Exploiting or Augmenting Labor?*

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Abstract

Changes in the ownership structure of firms, such as privatizations or foreign direct investment, can lead to productivity gains but could also lead to the exertion of market power. Disentangling these forces is crucial in order to understand the welfare implications of policies that lift ownership restrictions of domestic industries. However, we show that existing production models do not separately identify wage markdowns from (factor-biased) productivity differences. We propose a method to overcome this challenge and apply it to study the internationalization and privatization of the Chinese non-ferrous metal manufacturing and mining industries. We find that foreign-owned firms set wage markdowns similar to domestic private firms but lower compared to state-owned enterprises (SOEs). In addition, the labor-augmenting productivity of foreign firms is 25% higher than that of domestic private firms, and 65% lower at SOEs. Relying on a Hicks-neutral model would lead to the opposite conclusions regarding wage markdowns.

Keywords: Privatization, Foreign Direct Investment, Factor-Biased technological Change, Monopsony Power, Declining Labor Share

JEL Codes: L11, J42, O33

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1 Introduction

The productivity effects of policies that liberalize industries have been extensively documented. Privatizations of state-owned enterprises (Brown, Earle, & Telegdy, 2006; Hsieh & Song, 2015; Chen, Igami, Sawada, & Xiao, 2021), relaxations of foreign direct investment restrictions (Hasan, 2002; Lu & Yu, 2015; Lu, Sugita, & Zhu, 2019; Javorcik, 2004), and deregulation of regulated industries (Olley & Pakes, 1996) have all been found to spur productivity growth. However, changes in firm ownership could also affect market power, either on product or factor markets. For instance, state-owned enterprises (SOEs) often enjoy high market shares in local labor markets, which can result in the exertion of monopsony power (Rubens, 2023), and multinational enterprises might exert different degrees of monopsony power than local firms (Méndez & Van Patten, 2022; Lu et al., 2019; Dobbelaere & Kiyota, 2018). In order to fully understand the welfare effects of ownership changes such as SOE privatizations and acquisitions by multinational firms, it is, therefore, crucial to quantify how these different types of firms vary both in terms of their productivity levels and in terms of how much market power they exert. This 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; H. Fang, Wu, Zhang, & Zhou, 2022).

In this paper, we show that disentangling the directed technological effects of ownership changes from their potential effects on factor market competition is challenging because existing production models do not separately identify wage markdowns from labor-augmenting productivity. We propose a method to overcome this challenge, which relies on jointly estimating a labor supply model together with a non-Hicks-neutral production function. We apply this method to study how the privatization and internationalization of the Chinese non-ferrous metal manufacturing and mining industries affected both labor market power and labor-augmenting productivity growth. 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 (Shu, Xiuzhi, & Shu, 2011; Bayari, 2014; W. J. Brooks, Kaboski, Li, & Qian, 2021) and of labor-augmenting technological change (Loow, Abrahamsson, & Johansson, 2019; Loow, 2022) in these industries, which makes the answer to our question non-trivial. Second, these industries mimick the aggregate Chinese economy in terms of both the evolution of the labor cost share and of its ownership structure, which matters for external validity. Third, the non-ferrous mining and manufacturing industries allow estimating production functions with well-defined production quantities in physical units.

We start our analysis by showing three important stylized facts on both the Chinese non-ferrous metals industry and the aggregate of all Chinese manufacturing and mining industries. First, the aggregate cost share of labor declined substantially between 1999 and 2006. Second, the ownership structure of Chinese industries changed remarkably over this period due to the fast pace of privatization and foreign direct investment (FDI). Third, labor cost shares differ substantially by firm ownership type, with SOEs having the highest labor cost shares followed by domestic and foreign firms. The reallocation of labor from SOEs to private firms and from domestic to foreign firms played an important role in driving the decline in the aggregate cost share of labor.

In order to assess whether the decline of the labor cost share was driven by increasing wage markdowns or the labor-augmenting technological change and to investigate whether low labor cost shares at domestic and foreign-owned firms are due to monopsony power or high labor-augmenting productivity levels, we build and estimate a model of production with labor supply. Our analysis proceeds in three steps. We start by presenting a general model framework to make our non-identification argument, and to explain why a factor supply model needs to be added to the production model to achieve separate identification of factor price markdowns and factor-augmenting productivity levels. Second, we adopt concrete specifications for the production and labor supply model of non-ferrous metal manufacturers and mines. 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 assume that the labor supply of workers to differentiated employers is represented by the well-known nested logit model, in the tradition of Berry (1994) and following a recent class of monopsony and oligopsony models (Card, Cardoso, Heinig, & Kline, 2018; Azar, Berry, & Marinescu, 2019; Berger, Herkenhoff, & Mongey, 2022). We demonstrate our proposed identification approach using Monte Carlo simulations and show that it manages to identify both wage markdowns and latent technology differences between firms, in contrast to approaches that rely on Hicks neutrality. Next, we estimate our model for the non-ferrous metal manufacturing and mining industries. In identifying critical parameters of the labor supply curve, we use exogenous world price shocks on international metal exchanges as the labor demand shifters because these shocks are differentially passed through to exporters and non-exporters. To identify the production function, we rely on the usual timing assumptions on input decisions in the function of the arrival of both Hicks-neutral and labor-augmenting productivity shocks.

With our estimated model, we reach three conclusions. First, we find that labor markets are generally imperfectly competitive, with wage markdowns of 25% on average. Wage markdowns are similar between domestic private firms, SOEs, and foreign-owned firms. This suggests that neither privatizations or FDI inflows were associated with the exertion of monopsony power. Second, we find that labor-augmenting productivity is 25.1% higher at foreign firms and 65.3% 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. Labor-augmenting productivity grew rapidly throughout the entire sample period, by 16.3% per year on average. About 70% of the growth in labor-augmenting productivity can be attributed to a reallocation between firms, with the remaining 30% to within-firm productivity change. Overall, these patterns suggest that both privatization and foreign capital inflows had important benefits by reducing the degree of labor market power exerted over workers and by increasing labor-augmenting productivity. Strikingly, we also document that using a Hicks-neutral model would have led to the opposite conclusion that wage markdowns were sharply rising and were lower at SOEs. The reason for these opposite conclusions is that a Hicks-neutral model interprets low labor cost shares due to latent high labor-augmenting productivity as high wage markdown levels.

This paper contributes to three distinct literatures. First, we contribute to the literature on the effects of ownership changes on firm performance. On the one hand, it has been shown that private and foreign firms use different technologies and, hence, have different productivity levels, be it Hicks-neutral or factor-specific (Song, Storesletten, & Zilibotti, 2011; Sun, 2020; Leblebicioğlu & Weinberger, 2021; Chen et al., 2021). Second, it has been hypothesized that ownership changes have led to changes in factor market competition (Lu et al., 2019; Rubens, 2023). In order to evaluate which of these mechanisms is more important, it is imperative to use a model that can allow for both imperfect factor market competition and factor-biased technological change, as we do in this paper.

We also contribute to the literature that extends the cost-side markup estimation framework of De Loecker and Warzynski (2012). This approach has been widely used to estimate wage markdowns in a class of settings based on Hicks-neutrality (Morlacco, 2017; Yeh, Hershbein, & Macaluso, 2022; Mertens, 2019; Kroft, Luo, Mogstad, & Setzler, 2020; W. J. Brooks et al., 2021; Rubens, 2023). Meanwhile, another class of models relaxes Hicks-neutrality but relies instead on assuming perfectly competitive factor markets (Doraszelski & Jaumandreu, 2018; Demirer, 2019; Raval, 2023; Miller, Osborne, Sheu, & Sileo, 2022). We show that both types of models rely on the same variation in the data, relative input expenditure, to identify either the wage markdown or labor-augmenting productivity, while assuming away the other object. We contribute to this literature by proposing a novel approach that separately identifies markdowns from factor-augmenting productivity levels. In this regard, our paper is closely related to Chan, Mattana, Salgado, and Xu (2023), who also consider both imperfect labor market competition and labor-biased technological change in production function estimation with an extended non-parametric identification approach based on Gandhi, Navarro, and Rivers (2020). Compared to Chan et al. (2023), our approach does not require micro-level data such as matched employer-employee information. In addition, our approach allows for imperfect competition in product markets, and we study the labor cost share evolution rather than pass-through rates.

Third, our results relate to the literature that studies the mechanisms behind the decline in the labor share. In contrast to most previous research (Karabarbounis & Neiman, 2014; Autor, Dorn, Katz, Patterson, & Van Reenen, 2020; De Loecker, Eeckhout, & Unger, 2020), we focus on the *cost* share of labor rather than the *revenue* share of labor, and this allows us to abstract from changing markups. Existing models that explain the declining labor share by technological change, either within firms (Hubmer, 2023; Foster, Haltiwanger, & Tuttle, 2022) or between firms (Autor et al., 2020), assume competitive labor markets. In contrast, explanations of declining labor shares that point to increasing wage markdowns typically assume Hicks-neutrality (Yeh et al., 2022). In contrast, our approach allows decomposing the evolution of the aggregate labor cost share into factor-biased technological change and wage markdown growth.

The remainder of this paper is structured as follows. In Section 2, we present the data, industry background, and stylized facts to motivate the model. Section 3 presents a general framework to show the non-identification of wage markdowns and labor-augmenting productivity, and implements this framework in the context of the Chinese non-ferrous metals industries. Section 4 discusses the identification and estimation of this model and is followed by a discussion of the results in Section 5. Section 6 concludes.

2 Background and Stylized Facts

2.1 Data sources

Our empirical application focuses on the Chinese non-ferrous metal 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". We use four main data sources in the analysis. The first is the

Annual Survey of Industrial Production (ASIP), which is collected by the National Bureau of Statistics (NBS) of China (Brandt, Van Biesebroeck, & Zhang, 2014). The dataset covers manufacturing firms with more than five million RMB in annual sales ($\approx$ \$700k). For each firm, the ASIP provides data on employment, output, and elements of accounting statements. In particular, the NBS reports production quantities at the product-year level for a subset of establishments. In order to reduce measurement error in inputs, we trim the variable input revenue shares at the 1st and 99th percentile. Second, we use data on exports and imports at the HS 8-digit code-firm-destination-year level for all international transactions from China. We follow the conventional method to match firms from the China Customs Data to the ASIP (Feenstra, Li, & Yu, 2014; Yu, 2015; Manova & Yu, 2016). We use the firms' name, location, zip 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. The China Customs Dataset ranges from 2000 to 2006 while the ASIP from 1998 to 2007. Third, we use China's Population Census data of 2000 to compute county-level employment. Fourth, we use international market prices of various non-ferrous metals from the Bloomberg Industrial Metals Subindex, at the annual level. We match each non-ferrous metal in this dataset to the corresponding 4-digit CIC codes.[1]

2.2 Industry background

China became the world's largest manufacturer of nonferrous metals, such as aluminum, copper, lead, zinc, and nickel, in 2001 (Yanjia & Chandler, 2010). According to the statistics by the China Nonferrous Metal Association ('CMRA'), a government-endorsed industry association, the combined output of the primary nonferrous metals rose by 18.1 percent to 16.3 million tons from 2004 to 2005, ranking China No.1 in the world for a fourth consecutive year (2001-2005).[2] In 2008, nonferrous metal industries achieved an industrial-added value of 576.6 billion yuan, 1.9% of China's GDP, and employed more than three million workers (Fa, 2009). Technological upgrading has been key to sustaining industrial growth. Most large-scale nonferrous metal manufacturing plants were built or had their production equipment and processes upgraded within the last two decades (Yanjia & Chandler, 2010). Despite the fast pace of development in technological upgrading, the gap in research and development (R&D) investment between Chinese nonferrous metal industries and their global

[1] Appendix Table A9 summarizes the key characteristics of Chinese firms in the NFM manufacturing and mining sectors, which we use in subsequent regression analysis.

[2] For details, see http://www.china.org.cn/business/2006-06/06/content_1170482.htm.

competitors remains, as called out by Kang Yi, the president of the CMRA, “We can buy advanced equipment from foreigners, but we can’t buy real core technologies. Therefore, it is a pressing task for the sector to enhance independent innovation capabilities to raise international competitiveness" (Gong, 2006).

Non-ferrous metal equipment usage in China

During the time period studied, China’s underground mining technologies lagged behind the international frontier: domestic equipment was considered less inefficient and subject to more safety concerns than foreign technologies, both in rock drilling, charging, and shipping (Wu, Wu, Zhang, & Yang, 2007). Foreign advanced open-pit mining equipment has transitioned towards larger and more intelligent operations, and the imported underground mining equipment has a high degree of mechanization. Significant progress has also been made in foreign mining equipment automation, with the use of automated rock drilling rigs, remote-controlled explosives handling, and remote-controlled loading trucks.[3] Lasers have also been successfully applied to underground vehicle guidance systems, enabling these to operate unmanned. In contrast, China’s unmanned mining technology research is still in its infancy, and the development of mining automation equipment and mine production management control systems are far from reaching scale. Most underground mines in China still operate inefficiently small tunnels, and insufficiently coordinate underground operations (Z. Fang, Wang, & Huang, 2008). Heavy manual labor pervades nearly all underground production links (Z. Fang et al., 2008).[4] As a result, nearly 60% of mining equipment is imported from overseas. In 2004 alone, 485 ore loaders were imported into the country, with an import value of US $37.16 million (Wu et al., 2007). In Appendix B.1, we discuss three examples of imported machines in non-ferrous metal industries. Prior research has found evidence for technological change in mining industries to be directed (Loow et al., 2019; Loow, 2022).

Imported capital in NFM industries

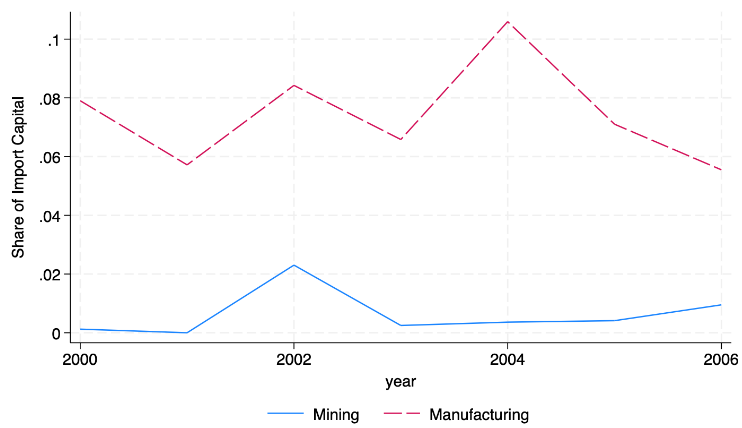
Figure 1 displays the share of total capital investment in the NFM manufacturing and metal industries that was imported throughout the sample period. For manufacturers, around 8% of capital investment was imported capital on average, with a peak of 10% in 2004. For

[3]For instance, the “Data Solo" automated rock drilling rig developed by Finnish company *Tamrock*, the rod handling system by *Atlas Copco*, and the “Rocmec2000" remote-controlled explosives truck by *Nitro Nobel*.

[4]For small-sized mines in China, small and single mining equipment or even manual labor is still being used. For the medium-sized and a few large-scale mines, despite mining equipment having higher levels of mechanization, they are outdated and lead to inefficiencies. Imported modern equipment is used in a few large and underground mines.

mining firms, capital imports are a much smaller share of capital investment. Mining capital imports increased from nearly zero percent of investment in 2000 to around 1% of capital investment in 2006, with temporary capital imports peaking at 2% in 2002. The top imported capital products in NFM manufacturing sectors are mechanical equipment with independent functions, casting machines, and electroplating, electrolysis or electrophoresis equipment and devices. The top imported capital equipments in mining industries are stirring machines, machines for sorting, screening, separating, or washing solid minerals, and drilling rigs.[5]

Figure 1: Capital imports as a share of total capital investment



Labor market and migration policy

Throughout the sample period, Chinese labor markets were rigid due to labor market regulations, such as the household registration system or the Hukou system. The Hukou system led to segregated labor markets and obstacles in labor migration across rural and urban sectors and regions. A Chinese citizen has a Hukou status associated with a place (i.e., prefecture city) and a sector (agricultural or nonagricultural) based on their parents' status. Residents registered as a specific Hukou type in a region could hardly make movements across agricultural and non-agriculture sectors and across places because the Hukou status is tied to access to job opportunities and local public goods (e.g., medical care and children's education). Although switching Hukou status to a new place is possible for college graduates who can find jobs offered by firms that sponsor Hukou conversion, it was generally much more challenging for low-skilled workers to change Hukou status. Given these regulations, we expect local labor markets to be segmented and labor supply to be not perfectly elastic, which could give rise to monopsony power by employers.

[5] A list of the top ten imported capital goods in NFM industries from 2000 to 2006 is in Appendix Table A4.

To reduce labor market segmentation, the Chinese government has made gradual reforms to the Hukou system, which aimed to reduce migration costs and encourage labor force mobility across space, such as abolishing the distinction between the rural and urban Hukou types. At the central government level, reforms were advocated to grant local Hukou to individuals in need in all small cities and towns, according to the Notice of the Joint Communist Party Central Committee and State Council State Council. Local governments were allowed some discretion to design their own reforms following the central government guidelines.[6] After these reforms, the labor market of China has become more market-oriented over time, with the growing importance of the urban private sector (M. R. Brooks and Ran (2003)).

Labor market features of NFM industries

Despite China's implementation of minimum wage policies, evidence suggests that firms, including State-Owned Enterprises (SOEs) in the mining sector, often circumvent these regulations. Notably, Shu et al. (2011); Bayari (2014) report that SOEs are prominent employers of migrant workers who receive wages below the mandated minimum without any form of insurance coverage. Appendix Table A2 delineates the labor force characteristics within the non-ferrous metal (NFM) industries in contrast to other urban sectors, revealing significant disparities in labor composition. Specifically, the NFM sector is characterized by a notably higher concentration of young, male, and migrant workers predominantly engaged in manual labor. Furthermore, the data indicates that the average labor force participant in the NFM sector is considerably less likely to possess a high school diploma than counterparts in other industries. This disproportionate representation of unskilled workers, combined with suboptimal labor market conditions in the Chinese NFM industries, potentially undermines the bargaining power of these workers. To sum up, the combination of potentially imperfect labor market competition, technological change, and policy-driven shifts in the industry's ownership structure render the Chinese NFM sector an interesting case study for examining changes in wage markdowns and labor-biased technological change over time, and differences in these changes between firms with different ownership structures.

2.3 Stylized facts

To motivate our research questions and model, we present three stylized facts on the evolution of labor cost shares and of firm ownership in China. We show these figures both for all Chinese manufacturing and mining industries, based on the entire Annual Survey of Indus-

[6]For detailed information on Chinese Hukou reforms at the national and local level, see https://www.cecc.gov/recent-chinese-hukou-reforms.

trial Production, and for the industries that constitute our empirical application, non-ferrous metal mines and manufacturers.

Fact 1: Privatization and foreign direct investment

We start by documenting the evolution of the ownership structure of the NFM industries and of all combined industrial sectors. We label firms as "foreign" if they are recorded as being foreign-owned or having foreign equity in the NBS statistics. Similarly, a "state-owned enterprise (SOE)" is recorded as being owned by the state or as holding state equity. Figure 2b plots the change in the total employment share of SOEs and foreign-owned firms in the NFM industries. The overall employment share of SOEs declined from 60% to 12% from 1999 to 2006. For NFMs, this decline was from 70% to 35%. The employment share of foreign-owned private firms doubled from 17% to 33% for all industries and from 7% to 10% for NFMs. In sum, there was both large-scale privatization and an inflow of foreign direct investment over this period, both in the aggregate and for the industries of our choice.

Fact 2: Falling cost share of labor

Labor cost shares declined substantially in China throughout the sample period, both in the aggregate and in the NFM industries. Figure 2a plots the evolution of the ratio of labor expenditure over total variable costs. The unweighted average labor cost share (i.e., the solid red line) fell from 12 % to 10% for all industries and from 9 % to 6% for NFMs between 1999 and 2006. The *weighted* average labor cost share, weighted by employment, fell from 8% to 6% for all industries and from 7% to 3% for NFMs. The falling labor cost share was for 60% due to within-firm changes in labor cost shares and for 40% due to the reallocation of labor from high labor cost share firms to low labor cost share firms.

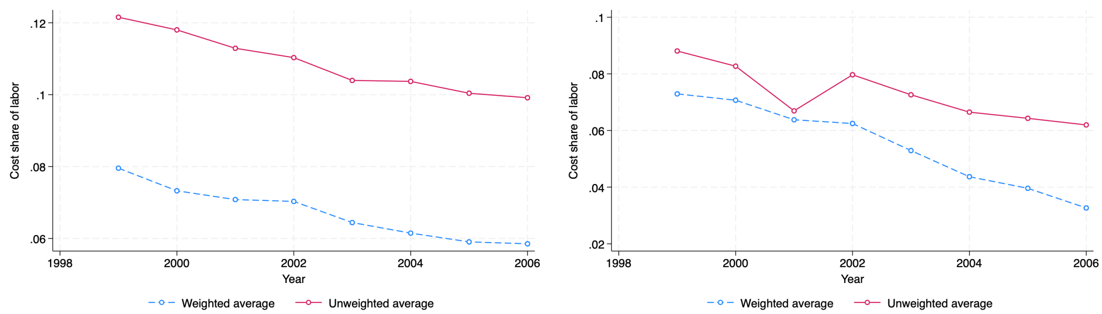
Fact 3: Cost share of labor is lower in foreign-owned and domestic private firms.

Third, we bring the previous two facts together by comparing the level and evolution of the labor cost share between firms of different ownership in Figure 2c. Three facts stand out. First, the labor cost share was systematically higher at SOEs compared to private firms, both in the aggregate and for NFM industries. Second, the labor cost share is not markedly different between domestic and foreign firms in the aggregate, but it is lower for foreign firms in the NFM industries. Hence, the decline in the aggregate cost share of labor was partially due to the reallocation of employment from SOEs to private firms for all industries and the reallocation from domestic to foreign firms in the NFM industries. Third, the cost share of labor declined over time for SOEs and domestic Chinese firms but not for foreign-owned

Figure 2: Labor cost shares and ownership change

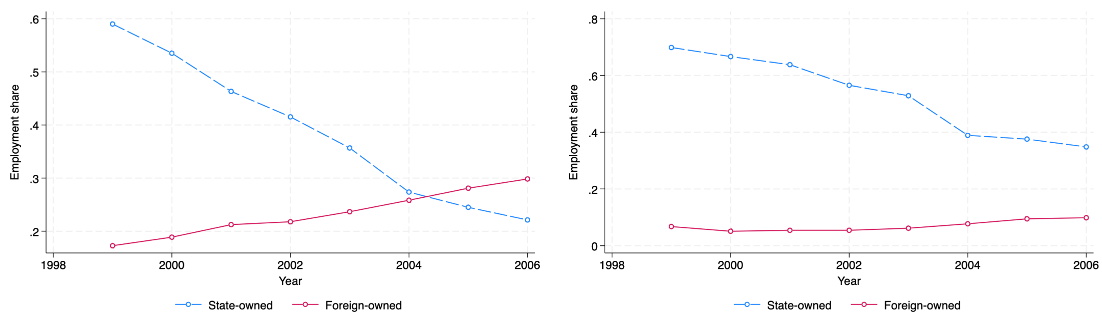
(a) Labor cost share

All industries **Non-ferrous metal industries**



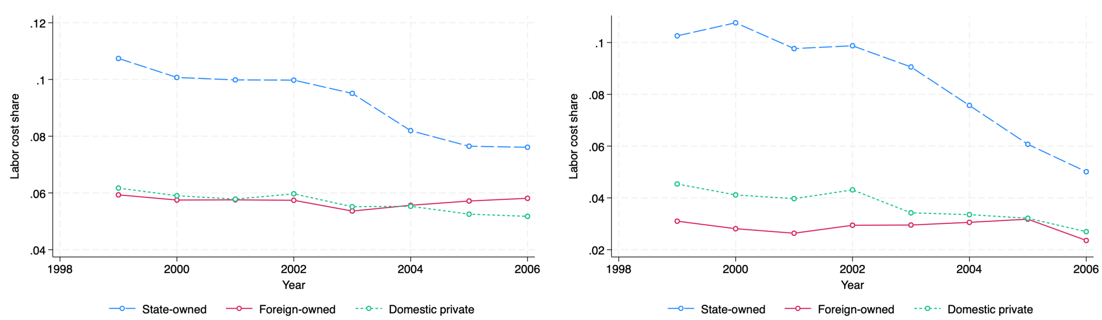
(b) Ownership change

All industries **Non-ferrous metal industries**



(c) Labor cost share by ownership

All industries **Non-ferrous metal industries**



Notes: The series in the left graphs are computed based on all CIC industries in the ASIP. The right graphs are based only on the industries with CIC codes starting with 09 (non-ferrous metal mining) and 33 (non-ferrous metal manufacturing).

firms.

What drove these observed declines in labor cost shares and differences in labor cost shares by ownership types? In what follows, we focus on two competing mechanisms: labor-augmenting technological change and increasing wage markdowns. In Section 3.1, we present a general model of production and labor supply in which we show that these two drivering forces are not separately identified in existing production-cost models. Section 3.2 presents a method to distinguish these two forces and estimates this model in the context of the Chinese non-ferrous manufacturing and mining industries.

3 Model

We start by discussing the identification challenge to separately identify factor-biased technological change from factor price markdowns using a general model, and lay out various possible solutions to this challenge. Next, we empirically implement this general model in the setting of Chinese non-ferrous metal manufacturing and mining industries.

3.1 General framework

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 terms of 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 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:

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

Firm behavior

We assume that both labor and materials are variable and 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, Goldberg, Khandelwal, and Pavcnik (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 expression (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.

Identification challenge

In what follows, we assume that intermediate input prices are exogenous to individual firms, $\psi^m_{ft} = 1$.[7] This implies that we only need to uncover the inverse labor supply elasticity ψ^l_{ft}. 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 relative markdown of labor wages and intermediate input prices is identified by the variation in relative variable input expenditure (i.e., cost shares), according to equations (6) and (7). More in general, if firms only vary 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 $\boldsymbol{\beta}$.

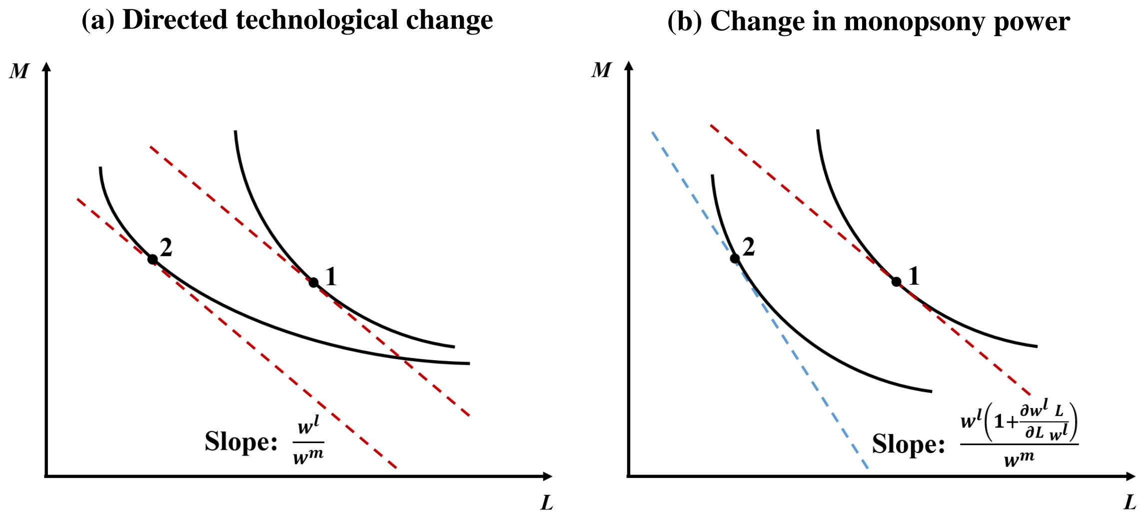
However, as soon as firms differ in terms of the labor-augmenting productivity level A_{ft}, this introduces unobserved variation in output elasticities across firms and time, as the output elasticities $\boldsymbol{\theta}_{ft}$ are a function of A_{ft}.[8] In this case, equation (7) has unknown variables on both its left- and right-hand side, 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. Intuitively, we cannot know whether variation in the relative input expenditure ratio $\alpha^m_{ft}/\alpha^l_{ft}$ is due to variation in output elasticities or in input supply elasticities. We visualize this argument in Figure 3. Panel 3a 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 3b, we show that the same change in input usage can be rationalized by a Hicks-neutral productivity shock but with an increase in the inverse labor supply elasticity, which rotates the isocost curve inward. Although bundles 1 and 2 imply identical cost shares of labor and materials, one cannot know whether their difference is due to factor-biased technological progress or due to a change in monopsony power.

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

[7] This is without loss of generality: one could uncover ψ^m_{ft} similarly to our approach to estimating ψ^l_{ft}, by imposing a model of conduct on the intermediate input market and by estimating an intermediate input supply curve, as in Rubens (2023).

[8] For instance, for the CES production function, a change in factor-biased technological parameters A_{ft} affects the output elasticities of inputs, which we will discuss in detail in Section 3.2.

Figure 3: Non-identification using only cost share variation



due to either markups or factor-augmenting productivity. However, they rely on the assumption of exogenous input prices, which allows the *cost share* variation $V_f^j W_f^j / \sum_j (V_f^j W_f^j)$ 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 markdown or factor-augmenting productivity.

Possible solutions

In general, there are 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, Okazaki, Onishi, & Wakamori, 2022; Miller et al., 2022; Delabastita & Rubens, 2022). However, firms are likely to use these technologies at various levels of intensity, and such heterogeneity makes it hard to measure the technology change precisely. In addition, some technological heterogeneities, such as intangible capital, are hard to fully capture and measure in the data. The second approach is to impose more structure on the supply market of each input j so as to identify the factor price markdowns ψ_{ft}^j. Next, this estimated inverse supply elasticity needs to be substituted into the cost minimization first order conditions, which are used when estimating the production function. This is the approach we follow in our empirical application below.

3.2 Model of the Chinese non-ferrous metal industries

Production

We implement the general framework from Section 3.1 in the context of the Chinese non-ferrous metal industries. 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):

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

The common parameters β^m and β^k govern how much material and capital contribute to output relative to labor. 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 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, Card et al. (2018), Berger et al. (2022), and Azar et al. (2019). Manufacturing workers i in labor markets ℓ choose between the set of firms in that market ($\mathcal{F}_\ell$). We define labor markets at the county level, similarly to earlier studies of Chinese labor markets (Fan, Liu, Qiu, & Zhao, 2020; Erten & Leight, 2021). The average Chinese county has a population of 432,815.[9] Each industry, as measured by the 4-digit CIC industry code, is assumed to be part of a different labor market nest n. As such, workers are allowed to switch between industries, and the substitutability of these industries is parametrized by the nesting parameter ς. Workers can also move out of non-ferrous metal mining or manufacturing, 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} and ϵ_{jft}, where ζ_{jn} captures random taste variation for nest n, whereas ϵ_{jft} is an i.i.d. type-I distributed manufacturer-worker utility shock u_{jft}. 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 varied over time. We implement this time variation as a linear trend: $\gamma_t = \gamma + \tilde{\gamma}_t t$

Wages enter utility in logs, rather than in levels, to allow for diminishing returns to income in terms of labor utility, as in Card et al. (2018), Berger et al. (2022), and Azar et al. (2019).

$$U_{jft} = \underbrace{\gamma \ln(W_{ft}) + \boldsymbol{\gamma}^X \mathbf{X}_{ft} + \xi_{ft}}_{\equiv \delta_{ft}} + \sum_n (d_{fn}\zeta_{jn}) + (1-\varsigma)\epsilon_{jft} \tag{10}$$

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 following equation:

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

where the parameter $D_{nt} \equiv \sum_{f\in\mathcal{F}_{it}^n} \exp\big(\delta_{ft}/(1-\varsigma)\big)$. The nesting parameter ς measures the extent to which the different nests are substitutable. The log labor market share s_{ft} is given by equation (11):

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

[9] This makes Chinese counties slightly smaller on average than U.S. metropolitan statistical areas (average population 636,803), as shown in Appendix Table A3. There are three layers of administrative units: first are provinces, autonomous regions, and centrally-controlled municipalities. County-level divisions are the third administrative layer. Most county-level divisions are administered as part of prefecture-level divisions, but some are administered directly by province-level divisions.

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

Intermediate input supply

We assume intermediate input markets are perfectly competitive, with a common input price W^m. Although we cannot verify this assumption in general due to a lack of firm-specific intermediate input prices, we test the competitive input market assumption for non-ferrous metal smelters, for which we observe the suppliers (i.e., mines) in the data. In Appendix C.3, we examine how the prices at mines of each metal type correlate with market structure in the smelting industry using that metal, and we do not find any significant relationship between downstream market structure and upstream metal prices. This pattern remains consistent with the assumption of price-taking buyers on intermediate input markets.

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^a_{ft} and υ^ω_{ft}. Capital investment decisions are assumed to be made before observing these productivity shocks at a time of $t-1$. In addition, we assume that the static input choices are made in order to minimize current variable costs, and wages are set non-cooperatively according to the Nash-Bertrand equilibrium on the labor market.

$$\min_{W_{ft}, M_{ft}} \Big(W^m_{ft} M_{ft} + W^l_{ft} L_{ft} - \lambda_{ft}(Q_{ft} - Q(.)) \Big) \tag{12}$$

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

$$\psi^l_{ft} - 1 = \frac{1-\varsigma}{\gamma_t(1 - \varsigma s^n_{ft} - (1-\varsigma)s_{ft})} \tag{13}$$

The above equation suggests that firms that have a large employment share in a market (i.e., smaller s^n_{ft} or s_{ft}) are often faced with a more inelastic labor supply, leading to higher wage markdowns.

4 Identification and estimation

We proceed to estimate the model using a sequential estimation procedure consisting of two steps. First, we estimate the labor supply function (11) using labor demand shifters. Second, we estimate the production function (8), which makes use of the labor supply estimates from the first step. We compute standard errors by bootstrapping this entire procedure with replacement within firms over time.

4.1 Estimating labor supply

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 variation in firms' exposure to international metal price shocks, as well as variation in these price shocks over time, as product (hence, labor) demand shocks. We include three variables as instrumental variables. First, we include the log world price of the metal that is mined or processed in the specific industry.[10] The assumption is that changes in global metal prices affect labor demand in the Chinese non-ferrous metal industry but not the firm's amenity, and thus, it does not affect labor utility directly. 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 in terms of their labor demand. Third, we include the number of firms in each labor market and year, providing cross-nest variation useful for identifying the nesting parameter.

Our identification strategy relies on the assumption that the decisions of individual firms cannot affect the world price for a given non-ferrous metal. To validate this assumption, 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.[11] We find that global market shares of the largest firm in each industry are below 20% except for four industries: Nickel manufacturing, Antimony manufacturing and mining, and Lead mining. As a robustness check, we re-estimate the labor supply model while excluding these industries in Appendix C.2 and find similar labor supply estimates.

We measure the outside option as the total county population minus total employment in non-ferrous metal 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 variables. First, we include sector-fixed effects to control for time-invariant variation in worker utility across sectors and space. Second, we include the export share of revenue at each firm because exporters could differ from non-exporters in terms of their working conditions. We also include the indicators for the firm being foreign-

[10] Daily price series of aluminum, aluminum alloy, copper, lead, nickel, tin, and zinc for years from 1999 to 2007 are obtained from the Bloomberg database.

[11] We use the 2006 USGS mineral summaries, U.S. Geological Service (2006), to compute global production shares of Chinese non-ferrous metal industries.

owned and state-owned, given that firms might derive non-pecuniary benefits from working at SOEs. 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).

4.2 Estimating production function

Elasticity of substitution

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.[12]

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

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 (14a), similarly to Blundell and Bond (2000), but for labor-augmenting productivity rather than 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, which characterize the timing assumption that wages are chosen after the productivity shock υ^a_{ft} is observed.

$$E\Big(\upsilon^a_{ft}(\sigma, \rho^a, c) | w^l_{ft-1}, w^l_{ft-2}, t\Big) = 0$$

Other production coefficients

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} that we have already estimated, and the parameter β^m that remains to be estimated:

[12] The derivation of Equation 14a is detailed in Appendix E.1.

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

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

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

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

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

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

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

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:

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

Markups and markdowns

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, as shown in equation (13).

4.3 Model comparison and simulations

Model comparison

As a means of comparison, we estimate two alternative functional forms next to the model specification above. First, we estimate the production model under the assumption of perfectly competitive labor markets, as in Doraszelski and Jaumandreu (2018). This follows the same estimation procedure as the one outlined above, but setting $\psi^l_{ft} = 1$. In the second exercise, we estimate a Hicks-neutral Cobb-Douglas model $q_{ft} = \beta^l l_{ft} + \beta^m m_{ft} + \beta^k k_{ft} + \omega_{ft}$, under the same timing assumptions as used for the CES model.[13] Using these two alternative specifications, we can compare the results from the benchmark model that allows for both labor-augmenting productivity and wage markdowns to a model with labor-augmenting productivity but without wage markdowns, and to a model with wage markdowns but without labor-augmenting productivity.

Monte Carlo simulations

In addition to estimating the above model using data on Chinese non-ferrous metal industries, we also carry out Monte Carlo simulations to show that our approach delivers consistent estimates under a data-generating process with imperfect competition and latent technology differences. For these simulations, which are outlined in Appendix A, we consider a slightly simplified version of our empirical model by assuming an elasticity of input substitution of one, which boils down to estimating a Cobb-Douglas production function with latent differ-

[13] We include the estimation details for the Cobb-Douglas model in Appendix C.1, and also estimate a translog production function in Appendix C.1.

ences in its coefficients. We also simplify the labor supply model by specifying a simple logit model without nests. As explained in Appendix A, we find that when the production function coefficients are homogeneous across firms and time, estimating markdowns using only the production function and relying on equation (7) leads to precise and unbiased estimates of the markdowns. However, once there is unobserved heterogeneity in the production function coefficients, this leads to biased output elasticities and markdown estimates when estimating the production function in the canonical approach. Moreover, the distribution of markdowns is incorrectly conflated with the latent variation in the production coefficients, as these two empirical objects are not separately identified. In contrast, our approach consistently estimates the production function coefficients and can back out the true distributions of both wage markdowns and output elasticities.

5 Results

5.1 Model estimates

Labor supply estimates

The labor supply estimates are in Table 1(a). The left column shows the estimates using OLS, the middle column shows the IV estimates with a constant wage coefficient, and the right column shows the IV estimates with a time-varying wage coefficient, which we will continue using throughout the paper. When instrumenting for wages and within-nest market shares, the wage coefficient is estimated at 3.24, compared to 0.172 when using OLS. As usual, the OLS estimates are downward biased because we confound labor supply and demand. The IV estimation including a time-varying wage coefficient yields a wage coefficient of 2.845 on average, which increases over time, although this time trend is not signficantly positive. An increasing wage coefficient implies an increasing labor supply elasticity over time, which is in line with increasingly competitive labor markets due to the Hukou and other labor market reforms. The nesting parameter is equal to 0.126 in the IV specification, which means that the different industries are close to being symmetric substitutes from the workers' perspectives. The resulting wage markdown moments are shown at the bottom of Table 1(a). At the average firm, wages are marked down by 25%, at the median firm, they are marked down by 24%. 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 significantly below the 'cost-side' markdown estimates, such as W. J. Brooks et al. (2021) and Yeh et al. (2022).

Labor demand estimates

The estimated elasticity of input substitution is reported in Table 1(b). When using OLS, in the first column, the estimated elasticity is 0.711, but this is likely biased because relative input usage is a function of unobserved labor-augmenting productivity. The dynamic panel estimator that assumes competitive labor markets, in the second column, finds an elasticity of substitution of 0.349, whereas the estimator that allows for imperfect labor market competition yields an estimate of 0.326. Given that the elasticity of substitution is below one, labor and materials are gross complements.[14]

Remaining production coefficients

The remaining production function parameters that are estimated in the second step of our estimation procedure are reported in Table 1(c). The first column reports the Cobb-Douglas estimates, by means of a comparison. 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. The output elasticity of labor is now estimated to be 0.067 on average, which is slightly below the Cobb-Douglas estimate, whereas the output elasticity of materials is 0.822 on average. In contrast to the Cobb-Douglas model, there is now considerable heterogeneity in the output elasticities of labor and materials.

Finally, the third column of Table 1(c) shows the CES estimates in the model that allows for imperfectly competitive labor markets. The output elasticities of labor and materials are now estimated at 0.094 and 0.933, respectively. Hence, allowing for imperfect labor market competition results in markedly different production estimates. Moreover, the distribution of these output elasticities differs depending on the assumptions of the labor market competition. In the model with competitive labor markets, all variation in cost shares is due to labor-augmenting productivity differences and relative input usage. In contrast, it is also due to wage markdown variation in the model with imperfectly competitive labor markets. Given that we want to allow for imperfect labor market competition, this last set of estimates will be the preferred estimates we will use throughout the remainder of the paper.

[14] Hence, we can rule out the explanation for the labor cost share decrease proposed by Karabarbounis and Neiman (2014) in the context of our industries.

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	0.172	0.011	3.240	0.844	2.845	1.080
Nesting parameter	ς	0.310	0.004	0.045	0.039	0.126	0.132
Constant factor	γ_0					-314.060	494.127
Time-varying factor	γ_t					0.158	0.246
1st stage F-stat: W^L_{ft}				5.378		5.378	
1st stage F-stat: s_{ft}				295.369		295.369	
1st stage F-stat: $W^L_{ft} \times year$						4.443	
Observations		33137		22780		22780	
Average markdown		0.825		0.232		0.250	
Median markdown		0.816		0.230		0.243	

(b)Elas. of substitution		OLS		GMM exo. wage		GMM endo. wage	
		Est.	S.E.	Est.	S.E.	Est.	S.E.
Elas. of substitution	σ	0.711	0.107	0.349	0.057	0.326	0.130
Observations		33146		12474		10459	

(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	0.072	.	.	.	.
Material coefficient	β^m	0.727	0.125	0.195	11.089	2.659	76.326
Capital coefficient	β^k	0.054	0.023	0.000	0.006	0.000	0.021
Serial correlation	ρ	1.028	0.020	0.727	0.194	0.983	0.181
Productivity shocks	ν	.	.	0.988	0.072	1.054	0.075
Observations		10433		10433		8782	
Output elas. of labor	θ^l_{ft}	0.074	0.072	0.067	0.003	0.094	0.022
Output elas. of materials	θ^m_{ft}	0.727	0.125	0.822	0.075	0.933	0.092
Output elas. of capital	θ^k_{ft}	0.054	0.023	0.098	0.061	0.027	0.072
Average markup		-0.011		0.116		0.255	
Median markup		-0.068		0.110		0.218	

Notes: Panel (a) includes industry fixed-effects and province fixed-effects. Panel (b) and (c) report block-bootstrapped standard errors with 200 draws.

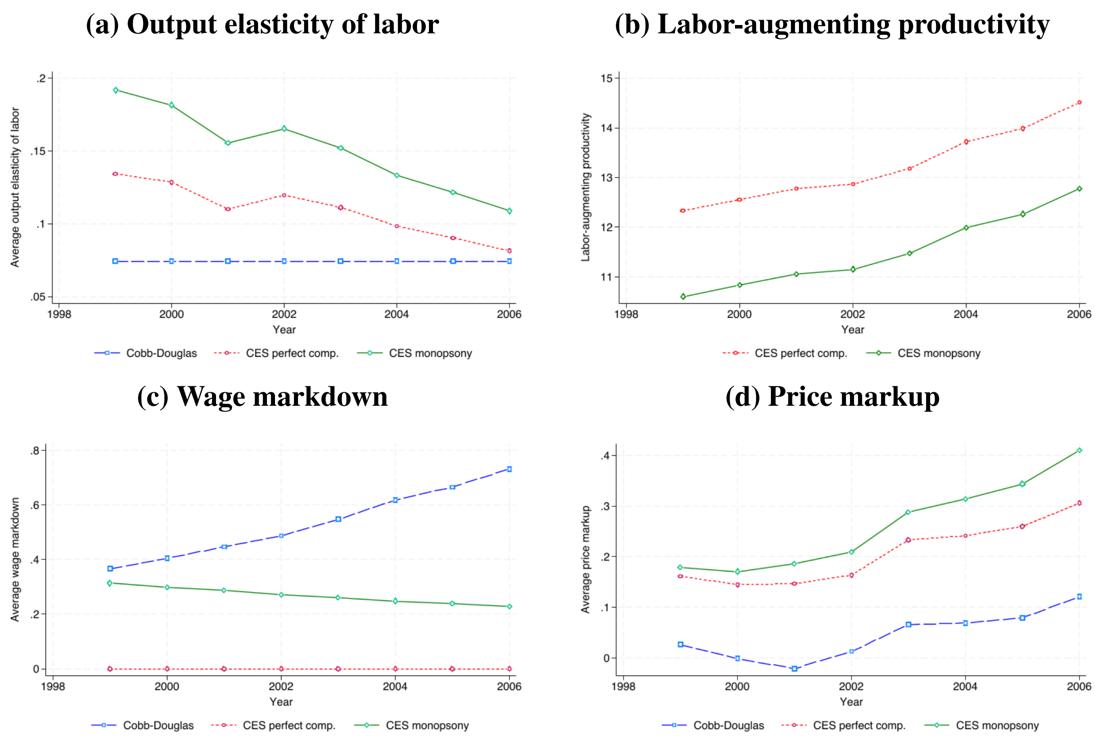
5.2 Markdowns, technology, and the cost share of labor

Markdowns and labor-augmenting productivity growth

Figure 4a compares the evolution of the average output elasticity of labor in the three model specifications, weighted by employment shares. In the Cobb-Douglas model, the output elasticity of labor is constant by construction. In the CES model with competitive labor markets, the average output elasticity of labor, weighted by employment, declines from 13% to 8% between 1999 and 2006. In contrast, it declines from 19% to 11% in the model with imperfect labor market competition. The reason for this decline is due to increasing labor-augmenting productivity, as can be seen in Figure 4b. Although the labor-augmenting productivity distributions estimated in both CES specifications differ, the evolution of median labor-augmenting productivity is similar in both models. The finding that there was a rapid growth in labor-augmenting productivity throughout the sample period is consistent with the earlier mentioned anecdotal evidence of mechanization in the non-ferrous manufacturing and mining industries.

In Figure 4c, we plot the evolution of the annual weighted average of the wage markdown, weighted across firms by employment usage. The weighted average markdown starts at 31% in the nested logit model and slightly declines over time to 23%. These figures are higher than the average and median markdowns, because larger firms set larger wage markdowns. In contrast, the wage markdown is estimated to increase sharply from 37% to 73% in the Cobb-Douglas model. 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. The decreasing wage markdowns over time is also consistent with the decreased stringency of labor market regulations, as was discussed earlier, although wage markdowns are still high by the end of the sample period. Finally, Figure 4d shows the weighted average markup, again weighted by employment shares. The perfect labor market competition model finds that price markups increased considerably, from 16% to 31%. In contrast, the preferred model that allows for monopsony power finds a larger increase in markups, from 18% to 41%: given that wage markdown fell, the model that assumes competitive labor markets underestimates the fall in marginal labor costs and, hence, underestimates markup growth.

Figure 4: Technological change, markdowns, and markups



Decomposing the cost share of labor

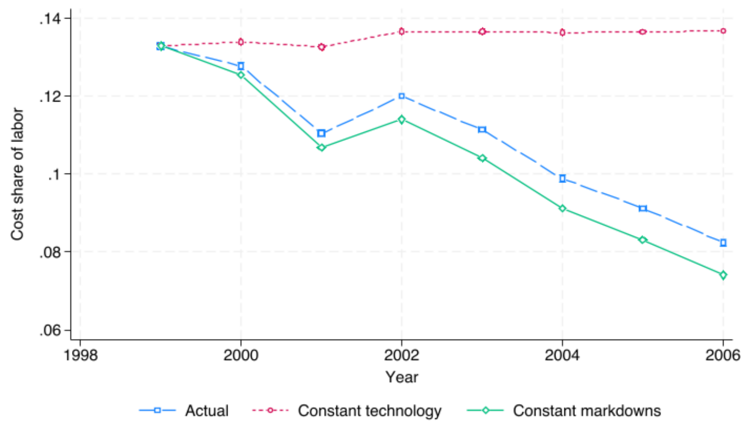
To quantify the contributions of labor-augmenting technological change and changing labor market competition to the aggregate labor cost share, we recompute two counterfactual changes in the labor cost share. We rewrite equation (6) to express the labor cost share as a function of factor output elasticities and the inverse labor supply elasticity:

$$\frac{W^l_{ft} L_{ft}}{W^l_{ft} L_{ft} + W^m M_{ft}} = \frac{\theta^l_{ft}}{\theta^l_{ft} + \theta^m_{ft} \psi^l_{ft}}$$

We take the weighted average of both sides of this equation. In the first counterfactual, we fix the aggregate output elasticity of labor at its 1999 value but let wage markdowns vary. Second, we keep the aggregate wage markdowns constant at their initial value but let the output elasticity of labor vary over time. The results of this exercise are visualized in Figure 5. Under the baseline model, the cost share of labor decreased by 38%. When we keep the output elasticity of labor constant, the labor cost share slightly increases, as wage markdowns declined over time. In contrast, under constant wage markdowns, the cost share of labor declines by 44% and closely mimics the observed labor cost share shown in

Figure 2a. This evidence suggests that the decline of the labor cost share was likely driven by technological change rather than by changing wage markdowns.

Figure 5: Decomposing the labor cost share



5.3 Privatization and FDI: labor-augmenting or labor-expoiting?

Differences by ownership structure

In Section 2, we showed that private firms have lower labor cost shares than SOEs, and foreign firms have lower labor cost shares than domestic firms. Are these differences due to different labor market power, or are they due to different labor-augmenting productivity? We examine this question by comparing the levels and evolution of labor-augmenting productivity and wage markdowns between firms of different ownership types. One important caveat in our analysis is that we do not make causal statements about the effects of ownership structure on either markdowns or labor-augmenting productivity. These differences could be due to the endogenous selection of firms into privatization or into receiving FDI, as was discussed in Chen et al. (2021), and to establish such causal relationships is beyond the scope of this paper.

In Table 3a, we regress the log labor-augmenting productivity level on the ownership indicators (the SOE and private firm dummies). We compare the model that imposes perfect labor market competition (i.e., column 2) to the model that allows for imperfect labor market competition (i.e., column 3). In both models, SOEs have significantly lower labor-augmenting productivity than private firms. In our preferred specification that allows for monopsony power, we find that labor-augmenting productivity is 25% higher at foreign firms and 65% lower at SOEs compared to domestic private firms. This evidence is in line with the earlier discussed anecdotal evidence of SOEs using outdated production technologies compared to private firms. A primary reason foreign-owned firms, domestic private firms, and SOEs differ in labor-augmenting productivity relates to their capital usage. In Table 2, we compare capital importing by ownership type. Foreign firms are 20 percentage points more likely to import capital compared to domestic private firms, SOEs are 2.3 percentage points more likely to import capital. When comparing capital imports as a share of total capital investment, the difference between foreign-owned and domestic firms becomes even less pronounced.

Table 2: Capital imports by ownership

	Capital imports dummy	Capital imports share
Foreign-owned	0.197	0.024
	(0.003)	(0.003)
State-owned	0.023	-0.000
	(0.002)	(0.002)
Constant	0.008	0.001
	(0.001)	(0.001)
Observations	38194	37753
R^2	0.128	0.003

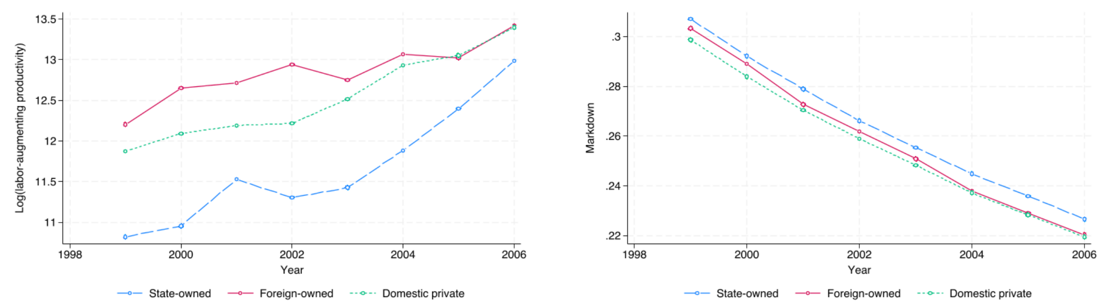
Notes: We control for sector fixed effects.

Throughout the sample period, labor-augmenting productivity grew on average by 16.3% per year. Table 3b shows that the productivity growth of foreign-owned firms was 9.0% lower compared to private enterprises, whereas the productivity growth of SOE firms is 4.6% higher. Hence, SOEs and domestic private firms have been catching up with foreign-owned firms in terms of labor-augmenting productivity growth as the technology gap between these different types of firms has narrowed over time.

Table 3c compares wage markdowns by ownership type. The first column uses the markdown estimates from the Hicks-neutral Cobb-Douglas model, whereas the third column shows the nested logit markdowns. The Hicks-neutral model finds that SOEs set markdowns that are 27% lower than private domestic firms, whereas foreign-owned firms set markdowns that are very similar to domestic private firms. In contrast, using the nested logit model, markdowns are 2.7% *higher* at SOEs, although this difference is not statistically different. This stark difference in findings is, again, due to latent variation in labor-augmenting productivity, which the Hicks-neutral model interprets as markdown variation. Having lower labor-augmenting productivity levels, SOEs have higher labor cost shares than private and foreign firms. The Hicks-neutral model interprets this as evidence for low markdowns, but the labor supply model shows the opposite, namely that SOES charge higher markdowns to their employees. We think that this is consistent with SOEs having larger labor market shares, despite the privatizations, and with SOEs being differentiated from other firms by offering unique amenities, such as job security and better employee benefits.

Figure 6: Directed technological change and wage markdowns by ownership

(a) Technological change **(b) Wage markdown**



We plot the evolution of labor-augmenting technology and wage markdowns by firm ownership in Panel 6a and 6b, respectively. All estimates are obtained from the CES model that allows for imperfect labor market competition. Although SOEs have significantly lower labor-augmenting productivity than firms with different ownership types, they have quickly been catching up in recent years. For comparison, the growth in labor-augmenting productivity is relatively gradual for foreign and domestic firms. In contrast, wage markdowns have declined steadily independently of firms' ownership types, from around 30 to 22% in between 1999 and 2006. This is consistent with the anecdotal evidence that labor markets became more competitive throughout this time period, as labor mobility restrictions became less stringent.

Accounting for labor-augmenting technological change

We investigate the source of the rising labor-augmenting productivity documented in Figure 6 and focus on the relative importance of privatization or foreign investments in explaining the technological change. To achieve this, we conduct a decomposition exercise similar to Melitz and Polanec (2015) that splits the change in labor-augmenting productivity into two key variables that capture the within-firm internal technological change and the reallocation

Table 3: Ownership, labor-augmenting productivity, and wage markdowns

	Hicks-neutral	CES: exo. wage	CES: endo. wage
(a) Labor-augmenting productivity			
Foreign-owned		0.188	0.224
		(0.056)	(0.155)
State-owned		-1.069	-1.057
		(0.148)	(1.721)
Growth rate		0.151	0.163
		(0.007)	(0.106)
Observations		38186	33146
R^2		0.271	0.284
(b) Changing productivity gap over time			
Foreign-owned $\times$ time		-0.097	-0.090
		(0.019)	(0.143)
State-owned $\times$ time		0.053	0.046
		(0.012)	(0.082)
Observations		38186	33146
R^2		0.273	0.285
(c) Wage markdown			
Foreign-owned	0.004		0.004
	(0.024)		(0.008)
State-owned	-0.321		0.027
	(0.106)		(0.034)
Growth rate	0.014		-0.044
	(0.008)		(0.090)
Observations	29058		32861
R^2	0.068		0.882

Notes: Independent variables 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 the log. We control for sector fixed effects.

across firms, respectively.[15]

Figure 7 reports the results for decomposing sectoral labor-augmenting productivity. Each dot reports the growth rates for a year relative to 1999. The left panels (a) and (c) report productivity growth attributable to each component of the decomposition: within-firm and reallocation across firms, where we use samples consisting of firms in NFM mining and manufacturing, respectively. The vast majority of labor-augmenting productivity growth comes from production reallocation across firms: the cross-term accounts for more than 60 percent of the aggregate labor-augmenting productivity growth.[16]

As most labor-biased technological change came from reallocation across firms, we further decompose the reallocation effect according to firm ownership: SOEs, domestic and foreign type, and these results are reported in the right panels (i.e., (b) and (d)). While sales reallocation for foreign firms contributes positively in all samples, its contribution to the overall effect of reallocation on labor-augmenting productivity is moderate in NFM mining sectors. These patterns show that foreign investments can only explain a small fraction of the general increase in labor-augmenting technological change.

The major contributor to the reallocation-induced productivity growth is the declining state-owned production and the rising importance of private enterprises. The reallocation term for SOEs is negative and decreased in all samples from 1999 to 2006, which implies that SOEs with higher labor-augmenting productivity lost market shares or that the more labor-intensive SOEs become less productive. The pattern is accompanied by positive reallocation of sales towards private firms with higher labor-augmenting productivity. Reallocation towards foreign-owned enterprises did not contribute to aggregate productivity growth in mining industries, whereas it did in NFM manufacturing industries. However, the reallocation margin from SOEs towards domestic private firms is much larger than towards foreign-owned enterprises.

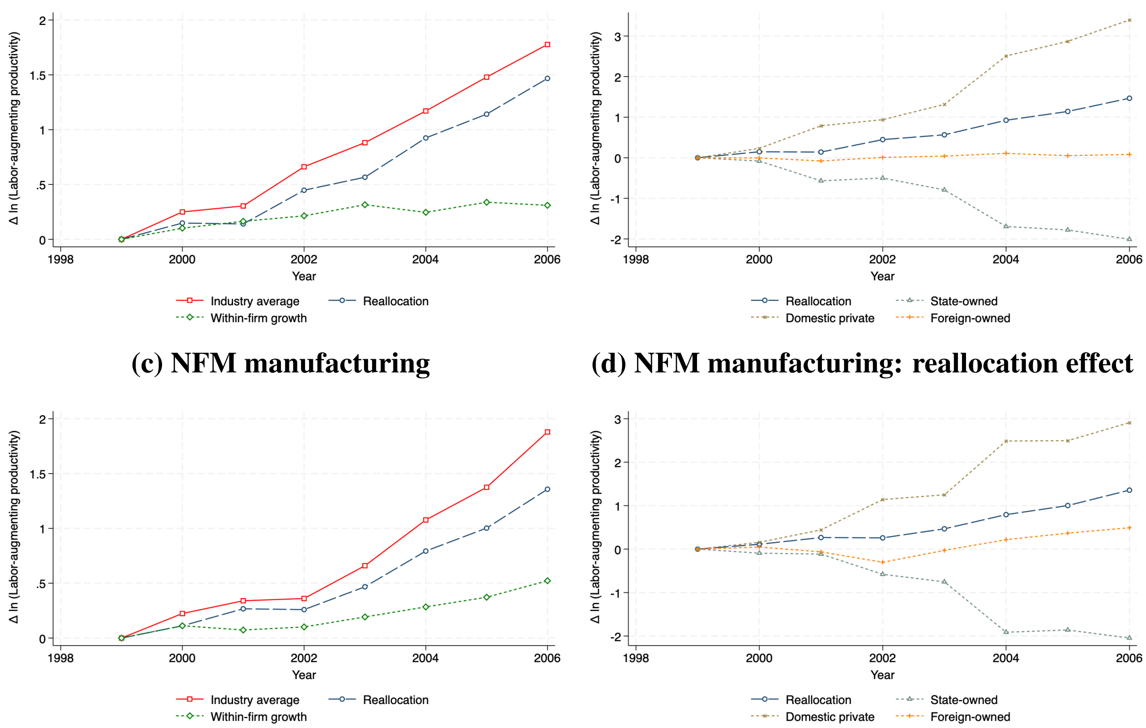
[15] We leave the detailed derivation of decomposition formula in Appendix E.2. In principle, the reallocation term consists of adjustments among surviving firms, as well as the creation and destruction of firms. However, in practice, we do not dig further into the underlying reasons for the reallocation channel due to imprecise measures of entry and exit. For instance, NBS data may fail to cover some firms simply due to sampling errors in the survey.

[16] Reallocation across firms explains on average 68% and 70% of the overall increase in labor-augmenting productivity for NFM mining and manufacturing sectors, respectively.

Figure 7: Decomposing factor-augmenting productivity in non-ferrous metal industries

(a) NFM mining **(b) NFM mining: reallocation effect**

(c) NFM manufacturing **(d) NFM manufacturing: reallocation effect**



5.4 Extensions and caveats

Unobserved conduct

Throughout the paper, we have imposed a conduct assumption on the labor market, i.e., the Nash-Bertrand wage-setting. When imposing a conduct assumption, there is a one-on-one relationship between the firm-level inverse labor supply elasticity $(\psi^l_{ft} - 1)$ and the wage markdown μ^w_{ft}, as was shown in equation (7). This has allowed us to point-identify the labor-augmenting productivity level A_{ft}. However, there is frequent evidence of collusive wage-setting in many markets. In particular, when conduct is unknown, the firm-level inverse labor supply elasticity $(\psi^l_{ft} - 1)$ can be consistent with a range of markdowns $[\underline{\mu}^w_{ft}; \overline{\mu}^w_{ft}]$, as shown in Delabastita and Rubens (2022). For instance, the lower bound $\underline{\mu}^w_{ft}$ could be the wage markdown in the absence of collusion, which corresponds to the Nash-Bertrand model in the main text, whereas the upper bound $\overline{\mu}^w_{ft}$ could be the wage markdown charged if firms fully collude on the labor market.

If conduct is unobserved, we can no longer point-identify the labor-augmenting productivity level A_{ft}: our estimation procedure would result in a different labor-augmenting productivity estimate depending on the conduct assumption. However, we could still put bounds on labor-augmenting productivity A_{ft} by estimating the production model both at the lower and upper bounds of the markdown interval. Another way forward could be to impose a strict distributional assumption on labor-augmenting productivity A_{ft}, which could be parametrized as a function of observables, such as the capital stock and the types of technologies used. In that case, we could identify conduct, as in Delabastita and Rubens (2022). The trade-off between imposing more assumptions on conduct or on the distribution of latent labor-augmenting productivity depends on whether the data environment contains more information about conduct or about technology heterogeneity. In addition, it is a matter of whether the main objective of the model is to uncover latent conduct or latent productivity differences.

Different models of labor market competition

Besides previous discussions on conduct assumption, our approach can be generalized to fit models of labor markets other than oligopsonistic competition. In our model, the inverse labor supply elasticity is a function of market shares and the parametrization of labor utility, which together give rise to the inverse firm-level labor supply elasticity under the Nash-Bertrand assumption. However, other classes of labor market models, such as search-and-matching models, also give rise to an upward-sloping labor supply function in the absence of oligopsonistic competition. In those cases, the markdown derivation in our model would have to be changed to fit the appropriate labor market model. However, the general approach of deriving wage markdowns from the labor supply side and substituting this into the production model in order to identify non-Hicks-neutral productivity can still be implemented.

6 Conclusion

In this paper, we show that prior production function estimation approaches do not separately identify factor price markdowns from factor-augmenting technology differences between firms. We propose a novel identification approach that relies on combining factor supply estimation and production function estimation, which requires taking a stance on the nature of factor market competition. Using Monte Carlo simulations, we show that our approach succeeds in separately identifying input price markdowns from unobserved technology differences between firms.

We apply our approach to study the drivers behind decreasing labor cost shares in China using two sectors: non-ferrous metal manufacturing and non-ferrous metal mining. We find that existing Hicks-neutral markdown estimators imply a strong growth in labor market power in both industries between 1999 and 2006, which fully attributes falling labor cost shares to rising monopsony power. In contrast, our estimator finds that wage markdowns declined slightly over time, which suggests that Chinese labor markets became more, not less, competitive over time. The main reason for declining labor cost shares was labor-saving technological change in both mining and manufacturing industries. Most of this productivity growth was due to reallocation of market shares between state-owned and domestic private firms, rather than within-firm productivity growth.

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A Monte Carlo simulations

In this Appendix, we illustrate our approach using simulated data, and use it to compare our approach to previous methods that did not allow for either latent technology differences or for imperfect factor market competition.

A.1 Model and simulated data set

Production function

On the production side, we simplify the CES model from the main text, and instead assume a Cobb-Douglas production function with two variable inputs L and M and no fixed inputs. This simpler model allows us to express input demand functions analytically in a closed-form. Crucially, we still allow for unobserved variation in the output elasticity of labor β^l_{ft} across both firms and time, which captures latent technology heterogeneity.

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

As in the main text, Hicks-neutral productivity follows an AR(1) transition process with serial correlation ρ and i.i.d. productivity shocks υ_{ft}:

$$\omega_{ft} = \rho\omega_{ft-1} + \upsilon_{ft} \tag{A2}$$

Solving the cost minimization problem, equation (4), delivers the following labor demand function in the Cobb-Douglas case, denoting factor prices as W^m_{ft}, W^l_{ft}:

$$L_{ft} = \Big[\frac{\beta^l_{ft}}{W^l_{ft}(\psi^l_{ft})}\Big(\frac{\beta^m \Omega_{ft}}{W^m_{ft}}\Big)^{\frac{\beta^m}{1-\beta^m}}\Omega_{ft}\Big]^{\frac{1-\beta^m}{1-\beta^l_{ft}-\beta^m}}$$

Labor supply

For the simulations, we simplify the nested logit model of the main text to a simple logit model without nests. Manufacturing workers i choose between the set of firms, F, with $f = 0$ indicating the outside option of being unemployed. Let the utility function of a worker depend on log wages $\ln(W_{ft})$, an unobserved amenity ξ_{ft}, and an i.i.d. type-I distributed manufacturer-worker utility shock υ_{ift}. Let mean utility be denoted δ_{ft}.

$$U_{ift} = \underbrace{\gamma \ln(W_{ft}) + \xi_{ft}}_{\equiv \delta_{ft}} + \upsilon_{ift} \tag{A3}$$

We normalize the utility of the outside option to zero, as usually: $U_{i0t} = 0$. Using the logit formula, the labor market share $s_{ft} = \frac{L_{ft}}{\sum_f L_{ft}}$ is given by:

$$s_{ft} = \frac{\exp(\delta_{ft})}{\sum_f \exp(\delta_{ft})}$$

Denoting the labor force as $\overline{L}$, the labor supply function $H(.)$ is given by:

$$L_{ft} = \frac{\exp(\gamma \ln(W_{ft}) + \xi_{ft})}{\sum_f \exp(\gamma \ln(W_{ft}) + \xi_{ft})} \overline{L}$$

Optimal intermediate input demand is equal to:

$$M_{ft} = \Big(\frac{\beta^m L_{ft}^{\beta^l_{ft}} \Omega_{ft}}{W^m_{ft}}\Big)^{\frac{1}{1-\beta^m}}$$

Simulation

We simulate a dataset of 50 labor markets that are observed during 10 years, with 5 firms per labor market. There are hence 250 firms that are observed during 10 years (N=2500). We compare two data generating processes (DGPs). In DGP1, there is no heterogeneity in the output elasticity of labor: $\beta^l_{ft} = \beta^l = 0.5$. In DGP2, there is unobserved heterogeneity in the output elasticity of labor, both in the cross-section and in the time-series: $\beta^l_{ft} \sim \mathcal{U}[\frac{1}{3}, \frac{2}{3}]$. In both DGPs, we assume a homogeneous output elasticity of materials, which we parametrize at $\beta^m = 0.3$.

We let intermediate input prices W^m_{ft} in the first year be distributed as a normal distribution $W^m_{f1} \sim \mathcal{N}(5, 0.05)$ and let it evolve by firm-level shocks that are $\mathcal{N}(0, 0.01)$ distributed. Similarly, we let the initial log productivity distribution be normally distributed $\omega_{f1} \sim \mathcal{N}(1, 0.01)$ and let the productivity shocks be $\mathcal{N}(0, 0.01)$ distributed. The serial correlation in productivity is set at $\rho = 0.6$. The resulting distribution of log productivity has a mean equal to 0.25 and standard deviation equal to 0.31. We normalize the total labor market size (population) to 1.

We let the Monte-Carlo simulation run using 200 draws. For each draw, we numerically solve for equilibrium wages and market shares of each firm in each year, meaning that labor demand and supply are equalized for every firm individually and for every market in the aggregate.

A.2 Estimation

Hicks-neutral approach

The existing 'production approach' to markdown estimation consists of assuming a scalar productivity residual, meaning that $\beta^l_{ft} = \beta^l$. The production function can then be estimated using a dynamic panel approach, or any other Hicks-neutral production function identification strategy. Taking ρ-differences, as in ? (?), the productivity shock can be written as:

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

Similarly to Ackerberg, Caves, and Frazer (2015), assuming that labor and materials are both variable inputs, the following moment conditions are formed for lags $r = 1$ up to $r = T - 1$, with the panel length being denoted T:

$$\mathbb{E}\Big[\upsilon_{ft}(\rho, \beta^l, \beta^m)| \begin{pmatrix} L_{ft-r} \\ M_{ft-r} \end{pmatrix} \Big]_{r=1}^{T-1} = 0 \tag{A4}$$

We estimate the production function coefficients using the moment conditions up to 2 lags. Using the estimated production function coefficients $\tilde{\beta}^l$, $\tilde{\beta}^m$, we can estimate the markdown as:

$$\tilde{\psi}^l_{ft} = \frac{\tilde{\beta}^l W^m_{ft} M_{ft}}{\tilde{\beta}^m W^l_{ft} L_{ft}} \tag{A5}$$

Our approach

As was laid out in the main text, we start by estimating the labor supply function, in order to estimate the parameter γ.

$$s_{ft} - s^0_{it} = \gamma \ln(W_{ft}) + \xi_{ft} \tag{A6}$$

In the simple logit model, the markdown ψ^l_{ft} can be recovered as:

$$\hat{\psi}^l_{ft} = 1 + \frac{1}{\gamma(1 - s_{ft})} \tag{A7}$$

From the first order conditions, one can express the output elasticity of labor as:

$$\hat{\beta}^l_{ft} = \frac{\hat{\psi}^l_{ft}\alpha^l_{ft}\beta^m}{\alpha^m_{ft}} \tag{A8}$$

Substituting this expression into the production function gives:

$$q_{ft} = \beta^m \underbrace{[\frac{\hat{\psi}^l_{ft}\alpha^l_{ft}l_{ft}}{\alpha^m_{ft}} + m_{ft}]}_{a_{ft}} + \omega_{ft} \tag{A9}$$

Denoting $a_{ft} \equiv \frac{\hat{\psi}^l_{ft}\alpha^l_{ft}l_{ft}}{\alpha^m_{ft}} + m_{ft}$, we can now write the productivity shock as

$$\upsilon_{ft} = q_{ft} - \rho q_{ft-1} - \beta^m(a_{ft} - \rho a_{ft-1})$$

The moment conditions to estimate β^m and ρ are given by:

$$\mathbb{E}\Big[\upsilon_{ft}(\rho, \beta^m)| \begin{pmatrix} L_{ft-r} \\ M_{ft-r} \end{pmatrix} \Big]_{r=1}^{T-1} = 0 \tag{A10}$$

We again estimate the production function parameters taking up to two lags. Using the estimated materials output elasticity $\hat{\beta}^m$, the full distribution of the output elasticities of labor can be recovered using $\hat{\beta}^l_{ft} = \frac{\hat{\psi}^l_{ft}\alpha^l_{ft}\hat{\beta}^m}{\alpha^m_{ft}}$.

A.3 Results

The estimates are reported in Table A1, and their distribution across the different simulation iterations is visualized in Appendix Figure A1. In panel (a) of Table A1, we compare our approach against the Hicks-neutral approach for DGP1, the data-generating process without unobserved heterogeneity in the labor coefficient. We find that the Hicks-neutral approach estimates the production coefficients and inverse labor supply elasticity without bias. In contrast, our model is less accurate, but overall still remain close to the true values.

In panel (b), we introduce DGP2, the data-generating process with latent differences in the labor coefficient. Now, the prior approach, which relied on Hicks-neutrality, is seriously biased: the labor coefficient is overestimated by 61%, whereas the materials coefficient is underestimated by 24%. In contrast, our approach infers the production coefficients almost without bias. The Hicks-neutral model estimates the inverse labor supply elasticity at 3.559, which is three times higher than the true value of 1.613, whereas our model estimates approximate the true value.

Table A1: Monte Carlo Simulations

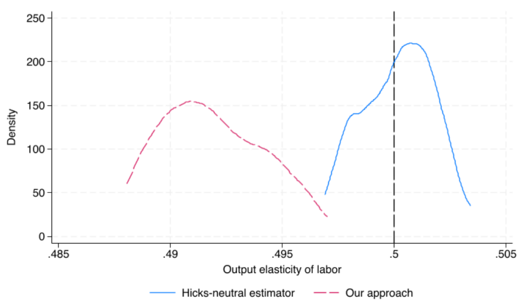
(a) DGP 1: Hicks-neutral		Hicks-neutral		Hetero. β^l exo. wage		Hetero. β^l endo. wage	
		Est.	S.E.	Est.	S.E.	Est.	S.E.
mean(β^l)	true = 0.5	0.500	0.003	0.508	0.000	0.492	0.003
sd(β^l)	true = 0	0.000	0.000	0.006	0.000	0.000	0.000
β^m	true = 0.3	0.300	0.000	0.492	0.000	0.300	0.000
ψ^l	true = 1.614	1.615	0.009	0.000	0.000	1.587	0.012
(b) DGP 2: Factor-biased		Hicks-neutral		Hetero. β^l exo. wage		Hetero. β^l endo. wage	
		Est.	S.E.	Est.	S.E.	Est.	S.E.
mean(β^l)	true = 0.5	0.805	0.048	0.508	0.000	0.496	0.002
sd(β^l)	true = 0.097	0.000	0.000	0.006	0.000	0.095	0.001
β^m	true = 0.3	0.228	0.004	0.492	0.000	0.303	0.001
ψ^l	true = 1.613	3.559	0.252	0.000	0.000	1.586	0.012

Notes: Monte-Carlo simulation with 200 iterations. We use the coefficients from OLS regressions as the initial values for GMM in the prior approach in DGP 1.

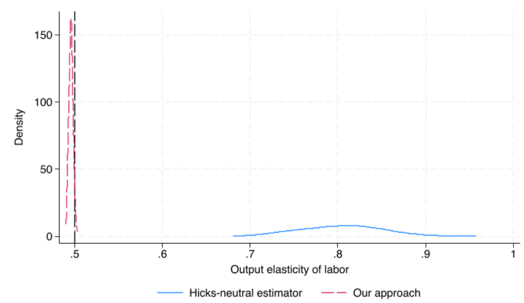
In Figure A2, we plot the estimated inverse labor supply elasticity estimates against the true output elasticity of labor, β^l_{ft} across observations in a single bootstrap iteration (the first of 200), for both our approach and for the Hicks-neutral estimator. In the Hicks-neutral model, the latent variation in the output elasticity of labor is interpreted as wage markdown variation: firms with high output elasticities of labor are estimated to set a low wage the inverse labor supply elasticity), because their cost share of labor is higher than average. In contrast, our estimator delivers inverse labor supply elasticity estimates that are independent of the output elasticity of labor, as is true in the underlying data generating process.

Figure A1: Monte-Carlo Simulations: visualization

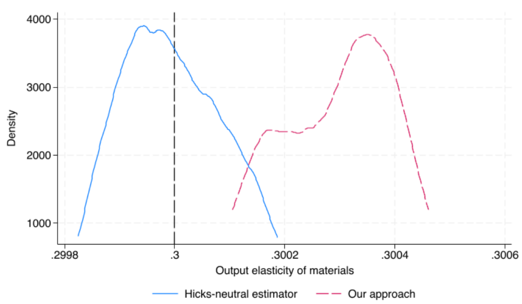
(a) $\hat{\beta}^l$: Hicks-neutral DGP



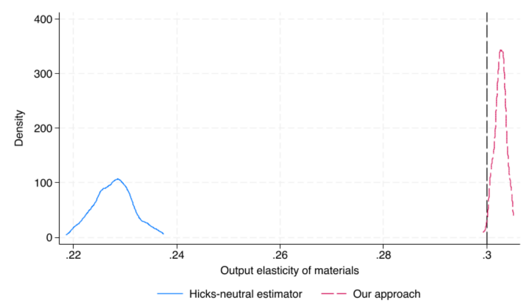
(b) $\hat{\beta}^l$: Factor-biased DGP



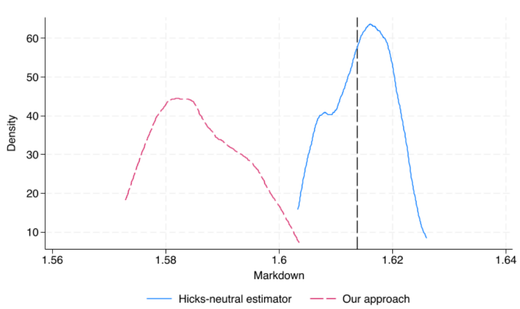
(c) $\hat{\beta}^m$: Hicks-neutral DGP



(d) $\hat{\beta}^m$: Factor-biased DGP



(e) $\hat{\psi}^l$: Hicks-neutral DGP



(f) $\hat{\psi}^l$: Factor-biased DGP

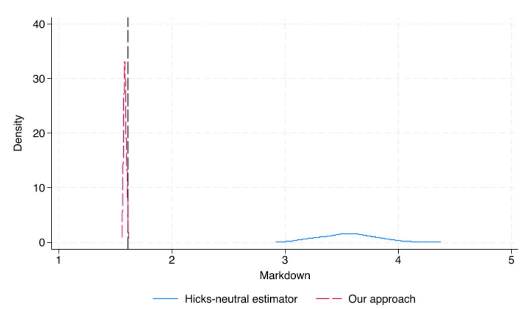
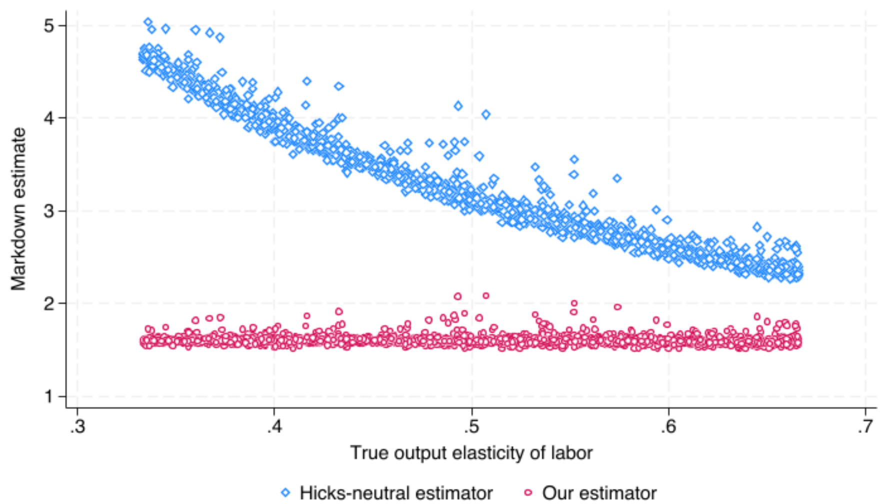


Figure A2: Correlation between the markdown estimate and the true β^l_{ft}



Notes: This Figure plots the markdown estimates against the true output elasticity β^l_{ft} across observations for the first draw of the Monte Carlo simulation, using the Hicks-neutral estimator (blue diamonds) and our estimator that allows for latent heterogeneity in the output elasticity (red circles).

B Additional industry background

B.1 Examples of mining technologies in China and abroad

Rotary drilling rigs

A rotary drilling rig is a construction machine suitable for hole-forming operations in building foundation engineering. In China, domestic produced rotary drilling rigs are used in small and med-size mines (e.g., YZ-12, YZ-35, and YZ-55 models), while large mines mainly use imported models (e.g., Atlas Copco DM30, DM45, and DM50 models). Figure A3 displays two models of rotary drilling rigs made by Chinese and foreign producers, respectively. According to Wang (2010), China's rotary drilling rigs have the following disadvantages compared to foreign products. First, Chinese models suffer from a lack of variety, with single power sources, limited functionalities, and uniform structural designs. Second, domestic drilling rigs mainly rely on mechanical transmissions, resulting in lower efficiency. Third, domestic model has a low degree of automation and remote control management via the Internet. Fourth, Chinese rotary drilling rigs tend to have higher energy consumption compared to their international counterparts.

Top hammer drill

Top hammer drills are primarily used for rock drilling operations in tunneling and mining. It mainly consists of two types, namely, fully hydraulic and pneumatic top hammer drills, with the former being low-energy consumption and high-production efficiency. In China, pneumatic top hammer drills are widely used in underground mines, which, however, have been largely replaced by fully hydraulic models in foreign countries (Wang, 2010). The fully hydraulic top hammer drilling rigs equipped in domestic open pit mines are all imported brands, such as the "ROC D7 model" made by *Atlas Copco* in Figure A3b, and there are no suppliers in China that could produce similar models of equipment (Wang, 2010).

Tunneling machinery

Tunneling machinery is used for drilling, blasting, and digging tunnels for extracting coal or minerals. During the studied period, the mechanization level for tunneling and drilling operations in underground mines was relatively low in China. These operations primarily rely on manual labor, often using handheld rock drilling machines. Only a few advanced mines have adopted imported fully hydraulic drilling machines, such as the "Boomer 282" model displayed in Figure A3c (Wang, 2010). For heavy-duty rock drilling machines, there is a strong reliance on imported equipment.

Figure A3: Examples of imported technologies

(a) Rotary drilling rig

(b) Top hammer drill

(c) Tunneling machinery

Notes: Images are obtained from dealers' websites:
(a) https://rockdrills.net/wp-content/uploads/2015/04/DM45-Spec-Sheet.pdf
(b) https://www.bossgoo.com/product-detail/atlas-copco-drill-rigs-and-rock-17969782.html
(c) https://fuchenglhd.com/blog/how-to-start-a-gold-mining-business/

B.2 Labor market characteristics

Table A2: Characteristics of NFM employment

	NFM industries	Other urban industries
Average age (years)	34.7	35.0
Share of male employment	74.5%	60.3%
Share of migrant workers	38.6%	32.7%
Share of unskilled employment	62.7%	60.3%
Share of production workers and equipment operators	53.4%	9.1%

Notes: The table compares the characteristics of labor force participants in non-ferrous metal industries and other urban sectors, excluding NFM, where urban sectors do not include agricultural industries. The summary statistics of Chinese counties are computed using the 2000 China Population Census Data. Unskilled workers refer to individuals without even high school degrees. Migrant workers are defined as those whose cities of birth and work are different. According to China's Occupational Classification and Code, production workers and equipment operators are identified as occupation codes, with the first digit being 5 or 6 (GBT 6565-2015).

Table A3: Chinese counties and US administrative divisions

Year	N	Mean	Std. Dev.	Min	Median	Max
China, counties:						
2000	2,871	432,815	341,182	517	354,706	6,445,777
US, micropolitan statistical areas:						
2000	576	50,730	27,784	13,004	42,403	182,193
US, metropolitan statistical areas:						
2000	366	636,803	1,478,595	49,832	222,299	18,323,002

Notes: The table compares the size of markets in the paper (i.e., Chinese counties) to alternative administrative divisions in the United States. The summary statistics of Chinese counties are computed using 2000 China Population Census Data, and those of the U.S. are from the County Business Patterns (CBP) from the Census Bureau.

Table A4: The top 10 imported capital goods in non-ferrous metal industries

Rank	HS 8-digit Code	Product Description
		Non-ferrous metal Manufacturing
1	84798990	Machines and mechanical equipment with independent functions
2	84543090	Casting machines
3	85433000	Electroplating, electrolysis or electrophoresis equipment and devices
4	84571010	Vertical machining center
5	84543010	Cold chamber die casting machine
6	84629110	Metal profile hydraulic extrusion press
7	85143000	Industrial or laboratory furnaces and ovens
8	84552210	Plate cold rolling mill
9	85141010	Controlled atmosphere heat treatment furnace
10	84798190	Machinery for handling metals, not listed
		Non-ferrous metal Mining
1	84743900	Mixing or stirring machines for solid minerals
2	84741000	Machines for sorting, screening, separating or washing solid minerals
3	84304129	Self-propelled drilling rig with drilling depth $<$ 6000 meters
4	84742090	Crushing or grinding machines for solid minerals
5	84742020	Ball mill type solid mineral crushing or grinding machine
6	84243000	Steam blasters, sandblasters and similar blasting machines
7	84303100	Self-propelled shearers, rock drills and tunnel boring machines
8	87041090	Off-highway freight motorized dump trucks
9	84148090	Air pumps, gas compressors, ventilation hoods, circulating air hoods
10	90328900	Automatic adjustment or control instruments and devices

Notes: The table lists top 10 capital goods imported by non-ferrous metal manufacturing and mining sectors, respectively, where each product is measured by a unique HS 8-digit code. The rank is based on the total imports from 2000 to 2006 from China custom data, and smaller rank index indicating a more imports.

C Extensions and robustness

C.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 (A11):

$$q_{ft} = \beta^l l_{ft} + \beta^m m_{ft} + \beta^l l_{ft} + \omega_{ft} \tag{A11}$$

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:

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

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

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

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.

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

The translog production estimates are reported in table A5 . The output elasticities of materials and capital are slightly higher than the estimates from Cobb-Douglas model, while the output elasticities of labor is lower and not statistically significant. The markup estimates result in negative numbers for both simple average and median. In Figure A4, we compare the evolution of the output elasticity of labor, of the wage markdown, and of the price markup between the translog model and our preferred specification, the CES function with imperfect labor market competition. The translog finds a declining output elasticity of labor, as in the CES model, but results in levels that are too low: the average output elasticity is close to zero, and becomes negative after 2001, which is theoretically impossible. Similarly, the wage markdown estimates look very implausible, which is logical given the nonsensical output elasticity of labor.

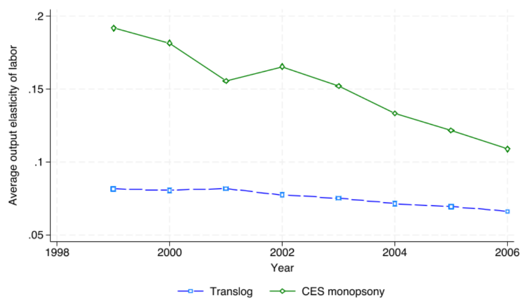
Table A5: Estimated Parameters of Translog Production Function

(c) Other prod. param.		Translog	
		Est.	S.E.
β^{l}		0.244	0.747
β^{m}		0.116	0.517
β^{k}		0.320	0.198
β^{ll}		-0.000	0.021
β^{mm}		0.036	0.019
β^{kk}		0.004	0.010
β^{lm}		-0.029	0.053
β^{mk}		-0.029	0.012
β^{lk}		0.004	0.028
β^{lmk}		0.001	0.002
Output elas. of labor	θ^{l}_{ft}	0.047	0.046
Output elas. of materials	θ^{m}_{ft}	0.733	0.095
Output elas. of capital	θ^{k}_{ft}	0.066	0.028
Average markup		-0.014	
Median markup		-0.060	

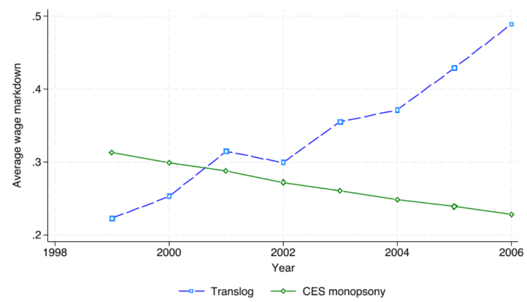
Notes: Block-bootstrapped standard errors with 200 draws.

Figure A4: Technological change, markdowns, and markups in the translog model

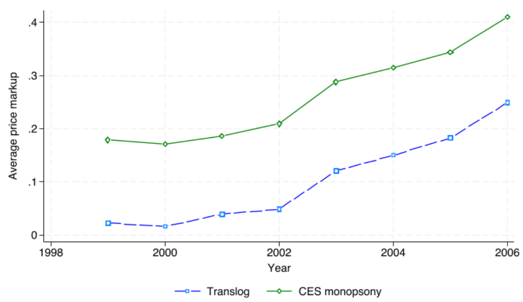
(a) Output elasticity of labor



(b) Wage markdown



(c) Price markup



C.2 Labor supply: alternative functional forms

Nested logit with linear labor utility

In this appendix, we specify an alternative labor supply model in which wages enter worker utility linearly, rather than loglinearly:

$$U_{jft} = \underbrace{\alpha w_{ft} + \boldsymbol{\gamma}\mathbf{X}_{ft} + \xi_{ft}}_{\equiv \delta_{ft}} + \sum_{g} (d_{fg}\gamma_{jg}) + (1-\sigma)\upsilon_{jft}$$

The corresponding markdown expression is:

$$\psi^{l}_{ft} = 1 + \frac{1-\sigma}{\alpha W_{ft}(1-\sigma s^{g}_{ft} - (1-\sigma)s_{ft})}$$

The resulting output elasticities, markdowns, and markups are shown in Figure A5 and Table A6. Figure A5 shows that the output elasticities, productivities, and markups from the linear utility model closely follow the trend of those from the loglinear utility model, while the markdown is an exception. In particular, Table A6 shows the average markdown from the linear utility model is 0.294, which is higher than the 0.250 estimate from the loglinear utility model. Using the linear wage utility model, we find that wage markdowns were fluctuating without a significant down- or upward trend throughout the sample period.

Table A6: Labor supply with linear labor utility

(a) Labor supply		OLS		IV		IV	
		Est.	S.E.	Est.	S.E.	Est.	S.E.
Wage coefficient	γ	0.001	0.001	0.147	0.035	0.235	0.095
Nesting parameter	ς	0.356	0.004	0.112	0.036	-0.073	0.165
Constant factor	γ_0					67.401	57.418
Time-varying factor	γ_t					-0.034	0.029
1st stage F-stat: W^L_{ft}				5.135		5.135	
1st stage F-stat: s_{ft}				295.369		295.369	
1st stage F-stat: $W^L_{ft} \times year$						5.143	
Observations		33137		22780		22780	
Average markdown		0.974		0.360		0.294	
Median markdown		0.978		0.346		0.282	

Notes: Coefficients on $\gamma, \gamma_0, \gamma_t$ are scaled up by 100.

Control for the exposure to the international market

When estimating labor supply, we use the international metal prices and firm's exposure to the international market as instruments. The assumption is that changes in global metal prices affect labor demand in the Chinese non- ferrous metal industry but not the firm's amenity, and thus, it does not affect labor utility directly. In addition, firms that export more are assumed to experience a larger effect of international price shocks in terms of their labor demand. In Table A7, we further test the validity of these assumptions. The first specification, "Low concentration", includes only firms whose global market share is below 20%. The second column, "Ownership type", includes an indicator for foreign-owned firms and an indicator for state-owned enterprises. The average markdown estimated in the ownership type model is close to the 0.25 in our main specification, but the one estimated in the low concentration model is much higher.

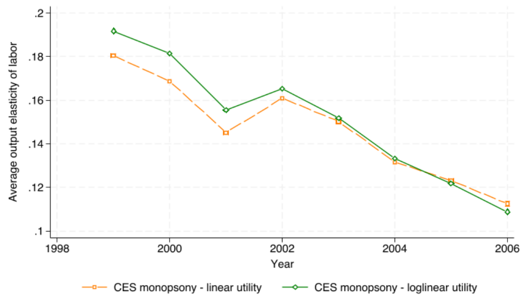
Table A7: Control for the exposure to the international market

(a) Labor supply		Low concentration		Ownership type	
		Est.	S.E.	Est.	S.E.
Wage coefficient	γ	-0.770	0.867	2.869	1.051
Nesting parameter	ς	0.474	0.075	0.134	0.134
Constant factor	γ_0	-1450.942	285.366	-403.760	490.659
Time-varying factor	γ_t	0.724	0.142	0.203	0.245
1st stage F-stat: W^L_{ft}		3.564		7.521	
1st stage F-stat: s_{ft}		305.039		318.505	
1st stage F-stat: $W^L_{ft} \times year$		3.558		6.021	
Observations		22295		22780	
Average markdown		0.737		0.249	
Median markdown		0.308		0.238	

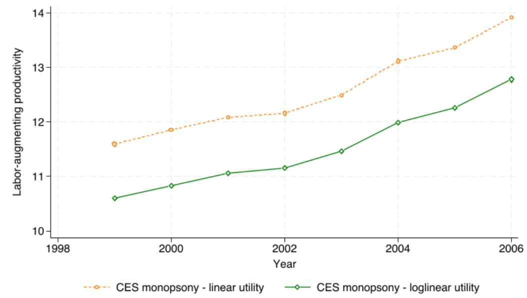
Notes: We control for industry fixed effects and firm's percentage of output exported. The column "Low concentration" includes only firms whose global market share is below 20%. The column "Ownership type" includes the foreign-owned dummy and state-owned dummy as additional controls.

Figure A5: technological change, markdowns, and markups with linear labor utility

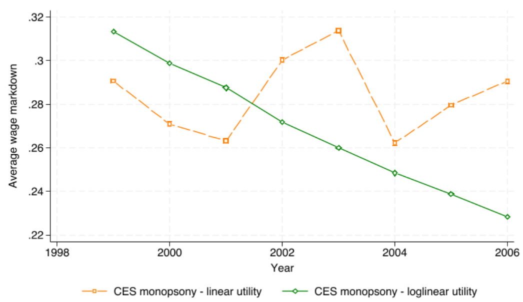
(a) Output elasticity of labor



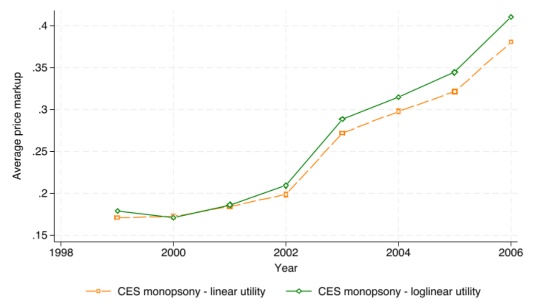
(b) Labor-augmenting productivity



(c) Wage markdown



(d) Price markup



C.3 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 non-ferrous metal manufacturers based on the output prices of non-ferrous metal 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 4-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 A8, 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.

Table A8: Test for exogenous input prices in manufacturing

	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 control for year fixed effects and sub-industry fixed effects.

D Data Appendix

D.1 Data cleaning

The 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 has 6,699 firms, 302 product codes, and a total of 32,114 observations in non-ferrous metal mining and manufacturing industry. The data includes a firm identifier, the product codes for each firm's production, the industry code they below 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 replace them with other 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 (NBER w24455). The ASIP dataset covers 28,016 firms and a total of 89,647 observations in non-ferrous metal mining and manufacturing industry. Using Chinese CPI, we deflate revenue, profit, wage bill, non-wage benefit, 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 construct a measure for the outside option, we merge the dataset with a census population dataset from 2000. In the end, we trim the dataset by dropping observations that have the top or bottom 1 percent intermediary input revenue share and labor revenue share.

D.2 Summary statistics

Table A9 shows the summary statistics for our compiled dataset. There are considerable heterogeneity in the firm size, as well as in the expenditures on labor and intermediate materials. The majority of firms are domestic private firms and do not engage in exporting.

Table A9: 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	38,186	1,482	1,326	1,238	848	1,691
World prices	26,092	1,979	4,577	892	302	1,832
Foreign-owned	38,194	0.090	0.286	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 wage per worker 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 foreign or state, respectively.

E Derivations

E.1 Derivation of equation (14a).

We derive equation (14a). The first order conditions of the cost minimization problem, (12) can be written as:

$$\frac{\partial P_{ft}Q_{ft}}{L_{ft}} = W^l_{ft} + \frac{\partial W^l_{ft}}{\partial L_{ft}} L_{ft}$$
$$\frac{\partial P_{ft}Q_{ft}}{M_{ft}} = W^m$$

Working out these expressions using the CES functional form of the production function, and dividing the two equations by each other, delivers:

$$(\frac{M_{ft}}{L_{ft}})^{\frac{1}{\sigma}}(A_{ft})^{\frac{\sigma-1}{\sigma}}\frac{1}{\beta^m} = \frac{W^l_{ft}\psi^l_{ft}}{W^m}$$

Rearranging and taking logs results in expression (14a).

E.2 Decomposition Method

We decompose productivity growth into within-firm internal technological change and reallocation across firms, similarly to Olley and Pakes (1996). Our method relies on Melitz and Polanec (2015) to decompose the reallocation term into surviving firms, firm entry, and firm exit. Denote the employment share of firm f in sector g and year t as s^g_{ft}, and let S^o_{gt}, N^o_{gt} and X^o_{gt} be the sets of the surviving, new, and exiting firms with ownership type being $o \in \mathbb{O}$ and $\mathbb{O} \equiv \{\text{SOE, Private, Foreign}\}$, respectively. They are defined by the following conditions $S^o_{gt} = F^o_{gt} \cap F^o_{g,t-k}$, $N^o_{gt} = \{f | f \in F^o_{gt} \text{and} f \notin F^o_{g,t-k}\}$ and $X^o_{gt} = \{f | f \notin F^o_{gt} \text{and} f \in F^o_{g,t-k}\}$, where F^o_{gt} is the set of all firms in sector g and year t whose ownership type is o. Hence, the decomposition uses the following sector-level aggregate, which then is long-differenced in the last step relative to the initial year, i.e., $t-k=1999$:

$$
\begin{aligned}
a_t^g - a_{t-k}^g = & \quad \sum_{o\in\mathbb{O}}\sum_{f\in F_{gt}^o} a_{ft}s_{ft}^g - \sum_{f\in F_{gt-k}^o} a_{f,t-k}s_{f,t-k}^g \\
= & \left.\begin{array}{lr} \sum_{o\in\mathbb{O}}\sum_{f\in N_{gt}^o} a_{ft}s_{ft}^g - \sum_{f\in X_{gt}^o} a_{f,t-k}s_{f,t-k}^g & \text{Entry \& exit} \\ + \sum_{o\in\mathbb{O}}\sum_{f\in S_{gt}^o} a_{f,t-k}(s_{ft}^g - s_{f,t-k}^g) & \text{Surviving firms - composition} \end{array}\right\} \text{Reallocation} \\
& + \sum_{o\in\mathbb{O}}\sum_{f\in S_{gt}^o} s_{ft}^g(a_{ft} - a_{f,t-k}) \quad \text{Surviving firms - within-firm growth}
\end{aligned}
$$

where a_t^g denote the average log labor-augmenting productivity in sector g. As shown in above equation, terms capturing within-firm internal technological change and reallocation across firms can further be split into different ownership.