A Reappraisal of Market Distortions and Manufacturing TFP Loss in China

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Abstract

A model of monopolistic competition makes it possible for us to measure the productivity of each individual firm and the market distortions it faces, and hence to quantitatively examine the potential impact of market distortions on aggregate Total Factor Productivity (TFP) within an industry. Nevertheless, substantial measurement errors could arise if incorrect values are assigned to the parameters in the model. In this paper, I develop a new econometric method that can consistently estimate output elasticities of capital and labor as well as price markup within an industry. Using the microdata for Chinese manufacturing firms, I find both large variations in price markup across industries and decreasing returns to scale in most of them. In addition, certain results from this study, based on such new estimates, differ significantly from those found in the literature: (1) Aggregate TFP in the Chinese manufacturing sector has grown up to 10% annually between 1999 and 2007; (2) Such a rapid growth is almost completely due to *pure* productivity improvement rather than narrowing distortions; and (3) Variance of TFP loss across industries is explained mostly by the differences in return to scale rather than those in market distortions. Finally, this study shows that substantial differences in market distortions and productivity exist among firms with different ownerships, and that extremely large-sized firms, especially the private domestic ones, should expand at the expense of small-size firms in China to reduce the loss of aggregate TFP.

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I. INTRODUCTION

Recent research has shown that output per capita varies across countries, not only because of differences in capital stock but also due to differences in total factor productivity (TFP). The differences in TFP are substantial even among developed countries, as discussed by Trefler (1993, 1995), and Hall and Jones (1999). A large volume of literature has emerged to investigate the causes of these large TFP differences. One strand of this literature has focused on differences in technology within representative firms. For example, Parente and Prescott (1994) show that only a modest disparity in technology adoption barrier is needed to account for huge TFP differences in a closed-economy model where research carried out by firms only increases their own productivity. Howitt (2000), using a simple open-economy extension of the Schumpeterian endogenous growth model, shows that long-run TFP differences are endogenously determined by the incentives to innovate and to accumulate capital. More recently, Klenow and Rodríguez-Clare (2005) show that modest barriers to international technology transfer can explain a significant portion of TFP differences across countries. Despite the different causes of substantial TFP disparities, however, all these models assume an aggregate production function of constant returns to scale (CRS), and do not account for heterogeneity in production units.

The other strand of the literature emphasizes the importance of capital and labor allocation across heterogeneous firms as a determinant of aggregate TFP. Restuccia and Rogerson (2008), for instance, consider a version of the neoclassical growth model where firms face idiosyncratic policy distortions. The policy they consider can be of the sort that levies taxes or provides subsidies to output or the use of capital and labor. Policy distortions are found to have substantial effects on aggregate output and measured TFP in their calibrated models for the United States. Hsieh and Klenow (2009) use a standard model of monopolistic competition to show how idiosyncratic distortions in capital and labor markets will lower aggregate TFP. They infer distortions from the residuals in first-order conditions following

Chari, Kehoe and McGrattan (2007), and provide quantitative evidence of the impact of resource misallocation on aggregate manufacturing TFP in China, India and the United States.

Hsieh and Klenow (2009) make two rigid assumptions in their monopolistic competition model: a CRS value-added production function and a constant price markup across industries. Both of the assumptions, however, are debatable. First, direct estimates or calibration studies of firm-level value-added production functions (e.g. Atkeson, Khan, and Ohanian 1996; Pavcnik 2003; Guner, Ventura, and Xu 2007) all point to a range of decreasing returns between 10% to 20%. Second, large variations in price markup and the importance of such variations have been discussed extensively in the literature of business cycles. Roeger (1995) first documents large variations in price markup across industries in the United States by calculating the price markup as the difference between the primal and dual measures of TFP. Hornstein (1993) finds that a model with a constant price markup cannot account for the volatilities in the U.S. data because it lacks an internal magnification mechanism. Gali (1994), using a model with a fixed number of firms, shows that variations in the composition of aggregate demand can lead to variations in price markup. More interestingly, Portier (1995) first finds the evidence of counter-cyclicality of price markup using the French data. Later, Rotemberg and Woodford (1999) show that implicit collusion among a fixed number of oligopolistic firms will lead to counter-cyclical movements in price markup; Edmunds and Veldkamp (2006) also prove that asymmetric information and counter-cyclical income dispersion will give rise to counter-cyclical price markup.

In fact, not only are the assumptions of a CRS production function and a constant price markup across industries debatable, they could also lead to substantial measurement errors in market distortions and TFP. Such potential measurement errors call for a new econometric method that can be used to consistently estimate output elasticities of capital and labor and price markup within an industry. This paper develops such a method by extending the idea

in Ackerberg, Caves, and Frazer (2006), which uses an intermediate input as the "proxy" for productivity shocks, to a monopolistic competition model. As they claim, a merit of their estimation strategy is that it does not suffer the possible collinearity problems encountered by Olley and Pakes (1996) and Levinsohn and Petrin (2003). However, one potential problem with their strategy is that output data are needed for estimation. But in reality, only value-added data are available in most of the cases, and they are used to replace output data directly. Nevertheless, using value-added data rather than output data in estimating production functions could lead to systematic biases. When the strategy in Ackerberg, Caves and Frazer (2006) is applied to a monopolistic competition model, such a potential problem disappears as the model itself links capital and labor inputs directly to value added. More important, this new econometric method based on a monopolistic competition model enables us to consistently estimate output elasticities of capital and labor as well as price markup within an industry.

In this paper, I reexamine the relationship between market distortions and TFP loss in the Chinese manufacturing sector within the framework of a monopolistic competition model. Ideally, the *efficient*[1] aggregate TFP of an industry should be unrelated to the market distortions in that industry if the model is correctly specified and consistently estimated. Applying my new econometric method to the same microdata for Chinese manufacturing firms as used by Hsieh and Klenow (2009), however, I find a close relationship between *measured efficient* aggregate TFP and the market distortions when assuming a CRS production function and a constant price markup in the model. And such a close relationship disappears when these two assumptions are relaxed. This finding, therefore, provides strong evidence for the measurement errors in market distortions and TFP when incorrectly imposing a CRS production function and a constant price markup in the model.

In addition, this paper shows that growth of aggregate TFP in China during 1999-2007

[1] The *efficient* aggregate TFP of an industry is achieved when all the firms within the industry face the same tax rates in both capital and labor markets.

is hardly due to its narrowing market distortions. Such a result differs significantly from Hsieh and Klenow's (2009) claim that China has boosted its TFP 2% per year during 1998-2005 by narrowing its absolute market distortions (measured as variance). In fact, this study shows that not only the absolute market distortions, but the relative market distortions (measured as coefficient of variation[2]) will also affect the degree of TFP loss. And their effects almost offset each other, leading to a stable degree of TFP loss in Chinese manufacturing sector. Therefore, the annual 10% growth of aggregate TFP in Chinese manufacturing sector during 1999-2007 is almost completely due to *pure* productivity improvement. More interestingly, this study finds that the variance of TFP loss across industries is mostly explained by differences in returns to scale rather than those in market distortions.

The rest of the paper proceeds as follows. In Section 2, I first sketch the monopolistic competition model used by Hsieh and Klenow (2009) to show how a firm's value added is determined, and how the allocation of capital and labor will affect the aggregate TFP of an industry. I then discuss in detail how the two assumptions of a CRS production function and a constant price markup could lead to substantial measurement errors in TFP. In Section 3, I briefly review the estimation strategies used by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2006). Extending Ackerberg, Caves, and Frazer's (2006) work to a monopolistic competition model, I develop a new estimation strategy that can be used to consistently estimate output elasticities of capital and labor as well as price markup within an industry. Section 4 describes the data used in this study. Section 5 presents various empirical results of interests. Finally, conclusions are drawn in section 6.

II. REVIEW OF MARKET DISTORTIONS AND TFP

[2] Coefficients of variation, defined as the standard deviation divided by the mean, is a normalized measure of dispersion of a probability distribution. Since the standard deviation must always be understood in the context of the mean, one should use the coefficient of variation for comparison instead of the standard deviation when comparing data sets with different units or widely different means.

II.A. The Benchmark Monopolistic Competition Model

To illustrate the impact of market distortions on aggregate productivity, I follow Hsieh and Klenow (2009) using a standard model of monopolistic competition with heterogeneous firms. Y_s is the output in industry s, which is itself a constant elasticity of substitution (CES) aggregate of N_s differentiated products:

$$Y_s = \left(\sum_{i=1}^{N_s} Y_{is}^{\frac{1}{\theta_s}} \right)^{\theta_s}, \tag{1}$$

where θ_s is the markup of product price over marginal cost when there is no tax on the firm's revenue. Each differentiated product i in industry s is produced with a Cobb-Douglas technology:

$$Y_{is} = A_{is} K_{is}^{\alpha_s} L_{is}^{\beta_s}, \tag{2}$$

where Y_{is} is the output, K_{is} the capital input, L_{is} the labor input, and A_{is} the productivity level. α_s and β_s, the capital and labor shares, are allowed to differ across industries but not across firms within the same industry. The sum of α_s and β_s is not necessarily equal to 1. That is, no restriction is imposed on the degree of returns to scale in this study.

Besides different productivity levels, firms in the same industry also face two idiosyncratic distortions that affect decisions regarding capital and labor inputs. The first, called the capital distortion τ_K by Hsieh and Klenow (2009), affects the marginal product of capital relative to labor. The other, called the output distortion τ_Y, increases the marginal product of capital and labor by the same proportion. So, the profit of firm i in industry s can be expressed as

$$\pi_{is} = (1 - \tau_{Yis}) P_{is} Y_{is} - w L_{is} - (1 + \tau_{Kis}) R K_{is}, \tag{3}$$

where P_{is} is the price of the product that firm i in industry s produces, w the price of labor input, and R the price of capital input.

Profit maximization yields the following standard conditions:

$$P_{is} = P_s Y_s^{\frac{\theta_s - 1}{\theta_s}} Y_{is}^{\frac{1-\theta_s}{\theta_s}}, \tag{4}$$

$$K_{is} = \left(\frac{\theta_s R}{\alpha_s}\right)^{-1} \frac{1-\tau_{Yis}}{1+\tau_{Kis}} P_{is} Y_{is}, \tag{5}$$

$$L_{is} = \left(\frac{\theta_s w}{\beta_s}\right)^{-1} (1 - \tau_{Yis}) P_{is} Y_{is}. \tag{6}$$

Based on the model above, we can express the distortions and productivity for each firm as

$$1 + \tau_{Kis} = \frac{\alpha_s}{\beta_s} \frac{wL_{is}}{RK_{is}}, \tag{7}$$

$$1 - \tau_{Yis} = \frac{\theta_s}{\beta_s} \frac{wL_{is}}{P_{is} Y_{is}}, \tag{8}$$

$$A_{is} = (P_s Y_s)^{1-\theta_s} P_s^{-1} \frac{(P_{is} Y_{is})^{\theta_s}}{K_{is}^{\alpha_s} L_{is}^{\beta_s}}. \tag{9}$$

The price of Y_s and the aggregate supply of capital and labor in the manufacturing industry s can be expressed as follows:

$$P_s = \left(\sum_{i=1}^{N_s} P_{is}^{\frac{1}{1-\theta_s}}\right)^{1-\theta_s}, \tag{10}$$

$$K_s = \sum_{i=1}^{N_s} K_{is} = \left(\frac{\theta_s R}{\alpha_s}\right)^{-1} \sum_{i=1}^{N_s} \frac{1-\tau_{Yis}}{1+\tau_{Kis}} P_{is} Y_{is}, \tag{11}$$

$$L_s = \sum_{i=1}^{N_s} L_{is} = \left(\frac{\theta_s w}{\beta_s}\right)^{-1} \sum_{i=1}^{N_s} (1 - \tau_{Yis}) P_{is} Y_{is}. \tag{12}$$

The TFP of industry s, defined as

$$TFP_s = \frac{Y_s}{K_s^{\alpha_s} L_s^{\beta_s}}, \tag{13}$$

can be expressed as

$$TFP_s = \frac{\left[\sum_{i=1}^{N_s} A_{is}^{\frac{1}{\theta_s-\gamma_s}} \left(\frac{1-\tau_{Yis}}{1+\tau_{Kis}}\right)^{\frac{\alpha_s}{\theta_s-\gamma_s}} (1-\tau_{Yis})^{\frac{\beta_s}{\theta_s-\gamma_s}}\right]^{\theta_s-\gamma_s}}{\left[\sum_{i=1}^{N_s} \varpi_{is} \frac{1-\tau_{Yis}}{1+\tau_{Kis}}\right]^{\alpha_s} \left[\sum_{i=1}^{N_s} \varpi_{is}(1-\tau_{Yis})\right]^{\beta_s}}, \tag{14}$$

where $\varpi_{is} = (P_{is}Y_{is}) / (P_sY_s)$ is firm i's share of value added in industry s. The *efficient* TFP of industry s is achieved when market distortions are equalized across firms within this industry:

$$TFPE_s = \left[\sum_{i=1}^{N_s} A_{is}^{\frac{1}{\theta_s-\gamma_s}}\right]^{\theta_s-\gamma_s}. \tag{15}$$

The efficiency loss in industry s due to the distortions in capital and labor markets, therefore, is measured by

$$E_s = \frac{TFP_s}{TFPE_s}. \tag{16}$$

The smaller this ratio is, the bigger the efficiency loss in industry s becomes due to the distortions in its capital and labor markets.

For the simplicity of discussion, I redefine $\kappa_{Lis} = 1 - \tau_{Yis}$ and $\kappa_{Kis} = (1-\tau_{Yis})/(1+\tau_{Kis})$[3]. κ_{Lis} denotes the distortion that only affects a firm's decision regarding labor inputs, while κ_{Kis} denotes the distortion that only affects a firm's decision regarding capital inputs. Let $\overline{\kappa}_{Ks}$ and $\overline{\kappa}_{Ls}$ denote the unweighted averages of κ_{Kis} and κ_{Lis} in industry s, respectively. And let $\widetilde{\kappa}_{Ks}$ and $\widetilde{\kappa}_{Ls}$ denote the weighted averages of κ_{Kis} and κ_{Lis} by each firm's value added in industry s, respectively.

TFP_s can be broken down into two parts:

$$TFP_s = TFP_s^1 \cdot TFP_s^2, \tag{17}$$

[3] A firm's optimal decision, correspondingly, is to maximize its profit $\widetilde{\pi}_{is} = P_{is}Y_{is} - \frac{1}{\kappa_{Lis}} wL_{is} - \frac{1}{\kappa_{Kis}} RK_{is}$.

where

$$TFP_s^1 = \left[\sum_{i=1}^{N_s} A_{is}^{\frac{1}{\theta_s - \gamma_s}} \left(\frac{\kappa_{Kis}}{\overline{\kappa}_{Ks}} \right)^{\frac{\alpha_s}{\theta_s - \gamma_s}} \left(\frac{\kappa_{Lis}}{\overline{\kappa}_{Ls}} \right)^{\frac{\beta_s}{\theta_s - \gamma_s}} \right]^{\theta_s - \gamma_s}, \tag{18}$$

and

$$TFP_s^2 = \left(\frac{\overline{\kappa}_{Ks}}{\widetilde{\kappa}_{Ks}} \right)^{\alpha_s} \left(\frac{\overline{\kappa}_{Ls}}{\widetilde{\kappa}_{Ls}} \right)^{\beta_s}. \tag{19}$$

If A_{is}, κ_{Lis} and κ_{Kis} are jointly lognormally distributed, and A_{is} is uncorrelated with κ_{Lis} and κ_{Kis}, one can prove that

$$\ln \left(\frac{TFP_s^1}{TFPE_s} \right) \approx \frac{\alpha_s \beta_s}{\theta_s - \gamma_s} \sigma_{K,L} + \frac{\alpha_s (\alpha_s + \gamma_s - \theta_s)}{2(\theta_s - \gamma_s)} \sigma^2_{\kappa_{Ks}} + \frac{\beta_s (\beta_s + \gamma_s - \theta_s)}{2(\theta_s - \gamma_s)} \sigma^2_{\kappa_{Ls}}, \tag{20}$$

where $\sigma_{K,L}$ is the covariance between $\ln(\kappa_{Ks})$ and $\ln(\kappa_{Ls})$, $\sigma^2_{\kappa_{Ks}}$ the variance of $\ln(\kappa_{Ks})$, and $\sigma^2_{\kappa_{Ls}}$ the variance of $\ln(\kappa_{Ls})$. So in this special case, one can see two facts: (1) The effects of market distortions on efficiency loss in industry s can be partially summarized by the variances of $\ln \kappa_{Lis}$ and $\ln \kappa_{Lis}$ and the covariance between $\ln \kappa_{Lis}$ and $\ln \kappa_{Lis}$; (2) The degree of efficiency loss in industry s also depends on the technology this industry adopts and the price markup in this industry. For simplicity, we denote $TFP_s^1/TFPE_s$ as E_s^1.

The second part, TFP_s^2, measures the relative values of unweighted averages of κ_{Lis} and κ_{Kis} to their corresponding value-added weighted averages. The relationships between $\overline{\kappa}_s$ and $\widetilde{\kappa}_s$ can be expressed as

$$\frac{\overline{\kappa}_s}{\widetilde{\kappa}_s} = \frac{1}{1 + \rho_{\kappa_s, \varpi_s} \cdot CV_{\kappa_s} \cdot \sigma_{N_s \varpi_s}}, \tag{21}$$

where $\rho_{\kappa_s, \varpi_s}$ denotes the correlation coefficient between κ_s, and ϖ_s, $\sigma_{N_s \varpi_s}$ the standard deviation of $N_s \varpi_s$. CV_{κ_s}, the coefficient of variation, is defined as the standard deviation of κ_{is} divided by the unweighted average of κ_{is}. For simplicity, we denote TFP_s^2 as E_s^2.

Overall, therefore, there are two kinds of dispersions in labor and capital markets that determine the difference between TFP_s and $TFPE_s$. One, measured by variance, is absolute and determines the difference between TFP_s^1 and $TFPE_s$ (the value of E_s^1). The other,

measured by coefficient of variation, is relative and determines the relative values of $\overline{\kappa}_s$ to $\widetilde{\kappa}_s$ (the value of E_s^2). By focusing only on the absolute one and ignoring the relative one, Hsieh and Klenow's (2009) study of the impact of market distortions on aggregate TFP could be potentially problematic.

II.B. Potential Measurement Errors of TFP

The focal point of Hsieh and Klenow (2009) is accounting for the impact of market distortions on cross-country aggregate TFP differences. They simply assume a CRS production technology ($\overline{\alpha}_s + \overline{\beta}_s = 1$) and a constant price markup $\overline{\theta}$ across industries. These two assumptions, however, may lead to substantial measurement errors, which in turn renders their conclusions questionable to some extent.

Suppose α_s and β_s are the real output elasticities of capital and labor inputs, respectively, and θ_s is the real price markup in industry s. According to equation (9),

$$A_{is} = (P_s Y_s)^{1-\theta_s} P_s^{-1} \frac{(P_{is} Y_{is})^{\overline{\theta}}}{K_{is}^{\overline{\alpha}_s} L_{is}^{\overline{\beta}_s}} \frac{(P_{is} Y_{is})^{\theta_s - \overline{\theta}}}{K_{is}^{\alpha_s - \overline{\alpha}_s} L_{is}^{\beta_s - \overline{\beta}_s}}. \tag{22}$$

If we denote the productivity measured by Hsieh and Klenow (2009) as

$$\overline{A}_{is} = (P_s Y_s)^{1-\overline{\theta}} P_s^{-1} \frac{(P_{is} Y_{is})^{\overline{\theta}}}{K_{is}^{\overline{\alpha}_s} L_{is}^{\overline{\beta}_s}}, \tag{23}$$

then

$$\frac{A_{is}}{\overline{A}_{is}} = \frac{(P_{is} Y_{is})^{\theta_s - \overline{\theta}}}{K_{is}^{\alpha_s - \overline{\alpha}_s} L_{is}^{\beta_s - \overline{\beta}_s}} \tag{24}$$

represents the measurement error of firm i's productivity. The efficient TFP of industry s defined by Hsieh and Klenow (2009) can be expressed as

$$\overline{TFPE}_s = \left[\sum_{i=1}^{N_s} \overline{A}_{is}^{\frac{1}{\overline{\theta}-1}} \right]^{\overline{\theta}-1} = \left\{ \sum_{i=1}^{N_s} \left[A_{is} \frac{(P_{is} Y_{is})^{\overline{\theta}-\theta_s}}{K_{is}^{\overline{\alpha}_s - \alpha_s} L_{is}^{\overline{\beta}_s - \beta_s}} \right]^{\frac{1}{\overline{\theta}-1}} \right\}^{\overline{\theta}-1}. \tag{25}$$

Based on the equations (15) and (25) that define $TFPE_s$ and $\overline{TFPE}_s$ respectively, one

could expect that $TFPE_s$ is not correlated with the dispersions of $\ln(\kappa_{Lis})$ and $\ln(\kappa_{Kis})$, but $\overline{TFPE}_s$ is.

III. ESTIMATION OF THE PRODUCTION FUNCTION

As discussed above, assigning incorrect values to θ_s, α_s, and β_s could generate substantial measurement errors of TFP and TFPE. Therefore, we need a new econometric method to consistently estimate α_s, β_s and θ_s. In this section, I discuss in detail a new estimation strategy that can be used to consistently estimate output elasticities of capital and labor as well as price markup within an industry.

III.A. Review of Production Function Estimation

Production functions relate productive inputs to outputs. In our special case of a value-added production function, productive inputs are just capital and labor. Consider the Cobb-Douglas production function in logs:

$$y_{it} = \alpha k_{it} + \beta l_{it} + \ln(A_{it}), \tag{26}$$

where y_{it} is the log of output, k_{it} the log of capital, l_{it} the log of labor input, and A_{it} the productivity level.

A well-known econometric issue in estimating production functions is the possibility that there are determinants in production functions that are not observed by the econometricians but observed by the firms. That is, $\ln(A_{it})$ can be broken down into two terms:

$$\ln(A_{it}) = \omega_{it} + \epsilon_{it}, \tag{27}$$

where ϵ_{it} represents a shock to productivity that is not observed or predicted by firms before making their input decisions at time t, whereas ω_{it} represents a shock that is observed or predicted by firms when they make input decisions. One can regard ω_{it} as the managerial

ability or organization capital of a firm following Atkeson and Kehoe (2005). Econometricians, however, cannot observe either ϵ_{it} or ω_{it}.

Since a firm's optimal choices of inputs k_{it} and l_{it} are generally related to the observed or predicted productivity shocks ω_{it}, OLS estimates of the coefficients α and β are biased and inconsistent. Two popular solutions to this endogeneity problem are the fixed-effects and the instrumental variables estimation techniques. Both of them, however, do not work well in practice. The fixed-effects method imposes an additional restriction: $\omega_{it} = \omega_{it-1}, \forall t$; whereas the instrumental variables method requires valid instrumental variables that may be difficult to find. More recently, Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazer (2006) take a more structural approach to identifying the production function. They use observed input decisions to control for the productivity shocks ω that are unobserved by econometricians. Their techniques have been employed in a large number of recent empirical studies (Pavcnik 2002; Topalova 2003; Blalock and Gertler 2004; and Alvarez and Lopez 2005).

III.B. Olley-Pakes Approach

Olley and Pakes (1996) first assume that the productivity term ω_{it} evolves exogenously following a first-order Markov process, i.e.,

$$\omega_{it} = E(\omega_{it}|\omega_{it-1}) + \xi_{it} = \Psi(\omega_{it-1}) + \xi_{it}, \tag{28}$$

where ξ_{it} is an innovation to productivity that is uncorrelated with k_{it}. Second, they assume that a firm's choice of labor for period t is a non-dynamic input. That is, labor input in the current period has no impact on the future profit of the firm. Different from labor input, capital is a dynamic input and it does impact the future profit of the firm since it is subject to an investment process. Based on these two assumptions, they further assume that a firm's

investment decision is determined only by ω_{it} and k_{it}:

$$i_{it} = f(\omega_{it}, k_{it}), \tag{29}$$

and that investment at period t is a strictly increasing function of the current productivity ω_{it}. So ω_{it} can be expressed as

$$\omega_{it} = f^{-1}(i_{it}, k_{it}). \tag{30}$$

The production function, hence, can be rewritten as

$$y_{it} = \beta l_{it} + \Phi(i_{it}, k_{it}) + \epsilon_{it}, \tag{31}$$

where $\Phi(i_{it}, k_{it}) = \alpha k_{it} + f^{-1}(i_{it}, k_{it})$.

At the first stage of the Olley-Pakes approach, one can obtain an estimate of the labor coefficient β, $\widehat{\beta}$, by treating f^{-1} non-parametrically. Moreover, one can also obtain an estimate of $\Phi(i_{it}, k_{it})$, $\widehat{\Phi}_{it}$. Note that given a guess of the capital coefficient α, one can reverse out the ω_{it}'s in all periods, i.e.,

$$\widehat{\omega}_{it}(\alpha) = \widehat{\Phi}_{it} - \alpha k_{it}. \tag{32}$$

At the second stage of the Olley-Pakes approach, one can identify the capital coefficient α by minimizing

$$\frac{1}{NT}\sum_t\sum_i \left[y_{it} - \widehat{\beta} l_{it} - \alpha k_{it} - \Psi\left(\widehat{\omega}_{it-1}(\alpha)\right)\right]^2 \tag{33}$$

where Ψ is the non-parametric function assumed for the Markov process.

III.C. Levinsohn-Petrin Approach

A shortcoming in the Olley-Pakes approach is that they assume an investment function that is strictly monotonic in ω_{ist}. In actual data, however, investment is often very lumpy, and one often sees zero. The Olley-Pakes approach requires discarding the data with zero investment, which causes an obvious efficiency loss. Levinsohn and Petrin (2003) overcome

this problem by selecting an intermediate input instead of investment as a "proxy" to reverse out the unobserved ω_{it}.

First, they assume that ω_{it} follows a first-order Markov process as Olley and Pakes (1996) do. Second, they assume that intermediate input m_{it} is decided after the firm observes its ω_{it}:

$$m_{it} = f(\omega_{it}, k_{it}), \tag{34}$$

where f is strictly monotonic in ω_{it}. Intermediate input m_{it} could be electricity, fuel and materials, and the like. In the Levinsohn-Petrin approach, although l_{it} is not necessarily assumed to be non-dynamic, it must be chosen after or at least simultaneously with m_{it}. Otherwise, l_{it} could impact the decision of m_{it}. Third, f is strictly monotonic in ω_{it}, so that ω_{it} can be expressed as

$$\omega_{it} = f^{-1}(m_{it}, k_{it}). \tag{35}$$

So,

$$y_{it} = \beta l_{it} + \Phi(m_{it}, k_{it}) + \epsilon_{it}, \tag{36}$$

where $\Phi(m_{it}, k_{it}) = \alpha k_{it} + f^{-1}(m_{it}, k_{it})$. α and β can be similarly estimated using the two-step procedure as in the Olley-Pakes approach.

III.D. Ackerberg-Caves-Frazer Approach

The first-stage in both the Olley-Pakes and the Levinsohn-Petrin approaches aims to identify β, the coefficient of labor input. However, both Basu (1999) and Ackerberg, Caves, and Frazer (2006) argue that even if all the assumptions they assume hold, there are still potentially serious identification issues due to collinearity in these two approaches. More specifically, l_{it} could be "collinear" with the nonparametric terms $\Phi(i_{it}, k_{it})$ and $\Phi(m_{it}, k_{it})$. For instance, in the Levinsohn-Petrin approach, as m_{it} and l_{it} are assumed to be chosen simultaneously after ω_{it} is observed by the firm, we can also assume that labor input is

decided according to

$$l_{it} = g(\omega_{it}, k_{it}). \tag{37}$$

Substituting equation (34) into (37) results in

$$l_{it} = g(f^{-1}(m_{it}, k_{it}), k_{it}) = h(m_{it}, k_{it}). \tag{38}$$

As l_{it} itself is a function of m_{it} and k_{it} only, there exists a perfect collinearity between l_{it} and the non-parametric function $\Phi(m_{it}, k_{it})$. So, at the first-stage of the Levinsohn-Petrin approach, one cannot simultaneously estimate $\Phi(m_{it}, k_{it})$ and β. In practice, one probably would not observe this collinearity problem directly, as a numerical estimate of β would be produced in the estimation. This numerical estimate, however, is just inconsistent.

Ackerberg, Caves, and Frazer (2006) allow labor to be "less variable" than materials, which makes sense as firms need time to train or fire workers. So,

$$m_{it} = f(\omega_{it}, k_{it}, l_{it}). \tag{39}$$

The value-added production function can be rewritten as

$$y_{it} = \alpha k_{it} + \beta l_{it} + f^{-1}(m_{it}, k_{it}, l_{it}) + \epsilon_{it}. \tag{40}$$

Clearly, both α and β can not be identified at the first stage. However, one does obtain an estimate, $\widehat{\Phi}_{it}$, of the composite term:

$$\Phi(\omega_{it}, k_{it}, l_{it}) = \alpha k_{it} + \beta l_{it} + f^{-1}(m_{it}, k_{it}, l_{it}). \tag{41}$$

As in the Olley-Pakes and Levinsohn-Petrin approaches, given a guess of the coefficients α and β, one can reverse out the ω_{it}'s in all periods, i.e.,

$$\widehat{\omega}_{it}(\alpha, \beta) = \widehat{\Phi}_{it} - \alpha k_{it} - \beta l_{it}. \tag{42}$$

At the second stage, one can identify the capital coefficients α and β by minimizing

$$\frac{1}{NT}\sum_t\sum_i \left[y_{it} - \beta l_{it} - \alpha k_{it} - \Psi\left(\widehat{\omega}_{it-1}(\alpha,\beta)\right)\right]^2. \tag{43}$$

III.E. A New Estimation Procedure under Monopolistic Competition

All the methods discussed above require output information. In most cases, however, only the value-added information is available. Using value-added data rather than output data in estimating the production function could, of course, lead to systematic biases. In this section, I present a new econometric method to that can be used to consistently estimate α_s, β_s and θ_s based on equation (9). Note that equation (9) relates capital and labor inputs directly to value added rather than output within the framework of a monopolistic competition model. So, we can avoid the biases from mis-specifying output as value added. However, one needs to carefully restrict this new estimation procedure to a monopolistic competition environment.

The aggregate price P_{st} can always be normalized to 1 without loss of generality using the data of industry-level price inflation. Based on equation (9), the value added of firm i in manufacturing industry s in period t in log form is determined by

$$\ln\left(P_{ist}Y_{ist}\right) = \tfrac{\alpha_s}{\theta_s}k_{ist} + \tfrac{\beta_s}{\theta_s}l_{ist} + \tfrac{\theta_s-1}{\theta_s}y_{st} + \tfrac{1}{\theta_s}\left(\varpi_{ist} + \epsilon_{ist}\right) \tag{44}$$

where $\ln A_{ist} = \varpi_{ist} + \epsilon_{ist}$. Similar to the Ackerberg-Caves-Frazer approach, we assume

$$m_{ist} = f(\omega_{ist}, k_{ist}, l_{ist}), \tag{45}$$

which gives us

$$\ln\left(P_{ist}Y_{ist}\right) = \tfrac{\alpha_s}{\theta_s}k_{ist} + \tfrac{\beta_s}{\theta_s}l_{ist} + \tfrac{\theta_s-1}{\theta_s}y_{st} + \tfrac{1}{\theta_s}f^{-1}(m_{ist}, k_{ist}, l_{ist}) + \tfrac{1}{\theta_s}\epsilon_{ist}. \tag{46}$$

Note that y_{st} is not correlated with ϵ_{ist}. So, at the first stage of our estimation procedure we can identify the coefficient θ_s as well as the semi-parametric function[4]

$$\Phi(m_{ist}, k_{ist}, l_{ist}) = \alpha_s k_{ist} + \beta_s l_{ist} + f^{-1}(m_{ist}, k_{ist}, l_{ist}). \tag{47}$$

Given a guess of the coefficients α_s and β_s, one can reverse out the ω_{ist}'s in all periods, i.e.,

$$\widehat{\omega}_{ist}(\alpha_s, \beta_s) = \widehat{\Phi}_{ist} - \alpha_s k_{ist} - \beta_s l_{ist}. \tag{48}$$

At the second stage of our estimation procedure, we can identify the coefficients α_s and β_s by minimizing

$$\frac{1}{NT}\sum_t\sum_i \left[\widehat{\theta}_s \ln\left(P_{ist}Y_{ist}\right) - (\widehat{\theta}_s - 1)y_{st} - \alpha_s k_{ist} - \beta_s l_{ist} - \Psi\left(\widehat{\omega}_{ist-1}(\alpha_s, \beta_s)\right)\right]^2. \tag{49}$$

IV. DATA

The data used in this study are from the Annual Surveys of Industrial Production from 1999 to 2007 conducted by the Chinese Government's National Bureau of Statistics. This Annual Survey includes all the non-state firms with more than RMB5 million in revenue and all the state-owned firms. The specific information used in this study includes a firm's industry classification, wage payments, value added and capital stock. Unlike Hsieh and Klenow (2009) who classify a firm's industry at the four-digit level, I use the three-digit level mainly to provide big enough sample sizes for estimation. Here I use wage payments rather than number of employees as the measurement of labor input because wage payments also include information of overtime work, quality of employees, and the like.

Hsieh and Klenow (2009) measure a Chinese firm's capital stock using its book value of fixed capital net of depreciation. Because firms only report their fixed capital stock at

[4]For the estimate of θ_s to be consistent, N_s must be big enough, whereas the total time periods T can be small. For the proof, one can refer to equations (9-9)-(9-18) in Greene (2007).

original purchase prices, this method would run the risk of introducing systematic biases related to firms' ages. Hence, in this paper, I construct the capital stock using a revised perpetual inventory method following Brandt, Biesebroeck, and Zhang (2011).

V. EMPIRICAL RESULTS

Hsieh and Klenow (2009) simply set β_s of Chinese manufacturing industry s to its value in the corresponding U.S. manufacturing industry, and $\alpha_s = 1-\beta_s$. They believe that market distortions are potentially important in China, and that the U.S. coefficients are better as they presume that the U.S. is comparatively undistorted both across plants and, more to the point here, across industries. The calibrated results for α_s and β_s, however, may not be as good as Hsieh and Klenow (2009) claim for several reasons: (1) The assumption of a CRS value-added production function could be seriously compromised; (2) Markets distortions in the United States may not be as small as Hsieh and Klenow (2009) believe; (3) China and the U.S. could adopt very different production technologies even in the same manufacturing industry.

In the new econometric method proposed in this study, however, all these factors that affect the quality of the calibrated α_s and β_s do not affect our estimated α_s and β_s. Note that the proposed estimation procedure here allows us to assume a CRS production function, i.e., $\alpha_s + \beta_s = 1$. In the following sections hence, when a CRS production function is assumed, α_s and β_s are estimated using the new econometric method with the restriction $\alpha_s + \beta_s = 1$.

V.A. Estimated Price Markups and Returns to Scale

According to the settings of our benchmark monopolistic competition model, P_{is} is the price that a firm i in industry s charges for its goods, whereas $(1-\tau_{Yis})P_{is}$ is what the firm really gets paid for. The relationship between the price that a firm charges and its marginal

cost can be expressed as

$$P_{is} = \frac{\theta_s}{1 - \tau_{Yis}} MC_{is}. \tag{50}$$

There is an identity that links return to scale to price markup:

$$\gamma_s = \frac{AC_{is}}{MC_{is}} = \frac{(1 - \tau_{Yis})P_{is}}{MC_{is}} \frac{AC_{is}}{(1 - \tau_{Yis})P_{is}} = \frac{\theta_s}{\pi_s}, \tag{51}$$

where π_s measure the profitability of industry s.

[about here: FIGURE I]

The panel on the left in Figure I describes the distribution of the estimated price markups for the Chinese manufacturing industries at the 3-digit level. We can see that about 85% of all the industries have a markup in the range of $[1, 1.5]$. Interestingly, around 8% of all the industries show a markup less than 1, suggesting that the firms in these industries charge an after-tax price below their marginal cost.

The middle panel in Figure I shows us the distribution of the estimated returns to scale. We can see that roughly 80 percent of all the industries have a decreasing returns to scale (DRS) value-added production function. And the returns to scale in most Chinese manufacturing industries is in the range of $[0.75, 1.15]$.

The panel on the right in Figure I presents the distribution of the estimated profitability. We can see that most of the Chinese manufacturing industries enjoy a profitability level in the range of $[1, 1.5]$. No manufacturing industries experience negative profitability.

[about here: FIGURE II]

Figure II shows the pairwise relationships among price markup, returns to scale and profitability. As we can see, the degree of returns to scale is positively correlated with price markup and negatively correlated with profitability. Interestingly, there is no significant correlation between price markup and profitability. Although the linear relationships examined

say nothing about causality, an intuitive guess is that the technology an industry adopts (the degree of returns to scale) strongly determines its price markup and profitability.

V.B. Measured Industrial TFPE, TFP, and TFP Loss

Table I presents the information of measured $\ln(TFPE)$ and $\ln(TFP)$ for selected years. The *real* Chinese manufacturing TFP, measured by the weighted average of $\ln(TFP)$ using value added of each industry, grows at an annual rate of 10.2% during 1999-2007. This growth rate is much higher than the rate of 6.2% that Bosworth and Collins (2007) report for the period 1993-2004 in the Chinese manufacturing sector. Other than the different periods that the two studies look at, it should also be noted that the CRS assumption is relaxed in this study when estimating the production function and measuring productivity, which could affect the measurement of $\ln(TFP)$.

The *efficient* Chinese manufacturing productivity level, measured by the weighted average of $\ln(TFPE)$ using value-added of each industry, grows at an annual rate of 9.8% between 1999 and 2007. It is interesting to note that $\ln(TFPE)$ grows much faster after 2003: the average annual growth rate is 8.3% before 2003 and 11.3% after 2003.

As the growth rates of $\ln(TFPE)$ and $\ln(TFP)$ are quite close during 1999-2007, the ratio of efficiency loss E in this period is quite stable. The ratio E is around 0.37 in the period of 1999-2007, which demonstrates that Chinese manufacturing sector could have increased its output by 170% if market distortions were equalized across firms within each industry.

[about here: TABLE I]

As E is stable, most of the TFP growth in the Chinese manufacturing sector is due to the *pure* productivity improvement. In other words, little TFP growth comes from the narrowing market distortions in capital and labor markets. This result differs significantly from what Hsieh and Klenow (2009) find in their study. They report that the narrowing market distortions in capital and labor markets contribute to one-third of the TFP growth

in the Chinese manufacturing sector during 1998-2005.

Table I also shows us large dispersions of $\ln(TFPE)$ and $\ln(TFP)$ across industries. In 1999, for example, the coefficients of variation of $\ln(TFPE)$ and $\ln(TFP)$ are 0.64 and 0.97, respectively. Due to the fast growth of $\ln(TFPE)$ and $\ln(TFP)$ between 1999 and 2007, these two statistics decrease to 0.52 and 0.75 in 2007, respectively.

[about here: FIGURE II]

Figure III plots the distributions of $\ln(TFPE)$, $\ln(TFP)$ and $\ln(E)$ for the years of 1999 and 2007. We can see that both the distribution curves of $\ln(TFPE)$ and $\ln(TFP)$ move signifficantly to the right from 1999 to 2007, indicating a solid improvement in both efficient and real productivity levels. However, the distribution curve of $\ln(E)$ shows no clear movement to the right from 1999 to 2007.

The large dispersions of $\ln(TFPE)$ motivate us to examine what factors determine the differences in $\ln(TFPE)$ across the Chinese manufacturing industries. Table II presents the empirical results: (1) The degree of return to scale is the most significant factor, which explains 95% of the variance of $\ln(TFPE)$; (2) Interestingly, although $TFPE$ of an industry can be expressed as the sum of all the firms' productivity within this industry (See equation (15)), the number of firms within industry explains very little of the variance of $\ln(TFPE)$. A possible reason is that the number of firms within an industry is endogenously determined by the technology it adoptes.

[about here: TABLE II]

V.C. Measured Market Distortions and Efficiency Loss

The dispersion of $\ln(E)$ is even larger than those of $\ln(TFPE)$ and $\ln(TFP)$. The

coefficient of variation for $\ln(E)$ is 1.11 in 1999 and drops to 0.96 in 2007. In the following section, I investigate the determinants of the large dispersions of $\ln(E)$ across the Chinese manufacturing industries. As discussed in section 2, both absolute and relative dispersions of market distortions can affect the degree of efficiency loss. So, we first look at the absolute dispersions, which are usually measured by standard deviation, difference between the 75th and 25th percentiles, and that between 90th and 10th.

Table III and IV present the absolute dispersions of market distortions in the Chinese manufacturing sector for selected years. First, one can see that the absolute distortions in capital market are uniformly bigger than those in labor market in all the selected years. Second, we observe a clear decline of the absolute distortions in capital market but not in labor market.

[about here: TABLE III and IV]

In Table V, I present the results of linear regressions of $\ln(E^1)$ on the factors that are supposed to affect its value based on equation (20). The absolute dispersions of market distortions can only explain 20% of the variance of $\ln(E^1)$ across the Chinese manufacturing industries. Adding θ_s to the regression helps to explain 13% more of the variance of $\ln(E^1)$; and further adding γ_s to the regression helps to explain an additional 39% of the variance of $\ln(E^1)$. These regression results suggest that the TFP loss in an industry is largely determined by the technology it adopts rather than the absolute dispersions of market distortions in this industry.

[about here: TABLE V]

As discussed in Section 5.1, roughly 80% of all the industries have a DRS value-added production function, and γ_s is likely to determine both θ_s and π_s. Now in Tables V, γ_s is also found as the most significant factor that determines the variance of $\ln(E^1)$ across the Chinese manufacturing industries. All this evidence shows that assuming a CRS production function when measuring TFP could lead to significant measurement errors.

As shown in Table V, the estimated coefficients of the variances of $\ln(\kappa_{Ls})$ and $\ln(\kappa_{Ks})$ are both negative. Hence, if the variances of $\ln(\kappa_{Ls})$ and $\ln(\kappa_{Ks})$ decline, one could expect E^1 to rise. Moreover, one can see that the semi-elasticity of E^1 to the variance of $\ln(\kappa_{Ks})$ is much smaller than that to the variance of $\ln(\kappa_{Ls})$. In the Chinese manufacturing sector during 1999-2007, we observe a clear decline in the variance of $\ln(\kappa_{Ks})$ but not in the variance of $\ln(\kappa_{Ls})$. Thus, it is not surprising that the rise in E^1 is not as big as one might expect, as shown in Table II.

Now let us turn to the relative dispersions, measured by coefficient of variation. As shown in equation (21), the relative values of $\overline{\kappa}_s$ to $\widetilde{\kappa}_s$ crucially depend on $\rho_{\kappa_{is},\varpi_{is}}$ (the correlation between κ_{is} and ϖ_{is}), CV_κ_{is} (the coefficient of variation of κ_{is}) and $\sigma_{N_s\varpi_{is}}$ (the standard deviation of $N_s\varpi_{is}$). And the sign of $\rho_{\kappa_{is},\varpi_{is}}$ determines the direction of how a change in CV_κ_{is} affects $\overline{\kappa}_s/\widetilde{\kappa}_s$. If $\rho_{\kappa_{is},\varpi_{is}}$ is negative, one could expect $\overline{\kappa}_s/\widetilde{\kappa}_s$ is bigger than 1 and is increasing in both CV_κ_{is} and $\sigma_{N_s\varpi_{is}}$.

As presented in Table VI and VII, both $\rho_{\kappa_{Ks},\varpi_s}$ and $\rho_{\kappa_{Ls},\varpi_s}$ are in fact negative in all the selected years, which means firms of bigger size in the Chinese manufacturing sector tend to face higher taxes in both capital and labor markets. Hence, the weighted averages of both $\overline{\kappa}_K/\widetilde{\kappa}_K$ and $\overline{\kappa}_L/\widetilde{\kappa}_L$ are bigger than 1. More importantly, figures in these two tables show that the weighted averages of both $\overline{\kappa}_K/\widetilde{\kappa}_K$ and $\overline{\kappa}_L/\widetilde{\kappa}_L$ decrease significantly from 1999 to 2007, and such changes are mainly due to the significant declines in CV_κ_K and CV_κ_L.

[about here: TABLE VI and VII]

While declining absolute dispersions of market distortions in an industry improve its efficiency, declining relative dispersions of market distortions deteriorate an industry's efficiency. These two effects offset each other, leading to a quite stable efficiency loss in the Chinese manufacturing sector, as shown in Table I. Hsieh and Klenow (2009) focus on the difference in the absolute dispersions of market distortions between the United States and

China, and examine the impact of this difference on TFP loss. However, they do not take into account the drastically declining relative dispersions of market distortions in the Chinese manufacturing sector since 1999 and ignore its impact on TFP loss.

V.D. Creative Destruction in Chinese Manufacturing Sector

In the past decade, one significant phenomenon in the Chinese manufacturing sector is the reconstruction of state-owned firms. Such a change is closely related to Chinese government's industrial policy of "grasping the big ones and letting go of the small ones" since 1994. Most of the big state-owned firms engage in the production of coal, oil, power, steel, aluminum, automobiles, airplanes, and telecommunication equipment. Under this policy, the share of state-owned firms in the Chinese manufacturing sector shrinks rapidly.

Table VIII shows that in 1999, 25.6% of the firms in the Chinese manufacturing sector are state owned, and they together contribute to 29.4% of the total value added. In 2007, however, only only 3.4% of the total firms are state-owned, and they only contribute to 6.6% of the total value added. Accompanying the rapid shrinking of state-owned firms is the thriving development of private domestic firms. As shown in the table, in 1999, only 9.9% of the total firms are private domestic ones, and they only account for 4.8% of the total value added. However, these numbers rise to 51.2% and 28.2%, respectively, in 2009. Table VIII also shows that state-owned firms in average are much bigger than private domestic ones. The relative size of state-owned firms to private domestic ones is 2.3 in 1999 and 3.5 in 2007.

[about here: TABLE VIII]

Table IX reports the regression results of $\ln(TFP)$ on firm type in selected years. The firm types omitted from the regressions are incumbents and private domestic firms.[5] In the selected years, exiting firms in the Chinese manufacturing sector have 22% to 36% lower

[5] Here a firm is classified as an exiting firm if it exits the industry within two years; and a firm is classified as an entering firm if it has operated in the market for less than 2 years; all the other firms are classified as incumbents.

TFP than incumbents, and new entrants have 7% to 9% lower TFP than incumbents.

[about here: TABLE IX]

Table IX also shows that the average TFP of state-owned firms is 96% lower than that of private domestic firms in the Chinese manufacturing sector in 1999. In 2005, however, this number drops down to only 43%. Such a change is due to the exiting of many low efficient state-owned firms during this period. Moreover, it is surprising to find that private foreign firms and collectively owned firms[6] have lower TFPs than private domestic firms in 1999. The advantage of private domestic firms in TFP gradually disappears since 1999. In 2005, there is no significant difference in TFP between private foreign firms and private domestic firms, and collectively owned firms even have 4% higher TFP than private domestic firms.

V.E. Policies and Resource Misallocation

In China, policies play an important role in determining the distortions in both capital and labor markets. Compared with private domestic firms, state-owned and collectively owned firms have advantages in both markets as they have better access to credit from state-owned banks and can provide better medical plans and pensions. Private foreign firms have advantages over private domestic ones in capital market as they also have better access to credit and preferential treatment provided specifically for them in China.

Table X presents the weighted averages of κ_K and κ_L in 1999 and 2007 for firms with different ownerships. First, the average κ_K and κ_L of state-owned firms in 1999 are much higher than 1, indicating that they received subsidies in both capital and labor markets. κ_K of private foreign firms in 1999 is also higher than 1. Second, among all the four types of firms, private domestic firms face the highest taxes in both capital and labor markets as expected. However, it is surprising that private foreign firms face lower taxes than collectively owned ones. Third, all types of firms faced higher taxes in both capital and labor markets in

[6] Those firms are partly private and partly local government owned.

2007 than in 1999. State-owned firms and private foreign firms, in general, no longer receive subsidies in 2007. Fourth, from 1999 to 2007, the distortions in capital markets deteriorate much faster than those in labor markets for all the four types of firms.

[about here: TABLE X]

Figure IV plots the "efficient" vs. actual distribution of firm's size by ownerships in 2007. Size here is measured as the firm's value added. In all the four types of ownerships, the hypothetical efficient distribution is much more dispersed than the actual one. If distortions were equalized within each industry, two main conclusions can be drawn: (1) Although the aggregate output would rise substantially, many firms across all the ownerships would still shrink; (2) There would be more extremely large-sized domestic private firms, but no more extremely large-sized state-owned firms. Such evidence suggests that domestic private firms with high productivity are seriously disadvantaged in both capital and labor markets, and reducing the tax burdens on these firms would significantly increase the output in the Chinese manufacturing sector.

[about here: FIGURE IV]

Table XI shows how the size of firms would change if distortions were equalized within each industry. The entries are unweighted shares of firms by ownership. The columns are sets of efficient firm size relative to actual size: $0.25-$ (the firm should shrink by 75% or more), $0.25-1$, $1-4$, and $4+$ (the firm should expand at least 4 times in size). When distortions are small, one could expect that firms would concentrate in the middle two sets. In China, state-owned firms with low productivity are more likely to exit (or be privatized), but less likely to shrink. In 1999, 82% of state-owned firms should be downsized by 75% or more to be efficient; in 2007, still 78% of them should be. Private domestic firms are the most inhibited in size: in 1999, 32% of them should have expanded, and in 2007 23%.

Many of them should have even expanded to be extremely large in size, based on Figure IV. Interestingly, around 10% of state-owned firms should have also expanded in 2007. However, Figure IV suggests most of them are relatively small firms.

[about here: TABLE XI]

V.F. TFP, Market Distortions, and Firm's Exit

After finding the big differences in $\ln(TFP)$, $\ln(\kappa_K)$ and $\ln(\kappa_L)$ among firms with different ownerships, I next look at the correlation between firm exit and $\ln(TFP)$, $\ln(\kappa_K)$ and $\ln(\kappa_K)$. Table XII shows the differences in $\ln(TFP)$, $\ln(\kappa_K)$ and $\ln(\kappa_L)$ among exiting firms with different ownerships in 1999 and 2005. First, exiting private domestic firms have the highest TFPs and face the highest taxes in both capital and labor markets, whereas exiting state-owned firms have the lowest TFPs and face the lowest taxes. Second, the differences in $\ln(\kappa_K)$ among exiting firms are much bigger than those in $\ln(\kappa_L)$, indicating that exiting private domestic firms face more distortions in capital market than in labor market. Lastly, the differences in $\ln(TFP)$, $\ln(\kappa_K)$ and $\ln(\kappa_L)$ among exiting firms have decreased significantly from 1999 to 2005, suggesting that the differences in market distortions for exiting firms have been narrowed greatly.

[about here: TABLE XII]

Table XIII presents the sensitivities of firm's exit on changes in $\ln(TFP)$, $\ln(\kappa_K)$ and $\ln(\kappa_L)$ across different firm types. Changes in $\ln(TFP)$, $\ln(\kappa_K)$ and $\ln(\kappa_L)$ have the biggest impact on private domestic firms, and all firms are most sensitive to changes in $\ln(TFP)$. It is surprising to some extent that all firms are much less sensitive to changes in $\ln(\kappa_K)$ than to changes in $\ln(\kappa_L)$. A log-point increase in capital tax is associated with only a 2% higher

exiting probability for private foreign firms, and an even lower 1% exiting probability for state-owned firms.

[about here: TABLE XIII]

VI. MEASUREMENT ERRORS

Measurement errors are always of crucial concern when estimating TFP in the literature. Just as Hsieh and Klenow (2009) also argue, it might be impossible to completely rule out arbitrary measurement errors, we are still able to gauge whether our results can be attributable to some specific forms of measurement errors. First, if the assumptions of CRS technology and a constant price markup across industries do not hold, we would expect the measured $\ln(TFPE_s)$ to be related to market distortions, as discussed before. However, if the model is correctly specified and all the parameters are consistently estimated, we would not expect $\ln(TFPE_s)$ to be related to any kind of market distortions within industry s. Second, as market distortions are assumed to be exogenous in our model, we would expect θ_s and γ_s to be uncorrelated to any measured market distortions, if there are no systematic biases in estimated θ_s and γ_s and measured market distortions.

Table XIV presents the regression results of $\ln(TFPE)$ on the variances of $\ln(\kappa_K)$ and $\ln(\kappa_L)$, the covariance between them, as well as the coefficients of variation of κ_K and κ_L. In our benchmark model that relaxes the two assumptions of a CRS technology and a constant price markup, since the variance of $\ln(TFPE)$ across industries can hardly be explained (only 2%) by the variables indicating all kinds of market distortions, we can claim that $\ln(TFPE)$ is not related to any kind of market distortions. With the assumptions of a CRS technology and a constant price markup, however, we can no longer make such a claim as much of the variance of $\ln(TFPE)$ can be explained by market distortions: 36% when $\theta = 1.5$ and 41% when $\theta = 1.25$. These results, therefore, suggest that there are large measurement errors in

Hsieh and Klenow (2009) as they assume constant return to scale in each industry and a constant price markup across industries.

[about here: TABLE XIV]

Table XV gives the results of regressing average distortions in capital and labor markets on price markup and return to scale. Although the estimated coefficients of θ_s and γ_s might be statistically significant, they can explain little variance in $\overline{\kappa}_{Ks}$, $\overline{\kappa}_{L_s}$, $\widetilde{\kappa}_{Ks}$ and $\widetilde{\kappa}_{Ls}$. Such results also indicate that there are few systematic errors in measured market distortions in this study, and provide us with a valid justification for assuming exogenous market distortions in the model.

[about here: TABLE XV]

VII. CONCLUSIONS

A large body of literature has stressed that market distortions can lead to misallocation of capital and labor across heterogenous firms, and hence reduce aggregate output and TFP. Within the framework a monopolistic competition model, in particular, one can infer the distortions that an individual firm faces from the residuals in its first-order conditions and hence quantitatively examine their impacts on aggregate TFP within an industry. However, substantial measurement errors in distortions and TFP can arise due to such rigid assumptions as a CRS production function and a constant price markup.

Extending the idea of using intermediate inputs to "proxy" for productivity shocks in the monopolistic competition model, I developed a new econometric method which can be used to consistently estimate the output elasticities of capital and labor, as well as the price markup, within an industry. Empirical results point to both large variations in price markup and decreasing return to scale in Chinese manufacturing sector, which in turn challenges certain

arguments in the existing literature: (1) Aggregate TFP in the Chinese manufacturing sector has grown up to 10% annually between 1999 and 2007; (2) Such a rapid growth is almost completely due to *pure* productivity improvement rather than narrowing distortions; and (3) Variance of TFP loss across industries can be explained mostly by the differences in return to scale rather than those in market distortions. In addition, I find substantial differences in market distortions and productivity among firms with different ownerships. To increase the aggregate output and TFP in the manufacturing sector, extremely large-sized firms, especially the private domestic ones, should expand at the expense of small-size firms in China.

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TABLES

TABLE I

$\ln(TFPE)$ AND $\ln(TFP)$

$Year$	$\ln(TFPE)$			$\ln(TFP)$			Efficiency Loss		
	$Ave.^1$	$Ave.^2$	SD	$Ave.^1$	$Ave.^2$	SD	E	E^1	E^2
1999	3.48	3.60	2.29	2.46	2.63	2.55	0.36	0.25	1.46
2003	3.80	3.93	2.17	2.83	3.00	2.46	0.38	0.27	1.41
2007	4.23	4.25	2.22	3.23	3.33	2.50	0.37	0.27	1.34

Note. $Ave.^1$ is the average weighted by each industry's share of value added, while $Ave.^2$ is the unweighted average. SD is the standard deviation from the unweighted average.

TABLE II

THE DETERMINANTS OF $\ln(TFPE)$

	$Model$ 1	$Model$ 2	$Model$ 3	$Model$ 4
$constant$	2.62^{***}	11.30^{***}	14.05^{***}	14.28^{***}
$\ln(Firm\ No.)$	0.20^{***}	0.33^{***}	0.24^{***}	0.25^{***}
θ_s		-8.20^{***}		-0.64^{***}
γ_s			-13.73^{***}	-13.19^{***}
$Adj.\ R^2$	0.01	0.51	0.96	0.96

Note. *** significant at 0.01 level, ** significant at 0.05, * significant at 0.1 level. No. of Obs=1303. Fixed effects of years are considered in all models.

TABLE III

ABSOLUTE DISPERSIONS OF MEASURED $\ln(\kappa_{Lis})$

$Year$	1999	2003	2007
SD	0.91	0.89	0.89
$75-25$	1.19	1.18	1.22
$90-10$	2.31	2.27	2.30
N	$121,957$	$158,632$	$179,583$

Note. Entries are the deviations of $\ln(\kappa_{Lis})$ from industry mean. Each industry is weighted by its share of valued added. SD is standard deviation, $75-25$ is the difference between the 75th and 25th percentiles, and $90-10$ the 90th vs. 10th percentiles. N is the number of firms.

TABLE IV

ABSOLUTE DISPERSIONS OF MEASURED $\ln(\kappa_{Kis})$

$Year$	1999	2003	2007
SD	1.19	1.14	1.08
$75-25$	1.54	1.48	1.43
$90-10$	3.02	2.86	2.75

Note. Entries are the deviations of $\ln(\kappa_{Kis})$ from industry mean. Each industry is weighted by its share of valued added. SD, $75-25$ and $90-10$ are samely defined as in Table IV. Number of firms is the same as in Table IV.

TABLE V

MARKET DISTORTIONS AND $\ln(E^1)$

	$Model$ 1	$Model$ 2	$Model$ 3	$Model$ 4
$constant$	-0.47^{***}	0.63^{***}	1.35^{***}	1.05^{***}
var_κ_{Ls}	-0.84^{***}	-0.68^{***}	-0.77^{***}	-0.86^{***}
var_κ_{Ks}	-0.10^{*}	-0.19^{***}	-0.15^{***}	-0.10^{***}
θ_s		-0.93^{***}		0.66^{***}
γ_s			-2.11^{***}	-2.66^{***}
$Adj.\ R^2$	0.20	0.33	0.69	0.72

Note. *** significant at 0.01 level, ** significant at 0.05, * significant at 0.1 level. No. of Obs=1299.

TABLE VI

$\overline{\kappa}_K/\widetilde{\kappa}_K$ AND CV_κ_K

$Year$	$\overline{\kappa}_K/\widetilde{\kappa}_K$	$\rho_{\kappa_K,\varpi}$	CV_κ_K	$\sigma_{N\varpi}$
1999	1.57	−0.06	1.73	3.31
2003	1.46	−0.05	1.68	3.31
2007	1.27	−0.05	1.36	3.69

Note. CV is coefficients of variation. Each industry is weighted by its share of value added.

TABLE VII

$\overline{\kappa}_L/\widetilde{\kappa}_L$ AND CV_κ_L

$Year$	$\overline{\kappa}_L/\widetilde{\kappa}_L$	$\rho_{\kappa_L,\varpi}$	CV_κ_L	$\sigma_{N\varpi}$
1999	1.74	−0.12	1.14	3.31
2003	1.69	−0.13	1.01	3.31
2007	1.59	−0.13	0.88	3.69

Note. CV is coefficients of variation. Each industry is weighted by its share of value added.

TABLE VIII

OWNERSHIP OF CHINESE FIRMS

Year	1999		2003		2007	
	Ave 1	*Ave* 2	*Ave* 1	*Ave* 2	*Ave* 1	*Ave* 2
Private Domestic	9.9	4.8	34.0	16.8	51.2	28.2
Private Foreign	17.4	23.3	20.2	27.9	19.7	29.7
Collective	47.2	42.6	35.5	41.1	25.7	35.6
State	25.6	29.4	10.3	14.2	3.4	6.6

Note. For each year, the entries in the first column are the percent of number of firms in each ownership category, and the entries in the second column are the percent of the value added of firms in each ownership category. Each industry is weighted by its value-added share.

TABLE IX

REGRESSIONS OF $\ln(TFP)$ ON FIRM TYPES

Year	1999	2002	2005
Exiting	-0.34^{***}	-0.22^{***}	-0.36^{***}
Entering	-0.09^{***}	-0.07^{***}	-0.08^{***}
Private Foreign	-0.19^{***}	-0.04^{***}	0.00
Collective	-0.08^{***}	-0.01	0.04^{***}
State	-0.96^{***}	-0.75^{***}	-0.43^{***}

Note. *** significant at 0.01 level, ** significant at 0.05, * significant at 0.1 level. The dependent variables are the deviation of $\ln(TFP)$ from the industry mean. Regressions are weighted least squares with the weights being industry value-added shares.

TABLE X

κ_L AND κ_K BY OWNERSHIP

Year	1999		2007	
	κ_K	κ_L	κ_K	κ_L
Private Domestic	0.61	0.59	0.38	0.57
Private Foreign	1.26	0.81	0.58	0.72
Collective	0.90	0.78	0.48	0.62
State	2.40	1.46	0.81	0.83

Note. $\ln(\kappa)$ is defined as the weighted average with weights being industry value-added shares.

TABLE XI

PERCENT OF FIRMS, EFFICIENT SIZE VS. ACTUAL SIZE

Year	1999				2007			
	$0.25-$	$0.25-1$	$1-4$	$4+$	$0.25-$	$0.25-1$	$1-4$	$4+$
Private Domestic	0.47	0.21	0.16	0.16	0.57	0.20	0.13	0.10
Private Foreign	0.64	0.18	0.10	0.08	0.69	0.17	0.09	0.05
Collective	0.56	0.19	0.13	0.12	0.62	0.18	0.11	0.09
State	0.82	0.10	0.05	0.04	0.78	0.12	0.06	0.04

TABLE XII:

$\ln(TFP)$, $\ln(\kappa_K)$ AND $\ln(\kappa_L)$ OF EXITING FIRMS BY OWNERSHIP

Year	1999			2005		
	$\ln(TFP)$	$\ln(\kappa_K)$	$\ln(\kappa_L)$	$\ln(TFP)$	$\ln(\kappa_K)$	$\ln(\kappa_L)$
State	-1.16^{***}	1.56^{***}	1.02^{***}	-0.75^{***}	0.86^{***}	0.65^{***}
Private Foreign	-0.38^{***}	0.86^{***}	0.44^{***}	-0.17	0.55^{***}	0.22^{***}
Collective	-0.22^{***}	0.40^{***}	0.29^{***}	-0.10^{***}	0.29^{***}	0.16^{***}

Note. *** significant at 0.01 level, ** significant at 0.05, * significant at 0.1 level. The dependent variables are the deviation of $\ln(TFP)$, $\ln(\kappa_L)$ and $\ln(\kappa_K)$ from their industry means. Regressions are weighted least squares with the weights being each industry's value-added share.

TABLE XIII

REGRESSION OF FIRM'S EXIT ON $\ln(TFP), \ln(\kappa_K)$ AND $\ln(\kappa_K)$ BY OWNERSHIP

Ownership	*Private Domestic*	*Private Foreign*	*Collective*	*State*
$\ln(TFP)$	-0.25^{***}	-0.14^{***}	-0.17^{***}	-0.15^{***}
$\ln(\kappa_K)$	-0.10^{***}	-0.02^{***}	-0.05^{***}	0.01^{***}
$\ln(\kappa_L)$	-0.17^{***}	-0.10^{***}	-0.11^{***}	-0.06^{***}

Note. *** significant at 0.01 level, ** significant at 0.05, * significant at 0.1 level. New entrants are excluded from the sample. The dependent variable is equal to 1 if a firm exits within two years, or 0 if not. Regressions are weighted least squares with the weights being each industry's value-added share, and pooled for all the years.

TABLE XIV

REGRESSION OF $\ln(TFPE)$ ON MARKET DISTORTIONS

	Benchmark Model	CRS, $\theta = 1.5$	CRS ($\theta = 1.25$)
$var_\ln(\kappa_K)$	0.47	0.10^{*}	0.19^{***}
$var_\ln(\kappa_L)$	2.35^{***}	1.79^{***}	1.78^{***}
$cov_\ln(\kappa_L)_\ln(\kappa_K)$	-2.53^{***}	-0.83^{***}	-0.75^{***}
CV_κ_K	0.78^{***}	-0.09^{**}	-0.16^{***}
CV_κ_L	-0.86^{***}	-0.14^{***}	-0.12^{***}
Adj. R^2	0.02	0.36	0.41

Note. *** significant at 0.01 level, ** significant at 0.05, * significant at 0.1 level. Regressions are pooled for all the years.

TABLE XV

REGRESSION OF MARKET DISTORTIONS ON PRICE MARKUP AND RETURNS TO SCALE

	$\overline{\kappa}_{Ks}$	$\overline{\kappa}_{Ls}$	$\widetilde{\kappa}_{Ks}$	$\widetilde{\kappa}_{Ls}$
θ_s	0.43^{***}	-0.22	0.41^{***}	0.41^{***}
γ_s	-0.94^{***}	-0.15	-0.42^{***}	-0.57^{***}
Adj. R^2	0.02	0.01	0.02	0.04

Note. *** significant at 0.01 level, ** significant at 0.05, * significant at 0.1 level. Regressions are pooled for all the years.

FIGURES

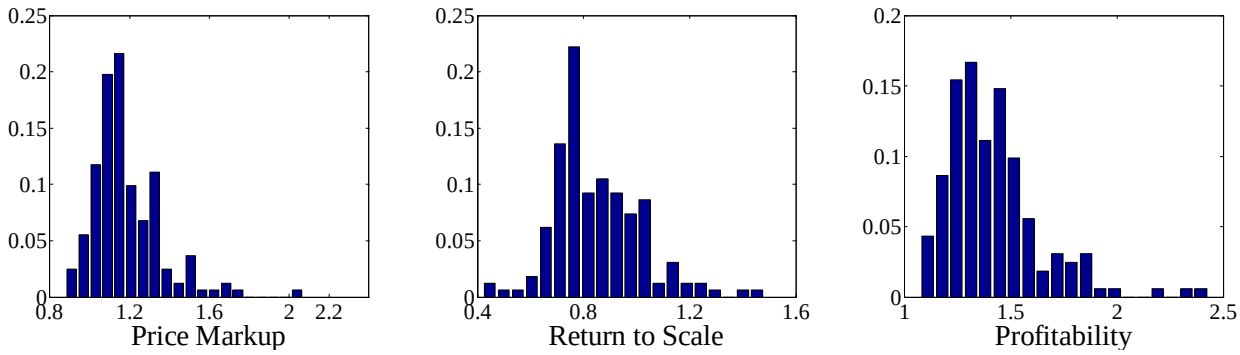

FIGURE I

Distributions of Price Markups, Returns to Scale and Profitabilities of Chinese Manufacturing Industries (3-digit Level, $N = 162$)[7]

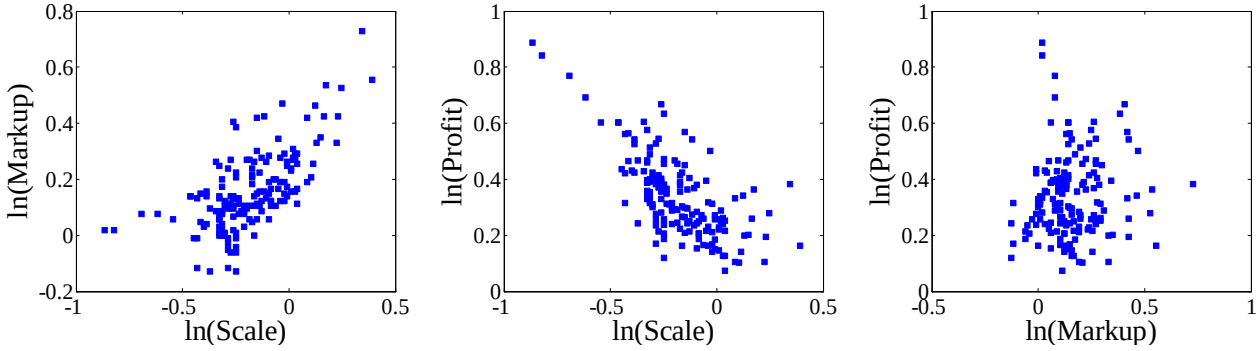

FIGURE II

Relationships among Price Markup, Returns to Scale and Profitability (3-digit Level, $N = 162$)

[7] As a consistent estimate of θ_s requires large N_s, I have droped the industries in which total firm numbers during 1999-2007 are less than 1000 throughout this paper. 10 of the total 172 industries were dropped.

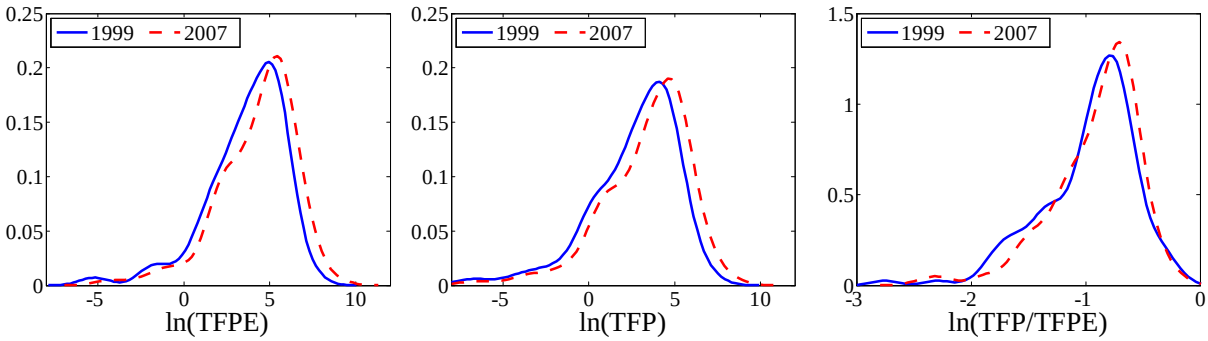

FIGURE III

Distributions of $\ln(TFPE)$, $\ln(TFP)$ and $\ln(TFP/TFPE)$

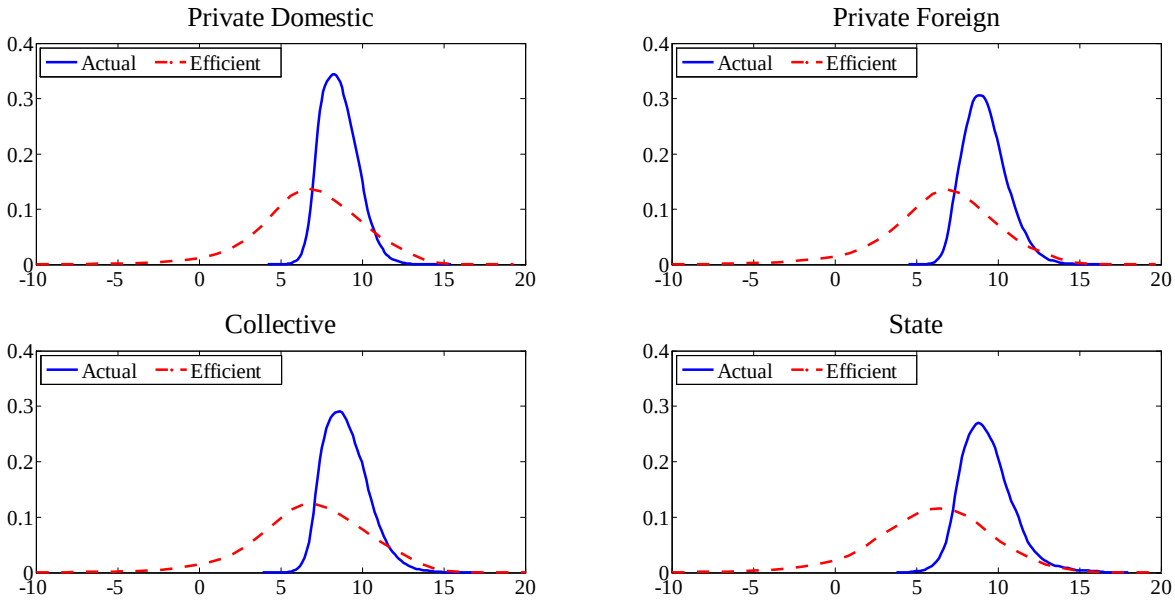

FIGURE IV

Distributions of ln(Value added) by Ownership