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Kuang-hui Chen*
Yoshihiro Hashiguchi †
March, 2024

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Keywords: Markups, Production functions, Output elasticity
JEL classification: D22, D24, L11

* Kobe University. (chen@people.kobe-u.ac.jp)
† Institute of Developing Economies, JETRO. (Yoshihiro_Hashiguchi@ide.go.jp)

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INSTITUTE OF DEVELOPING ECONOMIES (IDE), JETRO
3-2-2, WAKABA, MIHAMA-KU, CHIBA-SHI
CHIBA 261-8545, JAPAN

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A nonparametric production approach is proposed to estimate markups, which involves nonparametric estimation of the output elasticity function using cost share information. This approach helps avoid identification problems related to production function estimation, and the empirical issues highlighted by Raval (2023) are addressed. It is possible that factors such as differences in adjustment costs between inputs contribute to the issue and our nonparametric method accounts for this to some extent.

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1 Introduction

Competition among firms is fundamental for the well-functioning of a market economy. In economies characterized by limited competition, firms possess significant market power, enabling them to set prices for consumers that exceed production costs. This leads to a decrease in consumer surplus and an overall decline

*Kobe University. E-mail: chen@people.kobe-u.ac.jp

†Institute of Developing Economies-JETRO. E-mail: yoshihiro_hashiguchi@ide.go.jp

of the welfare of the economy. Furthermore, the absence of competition diminishes firms' motivation to exert efforts, resulting in Leibenstein's X-inefficiency within firms and a decline in investment in innovative activities, ultimately impeding economic growth. To formulate policies aimed at preventing or mitigating the negative effects of market power, it is essential to measure and understand the extent of competition among firms.

The markup of price over marginal cost has long been used to assess the market power, and the production approach, pioneered by Hall (1986, 1988) and extended by De Loecker and Warzynski (2012), has been widely used for estimation. This approach identifies the markup as the ratio of the output elasticity of a variable input to its cost share in revenue, having theoretical and empirical appeal.[1)] However, in recent years, two broad problems have been pointed out regarding it, raising doubts about its usefulness.

One is the problem of identifiability. Bond, Hashemi, Kaplan, and Zoch (2021) shows that when information about the output prices is unavailable and the output elasticity is estimated from a revenue-based production function, its ratio to the cost share provides no useful information about the markup. It is also pointed out that the commonly used proxy variable approach faces an identification problem if a gross output production function is to be estimated (Gandhi, Navarro, and Rivers, 2020).

The other is the problem that the estimates depend of which variable inputs are used and may yield contradictory results. Raval (2023) finds from seven datasets

[1)] Basu (2019), Syverson (2019), De Loecker, Eeckhout, and Unger (2020).

for six countries/regions that estimates based on labor are much more dispersed than those based on intermediate inputs, and they have the opposite time trend and are negatively correlated.

This study proposes a nonparametric production approach to markup estimation. Our approach involves nonparametric estimation of the output elasticity function using the cost share information, thereby avoiding the identification problems regarding production function estimation. With this approach, we estimated markups for Chinese and Indonesian manufacturing firms from 2003 to 2007 and compared the labor- and intermediate input-based estimates. We did find that labor-based estimates were more dispersed than intermediate input-based ones, but their dispersion was smaller than the estimates from the common approach. Additionally, our estimates did not exhibit the opposite time trend nor negative correlation.

The remainder of this paper is organized as follows. Section 2 outlines our approach. Section 3 reports the results of the above comparison. Section 4 concludes.

2 A Nonparametric Approach

2.1 Firm Behavior and the Markup

Consider a firm i operating in discrete time t, producing output Y_{it} using capital K_{it}, labor L_{it}, and intermediate inputs M_{it}. We assume that the relationship between these inputs and output is determined by a production function F and a Hicksneutral productivity shock ν_{it}.

Assumption 1 *The relationship between output and inputs takes the following form, and the productivity shock can be log-additively decomposed as* $\nu_{it} = \omega_{it} + \varepsilon_{it}$.

$$\begin{aligned} Y_{it} &= F(k_{it}, l_{it}, m_{it}) \exp\{\nu_{it}\} = F(k_{it}, l_{it}, m_{it}) \exp\{\omega_{it} + \varepsilon_{it}\} \\ \Leftrightarrow y_{it} &= f(k_{it}, l_{it}, m_{it}) + \omega_{it} + \varepsilon_{it}, \end{aligned} \tag{1}$$

where y_{it}*,* k_{it}*,* l_{it}*, and* m_{it} *are logs of* Y_{it}*,* K_{it}*,* L_{it}*, and* M_{it}*, respectively.* ω_{it} *represents the productivity level known to the firm when it makes period t decisions, encompassing factors such as technology, information, knowledge, or specific situations affecting firm i's productivity.* ε_{it} *is the ex-post productivity shock which is beyond the firm's ability to foresee.*

Let $\mathcal{I}_{it}$ represent the information set that the firm can use to solve its period t decision problem. Assumption 1 implies $\omega_{it} \in \mathcal{I}_{it}$, whereas $\varepsilon_{it} \notin \mathcal{I}_{it}$.

Assumption 2 *The capital* K_{it} *is determined using the information set* $\mathcal{I}_{i,t-1}$*, and the other input* $X_t \in \{L_{it}, M_{it}\}$ *is determined using* $\mathcal{I}_{it}$*.*

Given the infomation set $\mathcal{I}_{it}$ that contains K_{it} and ω_{it}, the firm chooses the variable input X_{it} to minimize short-run costs

Assumption 3 *The firm chooses its variable inputs to minimize short-run costs subject to producing a target level of output* Y_{it}*.*

Under Assumptions 1 to 3, the cost minimization problem for firm i is

$$\min_{L_{it},\ M_{it}} r_{it}K_{it} + w_{it}L_{it} + \rho_{it}M_{it}$$

$$\text{s.t. } \mathbb{E}[F(k_{it}, l_{it}, m_{it}) \exp\{\omega_{it} + \varepsilon_{it}\}|\mathcal{I}_{it}] = Y_{it},$$

where r_{it}, w_{it}, and ρ_{it} are unit prices of capital, labor, and intermediate inputs, respectively.

Let λ_{it} denote the Lagrange multiplier. The first-order conditions with respect L_{it} and M_{it} are respectibely

$$\begin{aligned} w_{it} &= \lambda_{it}\frac{\partial F(\cdot)}{\partial L_{it}} \exp\{\omega_{it}\}\, \mathbb{E}[\exp\{\varepsilon_{it}\}], \\ \rho_{it} &= \lambda_{it}\frac{\partial F(\cdot)}{\partial M_{it}} \exp\{\omega_{it}\}\, \mathbb{E}[\exp\{\varepsilon_{it}\}]. \end{aligned}$$

They yield share equations:

$$\begin{aligned} S_{it}^{L} \equiv \frac{w_{it}L_{it}}{p_{it}Y_{it}} &= \frac{\lambda_{it}}{p_{it}}\frac{\partial F(\cdot)}{\partial L_{it}}\frac{L_{it}}{F(\cdot)}\frac{\mathcal{E}}{\exp\{\varepsilon_{it}\}} = \frac{1}{\mu_{it}}G_L(k_{it}, l_{it}, m_{it})\frac{\mathcal{E}}{\exp\{\varepsilon_{it}\}}, \\ S_{it}^{M} \equiv \frac{\rho_{it}M_{it}}{p_{it}Y_{it}} &= \frac{\lambda_{it}}{p_{it}}\frac{\partial F(\cdot)}{\partial M_{it}}\frac{M_{it}}{F(\cdot)}\frac{\mathcal{E}}{\exp\{\varepsilon_{it}\}} = \frac{1}{\mu_{it}}G_M(k_{it}, l_{it}, m_{it})\frac{\mathcal{E}}{\exp\{\varepsilon_{it}\}}, \end{aligned} \tag{2}$$

where p_{it} is the output price, $\mathcal{E} = \mathbb{E}[\exp\{\varepsilon_{it}\}]$, $G_X(\cdot) \equiv \partial f(\cdot)/\partial x_{it}$ is the output elasticity with respect to a variable input X, and because the Lagrange multiplier λ_{it} is equal to the marginal cost MC_{it}, we have the fact that $\mu_{it} = p_{it}/\lambda_{it}$ is the markup:

$$\mu_{it} = p_{it}/MC_{it} = \left(1 - \frac{1}{\eta_{it}}\right)^{-1},$$

where $\eta_{it} \equiv -\frac{p_{it}}{Y_{it}}\frac{dY_{it}}{dp_{it}}$ is the price elasticity of demand.

2.2 Estimation

De Loecker and Warzynski (2012) proposed to derive a markup estimator from the share equations. We have from Equations (2)

$$\hat{\mu}_{it} = \frac{\hat{G}_X(k_{it}, l_{it}, m_{it})}{S_{it}^X \exp\{\hat{\varepsilon}_{it}\}}\hat{\mathcal{E}}, \quad X \in \{L, M\}$$

and can obtain $\hat{G}_X(\cdot)$, $\hat{\varepsilon}_{it}$, and $\hat{\mathcal{E}}$ by estimating the parameters of the production function. This production approach, however, is thought to suffer from identification problems as discussed in the introduction.

We employ an alternative approach which does not require estimating the production function parameters. Our approach exploits the log of Equations (2):

$$\log(S_{it}^X) - \log\mathcal{E} + \varepsilon_{it} = \log\left(G_X(k_{it}, l_{it}, m_{it})\right) - \tilde{\mu}_{it}, \quad X \in \{L, M\} \tag{3}$$

where $\tilde{\mu}_{it} \equiv \log\mu_{it}$.

We first use the assumption of Ackerberg, Caves, and Frazer (2015) to estimate ε_{it} and $\mathcal{E}$.

Assumption 4 *Let $m_{it} = \mathbb{M}(k_{it}, l_{it}, \omega_{it})$ be the intermediate input demand function. The function $\mathbb{M}$ is strictly increasing in ω_{it}.*

We have from this assumption

$$\omega_{it} = \mathbb{M}^{-1}(k_{it}, l_{it}, m_{it}).$$

Substituting into Equation (1) yields

$$\begin{aligned} y_{it} &= f(k_{it}, l_{it}, m_{it}) + \mathbb{M}^{-1}(k_{it}, l_{it}, m_{it}) + \varepsilon_{it} \\ &= \phi(k_{it}, l_{it}, m_{it}) + \varepsilon_{it}, \end{aligned}$$

and because ε_{it} is independent of k_{it}, l_{it}, and m_{it} under Assumptions 1 and 2, it can be estimated by non-parametric regression of y_{it} on k_{it}, l_{it}, and m_{it}.[2)] Using the estimate $\hat{\varepsilon}_{it}$, Equations (3) become

$$s_{it}^X \equiv \log(S_{it}^X) - \log\hat{\mathcal{E}} + \hat{\varepsilon}_{it} = \log\left(G_X(k_{it}, l_{it}, m_{it})\right) - \tilde{\mu}_{it}, \quad X \in \{L, M\} \tag{4}$$

where

$$\hat{\mathcal{E}} = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\exp(\hat{\varepsilon}_{it}).$$

We then introduce an assumption regarding the price elasticity of demand:

Assumption 5 *The price elasticity of output demand η_{it} a frim faces is not correlated with its inputs K_{it}, L_{it}, and M_{it}.*

2)We used a third-degree polynomial for this regression.

Under this assumption, the log markup $\tilde{\mu}_{it} = -\log\left(1 - \frac{1}{\eta_{it}}\right)$ is not correlated with k_{it}, l_{it}, and m_{it} and can also be estimated by non-parametric regression. Specifically, we approximated $G_X(k_{it}, l_{it}, m_{it})$ by a second-degree polynomial:

$$\begin{aligned} G_X(k_{it}, l_{it}, m_{it}) &\approx \gamma_0 + \gamma_k k_{it} + \gamma_l l_{it} + \gamma_m m_{it} + \gamma_{kk} k_{it}^2 + \gamma_{ll} l_{it}^2 \\ &\quad + \gamma_{mm} m_{it}^2 + \gamma_{kl} k_{it} l_{it} + \gamma_{km} k_{it} m_{it} + \gamma_{lm} l_{it} m_{it} \\ &= \mathbf{x}'\boldsymbol{\gamma} > 0, \end{aligned}$$

sloved the minimization problem:

$$\min_{\gamma} \sum_i \sum_t \left[s_{it}^X - \log\left(\mathbf{x}'\boldsymbol{\gamma}\right) \right]^2, \tag{5}$$

and obtained residuals e_{it}.[3)]

Our (log) markup estimator is

$$\hat{\tilde{\mu}}_{it} = -e_{it},$$

which has zero mean and should be considered as the relative markup of a firm.

[3)] This is an approach taken by Gandhi, Navarro, and Rivers (2020, p. 2994). The minimization was carried out by the Broyden-Fletcher-Goldfarb-Shanno algorithm using the derivative function of Equation (5).

3 Empirical Tests

We used Chinese and Indonesian manufacturing data for 2003–2007 to estimate firm-level markups by industy. We used the log share equations (4) for labor L and intermediate inputs M and investigated the difference between the resulting estimates.

Table 1 shows the number of firms and industries of our data, detailed description of which is provided in Appendix.

Dispersions

Figure 1 compares the distributions of the log markup estimates from labor's and intermediate inputs' share equations (log mu (L) and log mu (M), respectively). It also presents for comparison the distributions of estimates by the method of De Loecker and Warzynski (2012), assuming the Cobb-Douglas value-added production function (log mu (L, VA), hereafter referred to as DW estimates).[4)] As is pointed out by Raval (2023), the labor-based estimates are more dispersed than the intermediate input-based ones, but we obseve that our labor-based estimates are less dispersed than DW estimates.

Table 2 supports this observation. For both China and Indonesia, the IQR of our labor-based estimates is significantly larger than that of intermediate input-based estimates, but it is significantly smaller than the IQR of DW estimates.

[4)]Production functions were estimated using the method of Ackerberg, Caves, and Frazer (2015).

Time Trends

To compare the time-series behaviors of labor and intermediate-based markups, we conduct the following regression:

$$\hat{\hat{\mu}}_{it}^{X} = \alpha + \phi_t + \delta_j + u_{it}, \quad X \in \{L, M\}, \tag{6}$$

where $\hat{\hat{\mu}}_{it}^{X}$ denotes X-based estimates, and ϕ_t and δ_j are year- and industry-fixed effects, respectively.

Figure 2 depicts the estimates of year-fixed effects along with the 95% confidence intervals. Contrary to the finding of Raval, our labor- and intermediate input-based estimates did not show opposing patterns overtime.

Cross-Sectional Correlations

We investigated the cross-sectional correlation between the two estimates by the following regression:

$$\hat{\hat{\mu}}_{it}^{L} = \alpha + \beta \hat{\hat{\mu}}_{it}^{M} + \phi_t + \delta_j + u_{it}. \tag{7}$$

Table 3 presents the result. Here again, contrary to Raval (2023), our estimates were not negatively correlated with each other.

4 Conclusion

We proposed a nonparametric production approach to estimate markups, which involved nonparametric estimation of the output elasticity function using cost share information. This approach helps avoid identification problems related to production function estimation. We found that the empirical issues highlighted by Raval (2023) were addressed. While Raval attributes these problems to non-neutral productivity differences across firms, it is also possible that factors such as differences in adjustment costs between inputs contribute to the issue and our nonparametric method accounts for this to some extent.

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Appendix: Firm-level Data

A.1 China

China's data are based on unbalanced firm-level panel data on the manufacturing industry for 2003–2007. These data were obtained from the annual survey of industrial enterprises conducted by the National Bureau of Statistics. The survey encompasses firms with sales exceeding 5 million RMB in the mining, manufacturing, and public utilities industries.[1)] To construct a panel of manufacturing firms, we employed Firm IDs. [2)] In cases where there were missing or conflicting observations regarding the industry code within the same firm, they were standardized to the most recent available information.

The variables used to estimate markups were constructed as follows. Y_{it} is the total gross output, K_{it} is the total fixed assets, L_{it} is the number of employees, and M_{it} is the total intermediate input. The gross output and value-added were adjusted for price changes using an output deflator, whereas intermediate input is adjusted using an input deflator.[3)] Both deflators were normalized to the year 2003. These deflators are obtained from the online appendix of Brandt, Biese-

[1)]The unit of observation for China's data is a firm, not plant, suggesting a possibility that large firms may have multiple plants located in different regions. However, Brandt, Biesebroeck, and Zhang (2014) demonstrated that the share of single-plant firms included in this database exceeded 96% in 2007, indicating that the influence of multi-plant firms on our analysis is quite limited.

[2)]However, these IDs are often missing or subject to change over time. Therefore, following the approach of Hashiguchi (2020), we generated a new series of firm IDs using firm attributes, such as original firm IDs and firm names. The firm-matching algorithm is detailed in Appendix B of Hashiguchi (2020).

[3)]The value-added is used for the estimation of the Cobb-Douglas value-added function.

broeck, and Zhang (2012).[4)]

The deflator for total fixed assets was constructed using province-level investment deflators through the following steps:

(1) Firm-level total fixed-asset data at current prices are gathered by province. The province-level data are denoted by $\tilde{K}_{pt}$, where p denotes a province.

(2) The provincial nominal investment is calculated as $\tilde{I}_{it} = \tilde{K}_{pt} - (1-\delta)\tilde{K}_{p,t-1}$. Following Brandt, Biesebroeck, and Zhang (2012), the depreciation rate δ is set at 0.09.

(3) $\tilde{I}_{it}$ is deflated by a province-level investment deflator normalized to the year 2003, which is obtained from the China Statistical Yearbook. Using the deflated investment (I_{pt}), provincial deflated fixed assets are calculated as $K_{pt} = (1-\delta)K_{p,t-1} + I_{pt}$, where $K_{p0} = \tilde{K}_{p0}$.

(4) The deflator for total fixed assets by province can be calculated using $\tilde{K}_{pt}$ and K_{pt}.

The cost of intermediate input was calculated using the nominal value of intermediate inputs. When calculating the labor cost, we considered not only the nominal wage but also other financial burdens on employees. Specifically, in 2003, the labor cost includes expenses for employee welfare and unemployment insurance, in addition to the nominal wage. After 2004, the labor cost further encompasses expenses for healthcare, pension insurance, and housing fund, in addition to the previously mentioned costs. The cost share was obtained by dividing these costs

[4)] See their online appendix at `http://www.econ.kuleuven.be/public/n07057/china/`.

by the nominal gross output. In the calculation of labor markups using the traditional ratio estimator, we used the share of labor cost in the nominal value-added.

The following observations were considered outliers and were removed: observations with a non-positive value for Y_{it}, K_{it}, L_{it}, or M_{it}; observations with labor cost or intermediate cost shares are beyond the range of 0 to 1; and observations where Y_{it}/L_{it} or K_{it}/L_{it} in t is more than 1000 times or less than 0.001 the value in $t-1$;

A.2 Indonesia

Indonesia's data are derived from unbalanced plant-level data in the manufacturing industry for 2003–2007. These plant-level data are sourced from the annual survey of medium and large manufacturing establishments (IBS) conducted by Statistics Indonesia (Badan Pusat Statistik: BPS). The IBS survey encompasses all manufacturing plants with 20 or more employees, and plant IDs are utilized to construct a panel of observations. As with China's data, when there were missing or conflicting observations regarding the industry code within the same plant, they were standardized to the most recent available information.

The total gross output Y_{it} and the value-added were adjusted for price changes using the national-level GDP deflator normalized at the year 2003. The labor input, denoted as L_{it}, is the number of employees. The intermediate input, M_{it}, is the total intermediate input values adjusted for price changes using the national-level whole sale price index, normalized at the year 2003. The fixed capital stock K_{it} was calculated by the benchmark year method, expressed as $K_{it} = (1-\delta)K_{i,t-1} + I_{it}$, where I_{it} is a firm-level investment deflated by the national-level price index of gross capital formulations (GCF) normalized at the year 2003. Here, the depreciation rate δ was set at 0.05. The benchmark of the capital stock was constructed based on the firm-level total fixed assets deflated by the GCF price index which was normalized at the year 2003.[5)]

The cost of intermediate input is the nominal value of intermediate inputs. The cost of labor is the sum of wages and other incentives for workers. In the absence of detailed information regarding "other incentives" in the database, it is worth noting that before the year 2000, the data description did not explicitly mention "other incentives;" Instead, it included items such as pension contributions and overtime pay. Therefore, it can be inferred that these expenditure items are likely encompassed within the category of "other incentives." Finally, outliers are removed by the same method as applied to China's data.

[5)]The firm-level nominal fixed assets exhibited missing values over the years, and even within the same plant, there were instances where observations are absent on the year. Therefore, the observed nominal fixed assets for the most recent year for each plant was deflated by the GCF price index and used as the benchmark of the capital stock.

Table 1: Numbers of Firms and Industries

Year	China	Indonesia
2003	171,665	17,024
2004	244,065	17,151
2005	241,604	17,153
2006	269,884	22,202
2007	301,491	21,818
Industries[a]	30	22

[a] Industries are classified according to each country's two-digit codes. We merged code 30 (office electrical machines, and accounting and computing machinery) and 31 (other electrical machines and equipment) industries of Indonesia due to limited observations in the former.

Table 2: Inter-Quartile Range

	log mu (M)	log mu (L)	log mu (L, VA)
China	0.1090	0.6891	0.9788
	(0.0001)	(0.0010)	(0.0009)
Indonesia	0.0780	0.6440	0.8701
	(0.0005)	(0.0023)	(0.0036)

Note: Bootstrap standard errors based on 20 replications are in parentheses.

Table 3: Cross-Sectional Relationship between Markup Estimates

	Estimates	Std.Err.	CI_low	CI_high
China	0.285	0.021	0.243	0.327
Indonesia	−0.016	0.074	−0.163	0.131

Notes: Estimates based on Equation (7). The standard errors are clustered at the industry level. CI_low and CI_high denote the lower and upper bounds of 95% confidence intervals.

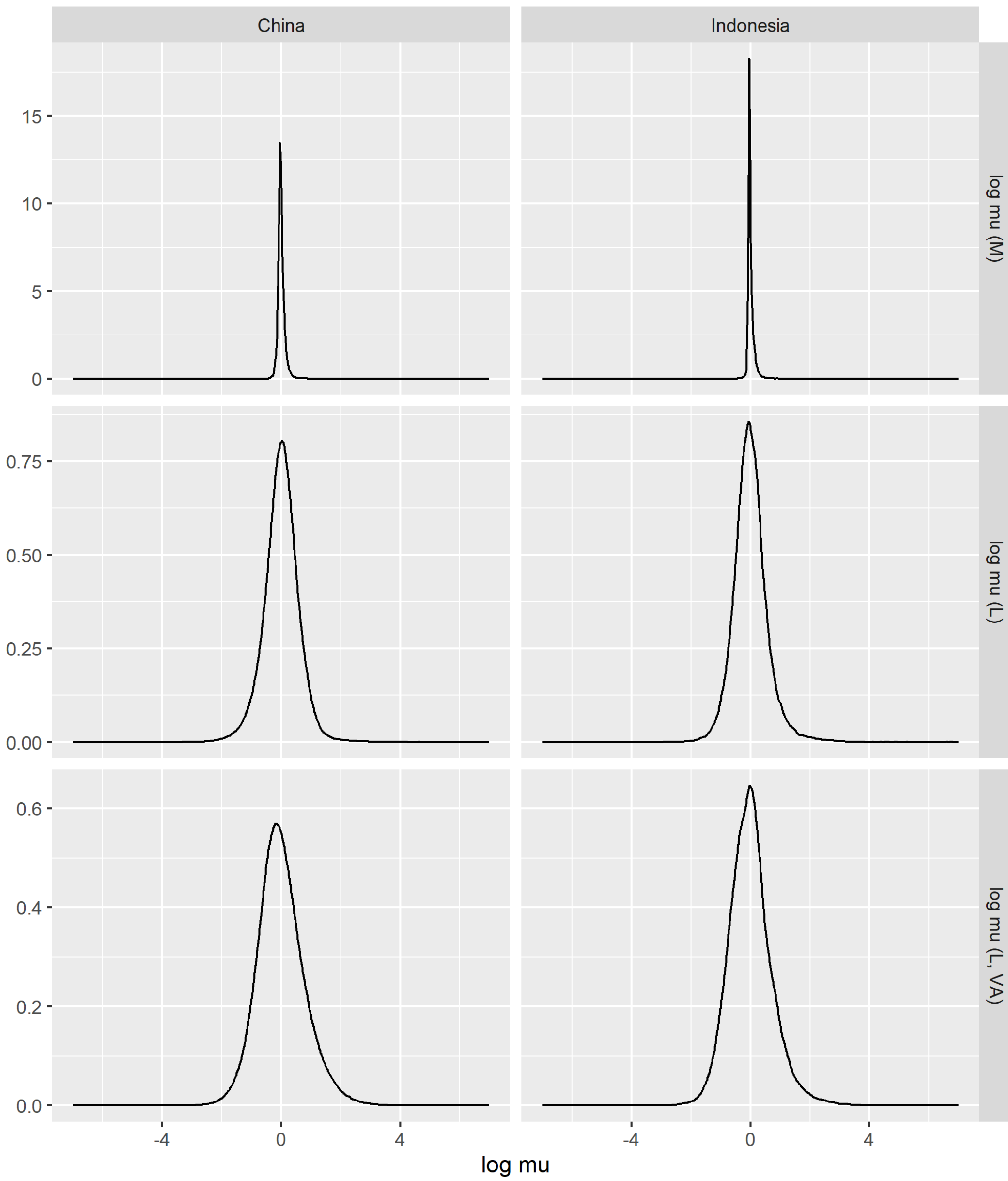

Figure 1: Markup Distributions

Notes: log mu (M) and log mu (L) denote the log markup estimates from labor's and intermediate inputs' share equations, respectively. log mu (L, VA) represents the log markups estimated by the method of De Loecker and Warzynski (2012), assuming the Cobb-Douglas value-added production function and using labor's elasticity and revenue share.

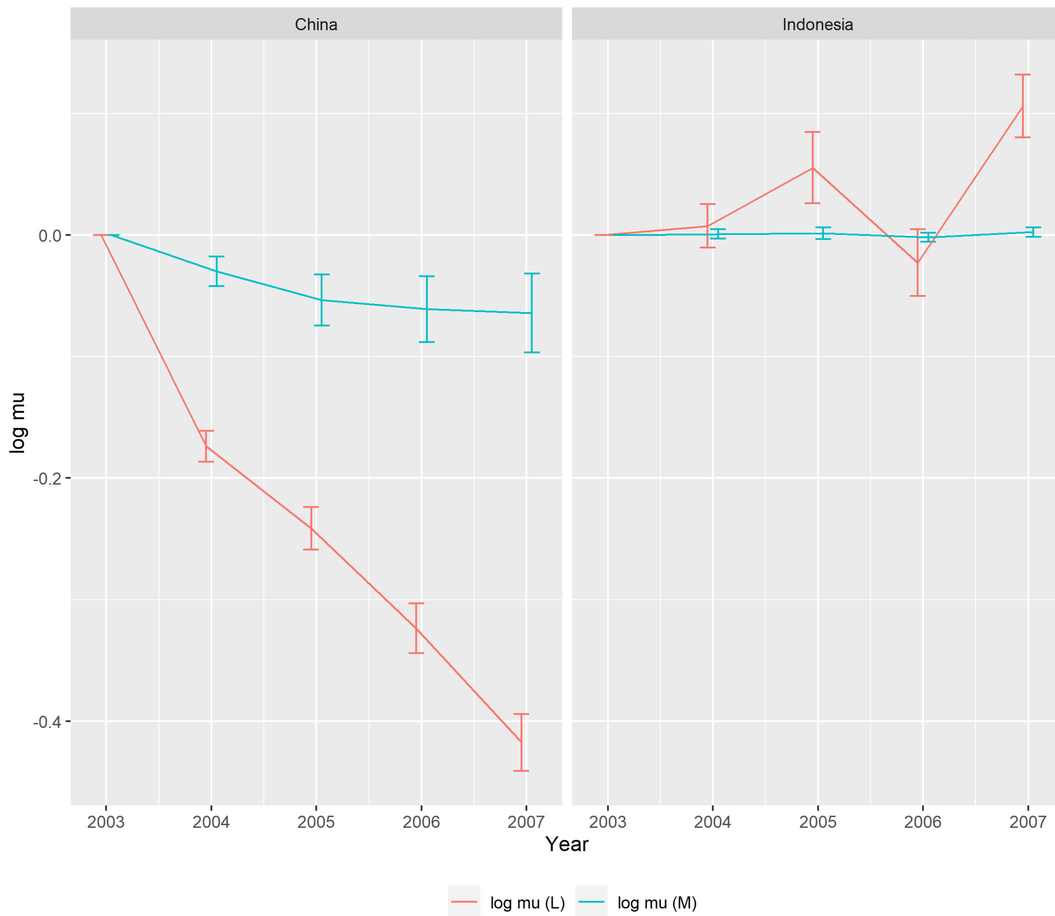

Figure 2: Markup Time Trends

Notes: The estimates of year-fixed effects (ϕ_t) of Equation (6) and their 95% confidence intervals (vertical bars). The confidence intervals are computed using standard errors clustered at the industry level.