Privatization, Distortions, and Productivity *

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Abstract

I develop a new framework for analyzing the direct and indirect effects of privatization on productivity and distortion. To do so, I propose a novel method to jointly estimate distortions, productivity and production function parameters. I then apply the method to Chinese National Bureau of Statistics (NBS) industrial annual surveys from 1998 to 2007. I find that when a firm is privatized, it immediately realizes a 5% increase in productivity, which is equivalent to one year of productivity growth for an average manufacturing firm in the sample. Coupled with the estimated persistent productivity process, overall privatization increases privatized firms' productivity about 14% at 2007. Meanwhile, privatization reduces distortions by 2%. Privatization directly contributes 5% in the aggregate productivity growth in the sample, mainly through its impact on firm productivity. In contrast, the gains from improved factor reallocation due to privatization appear to have limited effects on firm revenues and aggregate TFP.

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1 Introduction

The Privatization of State-Owned Enterprises (henceforth SOEs) is one of the leading economic policies shaping the transition of China toward a market economy. Within the manufacturing sector more than 1000 SOEs per year were privatized between 1998 and 2004, and around 500 per year were privatized between 2005 and 2007. From 1998 to 2007, the share of SOEs in revenue within the manufacturing sector declined from 30% to 8%, while the employment share of SOEs declined from 45% to 9%.

This paper seeks to understand *to what extent* and *through what channels* privatization has contributed to the rapid growth of GDP and TFP in China's manufacturing sector during this transition. Privatization, like many other industrial policies, affects firms' output and productivity through a direct effect on productivity and an indirect effect on resource allocation. Privatization is an important determinant of productivity and distortions, yet there is little empirical evidence of its direct and indirect effects. Therefore, understanding the consequences of privatization on both productivity and allocative efficiency is crucial for policy evaluation and subsequent reforms.

This paper explores the effect of privatization on productivity and distortion using Chinese National Bureau of Statistics (NBS) industrial annual surveys from 1998 to 2007. To guide empirical work, I first build a discrete time dynamic investment model where a firm chooses investment, labor and materials to generate revenue. The model features two kinds of shocks every period: a productivity shock and a distortion shock. Following the misallocation literature[1], the distortion is modelled as a wedge that moves firm's marginal revenues away from its marginal costs for all inputs to the same extent. To account for the direct effect of privatization, the model allows ownership and privatization to affect the evolution of productivity.

[1] In particular, Restuccia and Rogerson (2008), Hsieh and Klenow (2009), and more recently, David, Hopenhayn, and Venkateswaran (2015).

Next, I present a novel method to jointly identify distortions, productivity and the parameters in the revenue function. I then estimate these parameters of interest through structural estimation. Following the literature on production function estimation[2], the identification relies on the optimal material choice implied from the model, the timing of play and the evolution of productivity. To distinguish distortion from firm-level productivity uncertainties, I assume that the firm's dynamic input decisions depend on distortion and expected productivity as in Asker, Collard-Wexler, and De Loecker (2014), whereas its static input decision depends on both distortion and realized productivity as in Hsieh and Klenow (2009).

Finally, I use the estimated model to evaluate the impact of privatization on productivity and distortions at firm and aggregate level. I find that when a firm is privatized, it immediately realizes a 5% increase in productivity on average, which is equivalent to one year of productivity growth for an average manufacturing firm in the sample. Coupled with the estimated persistent productivity process, the long run gains from privatization appear to be even more important: It increases the privatized firms' productivity by 12% at 2007. Meanwhile, privatization immediately reduces distortions by 2%, which results in a 0.2% increase of revenue on average. In particular, firms with positive implicit tax before privatization benefit the most from the reduction of distortions. However, the gains from improved factor reallocation due to privatization appear to have limited effects on firm revenues in the long run.

Next turn to the aggregate effects of privatization on allocative efficiency and aggregate productivity growth (henceforth APG). Based on Melitz and Polanec (2015) and Collard-Wexler and Loecker (2015), I propose a decomposition method for APG to explicitly account for the direct effect of privatization. The decomposition suggests that with an annual 5% growth rate within the manufacturing sector, the direct

[2] In particular, the model and the identification augment the empirical production function estimation literature as in Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer (2006), and Gandhi, Navarro, and Rivers (2012) with micro-level distortions as modelled in Restuccia and Rogerson (2008) and Hsieh and Klenow (2009).

contribution of privatization to APG is about 5% in the sample. Given that only a limited number of firms are privatized, there is a fairly sizeable gain associated with the policy. Privatizations contribute to the aggregate productivity growth mainly through their direct impact on firm level productivity. In contrast, although the privatizations also reduce revenue distortions, the associated reallocation gains only contribute a small fraction to overall TFP growth.

The main contributions of this paper are threefold. First, the paper bridges the *direct* and *indirect* approaches in the misallocation literature and identifies a particular policy's effects on both productivity and distortions[3]. It links an important source of misallocation, ownership and privatization, to the measured distortions and productivity from the *indirect* approach. Moreover, this paper explicitly emphasizes the effect of privatization on both productivity and distortions. By contrast, Brown, Earle, and Telegdy (2006) and Braguinsky, Ohyama, Okazaki, and Syverson (2015), and De Loecker (2011) focus on policy's productivity effect, while Collard-Wexler and Loecker (2015) and Khandelwal, Schott, and Wei (2013) emphasize the reallocation effects.

Second, the paper extends the production function estimation literature by establishing a method that allows for both unobserved distortions and productivity. Gandhi et al. (2012) shows that *without distortion*, under Cobb-Douglas production function, the revenue elasticity of material is identified as average material revenue shares from firm's static first order condition. Conditional on this revenue elasticity, the rest of revenue function parameters are identified following procedures in Ackerberg et al. (2006). But with *unobserved distortion*, revenue share of material is a composition of revenue elasticity of material and distortion, therefore the average revenue share is no

[3]The definitions of *direct* and *indirect* approaches follow Restuccia and Rogerson (2013). The *direct* approach is to pick and measure one factor that is important for misallocation, and quantify the extent to which this factor generates misallocation and impact aggregate TFP. Instead, the *indirect* approach tries to focus on the net effect of an entire bundle of underlying factors on misallocation without attributing distortions to any specific underlying factor.

longer an unbiased estimator of static input elasticity. By contrast, this paper illustrates how to estimate production function with endogeneity problems from both unobserved productivity and distortion, as well as the transmission bias from allowing both static and dynamic inputs. It shows that lagged material, lagged material revenue shares, and current revenue jointly identify the revenue elasticity of material and persistence of productivity. With the estimated technology parameters, it is straightforward to back out the implied distortion and productivity at the firm-year level.

Third, the paper provides a framework to analyze the dispersions of marginal product of inputs with dynamically chosen inputs and distortions. In doing so, it reconciles two distinct views from the literature that whether researchers could measure distortion from marginal product of inputs[4]. This paper combines both distortions and dynamic inputs in a dynamic investment model, and estimates productivity, distortions, and production function parameters. The methodological innovation in this paper corrects the bias from ignoring unobserved distortions. Using the estimated distortions and productivity from the Chinese firm-level data, this paper finds that both channels are important to the dispersion of marginal revenue product of capital (MRPK). More importantly, distortions can be estimated from firm's static input choice, which is a composition of distortions, productivity, and estimated technology parameters.

The rest of the article proceeds as follows. Section 2 presents a dynamic investment model. Section 3 considers the identification of production function in the presence of unobserved distortions. Section 4 describes the data and measurements used in the empirical analysis. Section 5 presents the econometric specification and Section 6 presents the empirical results. Section 7 describes the relationship between the dispersion of marginal products of inputs and distortions. Section 8 concludes.

[4] Hsieh and Klenow (2009) uses the dispersion of marginal revenue product of capital (MRPK) to measure distortion with the underlying assumption that firms are static optimizers, which implies the input shares are unbiased estimators of production function parameters. However, Asker et al. (2014) shows that with capital adjustment costs and micro uncertainties, a distortion free economy could generate similar patterns of such dispersion.

2 A Dynamic Investment Model

Consider a single agent dynamic investment model. Time is discrete and infinite. There are two dynamic inputs—capital and labor, and a static input—material. In each period t, firms set the levels of capital and labor next period by making investment and hiring/firing decisions. With pre-determined capital and labor, they choose current period material as an additional input for production.

Moreover, there are two types of idiosyncratic shock every period. The first is a productivity shock, which directly influences the revenue. The revenue is determined by The levels of pre-determined dynamic inputs and the static input together with the productivity shock determine the amount of revenue produced. The other shock is the output distortion, which influences the revenue through input choices. In particular, the (output) distortion increases the marginal product of all inputs by the same proportion but is not part of the revenue, as in Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Thus, the distortion can be seen as an unobserved firm-year level implicit tax or subsidy on the output.

The timing is shown in figure 1:

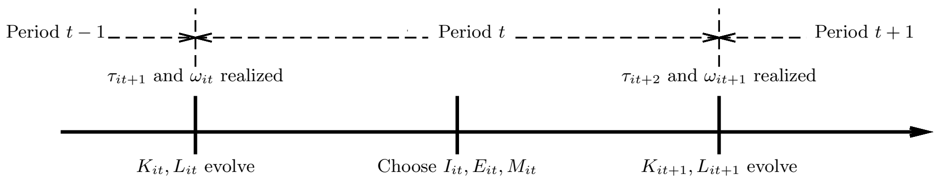
1. At the beginning of each period t, firm i carries capital K_{it}, labor L_{it}, period t productivity ω_{it}, period t distortions τ_{it}, and period $t+1$ distortions τ_{it+1}. Write w_t as the wage rate, r_t as the interest rate, and p_t^M as the material price for period t.

2. Next, taking a stream of input prices $\{w_t, r_t, p_t^M\}_{t=1}^{t=\infty}$ as given, firm i chooses material M_{it} to generate period t revenue, and makes investment I_{it} and hiring/firing decisions E_{it}. By doing so, the firm sets period $t+1$'s capital K_{it+1} and labor L_{it+1}.

3. After the firm made all its input choices, revenue R_{it} is recorded. Capital, labor, productivity and distortions evolve to their period $t+1$ level. Then firm i begins

its period $t+1$ operation.

Figure 1 The Time Line



Under the timing assumptions, firms' dynamic input decisions depend on distortions and expected productivity as in Asker et al. (2014), and the static input decision depends on both distortions and realized productivity as in Hsieh and Klenow (2009).

Write $\mathcal{I}_{it}$ for firm i's information set at the beginning of period t. The set consists of the history of its inputs, output and productivity until period t, and distortions until period $t+1$. Assume that productivity $\omega_{it} \in \mathcal{I}_{it}$ is a persistent Hicks neutral productivity shock, and follows a Markov process. Write the productivity process as follows:

$$\omega_{it+1} = \Phi(\omega_{it}, X_{it}) + \xi_{it+1}, \tag{1}$$

where $\Phi(\omega_{it}, X_{it})$ is the predictable component of the productivity, $X_{it} \in \mathcal{I}_{it}$ is a vector of observables that directly enter the productivity process 1, and ξ_{it+1} is innovation of the productivity process, where $\xi_{it+1} = \omega_{it+1} - \mathbb{E}[\omega_{it+1}|\mathcal{I}_{it}]$. By construction, $\xi_{it+1} \perp \mathcal{I}_{it}$, i.e., the innovation of productivity is orthogonal to any elements in the information set $\mathcal{I}_{it}$. With $\{\tau_{it}, \tau_{it+1}\} \in \mathcal{I}_{it}$, the distortions process is characterized by

$$\tau_{it+2} = \Upsilon(\tau_{it}, \tau_{it+1}, X_{it}) + \zeta_{it+2}.$$

Similar to the productivity process, $\Upsilon(\tau_{it}, \tau_{it+1}, X_{it})$ is the predictable component, and ζ_{it+2} is the innovation of distortions process, which is orthogonal to any elements in the information set $\mathcal{I}_{it}$. I further assume that innovations to productivity and distortions are both i.i.d. across firms.

The revenue generating technology is of Cobb-Douglas form

$$R_{it} = K_{it}^{\theta_k} L_{it}^{\theta_l} M_{it}^{\theta_m} \exp\left(\omega_{it}\right), \tag{2}$$

where θ_k, θ_l and θ_m are capital, labor and material coefficients respectively.

Capital and labor evolves as follows:

$$\begin{aligned} K_{it+1} &= (1-\delta^K)K_{it} + I_{it}, \\ L_{it+1} &= (1-\delta^L)L_{it} + E_{it}, \end{aligned}$$

where δ^K is the depreciation rate of capital, and δ^L is the depreciation rate of labor.

The cost of production $C(\omega_{it}, K_{it}, L_{it}, I_{it}, E_{it})$ is a function of the dynamic inputs–namely capital and labor–and the potential adjustment costs.[5] With output distortions τ_{it}, the perceived productivity is the sum of productivity ω_{it} and distortions τ_{it}. The firm's objective is to maximize the discounted adjusted (by distortions) profit streams by choosing inputs. Formally, the recursive form of firm i's problem is as follows

$$\begin{aligned} V(K_{it}, L_{it}, \omega_{it}, \tau_{it}, \tau_{it+1}, t) = \max_{I_{it}, E_{it}, M_{it}} & \exp(\tau_{it} + \omega_{it}) K_{it}^{\theta_k} L_{it}^{\theta_l} M_{it}^{\theta_m} \\ & - w_t L_{it} - p_t^M M_{it} - C(\omega_{it}, K_{it}, L_{it}, I_{it}, E_{it}) \\ & + \beta \mathbb{E}_{\omega,\tau} V(K_{it+1}, L_{it+1}, \omega_{it+1}, \tau_{it+1}, \tau_{it+2}, t+1) \end{aligned}$$

[5] Since the identification does not require first order condition of dynamic inputs, I do not specify the functional form of adjustment cost at this moment. I only assume that the static input M_{it} is not part of the adjustment cost.

subject to

$$
\begin{aligned}
K_{it+1} &= (1-\delta^K)K_{it} + I_{it}, \\
L_{it+1} &= (1-\delta^L)L_{it} + E_{it}, \\
\omega_{it} &= \Phi(\omega_{it-1}, X_{it-1}) + \eta_{it}, \text{and} \\
\tau_{it+2} &= \Upsilon(\tau_{it}, \tau_{it+1}, X_{it}) + \zeta_{it}.
\end{aligned}
$$

Here $\mathbb{E}_{\omega,\tau}$ is the expectation for transition of productivity and distortions, β is the discount rate for all firms.

Firms' optimal choices are characterized Proposition 1.

Proposition 1. *Given a stream of input prices* $\{w_t, p_t^M\}_{t=0}^{\infty}$ *and revenue function parameters* $\{\theta_k, \theta_l, \theta_m\}$*, firm i's optimal choice of material is a function of* $\{K_{it}, L_{it}, \omega_{it}, \tau_{it}\}$ *that satisfies the static first order condition*

$$
p_t^M = \exp(\tau_{it} + \omega_{it})\theta_m K_{it}^{\theta_k} L_{it}^{\theta_l} M_{it}^{\theta_m - 1}. \tag{3}
$$

The firm determines its next period capital and labor by a system of implicitly defined first order conditions with respect to capital and labor.

From this first order condition, we see the role of distortions τ_{it} in resource allocation. Distortions create wedges between the marginal cost of material, which is the price p_t^M, and the marginal revenue of material. When $\tau_{it} < 0$, the marginal cost is less than the marginal revenue, the firm faces implicit tax. When $\tau_{it} > 0$, the marginal cost is greater than the marginal revenue, the firm faces implicit subsidy. Only when $\tau_{it} = 0$, we have the marginal cost equals to the marginal revenue.

3 Identification Strategy

This section discusses the identification strategy. The goal is to empirically evaluate the effects of privatization on output and productivity. To do so, I estimate productivity ω_{it}, parameters in the revenue function $\{\theta_k, \theta_l, \theta_m\}$, and the unobserved distortions τ_{it} from a standard production dataset.

More specifically, I extend the identification technique adopted by Gandhi et al. (2012) to address three empirical concerns. The first concern is the endogeneity issue that all inputs are correlated with unobserved productivity and distortions. (See Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2006)). The second is the transmission-bias issue that the choice of static input depends on dynamic inputs. (See Marschak and Andrews (1944) and Gandhi et al. (2012).) Third, an additional identification issue arises with distortions in the firm's problem since these distortions are unobserved by the econometrician.

3.1 Illustration of Identification

Now I illustrate the identification using a single static production factor. Consider a dataset that contains an output variable—log revenue r_{it}, and a static input variable—log material m_{it} for firms $i \in \{1, \cdots, N\}$ and year $t \in \{1, \cdots, T\}$.

Assume that the revenue function is linear in logs

$$r_{it} = \theta_m m_{it} + \omega_{it}. \tag{4}$$

Following the empirical production function estimation literature, I further assume the productivity follows an autoregressive (AR(1)) process

$$\omega_{it+1} = \mu + \gamma \omega_{it} + \alpha \tau_{it+1} + \eta_{it+1}, \tag{5}$$

The first term μ is the intercept of the AR(1) process. The second term is the current productivity's contribution to the future productivity, and γ is the persistence parameter. The third term is the future distortions τ_{it} which serves as a control variable in the process. The last term is the productivity innovation η_{it+1}. Thus, this specification allow me to interpret η_{it+1} as the productivity innovation conditional on distortions τ_{it+1}.[6]

Finally, I assume that firms choose material m_{it} knowing both productivity ω_{it} and distortions τ_{it}.[7] Firms take input price p_t^M as given. The first order condition of material is

$$\ln p_t^M = \ln \theta_m + (\theta_m - 1)m_{it} + \omega_{it} + \tau_{it} \tag{6}$$

Combing the first order condition of material, Equation (6), and the revenue equation (4) we have the share equation:

$$\ln s_{it} \equiv \ln \frac{P_t^M M_{it}}{R_{it}} = \ln \theta_m + \tau_{it}. \tag{7}$$

Proposition 2 presents the key assumptions for identification and identification results for this special case.

Proposition 2. *Suppose the following assumptions are satisfied,*

1. *Productivity ω_{it} is persistent, i.e., $\gamma \neq 0$.*

2. *Distortions τ_{it} varies across firm i and year t.*

The technology parameter θ_m, productivity ω_{it} and distortions τ_{it} can be identified from the above equations (4), (5), (6), and (7) from production data.

[6] Another way to interpret this formulation is to assume firms are Bayesian: They are aware of the fact that distortions and productivity are correlated, and use distortions as a signal to forecast productivity.

[7] This timing assumption is consistent with both the production function estimation literature and static misallocation literature (e.g, Hsieh and Klenow (2009)), and is embedded in the dynamic investment model in section 2.

Proof. Starting with the revenue equation (4), the reduced form representation of log revenue is

$$\begin{aligned}
r_{it} &= \theta_m m_{it} + \omega_{it} \\
&= \frac{\theta_m}{1-\theta_m}(\omega_{it} + \tau_{it}) + \omega_{it} + \text{Constant} \\
&= \frac{1}{1-\theta_m}\omega_{it} + \frac{\theta_m}{1-\theta_m}\tau_{it} + \text{Constant} \\
&= \frac{\alpha+\theta_m}{1-\theta_m}\tau_{it} + \frac{\gamma}{1-\theta_m}\omega_{it-1} + \frac{1}{1-\theta_m}\eta_{it} + \text{Constant} \\
&= \frac{\alpha+\theta_m}{1-\theta_m}\tau_{it} - \frac{\gamma}{1-\theta_m}\tau_{it-1} + \gamma m_{it-1} + \frac{1}{1-\theta_m}\eta_{it} + \text{Constant} \\
&= \frac{\alpha+\theta_m}{1-\theta_m}\ln s_{it} - \frac{\gamma}{1-\theta_m}\ln s_{it-1} + \gamma m_{it-1} + \frac{1}{1-\theta_m}\eta_{it} + \text{Constant}.
\end{aligned}$$

The first line is the original definition of revenue function as in equation (4), and the second line uses the material first order condition (6) to replace material as a function of productivity and distortions. The third line replaces current productivity by the current distortions and lagged productivity from the AR(1) process described in equation (5). The fourth line uses the material first order condition again to replace productivity as a function of material and distortions. The last line uses the share equation (7) to replace the unobserved distortions with the observed shares. The final reduced form representation features all observed variables on both side of the equation. Under the assumptions in proposition 2, the three regressors at the RHS identify the three unknowns. □

The identification involves two different assumptions. First, the persistence of productivity plays a key role to link lagged inputs with current output. If the productivity is not persistent, i.e., $\gamma = 0$, the reduced form representation of the output is

$$r_{it} = \frac{\alpha+\theta_m}{1-\theta_m}\ln s_{it} + \frac{1}{1-\theta_m}\eta_{it} + \text{Constant}.$$

So we cannot separately identify α and θ_m in this case.

The second assumption requires distortions τ_{it} to vary across firm and year. If τ_{it} is a constant, there are no variation in the reduced form representation to provide information on the coefficients of $\ln s_{it}$ and $\ln s_{it-1}$. Consider a specific case as in Gandhi et al. (2012), where are no distortions, i.e., $\tau_{it} = 0$. The reduced form representation becomes

$$r_{it} = \gamma m_{it-1} + \frac{1}{1-\theta_m}\eta_{it} + \text{Constant}.$$

Regressing the output r_{it} on input m_{it} provides no information on the technology parameter θ_m. Gandhi et al. (2012) uses the share equation to get

$$\theta_m = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T} s_{it}}{NT}.$$

However, when τ_{it} is an unobserved nonzero constant, there is no general way to identify all the parameters.

The identification of this reduced form representation is consistent with empirical production function estimation literature starting from Olley and Pakes (1996): Productivity has a predictable component and an unpredictable component. By construction the unpredictable component is orthogonal to any element within firm's information set $\mathcal{I}_{it}$. In the current setting, η_{it} is not the entire productivity innovation but the part that is uncorrelated with current distortions.[8] However, it still bears the orthogonal property between productivity innovation η_{it} and elements in firm's information set $\mathcal{I}_{it-1}$. In the following discussions, I still refer η_{it} as the productivity innovation.

To summarize, adding unobserved distortions does not further complicate the identification: it even provides more variations that the econometrician can exploit to identify the system. This case illustrates that one can identify technology parameters,

[8] This setup is similar to the one in David et al. (2015).

productivity and distortions by only using the static choices.

3.2 General Identification with Multiple Inputs

Instead of restricting to the special case, now I explore the identification strategy by incorporating dynamic inputs, capital and labor, into the revenue function. In addition, I allow exogenous covariates in the productivity process. Comparing to the previous single input and output dataset, now there are two more input variables–log capital k_{it} and log labor l_{it}–and a vector of exogenous covariates x_{it} for firm i at year t.

The revenue function is as follows

$$r_{it} = \theta_l l_{it} + \theta_k k_{it} + \theta_m m_{it} + \omega_{it}, \tag{8}$$

where θ_l is the elasticity of labor to revenue, and θ_k is the elasticity of capital to revenue. The productivity process is specified as an AR(1) process

$$\omega_{it} = \mu + \gamma\omega_{it-1} + \alpha\tau_{it} + \pi x_{it} + \eta_{it}. \tag{9}$$

It is consistent with our general specification in equation (5). The first order condition for material m_{it} in this case is

$$\ln p_t^M = \ln\theta_m + (\theta_m - 1)m_{it} + \theta_k k_{it} + \theta_l l_{it} + \omega_{it} + \tau_{it}. \tag{10}$$

Combing the first order condition of material, Equation (10), and the revenue equation, Equation (8), we have the same share equation

$$\ln s_{it} \equiv \ln\frac{P_t^M M_{it}}{R_{it}} = \ln\theta_m + \tau_{it}. \tag{11}$$

Proposition 3 provides general identification results for a model with dynamic inputs and exogenous covariates in productivity process.

Proposition 3. *Consider the same assumptions in Proposition 2. The technology parameter $\{\theta_k, \theta_l, \theta_m\}$, parameters of covariates in the productivity process $\{\alpha, \pi\}$, the persistence of the productivity process γ, productivity ω_{it} and distortions τ_{it} can be identified from the above equations (8), (9), (10), and (11) using the production data.*

Proof. In this case, the reduced form representation of revenue is given by

$$\begin{aligned}\mathbb{E}[r_{it}] = \frac{\theta_k}{1-\theta_m}k_{it} + \frac{\theta_l}{1-\theta_m}l_{it} - \frac{\gamma\theta_k}{1-\theta_m}k_{it-1} - \frac{\gamma\theta_l}{1-\theta_m}l_{it-1} + \frac{\pi}{1-\theta_m}x_{it-1} \\ + \gamma m_{it-1} + \frac{\alpha+\theta_m}{1-\theta_m}\ln s_{it} - \frac{\gamma}{1-\theta_m}\ln s_{it-1} + \text{Constant.} \quad (12)\end{aligned}$$

The derivation is available in A.1. The identification of θ_m, γ and α are similar to the previous case where material is the only input. We can identify γ from the variations of m_{it-1}. We can also identify θ_m and α from variations of $\ln s_{it-1}$ and $\ln s_{it}$, which are proxy variables for distortions with differences in the means. The first line consists of dynamic inputs and exogenous covaraites. Given θ_m, we can directly identify π, θ_k, θ_l from variations of x_{it-1}, k_{it} and k_{it-1}, l_{it} and l_{it-1} respectively. In particular, adding dynamic inputs brings additional identification power for γ. Once we have all the technology parameters, we can back out firm-year level productivity ω_{it} and distortions τ_{it} from revenue equation (8) and share equation (11). □

3.3 Simulation

To compare different estimation methods, I first simulate a panel data set with inputs, outputs, productivity and distortions. I then estimate the production function parameters using different estimation methods. Finally I investigate their biases and asymptotic properties.

First, I simulate a firm-year level input and output dataset with number of firms

$N = 1000$, and number of years $T = 11$ years. I specify the technology parameters as $\theta_k = 0.1, \theta_l = 0.3, \theta_m = 0.5$ where $\{\theta_k, \theta_l, \theta_m\}$ are elasticity of capital, elasticity of labor and elasticity of material respectively. For productivity process, I set the intercept of the process $\mu = 0.1$ and the persistence parameter $\gamma = 0.7$. I set the correlation between distortion and productivity in the productivity process $\alpha = -0.4$. For distortion process, I set the intercept of the process $\psi = 0.1$ and the persistence parameter $\phi = 0.3$. I further specify the productivity innovation η_{it} and ζ_{it} from two independent standard normal distributions.

Next, I randomly draw k_{it} and l_{it} from uniform distribution from 5 to 15. For each firm i at $t = 1$, I draw distortions from a normal distribution with mean 0.2 and variance 0.5. Using ψ, ϕ and ζ_{it}, I then simulate the whole time series of distortion based on the AR(1) specification. For each firm i at $t = 1$, I draw distortions from a normal distribution with mean 2 and variance 0.5. Using μ, γ, α, τ_{it} and η_{it}, I simulate the productivity series. Assume material price is 1 through all the sample period.

For the endogenous variables, I use equation (3) to compute the optimal material inputs m_{it}. Then I use the revenue function (8) to generate revenue series r_{it}. To this end, the dataset contains $\{k_{it}, l_{it}, m_{it}, r_{it}, \eta_{it}, \omega_{it}, \tau_{it}\}_{i=1,t=1}^{i=N,t=T}$. The common observed dataset for an econometrician is $\{k_{it}, l_{it}, m_{it}, r_{it}\}_{i=1,t=1}^{i=N,t=T}$.

Finally, I estimate the parameters $\{\hat{\theta}_k, \hat{\theta}_l, \hat{\theta}_m, \hat{\gamma}\}$, and implied distribution of productivity $\hat{\omega}_{it}$ and distortions $\hat{\tau}_{it}$ using three different methods. The first is the ordinary least square (OLS), which directly regresses output on inputs. The second is the GNR method proposed by Gandhi et al. (2012) that assumes no distortions in the economy, i.e., $\tau_{it} = 0$ for all i and t. The third is the method proposed in section 3. For the last two methods I implement both Nonlinear least square (NLS) and generalized method of moments (GMM) approaches for comparison. I also compute a non-structural measure of productivity—labor productivity—which is defined as $\omega_{it}^{Labor} = r_{it} - l_{it}$. I compare it with the productivity measures implied from the structural methods. Since the estimation requires lagged value of inputs and outputs, I only use observations that are not the first year of the sample. To this end, the sample size reduces to 10000 firm-year observations. I repeat the simulation for 1000 times and plot the following asymptotic distributions of the estimates.

Comparing the estimates, the simulation results suggest that the method proposed in section 3 produces consistent estimators for the technology parameters, and the OLS and GNR methods produce biased estimates. Figure 2 depicts the results of simulation exercise for technology parameters, namely $\{\hat{\theta}_k, \hat{\theta}_l, \hat{\theta}_m, \hat{\gamma}\}$ with the true parameters at $\{0.1, 0.3, 0.5, 0.7\}$. The red line in each graph represents the true underlying values for the parameters. The simulation results suggest that with unobserved distortions, OLS attributes too much weight to the material inputs, producing an upward bias. The average estimates for θ_k and θ_l from OLS are 0.01 and 0.03, while the true parameter values are at 0.1 and 0.3, respectively. It also attributes too little to the capital and labor inputs, producing a downward bias. The average estimates from OLS for θ_m is 0.93, and the true value is at 0.5. With unobserved distortions, the GNR method performs worse than the OLS method: the bias for the technology parameters are even larger. Finally the method proposed in section 3 produces consistent estimates. Two different identification strategies, the nonlinear least square (NLS) and generalized method of moments (GMM) yield quite similar asymptotic properties.

Figure 2 is here.

I then turn to the implied distribution of productivity $\hat{\omega}_{it}$ and distortions $\hat{\tau}_{it}$. I use the mean of coefficients from the simulation exercises to compute the implied productivity and distortion distributions from the last simulated dataset. Figure 3 depicts the distribution of implied productivity and distortions. Figure 4 depicts the correlation between implied productivity from all these methods, labor productivity, and the true productivity. The results are two-folds. First, both the OLS and GNR methods underestimate the mean and the dispersion of productivity. Second, implied productivity from the OLS method has little correlation with the true productivity. The GNR method performs better.The implied productivity and distortions distributions are consistent under both NLS and GMM approaches using the method proposed in section 3.

Figure 3 is here.

Figure 4 is here.

Finally, I look at the implied correlation between productivity and distortions. Figure 5 depicts the correlation between implied productivity from all these methods and the true distortion. The method proposed in section 3 captures the right correlation between productivity and distortions, while the OLS and GNR methods produce much more negative correlation between the two, and labor productivity generates close to zero correlation.

Figure 5 is here.

4 Data and Variables

4.1 Production Data

The data is mainly from the National Bureau of Statistics (NBS) firm level survey. It contains annual firm-level data for the period 1998 to 2007 on all industrial firms, which are identified as being either state-owned, or are non-state firms with sales above 5 million RMB (hereafter referred to as the "above-scale"industrial firms). It covers industries from mining, manufacturing and electricity/gas/water production sectors. The raw data come as multiple cross-section files for each year. Following Brandt, Van Biesebroeck, and Zhang (2012), I adopt their code to link observations across years and compute capital stocks to produce a panel dataset with inputs, outputs and other information.[9]

I further clean the dataset for estimation. First, to be included in the sample, I require that firms have a minimum of two consecutive years of data. Then I link firm i's year t observation with its year $t-1$ observation and create a $(i, t, t-1)$ pair. Next I require that for any pair in the data, firm i should operate in the same two-digit industry. Moreover, there are no missing or negative values for current and lagged log revenue and inputs, namely capital, total wage bill, number of workers, material and revenue. Finally, I require there are no missing values for the following variables for both year t and year $t-1$: exporting value, firm age, provinces, registration type, and industrial classification.

4.2 Measurement

I outline the construction of some key variables in the empirical analysis here.

The first one is the ownership dummy, $\mathbb{1}_{i \in SOE,t}$. To construct this variable, I rely on firm's registration type. There are four general categories: State-owned, Collective, Private, and Foreign (Including Hong Kong, Macau and Taiwan). I record a firm i at year t with registration code 110 or 151 as a state-owned firm regardless of its capital composition.[10] Based on the ownership dummy, the privatization dummy $\mathbb{1}_{privatized,i,t-1}$ equals to 1 if firm i is a state-owned firm at year $t-1$ but a non-state-owned firm at year t.[11]

Furthermore, a substantial number of firms exit from the sample. The non-randomness of exit provides useful information on the selection on productivity. To address the potential selection bias, I follow Olley and Pakes (1996) to estimate

[9] I thank Jo Van Biesebroeck and Yifan Zhang for sharing the price data and code with me, and answering many questions about the data.

[10] Recent paper by Song and Hsieh (Forthcoming) and Bai, Lu, and Tao (2009) use capital composition as an alternative measurement of the control right.

[11] There is a small fraction of firms that have multiple switches in terms of their registration types. I drop those firms from the sample.

a probit model of exit on firm size, firm age, sales capital ratio, ownership and their interactions as well as year and provincial dummies to obtain the inverse mills ratio, and use it as a control variable in the productivity evolution equation.

Last, I construct two set of geographic dummies based on firms' registered zip code. One at province level and the other at region level. I first group the observations into provinces and then into four economic regions according to The Communist Party of China (2006) as there are large differences between regional and even provincial policy. Figure 6 depicts the four economic regions.

Figure 6 is here.

4.3 Summary Statistics

Table 1 illustrates the composition of privatization across years by industry. We do observe that the privatization is gradual over years. In our sample there are over 1500 privatization events in 1999, and it reduces to 330 in 2006. Moreover, there is uneven distribution across industries: Food processing and Nonmetal Mineral Products industry top the list with more than 1000 privatization events during the sample years.

Table 1 is here.

Table 2 decomposes privatization across years and provinces. Most of the privatization occurs in the eastern provinces, specially in Guangdong, Jiangsu and Shandong. However, western provinces in general have small number of privatization.

Table 2 is here.

Table 3 provides further summary statistics regarding to the input, output, and other relevant variables used in the empirical analysis.

Table 3 is here.

5 Econometric Specification

This section discusses how exactly I estimate the effects of privatization on productivity and distortions using the identification strategy in Section 3 and the data described in Section 4. I first assume the revenue function is Cobb-Douglas. The log revenue for firm i in 2-digit industry j at period t is a linear function of its period t log capital, labor material and productivity.

$$r_{it}^{j} = \theta_k^j k_{it} + \theta_l^j l_{it} + \theta_m^j m_{it} + \omega_{it}$$

where θ_k^j, θ_l^j, and θ_m^j are industry-specific input elasticity for capital, labor and material, respectively.

5.1 Productivity Process

I specify the productivity evolution process as

$$\omega_{it} = \mu + \sum_{n=1}^{N} \gamma_n \omega_{it-1}^{n} + \rho^{SOE} \mathbb{1}_{i \in SOE, t-1} + \rho^{Privatized} \mathbb{1}_{Privatized, i, t-1} + \rho^{After} \mathbb{1}_{After, i, t-1} + \alpha \tau_{it} + \phi \tau_{it-1} + \pi x_{it-1} + \eta_{it} \quad (13)$$

The first term is the intercept of the productivity process. The second term captures the lagged productivity's contribution to the current productivity. Here n is the order of lagged productivity to allow nonlinearity in the productivity process, and I follow De Loecker (2013) and Braguinsky et al. (2015) to specify $N = 3$. The third term captures the effect of lagged state ownership on the productivity process. Here $\mathbb{1}_{i \in SOE, t-1}$ is a dummy variable that equals 1 if and only if firm i is a SOE firm at year $t-1$. The fourth term captures the transitory effect of privatization on productivity process, and $\mathbb{1}_{Privatized, i, t-1}$ is a dummy variable that equals 1 if and only if firm i is privatized at year $t-1$ (i.e., firm i is a SOE firm at year $t-1$, but a non-SOE firm at year t). The fifth term captures the permanent effect of privatization on productivity. Here $\mathbb{1}_{\mathit{After,i,t\text{-}1}} = 1$ if firm i was privatized before or at year $t-1$, otherwise 0.[12] The seventh term captures the correlation between productivity and distortions for all firms. The eighth term captures the contribution of lagged distortions on current productivity. The ninth term captures the contribution from exogenous covariates

$$\pi x_{it-1} = \pi^{Export}\mathbb{1}_{Export,i,t-1} + \pi^{IMR} IMR_{it-1} + \pi^{T} Trend_j + \pi^{T2} Trend_j^2 + \pi_t + \pi_p, \quad (14)$$

where $\mathbb{1}_{Export,i,t-1}$ is a dummy variable that equals to 1 if firm i reports positive exporting value at year $t-1$. IMR_{it-1} is the inverse mills ratio to correct the survivor bias. $Trend_j$ and $Trend_j^2$ are the industry-specific linear and quadratic time trend. π_t and π_p are the year and province fixed effects.

Now I discuss three aspects of the specification of the productivity process. First, under this specification, both ownership and privatization can potentially change the levels of productivity process. In particular, there may be three effects on productivity process from the privatization: (a) Privatization directly affects productivity process through the term $\rho^{Privatized}\mathbb{1}_{Privatized,i,t-1}$. This is similar to a transitory shock in the productivity process. (b) Privatization changes the productivity with a permanent shift of the productivity level through $\rho^{After}\mathbb{1}_{After,i,t-1}$. This is similar to a permanent shock to the mean of the productivity process. (c) Except the above two channels, privatization indirectly changes future productivity via its effect on distortions.

Second, this specification allows both the lagged and current distortions τ_{it} entering the productivity process directly. Recall that firms know current distortions before they know current productivity with information set $\mathcal{I}_{it-1}$. Since there is a correlation between instantaneous productivity and distortions, firms can use current distortions as an additional variable to forecast current productivity. Third, the productivity

[12] This specification is similar to Brown et al. (2006) and Braguinsky et al. (2015).

innovation here is the part of the innovation that is uncorrelated with current distortion.[13]

5.2 Distortion Process

Distortions τ_{it} in the model measure the deviation from firm's first order condition. When $\tau_{it} > 0$ it means an implicit subsidy, and $\tau_{it} < 0$ it means an implicit tax. Therefore, potentially there are asymmetric effects from ownership and privatization on distortion process. I specify the distortions process to account for such asymmetric effects as follows

$$\begin{aligned}\tau_{it+1} = \mu^{\tau} + \sum_{n=1}^{N} \gamma_n^{\tau,c} \tau_{it}^n + \sum_{n=1}^{N} \gamma_n^{\tau,l} \tau_{it-1}^n + \\ \mathbb{1}_{\tau_{it} \le 0} \left(\rho_N^{\tau,SOE} \mathbb{1}_{i \in SOE,t-1} + \rho_N^{\tau,Privatized} \mathbb{1}_{Privatized,i,t-1} + \rho_N^{\tau,After} \mathbb{1}_{After,i,t} \right) + \\ \mathbb{1}_{\tau_{it} > 0} \left(\rho_P^{\tau,SOE} \mathbb{1}_{i \in SOE,t-1} + \rho_P^{\tau,Privatized} \mathbb{1}_{Privatized,i,t-1} + \rho_P^{\tau,After} \mathbb{1}_{After,i,t} \right) + \\ \phi^{\tau} \omega_{it-1} + \pi^{\tau} x_{it-1} + \eta_{it+1}^{\tau}. \quad (15)\end{aligned}$$

The first term is the intercept of the distortion process. The second and third terms capture the lagged and current distortions' contributions to the future distortions. The terms in the second and third lines of (15) reflect the asymmetric effects of ownership and privatization on the distortion process conditional on whether firm i at year t has implicit subsidy, i.e., $\tau_{it} > 0$ or it has implicit tax, i.e., $\tau_{it} \le 0$. The first term inside the parenthesis captures the effect of lagged state ownership $\mathbb{1}_{i \in SOE,t-1}$ on the distortion process. The second term captures the transitory effects of privatization $\mathbb{1}_{Privatized,i,t-1}$, and the third term reflects the permanent effect of privatization by $\mathbb{1}_{After,i,t}$. The last two terms capture the contribution of lagged productivity and other exogenous covariates on future distortions. The specification of control variables is the

[13] This is similar to David et al. (2015).

same as in the productivity process

$$\pi^\tau x_{it-1} = \pi^{\tau,Export} \mathbb{1}_{Export,i,t-1} + \pi^{\tau,IMR} IMR_{it-1} + \pi^{\tau,T} Trend_j + \pi^{\tau,T2} Trend_j^2 + \pi_t^\tau + \pi_p^\tau. \tag{16}$$

where the first term captures the correlation between distortions and exporting status. The second terms is the inverse mills ratio for survivor bias. The thid and fourth terms are the industry-specific linear and quadratic time trend. π_t and π_p are the year and province fixed effects.

Unlike the productivity process, there are a particular aspect of the specifications of distortion process worth discussing here. Under this specification, both ownership and privatization can potentially change the persistence and levels of distortion processes, conditional on whether the firm is being implicitly taxed or subsidized. In particular, there may be four effects on distortion processes from the privatization: (a) Privatization directly affects distortion process through the terms $\mathbb{1}_{Privatized,i,t-1}\mathbb{1}_{\tau_{it-1}\leq 0}$ and $\mathbb{1}_{Privatized,i,t-1}\mathbb{1}_{\tau_{it-1}>0}$. Conditional on the sign of τ_{it-1}, privatization acts like a transitory shock in the distortions processes. (b) Privatization changes future distortions with a permanent shift of the distortion level through $\mathbb{1}_{After,i,t-1}\mathbb{1}_{\tau_{it-1}\leq 0}$ and $\mathbb{1}_{After,i,t-1}\mathbb{1}_{\tau_{it-1}>0}$, conditional on the sign of τ_{it-1}. This is similar to a permanent shock to the mean of the productivity process. (c) Except the above two channels, privatization indirectly changes future distortions via its effect on productivity.

6 Results

This section presents the results in four steps: Section 6.1 reports the joint estimation results of productivity process and revenue function parameters. Section 6.2 reports the estimation results of distortion process and the correlation between the estimated productivity and distortions. Section 6.3 decomposes the effects of privatization on productivity and distortions at firm level. Section 6.4 presents the decomposition results of aggregate productivity growth.

6.1 Estimation Results of Productivity Process

I start with the joint estimation results for productivity process and revenue function parameters. I then report the cross-sectional results for productivity distributions.

I estimate separate revenue functions for 28 two-digit manufacturing industries.Table 4 reports the estimates of the parameters in revenue function and productivity process for select industries. Column (1) - (5) report the estimation results for the five largest two-digit manufacturing industries.[14] They are Food Processing (13), Textile (17), Raw Chemical and Chemical Products (26), Nonmetal Mineral Products (31), and Ordinary Machinery (35). Column (6) reports the estimation results for all firms across all 28 industries. In addition, I include industry fixed effects in the estimation in column (6).

Table 4 is here.

I now discuss the estimates that have substantive implications. First, the revenue elasticities of capital, labor and material (i.e., $\theta_k, \theta_l, \theta_m$) vary across industries. On average, elasticities of capital, labor and material range from 0.04 to 0.10, 0.08 to 0.18, and 0.60 to 0.74 respectively. In particular, textile (13) has the highest material elasticity and lowest capital elasticity comparing to the other 4 industries listed in Table 4.

Second, there is a positive effect of privatization on productivity process. Since the estimates $\rho^{Privatized}$–the coefficient associated with the privatization dummy–in Column (6) indicates the overall effect is 0.093, and the average productivity is around 2, the transitory shock to productivity is about 4.65%. Notice that the coefficient associated

[14] The top five largest two-digit industries are defined in terms of the number of observations.

with SOE dummy $\rho^{SOE} = -0.09$, which means the productivity of a SOE firm is 0.09 lower than that of an average private firm. The coefficient associated with the after privatization dummy $\rho^{After} = -0.02$ suggests that the privatized firms on average are less productive comparing to the private firms. The difference between ρ^{After} and ρ^{SOE} indicates a permanent increase in productivity for the firms that are privatizated.

Third, the estimated γ_1, γ_2, and γ_3 infer that productivity process is persistent. Therefore, the permanent increase of productivity induced by privatization benefits the privatized firms for all the following periods. The higher the persistence level of the productivity process, the larger the effects from privatization.

Fourth, $\pi^{Exporting}$ captures the correlation between productivity and exporting status. Whether the correlation is positive or negative depends on the industry that the firm belongs to. For instance, the correlation is negative in Textile (13), and positive in Ordinary Machinery (35).[15]

Finally, the estimated ϕ implies that lagged distortions contribute positively to the productivity process. Larger lagged implicit subsidy (tax) is associated with higher (lower) current productivity. The estimated α suggests that the current distortion is negatively correlated with the current productivity. A more productive firm is more likely to have implicit tax instead of implicit subsidy. Consistent with Restuccia and Rogerson (2008), this result suggests that potentially there are large gain from resource reallocation.

To summarize, the estimation of the productivity process suggests that privatization does improve the productivity of the privatized firms by a transitory shock and a permanent increase in productivity. The size of improvement is significant: it immediately realizes a 5% of the productivity increase, which is equivalent to the annual growth rate of the manufacturing sector in China. Since the productivity process is persistent, privatization has long run implications in productivity.

[15]The estimates are consistent with the explanation in Lu (2010) that exporting firms are less productive in high labor intensity industries.

Now turn to the cross sectional distribution of productivity. I decompose productivity based on different firm characteristics such as ownership and geographic differences.[16] Figure 7 depicts the estimated productivity distributions conditional on ownership (left) and economic regions (right). It is consistent with the estimation results that private firms are more productive comparing to the SOE firms. In particular, firms in Eastern region are more productive than firms in other regions.

Figure 7 is here.

6.2 Estimation Results of Distortion Process

In section 6.1, I jointly estimate the distortions, productivity and revenue function. In this section, I discuss the estimation results of distortion process. Using the estimated distortions, I first estimated the parameters in distortion process. I then report the cross-sectional results for distortions. Finally I present the correlation results between estimated productivity and distortions.

Beginning with the time-series regression, table 5 reports the estimation results for the distortion process. I separably report estimates for the top five largest industries in column (1)-(5), and report the estimates for all the firms in column (6).

Table 5 is here.

There are two aspects of the estimation results. First, SOE firms have larger distortions comparing to private firms. The estimated $\rho_P^{\tau,SOE}$ and $\rho_N^{\tau,SOE}$ capture the asymmetric effects of lagged state ownership on distortions when firms have implicit tax (i.e., $\tau_{it} \leq 0$) and implicit subsidy (i.e., $\tau_{it} > 0$), respectively. The estimated $\rho_P^{\tau,SOE}$ is 0.036. This implies that when restricting at firms with positive implicit subsidy at year t, SOE firms have higher implicit subsidy comparing to private firms. This effect is significant in almost all the industries and in the regression for all the firms. On the

[16] See discussions in Hsieh and Klenow (2009) and Brandt, Tombe, and Zhu (2013).

other hand, the estimates of $\rho_N^{\tau,SOE}$ is 0.041 for all the firms, which suggests that SOE firms do have significantly higher implicit tax when restricting to firms with implicit tax at year t.

Second, the estimated $\rho_N^{\tau,Privatized}$ and $\rho_P^{\tau,Privatized}$ capture the asymmetric transitory effects of privatization on distortions when firms have implicit tax and subsidy, respectively. Overall, it suggests that privatization lowers the implicit subsidy and tax but these effects vary across industries. The estimates for all the firms in column (6) suggest that privatization results in an immediate 0.08 reduction of the implicit tax and a 0.02 reduction of the implicit subsidy. Notice that the implicit tax (subsidy) for privatized firm at one year before privatization is 0.38(-0.38). These estimates result in a 5% decrease of the implicit subsidy and a 20% decrease of the implicit tax, respectively. However, the regressions for individual industries suggest less significant results. Weighted by the number of firms with implicit tax or subsidy, privatization reduces distortions about 2%. And if we immediately reduce the distortions by 2% on material usage and assume dynamic inputs are fixed, the reduction of distortions results in a 0.2% in terms of total revenue. Therefore, even though in the overall regressions there are statistical significant effects of privatization on distortions, the economic effects are at best second-order. I further estimate the productivity and distortion effects using propensity score matching in appendix B. The matched results produce similar patterns.

To summarize, the estimation of the distortion process suggests that privatization does improve the distortions of the privatized firms by a transitory shock and a permanent shift in distortions. It results in significant reduction of implicit tax and subsidy faced by those privatized firms. The magnitudes of the effects are large, especially for firms with implicit tax.

I then turn to the cross-sectional distributions of distortions. Figure 8 depicts the estimated distortion distributions conditional on ownership (left) and economic regions (right). In the sample, most of the observations are associated with implicit subsidy, while only a small fraction of the observations is associated with implicit tax. Moreover, it is consistent with the time-series estimation results that SOE firms have more dispersed distortion comparing to private firms. Last, firms in Eastern region have higher implicit subsidy than other regions.

Figure 8 is here.

I further correlate the estimated distortions with firm characteristics like ownership, exit dummy, exporting status and subsidy dummies. I regress the value and the absolute value of distortions $|\tau_{it}|$ on firm characteristics while controlling for firm level covariates including firm size, age, age square, year fixed effect, region fixed effect and industry fixed effect. Table 6 reports these estimates. These results suggest that a) the exit firms have larger absolute value of distortions; b) similar to the previous results, SOE firms have larger dispersion of distortions; c) exporting firms have smaller absolute value of distortions, and d) the subsidy dummy correlates positively with the level of distortion measure, which validates the implicit subsidy explanation when $\tau_{it} > 0$.

Table 6 is here.

Finally I analyze the correlation between productivity and distortions at the micro-level. Restuccia and Rogerson (2008) suggests that with uncorrelated distortions with productivity, the welfare consequences of distortions are relative small. With correlated distortions, there is a larger potential gain to remove distortions. Figure 9 plots micro level productivity and distortions by industry. It is quite obvious that productivity are negatively correlated with distortions, i.e., more productive firms face implicit tax, and less productive firms in general receives implicit subsidies.

Figure 9 is here.

6.3 Privatization on Distortions and Productivity

I decompose the effects of privatization on privatized firms' productivity and distortions in this section. To do that, I take a balanced sample firms that were eventually privatized within the sample period. This sample consists of 4000 firms from 1998 to 2007, which is about half of the privatized firms in the full sample. During the sample period, these firms experienced significant productivity growth. The median productivity is 2.19 in 1998 and 2.61 in 2007. The firm level distortions also change significantly. The median distortion is 0.23 and standard deviation is 0.42 in 1998. In 2007 they change to 0.19 and 0.37, respectively.

Next, I conduct counterfactual experiments on the productivity and distortion process. I compare the realized productivity and distortion distributions to the counterfactual distributions. The first and second counterfactual experiments alter the timing of privatization to see how productivity and distortion distributions would change. Specifically, the first counterfactual experiment asks what would change if there is no firm privatized. The second counterfactual experiment asks what would change if all SOE firms privatized at the beginning of the sample. The third counterfactual takes the timing of privatization as given, and decompose the effects of privatization into several components. Notice that privatization affects productivity and distortions via three effects: (a) The transitory effects captured by the privatization dummy $\mathbb{1}_{Privatized,i,t-1}$. (b) The permanent effects captured by the after dummy $\mathbb{1}_{After,i,t}$. (c) The indirect effects from lagged distortions and productivity. The third counterfactual asks how much do transitory, permanent and the indirect effect of privatization affect the end of sample productivity and distortions distributions. I report the counterfactual experiments as follows.

No Privatization I simulate the productivity and distortion process assuming privatization has no effects on both process. Alternatively this could be interpreted to have delayed privatization till end of the sample. Figure 12 left panel illustrates the counterfactual productivity and distortion distributions. It shows that without privatization, the productivity distribution shifts toward left with the median productivity drops from 2.61 to 2.31. This shows that privatization overall increase productivity by 14% for the privatized firms.However, even though the distortion distribution moves closer to 0, the optimal margin revenue equals marginal cost case, privatization does not contribute significantly to the reduction of distortions. Therefore, the productivity effects is much more important comparing to the reallocation effects from privatization.

Early Privatization I then alter the timing of privatization for these eventually privatized firms. The fractions of privatized firms are quite smooth over year: With on average 500 firms per year are privatized between 1998 to 2003, and 200 firms per year between 2004 to 2006. Figure 12 right panel illustrate the counterfactual productivity and distortion distributions when every firm in this sample is privatized at 1998. The overall productivity distribution shifts to the right with median productivity increases from 2.61 to 2.70. This suggests that early privatization would bring additional 4% of productivity. Similar to the previous counterfactuals, altering the timing of privatization does not results in significant change of distortion distributions.

This results highlight the differences between the effects of privatization on productivity and distortion process. In productivity process, the transitory component is significant and the timing of privatization contributes significantly to the productivity process. Here though the estimates suggest a statistical significant result from privatization on distortions, the decomposition results suggest that the reduction of distortions may be driven by factors other than distortions.

Decompose Privatization in Productivity Process The counterfactual results indicate that the timing of privatization does matter since the productivity process is persistent and privatization has both significant transitory and permanent effects on productivity. In the final counterfactual, I further decompose the contributions from the transitory and permanent components while fixing distortions and the true privatization timing.

Conditional on the true privatization date, I decompose the productivity gain from privatization into various components. From the section 5, there are three main channels: a) privatization acts as an transitory shock; b) privatization shifts the mean productivity; c) privatization changes the persistence of productivity process. To see how much the transitory component contributes to the productivity, I conduct additional two counterfactual experiments. The first one is to set $\mathbb{1}_{Privatized,i,t-1} = 0$ to shut down the transitory component. Figure 13 left panel depicts the counterfactual productivity distribution, with the median productivity is about 2% lower from 2.61 to 2.55. The second one is to set $\mathbb{1}_{After,i,t} = 0$ to shut down the permanent effect. Figure 13 right panel depicts this counterfactual productivity distribution. Even with the transitory component, the mean productivity drops significantly: it changes from 2.61 to 2.36, which is about a 10% decrease in mean productivity. The decomposition results suggest that the permanent effects accounts for over 80% of total privatization effects on productivity, whereas the rest 20% comes from the transitory component.

Figure 13 is here.

To summarize, when holding distortions the same, privatization affects firm level productivity the most by shifting the mean of the productivity process. The transitory component, though with a smaller magnitude, still contributes significantly to the productivity distribution. These two effects, joint with the persistence of productivity shape the realized productivity distribution at 2008.

6.4 Aggregate Productivity Decomposition of Reallocation

To understand the effect of privatization on aggregate productivity growth (APG), I extend the decomposition method proposed by Melitz and Polanec (2015) and Collard-Wexler and Loecker (2015) to explicitly account for the change in ownership. I then apply this method using the estimated productivity to decompose the APG in the data from 1999 to 2007.

Denote $\triangle\Omega$ the aggregate productivity growth between 1999 and 2007 in the sample. I show in appendix C that the aggregate productivity growth can be decomposed into various components using the following formula

$$\triangle\Omega = \frac{1}{2}\sum_{\phi}\Bigg[\underbrace{\triangle\bar{\omega}_t(\phi)}_{\text{Productivity Growth}} + \underbrace{\triangle\Gamma_t^{OP}(\phi)}_{\text{Reallocation Within Ownership}}\Bigg] + \underbrace{\triangle\Gamma_t^{B}}_{\text{Reallocation Between Ownership}} + \underbrace{\triangle\Gamma_t^{T}}_{\text{Transition Between Ownership}} + \underbrace{s_{E2}(\Omega_{E2} - \Omega_{S2})}_{\text{Entry}} + \underbrace{s_{X1}(\Omega_{S1} - \Omega_{X1})}_{\text{Exit}}. \quad (17)$$

Denote ϕ the index of ownership with $\phi = 1$ for SOE firms and $\phi = 0$ for private firms. The first term on the RHS captures the average within firm productivity improvement denoted as $\triangle\bar{\omega}_t(\phi)$, and reallocation effects within the particular ownership as $\triangle\Gamma_t^{OP}(\phi)$. The second term captures the reallocation between the two ownerships, denoted as $\triangle\Gamma_t^{B}$. And the third term $\triangle\Gamma_t^{T}$ captures the direct contribution from ownership switches to the aggregate productivity growth. The fourth and fifth terms capture the contributions from entry and exit, respectively. And notice that this decomposition uses the survivor groups to benchmark the entrants and exiters. I use the employment share as weight s_{it} in this exercise.[17]

[17] Collard-Wexler and Loecker (2015) uses market share for the weight. Here since I use revenue productivity, I use a specific production factor for the weight. The results are similar using other production factor or revenue.

Table 7 shows the decomposition results for the aggregate productivity growth using equation 17. There are three main results from this decomposition exercise.

Table 7 is here.

First, there is a large aggregate productivity growth within the manufacturing sector in the sample. During 1998 to 2007, the APG within the sample is 58%, which translates to a 5.2% annual growth rate.

Second, further decompose the productivity within each ownership, I find an average SOE firm became 44 percent more productive between 1999 and 2007. In addition, within the state sector, reallocation toward more-productive firms contributes positively but much less in terms of magnitude: It only accounts for 2 percent the increase of aggregate productivity. In the meanwhile, an average private firm became 37 percent more productive, which is lower than an average SOE firm.[18] However, the reallocation process plays a large role within the private sector. The reallocation within the private sector contributes nearly 10% of the aggregate productivity growth. Overall, this finding indicates that during the transition period, within firm productivity growth dominates the reallocation process in aggregate productivity growth.

Third, I find that the between-ownership reallocation component contributes negatively to the aggregate productivity growth. In 1998, the between covariance was 0.5 percent. However, it changes to -6 percent at the end of the sample.

Fourth, firm dynamics is still an important source of aggregate productivity growth. In total it contributes 6 percent to the aggregate productivity growth. However, the exit margin contributes positively and entry margin contributes negatively. This is a general feature of Melitz and Polanec (2015) as we use survivors as benchmark. The results suggest that the exiters are inferior in terms of their productivity, and so as the entrants.[19]

[18] Song and Hsieh (Forthcoming) also found similar patterns using different approach.

[19] The results are consistent with recent paper by Garcia-Macia, Hsieh, and Klenow (2015). However,

Fifth, privatization alone accounts for 4 percent in the aggregate productivity growth. Given in the sample there are over 8000 firms are privatized and only half of them are presented in the decomposition analysis, this number is large. From the previous discussion, privatization affects aggregate productivity mainly through its impact on firm-level productivity.

To summarize, privatizations contribute to the aggregate productivity growth mainly through their direct impact on firm level productivity. The decomposition results show that while within firm technology improvements account for more than 80% of aggregate TFP growth, the privatizations accounted for almost all of the contributions from the transition firms. Given that only a limited number of firms are privatized, there is a fairly sizeable gain associated with the policy. In contrast, although the privatizations also reduce revenue distortions, the associated reallocation gains only contribute a small fraction to overall TFP growth.

7 Misallocation: Distortions or Dynamic Inputs?

The analysis can also address an important question in the misallocation literature: How to measure distortions? Literature typically uses the dispersion of Marginal Revenue Product of Capital (henceforth MRPK) to measure distortions. (See Hsieh and Klenow (2009).) But Asker et al. (2014) argues that, when capital is a dynamic input, even in a distortion-free economy, dispersion in productivity contributes to the dispersion in MRPK. This implies that the dispersion of MRPK may not be a good measure of distortions with dynamic inputs.

Since my framework allows both distortions and dynamic inputs, I can address how much the dispersion of MRPK can be attributed to the distortions with dynamic inputs. Notice that I estimated productivity innovation and distortions in Section 6.1.

notice that I am using revenue productivity, the inferior productivity could be due to the low prices entrants charge, but not their quantity productivity.

Once I construct the measure of MRPK, I can evaluate how productivity innovation and the dispersion of distortions influence the dispersion of MRPK. Now I discuss how I measure MRPK.

Follow Asker et al. (2014), I measure the firm-year level MRPK as follows

$$MRPK_{it} = \log(\theta_k) + r_{it} - k_{it}, \tag{18}$$

where r_{it} is log revenue, k_{it} is log capital, and θ_k is the underlying revenue elasticity for capital.

Then for each industry-year, I compute the the dispersion of MRPK. Notice that the term $\log(\theta_k)$ of Equation (18) is a constant for industry level data. Thus, when I compute the dispersion of MRPK, it is equivalent to compute the unadjusted firm-year level MRPK

$$MRPK^U_{it} = r_{it} - k_{it}.$$

Figure 10 illustrates how productivity innovation (i.e., the volatility of TFPR) and the dispersion of distortions correlate with the distortion of MRPK. Each dot on the graph representing a specific industry year pair, and the size of the dot reflects the relative weights by total revenue of this particular industry year combination. The red solid line is an unweighted linear fitting line, and the blue dash line is an weighted linear fitting line. The left graph suggests that the dispersion MRPK is positively correlated to productivity innovation. The right suggests that the dispersion of MRPK is also positively correlated to the dispersion of distortions .

Figure 10 is here.

Next, I regress the dispersion of MRPK on productivity innovation and dispersion of distortions. I include industry and year fixed effects to control for other potential differences across industries and years. Table 8 reports the regression results. The first two columns present the regression results of dispersion of MRPK on productivity innovation. The last two columns present the regression results of dispersion of MRPK on dispersion of distortions. The results show that both productivity innovation and the dispersion of distortions have a positive effect on the dispersion of MRPK.

Table 8 is here.

The fact that there is a significant positive relationship between the dispersion of MRPK and productivity innovation is consistent with the result in Asker et al. (2014). This implies that, at industry level, productivity innovation does feed into dispersion of MRPK. Therefore, dynamic inputs are important factors contributing to the dispersion of MRPK. But this does not necessary imply that dispersion of distortions does not contribute to dispersion of MRPK. In fact, the dispersion of MRPK does indicate distortions. I now explain the evidence.

Figure 11 plots the relationship between dispersion of distortions and productivity innovation. It shows that there is a significant positive relationship between the two. Thus, in the region with higher value productivity innovation, there is larger dispersion of distortions. This fact provides a rationale to support the idea that unproductive firms survive because they receive more implicit subsidy, i.e., larger τ_{it}. To this end, these regression results clearly suggest that the dispersion of MRPK can provide information on both productivity and distortions, and these two channels are not mutually exclusive. To sum up, the results are consistent with both Hsieh and Klenow (2009) and Asker et al. (2014): First, the dispersions of MRPK do indicate distortions in the economy. Second, productivity innovation indeed amplifies dispersion of MRPK. In total, these two forces could explain a large proportion of dispersion in MRPK in the data.

Figure 11 is here.

8 Conclusion

This paper investigates the effects of privatization on productivity and distortions at both firm and aggregate levels. To do so, the paper first provides a novel method to identify and jointly estimate distortions, productivity and production function parameters from a standard production dataset. Next it goes on to provide evidence on the direct effects of privatization. Finally, the results suggest that aggregate productivity growth is mainly driven by the productivity improvement within firms. Despite much privatization, state-owned sector has grown faster relatively to private sector.

The results indicate that privatization does have large implications for productivity and distortions. The transitory and permanent increases of productivity after privatization stand out to be the most important forces that shape both firm-level and aggregate outcomes. Though it reduces distortions at firm level, the effects from distortions are quite limited in the data.

There are many caveats required in this paper. First, in this paper I only allow firm-year level idiosyncratic output distortions. That is, the distortions move firm's marginal revenues away from its marginal costs for all inputs to the same extent. However, there are large capital and labor distortions at firm year level in China as well. Since the current model only employs first order condition from the static input, it is possible to allow both capital and labor distortions.

Second, the framework in this paper could be applied to other policies, for instance, trade liberalization, subsidy program and government regulations. In doing so, it articulates the trade off of implementing certain policy–productivity enhancing and distortion reduction.

Third, there are many interpretations for the deviation of the firm level first order conditions: Different technologies, measurement error, dispersed input prices and many others. This paper emphasizes one particular interpretation: the output distortions. To account for other plausible sources that lead to similar findings is an important topic for future research.

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Appendix A General Identification

A.1 Derivation of Equation (12)

In this case, we have both dynamic and static inputs, together with exogeneous covariates in the productivity process. There are four equations at hand

$$
\begin{aligned}
r_{it} &= \theta_l l_{it} + \theta_k k_{it} + \theta_m m_{it} + \omega_{it} && (19)\\
\omega_{it} &= \mu + \gamma\omega_{it-1} + \alpha\tau_{it} + \pi x_{it-1} + \eta_{it} && (20)\\
\ln p_t^M &= \ln\theta_m + (\theta_m - 1)m_{it} + \theta_k k_{it} + \theta_l l_{it} + \omega_{it} + \tau_{it} && (21)\\
\ln s_{it} &= \ln\theta_m + \tau_{it} && (22)
\end{aligned}
$$

Using the above four equations (19), (20), (21), and (22), I derive the reduced form representation of (12)

$$
\begin{aligned}
r_{it} = \; & \theta_k k_{it} + \theta_l l_{it} + \theta_m m_{it} + \omega_{it}\\
= \; & \frac{\theta_k}{1-\theta_m}k_{it} + \frac{\theta_l}{1-\theta_m}l_{it} + \frac{\theta_m}{1-\theta_m}(\omega_{it}+\tau_{it}) + \omega_{it} + \text{Constant}\\
= \; & \frac{\theta_k}{1-\theta_m}k_{it} + \frac{\theta_l}{1-\theta_m}l_{it} + \frac{1}{1-\theta_m}\omega_{it} + \frac{\theta_m}{1-\theta_m}\tau_{it} + \text{Constant}\\
= \; & \frac{\theta_k}{1-\theta_m}k_{it} + \frac{\theta_l}{1-\theta_m}l_{it} + \frac{\pi}{1-\theta_m}x_{it-1} + \frac{\alpha+\theta_m}{1-\theta_m}\tau_{it} + \frac{\gamma}{1-\theta_m}\omega_{it-1} + \frac{1}{1-\theta_m}\eta_{it} + \text{Constant}\\
= \; & \frac{\theta_k}{1-\theta_m}k_{it} + \frac{\theta_l}{1-\theta_m}l_{it} - \frac{\gamma\theta_k}{1-\theta_m}k_{it-1} - \frac{\gamma\theta_l}{1-\theta_m}l_{it-1} + \frac{\pi}{1-\theta_m}x_{it-1} +\\
& \frac{\alpha+\theta_m}{1-\theta_m}\tau_{it} - \frac{\gamma}{1-\theta_m}\tau_{it-1} + \gamma m_{it-1} + \frac{1}{1-\theta_m}\eta_{it} + \text{Constant}\\
= \; & \frac{\theta_k}{1-\theta_m}k_{it} + \frac{\theta_l}{1-\theta_m}l_{it} - \frac{\gamma\theta_k}{1-\theta_m}k_{it-1} - \frac{\gamma\theta_l}{1-\theta_m}l_{it-1} + \frac{\pi}{1-\theta_m}x_{it-1} +\\
& \frac{\alpha+\theta_m}{1-\theta_m}\ln s_{it} - \frac{\gamma}{1-\theta_m}\ln s_{it-1} + \gamma m_{it-1} + \frac{1}{1-\theta_m}\eta_{it} + \text{Constant}.
\end{aligned}
$$

The identification follows Proposition 3 in the main text.

A.2 Link to Structural Estimation

I produce a generalized method of moment estimator to estimate the production function with unobserved distortions. This links the reduced form representation with the general structural approach proposed by Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2006).

In the reduced form representation of revenue, equation (12), the error term is $\eta_{it}/(1-\theta_m)$, a scaled version of the productivity innovation. Since I assume that $\eta_{it} \perp \Gamma_{it}$, this leads to an alternative estimation strategy: First guess $\{\theta_k, \theta_l, \theta_m\}$, we can compute the productivity conditional on the parameters as

$$\omega_{it}(\theta_k, \theta_l, \theta_m) = r_{it} - \theta_k k_{it} - \theta_l l_{it} - \theta_m m_{it}$$

Second, we can then derive the implied productivity innovation $\eta_{it}(\theta_k, \theta_l, \theta_m)$ from a AR(1) regression.

$$\omega_{it}(\theta_k, \theta_l, \theta_m) = \mu(\theta_k, \theta_l, \theta_m) + \gamma(\theta_k, \theta_l, \theta_m)\omega_{it-1}(\theta_k, \theta_l, \theta_m) + \alpha \ln s_{it} + \eta_{it}(\theta_k, \theta_l, \theta_m)$$

and obtain the estimates of productivity innovation $\hat{\eta}_{it}(\theta_k, \theta_l, \theta_m)$.

Finally we can construct moments implied by the markovian assumption of productivity process, i.e.,

$$\mathbb{E}\left[\hat{\eta}_{it}\left(\theta_k, \theta_l, \theta_m\right) \middle| \begin{array}{c} k_{it} \\ l_{it} \\ m_{it-1} \\ k_{it-1} \\ l_{it-1} \\ \ln s_{it} \\ \ln s_{it-1} \end{array}\right] = 0$$

Notice that the last two moments are the keys to identify all parameters of interests. Without these two instruments, the collinearity problem addressed by Gandhi et al. (2012) arises. The structural estimation shares very much the same intuition with the reduced form approach, and yields quite similar statistical properties in the simulation.

A.3 Beyond Cobb-Douglas

So far the identification seems to be heavily relied on the Cobb-Douglas form of production function. Here I extend the identification to allow for higher order polynomials to approximate the production function that is similar to Gandhi et al. (2012). I illustrate the identification using a second order approximation of the production function

$$r_{it} = \theta_m m_{it} + \theta_{mm} m_{it}^2 + \omega_{it}$$

and keep the same setting as in the illustration of identification section.

Using the structural form of estimation, given $\{\theta_m, \theta_{mm}, \mu, \gamma, \alpha\}$, the productivity innovation is

$$\eta_{it} = y_{it} - \theta_m m_{it} - \theta_{mm} m_{it}^2 - \mu - \gamma\left(y_{it-1} - \theta_m m_{it-1} - \theta_{mm} m_{it-1}^2\right) - \alpha\tau_{it}$$

There are two sets of instruments: the observed instruments m_{it-1}, m_{it-1}^2 and unobserved instruments τ_{it}, τ_{it-1}, and their interaction terms with lagged material $\tau_{it} m_{it-1}$ and $\tau_{it-1} m_{it-1}$. The transformation of instrument is

$$\begin{aligned} s_{it} &= \tau_{it} + \ln(\theta_m + 2\theta_{mm} m_{it}) \\ s_{it-1} &= \tau_{it-1} + \ln(\theta_m + 2\theta_{mm} m_{it-1}) \end{aligned}$$

And the moment condition for both observed and unobserved instruments are

$$\mathbb{E}\left[\eta_{it}(\theta_m, \theta_{mm}, \mu, \gamma) \middle| \begin{array}{c} m_{it-1} \\ m_{it-1}^2 \end{array} \right] = 0$$

$$\mathbb{E}\left[\eta_{it}(\theta_m, \theta_{mm}, \mu, \gamma) \middle| \begin{array}{c} \tau_{it} \\ \tau_{it-1} \end{array} \right] = 0$$

However, the unobserved instruments contain unknown parameters of interests. Since exp() is a strict monotone transformation of τ_{it}, $\exp(\tau_{it})$ is a valid instrument as well. The GMM with transformed unobserved instruments are

$$\mathbb{E}\left[\eta_{it}(\theta_m, \theta_{mm}, \mu, \gamma) \middle| \begin{array}{c} \exp(\tau_{it}) \\ \exp(\tau_{it-1}) \end{array} \right] = 0$$

Notice that

$$\tau_{it} = s_{it} - + \ln(\theta_m + 2\theta_{mm} m_{it})$$
$$\tau_{it-1} = s_{it-1} - + \ln(\theta_m + 2\theta_{mm} m_{it-1})$$

and

$$\exp(\tau_{it}) = \frac{\exp(s_{it})}{\theta_m + 2\theta_{mm} m_{it}}$$
$$\exp(\tau_{it-1}) = \frac{\exp(s_{it-1})}{\theta_m + 2\theta_{mm} m_{it-1}}$$

We can transform the moment condition such that

$$\eta_{it} \exp(\tau_{it}) = \frac{\eta_{it} \exp(s_{it})}{\theta_m + 2\theta_{mm} m_{it}} = \tilde{\eta}_{it} \exp(s_{it})$$
$$\eta_{it} \exp(\tau_{it-1}) = \frac{\eta_{it} \exp(s_{it-1})}{\theta_m + 2\theta_{mm} m_{it-1}} = \hat{\eta}_{it} \exp(s_{it-1})$$

with

$$\tilde{\eta}_{it} = \frac{\eta_{it}}{\theta_m + 2\theta_{mm} m_{it}}$$
$$\hat{\eta}_{it} = \frac{\eta_{it}}{\theta_m + 2\theta_{mm} m_{it-1}}$$

We now have three moment conditions

$$\mathbb{E}\left[\eta_{it}(\theta_m, \theta_{mm}, \mu, \gamma) \middle| \begin{array}{c} m_{it-1} \\ m_{it-1}^2 \end{array} \right] = 0$$

and

$$\mathbb{E}\left[\tilde{\eta}_{it}(\theta_m, \theta_{mm}, \mu, \gamma) \middle| \exp(s_{it}) \right] = 0$$

and

$$\mathbb{E}\left[\hat{\eta}_{it}(\theta_m, \theta_{mm}, \mu, \gamma) \middle| \exp(s_{it-1}) \right] = 0$$

Therefore, by transforming the moment conditions, the identification is still valid when extending to higher order polynomials.

Appendix B Matching Results for Productivity and Distortion Process

The estimated results in section 6.1 relies on cross year and provinces variations to identify the effects from privatization on productivity and distortions. The identification of the revenue function only requires that the unpredictable components of the productivity process is orthogonal to any elements in the firm's information set, which includes privatization. To alleviate potential selection issue, following Braguinsky et al. (2015) and ?, I rely on the propensity score matching for those privatized firms, and investigate the productivity and distortion effects in that sample.

I matched the privatized firms i which is privatized at year $t-1$ with SOEs that are not privatized on year $t-1$ or t from the same industry, region and exporting status, and with similar employment, productivity and distortion parameters. There are some privatized firms that the I cannot find matches. Finally I have a matched sample with 15279 observations. Table 9 compare the pre-privatized and post-privatized characteristics. The matched sample is much closer to the privatized sample comparing to any SOEs.

Table 9 is here.

This result suggests that privatization increases the productivity of the privatized firms comparing to a group of control firms that share similar firm level characteristics. The magnitude of the effect is about 4%, which is close to the estimated effect of privatization on productivity in section 6.1. However, the effect of privatization on distortions are insignificant, which is also consistent with the results in section 6.2. I further plot the mean productivity and mean absolute value of distortions around the privatization window in Figure 14.

Appendix C Decomposition with Ownership Switches

Olley and Pakes (1996) first decomposes the aggregate productivity, defined as a market share weighted productivity, into a industrial mean productivity and a covariance term between firm sizes and productivity. Bartelsman, Haltiwanger, and Scarpetta (2013) uses this approach to highlight the usage of the covariance term in approximating distortions across countries. Following Olley and Pakes (1996) and Melitz and Polanec (2015), I consider group-wide aggregate productivity within an industry. Define the aggregate market share of a group G of firms

$$s_{Gt} = \sum_{i \in G} s_{it}$$

where s_{it} is the market share of firm i at year t, and firm i belongs to group G at year t. The group aggregate (average) productivity is defined as

$$\Phi_{Gt} = \sum_{i \in G} \frac{s_{it}}{s_{Gt}} \phi_{it}$$

In the original Melitz and Polanec (2015), there are only three groups in the two cross sectional data for year t and year t', and with out loss of generality I assume $t' > t$. The first group S is for survivors, which could be found in both year t and t' data. The second group X is for exiters, which could only be found in year t's data. And the third group E is for entrants, which could only be found in year t''s data. Therefore we can decompose the aggregate productivity into group aggregate productivity

$$\begin{aligned}\Phi_t &= s_{St}\Phi_{St} + s_{Xt}\Phi_{Xt} = \Phi_{St} + s_{Xt}\left(\Phi_{Xt} - \Phi_{St}\right) \\ \Phi_{t'} &= s_{St'}\Phi_{St'} + s_{Et'}\Phi_{Et'} = \Phi_{St'} + s_{Et'}\left(\Phi_{Et'} - \Phi_{St'}\right)\end{aligned}$$

Following Melitz and Polanec (2015), the decomposition uses the survivors group as the benchmark for entrants and exiters, which is the key differences comparing to other decomposition method like Baily, Hulten, and Campbell (1992), Griliches and Regev (1995) and Foster, Haltiwanger, and Krizan (2001).

I then rewrite the aggregate productivity change between t' and t as the differences within the survivor group and entry and exit components. I can then further decompose the survivors components to an average productivity shift term and a difference in reallocation term within survivors using Olley and Pakes (1996) decomposition.

$$\begin{aligned}\triangle\Phi &= \underbrace{(\Phi_{St'} - \Phi_{St})}_{\text{Survivors}} + \underbrace{s_{Et'}(\Phi_{Et'} - \Phi_{St'})}_{\text{Entrants}} + \underbrace{S_{Xt}(\Phi_{St} - \Phi_{Xt})}_{\text{Exiters}} \\ &= \underbrace{\triangle\bar{\phi}_S}_{\text{Productivity shift}} + \underbrace{\triangle cov_S}_{\text{Reallocation}} + \underbrace{s_{Et'}(\Phi_{Et'} - \Phi_{St'})}_{\text{Entrants}} + \underbrace{S_{Xt}(\Phi_{St} - \Phi_{Xt})}_{\text{Exiters}}\end{aligned}$$

To address the transitions from State-owned firms to private firms, as well as the reallocation effects within each ownership during the transition period, I further build on Collard-Wexler and Loecker (2015) to decompose the reallocation effects among survivors to finer groups, state-owned firms and non state-owned firms. Following Collard-Wexler and Loecker (2015), for survivors with ownership $\phi \in (State, Non-State)$, I define the within-ownership aggregate productivity as

$$\begin{aligned}\Omega_t^S &= \sum_{\phi} s_t(\phi)\left(\bar{\omega}_t(\phi) + \sum_{i\in\phi}(\omega_{it} - \bar{\omega}_t(\phi))(s_{it} - \bar{s}_t(\phi))\right) \\ &= \sum_{\phi} s_t(\phi)\left(\bar{\omega}_t(\phi) + \Gamma_t^{OP}(\phi)\right)\end{aligned}$$

where $\bar{\omega}_t(\phi)$ is the average of productivity of group ϕ at year t, and $\Gamma_t^{OP}(\phi)$ is a OP covariance term within ownership ϕ at year t.

Similar, the Between-Ownership Decomposition for the survivors without transition in ownership is as follows: I focus on those firms which are survivors and do not have an ownership switch between t and t'. Denote $\bar{\Omega}_t = \frac{1}{2}\sum_\phi \Omega_t(\phi)$, which is the average productivity for those firms across ownerships. The aggregate productivity for those survivors (without ownership changes) is

$$\Omega_t^S = \bar{\Omega}_t + \sum_\phi \left(s_t(\phi) - 1/2\right)\left(\Omega_t(\phi) - \bar{\Omega}_t\right) = \bar{\Omega}_t + \Gamma_t^B$$

where Γ_t^B is the between-ownership term. Therefore, the aggregate productivity for survivors without a ownership change is defined as

$$\Omega_t^S = \frac{1}{2}\sum_\phi \left[\bar{\omega}_t(\phi) + \Gamma_t^{OP}(\phi)\right] + \Gamma_t^B$$

So far the exercise is quite similar to Collard-Wexler and Loecker (2015) except their focus is the technology and my focus is the ownership. The last piece is the contribution from those survivor firms which transit from state-owned to non-state-owned. Therefore, I decompose the survivor contribution into two components, first, the survivors that never change ownerships, and second, the survivors do change ownerships. To this end, the aggregate productivity growth is decomposed into eight components: Two within-ownership average productivity growth terms, two changes of within-ownership reallocation terms, one between ownership reallocation term, one between ownership transition term, and entry and exit components using survivor groups as benchmark.

$$\begin{aligned}\triangle\Omega =& \frac{1}{2}\sum_\phi \Bigg[\underbrace{\triangle\bar{\omega}_t(\phi)}_{\text{Productivity Growth}} + \underbrace{\triangle\Gamma_t^{OP}(\phi)}_{\text{Reallocation Within Ownership}}\Bigg] + \\ & \underbrace{\triangle\Gamma_t^B}_{\text{Reallocation Between Ownership}} + \underbrace{\triangle\Gamma_t^T}_{\text{Transition Between Ownership}} + \\ & \underbrace{s_{E2}(\Omega_{E2} - \Omega_{S2})}_{\text{Entry}} + \underbrace{s_{X1}(\Omega_{S1} - \Omega_{X1})}_{\text{Exit}}\end{aligned}$$

Appendix D Tables

Table 1 Privatization during 1999-2006, by industry.

This table shows the number of privatization events during 1999 to 2006 by two digit industrial classification. I record a firm i at year t with registration code 110 or 151 as a state-owned firm regardless of its capital composition. A firm i is privatized at year t if firm i is a state-owned firm at year t but a non-state-owned firm at year $t+1$. Industries are classified by 2-digit industrial classification code. I adopt the translation of industries from Bai et al. (2009).

Industry	ind	1999	2000	2001	2002	2003	2004	2005	2006	All Years
Food Processing	13	213	214	132	185	128	65	65	30	1032
Food Production	14	91	89	43	52	46	16	19	14	370
Beverage Production	15	100	89	55	61	54	17	17	11	404
Textile Industry	17	100	107	77	92	74	30	29	15	524
Garment and Other Fiber Products	18	13	21	5	12	11	11	6	4	83
Leather, Furs, Down and Related Products	19	14	11	6	5	4	5	2	1	48
Timber and Bamboo Processing	20	19	22	10	18	17	4	4	5	99
Furniture Manufacturing	21	9	3	2	5	2	0	2	1	24
Papermaking and Paper Products	22	38	36	20	48	43	10	11	5	211
Printing and Record Medium Reproduction	23	44	44	30	39	50	14	26	8	255
Cultural, Educational and Sports Goods	24	5	6	4	2	3	2	1	1	24
Petroleum Refining and Coking	25	11	23	14	11	16	9	10	6	100
Raw Chemical Materials and Chemical Products	26	180	172	112	154	156	45	57	31	907
Medical and Pharmaceutical Products	27	92	104	73	76	92	25	21	10	493
Chemical Fiber	28	5	8	8	5	7	3	3	1	40
Rubber Products	29	19	13	16	13	9	5	0	2	77
Plastic Products	30	29	20	18	22	19	5	5	8	126
Nonmetal Mineral Products	31	225	174	128	196	168	63	67	35	1056
Ferrous Metal Mining and Dressing	32	20	25	20	48	24	10	10	7	164
Nonferrous Metal Mining and Dressing	33	21	18	18	16	19	14	10	3	119
Metal Products	34	38	35	14	24	27	11	21	7	177
Ordinary Machinery	35	122	109	71	113	95	42	50	38	640
Special Purposes Equipment	36	94	96	67	88	84	24	43	16	512
Transport Equipment	37	78	88	57	83	92	30	59	31	518
Electric Equipment and Machinery	39	68	63	35	58	49	28	23	14	338
Electronic and Telecommunications	40	37	41	18	34	35	11	21	14	211
Instruments, meters, Cultural and Clerical Machinery	41	28	16	12	12	24	7	10	12	121
Other Manufacturing	42	9	7	7	4	3	2	4	0	36
Overall		1722	1654	1072	1476	1351	508	596	330	8709

Table 2 Privatization during 1999-2006, by provinces.

This table shows the number of privatization events during 1999 to 2006 by provinces. I record a firm i at year t with registration code 110 or 151 as a state-owned firm regardless of its capital composition. A firm i is privatized at year t if firm i is a state-owned firm at year t but a non-state-owned firm at year $t+1$. I group provinces into four regions, namely eastern, central, northeastern, and western.

Provinces	Region	1999	2000	2001	2002	2003	2004	2005	2006	All Years
Anhui	Central	105	46	42	48	37	23	23	8	332
Beijing	Eastern	15	81	18	26	57	18	37	27	279
Chongqing	Western	14	30	3	19	20	8	6	1	101
Fujian	Eastern	25	20	14	25	15	12	6	6	123
Gansu	Western	83	115	0	36	16	15	6	6	277
Guangdong	Eastern	226	89	30	55	74	26	40	26	566
Guangxi	Western	32	24	31	55	39	20	23	10	234
Guizhou	Western	13	13	10	28	29	12	10	10	125
Hainan	Eastern	1	2	1	9	16	0	6	2	37
Hebei	Eastern	77	75	65	70	65	37	41	19	449
Heilongjiang	Northeastern	61	34	35	46	23	18	17	9	243
Henan	Central	1	56	43	113	137	27	27	16	420
Hubei	Central	91	118	132	142	73	35	30	14	635
Hunan	Central	63	57	20	73	85	27	19	15	359
Inner Monglia	Western	47	10	15	24	14	5	8	6	129
Jiangsu	Eastern	236	153	152	159	99	25	37	22	883
Jiangxi	Central	47	95	56	61	23	13	17	5	317
Jilin	Northeastern	50	54	31	50	39	33	36	13	306
Liaoning	Northeastern	41	33	72	68	42	23	25	17	321
Ningxia	Western	12	11	4	1	5	7	4	1	45
Qinghai	Western	13	8	8	4	9	0	1	2	45
Shandong	Eastern	122	206	58	124	146	41	46	25	768
Shanghai	Eastern	54	42	42	33	88	22	28	13	322
Shannxi	Western	30	16	29	39	23	17	20	6	180
Shanxi	Central	31	26	42	33	31	10	27	12	212
Sichuan	Western	51	80	40	49	34	14	19	21	308
Tianjing	Eastern	10	18	0	20	19	8	22	9	106
Tibet	Western	2	9	0	4	1	0	0	0	16
Xinjiang	Western	36	14	15	24	20	2	4	0	115
Yunnan	Western	29	29	27	21	28	10	5	3	152
Zhejiang	Eastern	108	92	39	22	47	2	9	9	328
Overall		1726	1656	1074	1481	1354	510	599	333	8733

Table 3 Summary Statistics

Variable	Observations	Mean	Std	Min	Max
r_{it}	1377735	9.982	1.424	-0.317	19.135
k_{it}	1377735	8.657	1.591	-0.878	18.389
l_{it}	1377735	4.865	1.133	0.000	12.145
m_{it}	1377735	9.678	1.438	-1.005	18.942
r_{it-1}	1377735	9.863	1.349	-0.190	18.934
k_{it-1}	1377735	8.541	1.639	-0.935	18.389
l_{it-1}	1377735	4.858	1.130	0.000	12.025
m_{it-1}	1377735	9.581	1.372	-0.795	18.801
$\ln s_{it}$	1377735	-0.235	0.436	-12.841	11.645
$\ln s_{it-1}$	1377735	-0.228	0.432	-12.841	10.850
IMR_{it-1}	1377735	0.102	0.074	0.000	0.997
$\mathbb{1}_{i \in SOE,t}$	1377735	0.098	0.297	0.000	1.000
$\mathbb{1}_{i \in SOE,t-1}$	1377735	0.103	0.305	0.000	1.000
$\mathbb{1}_{i \in Exporting,t}$	1377735	0.264	0.441	0.000	1.000
$\mathbb{1}_{i \in Exporting,t-1}$	1377735	0.245	0.430	0.000	1.000
$\mathbb{1}_{Privatized,i,t-1}$	1377735	0.008	0.087	0.000	1.000

Table 4 Estimation Results For Revenue Function and Productivity Process: Selected Industries

This table presents the structural estimation results for the revenue function for various industries: Food Processing (13), Textile (17), Raw Chemical and Chemical Products (26), Nonmetal Mineral Products (31), and Ordinary Machinery (35). The dependent variables are firm i's log revenue r_{it} at year t. I use the Nonlinear Least Square (NLS) approach outlined in the main text. Robust standard errors are reported in the parenthesis and are clustered at school level. T tests of statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Industry Coefficients/Column	13 (1)	17 (2)	26 (3)	31 (4)	35 (5)	All (6)
θ_k	.0767***	.0688***	.0826***	.0784***	.0765***	.0785***
	(.0000153)	(.0000111)	(.0000202)	(.0000124)	(.0000237)	(1.80e-06)
θ_l	.121***	.13***	.132***	.125***	.139***	.135***
	(.0000339)	(.0000328)	(.0000377)	(.0000267)	(.0000571)	(3.90e-06)
θ_m	.65***	.663***	.634***	.652***	.623***	.652***
	(.000211)	(.000183)	(.00022)	(.000167)	(.000384)	(.0000223)
γ_1	.695***	.744***	.714***	.734***	.782***	.754***
	(.000144)	(.000139)	(.000367)	(.000118)	(.000222)	(.0000127)
γ_2	.0163***	.00657***	.0104***	.00805***	.00484***	.00672***
	(2.82e-06)	(3.80e-06)	(9.36e-06)	(3.85e-06)	(7.39e-06)	(4.52e-07)
γ_3	.00139***	.0021***	.00206***	.0021***	.00206***	.00189***
	(2.01e-08)	(2.12e-08)	(1.51e-08)	(1.81e-08)	(3.31e-08)	(2.06e-09)
ρ^{SOE}	-.12***	-.0838***	-.0796***	-.0742***	-.0774***	-.0925***
	(.0000386)	(.0000236)	(.0000168)	(.0000154)	(.0000263)	(2.59e-06)
$\rho^{Privatized}$	.108***	.0879***	.0935***	.0765***	.0871***	.093***
	(.000109)	(.000094)	(.0000659)	(.000051)	(.000107)	(8.60e-06)
ρ^{After}	-.0338***	-.0285***	-.0305***	-.0263***	-.0344***	-.0287***
	(.0000214)	(.0000147)	(.0000107)	(8.59e-06)	(.0000154)	(1.34e-06)
α	-.824***	-.835***	-.817***	-.855***	-.873***	-.851***
	(.0000815)	(.0000945)	(.000249)	(.0000678)	(.000124)	(6.99e-06)
ϕ	.612***	.627***	.61***	.635***	.628***	.629***
	(.000137)	(.000114)	(.000138)	(.0000905)	(.000231)	(.0000126)
π^{Export}	-.0279***	-.00454***	.00822***	-.00562***	.0097***	-.00105***
	(5.25e-06)	(1.28e-06)	(3.12e-06)	(2.29e-06)	(2.92e-06)	(1.74e-07)
π^{IMR}	-.355***	-.0376***	-.131***	-.0403***	.00366***	-.0814***
	(.00158)	(.000598)	(.00196)	(.000716)	(.0013)	(.0000619)
Number of Observations	87291	118140	103475	123919	102444	1439986
Adjusted R2	.822	.835	.858	.844	.868	.859

Table 5 Estimation Results For Distortion Process: Selected Industries

This table presents the reduced form estimation results for distortion process for various industries: Food Processing (13), Textile (17), Raw Chemical and Chemical Products (26), Nonmetal Mineral Products (31), and Ordinary Machinery (35). The dependent variables are firm i's log revenue r_{it} at year t. I use the Nonlinear Least Square (NLS) approach outlined in the main text. All the coefficients are significant at 1% level and I do not report the standard error, which is clustered at firm level.

Industry Coefficients/Column	13 (1)	17 (2)	26 (3)	31 (4)	35 (5)	All (6)
	(1)	(2)	(3)	(4)	(5)	(6)
$\gamma^{\tau,c}\_1$	0.303***	0.318***	0.346***	0.305***	0.338***	0.330***
	(21.46)	(26.70)	(29.12)	(28.75)	(27.19)	(95.82)
$\gamma^{\tau,c}\_2$	0.024***	0.036***	0.018***	0.033***	0.006	0.028***
	(5.27)	(4.90)	(2.91)	(5.93)	(0.75)	(13.11)
$\gamma^{\tau,c}\_3$	-0.001	-0.000	-0.003***	-0.000	-0.002**	-0.001**
	(-1.32)	(-0.09)	(-4.02)	(-0.23)	(-2.33)	(-2.57)
$\gamma^{\tau,l}\_1$	0.122***	0.149***	0.143***	0.126***	0.144***	0.148***
	(8.90)	(13.23)	(14.20)	(11.54)	(15.55)	(50.84)
$\gamma^{\tau,l}\_2$	0.004	0.002	0.003	-0.003	0.001	0.001
	(1.39)	(0.34)	(0.58)	(-0.71)	(0.25)	(0.93)
$\gamma^{\tau,l}\_3$	-0.002***	-0.002***	-0.001**	-0.002***	-0.001**	-0.002***
	(-4.22)	(-3.08)	(-2.49)	(-3.22)	(-2.27)	(-7.84)
$\rho^{\tau,SOE}\_P$	0.038***	0.060***	0.031***	0.022***	0.032***	0.036***
	(4.57)	(5.54)	(5.41)	(3.68)	(4.91)	(16.08)
$\rho^{\tau,SOE}\_N$	0.024	-0.029	-0.018	-0.011	-0.007	-0.041***
	(0.94)	(-0.76)	(-0.72)	(-0.67)	(-0.38)	(-8.54)
$\rho^{\tau,Privatized}\_P$	0.028	-0.033	-0.035*	-0.032*	-0.034	-0.017**
	(0.93)	(-1.24)	(-1.85)	(-1.94)	(-1.44)	(-2.35)
$\rho^{\tau,Privatized}\_N$	0.122*	-0.045	0.008	0.039	-0.009	0.082***
	(1.86)	(-0.49)	(0.19)	(0.75)	(-0.14)	(4.77)
$\rho^{\tau,After}\_P$	0.002	0.012	0.023***	0.023***	0.002	0.014***
	(0.21)	(1.42)	(3.34)	(3.30)	(0.24)	(5.14)
$\rho^{\tau,After}\_N$	-0.040	-0.014	0.008	-0.009	-0.035	-0.036***
	(-1.60)	(-0.53)	(0.36)	(-0.48)	(-1.01)	(-4.59)
ϕ^{τ}	-0.001	0.013	0.011	0.006	-0.013*	0.015***
	(-0.10)	(1.36)	(1.19)	(0.80)	(-1.84)	(6.78)
$\pi^{\tau,Export}$	0.005	-0.015***	-0.007*	-0.019***	-0.017***	-0.011***
	(1.13)	(-5.39)	(-1.90)	(-5.36)	(-4.96)	(-11.29)
$\pi^{\tau,IMR}$	0.115*	0.033	0.069	0.084**	-0.026	0.082***
	(1.83)	(0.78)	(1.14)	(2.06)	(-0.60)	(7.36)
Constant	0.177***	0.107***	0.111***	0.118***	0.176***	0.104***
	(5.17)	(4.26)	(3.95)	(5.53)	(7.84)	(14.87)
Observation	60,724	83,172	73,868	90,161	70,242	960,433
Adjusted R2	0.157	0.183	0.150	0.159	0.168	0.198

Table 6 Correlation between Distortions and Firm Characteristics

This table provides correlation between estimated log distortion and firm characteristics. $\mathbb{1}_{i,t}^{Exit}$ is a dummy variable equal to 1 if it is the last observation for firm i in the sample, and missing if $t = 2007$, and 0 otherwise. $\mathbb{1}_{i,t}^{State-Owned}$ is a dummy variable equal to 1 if firm i at year t's registration type is either 110 or 151, and 0 otherwise. $\mathbb{1}_{it}^{Exporting}$ is a dummy variable equal to 1 if firm i reports positive exporting value at year t, and 0 otherwise. $\mathbb{1}_{it}^{Subsidized}$ is a dummy variable equal to 1 if firm i reports positive subsidy received at year t, and 0 otherwise. All regressions include capital, age, and age square. Robust standard error are clustered both at firm and year level. T tests of statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable: Log Distortions					
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}\_Exit$		0.025*			
		(1.84)			
$\mathbb{1}\_State-Owned\,Firm$			0.017**		
			(2.05)		
$\mathbb{1}\_Exporting\,Firm$				-0.018***	
				(-3.87)	
$\mathbb{1}\_Subsidized\,Firm$					0.003*
					(1.92)
Constant	0.338***	0.330***	0.335***	0.334***	0.338***
	(23.64)	(24.03)	(22.76)	(23.98)	(23.63)
Covariates	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observation	1,377,735	1,135,835	1,377,735	1,377,735	1,377,735
R^2	0.049	0.047	0.049	0.049	0.049
Dependent Variable: Absolute value of Log Distortions					
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}\_Exit$		0.090***			
		(6.65)			
$\mathbb{1}\_State-Owned\,Firm$			0.143***		
			(18.10)		
$\mathbb{1}\_Exporting\,Firm$				-0.034***	
				(-2.65)	
$\mathbb{1}\_Subsidized\,Firm$					-0.001
					(-0.57)
Constant	0.408***	0.398***	0.367***	0.416***	0.408***
	(42.47)	(38.68)	(52.57)	(34.43)	(42.44)
Covariates	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observation	1,377,735	1,135,835	1,377,735	1,377,735	1,377,735
R^2	0.032	0.034	0.043	0.033	0.032

Table 7 Aggregate Productivity Growth Decomposition:1998-2007

This table presents the decomposition results for aggregate productivity growth between 1999 to 2007 using the estimated sample within the manufacturing sector.

Aggregate Productivity Growth	58.037
State	
Mean Productivity Growth	43.998
Reallocation Within State	1.916
Private	
Mean Productivity Growth	37.179
Reallocation Within Private	9.115
Between Ownership	-2.266
Transition	3.934
Entry	-21.473
Exit	27.598

Table 8 Dispersion of MRPK, Volatility and Distortions

This table shows that there are increasing relationship between industrial-year level of dispersion in marginal revenue product of capital (MRPK) and dispersion of productivity innovation. Dependent variable is $Std_{jt}(MRPK_{it})$, the standard deviation of firm-level MRPK at industry year level. $Std_{jt}(\eta_{it})$ is the standard deviation of firm level log productivity innovation at industry year level. Column (1) and (3) present unweighted regression results. Column (2) and (4) present weighted regression results that observations for industry j at year t are weighted by their revenue shares of total revenue in year t. Robust standard error are clustered at industry level. T tests of statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	$Std_{jt}(MRPK)$			
	(1)	(2)	(3)	(4)
$Std\_jt(\tau\_it)$	0.364***	0.351***		
	(3.73)	(3.44)		
$Std\_jt(\eta\_it)$			0.765***	0.844***
			(4.99)	(4.94)
Constant	1.338***	1.311***	1.157***	1.089***
	(21.35)	(19.36)	(13.57)	(11.54)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Weighted	No	Yes	No	Yes
Observation	252	252	252	252
R^2	0.883	0.885	0.896	0.903

Table 9 Propensity Score Matching: Sample

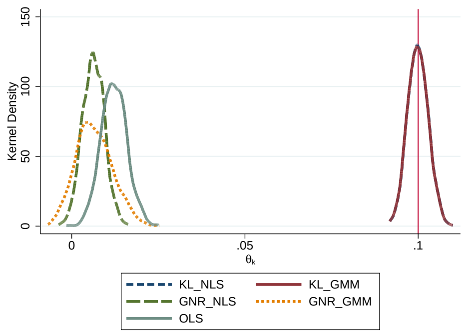
This table presents matching results. I matched the privatized firms i which is privatized at year $t-1$ with SOEs that are not privatized on year $t-1$ or t from the same industry, region and exporting status, and with similar employment, productivity and distortion parameters. T tests of statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Before Privatization	Privatized SOEs (A)	Non-Privatized SOEs (B)	Difference (B)-(A)	Test Statistics
ω_{it-1}	2.128	2.145	-0.017	-1.218
	(0.010)	(0.010)	(0.014)	
τ_{it-1}	0.259	0.257	0.002	0.153
	(0.008)	(0.007)	(0.011)	
τ_{it}	0.245	0.230	0.015	1.362
	(0.008)	(0.007)	(0.011)	
$InverseMillsRatio$	0.123	0.122	0.001	0.663
	(0.001)	(0.001)	(0.002)	
$\ln(Employment_{it-1})$	5.568	5.581	-0.014	-0.520
	(0.020)	(0.017)	(0.026)	
After Privatization				
ω_{it}	2.136	2.194	0.040***	-4.152
	(0.010)	(0.010)	(0.014)	
τ_{it+1}	0.213	0.230	0.018	-1.361
	(0.010)	(0.009)	(0.013)	

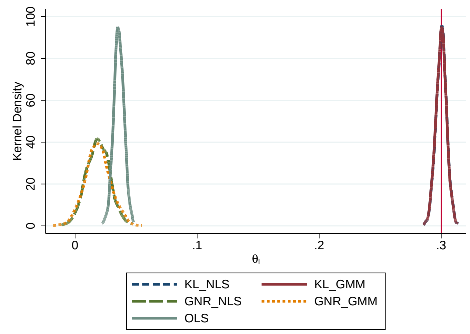
Appendix E Figures

Figure 2 Simulation Results for Technology Parameters

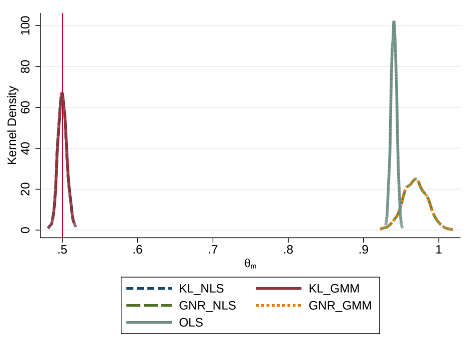
This set of figures presents the simulation results for estimated technology parameters as well as their asymptotic distributions. The true parameters are the redline within each graph. OLS denotes the method of directly regressing output on inputs. GNR_{NLS} denotes the method proposed by Gandhi et al. (2012) and is implemented using nonlinear least square, and GNR_{GMM} denotes the same method but is implemented using general method of moments. KL_{NLS} and KL_{GMM} denote the method proposed in section 3 via NLS and GMM.



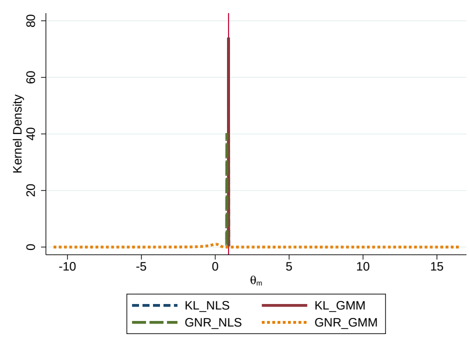
Estimates of θ_k



Estimates of θ_l



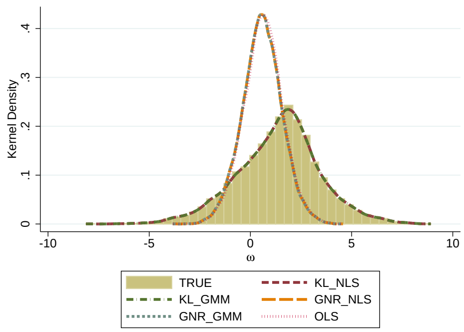
Estimates of θ_m



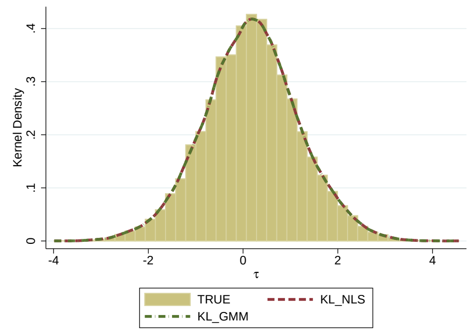
Estimates of γ

Figure 3 Simulation Results for Productivity and Distortions

This set of figures presents the simulation results for estimated productivity and distortions. OLS denotes the method of directly regressing output on inputs. GNR_{NLS} denotes the method proposed by Gandhi et al. (2012) and is implemented using nonlinear least square, and GNR_{GMM} denotes the same method but is implemented using general method of moments. KL_{NLS} and KL_{GMM} denote the method proposed in section 3 via NLS and GMM.



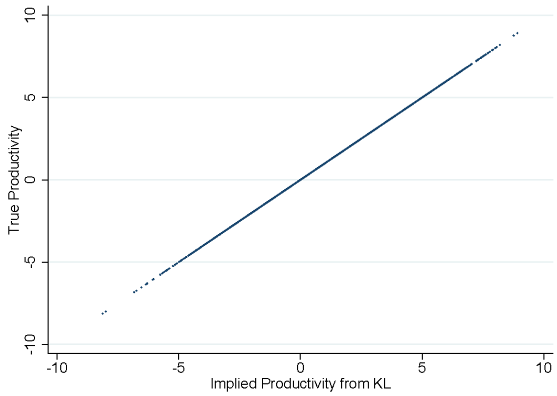
Implied ω_{it}



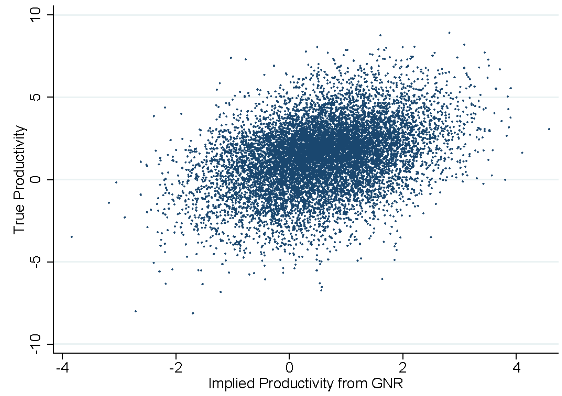
Implied τ_{it}

Figure 4 Simulation Results for Correlation between Productivity Measures

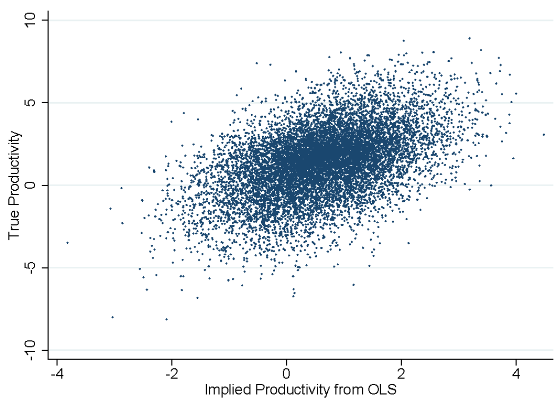
This set of figures presents the simulation results for the correlation between estimated productivity and the true productivity. OLS denotes the method of directly regressing output on inputs. GNR_{NLS} denotes the method proposed by Gandhi et al. (2012) and is implemented using nonlinear least square, and GNR_{GMM} denotes the same method but is implemented using general method of moments. KL_{NLS} and KL_{GMM} denote the method proposed in section 3 via NLS and GMM.



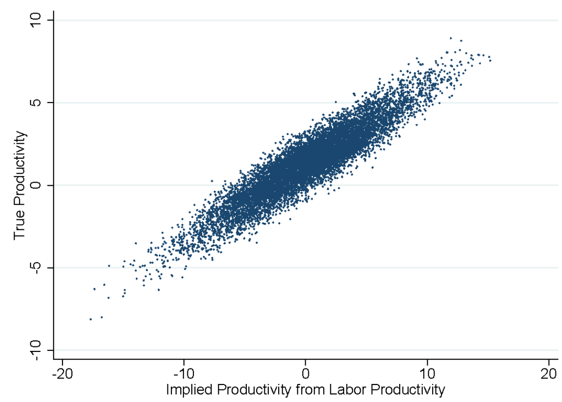
Correlation between of ω_{it}^{KL} and ω_{it}



Correlation between of ω_{it}^{GNR} and ω_{it}



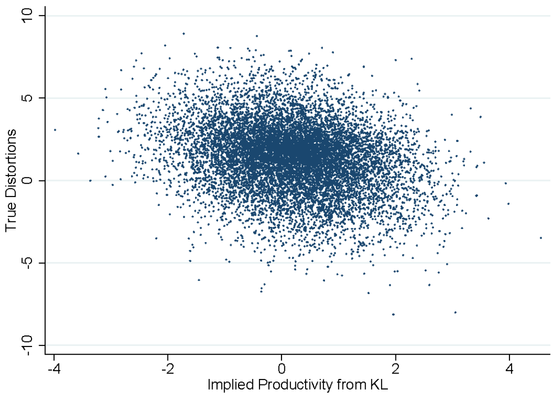
Correlation between of ω_{it}^{OLS} and ω_{it}



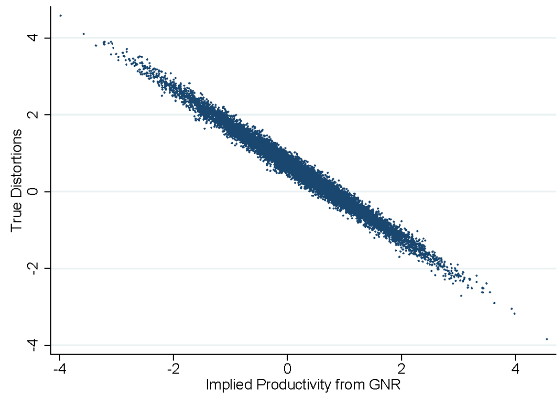
Correlation between of ω_{it}^{Labor} and ω_{it}

Figure 5 Simulation Results for Correlation between Productivity Measures and Distortions

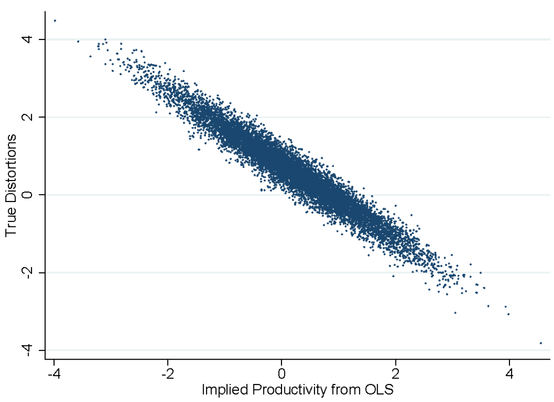
This set of figures presents the simulation results for the correlation between the estimated productivity and true distortion distribution. OLS denotes the method of directly regressing output on inputs. GNR_{NLS} denotes the method proposed by Gandhi et al. (2012) and is implemented using nonlinear least square, and GNR_{GMM} denotes the same method but is implemented using general method of moments. KL_{NLS} and KL_{GMM} denote the method proposed in section 3 via NLS and GMM.



Correlation between of ω_{it}^{KL} and τ_{it}



Correlation between of ω_{it}^{GNR} and τ_{it}



Correlation between of ω_{it}^{OLS} and τ_{it}

Correlation between of ω_{it}^{Labor} and τ_{it}

Correlation between of ω_{it} and τ_{it}

This set of figures presents the correlation between the estimated productivity and the estimated distortion across two digit industries, using the method proposed in section 3 via NLS.

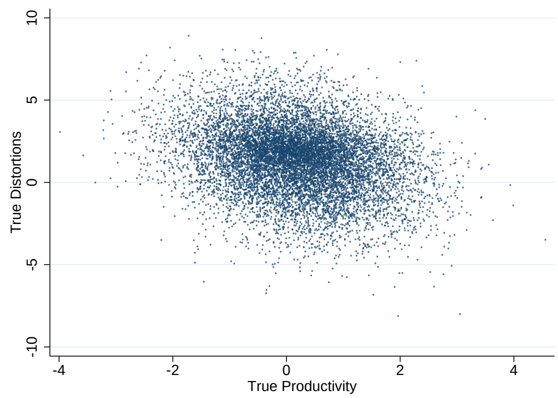


Figure 6 Four Economic Regions of China

This figure depicts the four economic regions in China according to The Communist Party of China (2006).

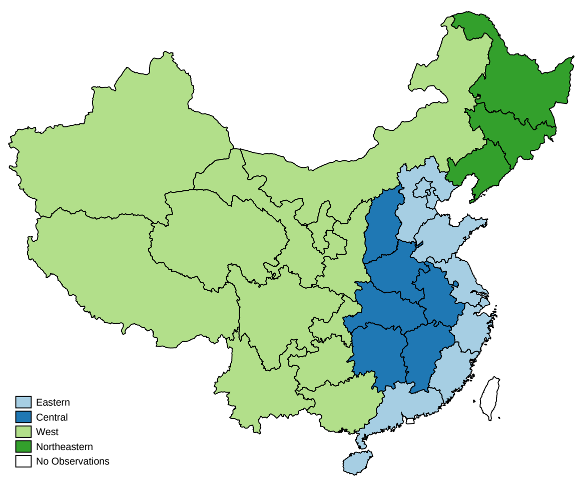


Figure 7 Productivity by Ownership and Regions

These figures depict the estimated distribution of productivity (adjusted by industry-year mean) by ownership and economic regions using the method proposed in section 3.

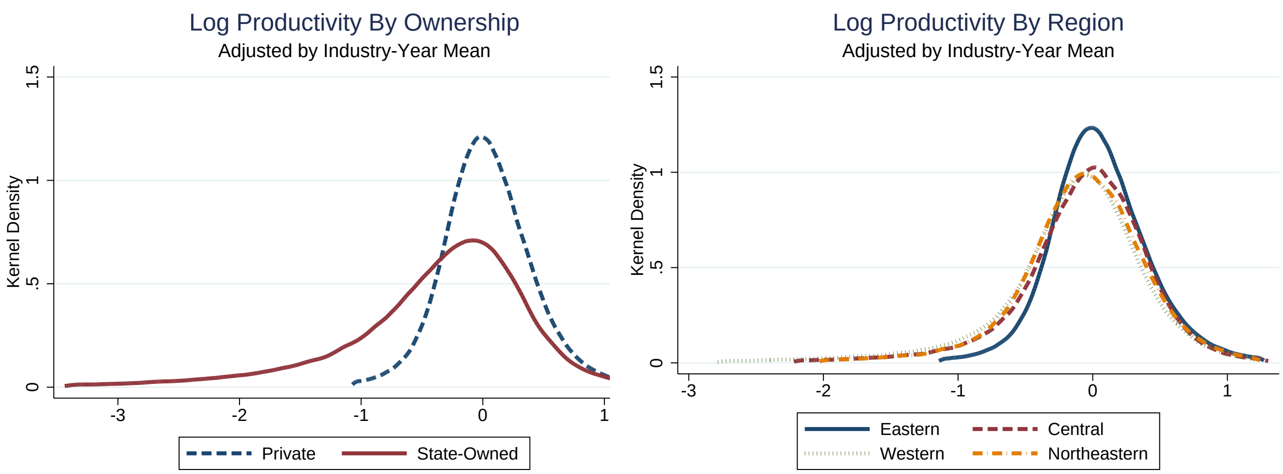


Figure 8 Distortions by Ownership and Regions

These figures depict the estimated distribution of distortions by ownership and economic regions using the method proposed in section 3.

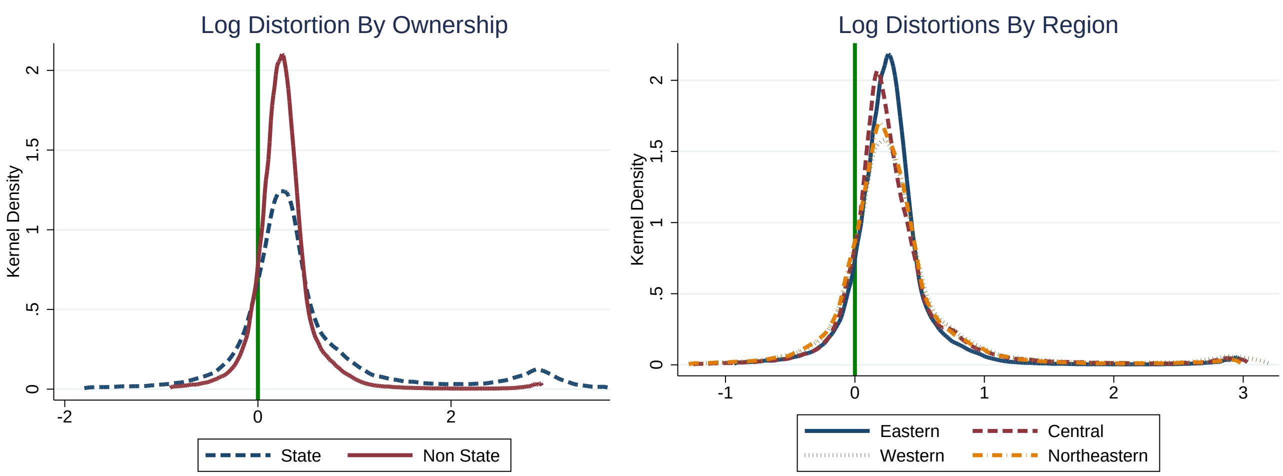


Figure 9 Correlation Between Distortions and Productivity

This figure depicts the correlation between the estimated distribution of productivity and distortions across industries using the method proposed in section 3.

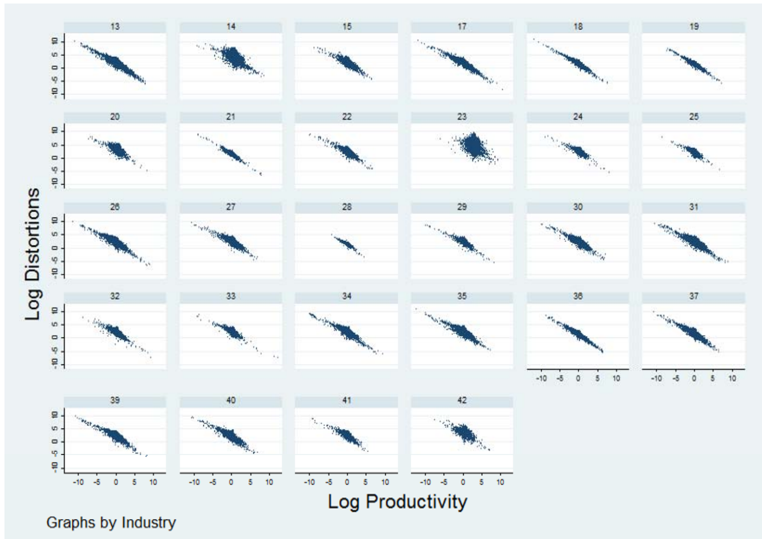


Figure 10 Dispersion of MRPK and Dispersion of Distortions and Productivity

These figures depict the relationship between industry-year level dispersion of log marginal revenue product of capital and the dispersion of productivity innovation and distortion dispersion. The productivity and distortions are estimated following the method proposed in section 3. The size of the ball represents the revenue share for a particular industry-year's contribution to the total revenue for that year. The red line represents the unweighted fitting line, and the dashed line represents the weighted fitting line.

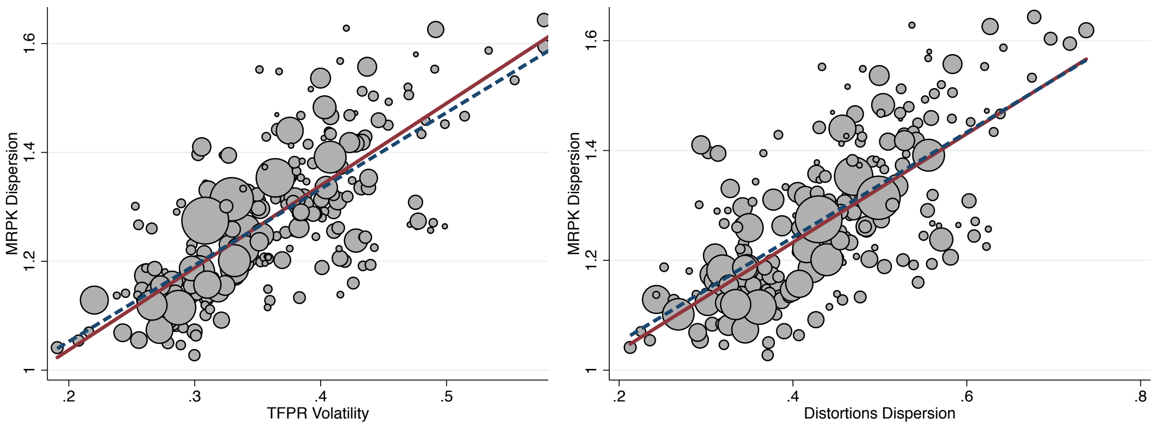


Figure 11 Dispersion of Distortions and Productivity

This figure depicts the relationship between industry-year level dispersion of productivity innovation and distortion dispersion. The productivity and distortions are estimated following the method proposed in section 3. The size of the ball represents the revenue share for a particular industry-year's contribution to the total revenue for that year. The red line represents the unweighted fitting line, and the dashed line represents the weighted fitting line.

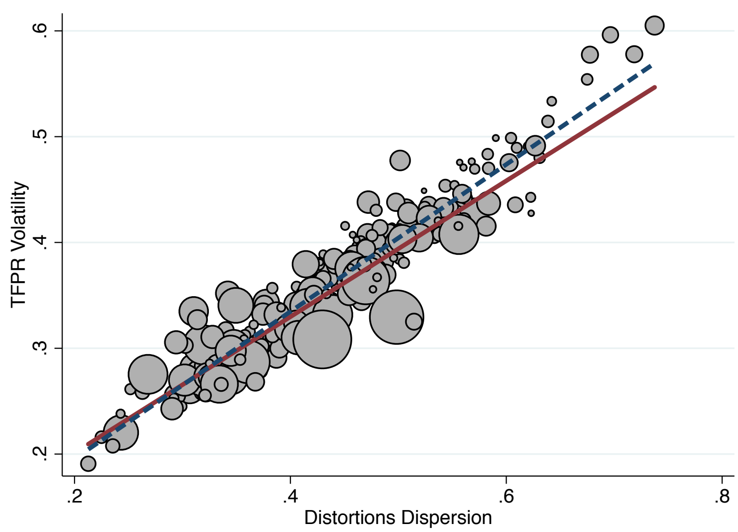
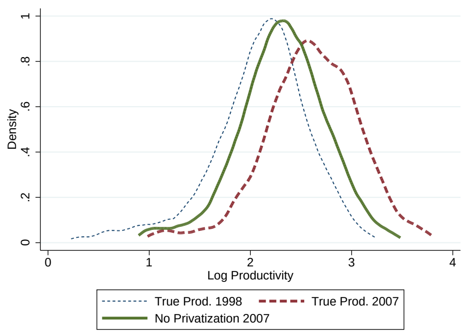


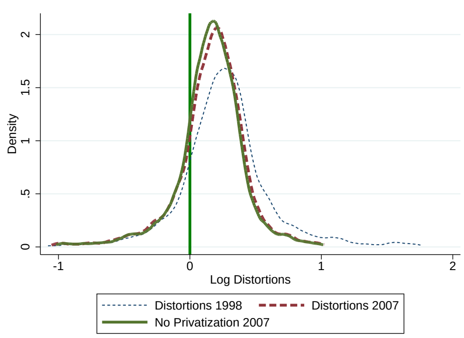
Figure 12 Decomposition of the Productivity Process

This set of figures presents the decomposition of the productivity process with privatization. I take a balanced sample of SOEs firms which eventually are privatized within the sample period and conduct counterfactual experiments on their productivity process. The dashed line is the productivity distribution in 1998. And the short-dashed line is the productivity distribution in year 2007. The counterfactual distributions are depicted using solid line in each figure. The top left panel shows the counterfactual distortion distribution when there is no privatization. The top right panel shows the counterfactual distortion distribution if privatization occurs at 1998. The bottom-left panel shows the counterfactual productivity distribution by removing the transitory components of privatization from the productivity process. The bottom-right panel shows the counterfactual productivity distribution by removing the permanent components of privatization from the productivity process. The simulated distortion process using realized distortion innovations and assume other covariates are exogenous.

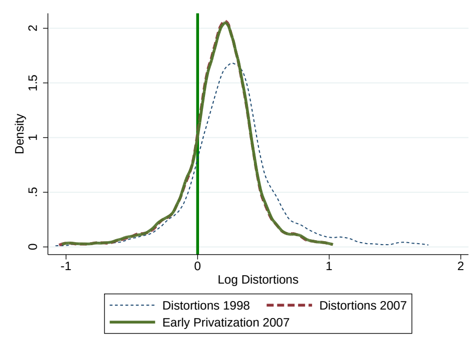


No Privatization: Productivity

Early Privatization: Productivity



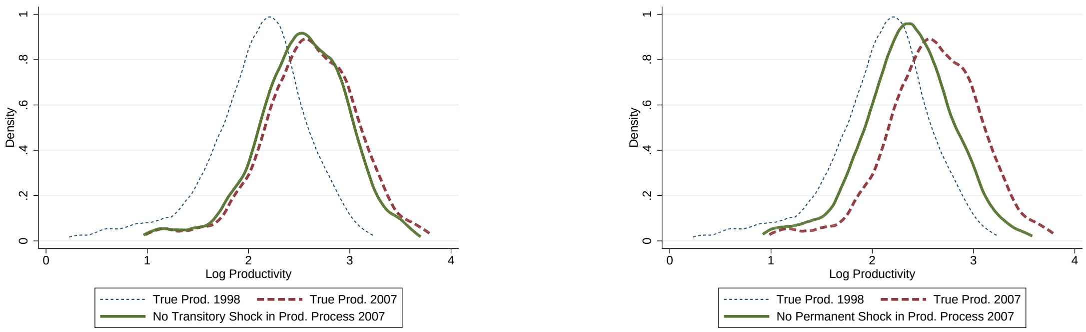
No Privatization: Distortions



Early Privatization: Distortions

Figure 13 Decomposition of the Productivity Process

This set of figures presents the decomposition of the productivity process with privatization. I take a balanced sample of SOEs firms which eventually are privatized within the sample period and conduct counterfactual experiments on their productivity process. The dashed line is the productivity distribution in 1998. And the short-dashed line is the productivity distribution in year 2007. The counterfactual distributions are depicted using solid line in each figure. The top left panel shows the counterfactual distortion distribution when there is no privatization while fixing distortions. The top right panel shows the counterfactual distortion distribution if privatization occurs at 1998 while fixing distortions. The bottom-left panel shows the counterfactual productivity distribution by removing the transitory components of privatization from the productivity process while fixing distortions. The bottom-right panel shows the counterfactual productivity distribution by removing the permanent components of privatization from the productivity process while fixing distortions. The simulated distortion process using realized distortion innovations and assume other covariates, including distortions are exogenous.

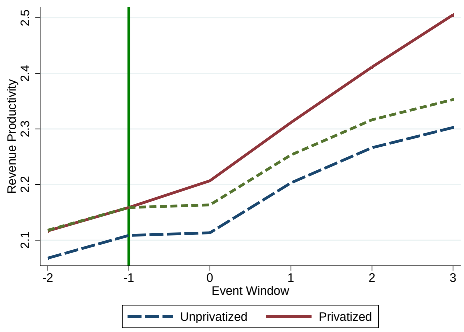


No Transitory Shock in Productivity Process

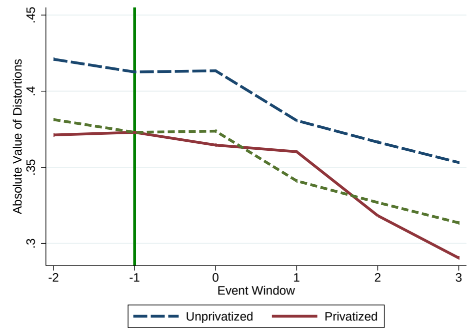
No Permanent Shock in Productivity Process

Figure 14 Matched Sample Productivity and Distortions Around Privatization Events

This set of figures presents mean of productivity and absolute distortions around the privatization window. It shows that productivity increases over time for privatized firm comparing to non privatized SOE firms. Absolute distortions decrease over time as well, but not differ significantly between the two groups.



Productivity



Absolute Distortions