University of Pittsburgh
Department of Economics
Dietrich School of Arts and Sciences

WORKING PAPER SERIES

20/003

Declining Market Competition in China

Daniel Berkowitz and Shuichiro Nishioka

April, 2020

University of Pittsburgh • Dietrich School of Arts and Sciences • Department of Economics
4700 Wesley W. Posvar Hall • 230 South Bouquet Street • Pittsburgh, PA 15260

Declining Market Competition in China

Daniel Berkowitz*and Shuichiro Nishioka†

April 17, 2020

Abstract

Using methods in Hall and Jorgenson (1967) and Barkai (2020), we find that pure profit shares rose 25.6 percentage points in China during a period when reforms were enacted that should have strengthened market competition. Increases in firms' markups accounts for roughly five-sixths of the increase of pure profit shares in manufacturing. Firms that raised markups operated primarily in industries where state owned enterprises (SOEs) were pervasive, net entry of firms was slow, and there was a strong reallocation of market shares to SOEs and a weak reallocation to competitive firms. While there was an overall decline in market competition, markets became more competitive in industries where SOEs had small market shares.

Keywords: Pure profit shares, labor's share, capital's share, markups, state owned enterprises, competition

JEL Classification: E25, O19, O52, P23, P31.

*Department of Economics, University of Pittsburgh, 4913 WW Posvar Hall Pittsburgh PA 15216, Tel: +1(412) 648-7072, Email: dmberk@pitt.edu

†John Chambers College of Business and Economics, West Virginia University, 1601 University Avenue Morgantown WV 26506-0625, Tel: +1(304) 293-7875, Email: shuichiro.nishioka@mail.wvu.edu

1 Introduction

Companies in which a national or subnational government holds a majority interest have a strong presence in emerging market economies including China, Brazil, Russia, Malaysia, India, and Indonesia.[1] These state owned enterprises (SOEs) can improve social welfare when they supply public goods and services that private firms tend to under provide such as electricity, water supplies, and financial services. And, because it can be difficult for private firms in emerging markets to obtain external finance, SOEs operating in activities that have substantial capital costs, for example, mineral extraction and road construction, can contribute to economic development.

The presence of SOEs, however, can reduce market competition for several reasons. First, SOEs that are less productive than private firms may receive concessions from the state including financial bailouts and soft-budget constraints (Lin and Tan, 1999; Kornai et al, 2003), access to cheap credit, and barriers to entry against more productive firms (see Song et al, 2011). These state concessions distort markets because they shift resources and market shares to less productive firms. And, resource may be misallocated, and markets may become less competitive when the state uses its SOEs to pursue political objectives such as over-staffing and investing in white elephant projects (Shleifer and Vishny, 1994).

Do SOEs operate as a drag on market competition? In particular, can unproductive SOEs that depend upon state concessions hold onto or even expand their market shares? Or, do the forces of competitive selection reallocate market shares from relatively unproductive SOEs to more productive private firms? China around the turn of the twenty-first century is an ideal setting for studying this issue for several reasons. First, China was enacting reforms that should have made markets more competitive: laws were enacted protecting the property rights of private businesses (Li et al, 2008); measures were taken to reduce internal product and labor mobility costs (Tombes and Zhu, 2019); and Chinese firms had to compete with more productive foreign firms after China joined the World Trade Organization (WTO) at the end of 2001. And, there is evidence indicating that domestic markets became competitive: in studies of manufacturing firms, Brandt et al (2012) document the massive entry of firms and impressive growth in firm-level productivity; and, Brandt et al (2017) and Yu and Lu (2015) show that firms' markups fell and became less dispersed following

[1] https://www.wisdomtree.com/blog/2014-12-04/emerging-markets-and-state-owned-enterprises; https://read.oecd-ilibrary.org/governance/the-size-and-sectoral-distribution-of-state-owned-enterprises_9789264280663-en#page16

China's accession to the WTO.

Second, during this period, China enacted reforms of "grasping the large and letting go of the small" that should have made the SOEs and domestic markets more competitive (see Hsieh and Song, 2015). Starting in the mid-1990s, unproductive SOEs that were burdens on local budgets were privatized and even liquidated. And, larger SOEs were consolidated and, put under less pressure to fulfill political objectives such as hiring excess labor, and, given more incentives to be more productive and profitable (Cooper et al, 2015). There is evidence that these reforms made SOEs and the markets in which they operated more competitive because the total factor productivity of the large SOEs that survived or newly entered during 1998-2007 was close to private firms (Hsieh and Song, 2015).

However, there is evidence suggesting there were major distortions in domestic markets associated with state interference and SOEs. Hsieh and Klenow (2009, pp.1419-1420) find evidence of massive resource misallocation in China's manufacturing sector, suggesting that the state issued capital subsidies and monopoly protections to select industries. Several studies document that provincial governments blocked local sales of non-local goods in order to protect their local SOEs (see Young, 2000; Bai et al, 2004; Bai and Liu, 2017; Barwick et al, 2020). Milhaupt and Zhang (2015, pp.679-680) suggest that the managers of SOEs had lots of cash for perks and empire building because the state collected no dividends from SOEs between 1994 and 2007,[2] even though SOEs (in particular those under direct jurisdiction of the central government) were highly profitable (see Kujis et al, 2005; Berkowitz et al 2017). Li et al (2015, section 2) argue that around the time China joined the WTO, SOEs began to monopolize upstream industries such as petroleum, natural gas, and electricity and, with protection of the state, the SOEs were able to maintain market power and charge high markups to firms in downstream industries.

Figure 1 provides an overview of market competition and illustrates the aggregate pure profit shares in manufacturing during 1998-2007. A firm's pure profit share is its value added net of payments to labor and capital costs divided by value added,[3] and the aggregate pure profit share is the sum of the product of each firm's pure profit share and its share of value added. Over a

[2] See Nicholas Borst, "SOE Dividends and Economic Rebalancing," (Peterson Institute for International Economy, May 11, 2012, http://www.piie.com/blogs/china/?p 1258).

[3] Except for the cost of capital, all variables required for calculating firm-level pure profit shares are reported in firms' balance sheet data. Later in this section, we describe how we can use Hall and Jorgenson's (1967) method to impute capital costs and Barkai's (2020) method for estimating pure profit shares.

period when aggregate revenues in manufacturing increased almost six-fold, aggregate pure profit shares increased a massive 25.6 percentage points,[4] and this can reflect market competition for two reasons. First, in the extreme case where all firms are charging higher markups because market competition weakens, firms enjoy higher pure profit shares, and aggregate pure profit shares increase through a *within-firm effect.* Second, in the polar opposite case where firms' markups are stable, but market shares are reallocated because there is competitive selection on firms that have high markups, aggregate profit shares increase through a *between-firm effect.* We provide a model of this relationship between firm-level markups, competitive selection and aggregate pure profits share in section 3.2 of the paper.

We find within-firm effects were about five times stronger than the between-firm effects, indicating that markets became less competitive. Firms in the chemical fertilizers versus textile goods industries provide an overview of our argument. The sales shares of SOEs in the chemical fertilizers and textile goods industries were ranked 13th (36.1-percent) and 107th (2.3-percent) out of the 136 3-digit CIC industries in 2007, respectively.[5] Consistent with the view that the state tends to protect its SOEs from competition, firms in the chemical fertilizers industry received concessions from the state including value added tax exemptions, subsidies on capital and intermediate goods, increases in tariff rates on imported final goods,[6] preferential loans, and debt forgiveness.[7] And, there was much less state intervention in textile goods. For example, prior to 1992, firms were heavily regulated and required to obtain permits for business commissions, expansions and distribution from the Department of Textile Industry (DTI). However, the DTI lost all of the authority by 2002 (Shen, 2008).

Figures 2 and 3 contain several proxies for market competition. As markets become more competitive, firm entry barriers fall, and there tends to be more net entry. Consistent with the view that competition should be stiffer in textiles, Panel A shows that net entry of firms grew by 97-

[4] In order to get a sense of the enormity of this trend, note that Barkai (2020) argues the 13.5 percentage points increase in pure profits shares that he calculates in the corporate non-financial sector in the United States over a thirty year period (1984-2014) is very large.

[5] The Chinese Industry Classification (CIC) system is similar to the International Standard Industrial Classification (ISIC) system. The classification of whether or not a firm is state owned enterprise (SOE) follows the definition in Hsieh and Song (2015, pp.301-302).

[6] The simple average of applied tariff rates across 4-digit sub-industries within the chemical fertilizers industry increased from 5.1-percent in 1998 to 11.1-percent in 2007. China used import tariff rate quotas to protect domestic producers.

[7] See the U.S. Trade Representative (USTR) NTE China, 2013, pp.5-9 and "An Assessment of China's Subsidies to Strategic and Heavyweight Industries," which was submitted to the U.S.-China Economic and Security Review Commission by Capital Trade Incorporated.

percent (from 1,466 to 3,869 firms) in textiles but only by 18.2-percent (from 1,640 to 1,967 firms) in chemical fertilizers.[8] As markets become more competitive, most firms tend to have smaller market shares, implying there is less market concentration. Panel B illustrates the Hirshman-Herfindahl index (HHI), where concentration falls as the HHI goes from one to zero. While textiles and chemical fertilizers initially have a similar HHI index, chemical fertilizers become more concentrated over the period.

Figure 3 illustrates trends in average and aggregate pure profit shares for survivor firms, where the latter is the sum of each firm's pure profit shares weighted by value added shares. Following China's accession to the WTO, nominal revenues in the manufacturing sector increased roughly six-fold.[9] Thus, a firm that had market power was in a good position to withhold output and increase its pure profits. Panel A shows that the aggregate pure profit share was only slightly larger and grew only slightly faster than the average pure profit share in chemical fertilizers. Thus, the aggregate pure profit share grew primarily through a within-firm effect, suggesting that firms gained market power. In contrast, Panel B shows that the average pure profit share in textile goods barely changed, whereas the aggregate pure profit share increased, most notably after 2005 when the United States, the European Union, and Canada eliminated quotas that they had imposed for decades on China's textiles and clothing (see Khandelwal et al, 2013, p.2174-75). Figure 3 Panel B is consistent with Khandelwal et al (2013) who find that the elimination of the quotas enabled more efficient firms to capture larger shares of the export market. And, the aggregate pure profit share increased through a between-firm effect.

In order to compute pure profit shares at the firm level, we adapt Barkai's (2020) industry level approach to firms and subtract each firm's labor and capital shares of value added from one. And, to compute capital shares, we use Hall and Jorgenson's (1967) ex-ante approach to impute capital costs from the opportunity costs of holding capital assets. While firm-level capital assets cannot be divided into distinct categories such as buildings versus equipment, we can construct firm-specific required rates of return on capital service using detailed firm-level data on debts and assets. Intuitively, a firm that relies heavily on financial institutions to acquire capital goods has a higher required return. However, a firm that finances its investments primarily from retained

[8] Total industry-level nominal sales grew 5.5-fold in textiles and 4-fold in chemical fertilizers.

[9] The six-fold nominal increase is close to the real growth because inflation during 1998-2007 was about 12.1-percent over the entire period, or roughly 1.15 percent per year.

earnings has a lower required return. We then calculate capital's share of value added in each firm using the constructed series of firm-level required capital returns and values of capital stock.

To determine whether market competition became stronger or weaker, we use a model that provides a firm-level foundations for aggregate pure profit shares and, highlights the importance of firms' markups. In the model, when a firm can increase its markups, it also increases its pure profit shares, leading to an increase in aggregate pure profit share through a within-firm effect. This prediction is consistent with the argument in De Loecker et al (2020) that a positive association between increases in firm-markups and aggregate profitability indicates a decline in market competition.[10] And, when markets become more competitive say, because China joined the WTO, then there is a reallocation of market shares to high markup firms, leading to an increase in aggregate pure profit shares through a between-firm effect. We find that the within-firm effect dominates: the 8.6 percent point increase in average markups account for roughly five-sixths of the 25.6-percentage point increase in pure profit shares. And, these within effects were concentrated in industries where SOEs were pervasive and had several characteristics suggestive of weak competition: net entry of firms was slow, and there was a strong reallocation of market shares to state owned firms and a weak reallocation to high markup firms.

Our paper contributes to several literatures. First, our findings that firm-level markups grew and, in some cases, do not strongly converge during 1998-2007 are different from Brandt et al (2017) and Lu and Yu (2015) who show that after China's entry to the WTO firm-level markups declined and sharply converged. Our results differ because of the timing of the analysis. Brandt et al (2017) and Lu and Yu (2015) studied how firms immediately adjusted to tariff cuts following China's accession to the WTO; and, thus, estimate markups assuming that only intermediates inputs are variable. This paper studies how firms operate during a ten year period in which there was a robust reallocation of labor and capital within SOEs that were being privatized and restructured and, labor markets became flexible (Feng et al, 2017). Thus, we take a longer term macroeconomic view and, following the approach in De Loecker et al (2020), we allow firm-level production functions to vary over time when we estimate markups. Our results are robust even if we assume that only intermediate inputs and labor are flexible inputs, and capital is a fixed input.

[10] An increase in average firm markups does necessarily indicate markets are not competitive. Notably, De Loecker et al (2020) argue that firms may increase their markups without earning large profits because they are recovering large operating costs. The model in this paper is based on Azmat et al (2012) and Autor et al (2020) who derive how a firm's optimal labor share is a function of its markup and other fundamentals.

Our results complement Bai et al (2019) who document how market were not competitive because the state made special deals with selected firms. Our paper is also related to Piketty et al (2019) who document the growth of income and wealth inequality in China during 1978-2015, which contains the period of our study. They show that the privatization of state assets such as housing is an important driver of this trend; and, we show that the partial privatization of SOEs set the stage for a pervasive state ownership underlying the rise of profit's share and the decline in labor's and capital share in manufacturing.

The next section describes the data and profit shares in the Chinese manufacturing sector. Section 3 contains the theory and empirical results; and section 4 concludes.

2 Pure Profit Shares

Capital Costs

To compute pure profit shares at the firm level similar to Barkai's (2020) application at the industry level, capital costs must be imputed at the firm level. However, as Syverson (2011) notes "obtaining capital costs is usually the practical sticking point." Thus, we follow Hall and Jorgenson (1967) and estimate the firm-level required rate of return on capital services using the opportunity costs of holding capital assets. This approach has applied mainly in macroeconomic studies including Caballero and Lyons (1992), Karabarbounis and Neiman (2018), and Barkai (2020).[11]

The method is applied to the Chinese firm-level data in the following manner. First, a real capital stock series is constructed using the perpetual inventory method as described in Brandt et al (2012). We have the book value of firms' fixed capital stock at the original purchase prices. Since these book values are the sum of nominal values for different years, they cannot be used directly. Thus, we use the first difference of nominal value of fixed capital stock ($BK_{it} - BK_{i,t-1}$) as a proxy for nominal investment and construct a real capital stock series using the following formula:

$$K_{it} = (1-\delta)K_{i,t-1} + (BK_{it} - BK_{i,t-1})/P_t \tag{1}$$

where BK_{it} is the book value of the capital stock for firm i in year t; and P_t is the investment deflator. To construct the real capital stock series, we then need to know the initial nominal value

[11]See also Timmer et al (2007) for the explanations for ex-ante versus ex-post approaches.

of the capital stock, which is projected from the perpetual inventory method:

$$BK_{i,t_0} = BK_{i,t_1}/(1+g)^{t_1-t_0}$$

where BK_{i,t_1} is the book value of capital stock when firm i first appears in the data set in year t_1, and g is the average growth rate of capital, calculated using province-industry level capital growth rate between the earliest available survey (1995) and the first year that the firm is included in the data set.[12] For firms established later than 1998, the initial book value of capital stock is taken directly from the dataset.

Using information on the age of firm i, we can obtain the projected book value of the capital stock for the initial year t_0 (BK_{i,t_0}), which can be thought of the initial nominal value of capital. In this case, the real capital stock is $K_{i,t_0} = BK_{i,t_0}/P_{t_0}$. We could also compute the real capital stock in each year, assuming an annual depreciation rate as 0.09 and using the perpetual inventory method as in equation (1). As a robustness check, we also use an alternative depreciation rate of 0.05 used in Hsieh and Klenow (2009) and find that our results are qualitatively similar.

To calculate a firm's opportunity cost of holding capital assets, we follow Jorgenson and Griliches (1967) and compute its required rate of return on capital services, r_t:

$$r_t K_{it} = P_t K_{it}(i^S + \delta - \Delta P/P) \tag{2}$$

where i^S is the country-level risk free interest rate (i.e., we use the saving interest rate, which is 2.5-percent on average over the period), δ is the depreciation rate as discussed above, and $\Delta P/P$ is the rate of appreciation for capital goods (i.e., we use the investment goods deflator, which is 3.3-percent on average over the period). Thus, the opportunity cost, $r_t K_{it}$, equals the interest rate that could be collected when the capital stock is traded in for a risk free asset, $P_t K_{it} i^S$, plus the avoided net depreciation in assets, $P_t K_{it}(\delta - \Delta P/P)$, which equals the current value of the capital stock time its depreciation net of appreciation.

To compute the equation above, we would ideally have data on disaggregated capital assets such as buildings and machines as in Barkai's (2020) application to the U.S. industry-level data.

[12] To be more concrete, we use 1995 industrial census and calculate the province-sector level growth rate for the book value of capital. Note that Brandt et al (2012) use the province-sector level aggregate capital stock growth, which ignores entry and exit. We instead use the province-sector level average capital stock growth.

However, this data is not available for Chinese firms. Thus, we apply this equation for each firm's real aggregate capital stock, $P_t K_{it}$. Setting the savings interest rate to 2.5-percent, the depreciation rate to 9-percent, and the appreciation rate to 3.3-percent, then $i^S + \delta - \Delta P/P$ equals 8.2-percent. This estimate is similar to Hsieh and Klenow (2009) who use 10-percent across all firms in China's manufacturing.

Next, we follow Hall and Jorgenson (1967) and compute an alternative measure for capital costs that accounts for firm-level debt and equity financing and the business income tax. In particular, this measure is implementable because we have firm-level debt-equity ratios, which generate firm-specific required rates of capital returns:

$$r_{it} K_{it} = P_t K_{it} \left(i_{it} + \delta - \Delta P/P \right) \frac{1 - z_{it}}{1 - \tau} \tag{3}$$

where the corporate tax rate is τ, which is 33.3-percent over the sample period, the weighted average cost of capital is $i_{it} = b_{it} i^L + (1 - \tau)(1 - b_{it}) i^S$ where b_{it} is the debt (liabilities) to asset (total assets) ratio at the firm level, and i^L is the loan interest rate (around 5.9-percent on average over the period), and the present value of depreciation deductions on investment is $z_{it} = \delta\tau / (i_{it} + \delta)$.

Figure 4 compares the required return to capital services (r_{it}) computed from Jorgenson and Griliches (1967), Hall and Jorgenson (1967), which is our baseline measure, and Hsieh and Klenow (2009). We find that the required rates of returns are higher when we use Hall and Jorgenson in equation (3) than when we use Jorgenson and Grilliches in equation (2); and the estimates using Hsieh and Klenow's (2009) assumptions are in the middle.

2.1 Pure Profit Shares and SOEs

We use the data from the Chinese Annual Surveys of Industrial Production (ASIP), which covers all state owned enterprises (SOEs) and private firms with total annual sales exceeding 5 million RMB per year or roughly 612,000 US dollars. A firm that produces good i at time t in industry j uses a production function that converts labor (L_{it}), capital (K_{it}), and intermediate inputs (M_{it}) into real output (Q_{it}). The corresponding input prices, wages (w_{it}), rental rates (r_{it}), and intermediate prices (p_{it}), are strictly positive, exogenous for firms, and firm-specific.

Because a firm's value added (VA_{it}) is its revenues ($R_{it} = P_{it} Q_{it}$) minus spending on intermediate inputs ($p_{it} M_{it}$), then a firm's value added is the sum of its pure profits (π_{it}), labor compensation ($w_{it}L_{it}$), and capital costs ($r_{it}K_{it}$). A firm's labor and capital shares are computed as $s_{it}^L = w_{it}L_{it}/VA_{it}$ and $s_{it}^K = r_{it}K_{it}/VA_{it}$, respectively; and, its pure profit share of gross value equals one minus labor share and capital shares:

$$s_{it} = \frac{\pi_{it}}{VA_{it}} = 1 - (s_{it}^L + s_{it}^K). \tag{4}$$

Throughout the paper, we show that the degree of market competition differs substantially across industries, depending on the pervasiveness of the SOEs. The classification of whether or not a firm is an SOE follows the definition in Hsieh and Song (2015, pp.301-302): a firm is state-owned when the share of its paid-in-capital "directly held by the state" is greater than or equal to 50-percent; or, the state (and not a collective, foreigner, or private person) is the controlling shareholder. The following procedure is used to split the sample of 136 industries into state quartiles. First, the state ownership share in each industry equals the sum of SOEs' revenues divided by its total revenues in 2007. Then, the industry-level state ownership share is sorted from the highest to the lowest. Finally, the 34 industries in the 75th or above percentile are placed in the top quartile; they are followed by the 34 industries in the second (50th-75th percentiles), the 34 industries in the third (25th-50th percentiles), and the 34 industries in the bottom (25th percentile or below) quartiles.

Table 1 reports the summary statistics that compare pure profit shares from equation (4) versus accounting profit shares.[13] The table shows that pure profit shares were higher than accounting profit shares. Aggregate pure profit share from all firms was 64.3-percent in 2007, which is higher than aggregate accounting profit share by 40.2 percentage points. This is because accounting profits deduct taxes, financial losses or gains, executive compensations, investments, some other unobserved benefits paid to workers, and one-time large expenses for capital goods and intermediate goods, while pure profits do not. The table also shows that pure profit shares grew faster than accounting profit shares. Aggregate accounting profit shares increased 13.1 percentage points for all firms, which is almost half the 25.6 percentage point growth rate in aggregate pure profit share. The rise in pure profit shares concentrated on the industries where SOEs were pervasive. Columns (3) and (6) shows that the difference between aggregate accounting and pure profit share is most pronounced in the top quartile where SOEs were most pervasive, and almost the same in the bottom

[13] For example, see Brooks et al (2019) who use accounting profits to derive firm-level markups.

quartile where SOEs were least pervasive.

Table 2 reports summary statistics for profit, labor, and capital shares of gross value added by SOE quartiles. During the sample period, pure profit shares increased by 36.8 percentage points in the top quartile for SOEs, and, then declined to 21.4, 20.2, and 9.3 percentage point increases in the second, third, and bottom quartiles, respectively. The rise of pure profit shares suppressed both labor's and capital's shares in all quartiles. For example, column (6) shows that labor shares declined by 14.6 percentage points in the top quartile, and, then declined to 9.2, 7.2, and 1 percentage point declines in the second, third, and bottom quartiles, respectively.[14,15]

2.2 Between and Within Analysis

In the introduction, chemical fertilizers and textile goods industries were examples of how the sharp increase in the aggregate pure profit share can reflect two different forms of market competition: (1) in the chemical fertilizers industry, there are within-firm effects where firms on average increase their pure profit shares; and (2) in the textile goods industry, there are between-firm effects where there was selection on firms with the highest markups or productivity (Khandelwal et al, 2013).

In order to generalize these examples, we conduct a standard between and within decomposition analysis for the sample of 34,571 survivor firms in the manufacturing sector. In subsequent sections, we show that firms that had higher markups had higher pure profit shares. Then, if market shares are reallocated to firms that have the highest markups, between-firm effects should explain most of the increase in aggregate pure profit shares. However, if competition softens, and firms can charge higher markups, then within-firm effects should explain the increase in pure profit shares. Thus,

[14] Our measure of labor's share is lower than the comparable figure from China's national accounts. This is because our labor compensation measure includes wage and unemployment insurance while labor compensation in the national accounts include wages and a broader set of benefits paid to labor. However, the trends in the labor shares are almost identical, suggesting that the omission of some types of benefits do not distort the results in the paper. In our empirical work, we do not follow the approach in Hsieh and Klenow (2009) and Brandt et al (2012) who inflate wage payments across all firms at the same rate for each year so that the aggregated firm-level labor share values are consistent with the values from the national accounts. Our main conclusions do not change even if we follow their approach.

[15] Our data excludes private manufacturing firms with sales less than 5 million RMB per year. Gollin (2002) notes that in the system of national accounts the income of small firms in which the proprietors are self-employed is generally treated as capital income. Gollin (2002) then finds that labor shares become more stable once the income of self-employed proprietors is treated as wage income. In China the income of self-employed proprietors is classified as labor income during 1997-2003 and then as capital income since 2004. However, this is not a problem for our analysis because there are no self-employed proprietors in our sample.

we use the following equation:

$$\triangle s_s \equiv \sum_{i \in s} \triangle \omega_i \bar{s}_i + \sum_{i \in s} \triangle s_i \bar{\omega}_i \tag{5}$$

where $\triangle s_s$ is the change in the aggregate profit share from the sample of survivor firms.

The first term on the right-hand side of equation (5) is the between-firm effect, $\sum_{i \in s} \triangle \omega_i \bar{s}_i$, where $\triangle \omega_i = \omega_{i,07} - \omega_{i,98}$ is the change in a firm's value added share in the manufacturing sector, and $\bar{s}_i = 0.5(s_{i,98} + s_{i,07})$ denotes a firm's average profit share during 1998-2007; and $\triangle s_i \bar{\omega}_i$ in the second term is the within-firm effect, where $\triangle s_i = s_{i,07} - s_{i,98}$ is the change in profit shares within a firm, and $\bar{\omega}_i = 0.5(\omega_{i,98} + \omega_{i,07})$ denotes a firm's average value added share within the manufacturing sector.

Columns (1)-(3) in Table 3 report the between, within, and total effects for the survivor firms. The first panel of Table 3 applies equation (5) to all survivor firms, and shows that the within-firm effects dominate between-firm effects and account 21.2 percentage points or, roughly 86-percent (five-sixths) of the overall increase in pure profit shares. Consistent with our view that firms can increase pure profit shares in the top state quartile industries such as chemical fertilizers where SOEs are pervasive, the within-firm effects account for 31.2 percentage points of the 36 percentage point increase in pure profit share in the top quartile. However, for firms in the bottom state quartile industries where the presence of SOEs is negligible, the between-firm effect accounts for 6.4 percentage points, or about 84-percent of the 7.6 percentage point increase in pure profit share.

During the sample period of 1998-2007, there was substantial net entry because the 118,018 and 268,452 firms in operation in 1998 and 2007 period greatly exceed the 34,571 survivors that operated in 1998 and 2007. In order to understand the impacts of firm exit and entry on pure profit shares, we use the following equation from Melitz and Polanec (2015):

$$\triangle s_{-s} \equiv \omega_{x,98}(s_{s,98} - s_{x,98}) + \omega_{e,07}(s_{e,07} - s_{s,07}). \tag{6}$$

In equation (6), $\triangle s_{-s}$ is the change in the aggregate profit share between entrants and exiters, $\omega_{x,98}$ ($\omega_{e,07}$) is the value added share of exiters in 1998 (entrants in 2007) in the full sample, and $s_{x,98}$, $s_{e,07}$, $s_{s,98}$, and $s_{s,07}$ are the aggregate pure profit shares for exiters in 1998, entrants in 2007, survivors in 1998, and survivors in 2007, respectively. Thus, the first term on the right hand side is the contribution of exit and is reported in column (4) in Table 3: it is the difference between the weighted average of survivors' profit share ($s_{s,98}$) and exited firms' profit share ($s_{x,98}$), weighted by the value added share of exiters in 1998 ($\omega_{x,98}$). The second term on the right hand is the contribution of entry and is reported in column (5): it is the difference in the aggregate averages between entrants' profit share ($s_{e,07}$) and survivors' profit share ($s_{s,07}$), weighted by the value added share of entrants ($\omega_{e,07}$).

The results reported in columns (4) and (5) in Table 3 indicate that exit and entry had a negligible impact. A potential reason for this is the way in which SOEs were restructured (see Hsieh and Song, 2015). The strategy of "grasping" the large SOEs and "letting go" of the small SOEs meant that exiting SOEs accounted for a relatively small share of value added. In addition, private sector entrants were relatively small and concentrated in competitive markets where state ownership was not pervasive.

3 Competition and Profit Shares

3.1 Markups

We derive markups in the next subsection, and then describe our model in subsection 3.2. Consistent with our model, the baseline markups are estimated under the assumption that labor, capital and intermediate inputs are all variable. However, we estimate markups under different assumptions about which inputs are variable and show how they compare with our baseline estimates.[16]

Short and Medium Run Markups

We first follow the approach in De Loecker and Warzynski (2012), De Loecker et al (2016), and De Loecker et al (2020), and derive markups from the following cost minimization problem for each firm i:

$$\mathcal{L} = p_{it}M_{it} + w_{it}L_{it} + r_{it}K_{it} + \lambda_{it}[Q_{it} - \Omega_{it}F(M_{it}, L_{it}, K_{it})]$$

where $Q_{it} = \Omega_{it}F(M_{it}, L_{it}, K_{it})$ is a general form of production functions, and the Lagrange multiplier (λ_{it}) is the firm's marginal cost for the output target, Q_{it}.

[16] See Basu (2019) for review of alternative methods for estimating markups.

In order to estimate markups, Brandt et al (2017) use an industry-level Cobb-Douglas production function that places no restrictions on returns to scale:[17]

$$Q_{it} = \Omega_{it} M_{it}^{\alpha^M} L_{it}^{\alpha^L} K_{it}^{\alpha^K}. \tag{7}$$

In this setup, the output elasticities (α^M, α^L, and α^K) are the same for each firm in an industry[18] and are constant over the sample period. Firms are heterogenous according to their productivity, denoted Ω_{it}, and, this shapes their entry and exit. And, the firm's only variable input is intermediates. Using the first order condition for intermediate inputs,[19] and imposing $Q_{it} = \Omega_{it} F(M_{it}, L_{it}, K_{it})$, where a firm's labor and capital are fixed, the cost-minimizing values of M_{it} and λ_{it}^s are obtained. It is assumed that a firm has market power and can find the price P_{it} at which it can sell Q_{it}. Then, the *short run* markup ($\mu_{it}^s = P_{it}/\lambda_{it}^s$) is the estimated industry-level output elasticity of intermediate inputs, $\hat{\alpha}^M$, divided by the firm's payments to intermediates as a share of its revenues:

$$\mu_{it}^s = \hat{\alpha}^M \frac{P_{it} Q_{it}}{p_{it} M_{it}}. \tag{8}$$

To estimate short-run markups, the data for revenues and payments for intermediate inputs are taken from firm-level balance sheet data; and, the estimated output elasticities of intermediate inputs come from production function estimates.

Next, we assume that both labor and intermediate inputs are variable inputs, and a firm produces a medium run target level of output (Q_{it}). Using the first order conditions[20] and imposing $Q_{it} = \Omega_{it} F(M_{it}, L_{it}, K_{it})$, the cost-minimizing values of M_{it}, L_{it}, and λ_{it}^m for reaching the output target are derived. Then, it follows that a firm's *medium run* markup ($\mu_{it}^m = P_{it}/\lambda_{it}^m$) is the sum of its estimated output elasticities of intermediate inputs and labor divided by its payments to materials and labor as a share of revenues:

$$\mu_{it}^m = \left(\hat{\alpha}^M + \hat{\alpha}^L\right) \frac{P_{it} Q_{it}}{p_{it} M_{it} + w_{it} L_{it}}. \tag{9}$$

[17] Appendix I reports the estimation results of production functions from the method similar to De Loecker et al (2016). See Table A3.

[18] Notation denoting an industry is suppressed.

[19] $p_{it} = \lambda_{it}^s \alpha^M \frac{Q_{it}}{M_{it}}$.

[20] $p_{it} = \lambda_{it}^m \alpha^M \frac{Q_{it}}{M_{it}}$ and $w_{it} = \lambda_{it}^m \alpha^L \frac{Q_{it}}{L_{it}}$.

In this setup, one single output elasticity of labor plus intermediate inputs ($\alpha^M + \alpha^L$), and the output elasticity of capital (α^K) are the same for each firm in an industry and constant over the sample period.[21] This approach allows for the output elasticity of labor and that of intermediate inputs to vary over time; however, we do not observe these changes. The additional data necessary to derive medium run markups is labor compensation, which comes directly from firm-level balance sheet data.

Baseline Long Run Markups

In our model, firms choose their optimal pure profit shares, which equals one minus their optimal capital and labor shares. Thus, to be consistent with this model, firms should optimize over their intermediates, labor, and capital. Olley and Pakes (1995) and Ackerberg et al (2015) argue that the adjustment time to hire labor and to install capital takes longer than purchasing and using intermediate inputs. Studies following this approach generally assume that it takes more than a year to adjust capital, less than a year to adjust labor, and firms can optimally choose intermediate inputs at any point in time. Thus, we assume that firms optimize all of their inputs as of 1998 and 2007, given their time-specific input prices and technologies.

In this setup, we can allow for each firm to have a firm-specific Cobb-Douglas production function that can change over time:

$$Q_{it} = \Omega_{it} M_{it}^{\alpha_{it}^M} L_{it}^{\alpha_{it}^L} K_{it}^{\alpha_{it}^K} \tag{10}$$

where the subscripts i and t denote a firm and a year (either 1998 or 2007), and each firm has an industry-specific scale elasticity of output, $\alpha_{it}^M + \alpha_{it}^L + \alpha_{it}^K = \rho_t$, that can vary during the sample period.

In this case, a firm chooses intermediates, labor, and capital, in order to minimize its cost of attaining the long run target output level (Q_{it}). The three first order condition are:

$$p_{it} = \lambda_{it}\alpha_{it}^M \frac{Q_{it}}{M_{it}}, w_{it} = \lambda_{it}\alpha_{it}^L \frac{Q_{it}}{L_{it}}, \text{ and } w_{it} = \lambda_{it}\alpha_{it}^K \frac{Q_{it}}{K_{it}}, \tag{11}$$

implying that the long run markup for any firm equals its industry's scale elasticity times its sales

[21] See De Loecker et al (2020).

divided its costs:[22]

$$\mu_{it} = \frac{\rho_t P_{it} Q_{it}}{p_{it} M_{it} + w_{it} L_{it} + r_{it} K_{it}}. \tag{12}$$

This expression for long run markups follows the approach in Diewert and Fox (2008) and is used as a robustness check in De Loecker et al (2020). To estimate this equation, we use firm-level balance sheet data for revenues, payments to labor and intermediates, imputed capital costs, and estimated scale elasticities.[23]

Table 4 reports summary statistics for short run, medium run, and long run markups. Several patterns emerge. First, while the weighted and simple means of medium and long run markups increased from 1998 to 2007, the short run weighted and simple means are constant. In our analysis, we use long run markups as our baseline measure because they allow production technologies (output elasticities of input) to vary over time, which, as emphasized by De Loecker et al (2020), is essential for studying the long run implications of markups for macroeconomic dynamics. Second, consistent with Lu and Yu (2015), the standard deviation of short run markups across firms declined substantially by 35.8-percent. However, the magnitudes of the decline in standard deviations is much smaller using the other markup measures. Finally, in appendix Table A4, we show that these markup measures are strongly correlated to each other, and long run markups are more strongly correlated with medium run markups and less strongly correlated with short run markups. Thus, in what follows, we use long run markups because they are consistent with our theory and show that our results are robust when we use medium run markups. We do not use short-run markups in subsequent analysis because, as previously discussed, they are relevant to studies of the immediate impacts including tariff reductions on markups but, not a longer run study.

3.2 Microfoundations of Aggregate Pure Profit Shares

To derive aggregate pure profit shares at any point in time, we first derive each firm's pure profit share and its value added and then derive the value added weighted sum over all firms in the man-

[22] When all the inputs are optimized, the first order conditions also imply, for example for intermediate inputs, that $\alpha_{it}^M = \rho_t p_{it} M_{it}/(p_{it} M_{it} + w_{it} L_{it} + r_{it} K_{it})$. In other words, we can approximate firm-specific and time-variant output elasticities from corresponding cost shares, $p_{it} M_{it}/(p_{it} M_{it} + w_{it} L_{it} + r_{it} K_{it})$, and industry- and time-specific scale elasticities, ρ_t.

[23] Following De Loecker et al (2020), the log of firm output is regressed on the sum of the log of each factor input times its cost share, and the estimated regressor is the scale elasticity for an industry in a period.

ufacturing sector. Thus, we first use the first order conditions for all inputs and derive expressions for labor's and capital's shares, s_{it}^L and s_{it}^K:[24]

$$s_{it}^L = \frac{\alpha_{it}^L}{\mu_{it} - \alpha_{it}^M} \text{ and } s_{it}^K = \frac{\alpha_{it}^K}{\mu_{it} - \alpha_{it}^M}. \tag{13}$$

And, pure profit shares are one minus labor's share and capital's share:

$$s_{it} = \frac{\mu_{it} - \rho_t}{\mu_{it} - \alpha_{it}^M} \tag{14}$$

where $\rho_t > \alpha_{it}^M$ because $\alpha_{it}^M + \alpha_{it}^L + \alpha_{it}^K = \rho_t$.

Equations (13) and (14) predict that when a firm increases its markups, it reduces its labor and capitals shares, and, thus, increases its pure profit shares. Equation (14) captures within-firm effects of markups on aggregate pure profit shares; and it also shows that, conditional on markups, pure profit shares are increasing in a firm's output elasticity of intermediate inputs and decreasing in its scale elasticity.

The predicted pure profit shares in equation (14) closely match the estimated aggregate pure profit shares in 1998 and 2007 reported in Table 1. Using data in Table 4 and Table A5, the weighted average firm-level markup, the scale elasticity, and the output elasticity of intermediate inputs in 1998 was 1.168, 1.066, and 0.898, respectively; and the predicted aggregate pure profit share in 1998 was 0.379, which is slightly lower than our estimate of the aggregate share, 0.387. Similarly, the predicted average pure profit share in 2007 is 0.652, which is mildly higher than our estimate, 0.643.

The substantial changes of 25.6 and 27.3 percentage points in the estimated and predicted aggregate pure profit shares stem from increases in markups and intensiveness of intermediate inputs in production. Between 1998 and 2007, the aggregate markups increased by 10.3 percentage points (from 1.168 to 1.271), and the aggregate output elasticities of intermediate inputs increased by 6.9 percentage points (from 0.898 to 0.967);[25] however, the average scale elasticity was relatively stable and increased by 1.2 percentage points (from 1.066 to 1.078). Figures 5 and 6 show that the

[24] The labor share equation is a familiar formula in Azmat et al (2012) and Karabarbounis and Neiman (2014) that captures a within-firm effect and identifies firm's labor share as a function of its markups and output elasticities of labor.

[25] Brandt et al (2012) and Yu and Lu (2015) have detailed production function estimates for the manufacturing and also show that production functions in the manufacturing sector are highly intensive in intermediate inputs.

changes in markups and output elasticities of intermediate inputs grew most rapidly in the quartile where SOEs were most pervasive, which is consistent with the observation that the aggregate pure profit share grew most rapidly in the same quartile (see Table 1).

In order to capture the between-firm effects of markups on aggregate pure profit shares, we use the first order conditions and derive an expression for a firm's value added:

$$VA_{it} \equiv (1 - \alpha_{it}^M/\mu_{it}) R_t ms_{it}(\mu_{it}). \tag{15}$$

The first term, $(1 - \alpha_{it}^M/\mu_{it} = VA_{it}/R_{it})$ is a firm's value added share of revenue and, does not change over time because α_{it}^M and μ_{it} grow at roughly the similar rate for firms.[26] And, the second term, $(R_t = \sum_i R_{it})$, which is the size of the firm's industry is not firm-specific and, thus, has no firm-between effects. The third term explains the positive association between a firm's value added and market share. Moreover, a firm's market share should increase as its markups increases, which captures the reallocation of market shares to the highest markup firms. This property holds in the standard Cournot oligopoly model with heterogeneous marginal costs[27] as well as monopolistic competition and product differentiation models in Atkeson and Burstein (2008) and Feenstra and Weinstein (2017). We will test for this association in later in the paper.

3.3 Components of Industry Markups

To understand why markups grew more rapidly in the industries where SOEs were pervasive, we decompose the growth in markups at the industry level. In particular, using all the first order conditions, we can derive the following form of marginal cost (λ_t) that corresponds to industry-level production function in equation (10) as a function of the average of input prices (p_t, w_t, and r_t), weighted by their cost shares, scale effects, and productivity (Ω_t):

$$\lambda_t = \frac{1}{\Omega_t} Q_t^{1/\rho_t - 1} [p_t^{cs_t^M} w_t^{cs_t^L} r_t^{cs_t^K}] = \frac{c_t}{\Omega_t} Q_t^{1/\rho_t - 1} \tag{16}$$

where cs_t^M, cs_t^L, and cs_t^K are cost shares of corresponding inputs, which are the corresponding output elasticities of each factor divided by the scale elasticity of output, c_t denotes unit costs, and

[26] At the aggregate level, markups grew 8.6 percentage points, and the output elasticity of intermediate inputs grew by 6.9 percentage points. Thus, the change in the first term on average was less than 2 percentage points.

[27] Our theoretical narrative for this model is available upon request.

$Q_t^{1/\rho_t - 1}$captures the effect of scale on marginal costs.

We also derive productivities as residuals from the industry-level production function in equation (10),[28] and use the following equation for markups:

$$\mu_t = \frac{P_t \Omega_t}{c_t} Q_t^{1-1/\rho_t} \tag{17}$$

where μ_t equals the scale elasticity times revenues divided by total costs at the industry level.

Using the detailed 4-digit industry-level output and input prices from Brandt et al (2017) as well as imputed cost shares, we can use equation (17) and decompose the growth in markups into the growth in output prices, productivities, scale, and weighted input costs:

$$\Delta \ln(\mu_t) = \Delta \ln(P_t) + \Delta \ln(\Omega_t) + \Delta(1 - 1/\rho_t) \ln(Q_t) - \Delta \ln(c_t). \tag{18}$$

Table 5 reports the results of the decomposition. Column (1) shows that markups grew the fastest in the top quartile where SOEs were most pervasive, and this difference between the quartile where SOEs were most pervasive and the other three quartiles is statistically significant. In columns (2) through (5), the growth in markups for the different quartiles is decomposed into the growth of the output price, productivity, scale effects, and weighted input cost, respectively. Although standard deviations across industries are often large, and not all differences are statistically significant, cross-quartile differences in nominal prices are systematic. Output prices increased most rapidly in the top quartile, and input prices grew much slower in the top three quartiles than in the bottom quartile. As a result, markups grew most rapidly in top quartile where SOEs were most pervasive.

Columns (6)-(11) decomposes the components of the growth of the weighted input prices into the growth in intermediate prices, wages, and required returns to capital services as well as the changes in cost shares of corresponding inputs. It is notable that wages grew most rapidly in the top quartile, and intermediate input prices grew slowly in the top three quartiles. In addition, the cost share of intermediate inputs increased the most in the top state quartile and increased the least in the bottom quartile. It is a reasonable speculation that firms in the upper quartiles may have found that it was relatively easy to reduce costs of intermediate inputs because they had access to

[28]
$$\ln(\Omega_t) = \ln(Q_t) - \alpha_t^M \ln(M_t) - \alpha_t^L \ln(L_t) - \alpha_t^K \ln(K_t).$$

cheaper inputs due to tariff cuts after China's entry to the WTO.

3.4 Competitive Selection

In this section, we check for the importance of competitive selection and estimate the association between market shares and markups. We define a market in a year as a 136 3-digit CIC industry or a 136 3-digit CIC industry in each of four supra regions (North, East, South, and West). A firm's market share is its sales divided by overall sales in its market, where sales include both domestic and foreign transactions. Table 6 reports several summary statistics. In 1998, there were 35,092 SOEs and 82,992 private (including collective and foreign) firms; and, by 2007, the number of SOEs was cut by more than two-thirds, to 11,561, while the number of private firms more than tripled, to 256,891. However, the market share of the average SOE became larger than the average private firm. In 1998, the average market share of SOEs was 0.55-percent and marginally higher than 0.43-percent for private firms. However, SOE shares increased to 0.75-percent as the larger SOEs consolidated; and private market shares decreased to 0.18-percent. This increase in market shares of SOEs was most pronounced in the top quartile and went form 0.67-percent in 1998 to 1.1-percent in 2007.

To examine empirical associations between market shares and markups, we regress a firm's market share on its markups. If there is competitive selection, consistent with standard imperfect competition models including the Cournot oligopoly model with heterogeneous marginal costs and product differentiation models (e.g., Atkeson and Burstein, 2008; Feenstra and Weinstein, 2017), we would expect a strong positive association between a firm's markups and its market share. We also include the SOE dummy variable as this captures how connections to the state can also matter for a firm's market share.

Table 7 reports the results. In all the specifications, the firm-level markup variable is positively and statistically significantly associated with firm-level market shares, indicating there is competitive selection. Columns (1)-(3) use the entire sample during 1998-2007; and, the sign of the SOE dummy variable is negative, which is consistent with the expectation that there was negative selection on state connections in a period when the private sector was growing. However, when we exclude exports from the measure of market shares in column (3), the SOE dummy is statistically insignificant.

Columns (4) and (6) are the cross-sectional results for the top quartile of state ownership in 1998 and 2007. In 1998, there was selection on markups and, a one percent higher markup was associated with a 0.89-percent higher market share; and, there was no selection on state ownership. However, by 2007, the markup elasticity of market shares fell from 0.89 to 0.58 and, conditional on fixed effects and other variables, SOEs on average had 284 percent larger (i.e., exp(1.044)) market shares than private firms. These results indicate selection on political connections strengthened, and competitive selection weakened. This is consistent with our findings in Table 3 that between-firm effects were negligible in this quartile.

Columns (5) and (7) contain results for the bottom quartile where state ownership was least pervasive. Between 1998 and 2007, the markup elasticity of market shares increase from 0.50 to 0.97, indicating that reallocation of market shares to competitive firms became stronger. However, while there was no selection on SOEs in 1998, by 2007, surviving SOEs had 118-percent (i.e., exp(0.162)) market shares, on average, than private firms. And, this increase in selection on both markups and SOEs is consistent with moderate between-firm effects in this quartile reported in Table 3.

4 Conclusions

We have documented that aggregate pure profit shares in China's manufacturing sector grew a striking 25.6 percentage point during a ten-year period. And, we use a simple firm-level model to understand whether this trend is indicative of weaker or stronger market competition. In this model, when competition is weak, and firms charge higher markups, aggregate pure profit share can increase because of a within-firm effect; and, when there is a reallocation of market shares to high markup firms, and competition is stiff, aggregate pure profit share can also increase because of a between-firm effect. We have found that within-firms effect are roughly five times stronger than between-firm effects, indicating that market competition has declined. And, firms that raised their markups operated primarily in industries where state ownership was pervasive, and had the sharpest increases in the intermediate-intensiveness of their production technologies.

This paper also raises concerns about state owned firms. Sectors where state ownership were pervasive had the sharpest increase in markups and pure profits shares and did not have impressive productivity growth. And, while state ownership declined during the period of our study, there is some evidence that state ownership has been expanding since 2008. Moreover, there is evidence that after 2008 (see Brandt et al, 2018) that productivity growth in Chinese manufacturing fell sharply. While the connection between the pervasiveness of the state ownership, market competition, and productivity growth is somewhat speculative at this point, this is an important area for future research.

Appendix

I. Estimation Method

We follow an approach proposed by De Loecker et al (2016) and obtain production function parameters and unobserved input price parameters for the 28 2-digit sectors. We follow Brandt et al (2017) and De Loecker et al (2020) and estimate the Cobb-Douglas production functions that allow variable returns to scale. While De Loecker et al (2016) propose to control for input price variations across firms using information on firm-level output prices by assuming producers of more expensive products use more expensive inputs, we do not observe the direct measure of output or input prices at the firm level. Thus, we follow their intuition and approximate unobserved input prices using a dummy variable for SOEs, a dummy variable for exporters, and controlling for domestic market shares of each firm. Because we do not have firm-level output prices, it is crucial to have detailed deflators. We use the deflators from Brandt et al (2017) who construct an output deflator at the most detailed industry level possible.

To estimate production functions in equation (7), we follow the timing assumption in Ackerberg et al (2015) that firms need more time to optimize labor and install capital than purchase intermediate inputs. It follows from this timing assumption that a firm's demand for intermediate inputs depends on its productivity and the predetermined amounts of labor and the current stock of capital. We also follow De Loecker et al (2016) and handle unobserved input price biases with an exporter dummy (d_{it}^{ex}), an SOE dummy (d_{it}^{soe}), and log domestic market share (ms_{it}^{d}):

$$m_{it} = h_t\left(\omega_{it}, l_{it}, k_{it}, d_{it}^{ex}, d_{it}^{soe}, ms_{it}^{d}\right)$$

where lowercase variables are logged variables (e.g., $l_{it} = \ln(L_{it})$).

Following Ackerberg et al (2015), we assume the above equation can be inverted with log productivity:

$$\omega_{it} = h_t^{-1}\left(m_{it}, l_{it}, k_{it}, d_{it}^{ex}, d_{it}^{soe}, ms_{it}^{d}\right).$$

We then approximate log real output (q_{it}) with the second order polynomial function of the three inputs and that interacted with the three variables for input price biases and separate the predicted value ($\hat{\Phi}_t$) from the idiosyncratic error term (ϵ_{it}):

$$q_{it} \approx \Phi_t\left(m_{it}, l_{it}, k_{it}, d_{it}^{ex}, d_{it}^{soe}, ms_{it}^{d}\right) + \epsilon_{it}. \tag{19}$$

Next, we compute the corresponding value of productivity for any combination of parameters. The parameter we need to estimate has a constant term and output elasticities (α_s^M, α_s^L, and α_s^K) and, also unobserved input price biases, the interactions of the three variables (d_{it}^{ex}, d_{it}^{soe}, and $\ln(ms_{it}^{d})$) with m_{it} (β_s^{ex}, β_s^{soe}, and β_s^{ms}). This enables us to express the log of productivity as the predicted log output minus the logged contribution of three inputs:

$$\bar{\omega}_{it} = \hat{\Phi}_t - \left(c_s + \bar{\alpha}_s^M m_{it} + \bar{\alpha}_s^L l_{it} + \bar{\alpha}_s^K k_{it} + \bar{\beta}_s^{ex} m_{it} d_{it}^{ex} + \bar{\beta}_s^{soe} m_{it} d_{it}^{soe} + \bar{\beta}_s^{ms} m_{it} ms_{it}^{d}\right).$$

Our generalized method of moments (GMM) procedure assumes that firm-level innovations to productivity, ζ_{it}, do not correlate with the predetermined choices of inputs. To recover ζ_{it}, we assume that productivity for any set of parameters ($\bar{\omega}_{it}$) follows a first order Markov process. As in De Loecker (2013) argue, we introduce the two dummy variables follow a Markov process because they influence the evolution of firm-level productivities. While Brandt et al (2017) include input and output tariffs in the Markov process in their study of how firms immediately respond to tariff cuts, we use the SOE and export dummy variables in our longer term macro study of markups.. The results that include these additional controls do not change the main conclusions. Thus, we can approximate the productivity process with the following function:

$$\bar{\omega}_{it} = \gamma_0 + \gamma_1 \bar{\omega}_{i,t-1} + \gamma_2 d_{it}^{ex} + \gamma_3 d_{it}^{soe} + \zeta_{it}.$$

From the equation above, we can recover the innovation to productivity (ζ_{it}) for a given set of the parameters. Since the innovation to productivity (ζ_{it}) cannot be correlated with the current choice of capital (k_{it}) and the lagged choices of labor and intermediate inputs ($m_{i,t-1}$ and $l_{i,t-1}$), we use the following moment condition to estimate the parameters:

$$E\left[\zeta_{it}(\Omega)\mathbf{Y}_{it}\right] = 0 \tag{20}$$

where $\mathbf{Y}_{it} = \{k_{it},\, l_{i,t-1},\, m_{i,t-1},\, d^{ex}_{i,t-1}m_{i,t-1},\, d^{soe}_{i,t-1}m_{i,t-1},$ and $\ln(ms^{d}_{i,t-1})m_{i,t-1}\}$.

Before we report the GMM results in Table A3, we report the OLS results in Table A2. Although the OLS results cannot solve the endogeneity and simultaneity biases, it still provides us with the sense of the data. We find that Chinese manufacturing firms use technologies that are intensive in intermediate inputs, and output elasticities of intermediate inputs increased by around 2-3 percentage points over the period.

Table A3 reports the estimated parameters at the 2-digit or 3-digit industry level. The results are consistent with our understanding that Chinese firms use intermediate inputs intensively. The mean output elasticity of labor is 0.095 (0.099); and that of output elasticities of intermediate inputs is 0.862 (0.865) at the 2-digit (3-digit) level.

II. Output Elasticities

Table A5 reports the summary statistics for output elasticities of labor, capital, and intermediate inputs from the full and survivor samples of firms in 1998 and 2007 as well as the aggregates by the state quartiles. Our measure of output elasticities are the products of industry- and time-specific scale elasticities of output and firm-level cost shares of corresponding inputs. The first panel of the table shows that the aggregate average of the output elasticities of labor and capital from the full sample of the firms declined by 1.9 percentage points and 3.8 percentage points, respectively; however, the output elasticities of intermediate inputs increased by 6.9 percentage points over the period. And, the results are very similar even if we use the sample from the survivor firms. Overall, Chinese manufacturing firms use more intermediate inputs and less labor and capital over the period. And, consistent with the production function parameters in Table A3, Chinese manufacturing firms use production technologies that are intensive in intermediate inputs.

The second panel of the table shows that the aggregate averages of the output elasticities of intermediate inputs increased the most (by 9.0 percentage points) in the top state quartile, and it declined to 5.9, 6.5, and 3.3 percentage points in the second, third and bottom quartiles.

References

[1] Ackerberg, D., K. Caves, and G. Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 83, 2411-2451, 2015.

[2] Atkeson, A, and A. Burstein, "Pricing-to-Market, Trade Costs, and International Relative Prices," *American Economic Review*, 98(5), 1998-2031, 2008.

[3] Autor, D.H. D. Dorn, L.F. Katz, C. Patterson, and J. Van Reenan, "The Fall of the Labor Share and the Rise of Superstar Firms," mimeo, MIT, Harvard, 2020.

[4] Azmat, G., A. Manning, and J. Van Reenen, "Privatization and the Decline of Labour' Share: International Evidence from Network Industries," *Economica*, 79, 470-492, 2012.

[5] Bai, C., Y. Du, Z. Tao, and Y. S. Tong, "Local Protectionism and Regional Specialization: Evidence from China's Industries," *Journal of International Economics*, 63, 397–417, 2004.

[6] Bai, J., and J. Liu, "The impact of Local Trade Barriers on Export Activities, Firm Performance, and Resource Misallocation," Working Paper, 2017.

[7] Bai, C., C-T Hsieh, and Z.M. Song, "Special Deals with Chinese Characteristics," in NBER Macroeconomics Annual 2019, 34, Martin S. Eichenbaum, Erik Hurst, and Jonathan A. Parker, editors.

[8] Barkai, S., "Declining Labor and Capital Shares," forthcoming *Journal of Finance*, 2020.

[9] Barwick, P.J., S. Cao, and S. Li, "Local Protectionism, Market Structure, and Social Welfare: China's Automobile Market," mimeo, 2020.

[10] Berkowitz, D., H. Ma, and S. Nishioka, "Recasting the Iron Rice Bowl: The Reform of China's State Owned Enterprises," *Review of Economics and Statistics*, 99(4), 735-747. 2017.

[11] Basu, S., "Are Price-Cost Markups Rising in the United States? A Discussion of the Evidence," *Journal of Economic Perspectives*, 33(3), 3-22, 2019.

[12] Brandt, L., J. Van Biesebroeck, and Y. Zhang, "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics*, 97, 339-351, 2012.

[13] Brandt, L., J. Van Biesebroeck, L. Wang, and Y. Zhang, "WTO Accession and Performance of Chinese Manufacturing Firms," *American Economic Review*, 107(9), 2784-2820, 2017.

[14] Brandt, L., T. Tombe, and X. Zhu, "Factor Market Distortions Across Time, Space and Sectors in China," *Review of Economic Dynamics*, 16(1), 39-58, 2013.

[15] Brooks, W.J., J.P. Kaboski, Y.A. Li, and W. Qian, "Exploitation of Labor? Classical Monopsony Power and Labor's Share," *NBER Working Paper* 25660.

[16] Caballero, R.J., and R.K. Lyons, "External Effects in U.S. Procyclical Productivity," *Journal of Monetary Economics*, 29, 209-225, 1992.

[17] Cooper, R., G. Gong and P. Yan, "Dynamic Labor Demand in China: Public and Private Objectives," *RAND Journal of Economics*, 46(3), 577-610, 2015.

[18] De Loecker, J., "Detecting Learning by Exporting," *American Economic Journal: Microeconomics*, 5(3), 1–21, 2013.

[19] De Loecker, J., J. Eeckhout, and G. Unger, "The Rise of Market Power and the Macroeconomic Implications," forthcoming *Quarterly Journal of Economics,* 2020.

[20] De Loecker, J., and F. Warzynski, "Markups and Firm-Level Export Status," *American Economic Review*, 102(6), 2437-2471, 2012.

[21] Diewert, W.E., and K.J. Fox, "On the Estimation of Returns to Scale, Technical Progress and Monopolistic Markups," *Journal of Econometrics*, 145, 174-193, 2008.

[22] Feenstra, R.C., and D.E. Weinstein, "Globalization, Markups, and US Welfare." *Journal of Political Economy*, 125(4), 1040-1074, 2017.

[23] Feng, S., Y. Hu, and R. Moffitt, "Long run trends in unemployment and labor force participation in urban China," *Journal of Comparative Economics*, 45 (2), 304-324, 2017.

[24] Gollin, D., "Getting Income Shares Right," *Journal of Political Economy*, 110(2), 458-474, 2002.

[25] Hall, R.E., and D.W. Jorgenson, "Tax Policy and Investment Behavior," *American Economic Review*, 57(3), 391-414, 1967.

[26] Hsieh, C-T, and P.J. Klenow, "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124(4), 1403-1448, 2009.

[27] Hsieh, C-T, and Z. Song, "Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China," *Brookings Papers on Economic Activity*, 2015(1), 295-346, 2015.

[28] Jorgenson, D.W., and Z. Griliches, "The Explanation of Productivity Change," *Review of Economic Studies*, 34(3), 249-283, 1967.

[29] Karabarbounis, L., and B. Neiman, "The Global Decline of the Labor Share," *Quarterly Journal of Economics*, 129(1), 206-223, 2014.

[30] Karabarbounis, L., and B. Neiman, "Accounting for Factorless Income," NBER Working Paper #24404, 2018.

[31] Kornai, J., E. Maskin, and G. Roland, 2003, "Understanding the Soft Budget Constraint," *Journal of Economic Literature*, 41(4), 1095-1136, 2003.

[32] Kujis, L., W. Mako, and C. Zhang, "SOE Dividends: How Much and to Whom?" World Bank, Washington DC #56651, 2005.

[33] Li X., X. Liu and Y, Wang, "A Model of China's State Capitalism," *HKUST Institute for Emerging Market Studies*, WP 2015-12, 2015.

[34] Lin, J.Y., and G. Tan, "Policy Burdens, Accountability, and the Soft Budget Constraint," *American Economic Review*, 89(2), 426-31, 1999.

[35] Lu, Y., and L. Yu, "Trade Liberalization and Markup Dispersion: Evidence from China's WTO Accession," *American Economic Journal: Applied Economics* 7(4), 221-253, 2015.

[36] Melitz, M., and S. Polanec, "Dynamic Olley-Pakes Productivity Decomposition with Entry and Exit," *RAND Journal of Economics* 46(2), 362-375, 2015.

[37] Milhaupt, C.J., and Z. Zheng, "Beyond Ownership: State Capitalism and the Chinese Firm," *Georgetown Law Journal*, 665-722, 2015.

[38] Olley, G.S., and A. Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6), 1263-1297, 1996.

[39] Piketty, T., L., Yang, and G.l., Zucman., “Capital Accumulation, Private Property, and Rising Inequality in China, 1978–2015,” *American Economic Review*, 109(7), 2469-2496, 2019.

[40] Shen, D, “What’s Happening in China’s Textile and Clothing Industries?” *Clothing & Textiles Research Journal*, 26(3), 203-222, 2008.

[41] Song, Z., K. Storesletten, and F. Zilibotti, “Growing Like China,” *American Economic Review*, 101 (1), 196-233, 2011.

[42] Shleifer, A., and R. W. Vishny, “Politicians and Firms,” *Quarterly Journal of Economics*, 109(4), 995-1025, 1994.

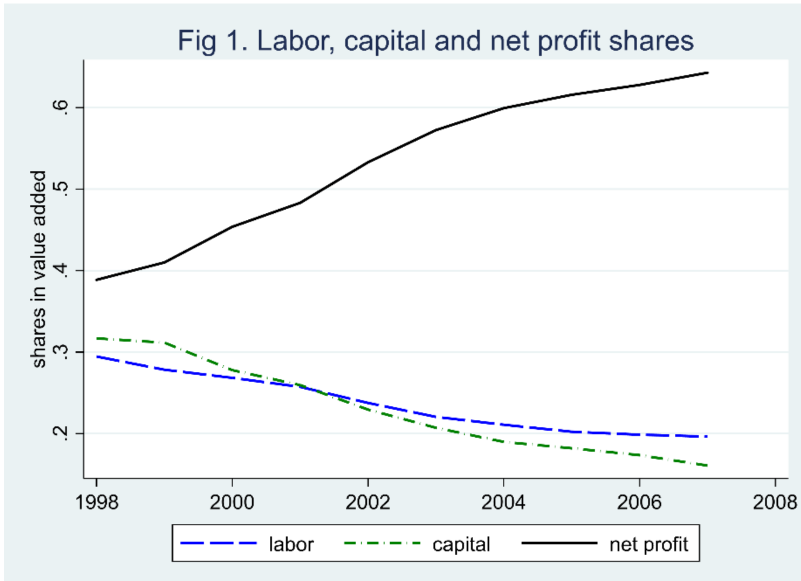
[43] Song, Z., K. Storesletten, and F. Zilibotti, “Growing Like China,” *American Economic Review*, 101(1), 196-233, 2011.

[44] Syverson, C., “What Determines Productivity?” *Journal of Economic Literature*, 49(2), 326-65, 2011.

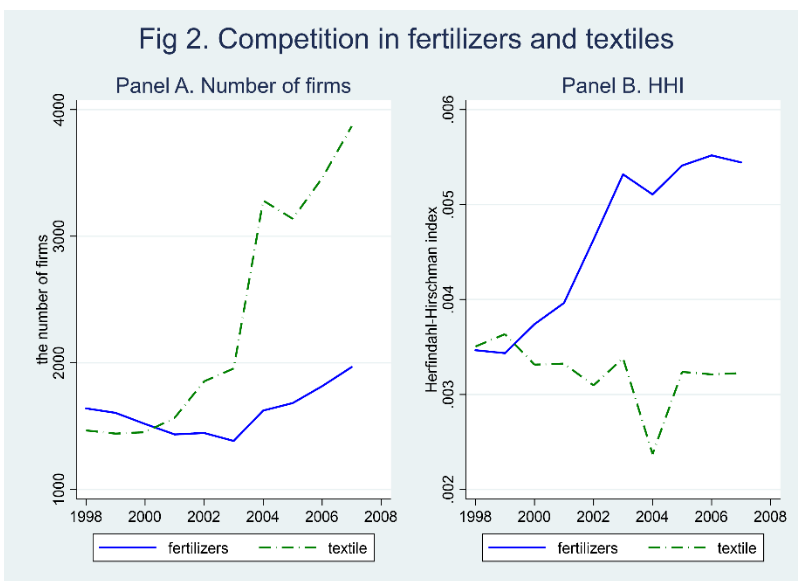
[45] Timmer, M.P., T. van Moergastel, E. Stuivenwold, G. Ypma, M. O’Mahony, and M. Kangasniemi, "EU KLEMS Growth and Productivity Accounts Version 1.0 Part I Methodology," Working Paper, 2007.

[46] Young, A., “The Razor’s Edge: Distortions and Incremental Reform in the People’s Republic of China,” *Quarterly Journal of Economics*, 115(4), 1091-1135, 2000.

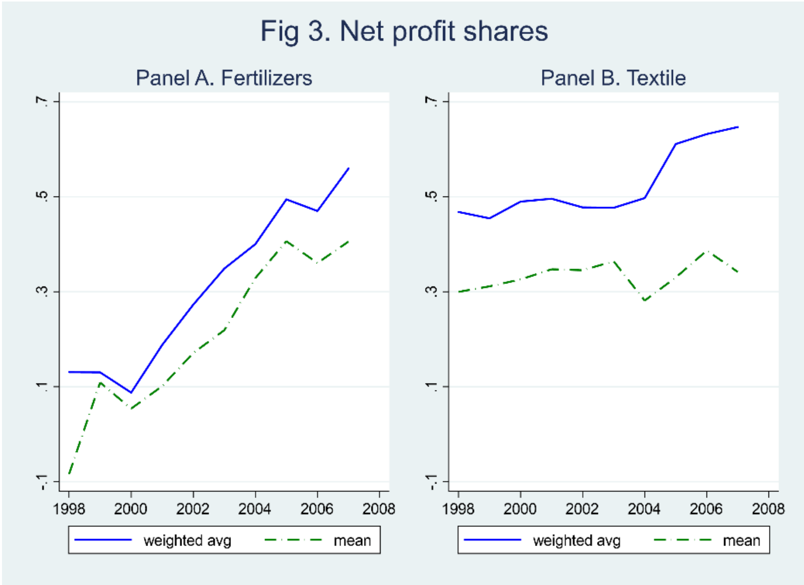
Figures and Tables



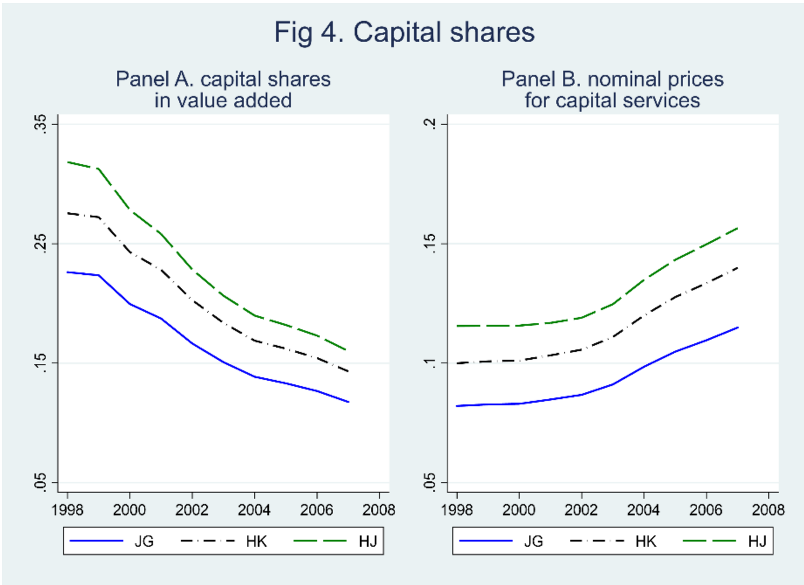
Notes: (1) Net profit shares include tax payments, executive compensations, and some unobserved non-wage compensation for labor. (2) Prices for capital services are computed from Hall and Jorgenson's (1967) approach that accounts for corporate tax and liability at the firm level.



Notes: (1) See the text for an explanation of why we choose chemical fertilizers (262) and textile goods (175) as examples. (2) The Herfindahl-Hirschman index (HHI) equals the sum of the squares of total sales of each firm in a market.



Notes: (1) We use the sample of survivor firms, (2) The top and bottom 2.5-percent of firm-level net profit share for each year and industry are outliers and dropped.



Notes: (1) See equations (3) and (4) for Jorgenson and Griliches (1967) and Hall and Jorgenson (1967) methods of computing capital returns. (2) Hsieh and Klenow (2009) use 10 percent real rate of capital returns.

Table 1. Pure versus accounting profit shares

	Pure profit shares			Accounting profit shares		
	1998	2007	Δ	1998	2007	Δ
	(1)	(2)	(3)	(4)	(5)	(6)
Aggregate						
All firms	0.387	0.643	0.256	0.111	0.241	0.131
Survivors	0.378	0.632	0.254	0.142	0.262	0.120
Within the industry state quartile						
75th percentile or above	0.288	0.656	0.368	0.088	0.273	0.185
50th - 75th percentiles	0.428	0.642	0.214	0.154	0.237	0.083
25th - 50th percentiles	0.464	0.667	0.202	0.106	0.207	0.101
25th percentile or below	0.481	0.574	0.093	0.117	0.210	0.093

Notes: (1) The classification of whether or not a firm is state-owned enterprise (SOE) follows the definition in Hsieh and Song (2015, pp.301-302): a firm is state-owned when the share of its paid-in-capital "directly held by the state" is greater than or equal to 50-percent; or, the state (and not a collective, foreigner, or private person) is the controlling shareholder. (2) The following procedure is used to split the sample of 136 industries into state quartiles. First, the state ownership share in each industry equals the sum of SOEs' revenues divided by its total revenues. Then, the industry-level state ownership share is sorted from the highest to the lowest. Finally, the 34 industries in the 75th or above percentile are placed in the top quartile; they are followed by the 34 industries in the second (50th-75th percentiles), the 34 industries in the third (25th-50th percentiles), and the 34 industries in the bottom (25th percentile or below) quartiles. (3) We report the means that are weighted by firm-level value added for the sample of all firms, survivors, or all firms in each state quartile. (4) The notation "Δ" represents the percentage point change.

Table 2. Summary statistics for profit, labor and capital shares in value added

	Pure profit shares			Labor shares			Capital shares		
	1998	2007	Δ	1998	2007	Δ	1998	2007	Δ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Aggregate									
All firms	0.387	0.643	0.256	0.294	0.196	-0.098	0.318	0.160	-0.158
Survivors	0.378	0.632	0.254	0.296	0.198	-0.098	0.326	0.170	-0.156
Within the industry state quartile									
75th percentile or above	0.288	0.656	0.368	0.296	0.150	-0.146	0.416	0.193	-0.222
50th - 75th percentiles	0.428	0.642	0.214	0.290	0.198	-0.092	0.282	0.159	-0.123
25th - 50th percentiles	0.464	0.667	0.202	0.276	0.203	-0.072	0.260	0.130	-0.130
25th percentile or below	0.481	0.574	0.093	0.322	0.312	-0.010	0.197	0.114	-0.083

Notes: (1) We report the means that are weighted by firm-level value added for the sample of all firms, survivors, or all firms in each state quartile. (2) The notation "Δ" represents the percentage point change.

Table 3. Between and within decompositions for profit shares

	Survivors			Exit and entry		All firms
	Between	Within	(1)+(2)	Exit	Entry	(3)+(4)+(5)
	(1)	(2)	(3)	(4)	(5)	(6)
Aggregate						
All firms	0.042	0.212	0.254	-0.009	0.011	0.256
Within the industry state quartile						
75th percentile or above	0.048	0.312	0.360	-0.003	0.010	0.368
50th - 75th percentiles	0.006	0.184	0.190	-0.015	0.039	0.214
25th - 50th percentiles	0.070	0.102	0.172	0.026	0.005	0.202
25th percentile or below	0.064	0.012	0.076	0.009	0.008	0.093

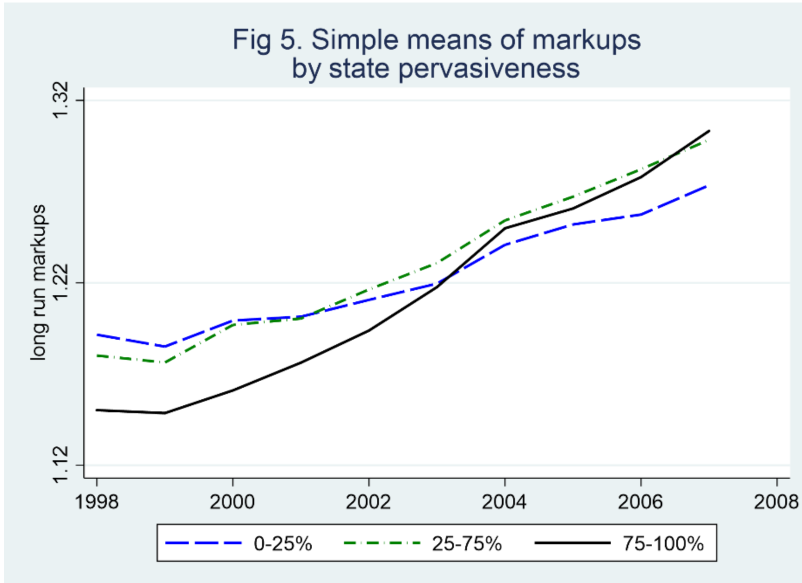
Notes: (1) The notation "Δ" represents the percentage point change. We report the means and percentiles from the sample of survivors. (2) Exit and entry terms are from Melitz and Polanec (2015).

Table 4. Summary statistics for markups

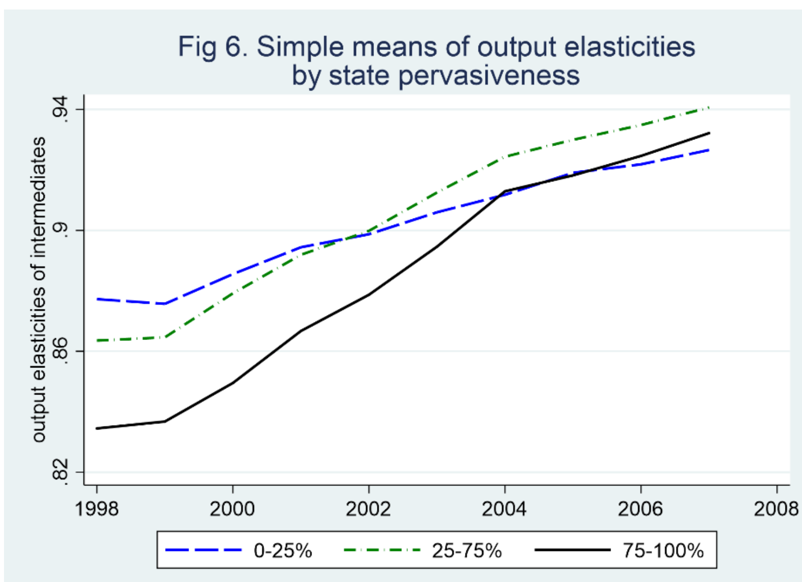
	1998		
	Model 1	Model 2	Model 3
	(Short run)	(Medium run)	(Long run)
	(1)	(2)	(3)
Weighted mean	1.200	1.184	1.168
Simple mean	1.235	1.156	1.175
s.d.	0.541	0.343	0.320

	2007		
	Model 1	Model 2	Model 3
	(Short run)	(Medium run)	(Long run)
	(1)	(2)	(3)
Weighted mean	1.210	1.218	1.271
Simple mean	1.235	1.205	1.293
s.d.	0.347	0.285	0.274

Notes: (1) We derived markups for Models 1 and 2 from the output elasticities estimated at the 2-digit industries (see Table A2). Model 1 uses the first order condition of intermediate inputs (see Brandt et al, 2017) to compute short run markups, whereas Model 2 uses the first order conditions of intermediate inputs and labor to compute medium run markups. Model 3 derives markups from all the first order conditions, which is the scale elasticity times revenues divided by total costs. (2) Top and bottom 0.5% of samples for each year are outliers and are dropped for Models 1 and 2. (3) We use the firm-level revenues as weights for Models 1 and 2 and the firm-level total costs as weights for Model 3.



Notes: (1) Markups are computed from scale elasticities time total revenues divided by total costs. (2) We report the simple means across all firms for each state quartile. Top and bottom 0.5% values of the yearly entire sample are outliers, and thus, they are dropped.



Notes: (1) Output elasticities of intermediates are scale elasticities time cost shares of intermediate inputs. (2) We report the simple means across all firms for each state quartile. Top and bottom 0.5% values of the yearly entire sample are outliers, and thus, they are dropped.

Table 5. Summary statistics for long run markups and components

	Δln(μ)	Components of markups				Components of input costs			Cost shares of inputs		
		Price	TFP	Scale	Costs	Δln(p)	Δln(w)	Δln(r)	materials	labor	capital
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mean across industries within the quartile											
75th percentile or above	0.132	0.111	0.137	0.114	0.253	0.190	1.114	0.310	0.069	-0.029	-0.040
50th - 75th percentiles	0.104	0.071	0.134	0.137	0.258	0.199	1.037	0.293	0.049	-0.020	-0.028
25th - 50th percentiles	0.103	0.075	0.116	0.142	0.251	0.194	1.027	0.291	0.038	-0.011	-0.027
25th percentile or below	0.068	0.085	0.141	0.147	0.326	0.268	0.955	0.303	0.010	0.007	-0.018
Mean difference from the top quartile											
50th - 75th percentiles	-0.029**	-0.040	-0.003	0.023	0.006	0.008	-0.077**	-0.017*	-0.020**	0.008	0.011*
(standard error)	(0.012)	(0.051)	(0.052)	(0.015)	(0.030)	(0.035)	(0.034)	(0.010)	(0.010)	(0.005)	(0.006)
25th - 50th percentiles	-0.029**	-0.036	-0.021	0.028*	-0.001	0.004	-0.087***	-0.019*	-0.031***	0.018***	0.013**
(standard error)	(0.013)	(0.046)	(0.055)	(0.015)	(0.039)	(0.043)	(0.032)	(0.010)	(0.009)	(0.005)	(0.005)
25th percentile or below	-0.064***	-0.026	0.004	0.033**	0.074*	0.078	-0.160***	-0.007	-0.059***	0.036***	0.022***
(standard error)	(0.012)	(0.044)	(0.054)	(0.016)	(0.043)	(0.049)	(0.043)	(0.009)	(0.009)	(0.005)	(0.005)
Observations	136	136	136	136	136	136	136	136	136	136	136

Notes: (1) Changes in this table, Δ%, are computed from log differences and equal percentage growth during 1998 to 2007. All industry variables are normalized to the initial year. (2) In the first panel, we report the mean across 34 industries within each quartile for 1998 and 2007 values and the changes between the two years. (3) In the second panel, we regress each variable from 136 industries with quartile fixed effects. We report the standard errors that are clustered at the industry level in the second panel. ***, **, and * indicate that industry-level variables are statistically different from the industries in the top quartile at the 1%, 5%, and 10% confidence levels.

Table 6. Market shares by state ownership

	SOEs		Private firms	
	1998	2007	1998	2007
	(1)	(2)	(3)	(4)
All firms				
Number of firms	35,092	11,561	82,992	256,891
Mean market shares	0.55%	0.75%	0.43%	0.18%
Top state quartile				
Number of firms	12,044	50,191	17,834	4,468
Mean market shares	0.67%	1.09%	0.31%	0.17%
Bottom state quartile				
Number of firms	4,652	1,158	24,645	71,516
Mean market shares	0.42%	0.41%	0.47%	0.18%

Notes: Mean market shares report simple means across firms.

Table 7. Market shares and long run markups at the firm level

Dependent variable:	ln (market shares)						
	1998-2007			1998		2007	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln (long run markups)	0.905***	0.913***	1.038***	0.893***	0.503***	0.583***	0.968***
	(0.033)	(0.032)	(0.039)	(0.097)	(0.064)	(0.056)	(0.052)
SOE dummy	-0.220**	-0.186**	-0.058	-0.120	-1.276***	1.044***	0.162**
	(0.084)	(0.087)	(0.084)	(0.173)	(0.107)	(0.097)	(0.074)
Markets							
3-digit industries	Yes	No	No	No	No	No	No
3-digit industries × 4 regions	No	Yes	No	Yes	Yes	Yes	Yes
3-digit industries × 4 regions w/o exports	No	No	Yes	No	No	No	No
Fixed effects							
3-digit industries	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample							
SOE quartiles	All	All	All	Top	Bottom	Top	Bottom
Year	All	All	All	1998	1998	2007	2007
Observations	1,689,894	1,689,894	1,582,551	29,878	29,297	54,659	72,674
R-squared	0.359	0.412	0.297	0.299	0.461	0.400	0.532

Notes: (1) Standard errors that are clustered at the industry level are in the parentheses. (2) ***, **, and * indicate that they are statistically different from zeros at the 1%, 5%, and 10% confidence levels. (3) We use definitions of a market that exclude external sales (columns (3)) and include external sales (all other columns).

Appendix Tables

Table A1. Summary statistics by the industry SOE shares

	Number of firms			SOE shares in revenues			Revenue shares		
	1998	2007	Survivors	1998	2007	Δ	1998	2007	Δ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Within the industry state quartile									
75th percentile or above	29,878	54,659	9,591	0.628	0.362	-0.266	0.394	0.414	0.020
50th - 75th percentiles	29,421	67,221	8,689	0.317	0.111	-0.206	0.211	0.213	0.001
25th - 50th percentiles	29,422	73,898	8,608	0.221	0.045	-0.176	0.233	0.235	0.002
25th percentile or below	29,297	72,674	7,683	0.089	0.016	-0.074	0.162	0.138	-0.024
Total	118,018	268,452	34,571	0.380	0.186	-0.194	1.000	1.000	0.000

Notes: SOE shares in revenues and revenues shares across the quartiles are aggregated values.

Table A2. Production function parameters (OLS)

Dependent variable:	ln (real output)						
	1998-2007			1998		2007	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α^M (intermediate inputs)	0.902***	0.903***	0.888***	0.878***	0.879***	0.891***	0.904***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)
α^L (labor)	0.043***	0.041***	0.060***	0.062***	0.053***	0.059***	0.064***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
α^K (capital)	0.036***	0.036***	0.035***	0.029***	0.044***	0.037***	0.036***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.004)
SOE dummy	-0.081***	-0.084***	-0.048***	-0.078***	-0.047***	0.002	-0.012*
	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)
Exporter dummy	-0.004	-0.003	-0.001	0.012***	0.006	-0.018***	-0.015**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)
Fixed effects							
2-digit industries	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions	No	Yes	Yes	Yes	Yes	Yes	Yes
Year	No	No	Yes	No	No	No	No
Sample							
SOE quartiles	All	All	All	All	Survivors	All	Survivors
Year	All	All	All	1998	1998	2007	2007
Observations	1,689,894	1,689,894	1,689,894	118,018	28,028	268,452	28,028
R-squared	0.957	0.957	0.960	0.960	0.965	0.959	0.975

Notes: (1) Standard errors that are clustered at the industry level are in the parentheses. (2) ***, **, and * indicate that they are statistically different from zeros at the 1%, 5%, and 10% confidence levels.

Table A3. Summary statistics for production function parameters (GMM)

	2-digit industries					3-digit industries				
	Mean	s.d.	Min	Max	% (>0)	Mean	s.d.	Min	Max	% (>0)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Output elasticities										
α^M (intermediate inputs)	0.862	0.107	0.635	1.012	1.000	0.865	0.170	0.062	1.244	1.000
α^L (labor)	0.095	0.102	0.007	0.429	1.000	0.099	0.133	0.004	0.772	1.000
α^K (capital)	0.043	0.068	-0.060	0.215	0.857	0.027	0.072	-0.220	0.345	0.846
Scale elasticity	1.000	0.056	0.882	1.133	1.000	0.991	0.125	0.270	1.572	1.000
Input price biases										
β^{ex} (exporter dummy)	0.004	0.005	-0.012	0.015	0.821	0.007	0.070	-0.350	0.583	0.831
β^{soe} (SOE dummy)	0.002	0.017	-0.005	0.080	0.321	0.101	0.591	-0.059	5.418	0.603
β^{ms} (log market share)	0.008	0.010	-0.009	0.029	0.821	0.006	0.022	-0.059	0.161	0.735

Notes: (1) We use the method in De Loecker et al (2016). See Appendix I. (2) We drop 5 2-digit industries and 32 3-digit industries to compute the statistics because their output elasticities of labor or intermediate inputs are negative.

Table A4. Correlation matrix across various markup measures

	1998			2007		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Model 1: Short run	1.000			1.000		
Model 2: Medium run	0.755	1.000		0.765	1.000	
Model 3: Long run	0.599	0.841	1.000	0.663	0.841	1.000

Notes: See Table 4 for the models we use to derive markups.

Table A5. Summary statistics for

Output elasticities of labor, capital and intermediate inputs

	Intermediates			Labor			Capital		
	1998	2007	Δ	1998	2007	Δ	1998	2007	Δ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Aggregate									
All firms	0.898	0.967	0.069	0.081	0.061	-0.019	0.087	0.049	-0.038
Survivors	0.892	0.960	0.068	0.083	0.062	-0.021	0.091	0.052	-0.038
Within the industry state quartile									
75th percentile or above	0.867	0.957	0.090	0.082	0.046	-0.036	0.115	0.058	-0.056
50th - 75th percentiles	0.906	0.965	0.059	0.082	0.064	-0.018	0.079	0.051	-0.028
25th - 50th percentiles	0.927	0.992	0.065	0.071	0.060	-0.011	0.066	0.038	-0.028
25th percentile or below	0.926	0.959	0.033	0.090	0.104	0.014	0.055	0.038	-0.017

Notes: The notation "Δ" represents the percentage point change. We report the weighted means.