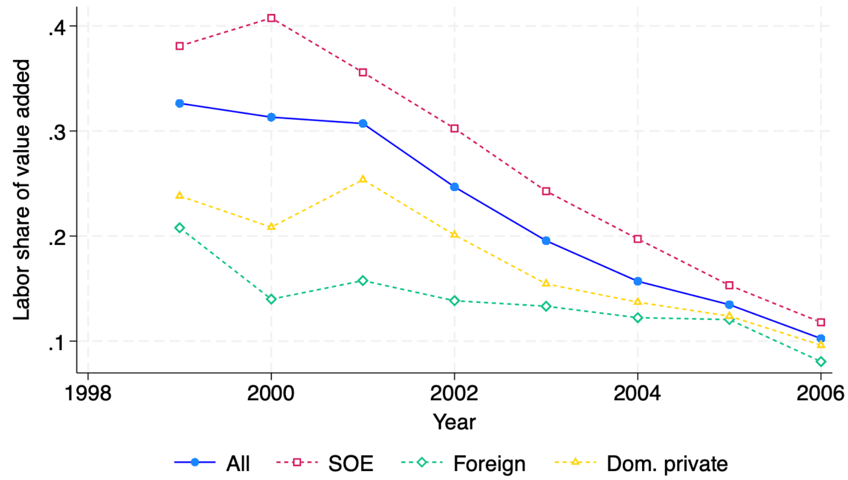
Figure A1: Labor Share of Variable Costs, All industries



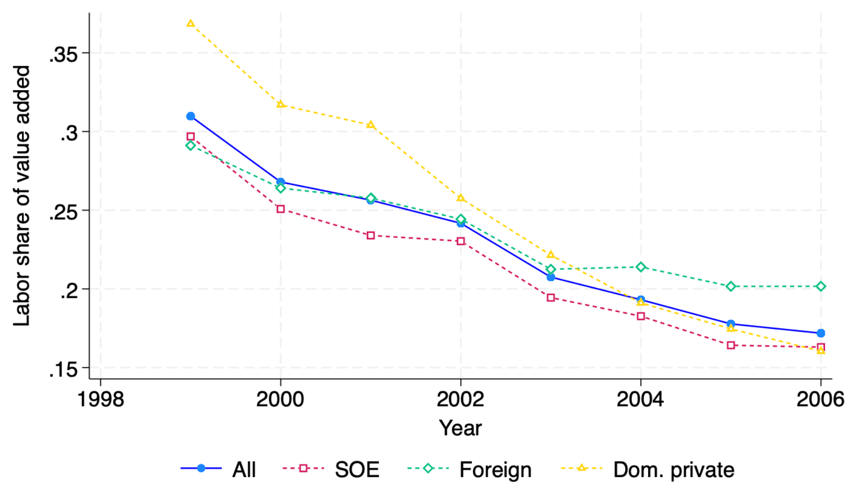
Notes: This graph plots the aggregate variable cost share of labor for all manufacturing and mining industries in China.

Figure A2: Labor Share of Value Added

(a) NFM industries



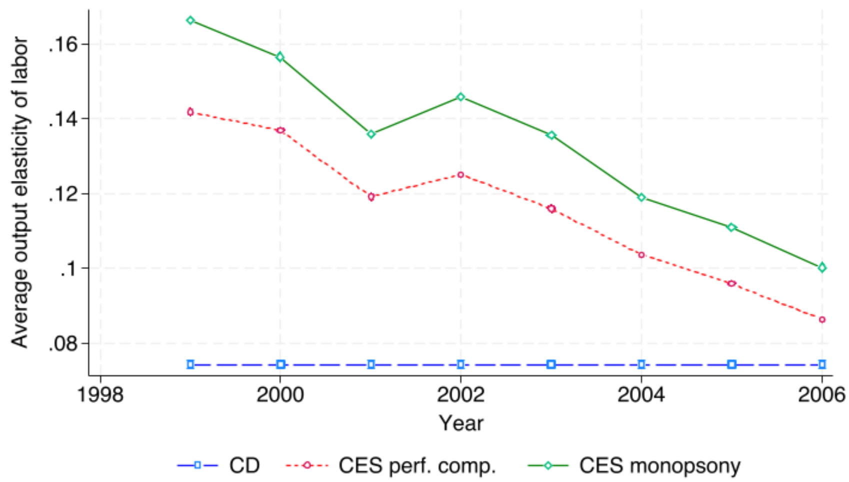
(b) All industries



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

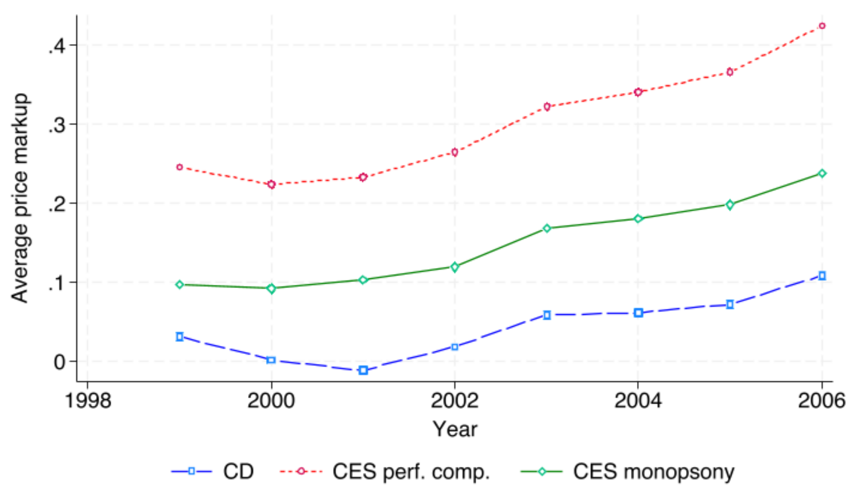
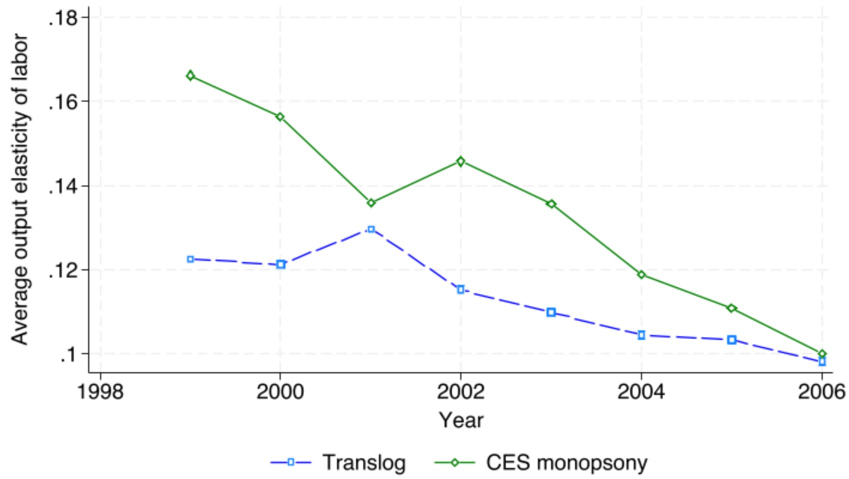


Figure A4: Translog Production Function

(a) Output Elasticity of Labor



(b) Wage Markdown

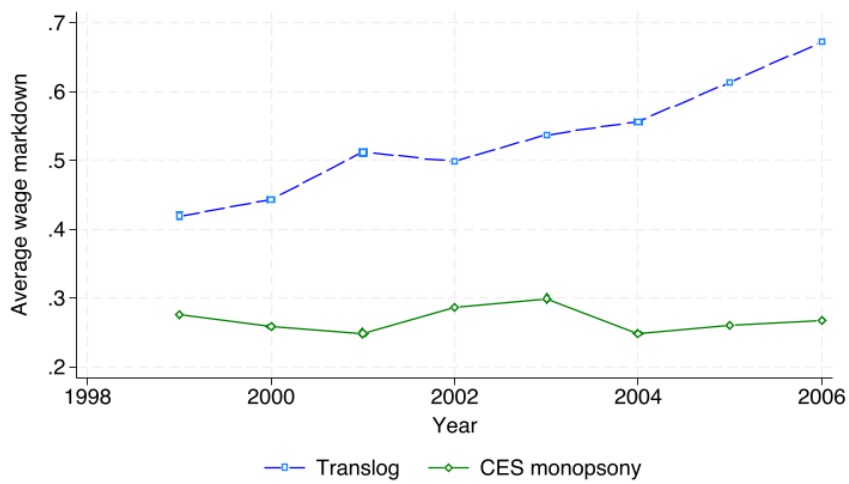
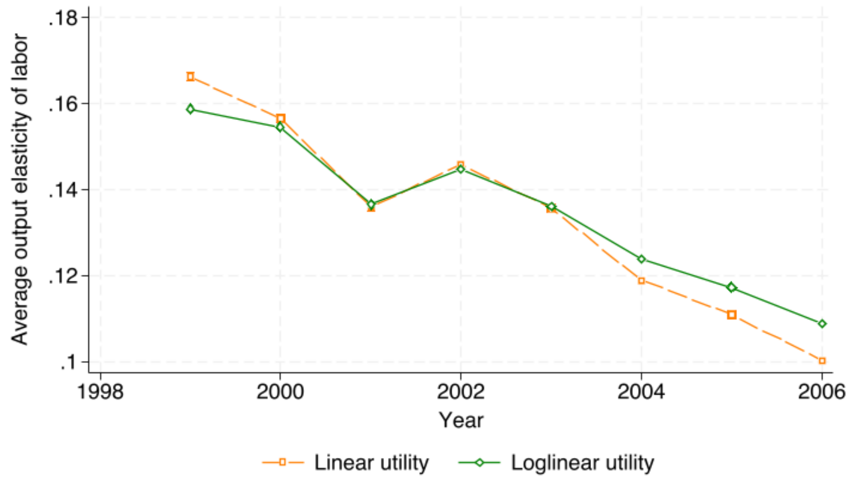


Figure A5: Loglinear Labor Supply Function

(a) Output Elasticity of Labor



(b) Wage Markdown

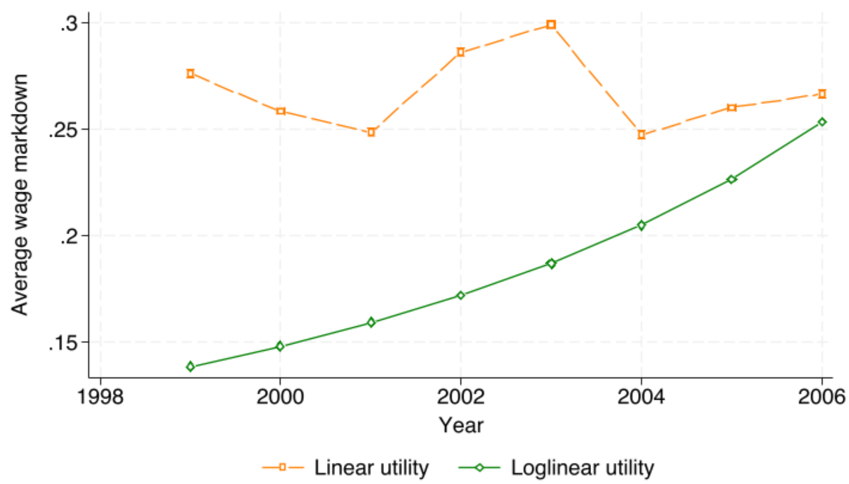


Table A1: Summary Statistics

	Observations	Mean	Std. dev.	Median	p25	p50
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

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	0.987
β^m		0.593	0.981
β^k		0.297	0.297
β^{ll}		0.009	0.031
β^{mm}		0.020	0.042
β^{kk}		0.003	0.008
β^{lm}		-0.038	0.071
β^{mk}		-0.026	0.024
β^{lk}		-0.013	0.039
β^{lmk}		0.002	0.003
Output elas. of labor	θ^l_{ft}	0.037	0.088
Output elas. of materials	θ^m_{ft}	0.770	0.126
Output elas. of capital	θ^k_{ft}	0.052	0.034
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		0.164	0.881
β_0^k		3.496	6.675
β_1^k		-0.002	0.198
β^k		0.007	395.845
Serial correlation	ρ	0.865	0.121
Returns to scale	ν	0.971	0.238
Observations		9867	
Output elas. of labor	θ_{ft}^l	0.069	0.007
Output elas. of materials	θ_{ft}^m	0.640	0.095
Output elas. of capital	θ_{ft}^k	0.262	0.092
Average markup		-0.122	
Median markup		-0.107	

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	0.964	0.000
Nesting parameter ς	0.036	0.000
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	1.869	4.397
Nesting parameter	ς	-0.250	0.774
Constant factor	γ_0	625.654	1391.759
Time-varying factor	γ_t	-0.311	0.693
Dummy: Foreign-owned		9.129	70.072
Dummy: Foreign-owned $\times$ wage		-0.770	3.965
Dummy: SOE		42.680	79.265
Dummy: SOE $\times$ wage		-2.933	5.715
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		0.060	
Median markdown		0.051	

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 Intermediate Input Prices

	Counties	Prefectures/Cities
Dummy: 1 firm	-0.167	0.348
	(0.141)	(0.128)
Dummy: 2 firms	-0.216	0.199
	(0.177)	(0.141)
Dummy: 3 firms	-0.104	-0.108
	(0.236)	(0.244)
Observations	561	773
R^2	0.551	0.534

Notes: We regress average mining output prices per geographical unit and 4-digit industry on the number of downstream (manufacturing) firms in that geographical unit, in the corresponding buyer industry. We control for year and industry fixed effects.

Table A7: Test Exogeneity of World Prices

	Log(world price)			
	Est.	S.E.	Est.	S.E.
Log(labor-augmenting productivity)	0.003	0.010	-0.001	0.014
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%.