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The Aggregate Labor Share and Distortions in China ^{*}

Xiaoyue Zhang[†] Junjie Xia[‡]

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Abstract

This paper shows that in an economy where distortions prevent firms from using their profit-maximizing amounts of capital and labor, removing these distortions can generate both an efficiency gain and a higher aggregate labor share. We use firm-level data on Chinese manufacturing, mining, and public utilities in 2005 and estimate a general equilibrium model with heterogeneous productivity, technology, demand elasticities, and distortions across firms. We find that the distortions cause most firms to be too small. Removing them raises the aggregate demand for labor and, holding the aggregate labor and capital fixed, increases the wage by 57%. Consequently, the aggregate labor share rises by 24 percentage points. Aggregate productivity quadruples.

Keywords: Distortions, aggregate labor share, latent market structure, firm heterogeneity

JEL Codes: C4, D3, E1, L6, O1, O5

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1 Introduction

The classical debate on the trade-off between efficiency and fairness of revenue distribution has been reignited by recent studies on declining aggregate labor shares. The growth of superstar firms and the new wave of labor-replacing technology such as robotization and artificial intelligence raise efficiency but reduce aggregate labor shares (Autor et al. (2020) on superstar firms; Acemoglu (2003), Acemoglu and Restrepo (2018), and Jones and Liu (2024) on technology). This paper shows that in an economy where distortions prevent firms from using their profit-maximizing amounts of capital and labor, removing these distortions can raise aggregate labor demand and, as a consequence, generate both an efficiency gain and a higher aggregate labor share. Examples of these distortions are a lack of access to financial credits, adjustment frictions, and regulations. We estimate a general equilibrium model with heterogeneous productivity, technology, demand elasticities, and distortions across firms using firm-level data on Chinese manufacturing, mining, and public utilities in 2005. Holding the aggregate labor and capital fixed, we quantify that the aggregate labor share out of the aggregate revenue would increase by 24 percentage points due to a 57% increase in the wage and that the aggregate productivity would quadruple.

While removing the distortions generates efficiency gains, it does not guarantee a higher aggregate labor share. Changes in the aggregate labor share depends on whether distortions cause individual firms to substitute away from labor and how resources are allocated across firms in the general equilibrium. We predict an increase in the aggregate labor share for the Chinese firms in 2005 because the distortions cause most firms to be too small. Removing the distortions allows these firms to grow larger and unleash their suppressed labor demand. As a result, the aggregate labor demand increases, which under fixed aggregate labor and capital supply, raises the wage and the aggregate labor share.

Distortions affect firm sizes in two ways: changing the labor-capital ratios and changing the capital and labor use proportionally without altering the ratios. Accordingly, we divide the distortions into input and output distortions. Formally, the input distortions are the firm-level wedges between observed cost ratios and the production-elasticity ratios of labor and capital. The output distortions explain the remaining gap between the observed firm sizes and theoretical profit-maximizing sizes. Markups predicted by demand elasticities are excluded from the distortions.

Our paper provides estimates of firm-level input and output distortions and quantifies the impact of these distortions on the aggregate labor share. The method of quantifying the aggregate productivity gain is the same as Hsieh and Klenow (2009) except that we use refined firm-level estimated parameters. Due to the firm-level estimates, we are able to investigate

how the distortions affect the aggregate labor share, which type of the distortions—input or output distortions—plays the main role, and how the labor allocation changes across firms and industries.

The firm-level distortions are quantified by estimating a general equilibrium model with rich firm heterogeneity. We model firm heterogeneity using firm-specific productivity and distortions and industry-specific technology. Demand elasticities are allowed to vary within and across industries. On the supply side, we use Cobb-Douglas production functions with constant returns to scale on labor and capital.¹ Production functions are the same within industry except for firm-specific productivity but differ across industries. On the demand side, we assume nested constant elasticities of substitutions (nested CES). The nest structure is latent up to industry categories, i.e. an industry can contain multiple nests, but a nest only belongs to one industry. Firms inside the same nest face the same constant elasticity of substitution, but the elasticities vary across nests. The elasticities of substitution across nests equal 1. We choose a nested CES demand with a latent nest structure to keep the demand side flexible yet parsimonious. Cobb-Douglas production functions offer us simple general equilibrium conditions for estimating firm heterogeneity. We assume a perfectly competitive factor market where all the firms pay the same wage and capital rental rate.

We use the Chinese Annual Survey of Industry in 2005 to estimate the demand and supply parameters. The survey covers all the state-owned firms and non-state firms that have revenues above 5 million RMB (\$600,000). The latter is also called above-scale non-state firms in the survey. We observe firms' 4-digit industry codes from the Chinese GB/T 4754 standard, which are comparable to the 4-digit International Standard Industrial Classification (Brandt et al. (2012)). The nest structure of our nested CES demand specification is estimated from the data under the assumptions that a nest belongs to only one industry and that the logarithm of firms' revenue-cost ratios are firms' markups predicted by their demand elasticities plus an idiosyncratic error term. The error term follows a normal distribution within a nest. Under these assumptions, the distribution of firm-level revenue-cost ratios within an industry is a mixture normal distribution with an unknown number of components. We estimate firms' demand elasticities and the latent nest structure by estimating a mixture normal distribution for each industry. We then use the observed firm-level expenditure ratios of labor and capital to estimate production elasticities of substitution assuming that the mode of input distortions within an industry is 0 and that the production elasticities are the same within an industry. We choose the mode because industry-level distributions of

¹Due to the unitary elasticity of substitution of Cobb-Douglas production functions, the changes in the aggregate labor share is driven by removing the gaps between the firm-level observed labor shares and the theoretical profit-maximizing labor shares and by the reallocation of capital and labor across firms.

capital-labor ratios are generally skewed, with tails that do not fit normal distributions, and we want to reduce the impact of heavy tails and skewness on the estimates. Finally, we use the estimated demand and supply parameters to calculate the input and output distortions using the firm-level labor and capital expenditure shares out of value added. Firms are estimated to be too small, i.e. facing output distortions, when their observed labor and capital shares out of value added are too low and cannot be explained by their demand elasticities.

Our results show that the aggregate labor share would increase by 24 percentage points when firms can utilize the profit-maximizing amounts of capital and labor. Under the assumption of fixed aggregate capital and labor, the increase in the labor share is driven by a 57% increase in the wage. This increase is almost entirely driven by the output distortions. At the firm level, about 74% of the firms are too small due to the output distortions. In terms of the distortions on labor-capital ratios, about half of the firms overuse labor and the other half underuse labor relative to their capital use.² The joint impact of the input and output distortions at the firm level is that 76% of the firms' labor shares are lower than their profit-maximizing values. Intuitively, when removing the distortions, 76% firms' demand for labor increases, which aggregates to a higher aggregate labor demand. Equilibrium wage increases to clear the market and labor is reallocated to firms' with a higher increase in labor demand. Because the aggregate demand for labor increases disproportionately more than the increase in the aggregate production, the aggregate labor share increases.

The classical misallocation model in [Hsieh and Klenow \(2009\)](#) (hereafter HK) relies on a rigid nested CES demand structure in which a nest is an industry and that all the nests have the same demand elasticity. Recent studies such as [Haltiwanger et al. \(2018\)](#) point out that the underlying assumptions of the rigid nested CES demand are likely violated and that the quantified efficiency costs of misallocation are biased. Despite attempts to generalize the demand assumptions ([Liang \(2023\)](#) compares the predicted efficiency costs using alternative demand structures), it is difficult to balance a demand structure's flexibility and its ability to provide general equilibrium conditions simple enough for estimation using firm-level data. We follow [Baqee and Farhi \(2020\)](#)'s generalization by allowing an arbitrary number of nests in each industry in a nested CES demand. We take [Baqee and Farhi \(2020\)](#) one step further by estimating the nest structure and nest-specific demand elasticities using firm-level data.

Removing distortions in HK-style models, i.e. Cobb-Douglas production functions and CES demand, always generate efficiency gains. Our predicted TFP gains are significantly higher than the 30–50% increase predicted by HK. The difference is because HK sets demand elasticities at 3, a value below estimates using firm-level data ([Edmond et al. \(2019\)](#), [Baqee](#)

²This result is not due to the zero-mode assumption on input distortions because industry-level distributions of labor-capital ratios are skewed and their medians generally do not equal their modes.

and Farhi (2020), De Loecker and Warzynski (2012), De Loecker et al. (2020), Feenstra and Weinstein (2017), Peters (2020)). When using estimated demand elasticities, HK’s predicted TFP gains are close to our prediction (Zhang and Xia (2022)).

The remainder of the paper is organized as follows. We introduce the data set in Section 2 and describe our theoretical model in Section 3. Section 4 explains our estimation strategy and Section 5 presents our results. We discuss the robustness of our results in Section 6. Section 7 concludes. The Appendix provides the details of data cleaning, the derivation of theoretical results of Section 3, and a discussion of alternative ways of inferring firm-level markups. Supplemental figures are also presented in the Appendix.

2 Data

Our data source is the annual survey conducted by the National Bureau of Statistics (NBS) in China in 2005.³ The annual surveys have been used by previous studies including Hsieh and Klenow (2009) (hereafter HK), Brandt et al. (2012), and David and Venkateswaran (2019). The surveys include all the state-owned firms and all the non-state firms with revenues above 5 million RMB (\$600,000). The survey in 2005 contains about 230,000 firms. It covers manufacturing, mining, and public utilities. The industry classification used in this paper has 523 industries.

The data contains information on firm-level value added, wage expenditure, fixed assets, revenues, and costs. When cleaning the data, we drop unreasonable observations in terms of accounting as in Brandt et al. (2012), such as negative value added, negative debts, and negative revenues. Appendix A lists all the criteria that trigger dropping an observation. We calculate the net present value of depreciated real capital also following Brandt et al. (2012). The net present value of depreciated real capital is our measure of capital. Value added is the monetary value of a firm’s products produced in the year after netting out intermediate input costs. The monetary value per product is the average sales price of the product in the year. Revenues in the data are the monetary value of the products sold by a firm in the year, which can differ from the value of products produced in the year. Following HK, we trim the 1% tails of value added, labor and capital shares of value added, revenue-cost ratios, capital, and labor expenditure.

Table 1 provides the summary statistics of firm-level labor and capital shares out of value added, cost shares of labor and capital out of value added, and cost-revenue ratios. The summary statistics are weighted by value added. The unweighted summary statistics are in Table 6 in Appendix A. The labor share is the firm-level labor expenditure divided by value

³We acquired the data through Peking University’s data center.

TABLE 1: Summary statistics weighted by firm-level value added

	Mean	Standard Deviation	10th Percentile	1st Quartile	Median	3rd Quartile	90th Percentile
labor share	0.26	0.28	0.04	0.08	0.17	0.34	0.55
adj. labor share	0.42	0.26	0.11	0.21	0.38	0.60	0.78
capital share	0.17	0.23	0.02	0.04	0.10	0.21	0.38
cost share	0.59	0.37	0.18	0.32	0.55	0.79	1.02
cost/revenue (total)	0.83	0.13	0.67	0.78	0.87	0.92	0.96

Notes: Total number of firms is 229,282. Capital rental rate is assumed 0.2. Cost share is adjusted labor share plus capital share.

added. The annual survey collects firms' wage expenditure, but it does not collect firms' expenditure on non-wage labor compensation. The aggregate labor share calculated using the reported wage expenditure in the data is 26%, but the [Bai and Qian \(2010\)](#) estimate that the aggregate labor share of manufacturing, mining, and public utilities in China in 2005 is 42%. We assume a constant ratio between unobserved non-wage compensation to wage compensation at the firm level and adjust the firm-level labor expenditure so that the aggregate labor share out of value added is 42%. This assumption of a constant ratio is used in HK to solve the same problem, but they target the 0.5 aggregate labor share in manufacturing reported in the Chinese input-output tables and the national accounts. Their targeted aggregate labor share does not include mining and public utilities that the annual survey covers.

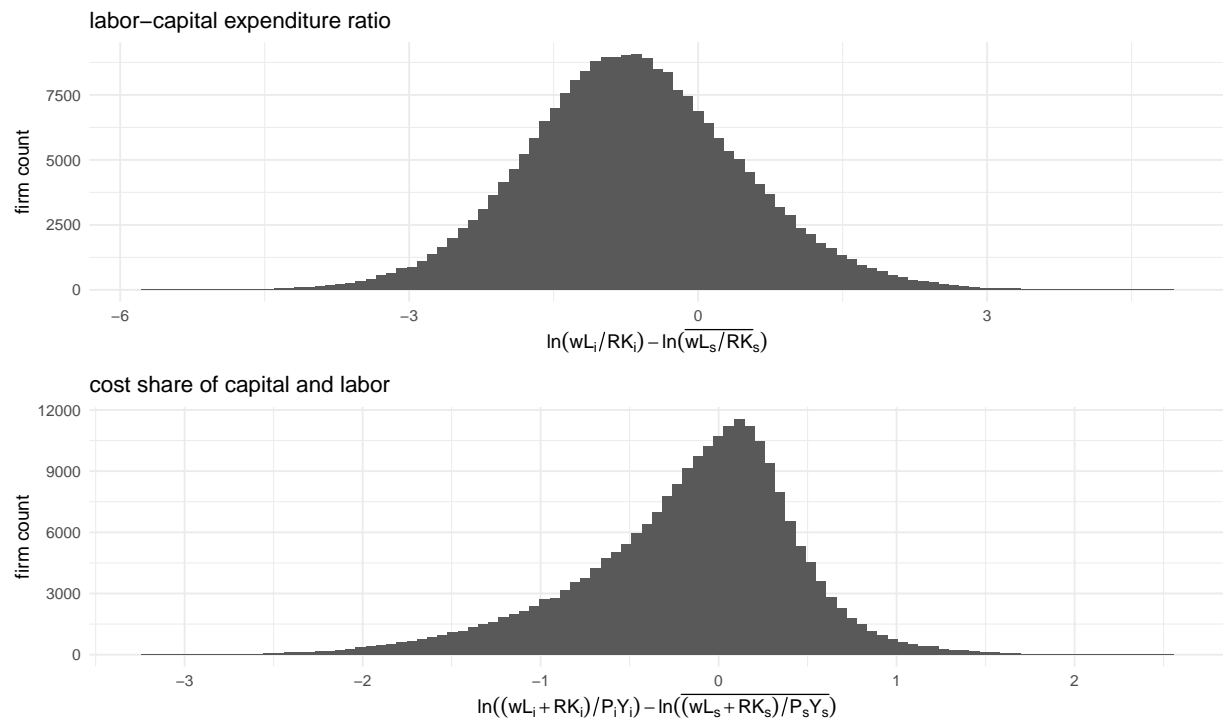
The capital share in Table 1 is firm-level capital multiplied by the capital rental rate and divided by value added. We assume the capital rental rate to be 0.2 following [Bai Chong-En et al. \(2006\)](#) and [Sun et al. \(2011\)](#).⁴ The aggregate capital share in our data is 17%. Chinese Year Book for 2005 reports that the national income share of capital is 15%, but the national income includes construction sector, service sector, and the agriculture sector in addition to manufacturing, mining, and public utilities sector in our data. The cost share in Table 1 is the sum of capital and adjusted labor shares.

The last row in Table 1 is firms' cost-revenue ratios calculated using firms' reported total costs and total revenues. They are different from the cost shares, which is the share of firms' capital-and-labor expenditure out of their value added. The last two rows of Table 1 show that firms' labor-and-capital cost shares are on average smaller than cost-revenue ratios and that the variation in firms' labor-and-capital cost shares is larger than the one in the cost-revenue ratios.

Figure 1 demonstrates the variation in firm-level labor-capital expenditure ratios and

⁴HK uses a hypothetical 0.1 rental rate.

FIGURE 1: Distribution of the normalized labor-capital expenditure ratios and labor-and-capital cost shares



in industry s .

Notes: $\overline{wL_s/RK_s}$ is the average of firm-level labor-capital expenditure ratios wL_i/RK_i in industry s . $\overline{(wL_s + RK_s)/P_s Y_s}$ is the average of firm-level cost shares of labor and capital $(wL_i + RK_i)/P_i Y_i$

firm-level cost shares of labor and capital out of value added. For comparison across industries, the expenditure ratios and cost shares are normalized by industry averages. The distribution of firms' normalized labor-capital expenditure ratios looks symmetric, but the mode is negative. The distribution of firms' normalized labor-and-capital cost shares is skewed to the left with a mode slightly above 0. This implies that most firms' labor-capital ratios are below their industry average and that there is a large share of firms whose labor-capital cost shares out of the value added are lower than their industry average. Besides, the dispersion of the normalized cost shares is smaller than the one of the normalized expenditure ratios.

FIGURE 2: Within-industry coefficients of variation of the expenditure ratios and the cost shares

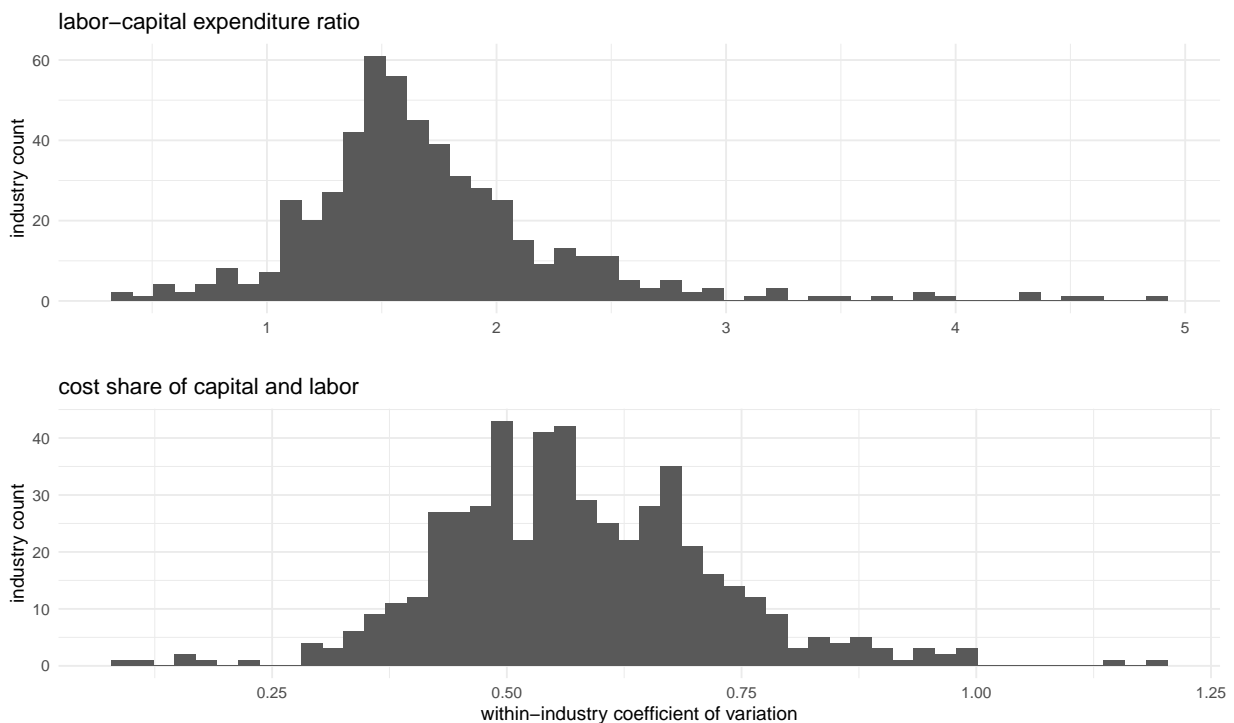


Figure 2 continues investigating the within-industry dispersion in the expenditure ratios and the cost shares. It plots the distribution of within-industry coefficients of variation for labor-capital expenditure ratios and labor-and-capital cost shares. The within-industry coefficients of variation measure the size of the variation within an industry. Figure 2 shows that the variation differs across industries. Similar to Figure 1, the variation is larger for the expenditure ratios than for the cost shares. Figure 1 and 2 motivate us to use industry-specific distributions of input distortions and do not impose any restrictions on the distributions of output distortions.

FIGURE 3: Within-industry skewness and kurtosis of the capital-labor expenditure ratios

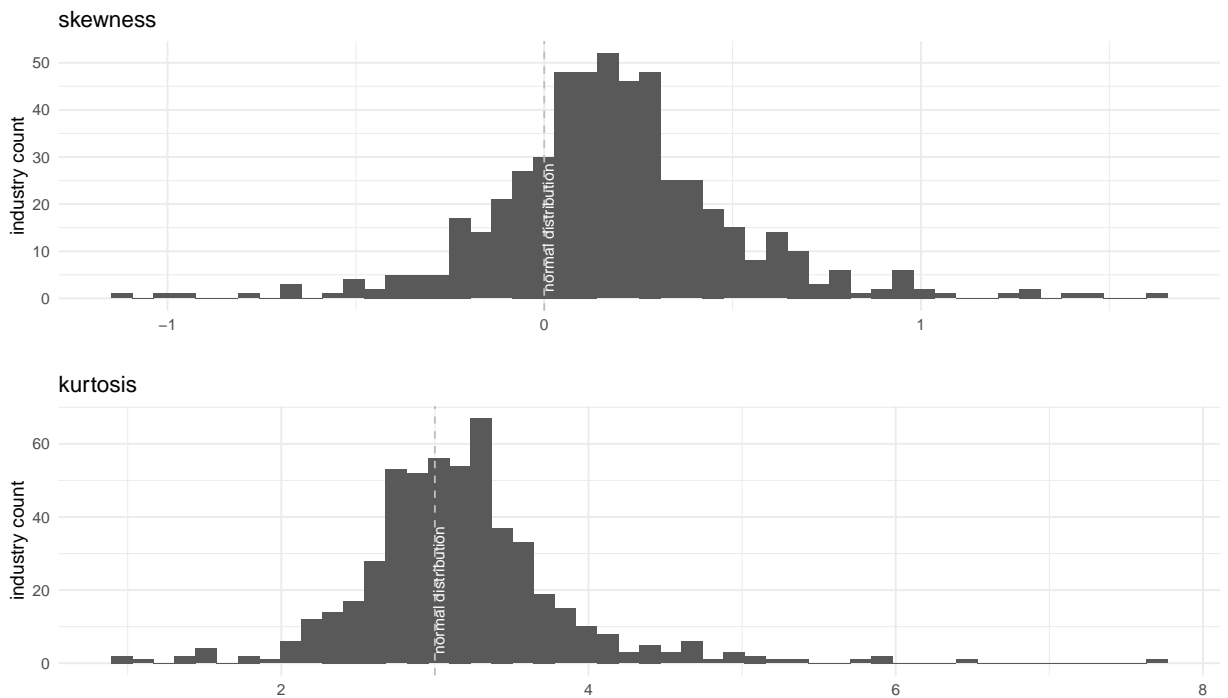
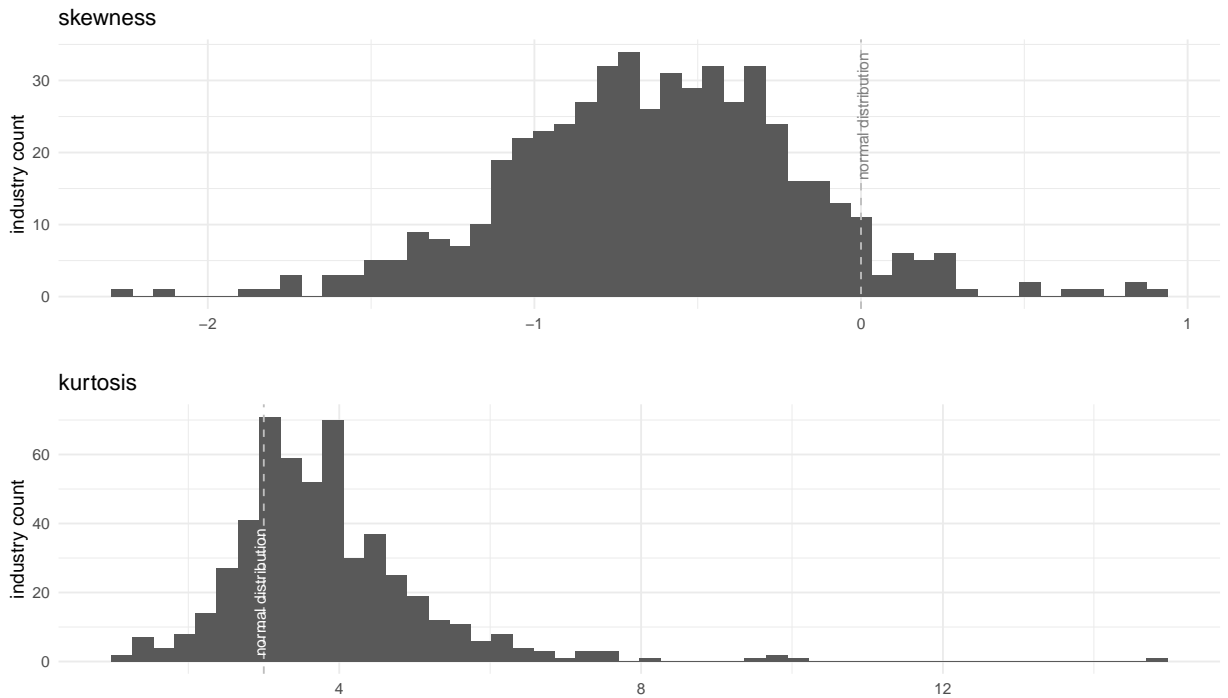


FIGURE 4: Within-industry skewness and kurtosis of the capital-labor cost shares



Although the distribution of the normalized labor-capital expenditure ratios in Figure 1 looks symmetric, the symmetry is due to pooling all the industries together. Figure 3 displays the industry-level skewness and kurtosis of the logarithm of firms' labor-capital expenditure ratios. 76% of the industries are skewed to the right and 60% have tails thicker than normal distributions. This motivates us to assume the mode of input distortions in an industry to be 0 to reduce the influence of skewness and thick tails. Figure 4 is the same plot as Figure 3 but for the logarithm of firms' labor-capital cost shares. 94% of the industries are skewed to the left and 76% have tails thicker than normal distributions.

3 Model

In this section, we first introduce the model which we use to describe the economy. The formal definition of the input and output distortions are provided in this part. We then derive the general equilibrium conditions and provide the predicted changes in the aggregate labor share and the aggregate productivity. In the last part of the section, we offer two special cases to demonstrate how the distortions affect the economy.

3.1 Model setup

The economy has S number of industries $\{s_1, \dots, s_S\}$. Firms inside an industry have the same Cobb-Douglas production function upto firm-specific productivity A_i :

$$F_i(k, l) = A_i k^{1-\alpha_{s(i)}} l^{\alpha_{s(i)}} \quad (1)$$

where i denotes firm i and $s(i)$ is the industry firm i belongs to.

Without distortions, firm i 's profit when choosing $k = K_i$, $l = L_i$, and $p = P_i$ is:

$$\Pi_i(P_i, K_i, L_i) = F_i(K_i, L_i)P_i - wL_i - RK_i \quad (2)$$

where w is the wage and R is the capital rental rate. Firm i takes wage and capital rental rate as given and chooses price P_i , capital K_i , and labor L_i to maximize its profits $\Pi_i(\cdot)$. The wage and the capital rental rate are the same for all the firms in the economy.

On the demand side, there is a representative consumer with a nested constant elasticities of substitutions (nested CES) utility:

$$\bar{y} \equiv \prod_g \bar{y}_g^{\beta_g} \quad (3)$$

where $\bar{y}_{g(i)} = \left(\sum_{i \in \mathcal{G}(g)} y_i^{\frac{\epsilon_g - 1}{\epsilon_g}} \right)^{\frac{\epsilon_g}{\epsilon_g - 1}}$ and $g(i)$ is the nest of firm i . The variable y_i denotes the amount of firm i 's product consumed by the representative consumer. $\mathcal{G}(g)$ is the set of firms in nest g , and they face the same demand elasticity ϵ_g . The representative consumer takes price of each product as given and chooses the value of $y_i = Y_i$ to maximize the utility \bar{y} .

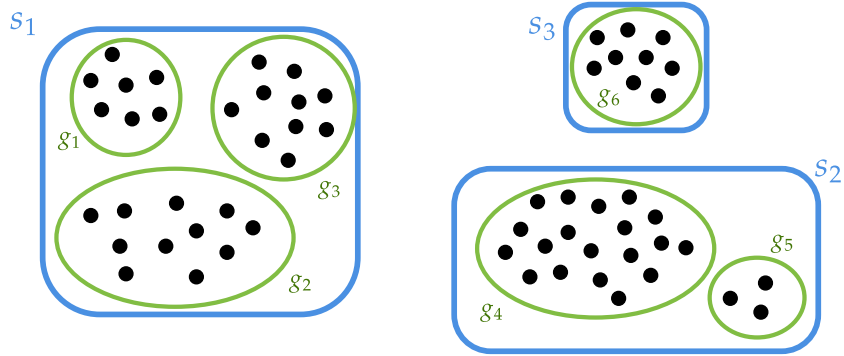
A nest can only belong to one industry but an industry can have multiple nests:

$$\bigcup_{g \in \{g_1, \dots, g_s\}} \{i | g(i) = g\} = \mathcal{S}(s) \quad (4)$$

$$\{i | g(i) = g_l\} \cap \{i | g(i) = g_m\} = \emptyset, \text{ for } \forall g_l \neq g_m \quad (5)$$

where $\{g_1, \dots, g_s\}$ is the set of nests which contain firms in industry s . $g(i)$ denotes the nest of firm i , and $\mathcal{S}(s)$ is the set of firms in industry s . Equation (4) means that the set of firms in industry s is the union of firms in nests $\{g_1, \dots, g_s\}$. Equation (5) means that there is no overlap between any two nests. Figure 5 provides an illustrative example of a three-industry economy. Industry s_1 has 3 nests, g_1 , g_2 , and g_3 . Industry s_2 has 2 nests g_4 and g_5 . Industry s_3 has 1 nest g_6 .

FIGURE 5: An illustrative example of a three-industry economy



Notes: Black dots are firms, green circles are nests, and blue squares are industries.

The total amounts of labor and capital in the economy is fixed:

$$\sum_i L_i = \bar{L}, \quad \sum_i K_i = \bar{K} \quad (6)$$

where \sum_i sums over all the firms in the economy.

In the general equilibrium, on the supply side, each firm takes wage w and capital rental rate R as given and maximizes their profits by choosing the amounts of capital and labor to use and setting their prices under Chamberlinian monopolistic competition. The Chamberlinian monopolistic competition means that firms do not take into account the impact of their pricing and production decisions on other firms' pricing and production decisions. On the demand side, the representative consumer takes each product's price P_i as given and maximizes its utility \bar{Y} net of the expenditure on the products, $\sum_i P_i Y_i$. Wage w and capital rental rate R clear the market for capital and labor. Formally, the economy's general equilibrium is representative by a vector $\{\{P_i, K_i, L_i\}_i, w, R\}$ that satisfies

$$\{Y_i\}_i = \arg \max_{\{y_i\}_i} \prod_g \left[\left(\sum_{i \in \mathcal{G}(g)} y_i^{\frac{\epsilon_g - 1}{\epsilon_g}} \right)^{\frac{\epsilon_g}{\epsilon_g - 1}} \right]^{\beta_g} - \sum_i P_i y_i \quad (7)$$

$$\{P_i, K_i, L_i\} = \arg \max_{p, k, l} p F_i(k, l) - w l - R k \text{ for } \forall i \quad (8)$$

$$Y_i = F_i(K_i, L_i) \quad (9)$$

$$\bar{L} = \sum_i L_i \quad (10)$$

$$\bar{K} = \sum_i K_i \quad (11)$$

Except for wage w , capital rental rate R , and nest g , we use lower-case letters to denote variables and upper-case letters to denote the values these variables take. Equation (7) is the representative consumer's problem, and Equation (8) is the firms' problem. Equation (9), (10), and (11) clear the goods market, the labor market, and the capital market.

The distortions $1 + \tau_i^I$ and $1 - \tau_i^Y$ prevent firms from using their profit-maximizing capital and labor, and are defined as the deviations from the firm-level first-order conditions:

$$\ln(1 + \tau_i^I) \equiv \ln \left(\frac{w L_i}{R K_i} \right) - \ln \left(\frac{\alpha_{s(i)}}{1 - \alpha_{s(i)}} \right) \quad (12)$$

$$\ln(1 - \tau_i^Y) \equiv \ln \left(\frac{w L_i + R K_i}{P_i Y_i} \right) - \ln \left(\frac{\epsilon_{g(i)} - 1}{\epsilon_{g(i)}} \right) \quad (13)$$

where $1 + \tau_i^I$ is firm i 's input distortion and $1 - \tau_i^Y$ is firm i 's output distortion.

Intuitively, the input distortions are the firm-level wedges between firms' expenditure ratios and production elasticities ratios of labor and capital. The output distortions are the firm-level wedges between the labor-and-capital cost shares and the inverse of the markups predicted by the demand elasticities. We require $1 + \tau_i^I > 0$ and $1 - \tau_i^Y > 0$ because the

expenditure ratios and the cost shares are positive. Firm i overuses labor relative to capital when $1 + \tau_i^I > 1$ and underuses labor relative to capital when $0 < 1 + \tau_i^I < 1$. Firm i is too small, i.e. proportionally underuses both labor and capital, when $0 < 1 - \tau_i^Y < 1$ and too big when $1 - \tau_i^Y > 1$.

The decomposition of firm i 's revenue is:

$$\underbrace{P_i Y_i}_{\text{revenue}} = \underbrace{wL_i + RK_i}_{\substack{\text{expenditure on} \\ \text{labor and capital} \\ \text{(contains input} \\ \text{distortions)}}} + \underbrace{P_i Y_i \frac{1}{\epsilon_{g(i)}} (1 - \tau_i^Y)}_{\text{operating surplus}} + \underbrace{\tau_i^Y P_i Y_i}_{\substack{\text{collected in} \\ \text{output distortions}}} \quad (14)$$

We call $P_i Y_i \frac{1}{\epsilon_{g(i)}} (1 - \tau_i^Y)$ firm i 's operating surplus to distinguish it from firm i 's realized profit. The operating surplus is the profits earned due to demand elasticities $\epsilon_{g(i)}$. Profits are revenues net of costs. Whether profits equal operating surplus depends on whether revenues collected in output distortions are costs or profits.

Aggregating Equation (14) over all the firms in the economy gives the decomposition of the aggregate revenue in this economy :

$$\underbrace{\bar{P}\bar{Y}}_{\substack{\text{aggregate} \\ \text{revenue}}} = \underbrace{wL + RK}_{\substack{\text{aggregate expenditure} \\ \text{on labor and capital} \\ \text{(contains input} \\ \text{distortions)}}} + \underbrace{\sum_i P_i Y_i \frac{1}{\epsilon_{g(i)}} (1 - \tau_i^Y)}_{\text{aggregate operating surplus}} + \underbrace{\sum_i \tau_i^Y P_i Y_i}_{\substack{\text{collected in} \\ \text{output distortions}}} \quad (15)$$

Our model setup is very similar to [Hsieh and Klenow \(2009\)](#) except for the unobserved nest structure within industries and the ownership of revenues collected through distortions. When estimating the model in Section 4, we define that this part of revenue is distributed between firms' cost and profits by a firm-specific ratio. We do not introduce this assumption in the current section to show that the formula for the predicted change in labor share does not rely on this assumption.

3.2 Predicted changes in the aggregate labor share

The predicted change in the aggregate labor share due to removing the distortions is the difference in the aggregate labor share with and without the distortions. Solving the general

equilibrium defined in the previous section gives the equilibrium aggregate labor share

$$\frac{w\bar{L}}{\bar{P}\bar{Y}} = \sum_g \sum_{i \in \mathcal{G}(g)} \beta_g \cdot \underbrace{(1 - \tau_i^Y) \frac{\epsilon_{g(i)} - 1}{\epsilon_{g(i)}} \cdot \frac{\alpha_{s(i)}(1 + \tau_i^I)}{1 + \alpha_{s(i)}\tau_i^I}}_{\text{firm-level labor shares}} \cdot \underbrace{\frac{\gamma_i^{1-\epsilon_{g(i)}}}{\sum_{i \in \mathcal{G}(g(i))} \gamma_i^{1-\epsilon_{g(i)}}}}_{\text{firm-level market shares}} \quad (16)$$

where

$$\gamma_i \equiv \underbrace{\frac{1}{1 - \tau_i^Y}}_{(a)} \cdot \frac{1}{A_i} \underbrace{\left[(1 + \tau_i^I)^{-\alpha_{s(i)}} \cdot (1 - \alpha_{s(i)}) + (1 + \tau_i^I)^{1-\alpha_{s(i)}} \cdot \alpha_{s(i)} \right]}_{(b)} \quad (17)$$

Removing the distortions reallocates capital and labor across firms. The reallocation's impact on the aggregate labor share can be interpreted in two parts: how individual firms' labor shares change and how their market shares change. Equation (16) and Equation (17) show that the two parts are affected by both input and output distortions.

A closer examination of Equation (17) offers insights on how the distortions alter firms' market shares. In Equation (17), Part (a) is the impact of the output distortions, which serve as a factor on firms' productivity A_i since they distort capital and labor use proportionally. When $1 - \tau_i^Y < 1$, the output distortion causes firm i to appear less productive than it actually is. Part (b) shows that the input distortions affect firm sizes by raising marginal costs.

The aggregate labor share without distortions is:

$$\frac{w^*\bar{L}}{\bar{P}^*\bar{Y}^*} = \sum_g \beta_g \frac{\epsilon_g - 1}{\epsilon_g} \alpha_{s(g)} \quad (18)$$

where $s(g)$ denotes the industry that nest g belongs to. The predicted change in the aggregate labor share due to removing the distortions is:

$$\begin{aligned} \frac{w^*\bar{L}}{\bar{P}^*\bar{Y}^*} - \frac{w\bar{L}}{\bar{P}\bar{Y}} &= \sum_g \beta_g \frac{\epsilon_g - 1}{\epsilon_g} \alpha_{s(g)} \\ &\quad - \sum_g \sum_{i \in \mathcal{G}(g)} \beta_g \cdot (1 - \tau_i^Y) \frac{\epsilon_{g(i)} - 1}{\epsilon_{g(i)}} \cdot \frac{\alpha_{s(i)}(1 + \tau_i^I)}{1 + \alpha_{s(i)}\tau_i^I} \cdot \frac{\gamma_i^{1-\epsilon_{g(i)}}}{\sum_{i \in \mathcal{G}(g(i))} \gamma_i^{1-\epsilon_{g(i)}}} \end{aligned} \quad (19)$$

Firm i 's equilibrium marginal cost mc_i is:

$$mc_i = R \cdot A_i^{-1} \underbrace{\left[\frac{R}{w} \cdot \frac{\alpha_{s(i)}}{1 - \alpha_{s(i)}} \cdot (1 + \tau_i^I) \right]^{-\alpha_{s(i)}}}_{(a)} \cdot \underbrace{\left[1 + \frac{\alpha_{s(i)}}{1 - \alpha_{s(i)}} (1 + \tau_i^I) \right]}_{(b)} \quad (20)$$

Part (a) in Equation (20) is how much capital is needed for firm i to produce 1 unit of product. It is affected by firm i 's productivity A_i , production technology $\alpha_{s(i)}$, the price of capital relative to labor $\frac{R}{w}$, and the input distortion which prevents firm i from reaching its profit-maximizing capital-labor ratio. Multiplying Part (a) by R gives how much firm i spends on capital for 1 unit of production. Part (b) is how much cost firm i needs to spend on capital and labor when spending 1 unit on capital. Multiplying R , Part (a), and Part (b) together gives firm i 's marginal cost.

Firm i 's equilibrium price P_i is its marginal cost mc_i times the markup due to its demand elasticity $\frac{\epsilon_{g(i)}}{\epsilon_{g(i)} - 1}$ and the output distortion $\frac{1}{1 - \tau_i^Y}$:

$$P_i = mc_i \cdot \frac{\epsilon_{g(i)}}{\epsilon_{g(i)} - 1} \cdot \frac{1}{1 - \tau_i^Y}$$

Firm i 's equilibrium market share out of its nest is:

$$\frac{P_i Y_i}{\bar{P}_{g(i)} \bar{Y}_{g(i)}} = \frac{\gamma_i^{1 - \epsilon_{g(i)}}}{\sum_{i \in \mathcal{G}(g(i))} \gamma_i^{1 - \epsilon_{g(i)}}} \quad (21)$$

When $\frac{1}{1 - \tau_i^Y} > 1$, firm i 's production is smaller than the production predicted by its marginal cost.

3.3 Predicted changes in the aggregate productivity

The formula for the aggregate productivity gain from removing the distortions is

$$\text{TFP gains} = \frac{Y^*}{Y} = \prod_g \underbrace{\left[\frac{\text{TFP}_g^*}{\text{TFP}_g} \right]^{\beta_g}}_{\text{gains within nests}} \cdot \underbrace{\left[\left(\frac{L_g^*}{L_g} \right)^{\alpha_{s(g)}} \left(\frac{K_g^*}{K_g} \right)^{1 - \alpha_{s(g)}} \right]^{\beta_g}}_{\text{gains across nests}} \quad (22)$$

Nest g 's TFP is defined as $\text{TFP}_g = \frac{Y_g}{K_g^{1 - \alpha_{s(g)}} L_g^{\alpha_{s(g)}}}$, where L_g and K_g are labor and capital used in nest g and Y_g is the total production of nest g . We denote equilibrium values without distortions by a superscript * .

Similar to the derivation in [Hsieh and Klenow \(2009\)](#), the gains within nests are:

$$\frac{\text{TFP}_g^*}{\text{TFP}_g} = \left(\frac{\sum_{i \in \mathcal{G}(g)} \left(\frac{1}{A_i} \right)^{1-\epsilon_g}}{\sum_{i \in \mathcal{G}(g)} \left(\frac{\Gamma_i}{A_i} \right)^{1-\epsilon_g}} \right)^{\frac{\epsilon_g}{\epsilon_g-1}} \quad (23)$$

$$\cdot \left(\frac{\sum_{i \in \mathcal{G}(g)} \left(\frac{1}{A_i} \right)^{1-\epsilon_g}}{\sum_{i \in \mathcal{G}(g)} \left(\frac{\Gamma_i}{A_i} \right)^{1-\epsilon_g} \frac{1-\tau_i^Y}{1+\tau_i^I}} \right)^{-1+\alpha_{s(g)}} \cdot \left(\frac{\sum_{i \in \mathcal{G}(g)} \left(\frac{1}{A_i} \right)^{1-\epsilon_g}}{\sum_{i \in \mathcal{G}(g)} \left(\frac{\Gamma_i}{A_i} \right)^{1-\epsilon_g} (1-\tau_i^Y)} \right)^{-\alpha_{s(g)}}$$

where $\Gamma_i \equiv \frac{(1+\tau_i^K)^{1-\alpha_g}}{1-\tau_i^Y}$.

The gains across nests are calculated using the ratios between nest-level labor and capital usage before and after the reallocation, as shown in Equation (22). The ratios can be written as:

$$\frac{L_g^*}{L_g} = \frac{w^* L_g^* / (w^* L)}{w L_g / (w L)}$$

$$\frac{K_g^*}{K_g} = \frac{K_g^* / K}{K_g / K}$$

Since $w L_g / (w L)$ and K_g / K are directly observed, we only need to calculate $w^* L_g^* / (w^* L)$ and K_g^* / K :

$$\frac{w^* L_g^*}{w^* L} = \frac{\beta_g \cdot \frac{\alpha_{s(g)}}{\epsilon_g / (\epsilon_g - 1)}}{\sum_g \beta_g \cdot \frac{\alpha_{s(g)}}{\epsilon_g / (\epsilon_g - 1)}}$$

$$\frac{K_g^*}{K} = \frac{\beta_g \cdot \frac{1-\alpha_{s(g)}}{\epsilon_g / (\epsilon_g - 1)}}{\sum_g \beta_g \cdot \frac{1-\alpha_{s(g)}}{\epsilon_g / (\epsilon_g - 1)}}$$

Details on the derivations used in this section are in [Appendix B](#).

3.4 Some special cases of the distortions

To illustrate how the input and output distortions affect the economy and the aggregate labor share, we analyze two special cases of the distortions.

Case 1: $\tau_i^I = 0$ and $\tau_i^Y = \tau \in (0, 1)$

Since input distortions are 0 and output distortions are the same for all the firms, the distortions do not affect how capital and labor are allocated across firms. The aggregate

labor share after removing the distortions would increase:

$$\frac{w^* \bar{L}}{\bar{P}^* \bar{Y}^*} - \frac{w \bar{L}}{\bar{P} \bar{Y}} = \tau \sum_g \beta_g \frac{\epsilon_g - 1}{\epsilon_g} \alpha_{s(g)} > 0$$

When normalize $\bar{P} \bar{Y}$ and $\bar{P}^* \bar{Y}^*$ to 1, the wage would be $\frac{1}{1-\tau} > 1$ times higher when the distortions are removed:

$$\frac{w^*}{w} = \frac{1}{1-\tau} > 1$$

Although the distortions cause the wage to be lower, the real output does not change. This occurs because the distortions have no impact on how capital and labor are allocated, therefore no impact on the real output.

Case 2: $\tau_i^I = \tau$ and $\tau_i^Y = 0$

In this case, there is no output distortions, but the input distortions cause labor to be more expensive relative to capital if $\tau \in (-1, 0)$ and cheaper if $\tau > 0$. Therefore firm-level labor share is lower than their distortion-free values when $\tau \in (-1, 0)$ and higher if $\tau > 0$. The input distortions are the same for all the firms, which means the marginal costs of all the firms in the same nest are raised by the same factor. As a consequence, firms' market shares within nests are the same as the distortion-free ones:

$$\frac{P_i Y_i}{\bar{P}_{g(i)} \bar{Y}_{g(i)}} = \frac{A_i^{\epsilon_{g(i)}-1}}{\sum_{i \in \mathcal{G}(g(i))} A_i^{\epsilon_{g(i)}-1}} = \frac{P_i^* Y_i^*}{\bar{P}_{g(i)}^* \bar{Y}_{g(i)}^*}$$

However, because industries have different production technology α_s , labor will be reallocated across industries, which affects allocation efficiency.

When $\tau \in (-1, 0)$, for industries with a lower α_s , labor is less important, and therefore they have a smaller desire to keep using labor compared to industry with a higher α_s . The input distortions let high α_s industry to overuse labor and low α_s industry to underuse labor. Consequently, when removing the input distortions, labor would be reallocated from nests in high α_s industries to nests in low α_s industries:

$$\bar{L}_g^* - \bar{L}_g = \bar{L} \left(\frac{\beta_g \frac{\epsilon_g-1}{\epsilon_g} \alpha_{s(g)}}{\sum_g \beta_g \frac{\epsilon_g-1}{\epsilon_g} \alpha_{s(g)}} - \frac{\beta_g \frac{\epsilon_g-1}{\epsilon_g} \alpha_{s(g)} \cdot \frac{1}{1+\tau \alpha_{s(g)}}}{\sum_g \beta_g \frac{\epsilon_g-1}{\epsilon_g} \alpha_{s(g)} \cdot \frac{1}{1+\tau \alpha_{s(g)}}} \right)$$

The \bar{L}_g is the \bar{L}_g^* weighted by $\frac{1}{1+\tau \alpha_{s(g)}}$. The smaller the weights, the smaller the amount of labor is used in the nest under the distortions. Because the aggregate labor is fixed, the

nest with the smallest weight will use more labor after the distortions are removed. Because the weights are positively correlated with α_s , nests with the smallest α_s will use more labor after the distortions are removed. Since labor allocation across nests is different from the profit-maximizing allocation, the real output is lower due to the distortions.

When $\tau > 0$, the reallocation of labor is in the opposite direction, but removing the distortions still provides efficiency gains.

Due to the reallocation of labor across industries after the distortions are removed, the aggregate labor share would increase if $\tau \in (-1, 0)$ and decrease if $\tau > 0$:

$$\frac{w^* \bar{L}}{\bar{P}^* \bar{Y}^*} - \frac{w \bar{L}}{\bar{P} \bar{Y}} = \sum_g \beta_g \frac{\epsilon_g - 1}{\epsilon_g} \alpha_{s(g)} \cdot \frac{\tau(\alpha_{s(g)} - 1)}{1 + \tau \alpha_{s(g)}} \Rightarrow \begin{cases} > 0 \text{ if } \tau \in (-1, 0) \\ < 0 \text{ if } \tau > 0 \end{cases}$$

In terms of the impact on the wage, the wage would be higher if $\tau \in (-1, 0)$ and lower if $\tau > 0$:

$$\frac{w^*}{w} = \frac{\sum_g \beta_g \frac{\epsilon_g - 1}{\epsilon_g} \alpha_{s(g)}}{\sum_g \beta_g \frac{\epsilon_g - 1}{\epsilon_g} \alpha_{s(g)} \frac{1 + \tau}{1 + \tau \alpha_{s(g)}}} \Rightarrow \begin{cases} > 1 \text{ if } \tau \in (-1, 0) \\ < 1 \text{ if } \tau > 0 \end{cases}$$

Summary of the two special cases

The first special case shows that the homogeneous output distortions lower the aggregate labor share because they reduce each firm's labor share but it does not change the real output since the allocation of capital and labor is unaffected. The second special case shows that different from homogeneous output distortions, homogeneous input distortions affect both the aggregate labor share and the total production. While removing the homogeneous input distortions always raises the aggregate output, the impact on the aggregate labor share depends on the sign of the homogeneous input distortions.

4 Identification and estimation

We observe firms' labor expenditure, capital, value added, total revenues, and total costs. To estimate the model, we need to make three additional assumptions:

- A.1 The logarithm of firm i 's total revenue-and-cost ratio equals the logarithm of its markup predicted by its demand elasticity plus a firm idiosyncratic error term η_i :

$$\ln \left(\frac{\text{revenues}_i}{\text{costs}_i} \right) = \ln \left(\frac{\epsilon_{g(i)}}{\epsilon_{g(i)} - 1} \right) + \eta_i$$

The idiosyncratic term η_i within a nest follows a normal distribution: $\eta_i \sim \mathcal{N}(0, \sigma_{g(i)})$ for $\forall i \in \mathcal{G}(g)$

A.2 Capital rental rate is 0.2

A.3 The mode of input distortions $\ln(1 + \tau_i^I)$ within an industry is 0, and the distribution is:

$$\ln(1 + \tau_i^I) \sim 2\kappa_s \mathbb{1}[\tau_i^I < 0] \mathcal{N}(0, \delta_{s(i),-}) + 2(1 - \kappa_s) \mathbb{1}[\tau_i^I > 0] \mathcal{N}(0, \delta_{s(i),+}) \text{ for } i \in \mathcal{S}(s) \quad (24)$$

where κ_s , $\delta_{s(i),-}$, and $\delta_{s(i),+}$ are parameters

Assumption A.1 implies that the part of revenues collected in output distortions is divided between costs and profits at the $\frac{\epsilon_{g(i)} - 1}{\epsilon_{g(i)}}$ ratio, i.e. $\frac{\epsilon_{g(i)} - 1}{\epsilon_{g(i)}}$ of the output-distortion part of the revenue is cost and $\frac{1}{\epsilon_{g(i)}}$ is profit. The decomposition of firm i 's revenue becomes:

$$\underbrace{P_i Y_i}_{\text{revenue}} = \underbrace{wL_i + RK_i + \frac{\epsilon_{g(i)} - 1}{\epsilon_{g(i)}} \tau_i^Y P_i Y_i}_{\text{total cost}} + \underbrace{\frac{1}{\epsilon_{g(i)}} (1 - \tau_i^Y) P_i Y_i + \frac{1}{\epsilon_{g(i)}} \tau_i^Y P_i Y_i}_{\text{total profit}}$$

In Section 6.2, we discuss how our results would change if the cost-profit ratio within the output-distortion revenue is not $\epsilon_{g(i)} - 1$. In Appendix C, we explain why we choose revenue-cost ratios over other methods to quantify markups.

The parametric distributions of the idiosyncratic error term η_i imply that the revenue-cost ratios of firms inside industry s follow a mixture normal distribution:

$$\ln \left(\frac{\text{revenues}_i}{\text{costs}_i} \right) \sim \sum_{g \in \{g | \mathcal{G}(g) \subset \mathcal{S}(s)\}} \omega_g \mathcal{N} \left(\ln \left(\frac{\epsilon_g}{\epsilon_g - 1} \right), \sigma_g \right) \text{ for } i \in \mathcal{S}(s) \quad (25)$$

where $\{g | \mathcal{G}(g) \subset \mathcal{S}(s)\}$ is the set of nests inside industry s , and ω_g is the weight of nest g . The weight ω_g is the ex-ante probability that a firm in industry s belongs to nest g . The sum of all the weights in industry s equals 1, i.e. $\sum_{g \in \{g | \mathcal{G}(g) \subset \mathcal{S}(s)\}} \omega_g = 1$.

Assumption A.2 sets capital rental rate to 0.2 because Bai Chong-En et al. (2006) and Sun et al. (2011) quantify the Chinese capital return rate in 2005 as 20%.

We measure $P_i Y_i$ using firm i 's value added because our production functions model labor and capital as the only production inputs. Firm i 's labor and capital share, $\frac{wL_i}{P_i Y_i}$ and $\frac{RK_i}{P_i Y_i}$, are the observed labor and capital expenditure, wL_i and RK_i , divided by firm i 's value added $P_i Y_i$.

The parametric distribution function of the input distortions $\ln(1+\tau_i^L)$ in Assumption A.3 has mode 0 and is asymmetric. We pick this parametric distribution over normal distributions because we are concerned that the distributions of the input distortions within industries are asymmetric and that the average input distortions may not be 0. In the distribution function of Equation (24), κ_s is the share of firms in industry s whose labor-capital expenditure ratios are less than $\frac{\alpha_{s(i)}}{1-\alpha_{s(i)}}$. κ is multiplied by a factor of 2 so that the likelihood adds up to 1.

Under Assumption A.3, Equation (12) provides the distribution of $\ln\left(\frac{wL_i}{RK_i}\right) - \ln\left(\frac{\alpha_{s(i)}}{1-\alpha_{s(i)}}\right)$:

$$\begin{aligned} \ln\left(\frac{wL_i}{RK_i}\right) - \ln\left(\frac{\alpha_{s(i)}}{1-\alpha_{s(i)}}\right) &\sim 2\kappa_s \mathbb{1}\left[\frac{wL_i}{RK_i} < \frac{\alpha_{s(i)}}{1-\alpha_{s(i)}}\right] \mathcal{N}(0, \delta_{s(i),-}) \\ &\quad + 2(1-\kappa_s) \mathbb{1}\left[\frac{wL_i}{RK_i} > \frac{\alpha_{s(i)}}{1-\alpha_{s(i)}}\right] \mathcal{N}(0, \delta_{s(i),+}) \text{ for } i \in \mathcal{S}(s) \end{aligned} \quad (26)$$

Using Equation (25), we estimate the nest structure and demand elasticity $\epsilon_{g(i)}$ by estimating a mixture normal distribution with an unknown number of components for each of the industry. Because mixture normal estimation is sensitive to outliers, we treat nests containing less than 5% of firms in their industries and nests with less than 10 firms as outliers and drop them. We use Equation (26) and the Maximum Likelihood Estimation to obtain production elasticities α_s . Equation (12) and (13) are used to calculate τ_i^L and τ_i^Y .

We calculate firm productivity following Hsieh and Klenow (2009) because, like them, we only care about firms' productivity relative to other firms in the same nest:

$$A_i \propto \frac{(P_i Y_i)^{\frac{\epsilon_g}{\epsilon_g-1}}}{K_i^{1-\alpha_{s(i)}} L_i^{\alpha_{s(i)}}} \text{ for } i \in \mathcal{G}(g) \quad (27)$$

5 Results

In this section, we will first present the estimated nest structure, demand elasticities, production elasticities, and distortions. We then use these parameters to predict how and why the aggregate labor share would change when removing the distortions, followed by the predicted aggregate productivity.

5.1 Estimated parameters and distortions

We plot the distribution of industries by their estimated number of nests in Figure 6 and the distribution of industry sizes for industries with the same number of nests in Figure 7. The first plot displays the estimated nest structure measured by industries' nest counts, and

FIGURE 6: Distribution of industries by their number of nests

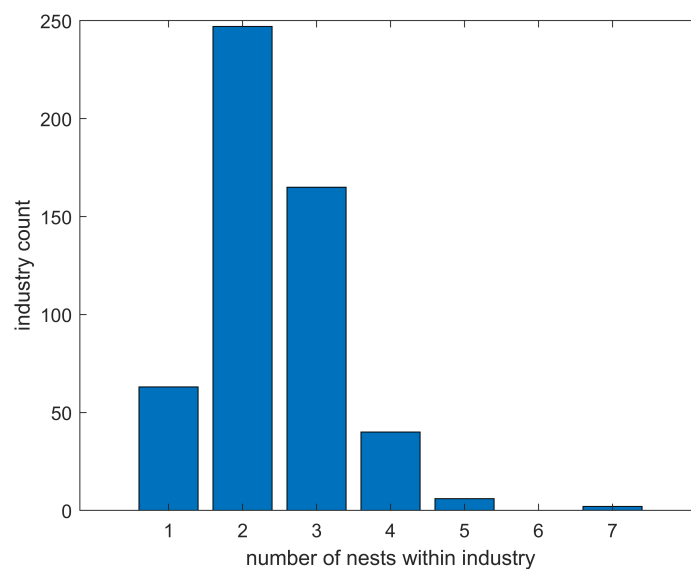
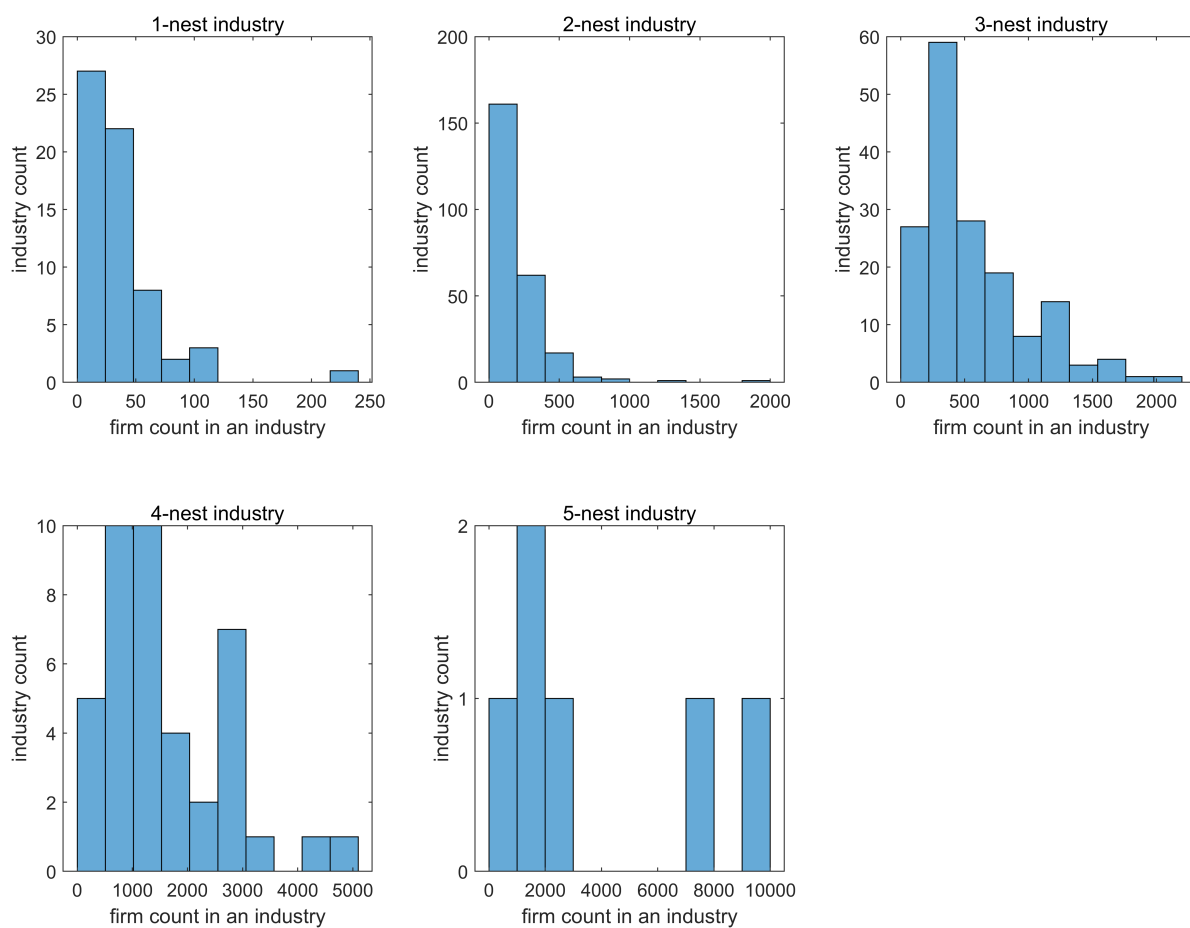


FIGURE 7: Distribution of industry firm counts



the second plot demonstrates whether industries with more firms tend to have more nests. Most of the industries are estimated to have either 2 or 3 nests. The industry with the largest number of nests is estimated to have 7 nests (Figure 6). Industries with more nests generally contain more firms (Figure 7). In total, we estimate that there are 1256 nests in the economy.

The first three rows of Table 2 are the summary statistics of firms’ demand elasticities. The first row is unweighted, the second row is weighted by firms’ costs, and the third row is weighted by firms’ revenues. The average demand elasticities is 9.34 and 10.19 if weighted by revenues and 10.69 if weighted by costs. To compare our estimated demand elasticities to the estimates in existing studies, we calculate the weighted average markups predicted by the demand elasticities, i.e. $\frac{\epsilon_g}{\epsilon_g - 1}$. We use two types of weights, firm costs and revenues. Our cost-weighted average markup is 1.15, which coincides with the 1.15 cost-weighted average markups in Edmond et al. (2019). It is also consistent with Baqaee and Farhi (2020)’s estimate when using the method developed by De Loecker and Warzynski (2012). De Loecker and Warzynski (2012) themselves estimate average markups to be between 1.10 and 1.28, a range contains our estimate. In terms of sales-weighted average markup, ours is 1.18, which is below the estimate from De Loecker et al. (2020) whose sales-weighted average markups are 1.20 in 1980 and 1.60 in 2012. Our median markup is 1.12 when weighted by costs and 1.14 when weighted by revenues, lower than the 1.30 median by Feenstra and Weinstein (2017). All these studies mentioned so far use American data. Our estimates are either the same or a bit lower than their estimates. Compared to firms from developing countries, our 1.15 average is higher than the 1.12 average markups found by Peters (2020) using Indonesian data.

TABLE 2: Summary statistics of selected estimated parameters

	Mean	St. Dev.	Pctl(10)	Pctl(25)	Median	Pctl(75)	Pctl(90)
ϵ_g	9.34	5.21	4.07	5.68	8.30	11.29	14.92
ϵ_g (cost) ¹	10.69	6.22	4.69	6.72	9.44	13.34	17.21
ϵ_g (revenue) ²	10.19	6.11	4.33	6.15	9.07	12.46	16.51
α_s	0.78	0.10	0.67	0.74	0.80	0.85	0.90
α_s (cost) ¹	0.77	0.09	0.66	0.73	0.78	0.84	0.89
α_s (revenue) ²	0.77	0.10	0.65	0.73	0.78	0.84	0.89

¹ The distribution is weighted by firms’ costs.

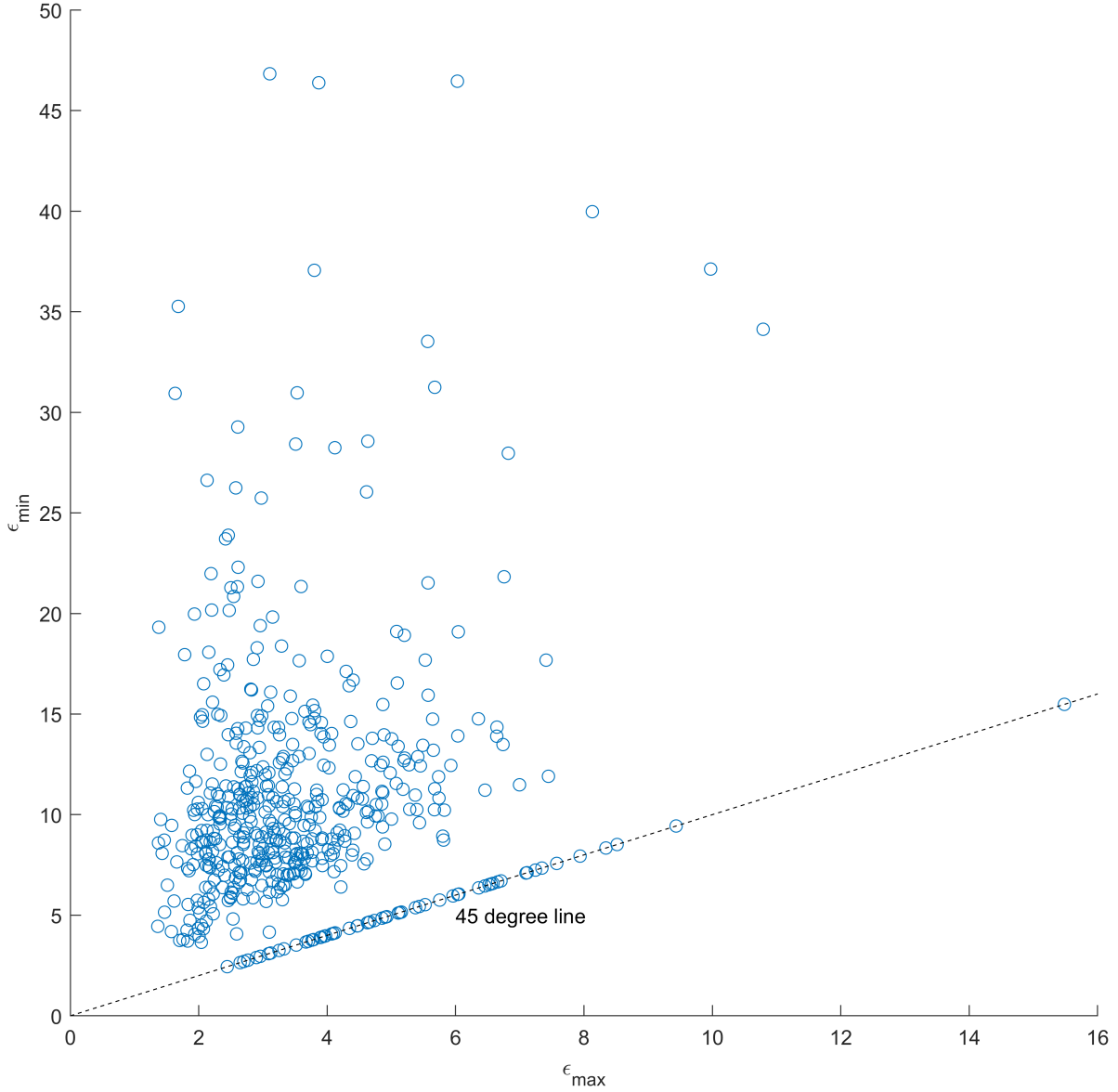
² The distribution is weighted by firms’ revenues.

The last three rows of Table 2 record the summary statistics of labor production elasticities, α_s . Similar to the first three rows, the forth row is unweighted, the fifth row is weighted

by costs, and the sixth row is weighted by revenues across all the firms.

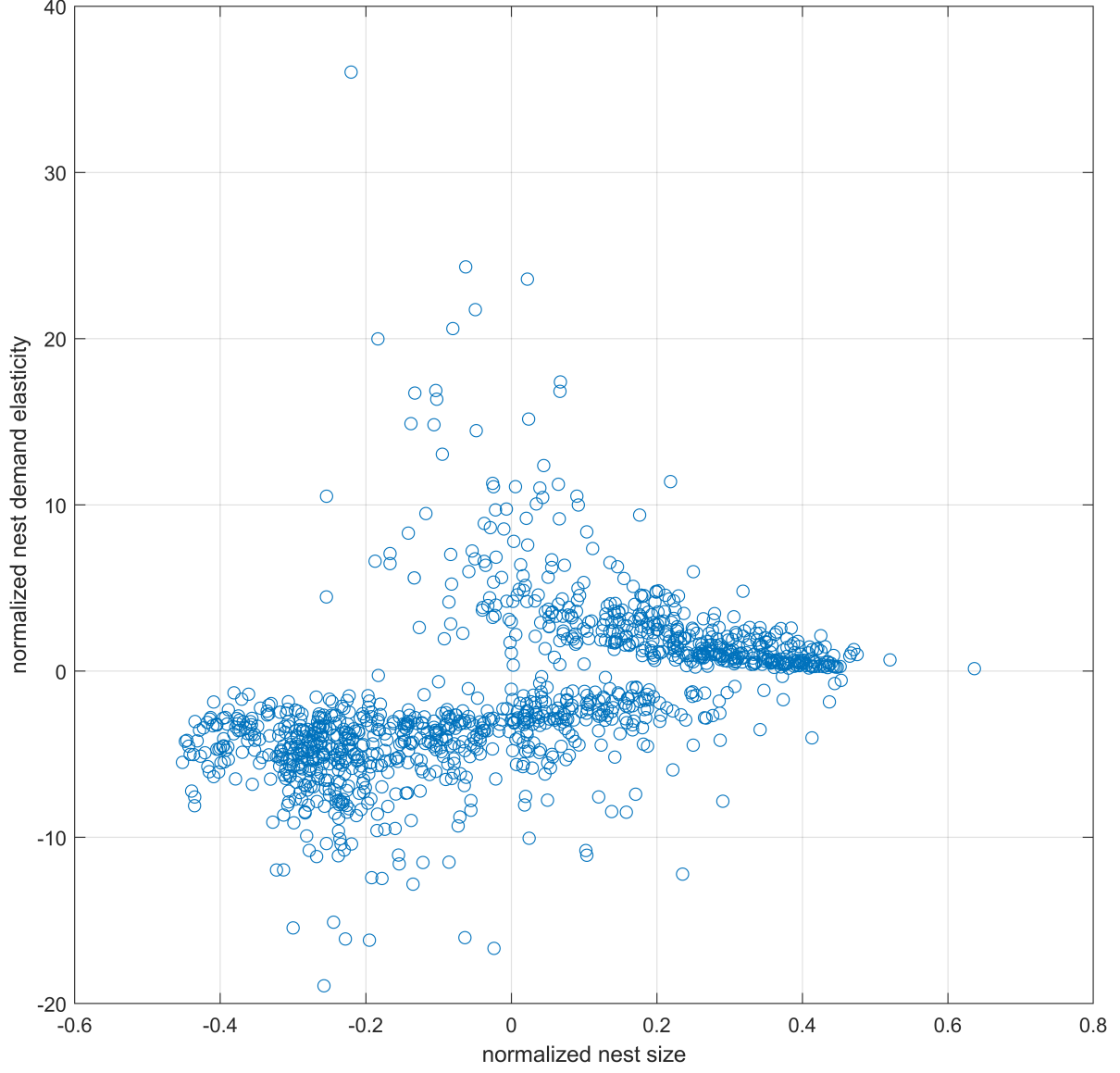
We plot an industry's largest demand elasticity ϵ_{\max} against its smallest demand elasticity ϵ_{\min} in Figure 8 to display the dispersion of demand elasticities within industries. Each point represents an industry. Industries with one nest lie on the 45 degree line because their maximum and minimum demand elasticities are the same.

FIGURE 8: Maximal and minimal estimated demand elasticities within industries



In general, we expect competition to be stronger and hence demand elasticities to be higher in markets with more firms. Figure 9 shows that larger nests in an industry—nests with positive normalized nest sizes—tend to have larger demand elasticities ϵ_g compared to smaller nests in the same industry—nests with negative normalized nest sizes. The nest

FIGURE 9: Nest sizes and demand elasticities



Notes: Normalized nest size is $\frac{N_g}{N_{s(g)}} - \frac{1}{G_{s(g)}}$, where N_g and $N_{s(g)}$ are the firm counts of nest g and industry $s(g)$, and $G_{s(g)}$ is industry $s(g)$'s nest count. Normalized nest demand elasticity is $\epsilon_g - \bar{\epsilon}_{s(g)}$, where $\bar{\epsilon}_{s(g)}$ is the average demand elasticity of firms in industry $s(g)$, $\bar{\epsilon}_{s(g)} = \frac{1}{N_s} \sum_{i \in S(s)} \epsilon_i$. We remove industries with only 1 nest.

size is a nest’s firm count. Since different industries have different demand elasticities due to industry-specific features, we normalize the nest size by first dividing it by its industry’s firm count and then subtracting the inverse of the number of nest in the industry. We normalize the demand elasticities by subtracting from them the industry average demand elasticity. Figure 9 shows that nests whose sizes are above the industry average tend to have above average demand elasticities and nests whose sizes are below the industry average tend to have below average demand elasticities, i.e. most of industries fall in the upper-right and the lower-left part of the plot.

There are in total 523 industries and 1256 nests, therefore it is difficult to report all the estimated demand elasticities. We calculate the average demand elasticities at the 2 digit industry level and report here a selection of the 2-digit industries. Oil and gas extraction, tobacco, and pharmaceutical industries have low demand elasticities. This is in line with the intuition that these industries usually have strong market power. The second observation is that although sometimes larger industries have higher demand elasticities, such as the textile industry, it is not always the case. For example, the pharmaceutical industry contains 1.5 times more firms than the rubber products industry but its demand elasticity is about 1/2 of that of the rubber products industry.

TABLE 3: Average demand elasticities at the 2-digit industry level for selected industries

Industry	ϵ	Firm counts
Oil and gas extraction	2.80	33
Agricultural and Sideline Food Processing	7.90	12273
Tobacco	2.78	102
Textile	10.05	20183
Pharmaceutical	2.99	4267
Rubber products	6.67	2699

5.2 Estimated distortions

Figure 10 presents the distributions of firms’ input and output distortions. The distribution of input distortions is roughly symmetric around 0 even though we do not assume 0 median or mean for input distortions. Output distortions are skewed to the left. The distribution of input and output distortions implies that about half of the firms underuse labor relative to capital but most of the firms are too small.

We then examine whether the distortion distributions differ by ownership types, export status, patent status, whether receiving loans, and whether receiving subsidies.

FIGURE 10: Estimated distortions $\log(1 - \tau_i^Y)$ and $\log(1 + \tau_i^I)$

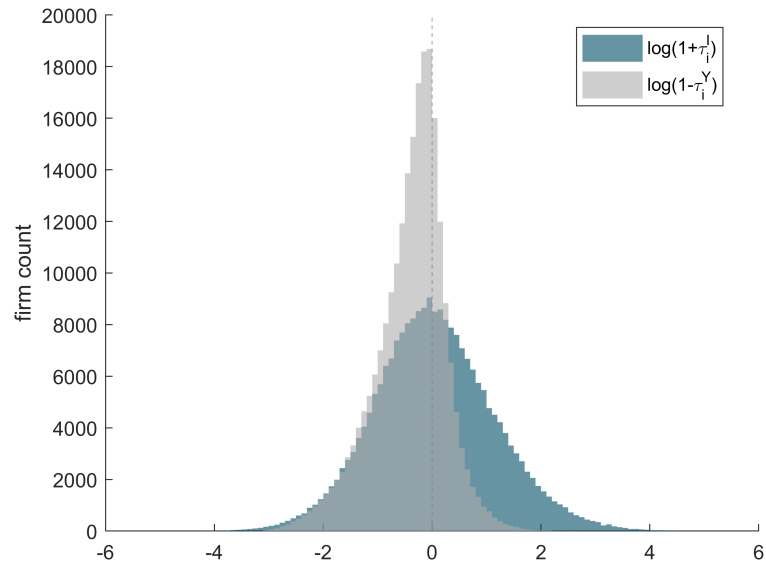


FIGURE 11: Estimated distortions $\log(1 - \tau_i^Y)$ and $\log(1 + \tau_i^I)$ by ownership

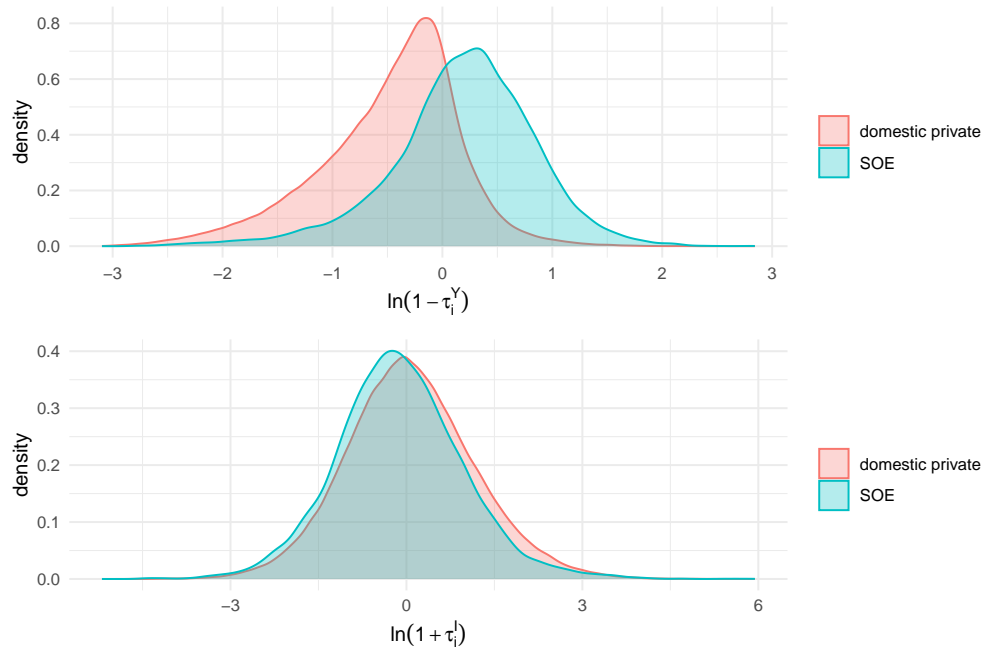


Figure 11 shows that state owned enterprises (SOEs) tend to be bigger than their profit-maximizing sizes (positive $\ln(1 - \tau_i^Y)$), whereas domestic private firms tend to be smaller than their profit-maximizing sizes (negative $\ln(1 - \tau_i^Y)$). SOEs are slightly more likely to overuse capital relative to labor (negative $\ln(1 + \tau_i^I)$) compared to domestic private firms. This is consistent with the idea that SOEs tend to grow excessively large due to political interventions and cheap capital credits and that domestic private firms are generally restrained from reaching their full potentials due to limited access to the financial market. However, we do not see a strong difference for the other categories we consider. The results are in Appendix D.

5.3 Predicted impact of removing the distortions

TABLE 4: Observed and predicted aggregate labor shares (%)

	with input and output distortions	with only input distortions	without distortions
wL/PY	42	65.03	65.88

The aggregate labor share with input and output distortions, or in other words the one observed in the data, is 42%. Removing all the distortions raises the aggregate labor share to 66%, i.e. an increase of 24 percentage points. This change is primarily driven by the output distortions because removing the output distortions alone raise the aggregate labor share to 65%. Table 4 summarizes these predicted aggregate labor shares.

The distributions of distortions in Figure 10 imply that half of the firms would reduce their labor demand after removing the input distortion but the other half would raise their labor demand. Removing the output distortions would raises 70% of the firms' labor demand.

Figure 12 presents the distribution of changes in firm-level labor shares, i.e. combining the impact of input and output distortions on labor shares. 76% the firms' labor shares increase after removing the distortions.

Figure 13 is the distribution of changes in firm-level labor-capital expenditure ratios. It is the same as the distribution of the input distortions in Figure 10 because the changes in firm-level expenditure ratios equal input distortions.

The reallocation across firms increases the dispersion of firm sizes (using Equation (21)). More specifically, it causes some firms to grower bigger and others to shrink as shown in the distribution of firm sizes with and without the distortions in Figure 14. As a consequence, market concentration increases. Figure 15 plots the distribution of industry Herfind-

FIGURE 12: Predicted changes in firm-level labor shares

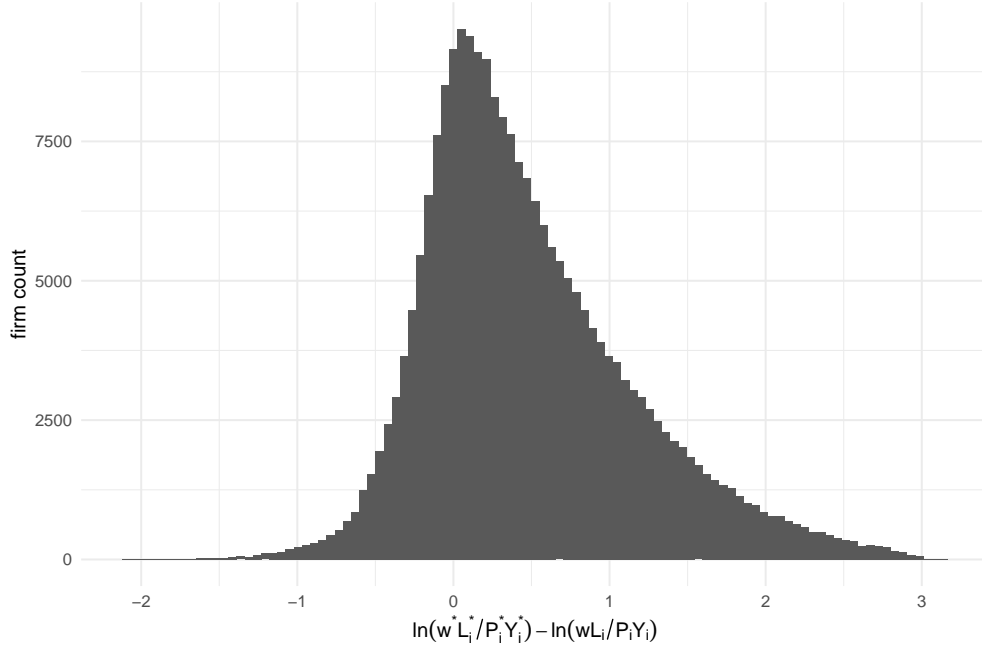
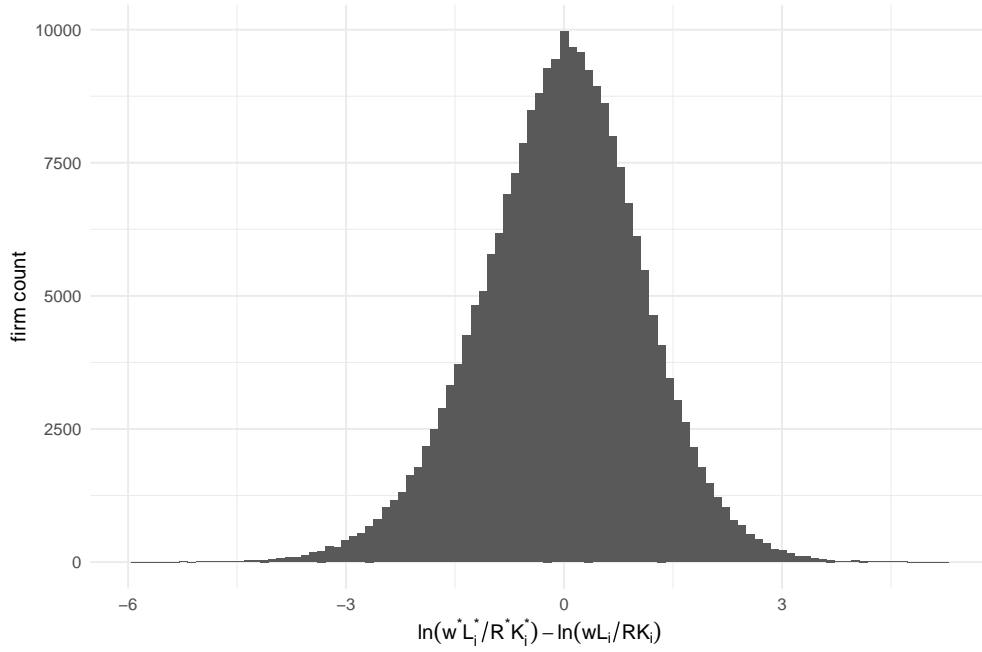


FIGURE 13: Predicted changes in firm-level expenditure ratios of labor and capital



ahl–Hirschman index. Removing the distortions shifts the distribution of industry Herfindahl–Hirschman index to the right. Some industry’s Herfindahl–Hirschman index becomes almost 10000, which implies that almost the entire industry is served by one firm.

Due to the unitary elasticity of substitution across industries, removing the distortions

FIGURE 14: Distribution of firm shares with and without distortions

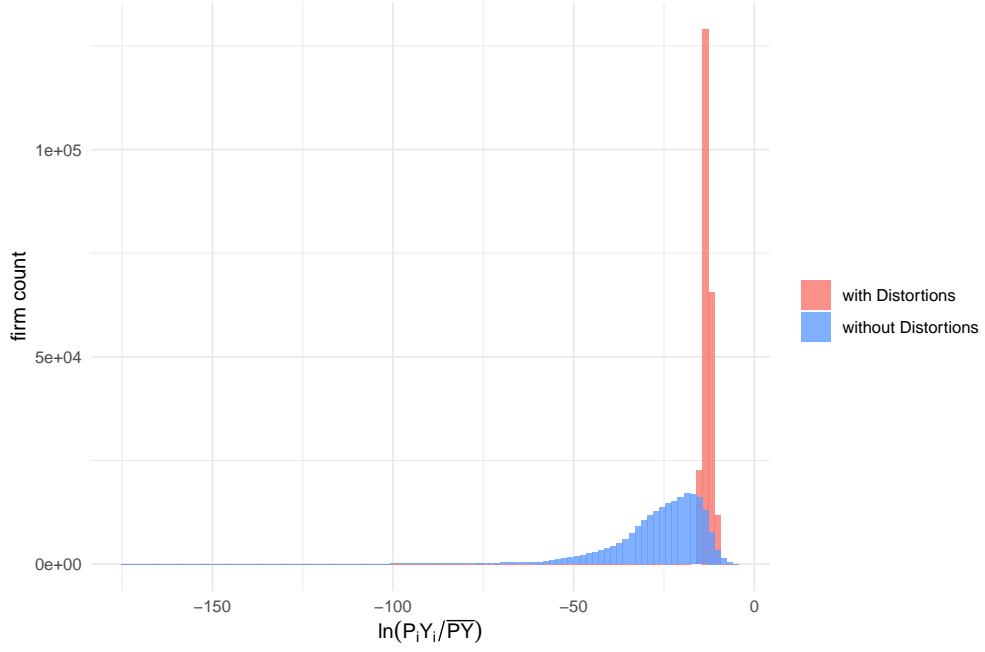
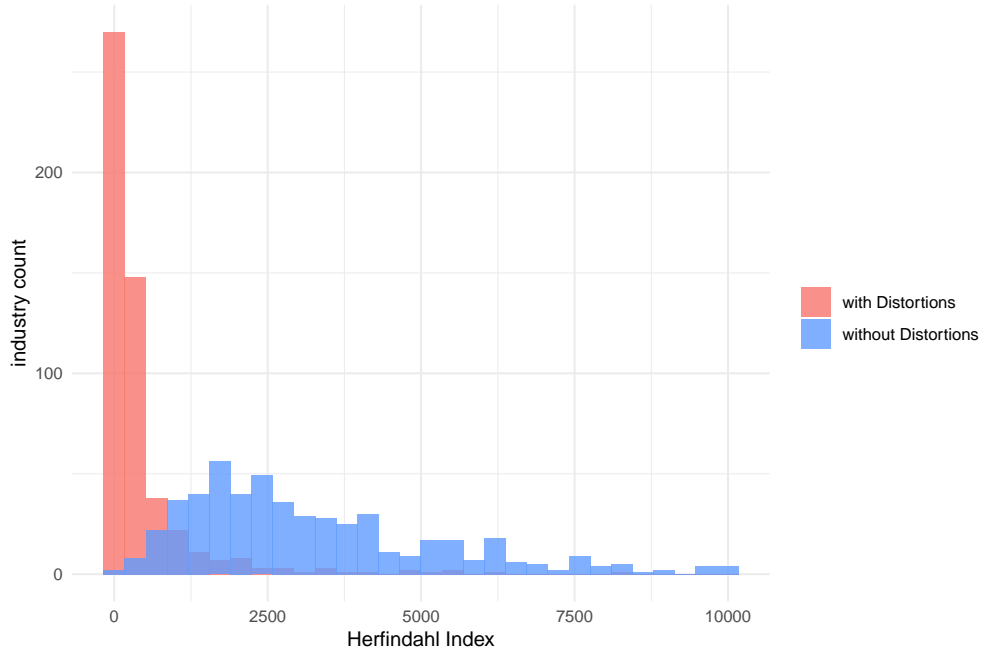
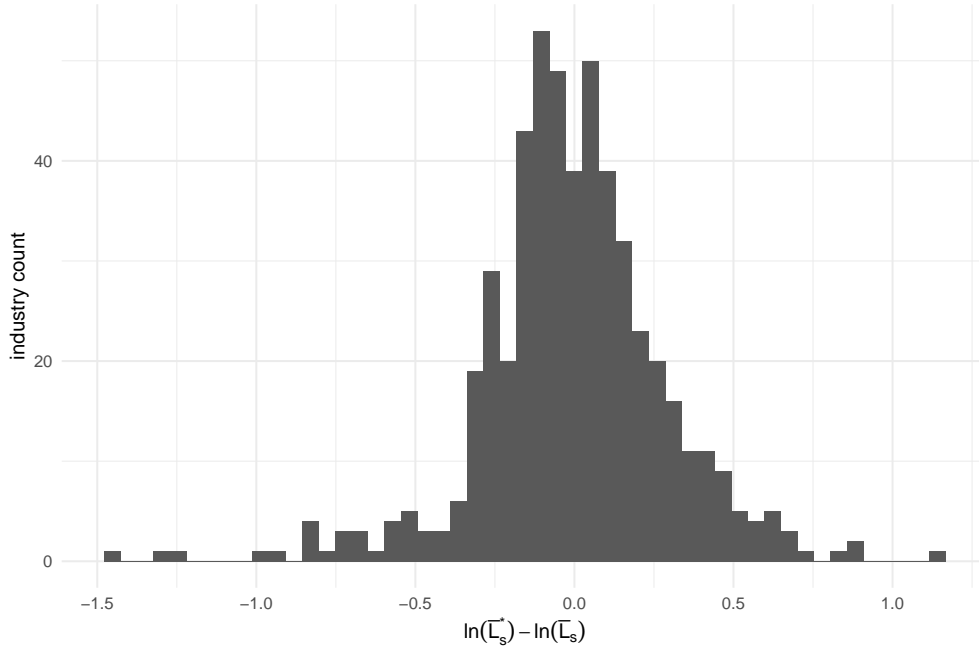


FIGURE 15: Industry Herfindahl–Hirschman index with and without distortions



does not alter industry shares $\frac{\bar{P}_s \bar{Y}_s}{P Y}$. However, removing the distortions alters industry-level labor demand and consequently changes the industry-level labor use. We plot the distribution of the changes in industry-level labor use in Figure 16. The distribution has a positive skewness, indicating that more than half of the industries increase their labor use.

FIGURE 16: Changes in industry-level labor use



Comparing the changes in industry-level labor use in Figure 16 to the changes in industry-level labor share in Figure 17, we can see that although only half of the industries' labor uses increase, the majority of the industries increase their labor shares. The additional increase in labor share is due to the higher wage after the distortions are removed. The distortions force industries to be too small and hinder the optimal allocation of capital and labor within the industries. When the distortions are removed, firms grow larger and so do industries. The aggregate labor demand increases which raises the equilibrium wage.

In terms of changes in firms' marginal costs when holding the capital rental rate and the wage fixed, only input distortions are relevant because output distortions proportionally change capital and labor usage and therefore do not affect marginal costs directly. Removing input distortions allows firms to reach their profit-maximizing labor-capital ratios and consequently reduces firms' marginal costs, as it is discussed when introducing the formula of marginal costs (Equation (20)). Figure 18 plots the predicted changes in firms' marginal costs from removing the input distortions holding the wage and the capital rental rate fixed. The majority of firms' marginal costs is reduced by less than 50% but the distribution has a long left tail, indicating a small share of firms experiences a 95% ($1 - e^{-3} = 95\%$) reduction in their marginal costs.

Table 5 displays the predicted aggregated productivity and the decomposition by within nest gains and gains due to reallocation across nests. The predicted TFP gains are significantly higher than the 30 – 50% increase by Hsieh and Klenow (2009). The difference is

FIGURE 17: Changes in industry-level labor shares

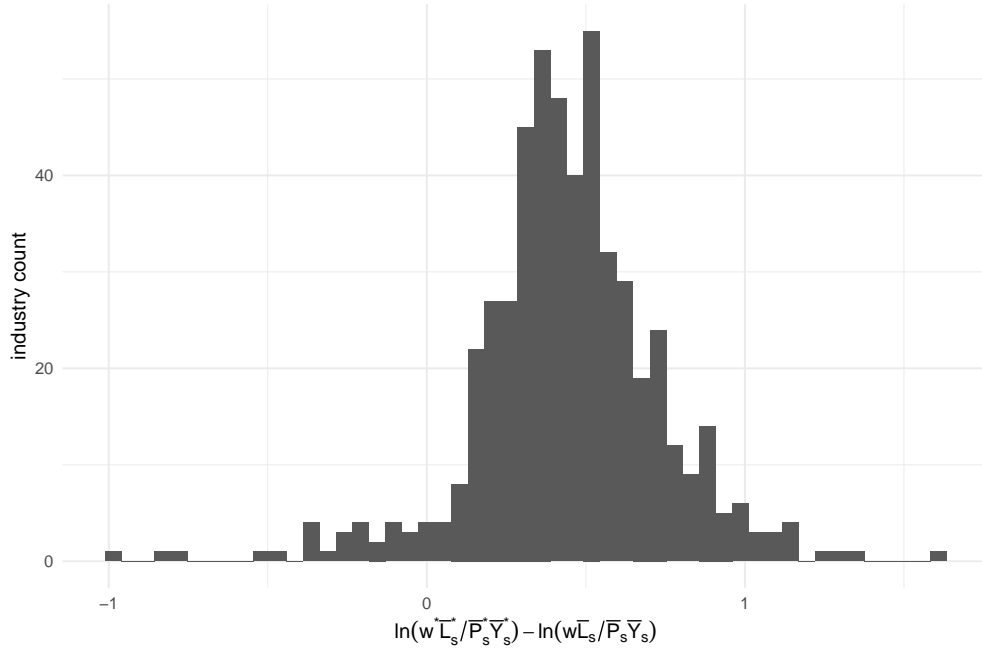
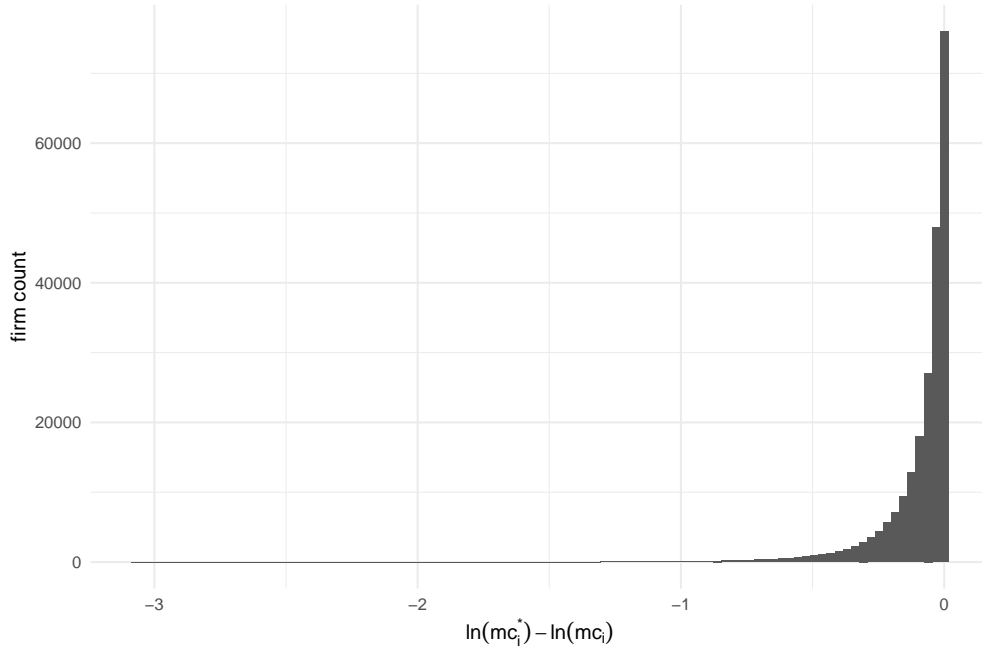


FIGURE 18: Changes in firm marginal costs



because [Hsieh and Klenow \(2009\)](#) set demand elasticities at 3, a value below estimates using firm-level data ([Edmond et al. \(2019\)](#), [Baqaee and Farhi \(2020\)](#), [De Loecker and Warzynski \(2012\)](#), [De Loecker et al. \(2020\)](#), [Feenstra and Weinstein \(2017\)](#), [Peters \(2020\)](#)). When using estimated demand elasticities, [Hsieh and Klenow \(2009\)](#)'s predicted TFP gains are close to

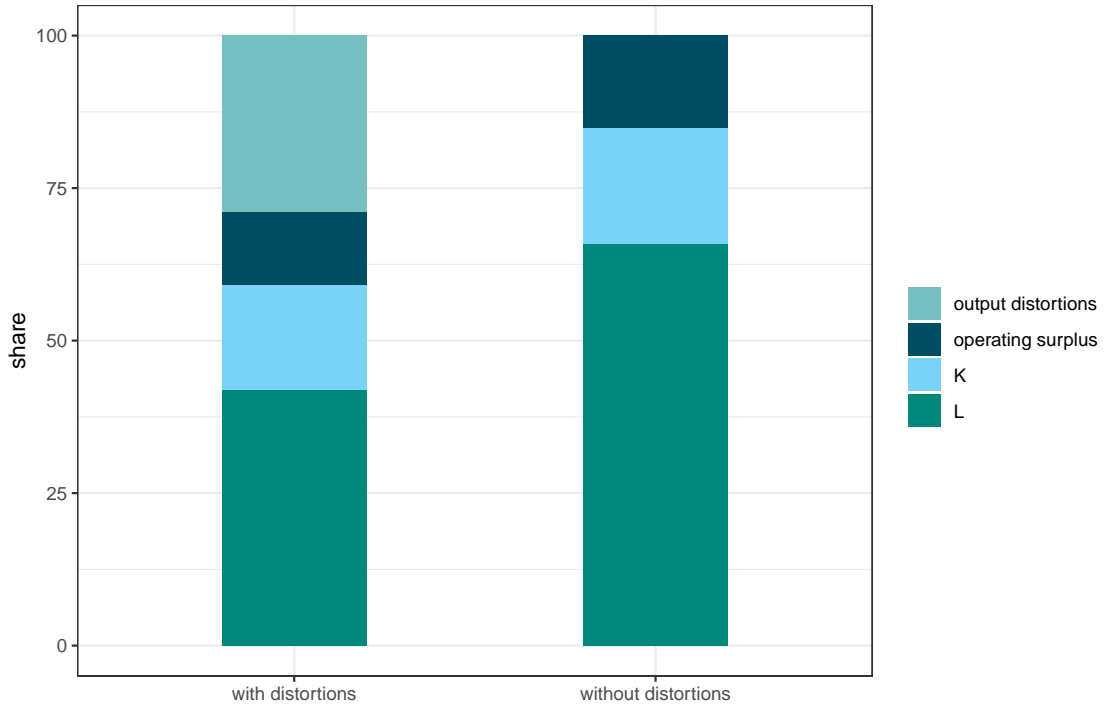
our prediction (Zhang and Xia (2022)).

TABLE 5: TFP gains in China (2005)

within industry (%)	across industry (%)	total (%)
296.8	3.4	310.3

We conclude the result section by the decomposition of the aggregate revenue (Figure 19). With distortions, labor collects 42% of the aggregate income, capital 17%, output distortions 29%, and firms' operating surplus 12%. Firms' operating surplus is the part of the profits due to markups predicted by demand elasticities. After removing the distortions, labor receives 66%, capital 19%, and operating surplus 15%, which is also the profit share since there is no distortion any more.

FIGURE 19: Decomposition of the aggregate revenue



6 Robustness

In this section, we discuss how to interpret our results if some of our assumptions are violated.

6.1 Heterogeneous ratios between observed and unobserved labor compensation

If the ratios between observed and unobserved labor compensation vary across firms, correcting labor shares using a common factor would treat the variation in unobserved labor shares as the input distortions. If the variation in unobserved labor shares move in the same direction as the input distortions, we overestimate the input distortions. Because our results show that the main impact on the aggregate labor share is from the output distortions, the heterogeneous ratios between observed and unobserved labor compensation should have a marginal impact on the aggregate labor share change. However, if the variation in unobserved labor shares move in the same direction as the input distortions, we would underestimate the input distortions and possibly the impact of the input distortions on the aggregate labor share.

6.2 Profits from the output-distortion part of firm revenues are not $\frac{1}{\epsilon_g} \tau_i^Y P_i Y_i$

In the main results, we assume that $\frac{1}{\epsilon_g}$ of firms' output-distortion revenue is profits. This means that firms' revenue-cost ratios are not affected by the output distortions:

$$\ln \left(\frac{\text{cost}_i}{\text{revenue}_i} \right) = \ln \left(\frac{\epsilon_{g(i)} - 1}{\epsilon_{g(i)}} \right) + \eta_i$$

When this is not the case, our estimated demand elasticities can be contaminated by output distortions. In the extreme case where the output-distortion part of revenues are all profits, the logarithm of firms' revenue-cost ratios are:

$$\ln \left(\frac{\text{cost}_i}{\text{revenue}_i} \right) = \ln \left(\frac{\epsilon_{g(i)} - 1}{\epsilon_{g(i)}} \right) + \ln(1 - \tau_i^Y) + \eta_i$$

When the output-distortion part of revenues are all costs, the logarithm of firms' revenue-cost ratios are:

$$\ln \left(\frac{\text{cost}_i}{\text{revenue}_i} \right) = \ln \left(1 - (1 - \tau_i^Y) \frac{1}{\epsilon_{g(i)}} \right) + \eta_i$$

In both scenarios, we expect to see the variation in the revenue-cost ratios to be the same as or very close to the variation in the cost shares of labor and capital because both contains the variation from demand elasticities and from output distortions. However, our data shows that the standard deviation of firms' cost shares of labor and capital is 0.42 and the standard

deviation of firms cost-revenue ratios is 0.12, i.e. the cost shares are more volatile than the cost-revenue ratios. We interpret this as a suggestion that the data is better described by assuming the cost-revenue ratios do not contain the output distortions $1 - \tau_i^Y$.

6.3 Heterogeneity in firms' capital-labor expenditure shares reflects heterogeneous technology

Our paper argues for the importance of taking into account firm heterogeneity when evaluating the impact of removing the distortions, but we assume away production technology difference within industry apart from firm-specific productivity A_i . If the production technology differs across firms within industries, i.e. α_i is firm-specific, both the input distortions and this technology heterogeneity will contribute to the dispersion of firm-level expenditure ratios between labor and capital:

$$\ln\left(\frac{wL_i}{RK_i}\right) = \ln(1 + \tau_i^I) + \ln\left(\frac{\alpha_i}{1 - \alpha_i}\right)$$

If the input distortions τ_i^I are uncorrelated with technology α_i , the variation of firms' labor-capital expenditure shares is the sum of the variation of input distortions and technology:

$$\text{Var}\left(\frac{wL_i}{RK_i}\right) = \text{Var}(1 + \tau_i^I) + \text{Var}\left(\frac{\alpha_i}{1 - \alpha_i}\right)$$

In this case, we overestimate the input distortions because we attribute some of the technology heterogeneity to input distortions. However, we argue that it is unlikely to change the estimated impact on the aggregate labor share because technology heterogeneity does not affect the estimated output distortions, and our predicted labor share change is primarily driven by the output distortions.

7 Conclusion

Reallocating capital and labor to increase the total production and to ensure that labor receives a fair share of the aggregate income is important for both economists and policymakers. Grossman and Oberfield (2022) observe that there is a radical but currently popular concern that the aggregate labor share in the national income might fall to zero due to market concentration and technological progress, such as further automation and the adoption of artificial intelligence. The problem of how to pursue higher productivity and

to avoid a falling labor share is difficult when increasing productivity lowers labor share. This paper revisits the classical misallocation problem of capital and labor and shows that when distortions prevent firms from reaching their profit-maximizing sizes, removing these distortions simultaneously raise aggregate productivity and the aggregate labor share under the assumption of fixed aggregate labor and capital. This win-win outcome occurs because removing the distortions releases pent-up labor demand, increases aggregate labor demand, and raises the aggregate labor share through an elevated wage. The implication is that when most firms in an economy are too small compared to their profit-maximizing sizes, policy makers should prioritize improving the allocation efficiency of capital and labor.

Our quantified labor-share increase is under the assumption that the aggregate labor and capital is fixed. Removing these distortions unleashes firms' demand for labor and pushes up wage by 57% since firms have to fight for labor. This should be interpreted as a short-term impact because, in the long run, the 57% wage increase will attract a huge inflow of labor, especially in the Chinese context where the agriculture sector employs 45% of national aggregate workers but its wage is only 50% of the one in the manufacturing sector and even lower than the mining sector and the public utilities sector (Chinese Annual Yearbook). The socioeconomic impact of a worker migration of this magnitude would not be trivial as suggested by [Pellegrina and Sotelo \(2021\)](#) and should be well thought of by economists and policymakers.

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Appendix

A Data

We drop observations with negative value added, negative wage expenditures, negative capital, negative total assets, negative account receivable, negative total debts, negative long-term debts, negative account payable, negative exports, negative sales, and negative costs. We also drop observations whose account receivable is larger than total assets, total debts larger than total assets, account payable larger than liquid debts, and profits larger than sales. If a firm's costs are missing but its sales and profits are observed, then its costs are sales minus profits. The survey reports firms' net value of capital and investment. To calculate depreciated net value of capital, we use perpetual annuity method following [Brandt et al. \(2012\)](#).

TABLE 6: Summary statistics unweighted across firms

	Mean	Standard Deviation	10th Percentile	1st Quartile	Median	3rd Quartile	90th Percentile
labor share	0.32	0.32	0.06	0.12	0.23	0.42	0.65
adj. labor share	0.49	0.26	0.16	0.28	0.47	0.68	0.85
capital share	0.19	0.30	0.02	0.05	0.10	0.22	0.43
cost share	0.68	0.42	0.24	0.40	0.64	0.87	1.13
cost/revenue	0.85	0.12	0.70	0.80	0.88	0.93	0.96

Notes: Total number of firms is 229,282. Capital rental rate is assumed 0.2. Cost share is adjusted labor share plus capital share.

B Derivation

Solving the firms' problem in Equation (8) gives firm i 's marginal cost mc_i and price P_i :

$$mc_i = R \cdot A_i^{-1} \left[\frac{R}{w} \cdot \frac{\alpha_{s(i)}}{1 - \alpha_{s(i)}} \cdot (1 + \tau_i^I) \right]^{-\alpha_{s(i)}} \cdot \left[1 + \frac{\alpha_{s(i)}}{1 - \alpha_{s(i)}} (1 + \tau_i^I) \right] \quad (28)$$

$$P_i = mc_i \cdot \frac{\epsilon_{g(i)}}{\epsilon_{g(i)} - 1} \cdot \frac{1}{1 - \tau_i^Y} \quad (29)$$

Combining Equation (33), (28), and (29) gives firm i 's market share out of nest $g(i)$:

$$\frac{P_i Y_i}{\bar{P}_{g(i)} \bar{Y}_{g(i)}} = \frac{\gamma_i^{1-\epsilon_{g(i)}}}{\sum_{i \in \mathcal{G}(g(i))} \gamma_i^{1-\epsilon_{g(i)}}} \quad (30)$$

where

$$\gamma_i \equiv \frac{1}{1 - \tau_i^Y} \cdot \frac{1}{A_i} \left[(1 + \tau_i^I)^{-\alpha_{s(i)}} \cdot (1 - \alpha_{s(i)}) + (1 + \tau_i^I)^{1-\alpha_{s(i)}} \cdot \alpha_{s(i)} \right] \quad (31)$$

Substitute Equation (32) and (30) for $\frac{\bar{P}_g \bar{Y}_g}{\bar{P} \bar{Y}}$ and $\frac{P_i Y_i}{\bar{P}_{g(i)} \bar{Y}_{g(i)}}$ gives Equation (16):

$$\frac{w \bar{L}}{\bar{P} \bar{Y}} = \sum_g \sum_{i \in \mathcal{G}(g)} \beta_g \cdot \underbrace{(1 - \tau_i^Y) \frac{\epsilon_{g(i)} - 1}{\epsilon_{g(i)}} \cdot \frac{\alpha_{s(i)} (1 + \tau_i^I)}{1 + \alpha_{s(i)} \tau_i^I}}_{\text{firm-level labor shares}} \cdot \underbrace{\frac{\gamma_i^{1-\epsilon_{g(i)}}}{\sum_{i \in \mathcal{G}(g(i))} \gamma_i^{1-\epsilon_{g(i)}}}}_{\text{firm-level market shares}}$$

The aggregate labor share is:

$$\begin{aligned} \frac{w \bar{L}}{\bar{P} \bar{Y}} &= \sum_g \frac{\bar{P}_g \bar{Y}_g}{\bar{P} \bar{Y}} \cdot \frac{w \bar{L}_g}{\bar{P}_g \bar{Y}_g} \\ &= \sum_g \frac{\bar{P}_g \bar{Y}_g}{\bar{P} \bar{Y}} \sum_{i \in \mathcal{G}(g)} \frac{w L_i}{P_i Y_i} \cdot \frac{P_i Y_i}{\bar{P}_{g(i)} \bar{Y}_{g(i)}} \\ &= \sum_g \frac{\bar{P}_g \bar{Y}_g}{\bar{P} \bar{Y}} \sum_{i \in \mathcal{G}(g)} (1 - \tau_i^Y) \cdot \frac{\alpha_{s(i)} \cdot (1 + \tau_i^I)}{1 + \alpha_{s(i)} \tau_i^I} \cdot \frac{\epsilon_{g(i)} - 1}{\epsilon_{g(i)}} \cdot \frac{P_i Y_i}{\bar{P}_{g(i)} \bar{Y}_{g(i)}} \end{aligned}$$

where $\bar{P} \bar{Y} \equiv \sum_i P_i Y_i$ is the aggregate revenue, $\bar{P}_g \equiv \sum_{i \in \mathcal{G}(g)} \frac{P_i Y_i}{\bar{Y}_{g(i)}}$ is the price index of nest g , $\bar{L}_g \equiv \sum_{i \in \mathcal{G}(g)} L_i$ is the total amount of labor used in nest g . The first two equations use the fact that $w \bar{L} = \sum_g w \bar{L}_g$ and $w \bar{L}_g = \sum_{i \in \mathcal{G}(g)} w L_i$. The third equation uses the definition of the distortions in Equation (12) and (13).

Solving the representative consumer's problem in Equation (7) gives nests' market shares and firms' shares within nests:

$$\frac{\bar{P}_g \bar{Y}_g}{\bar{P} \bar{Y}} = \beta_g \quad (32)$$

$$\frac{P_i Y_i}{\bar{P}_{g(i)} \bar{Y}_{g(i)}} = \frac{P_i^{1-\epsilon_{g(i)}}}{\sum_{i \in \mathcal{G}(g(i))} P_i^{1-\epsilon_{g(i)}}} \quad (33)$$

Solving the general equilibrium gives us the aggregate labor share in Equation (16)

C Inferring markups using revenue-cost ratio versus other methods

Inferring markups without observed prices, physical production, and physical inputs is difficult. Generally, there are three methods for estimating markups: the demand approach, the production approach, and the accounting approach. Developed by [Berry et al. \(1995\)](#), the demand approach models consumers' choices among products and infers markups from parameters in consumers' utility functions. This method requires product prices, sales in units of products, and some observed characteristics of the products. The production approach measures markups as the ratio of production elasticities to cost share of a variable input ([De Loecker and Warzynski \(2012\)](#)). Although it does not require prices, applying it to markets with heterogeneous markups and heterogeneous production functions creates various problems when physical production and physical inputs are replaced by revenue production and input expenditure (See [Bond et al. \(2021\)](#) for detailed explanations. A brief discussion on this is offered below). The accounting approach does not require any econometric assumption apart from that the marginal cost equals the average cost. This approach only needs cost and revenue data.

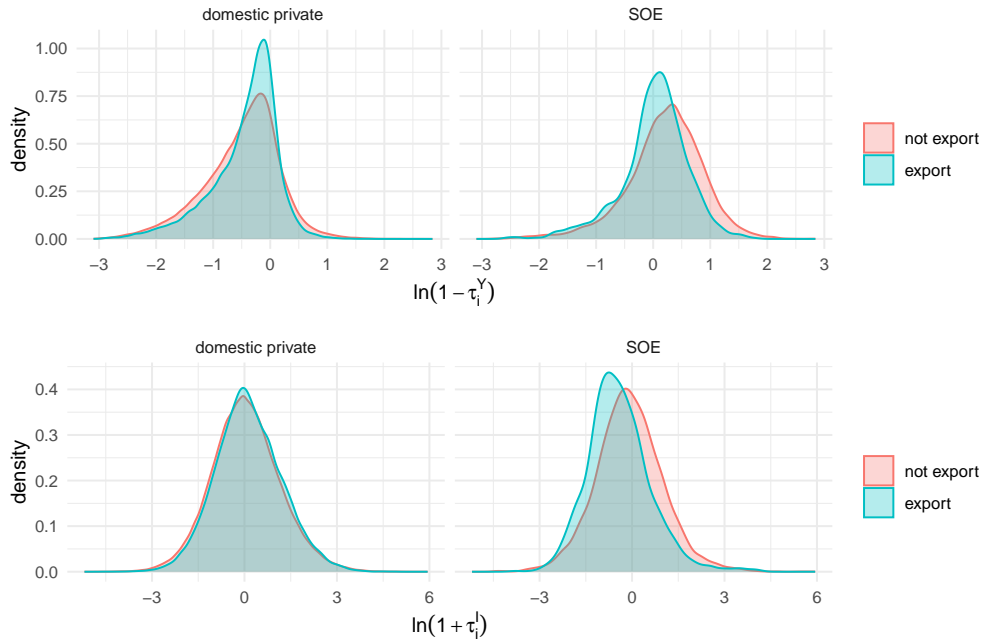
We do not observe prices and units of products sold, so only the production approach and the accounting approach are feasible. In fact, these are the methods used by many papers that infer firm-level markups using similar data as ours, such as [De Loecker and Warzynski \(2012\)](#), [Liu \(2019\)](#), [Autor et al. \(2020\)](#), [De Loecker et al. \(2020\)](#) and [Baqae and Farhi \(2020\)](#). We prefer using the accounting approach because we assume constant returns to scale and that the measurement errors are independent and identically distributed.

Dealing with the bias in the production approach is a lot of more difficult if not completely unfeasible. There are four sources of bias in the production approach under our setup when physical production and physical inputs are not observed and when firms have heterogeneous markups. The first one results from replacing production elasticities by revenue elasticities. If the revenue elasticities are consistently estimated, the estimated markups by the production approach should always be 1 ([Bond et al. \(2021\)](#)). Secondly, the assumption of variable input is very restrictive and it is almost impossible to find a truly variable input in data. Besides, the production approach also requires that the variable input do not affect demand and it can be common for inputs, such as labor inputs for marketing, to affect demand ([Bond et al. \(2021\)](#)). Most commonly used variable inputs are material and energy but we observe neither in our data. The last two sources are related to the consistency of estimated production elasticities using revenue data. In order to estimate production elasticities, the production approach needs to estimate production functions using [Olley and Pakes \(1996\)](#),

Levinsohn and Petrin (2003), or Akerberg et al. (2015). However, when revenue production is used in the place of physical production, Klette and Griliches (1996) demonstrates that heterogeneous markups can bias the estimated production elasticities downward. Last but not the least, even if one successfully corrects this bias by controlling for industry-level sales and prices, weak instruments can still plague the estimators (Bond et al. (2021)). Although Ridder et al. (2021) shows that estimated markups using revenue gives the correct dispersion but this requires using material as variable input. We only observe labor and capital. Since labor and capital are far from being variable, applying the production approach in our case is problematic.

D Other results

FIGURE 20: Estimated distortions $\log(1 - \tau_i^Y)$ and $\log(1 + \tau_i^I)$ by export status



Within ownership, SOEs that export or have patents are less likely to be excessively large than non-export SOEs, but they tend to have lower labor-capital ratios (Figure 20 and 21). This suggests that SOEs more exposed to market competition, i.e. exporting SOEs, and SOEs that has more competency, i.e. SOEs with patents, face smaller size distortions. The impact of loans and subsidies are overall small. They do not affect the distribution of output distortions, but firms with loans or subsidies tend to have slightly negative input distortions, i.e. slightly lower labor-capital ratios (Figure 22 and Figure 23).

FIGURE 21: Estimated distortions $\log(1 - \tau_i^Y)$ and $\log(1 + \tau_i^I)$ by patent status

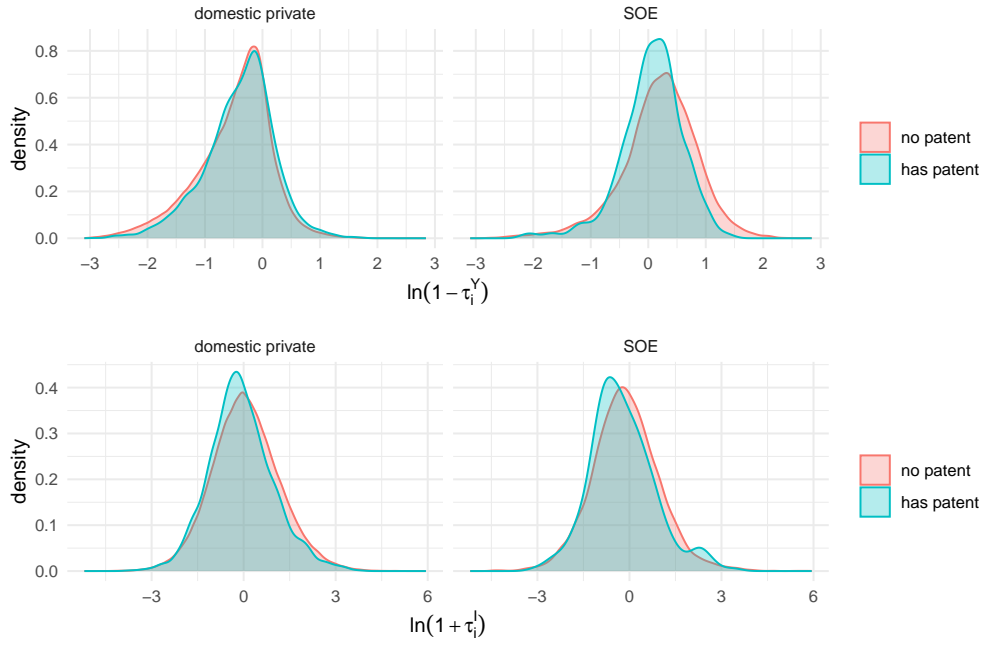


FIGURE 22: Estimated distortions $\log(1 - \tau_i^Y)$ and $\log(1 + \tau_i^I)$ by loan status

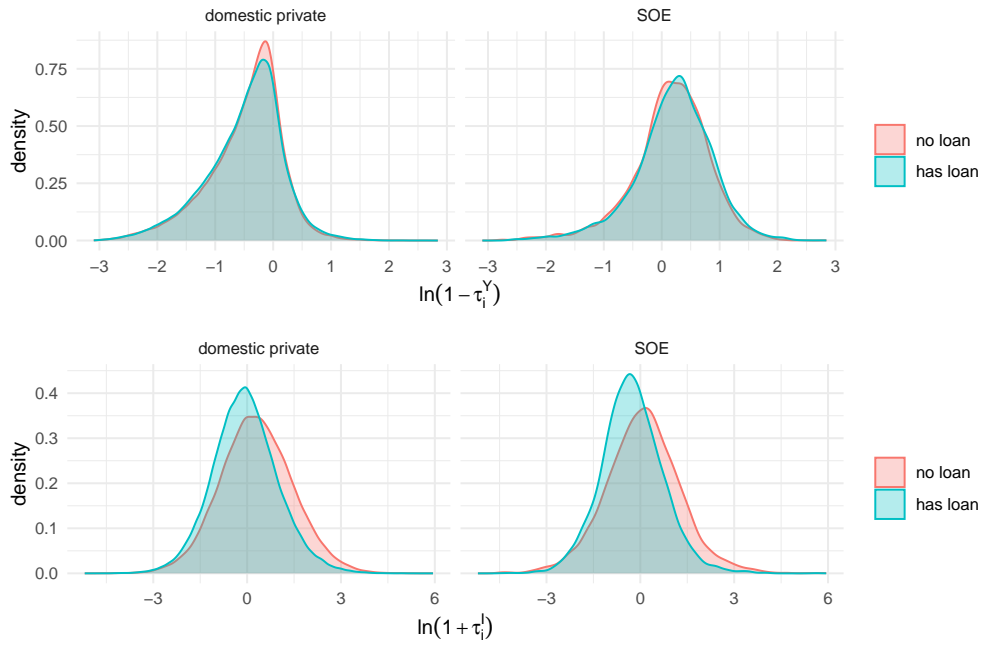


FIGURE 23: Estimated distortions $\log(1 - \tau_i^Y)$ and $\log(1 + \tau_i^I)$ by subsidy status

