# Markups and Declining Labor Shares: Evidence from China

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**Abstract**

Around the time that China joined the WTO, its labor shares fell while its product markups converged (e.g. Brandt et al, 2017; Lu and Yu, 2015). We show that markup convergence is a major force driving declining labor shares. We build a theory showing that firms' labor shares are decreasing and convex in markups. Consistent with this theory, we find the downward impact of markup increases on labor shares in initially unprofitable firms robustly dominates the upward impact of markup declines in initially profitable firms. The impact of markup convergence on labor shares dominates alternative explanations including capital-labor substitution.

Keywords: Labor's share, Markups, China, WTO, Employment protections, Capital-labor substitution
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# 1 Introduction

Labor shares in China have declined over China's accession to the World Trade Organization (WTO) in 2001, and the manufacturing sector has been a major contributor to this trend (Bai and Qian, 2010; Qian and Zhu, 2012). Figure 1 illustrates that labor's share in Chinese manufacturing declined almost eight percentage points during the period, and this is an exceptionally rapid per-decade decline for most countries since 1975 (see Karabarbounis and Neiman, 2014, Figure 3). It is also well documented that the potential profitability of the firms, or markups, had converged due to efficiency gains in productivity over China's accession to WTO (see Brandt et al, 2017; Lu and Yu, 2015).

This paper shows that markup convergence is a major force driving declining labor shares in Chinese manufacturing. We build a theory which predicts that a firm's labor share is decreasing and convex in markups (see also, Autor et al, 2017; Azmat et al 2012). Consistent with this theory, we find that the downward impact of markup increases in initially unprofitable firms on labor shares robustly dominates the upward impact of markup declines in initially profitable firms. A counter-factual analysis shows that the effect of markup convergence dominates a broad set of alternative explanations for declining labor shares including waning employment protections (see Azmat et al, 2012; Blanchard and Giavazzi, 2003), capital-labor substitution (Karabarbounis and Neiman, 2014; Piketty, 2014) and, also, entry and exit of firms.

Reforms enacted in China starting in the mid-1990s provide a unique opportunity to quantify several potential drivers of declining labor shares. Regarding markup convergence, the Chinese state has traditionally been biased against private activity: for example, the state could arbitrarily regulate and even shut down private firms and block entry and make it difficult for them to get external finance (Li et al, 2008). However, during 1998-2007, especially after China's accession into WTO, the entry of private firms was liberalized and measures designed to protect private property rights were enacted; moreover, product market distortions were mitigated because input and output tariffs were cut (Brandt, Biesebroeck and Zhang, 2012). These policies made product markets more competitive: profitable private firms entered and unprofitable firms exited; firms that were operating with thin or even negative profit margins became more profitable; and, the overall distribution of markups became less dispersed (Lu and Yu, 2015).

Regarding employment protections, China's state-owned enterprises (SOEs) have traditionally been under political pressure to function as "iron rice bowls" and provide job security to their employees. However, during 1998-2007 SOEs came under pressure to operate profitably so that the political pressure on SOEs to hire labor became less intense (see, for example, Cooper et al, 2015). Regarding capital-labor substitution, Karabarbounis and Neiman (2014) document at the cross-country level that an important reason for the decline in labor shares is that the "capital-labor substitution elasticity" in many country-level production functions exceeds unity and the cost of investment goods and machinery (for example, computers and equipment) has fallen relative to labor.[1] However, these results are controversial because most microeconometric studies find that the substitution elasticity of capital and labor is less than one (see León-Ledesma et al, 2010; Chirinko et al, 2011; Oberfield and Raval, 2014; Acemoglu 2003, p.3 and Footnote 3; Antràs, 2004, section I).[2] China is an ideal environment for studying the impact of capital-labor substitution on labor's share because the capital-labor substitution elasticity exceeds unity in most manufacturing sectors (Berkowitz et al, 2017).

This paper develops a firm-level partial-equilibirum model that makes predictions about the impact of product market markups, employment protections and capital-labor substitution on firm-level labor shares. In order to conduct a counter-factual analysis, the model is estimated and its structural parameters are used to predict the firm-level distribution of labor shares in 1998. Then, to decompose the change in the distribution of labor's share by the changes in markups, the relative cost of capital to labor and employment protections, and also firm-level entry and exit, the 1998 firm-level values of each of the factors are replaced, one by one, with the 2007 values. Following this procedure, we can examine how the cumulative distribution of labor's shares shifts due to the change of a particular factor. Then, quantile regression methods in Koenker and Bassett (1978) and Firpo, Fortin and Lemieux (2009) are used to test for the statistical significance of the shifts in the distributions.

We find that markup convergence (where the markup distribution shifted rightward) is the major reason for declining in labor shares. Declining employment protections play a strong secondary role and, somewhat surprisingly, the force of capital-labor substitution accounts for only about 15-percent of the average decline in labor shares. Our paper is similar to the Autor et al (2017) study

[1] Duffy and Papageorgiou (2000) also find that the substitution elasticity of capital for labor in country-level production functions often exceeds unity.

[2] Oberfield and Raval (2014), however, do find that the capital-labor substitution elasticity is about 1.1 in India.

of the United States because we exploit massive firm-level heterogeneity in order to understand declining labor shares. However, our findings are quite different. While Autor et al (2007) highlight how highly productive "super-star" firms that charge high markups and pay low labor shares have gained market shares, our study emphasizes how initially unprofitable firms improved their productivity and, thus, charged higher markups and paid lower labor shares.

The next two sections describe the data and the model. Section 4 provides a brief overview of the paper's estimation strategy; section 5 presents the counter-factual analysis and section 6 concludes.

## 2 Labor Shares at the Firm Level

The data is taken from the Chinese Annual Surveys of Industrial Production (ASIP), which covers all SOEs and private firms with total annual sales exceeding 5 million RMB per year or roughly 612,000 US dollars.[3] Our major firm-level outcome variable is payments to labor as a share of value added or labor's share:

$$LS_{it} = \frac{w_{it}N_{it}}{VA_{it}} \tag{1}$$

where $w_{it}N_{it}$ is labor compensation of firm $i$ in year $t$, and $VA_{it}$ is a measure of value added using the production approach.[4]

Our baseline measure of aggregate labor shares is lower than the comparable figures from the 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. The results in this section and for the rest of the paper are robust when we follow the approach in Hsieh and Klenow (2009) and Brandt et al (2012) and inflate wage payments so that the aggregated firm-level labor share values are consistent with the values from the national accounts.

Our labor shares measure 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

[3] We use an average exchange rate of 8.17 RMB per dollar during 1998-2007. Following Brandt et al (2012) we track firms over time by using each firm's ID, name, industry, address and other information. One sixth of all firms that are observed for more than one year change their official ID over the sample period.

[4] This approach computes value added from gross output minus operating costs.

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. While this change could partly explain the drop in aggregate labor shares in manufacturing between 2003 and 2004, it does not explain the decline during 1998-2003 and during 2004-2007. Moreover, our study is not concerned with changes in aggregate labor shares but with changes in the distribution of firm-level labor shares.

Another concern is that equity pay schemes became more important in SOEs that were either privatized or corporatized. Thus, some of the manager income reported as labor income in pre-corporatization SOEs or pre-privatization SOEs became capital income after these SOEs were corporatized or privatized and this change in income accounting could be the major reason why labor shares fell. If this was an issue, we would observe that aggregate labor shares are much more stable in the balanced sample that excludes the corporatized and privatized SOEs. However, aggregate labor shares decline substantially by 6.6% points in this sample, which is close to the 8.2% decline for the complete balanced sample. While income accounting changes could be part of the reason for the 1.6% point sharper drop in the complete balanced panel, the theoretical analysis in the next section also predicts that corporatized SOEs and privatized SOEs would cut labor shares more steeply than SOEs that were neither corporatized nor privatized because they were under less pressure to hire excess labor.[5]

Table 1 contains summary statistics for labor shares. Firms may be SOEs or private firms where private firms include domestically owned and foreign owned private firms, as well as hybrid forms of ownership. Firms are classified into those that operated in both 1998 and 2007 (continuers) and those that either exited after 1998 or entered before 2007 (exit and entry). Continuers include firms that had no ownership changes (SOE to SOE, and private to private) and those that changed including SOEs in 1998 that were private as of 2007 or earlier (SOE to private) and private firms in 1998 that were SOEs as of 2007 or earlier (private to SOE). Within the continuer group in 1998, labor shares were much higher in the SOE to SOE (47.7%) versus the private to private group (28.3%); however, labor shares fell more steeply in the SOE to SOE group (-11.2% points) than in the private to private group (-1.3% points). And, within the group of continuers that changed

[5] Our empirical results also support this view. See Section 4.2.

ownership there is a quantitatively steeper decline for the SOE to private group (-13.6% points). Also, labor shares fell by 8.1% points in firms that exited and entered.

Casual observation of these results from Table 1 suggests that SOE to SOE firms and SOE to private firms and entry and exit were responsible for the significant decline in labor shares in China and, private to private firms at best played a minor role. However, in what follows we will show that a major force for driving down labor shares is that initially unprofitable firms that subsequently survived, whether initially private or state owned, were highly productive. These productivity gains drove up their markups which, in turn, pushed down their labor shares.

# 3 Theoretical Considerations

In this section a model based on Azmat et al (2012) and Karabarbounis and Neiman (2014) is built, which will be subsequently estimated and then used for a decomposition analysis of how product market markups (and their dispersion), employment protections and capital-labor substitution shape the evolving distribution of labor's share. We consider an economy inhabited by firms that vary according to their capital intensity, markups, ownership, and productivity. In this economy there is a firm $i$ in sector $s$ in period $t$ that uses a sector-specific constant returns to scale production function that converts augmented labor ($N_{it}$),[6] the real stock of physical capital ($K_{it}$) and real spending on materials ($M_{it}$) into a real output ($Q_{it}$):[7]

$$Q_{it} = \omega_{it} \left[ a_s (N_{it})^{\frac{\sigma_s - 1}{\sigma_s}} + (1 - a_s) (K_{it})^{\frac{\sigma_s - 1}{\sigma_s}} \right]^{\frac{\alpha_s \sigma_s}{\sigma_s - 1}} (M_{it})^{1 - \alpha_s}. \tag{2}$$

Each firm is differentiated by its Hicks-neutral productivity, $\omega_{it}$. The parameters of the sectoral production function include a weight on labor versus capital in factor inputs, $a_s$, where $0 < a_s < 1$; the sector-specific elasticity of substitution between capital and labor, $\sigma_s$, where $0 \leq \sigma_s < +\infty$; and the relative weight between the factor inputs and intermediate inputs, $\alpha_s$, where $0 < \alpha_s < 1$.

Product markets are imperfectly competitive and each firm $i$ sets a markup in each time period $t$ ($\mu_{it}$), which is the ratio of the product price product ($p_{it}$) to the marginal cost of producing

[6] Our measure of labor equals the head count of employees multiplied by the differences in human capital across China's four regions. The results do not change even if we simply use the head count of employees.

[7] The assumptions of constant returns to scale and a Cobb-Douglas (unit elasticity of substitution) relation between materials and factors are validated in the appendix of Berkowitz et al (2017).

$Q_{it}$. Firms can be privately owned or state owned (SOEs) and, in general SOEs are under political pressure to preserve jobs while private firms are not. In order to capture this difference, let $\phi_t$ denote the employment protection parameter applied to SOEs in period $t$ and let $1-1/\phi_t$ denote the SOE's political benefit of hiring an additional worker:

$$\phi_t = 1 \text{ for private firms, } \ \phi_t \geq 1 \text{ for SOEs.} \tag{3}$$

Input markets are competitive, where input prices for labor, capital and materials are exogenous variables for firms, and, are denoted, $w_{it}$, $r_{it}$, and $\tilde{p}_{it}$, respectively. A firm $i$ in sector $s$ in period $t$ chooses inputs ($N_{it}$, $K_{it}$, and $M_{it}$) in order to maximize a payoff, $U_{it}$, that includes profits and the political benefits of providing paid employment:

$$U_{it} = \Pi_{it} + \left(1 - \frac{1}{\phi_t}\right) w_{it} N_{it} \tag{4}$$

where

$$\Pi_{it} = p_{it} Q_{it} - w_{it} N_{it} - r_{it} K_{it} - \tilde{p}_{it} M_{it}. \tag{5}$$

Combining the first order conditions with respect to labor and capital, firm-level capital intensity can be written as:

$$\frac{K_{it}}{N_{it}} = \phi_t^{-\sigma_s} \left(\frac{r_{it}}{w_{it}} \frac{a_s}{1-a_s}\right)^{-\sigma_s} \tag{6}$$

where $\phi_t^{-\sigma_s}$ is the impact of employment protections on capital intensity and $\left(\frac{r_{it}}{w_{it}} \frac{a_s}{1-a_s}\right)^{-\sigma_s}$ includes the impact of the relative cost of capital to labor on capital intensity. By inspection of equation (6), a one-percent decline in either the relative cost of capital ($\frac{r_{it}}{w_{it}}$) or political pressure ($\phi_t$) will cause firms to increase capital intensity by $\sigma_s$ percent.

Using the first order condition for materials, we can obtain an empirical expression for markups:

$$\mu_{it} = (1-\alpha_s) \frac{p_{it} Q_{it}}{\tilde{p}_{it} M_{it}}. \tag{7}$$

Equation (7) can be rewritten into the following standard definition of a firm-level markup:

$$\mu_{it} = \frac{p_{it}}{MC_{it}} \tag{8}$$

where

$$MC_{it} = \frac{b_s}{\omega_{it}} \left[ (a_s)^{\sigma_s} (w_{it})^{\sigma_s - 1} + (1 - a_s)^{\sigma_s} (r_{it})^{\sigma_s - 1} \right]^{\frac{\alpha_s}{\sigma_s - 1}} (\tilde{p}_{it})^{1-\alpha_s} \tag{9}$$

where $b_s = (\alpha_s)^{-\alpha_s} (1 - \alpha_s)^{-(1-\alpha_s)}$ and marginal costs ($MC_{it}$) are decreasing in productivity ($\omega_{it}$) and increasing in input prices ($w_{it}, r_{it}$ and $\tilde{p}_{it}$).

Equation (8) and the subsequent expression for marginal cost, equation (9), indicates that markups can increase for several reasons: firms are able to charge higher output prices ($p_{it}$); or, firms could enjoy lower marginal costs because they are more productive and/or because their input prices fall.[8]

Finally, using the first order conditions for labor, capital and materials and the relationship between revenue and value added, a firm's labor share can be written as a function of the relative cost of capital to labor ($r_{it}/w_{it}$), markups ($\mu_{it}$) and the employment protections parameter ($\phi_t$):

$$\frac{w_{it} N_{it}}{VA_{it}} = \frac{\phi_t}{\mu_{it} - 1 + \alpha_s} \left[ \frac{\partial Q_{it}/Q_{it}}{\partial N_{it}/N_{it}} \right] \tag{10}$$

where

$$\frac{\partial Q_{it}/Q_{it}}{\partial N_{it}/N_{it}} = \alpha_s \left[ 1 + \left( \frac{1 - a_s}{a_s} \right)^{\sigma_s} \phi_t^{1-\sigma_s} \left( \frac{r_{it}}{w_{it}} \right)^{1-\sigma_s} \right]^{-1}. \tag{11}$$

The system of equations (10) and (11) shows how $r_{it}/w_{it}$ (the relative cost of capital to labor), $\phi_t$ (employment protections) and $\mu_{it}$ (markups) determines firm-level labor shares.[9] If capital and labor are substitutes ($\sigma_s > 1$), a decline in the relative cost of capital to labor in equation (11) causes a firm to cut its payments to labor as a share of value added because it weakens the output elasticity of labor in equation (10). For purposes of interpretation, it is important to note that the decline in $\frac{r_{it}}{w_{it}}$ is a change in market valuations of capital versus labor and captures the capital-labor substitution effects in Karabarbounis and Neiman (2014).

[8] See Appendix 3 for a more detailed discussion.

[9] In Appendix 2, we show the general validity of the system using the conventional regression methods.

Equation (10) replicates the result in Azmat et al (2012) and Karabarbounis and Neiman (2014) that higher markups ($\mu_{it}$) cause a firm to lower its labor shares. Equations (10) and (11) illustrate that the employment protection parameter ($\phi_t \geq 1$) can have a direct and an indirect effect on labor shares. By inspection of equation (10), a decline in $\phi_t$ directly lowers labor shares because it shrinks the difference between the marginal benefit of labor and the wage rates (Azmat et al, 2012). Moreover, equation (11) indicates that when $\sigma_s > 1$, a decline in $\phi_t$ indirectly lowers labor shares because it weakens the output elasticity of labor. And, the decline in $\phi_t$ reflects political decisions that influence hiring and firing of labor and is not a part of the capital-labor substitution mechanism in Karabarbounis and Neiman (2014) which is driven by a decline in $\frac{r_{it}}{w_{it}}$. Thus, in our counter-factual analysis, we will distinguish between the impact of changes in $\frac{r_{it}}{w_{it}}$ and $\phi_t$.

The second derivative of equation (10) with is decreasing in markups and, decreasing in the relative cost of capital to labor when $\sigma_s > 1$. Thus, labor shares are decreasing and convex in markups and the relative cost of capital to labor when $\sigma_s > 1$. As we will show in section 4.3, an important implication is that an increase in markups has a stronger downward push on labor shares in firms that have tight or even negative profit margins than in highly profitable firms.

# 4 Empirical Strategy

In order to conduct a counter-factual analysis, the production function in equation (2) is estimated using the generalized method of moments (GMM) procedure from De Loecker and Warzynski (2012). This method is ideal for our empirical exercise because recent methods for estimating the elasticity of substitution between capital and labor developed by Chirinko, Fazzari and Meyer (2011), Karabarbounis and Neiman (2014), and Oberfield and Raval (2014) can only identify $\sigma_s$ but cannot fully identify other parameters ($\alpha_s$ and $a_s$). Moreover, while Oberfield and Raval (2014) base their estimation on the assumption that local capital markets are integrated within the United States, this assumption is not plausible in China.[10]

Production functions in equation (2) are estimated for each of the 136 3-digit sectors. The estimated weights on factor inputs ($\hat{\alpha}_s$) and labor relative to capital ($\hat{a}_s$) are on average 0.169 and 0.548; and the elasticity of substitution between labor and capital ($\hat{\sigma}_s$) exceeds unity for 130

[10] See Hsieh and Klenow (2009) and Brandt et al (2013) for evidence that local capital markets in China are not integrated.

out of 136 sectors and on average is 1.553, which is larger than the previous microeconometric estimates from developed countries (see Acemoglu, 2003, p.3 Footnote 3). A detailed discussion of the estimation methods and robustness is contained in Appendix 1 of this paper and Berkowitz et al (2017).[11]

## 4.1 Labor Shares and Markups

In order to calculate markups, the estimated production function parameters for each of the 136 3-digit sectors, as well as the observed firm-level values of the revenue share of intermediate inputs ($\tilde{p}_{it}M_{it}/p_{it}Q_{it}$), are inserted into equation (7). Table 1 reports the median values of markups and capital-labor ratios in 1998 and 2007. Median markups are stable for SOE continuer firms (SOE to SOE and private to SOE); and, markups increase in private continuer firms (2.3% for private to private firms and 1.3% for SOE to private firms). However, the overall 2.2% increase in markups is small compared to the overall 28.8% increase in capital-labor ratios, suggesting that the impact of markups should be relatively weak.

While the increase in the markup level at the median values is modest, Tables 2 and 3 show that there are striking changes in markups, productivity and labor shares at the lower and upper tails of the markup distribution.[12] Table 2 illustrates that the share of unprofitable firms[13] (markups less than one) fell by 5.7% points and the share of profitable firms (markups exceeding 1.2) increased by 3.3%. To illustrate the dynamic changes in markups, Table 3 splits the sample into firms with markups less than one, between one and 1.2, and greater than 1.2 in 1998 and, reports changes in their median values of labor shares, markups, and productivities during 1998-2007. Here, the decline in labor shares is most profound (-16.2% points) for initially low markup firms; and, their productivity gains (a +35.4% increase) and markup gains (a +10.9% increase) are strongest. And, there is a gain in labor shares (a 4.4% point increase) for firms that had high markups in 1998; their productivity growth (a +13.2% increase) was slowest, and their markup declined (a -9.4% decrease).[14]

[11] A potential caveat with our estimation is that we use sectoral level price deflators and convert firm-level revenues to outputs. As recently argued in De Loecker et al (2016), a problem with this approach is that we might end up estimating revenue production functions instead of output production functions. In Appendix 1, we draw on results from Gorodnichenko (2007) and use his sensibility tests to show that we are estimating output production functions and not revenue production functions.

[12] The results are robust when we use the 3-year moving average values of markups, productivities, and labor shares.

[13] This share is the number of unprofitable firms divided by the number of all firms in each ownership group.

[14] The markup in equation (8) can be rewritten: $\mu_{it} = \omega_{it} C(p_{it}, w_{it}, r_{it}, \tilde{p}_{it})$ where $C(p_{it}, w_{it}, r_{it}, \tilde{p}_{it}) =$

As we will document subsequently, markup convergence drives declining labor shares for three reasons. First, initially low markup firms that paid high labor share rapidly improved their productivity, which led them to increase their markups and, thus, lower their labor shares. At the same time, initially high markup firms that paid low labor shares had slower productivity growth; thus, their markups fell and they paid higher labor shares. Finally, because our theory predicts that labor shares are decreasing and convex in markups, the downward impact on labor shares at the lower end of the markup distribution should have dominated the upward impact on labor shares at the upper end of the markup distribution. Thus, our results from China are quite different from those in Autor et al (2017), who show that labor shares in United States declined because high markup "super star" firms over time gained larger market shares.

### 4.2 Employment Protections

Combining the labor share in equation (10) with equations (6) and (11), the model implies that the log employment protection parameter in year $t$ is a function of the estimated production function parameters, estimated firm-level markups, and observed firm-level labor shares $(w_{it}N_{it}/VA_{it})$ and capital intensities $(K_{it}/N_{it})$:

$$\ln(\tilde{\phi}_t) = \ln\left(\frac{w_{it}N_{it}}{VA_{it}}\right) + \ln\left(\hat{\mu}_{it} - 1 + \hat{\alpha}_s\right) - \ln\left(\hat{\alpha}_s\right) + \ln\left[1 + \left(\frac{1-\hat{a}_s}{\hat{a}_s}\right)\left(\frac{K_{it}}{N_{it}}\right)^{\frac{\hat{\sigma}_s - 1}{\hat{\sigma}_s}}\right].$$

We then use the following equation to estimate the employment protection parameters:

$$\ln(\tilde{\phi}_t) = \sum_t \pi_t D_{it}^{SOE} + e_{it}$$

where $D_{it}^{SOE}$ is the dummy variable for two types of the SOEs (incumbent SOEs, or restructured SOEs which include privatized and exited SOEs). The error term consists of year-, province-, and sector-specific components: $e_{it} = \sum_t \theta^t D_{it}^t + \sum_p \theta^p D_{it}^p + \sum_s \theta^s D_{it}^s + \varepsilon_{it}$ and $\varepsilon_{it}$ is a random variable that is independently and identically distributed.

$p_{it}/\left\{b_s\left[(a_s)^{\sigma_s}(w_{it})^{\sigma_s-1} + (1-a_s)^{\sigma_s}(r_{it})^{\sigma_s-1}\right]^{\frac{\alpha_s}{\sigma_s-1}}(\tilde{p}_{it})^{1-\alpha_s}\right\}$. In fact, when we use the industry-level deflators for $p_{it}$ and $\tilde{p}_{it}$, we find that $C(p_{it}, w_{it}, r_{it}, \tilde{p}_{it})$ declined by 21.2%, and the magnitude of the decline is similar across the three markup groups. This means that if productivity growth is less (more) than +21.2%, markups will decline (increase). The strong positive correlation between productivity $(\omega_{it})$ and markups $(\mu_{it})$ is further discussed in Appendix 3.

Because the state chose to keep the continuer SOEs, we would expect that the estimated political benefit of protecting jobs ($1 - 1/\hat{\phi}_t$ where $\hat{\phi}_t = \exp(\hat{\pi}_t)$) would be stronger in these incumbent SOEs than in SOEs that the state let go through either exit or privatization. Table 4 reports the political benefit estimated from the balanced sample. Consistent with our expectations, in 1998 the estimated political benefit of hiring excess labor was 50.8% of incumbent SOE profits and 39.1% of privatized SOE profits; and in 2007 the estimated political benefits became lower for the both samples (37.0% for incumbent SOE and 11.1% for privatized SOE). Consistent with the findings of Cooper et al (2015) that after the enactment of reforms SOEs continued to take actions to preserve jobs and faced higher costs of workforce adjustment than private firms, by the end of sample period (2007), there was still a substantial political benefit of hiring excess labor for incumbent SOEs.

Figure 2 also illustrates that the political pressure to protect jobs is declining on an annual basis in both incumbent and privatized SOEs. Thus, consistent with our theory, this decline in employment protections drives down labor shares in SOEs through a direct channel and an indirect capital-labor substitution channel (because $\sigma_s > 1$), which in turn would cause firm-level labor shares for incumbent and privatized SOEs to fall.

### 4.3 Heterogeneity in Labor Shares

In this sub-section, we show that accounting for firm-level heterogeneity is critical for understanding the distribution of labor shares. In particular, the theoretical predictions of our model are illustrated using private firms in the synthetic fabrics sector in 2007. Synthetic fabrics is a representative example of Chinese manufacturing because its elasticity of substitution is close to the cross-sectoral median value ($\hat{\sigma}_{synthetic\ fabrics} = 1.476 < \ \hat{\sigma}_{median} = 1.489$) and its factor input share is close to the cross-sectoral median value ($\hat{\alpha}_{synthetic\ fabrics} = 0.171 > \ \hat{\alpha}_{median} = 0.163$). This means that Chinese manufacturing industries are intensive in intermediate inputs, and labor and capital are substitutes in the production processes. The system of three equations (6), (10) and (11) is used to calculate the predicted values of labor shares. In particular, using the estimated parameters for production functions ($\hat{\sigma}_{s,}$, $\hat{\alpha}_s$ and $\hat{a}_s$) and a median value for capital intensity or markups, we show how firm-level differences in their capital intensity and markups shape within-sector differences in labor shares.

Consistent with our theoretical model, Figure 3 illustrates that labor shares are decreasing and diminishing (convex) in capital intensity.[15] For example, predicted labor shares decline more sharply from the 25th percentile value to the median of capital intensity (by 4.7% points from 0.543 when capital intensity is 0.469 to 0.497 when capital intensity is 1.080) than from the median to the 75th percentile value (by 3.2% points from 0.497 when capital intensity is 1.080 to 0.465 when capital intensity is 1.853).

And, consistent with our theory, Figure 4 shows labor shares are decreasing and convex in markups.[16] For example, the 25th percentile, the median and the 75th percentile values of markups are 0.966, 1.048 and 1.134, respectively. Importantly, a small increase in markups is associated with a substantial decline in labor shares. For example, the 0.082 gain in markups when moving from the 25th percentile value to the median of markups causes a 29.5 percentage point decline in labor shares (from 0.792 to 0.497). And, since labor shares are decreasing and convex in markups, the impact of gains in markups is less potent when markups are higher.

# 5 Counter-factual Analysis

## 5.1 Predicted Distributions

Before conducting the counter-factual analysis, we check for how well our theory actually predicts the evolving cumulative distribution of labor shares. Table 5 contains the summary statistics for the actual and predicted distributions of labor shares in 1998 and 2007. Because firm-level labor shares and markups are widely distributed, and many firms in 1998 have labor share values exceeding one and/or markups less than unity, we use a liberal cutoff rule for building our sample. In particular, firms that have markup values less than the 5th percentile value of 1998 (0.913) in either 1998 or 2007, and firms that have the labor share values greater than the 97.5 percentile value of 1998 (2.579) in either 1998 or 2007 are dropped. Thus, there are 110,382 (257,938) firms in 1998 (2007) in the data. We have 110,808 (257,211) in 1998 (2007) for conducting the counter-factual analysis.

In order to check for the goodness of fit of our theory, the distribution of "predicted" labor shares are compared with the "actual" labor shares. Table 5 shows that in each year, the predicted

[15] We obtained the predicted labor shares for private firms in the sector in 2007 using the estimated production parameters, the reported firm-level capital intensity, and the median value of markups (1.048). The median value of markups is common across all private firms in a sector.

[16] We use the estimated production parameters, the median value of capital intensity (1.080), and the estimated firm-level values of markups.

labor shares for the mean, the 10th, 25th, 50th, 75th and 90th percentiles are always higher than the actual labor shares. This is because, as already discussed in Section 2, our labor compensation data do not include all of non-wage compensations.[17] However, we focus on the ability of the theory to predict the shift in the distribution over the period. And, in fact, the change reported in the actual and predicted distributions were close, although our theory under-predicts the percentile values of the shifts in labor's shares. Overall, the theory and the empirical parameters we estimate predict the change in the wide distribution of labor's share in 1998 versus 2007 accurately.

### 5.2 Counter-factual Analysis

In order to conduct a counter-factual analysis we need to isolate the separate contribution of changes in capital intensity (the capital-labor substitution channel), employment protections, and markups; and, we are also interested in the contribution of exit and entry. Thus, six models are prepared, of which the first (Model 1) is simply the predicted distribution from the entire sample in 1998 (Table 5 "Predicted" in 1998) and the last (Model 6) is the predicted distribution from the entire sample in 2007 (Table 5 "Predicted" in 2007).

Starting from Model 1 (the predicted distribution from the entire 1998 sample), Model 2 is obtained by dropping firms that exited from the sample after 1998. Thus, Model 2 is the predicted distribution of labor shares from the balanced sample using the 1998 values of firm-level capital intensities, firm-level markups, and the employment protection parameter. And, by moving from Model 1 to Model 2, we can isolate the impact of the exit of the firms.

Model 3 is obtained by replacing the 1998 values of capital intensity in Model 2 with the 2007 values that are adjusted with the 1998 values of political pressure on excess employment using the following manipulation of equation (6):

$$\frac{K_{i,2007}}{N_{i,2007}}\left(\frac{\hat{\phi}_{2007}}{\hat{\phi}_{1998}}\right)^{\sigma_s} = \left(\hat{\phi}_{1998}\frac{r_{i,2007}}{w_{i,2007}}\frac{a_s}{1-a_s}\right)^{-\sigma_s}.$$

And, by moving from Model 2 to Model 3, we simulate the counter-factual impact of the capital-labor substitution. Note that this channel focuses only on how the change in the relative cost of capital to labor, $\frac{r_{i,2007}}{w_{i,2007}}$, drives capital-labor substitution. Thus, employment protection parameters

[17] The predicted labor shares for the mean, the 10th, 25th, 50th, 75th, and 90th percentile values are always lower than the labor shares with the adjustments made by Hsieh and Klenow (2009) and Brandt et al (2012) so that the aggregate firm-level labor shares reasonably match the national aggregate figures.

are fixed at the 1998 level ($\hat{\phi}_{1998}$).

Model 4 is then obtained by taking out the 1998 markups in Model 3 and replacing them with the 2007 markups. And, the difference between Model 4 and Model 3 is the simulated impact of the changes in markups. Similarly, Model 5 is recovered when the 1998 employment protection parameters in Model 4 is replaced with the 2007 parameters. And, the difference between Model 5 and Model 4 is the simulated impact of employment protections. Finally, we add the newly entered firms into the balanced sample in Model 5 and recover the predicted distribution from the entire sample in 2007 (Model 6). And, the difference between Models 5 and 6 simulates the contribution of entry.[18]

Our counter-factual decomposition relies on the methods from the wage inequality literature (e.g., Machado and Mata, 2005; Autor, Katz and Kearney, 2008; Firpo et al, 2009). However, while the wage inequality literature uses wages as the outcome variable and considers the supply side of labor markets, we consider labor shares as the outcome of each firm's optimal demand for inputs and supply of output.

During 1998-2007, capital intensities increased, the number of unprofitable private firms declined, and political pressures on SOEs to protect jobs declined. Moreover, the capital-labor substitution elasticity was generally greater than unity in the manufacturing sector. Thus, consistent with our theory, the counter-factual distribution of labor shares shifts to the left when the 1998 values of capital intensities, markups and the employment protection parameters are replaced, one by one, with the 2007 values. In addition, the exit and entry do not drive down labor shares.[19] This finding is not surprising because the labor share values of entire and balanced sample are almost identical for both years.

In Table 6, we report the differences between the Models 1 and 2 (the effect of exit), between the Models 2 and 3 (the capital-labor substitution channel), between Models 3 and 4 (the markup channel), between Models 4 and 5 (the employment protections channel), and between the Models 5 and 6 (the effect of entry) at the different quantiles. We also provides standard errors using the conditional and unconditional quantile regressions proposed by Koenker and Bassett (1978) and Firpo et al (2009). In particular, we use:

[18] Although we cannot change the order of Models 1 ,2, 5 and 6, the current order of the decomposition from Model 3 to Model 5 is arbitrary. Our results are robust even if we reverse the order of Models 3, 4 and 5. In this case, the impact of the capital-labor substitution is slightly smaller than that in Table 6.

[19] See Table A3 in Appendix for the summary statistics of the cumulative distributions in Models 1-6.

$$PLS_q^m = PLS_q^{m'} + \beta^m(q) \tag{12}$$

where $PLS_q^m$ ($PLS_q^{m'}$) is the $q$th quantile value of the predicted labor share for $m$th ($m'$th) model from Models 1 through 6, and $\beta^m(q)$ is the actual difference in predicted labor shares between the two models. The standard errors are bootstrapped with 100 replications.

Because the conditional and unconditional estimates and standard errors are quite similar, for the sake of brevity, we present the conditional results. The largest contributor to declining labor shares is increasing markups at the 75th percentile, which accounts for a 6.2% point drop in labor shares. As shown in Table 1, within the set of continuer firms (the balanced panel) the increase in markups occurs primarily in private firms (i.e, private throughout the period or SOEs that were privatized). And, Table 3 shows that firms that were unprofitable had the strongest markup increases. Thus, private firms that were initially unprofitable were most responsible for the decline in labor shares in the upper quantiles. By inspection, capital-labor substitution accounts for between 1.0% to 1.4% point declines in labor shares in the 25th, 50th, and 75th percentiles. Overall, the contribution of markups is quantitatively strong throughout the cumulative distribution relative to the contributions of capital-labor substitution and declining employment protections, and firm exit and entry.

In order to get a better sense of the importance of alternative factors for the labor share distribution, we estimate equation (12) for $q$ from the 0.15 percentile to the 0.85 percentile on 0.05 point intervals. In Figure 5, we plot $\beta^m(q)$ on the vertical axis and $q$ in the horizontal axis for (Model 3 versus Model 2 - changes in the relative cost of capital to labor), (Model 4 versus Model 3 - changes in markups), or (Model 5 versus Model 4 - changes in political pressure for employment protections). As shown in Figure 5, capital-labor substitution has shifted leftward in all quantiles of the labor share distribution, but its effects have been the weakest for almost all the percentiles except for the 15th and 25th percentiles. Moreover, the changes in markups have the strongest impact on declining labor shares.

# 6 Conclusions

Over the period of China's accession to WTO, labor shares in China fell dramatically, and we show that markup convergence contributed the most for this decline. We develop a firm-level theory which predicts that a firm's labor share is decreasing and convex in markups (see also Autor et al, 2017; Azmat et al 2012). Consistent with this theory, we show that the downward impact of markup increases in initially unprofitable (low-markup) firms on labor shares robustly dominates the upward impact of markup declines in initially profitable (high-markup) firms. A counterfactual analysis shows that the effect of markup convergence dominates a broad set of alternative explanations for declining labor shares including waning employment protections (see Azmat et al, 2012; Blanchard and Giavazzi, 2003), capital-labor substitution (Karabarbounis and Neiman, 2014; Piketty, 2014) and, also, entry and exit of firms. Our results from China are quite different from the Autor et al (2017) study of the United States. While Autor et al (2007) highlight how highly productive "super-star" firms that charge high markups and pay low labor shares have gained market shares, our study emphasizes how initially unprofitable firms improved their productivity and, thus, charged higher markups and paid lower labor shares.

# Appendix

## Appendix 1: Production Function Estimation

We report the complete discussion of the estimation method and robustness checks in Berkowitz et al (2017). This paper follows an approach proposed by De Loecker and Warzynski (2012) and obtains the production function parameters ($\hat{\sigma}_s$, $\hat{\alpha}_s$, $\hat{a}_s$) for the 136 3-digit sectors.

To estimate the production function in equation (2), we use 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 and Warzynski (2012) and assume that the status of export, which is approximated by an exporter dummy ($D^e_{it}$), is essential for the choice of intermediate inputs:

$$\ln(M_{it}) = h_t\left[\ln(\omega_{it}), \ln(N_{it}), \ln(K_{it}), D_{it}^e\right].$$

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

$$\ln(\omega_{it}) = h_t^{-1}\left[\ln(N_{it}), \ln(K_{it}), \ln(M_{it}), D_{it}^e\right].$$

We then approximate $\ln(Q_{it})$ with the second-order polynomial function of the three inputs and that interacted with an exporter dummy:

$$\ln(Q_{it}) \approx \Phi_t\left[\ln(N_{it}), \ln(K_{it}), \ln(M_{it}), D_{it}^e\right] + \epsilon_{it} \tag{13}$$

where the variables $Q_{it}$ and $M_{it}$ are deflated with industry-level output and input deflators from Brandt et al (2012) and, the real capital stock series is constructed using the perpetual inventory method.

As argued in Gorodnichenko (2007), the industry-level output deflator does not necessarily provide a perfect measure of the output price since firms in the same industry often charge very different prices and enjoy different markups. Thus, ideally real output would be obtained by deflating revenues with a firm-level deflator as in De Loecker et al (2016). Alternatively, since we do not have reliable firm-level deflators, we use Proposition 1 in Gorodnichenko (2007) and verify not only two critical assumptions underlying our theory (constant returns to scale in production and competitive factor markets) but also our estimates of markups.

Next, we obtain the predicted value of equation (13), $\hat{\Phi}_t$, and compute the corresponding value of productivity for any combination of parameters $\Omega = (\bar{\alpha}_s, \bar{\sigma}_s, \bar{a}_s)$. This enables us to express the log of productivity $\ln(\bar{\omega}_{it}(\Omega))$ as the predicted log output minus the logged contribution of three inputs:

$$\ln(\bar{\omega}_{it}(\Omega)) = \hat{\Phi}_t - \frac{\bar{\alpha}_s\bar{\sigma}_s}{\bar{\sigma}_s - 1}\ln\left[\bar{a}_s(N_{it})^{\frac{\bar{\sigma}_s-1}{\bar{\sigma}_s}} + (1-\bar{a}_s)(K_{it})^{\frac{\bar{\sigma}_s-1}{\bar{\sigma}_s}}\right] - (1-\bar{\alpha}_s)\ln(M_{it}).$$

Our generalized method of moments (GMM) procedure assumes that firm-level innovations to productivity, $\zeta_{it}(\Omega)$, do not correlate with the predetermined choices of inputs. To recover

$\zeta_{it}(\Omega)$, we assume that productivity for any set of parameters, $\bar{\omega}_{it}(\Omega)$, follows a non-parametric first order Markov process, and then we can approximate the productivity process with the third order polynomial:

$$\ln(\bar{\omega}_{it}(\Omega)) = \gamma_0 + \gamma_1 \ln(\bar{\omega}_{i,t-1}(\Omega)) + \gamma_2 \left[\ln(\bar{\omega}_{i,t-1}(\Omega))\right]^2 + \gamma_3 \left[\ln(\bar{\omega}_{i,t-1}(\Omega))\right]^3 + \zeta_{it}(\Omega).$$

From this third order polynomial, we can recover the innovation to productivity, $\zeta_{it}(\Omega)$, for a given set of the parameters. Since the productivity term, $\ln(\bar{\omega}_{it}(\Omega))$, can be correlated with the current choices of flexible inputs, $\ln(N_{it})$ and $\ln(M_{it})$, but it is not correlated with the predetermined variable, $\ln(K_{it})$,the innovation to productivity, $\zeta_{it}(\Omega)$, will not be correlated with $\ln(K_{it})$, $\ln(N_{i,t-1})$, and $\ln(M_{i,t-1})$. Thus, we use the moment condition similar to De Loecker and Warzynski (2012):

$$m_s(\Omega) \equiv E\left[\zeta_{it}(\Omega)\begin{pmatrix} \ln(K_{it}) \\ \ln(N_{i,t-1}) \\ \ln(K_{it})\ln(N_{i,t-1}) \\ \left[\ln(K_{it})\right]^2 \\ \left[\ln(N_{i,t-1})\right]^2 \\ \ln(M_{i,t-1}) \end{pmatrix}\right] = 0 \tag{14}$$

and search for the optimal combination of $\hat{\alpha}_s$, $\hat{\sigma}_s$, and $\hat{a}_s$ by minimizing the sum of the moments (and driving it as close as possible to zero) using the standard weighting procedure for plausible values of $\Omega$.

## Appendix 2: Validation of the Theory

A simple expression for labor share's of value added can be derived:

$$LS_{it} = \frac{F(\cdot)}{G(\cdot)}\phi_t$$

where $\phi_t$ is the political weight for excess employment, the output elasticity of labor is $F(\cdot) = \hat{\alpha}_s\left[1 + \left(\frac{1-\hat{a}_s}{\hat{a}_s}\right)\left(\frac{K_{it}}{N_{it}}\right)^{\frac{\hat{\sigma}_s - 1}{\hat{\sigma}_s}}\right]^{-1}$, and the markup effect is $G(\cdot) = \hat{\mu}_{it} - 1 + \hat{\alpha}_s$.

As validation test of our theory of firm-level labor shares, we estimate the variants of the following equation:

$$\ln(LS_{it}) = \delta^{\sigma} \ln [F(\cdot)] + \delta^{\mu} \ln [G(\cdot)] + \sum_t \delta_t^{\phi} D_{it}^{SOE} + e_{it} \tag{15}$$

This estimating equation enables us to recover the implied sectoral political pressure to protect employment, $\phi_t$, similar to our baseline method. In the equation, $D_{it}^{SOE}$ is a dummy variable that equals one for an SOE and is zero otherwise. The first set of estimating equations include province-, sector- and year-specific fixed effects. The remaining estimating equations include firm-fixed effects. We also include the one-year lagged value of log labor share to capture the dynamic character of the analysis.

In the first set of estimating equations (15), we use ordinary least squares (OLS). For each explanatory variable, we report the estimated parameters and their standard errors (clustered at the 3-digit CIC level) in parentheses for the entire sample and the balanced sample. Models 1 and 2 are variants of equation (15) with sector-, province-, and year-fixed effects. These two models also include the interactions of year-fixed effects and the SOE dummy, which are used to capture the year-specific average difference in labor's share after controlling for the output elasticity of labor and the markup term.

Consistent with the predictions of our theory, the results in Table A1 indicate that labor's share is positively associated with the output elasticity of labor and political weight on excess employment, and negatively associated with the markup term. These associations are precisely estimated and statistically significant at the 1% confidence level. However, while the theory predicts that the expected coefficients for the markup term are negative one, the estimated coefficients are negative but lower in absolute magnitude than one. Models 3 and 4 use firm-fixed effects instead of sector- and province-fixed effects. Since firm-fixed effects can include the contributions for ownership-specific effects such as the political weights, only the output elasticity of labor and the markup term can be estimated. The empirical results validate our theoretical predictions.

Models 5 through 8 focus on the dynamic character of labor's share. Estimating the objective parameters consistently requires that several standard econometric issues are dealt with. The first issue is serial correlation. The log labor share for firm $i$ at year $t$ (i.e., $\ln(LS_{it})$) correlates with its lagged value (i.e., $\ln(LS_{i,t-1})$). The second issue is simultaneity and endogeneity. In particular, capital intensity in the output elasticity of labor is a function of the political weight on excess employment ($\phi_t$) times the relative cost of capital ($r_{it}/w_{it}$) as in equation (6).

Another issue is that the markup can be endogenous when it is computed as the marginal product of labor divided by the labor share of revenue if labor is a flexible input (i.e., De Loecker and Warzynski, 2012). In order to overcome this endogeneity issue, the markup is computed by dividing the marginal product of intermediate inputs with the revenue share of intermediate inputs. To deal with endogeneity and serial correlation simultaneously, we use Arellano and Bond's (1991) differenced GMM procedure and Blundell and Bond's (1998) system GMM procedure as well. We report the results of the various specifications for the entire sample, depending on whether the two terms are treated as endogenous variables in addition to the lagged log labor share. Again, because of the inclusion of time-differencing or firm-fixed effects, the political weight on employment is dropped. Nevertheless, results are similar with the estimated coefficients on the markup term closer to the theoretical prediction. Overall, the results in Table A1 support our theoretical predictions of just how labor-capital substitution, markups and political pressure to protect employment influence labor's share.

## Appendix 3: Markups and Productivity

The assumption of constant returns to scale enables us to derive equation (8) from the cost minimization problem of unit production. In particular, we solve the following optimization problem:

$$\min_{N_{it},K_{it},M_{it}} \left[w_{it}N_{it} + r_{it}K_{it} + \tilde{p}_{it}M_{it}\right] - \lambda\left[Q_{it} - 1\right]$$

and derive the marginal costs as a function of exogenous input prices ($w_{it}$, $r_{it}$ and $\tilde{p}_{it}$):

$$c_{it}\left(\cdot\right) = \frac{b_s}{\omega_{it}}\left[\left(a_s\right)^{\sigma_s}\left(w_{it}\right)^{\sigma_s - 1} + \left(1 - a_s\right)^{\sigma_s}\left(r_{it}\right)^{\sigma_s - 1}\right]^{\frac{\alpha_s}{\sigma_s - 1}}\left(\tilde{p}_{it}\right)^{1-\alpha_s}$$

where $b_s = \left(\alpha_s\right)^{-\alpha_s}\left(1 - \alpha_s\right)^{-(1-\alpha_s)}$.

Using equations (2) and (6), the estimated parameters ($\hat{\alpha}_s$, $\hat{\sigma}_s$, $\hat{a}_s$, and $\hat{\phi}_t$), the average wage within each firm ($w_{it}$ is measured by dividing the firm's wage bill by its labor) and capital intensities ($K_{it}/N_{it}$), we can predict the user cost of capital ($\hat{r}_{it}$) and productivity ($\hat{\omega}_{it}$). We then predict the marginal cost ($\hat{c}_{it}\left(\cdot\right)$) from these parameters and variables. Note that we use the industry-level price deflators from Brandt et al (2012) to approximate output and materials prices, $p_{it}$ and $\tilde{p}_{it}$.

To understand the demand-side ($p_{it}$) and supply-side ($c_{it}(\cdot)$) determinants of markups, we estimate the variants of the following equation:

$$\ln(\mu_{it}) = \delta^p \ln[p_{it}] + \delta^c \ln[\hat{c}_{it}(\cdot)] + e_{it} \tag{16}$$

where we expect $\delta^p = 1$ and $\delta^c = -1$.

The first two models of estimating equation (16) include firm-fixed effects; the next two models use time differenced variables; and the last four models use the differenced and system GMM procedures to deal with endogeneity and serial correlation. Consistent with the predictions of our theory, the results in Table A2 indicate that log markups are positively associated with the output prices and negatively associated with the marginal costs. These associations are precisely estimated and statistically significant at the 1% confidence level although the estimated coefficients are slightly smaller in absolute magnitude than the theoretically expected values. These simple models can explain more than 74% of the within-firm variation in log markups, indicating that industry-level output prices and firm-level marginal costs can account for the majority of the changes in markups.

Models 2, 4, 6 and 8 separate log marginal costs into log productivity and log input costs:

$$\ln[\hat{c}_{it}(\cdot)] = -\ln(\hat{\omega}_{it}) + \ln\left\{b_s\left[(a_s)^{\sigma_s}(w_{it})^{\sigma_s-1} + (1-a_s)^{\sigma_s}(r_{it})^{\sigma_s-1}\right]^{\frac{\alpha_s}{\sigma_s-1}}(\tilde{p}_{it})^{1-\alpha_s}\right\}.$$

In the case of productivity, the estimated effects are close to the magnitude of unity that is predicted by our theory. However, while the estimated effects for input costs are, as expected, negative, they are higher (less negative) than the theoretically expected value of minus one. Overall, the results in Table A2 support our theoretical predictions of how markups within firms evolve over the period.

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# Figures and Tables

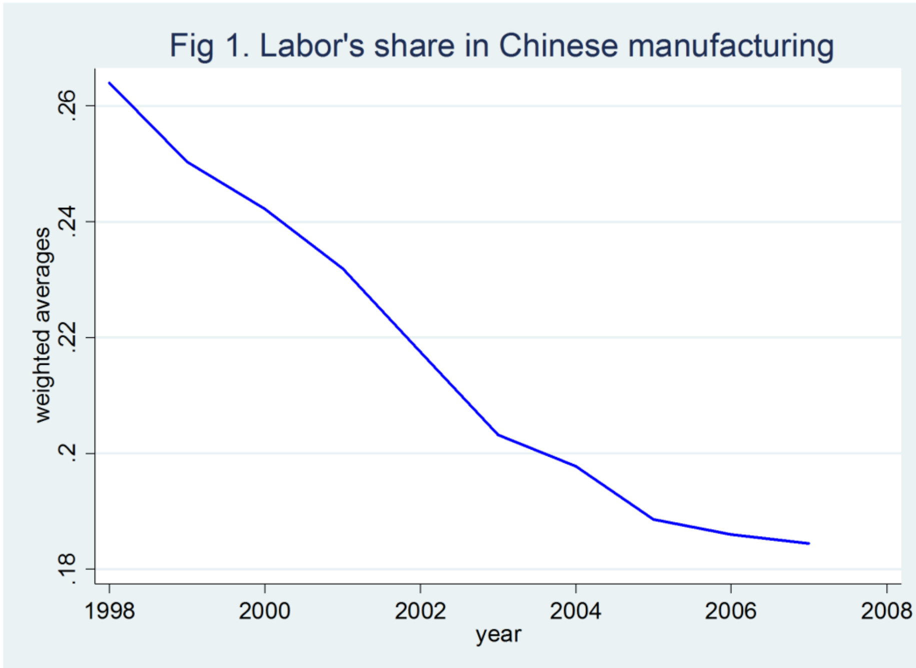



Table 1: Summary statistics by firm ownerships

1. Labor shares by firm ownerships

| | Sample | | | Labor share | | |
|---|---|---|---|---|---|---|
| | 1998 | 2007 | change | 1998 | 2007 | change |
| All firms | 119,185 | 270,368 | 126.8% | 32.0% | 24.8% | -7.1% |
| Continuer firms: | 35,104 | 35,104 | - | 31.1% | 27.8% | -3.3% |
| SOE to SOE | 3706 | 3706 | - | 47.7% | 36.6% | -11.2% |
| Private to private | 26692 | 26692 | - | 28.3% | 26.9% | -1.3% |
| SOE to private | 3925 | 3925 | - | 39.1% | 25.5% | -13.6% |
| Private to SOE | 781 | 781 | - | 28.5% | 27.8% | -0.6% |
| Exit and entry: | 84081 | 235264 | 179.8% | 32.5% | 24.4% | -8.1% |

2. Markup and Capital-Labor ratios by firm ownerships

| | Markup ratio | | | Capital-labor ratio | | |
|---|---|---|---|---|---|---|
| | 1998 | 2007 | change | 1998 | 2007 | change |
| All firms | 1.096 | 1.121 | 2.2% | 0.357 | 0.460 | 28.8% |
| Continuer firms: | 1.098 | 1.119 | 1.9% | 0.421 | 0.578 | 37.5% |
| SOE to SOE | 1.116 | 1.122 | 0.5% | 0.579 | 0.713 | 23.1% |
| Private to private | 1.093 | 1.117 | 2.3% | 0.323 | 0.519 | 61.0% |
| SOE to private | 1.119 | 1.134 | 1.3% | 0.505 | 0.684 | 35.7% |
| Private to SOE | 1.100 | 1.094 | -0.6% | 0.490 | 0.677 | 38.2% |
| Exit and entry: | 1.096 | 1.121 | 2.3% | 0.334 | 0.442 | 32.2% |

*Notes*: (1) Firm ownerships are based on their ownerships in years 1998 and 2007. Exited firms are the firms that operated in 1998 but did not operate in 2007. Entrants are the firms that did not operate in 1998 but operated in 2007. (2) “change” for labor shares is the percentage point change over 1998-2007. Otherwise, it is the percentage change.

Table 2: The share of unprofitable and profitable firms

| | Share of firms with markups < 1 | | | Share of firms with markups > 1.2 | | |
|---|---|---|---|---|---|---|
| | 1998 | 2007 | change | 1998 | 2007 | change |
| All firms | 26.7% | 21.1% | -5.7% | 28.6% | 31.9% | 3.3% |
| Continuer firms: | 25.5% | 21.2% | -4.3% | 28.5% | 32.3% | 3.8% |
| SOE to SOE | 26.4% | 24.1% | -2.3% | 35.0% | 35.6% | 0.6% |
| Private to private | 25.6% | 20.8% | -4.8% | 26.9% | 31.4% | 4.5% |
| SOE to private | 23.6% | 20.4% | -3.2% | 33.2% | 36.8% | 3.6% |
| Private to SOE | 26.4% | 25.6% | -0.8% | 30.0% | 27.8% | -2.2% |
| Exit and entry: | 27.3% | 21.0% | -6.2% | 28.6% | 31.8% | 3.2% |

*Notes*: This share is the number of unprofitable and profitable firms divided by the number of all firms in each ownership group.

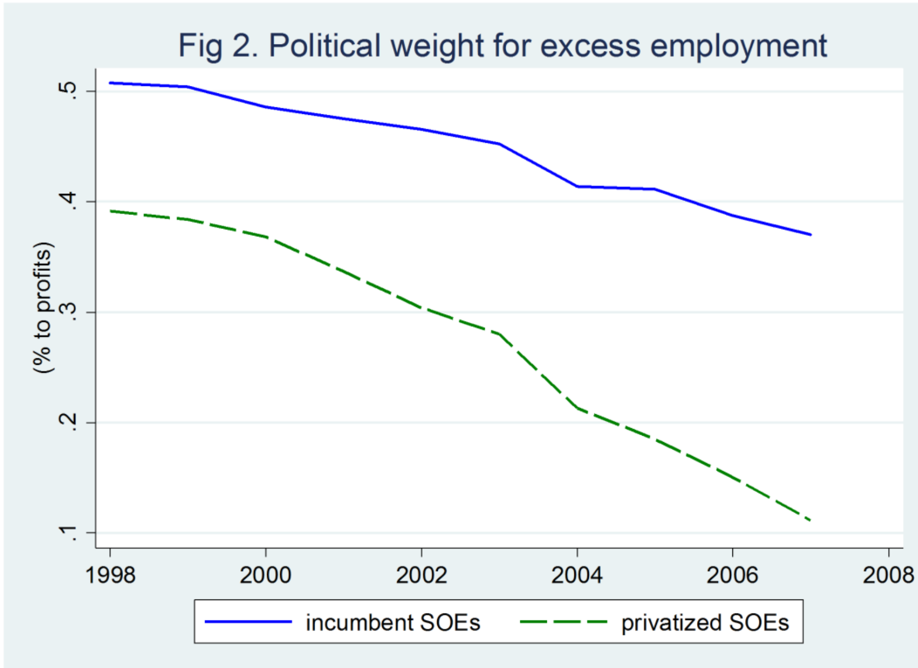
Table 3: Labor share and productivity by markup groups in 1998

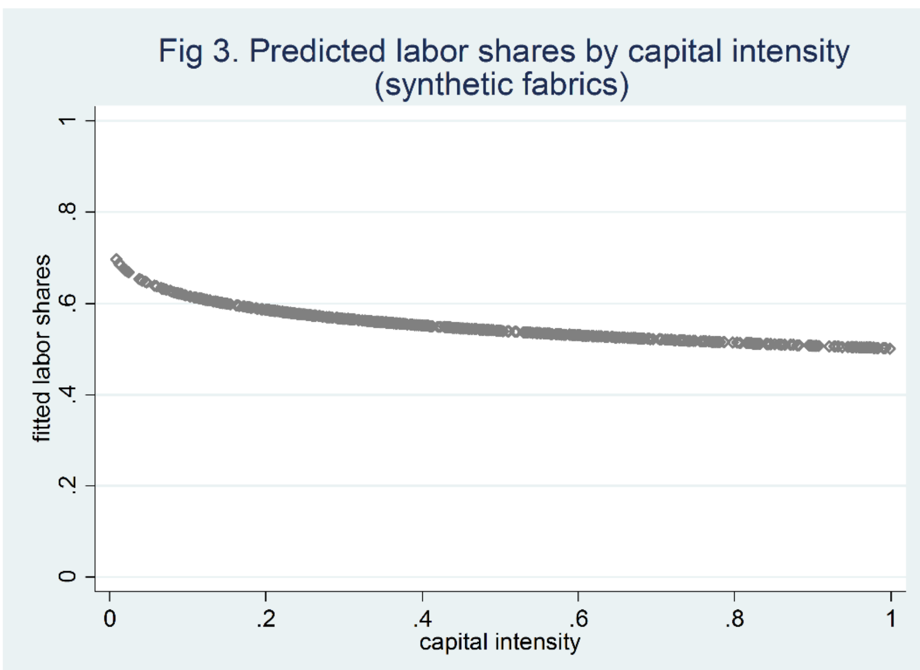
| | # of firms (share) | Labor share | | | Markup | | | Productivity | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 1998 | 2007 | change | 1998 | 2007 | change | 1998 | 2007 | change |
| Markup ratio in 1998 | | | | | | | | | | |
| Markups < 1 | 8946 (0.25) | 44.9% | 28.6% | -16.2% | 0.937 | 1.039 | 10.9% | 1.232 | 1.669 | 35.4% |
| 1 ≤ Markups ≤ 1.2 | 16147 (0.46) | 30.9% | 27.7% | -3.2% | 1.091 | 1.120 | 2.6% | 1.301 | 1.629 | 25.2% |
| 1.2 < Markups | 10011 (0.29) | 22.5% | 26.9% | 4.4% | 1.317 | 1.193 | -9.4% | 1.501 | 1.699 | 13.2% |

Table 4: Estimates for the SOEs' political benefit of excess employment

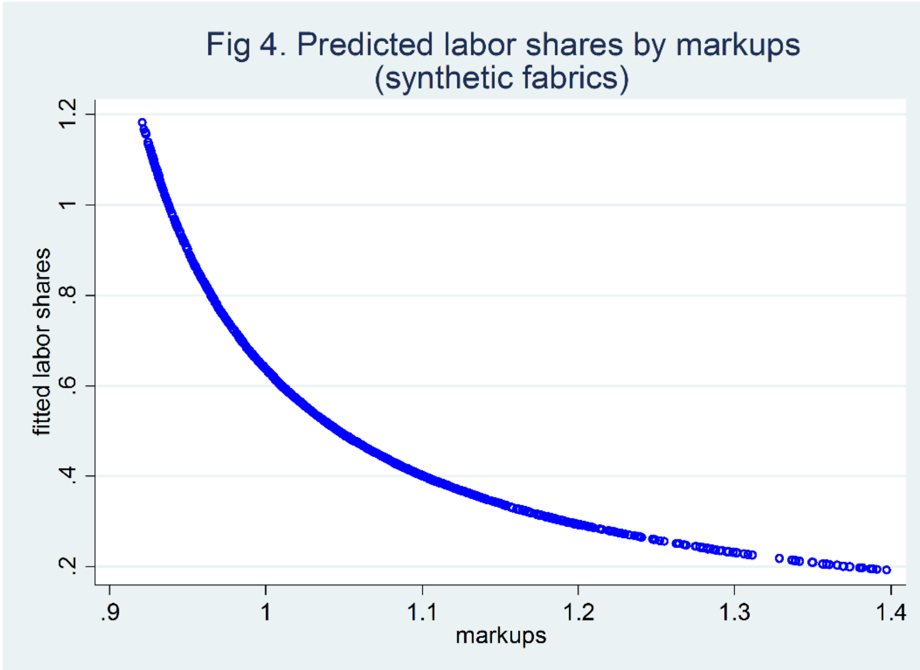
| | Incumbent SOEs | Privatized SOEs |
|---|---|---|
| Implied political weight in 1998 ($1\text{-}1/\phi_{98}$) | 0.508 | 0.391 |
| Estimated coefficient ($\pi_{98}$) | 0.708*** | 0.142*** |
| (standard errors) | (0.047) | (0.036) |
| Implied political weight in 2007 ($1\text{-}1/\phi_{07}$) | 0.370 | 0.111 |
| Estimated coefficient ($\pi_{07}$) and standard errors | 0.462*** | 0.019 |
| (standard errors) | (0.040) | (0.044) |
| Observations | 294,644 | 266,594 |
| R-squared | 0.329 | 0.316 |

*Notes*: (1) We use balanced sample. (2) Standard errors that are clustered at the 3-digit sectoral level are in parentheses. (3) All coefficients are statistically significant at the 1% confidence level. (4) All specifications include sector-, province-, and year-fixed effects.




*Notes*: (1) We obtained the predicted labor shares for all private firms in the sector in 2007 using the estimated production parameters, the reported capital intensity, and the median value of markups (1.048). (2) In this figure, we report the range of capital intensity from 0 to 1.



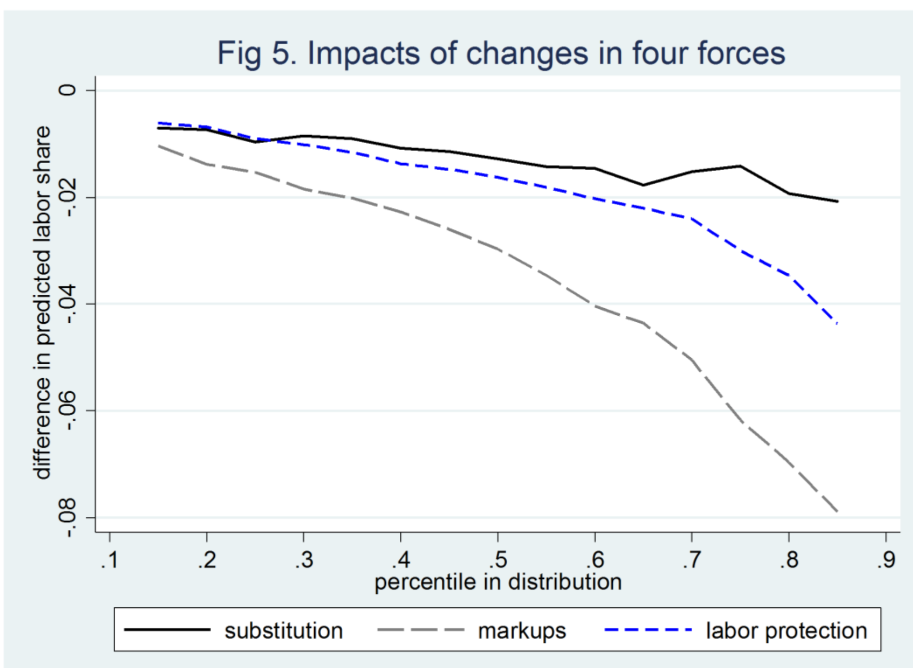

*Notes*: (1) We obtained the predicted labor shares for all firms in the sector in 2007 using the estimated production parameters, the median value of capital intensity (1.098), and the estimated values of markups. The political weight to protect jobs is set to zeros. (2) In this figure, we report the range of markups from 0.92 to 1.4.

Table 5: Actual and predicted distributions of labor shares

| | Actual | | | Predicted | | |
|---|---|---|---|---|---|---|
| | 1998 | 2007 | change | 1998 | 2007 | change |
| Summary statistics | | | | | | |
| Mean | 0.404 | 0.316 | -0.088 | 0.470 | 0.414 | -0.056 |
| Standard deviation | 0.376 | 0.289 | -23.1% | 0.377 | 0.329 | -12.7% |
| Skewness | 2.189 | 2.300 | 5.1% | 1.908 | 2.152 | 12.7% |
| Kurtosis | 9.464 | 11.786 | 24.5% | 7.764 | 9.674 | 24.6% |
| Observation | 110,382 | 257,938 | 133.7% | 110,808 | 257,211 | 132.1% |
| Percentiles | | | | | | |
| 10th percentile | 0.071 | 0.052 | -0.019 | 0.129 | 0.122 | -0.007 |
| 25th percentile | 0.149 | 0.112 | -0.037 | 0.215 | 0.196 | -0.019 |
| 50th percentile | 0.303 | 0.239 | -0.063 | 0.365 | 0.324 | -0.041 |
| 75th percentile | 0.530 | 0.433 | -0.097 | 0.604 | 0.524 | -0.080 |
| 90th percentile | 0.839 | 0.657 | -0.182 | 0.943 | 0.811 | -0.132 |

Table 6: Conditional and unconditional quantile regressions

| | Model 1 to 2 (exit) | Model 2 to 3 (substitution) | Model 3 to 4 (markups) | Model 4 to 5 (protection) | Model 5 to 6 (entry) |
|---|---|---|---|---|---|
| Changes in mean values | 0.013 | -0.012 | -0.040 | -0.024 | 0.007 |
| Conditional regressions | | | | | |
| 25th percentile | 0.008*** | -0.010*** | -0.015*** | -0.009*** | 0.007*** |
| (standard errors) | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) |
| 50th percentile | 0.010*** | -0.013*** | -0.030*** | -0.016*** | 0.008*** |
| (standard errors) | (0.002) | (0.003) | (0.003) | (0.002) | (0.002) |
| 75th percentile | 0.014*** | -0.014*** | -0.062*** | -0.030*** | 0.012*** |
| (standard errors) | (0.004) | (0.005) | (0.005) | (0.004) | (0.003) |
| Unconditional regressions | | | | | |
| 25th percentile | 0.008*** | -0.009*** | -0.015*** | -0.009*** | 0.007*** |
| (standard errors) | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) |
| 50th percentile | 0.010*** | -0.013*** | -0.030*** | -0.016*** | 0.007*** |
| (standard errors) | (0.002) | (0.003) | (0.003) | (0.002) | (0.002) |
| 75th percentile | 0.013*** | -0.013** | -0.060*** | -0.031*** | 0.012*** |
| (standard errors) | (0.004) | (0.005) | (0.005) | (0.004) | (0.003) |



## Appendix: Figures and Tables

Table A1: Log labor shares panel estimations with firm-fixed effects

| | OLS | | Fixed Effects | | Difference GMM | | System GMM | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 |
| Sample | All | Balanced | All | Balanced | All | All | All | All |
| Endogenize the two effects | - | - | - | - | No | Yes | No | Yes |
| Output elasticity of labor ($\delta^{\sigma}$) | 1.147*** | 1.331*** | 1.053*** | 1.205*** | 1.014*** | 0.986*** | 1.094*** | 1.138*** |
| | (0.051) | (0.056) | (0.037) | (0.058) | (0.016) | (0.015) | (0.016) | (0.014) |
| Markup effect ($\delta^{\mu}$) | -0.470*** | -0.455*** | -0.579*** | -0.568*** | -0.636*** | -0.605*** | -0.661*** | -0.612*** |
| | (0.011) | (0.016) | (0.006) | (0.009) | (0.002) | (0.001) | (0.001) | (0.001) |
| Political weight ($\delta^{\varphi}{}_{1998}$) | 0.764*** | 0.556*** | | | | | | |
| | (0.028) | (0.036) | | | | | | |
| Political weight ($\delta^{\varphi}{}_{2007}$) | 0.318*** | 0.345*** | | | | | | |
| | (0.023) | (0.029) | | | | | | |
| Lagged log labor share | | | | | 0.167*** | 0.070*** | 0.266*** | 0.159*** |
| | | | | | (0.004) | (0.002) | (0.002) | (0.002) |
| Year-fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm-fixed effects | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector- and province-fixed effects | Yes | No | No | No | No | No | No | No |
| Observations | 1,673,371 | 280,255 | 1,673,371 | 280,255 | 826,348 | 826,348 | 1,177,948 | 1,177,948 |
| Number of firm fixed effects | | | 453,333 | 28,290 | 253,409 | 253,409 | 336,384 | 336,384 |
| # of instrumental variables | | | | | 39 | 111 | 47 | 135 |

*Notes*: (1) The entire sample consists of 1,704,372 observations, which is an unbalanced panel of 457,610 manufacturing firms. From this sample, we drop the top and bottom 0.25% of observations for labor share, the output elasticity of labor, or the markup term as outliers. (2) Difference GMM is Arellano and Bond (1991), and System GMM is Blundell and Bond (1998). (3) Standard errors that are clustered at the 3-digit sectoral level are in parentheses. (4) All coefficients are statistically significant at the 1% confidence level.

Table A2: Log markups panel estimations with firm-fixed effects

| | Fixed Effects | | Differencing | | Difference GMM | | System GMM | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 |
| Log output price ($\delta^p$) | 0.840*** | 0.666*** | 0.879*** | 0.770*** | 0.925*** | 0.682*** | 0.931*** | 0.674*** |
| | (0.017) | (0.023) | (0.012) | (0.018) | (0.003) | (0.004) | (0.003) | (0.004) |
| Log marginal cost ($\delta^c$) | -0.885*** | | -0.925*** | | -0.936*** | | -0.939*** | |
| | (0.012) | | (0.010) | | (0.002) | | (0.002) | |
| Log TFP | | 0.905*** | | 0.983*** | | 0.993*** | | 0.983*** |
| | | (0.011) | | (0.007) | | (0.001) | | (0.001) |
| Log input costs | | -0.678*** | | -0.401*** | | -0.541*** | | -0.540*** |
| | | (0.022) | | (0.019) | | (0.002) | | (0.002) |
| Lagged log markup | | | | | 0.021*** | 0.085*** | 0.026*** | 0.069*** |
| | | | | | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 1,457,365 | 1,457,365 | 1,069,736 | 1,069,736 | 774,072 | 774,072 | 1,069,736 | 1,069,736 |
| R-squared | 0.735 | 0.755 | 0.775 | 0.827 | | | | |
| Number of firm fixed effects | 352,316 | 352,316 | | | 223,631 | 223,631 | 281,921 | 281,921 |
| # of instrumental variables | | | | | 39 | 40 | 47 | 48 |

*Notes*: (1) From the entire sample, we drop the top and bottom 0.25% of observations for markups, wage rate or the predicted user cost of capital. (2) Standard errors that are clustered at the 3-digit sectoral level are in parentheses. (3) All coefficients are statistically significant at the 1% confidence level. (4) The results from the balanced sample are available upon request.

Table A3: Summary statistics for counterfactual distributions

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| Exogenous values | | | | | | |
| Sample | All | Balanced | Balanced | Balanced | Balanced | All |
| Capital intensity | 1998 | 1998 | 2007 | 2007 | 2007 | 2007 |
| Markup | 1998 | 1998 | 1998 | 2007 | 2007 | 2007 |
| Employment protection | 1998 | 1998 | 1998 | 1998 | 2007 | 2007 |
| Summary statistics | | | | | | |
| Mean | 0.470 | 0.483 | 0.471 | 0.430 | 0.407 | 0.414 |
| Standard deviation | 0.377 | 0.383 | 0.379 | 0.351 | 0.330 | 0.329 |
| Skewness | 1.908 | 1.921 | 1.965 | 2.170 | 2.254 | 2.152 |
| Kurtosis | 7.764 | 7.782 | 8.026 | 9.437 | 10.251 | 9.674 |
| Observation | 110,808 | 32,210 | 32,216 | 32,266 | 32,317 | 257,211 |
| Percentiles | | | | | | |
| 10th percentile | 0.129 | 0.137 | 0.131 | 0.123 | 0.119 | 0.122 |
| 25th percentile | 0.215 | 0.224 | 0.214 | 0.199 | 0.189 | 0.196 |
| 50th percentile | 0.365 | 0.375 | 0.362 | 0.333 | 0.316 | 0.324 |
| 75th percentile | 0.604 | 0.618 | 0.604 | 0.542 | 0.512 | 0.524 |
| 90th percentile | 0.943 | 0.965 | 0.949 | 0.849 | 0.795 | 0.811 |

*Notes*: (1) We limit the sample to the range of labor shares from 0 to 2.579 (97.5 percentile value of labor's share in 1998) and the range of markups greater than 0.913 (10 percentile value of markups in 1998). (2) Model 1 uses the predicted value of labor shares using the 1998 values of capital intensity, markup, and political weight for entire sample, Model 2 uses the same predicted value of Model 1 for the balanced sample that excludes the exiters; Model 3 uses the 1998 values of markup and political weight and the 2007 values of adjusted capital intensity for the balanced sample; Model 4 uses the 2007 values of capital intensity and markup and the 1998 values of political weights for the balanced sample; Model 5 uses the 2007 values of three variables for the balanced sample; Model 6 uses the same predicted values of Model 5 but includes the sample of new entry.