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Misallocation and Manufacturing TFP in China and India*

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Resource misallocation can lower aggregate total factor productivity (TFP). We use micro data on manufacturing establishments to quantify the extent of this misallocation in China and India compared to the U.S. in recent years. Compared to the U.S., we measure sizable gaps in marginal products of labor and capital across plants within narrowly-defined industries in China and India. When capital and labor are hypothetically reallocated to equalize marginal products to the extent observed in the U.S., we calculate manufacturing TFP gains of 25-40% in China and 50-60% in India.

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I. Introduction

Large differences in output per worker between rich and poor countries have been attributed, in no small part, to differences in Total Factor Productivity (TFP).¹ The natural question then is: what are the underlying causes of these large TFP differences? Research on this question has largely focused on differences in technology within representative firms. For example, Howitt (2000) and Klenow and Rodríguez-Clare (2005) show how large TFP differences can emerge in a world with slow technology diffusion from advanced countries to other countries. In these models, the inefficiencies preventing low TFP countries from reaching the frontier are internal to firms. They are models of *within*-firm inefficiency, with the inefficiency varying across countries.

A recent paper by Restuccia and Rogerson (2007) takes a different approach. Instead of focusing on the efficiency of a representative firm, they suggest that the misallocation of resources across firms can potentially have important effects on aggregate TFP. For example, imagine an economy with two firms that have identical technologies but in which the firm with political connections benefits from subsidized credit (say from a state-owned bank) and the other firm (without political connections) can only borrow at high interest rates from informal financial markets. Assuming that both firms equate the marginal product of capital with the interest rate, the marginal product of capital of the firm with access to subsidized credit will be lower than the marginal product of capital of the firm that only has access to informal financial markets. This is a clear case of capital misallocation: aggregate output would be higher if capital was reallocated from the firm with a low marginal product of capital to the firm with a high marginal product of capital. The misallocation of capital results in low aggregate output per worker and TFP.

More broadly, there are many institutions and policies that will potentially result in a misallocation of resources across firms. For example, the McKinsey Global Institute (1998) argues that a key factor behind low productivity in the retail sector in Brazil is that labor market regulations drive up the cost of labor for supermarkets, but do not affect retailers in the informal sector. Therefore, despite their low productivity, the lower cost

¹ See Caselli (2005), Hall and Jones (1999), and Klenow and Rodríguez-Clare (1997).

of labor faced by informal sector retailers makes it possible for them to command a large share of the Brazilian retail sector. Lewis (2004) describes many similar case studies from the McKinsey Global Institute.

Our goal in this paper is to provide quantitative evidence on the impact of resource misallocation on aggregate TFP. We use a standard model of monopolistic competition with heterogeneous firms, essentially Melitz (2003) without international trade, to show how distortions that drive wedges between the marginal products of capital and labor across firms will lower aggregate TFP.² A key result we exploit is that *revenue* productivity should be equated across firms in the absence of distortions. Therefore, to the extent that revenue productivity differs across firms, we can use this to recover a measure of the firm-level distortions.

We use this framework to measure the contribution of resource misallocation to aggregate manufacturing productivity in China and India versus the U.S. China and India are of particular interest not only because of their size and relative poverty, but because they have carried out reforms that may have contributed to their rapid growth in recent years.³ We use plant-level data from the Chinese Industrial Survey (1998-2005), the Indian Annual Survey of Industries (1987-1994) and the U.S. Census of Manufacturing (1977, 1987, 1997) to measure dispersion in the marginal products of capital and labor within individual 4-digit manufacturing sectors in each country. We then measure how much aggregate manufacturing output in China and India would increase if capital and labor were to be reallocated to equalize marginal products across plants within each 4-digit sector *to the extent observed in the U.S.* The U.S. is a critical benchmark for us, as there may be measurement error and factors omitted from the model (such as adjustment costs and markup variation) that generate gaps in marginal products even in a comparatively undistorted country such as the U.S.

² In terms of the resulting size distribution, the model is a cousin to the Lucas (1978) span of control model. Atkeson and Kehoe (2005) show that these models are isomorphic along some dimensions.

³ See Kochar et al. (2006), Aghion et al. (2006) and *The Economist* (2006b), for discussion of Indian reforms, and Young (2000, 2003) and *The Economist* (2006a) for Chinese reforms. Farrell and Lund (2006) discuss how capital continues to be misallocated in China and India, while Allen, Chakrabarti, De, Qian and Qian (2006) study India in particular, and Dobson and Kashyap (2006) and Dollar and Wei (2007) examine capital misallocation in China.

We find that moving to “U.S. efficiency” would increase TFP by 30-45% in China and 40-50% in India. The output gains would be roughly twice as large if capital accumulated in response to aggregate TFP gains. We find little evidence that India reaped efficiency gains from 1987 to 1994, but China may have boosted its TFP by 1% per year from 1998-2005 by winnowing its distortions. In both India and China, larger plants within industries appear to have higher marginal products, suggesting they should expand at the expense of smaller plants. The pattern is much weaker in the U.S., suggesting it is not simply due to adjustment costs or markups increasing in size.

Although Restuccia and Rogerson (2007) is the closest predecessor to our investigation in model and method, there are many others.⁴ In addition to Restuccia and Rogerson (2007), there are three papers in particular that our work builds upon. First, we follow the lead of Chari, Kehoe and McGrattan (2007) in inferring policy distortions from residuals in equilibrium conditions. Second, the distinction between a firm’s physical productivity and its revenue productivity highlighted by Foster, Haltiwanger, and Syverson (2007) is central to our estimates of resource misallocation. Third, Banerjee and Duflo (2006) emphasize the importance of resource misallocation in understanding aggregate TFP differences across countries, and present suggestive evidence that gaps in marginal products of capital in India could play a large role in India’s low manufacturing TFP relative to the U.S.⁵

The rest of the paper proceeds as follows. We sketch a model of monopolistic competition with heterogeneous firms to show how the misallocation of capital and labor lowers aggregate TFP. We then take this model to the Chinese, Indian, and U.S. plant data to try to quantify the drag on productivity in China and India due to misallocation in manufacturing. We lay out the model in section II, describe the datasets in section III,

⁴ A number of other authors have focused on specific mechanisms that could result in resource misallocation. Hopenhayn and Rogerson (1993) studied the impact of labor market regulations on allocative efficiency; Lagos (2006) is a recent effort in this vein. Caselli and Gennaioli (2003) and Buera and Shin (2007) model inefficiencies in the allocation of capital to managerial talent, while Guner, Ventura and Xu (2006) model misallocation due to size restrictions. Parente and Prescott (2000) theorize that low TFP countries are ones in which vested interests block firms from introducing better technologies.

⁵ See Bergoeing, Kehoe, Kehoe, and Soto (2002), Galindo, Schiantarelli, and Weiss (2007), Bartelsman, Haltiwanger, and Scarpetta (2006), and Alfaro, Charlton and Kanczuk (2007) for related empirical evidence in other countries.

and present empirical results in section IV. In section V we carry out a number of robustness checks, and we offer some tentative conclusions in section VI.

II. Resource Misallocation and TFP

This section sketches a standard model of monopolistic competition with heterogeneous firms to illustrate the effect of resource misallocation on aggregate productivity. In addition to differing by their level of efficiencies (as in Melitz, 2003), we assume that firms potentially face different output and capital distortions.

We assume that there is a single final good Y produced by a representative firm facing perfectly competitive output and factor markets. This firm combines the output Y_s of S manufacturing industries using a Cobb-Douglas production technology:

$$(2.1) \quad Y = \prod_{s=1}^S Y_s^{\theta_s}, \text{ where } \sum_{s=1}^S \theta_s = 1.$$

Cost minimization implies:

$$(2.2) \quad P_s Y_s = \theta_s P Y.$$

Here, P_s refers to the price of industry aggregate output Y_s and $P \equiv \prod_{s=1}^S \left(\frac{P_s}{\theta_s} \right)^{\theta_s}$ represents

the price of the final good (we set the final output good as the numeraire, so $P=1$).

Aggregate industry output Y_s is itself a CES aggregate of M_s differentiated products:

$$(2.3) \quad Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

The production function for each differentiated product is given by a Cobb-Douglas function of firm TFP, capital, and labor:

$$(2.4) \quad Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}$$

Note that capital and labor shares are allowed to differ across industries (but not across firms within an industry).⁶

Since there are two factors of production, we can separately identify distortions that affect both capital and labor from distortions that change the marginal product of one of the factors relative to the other factor of production. We will denote distortions that increase the marginal products of capital *and* labor by the same proportion as an output distortion τ_Y . For example, τ_Y would be large for firms that face government restrictions on size or high transportation costs, and low in firms that benefit from public subsidies. In turn, we will denote distortions that raise the marginal product of capital relative to that of labor as the capital distortion τ_K . For example, τ_K would be large for firms that do not have access to credit, but small for firms with access to cheap credit (by business groups or state-owned banks).

Profits are given by

$$(2.5) \quad \pi_{si} = (1 - \tau_{Ysi}) P_{si} Y_{si} - w L_{si} - (1 + \tau_{Ksi}) R K_{si}.$$

Profit maximization yields the standard condition that the firm's output price is a fixed markup over its marginal cost:

$$(2.6) \quad P_{si} = \frac{\sigma}{\sigma - 1} \left(\frac{w}{1 - \alpha_s} \right)^{1 - \alpha_s} \left(\frac{R}{\alpha_s} \right)^{\alpha_s} \frac{(1 + \tau_{Ksi})^{\alpha_s}}{A_{si} \cdot (1 - \tau_{Ysi})}.$$

The capital-labor ratio is given by

$$(2.7) \quad \frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1 - \alpha_s} \cdot \frac{w}{R} \cdot \frac{1}{(1 + \tau_{Ksi})},$$

⁶ In section V below, on robustness checks, we relax this assumption by replacing the plant-specific capital distortion with plant-specific factor shares.

the allocation of labor by

$$(2.8) \quad L_{si} \propto \frac{A_{si}^{\sigma-1} (1 - \tau_{Ysi})^\sigma}{(1 + \tau_{Ksi})^{\alpha_s(\sigma-1)}},$$

and firm output by

$$(2.9) \quad Y_{si} \propto \frac{A_{si}^\sigma (1 - \tau_{Ysi})^\sigma}{(1 + \tau_{Ksi})^{\alpha_s \sigma}}.$$

As can be seen, the allocation of resources across firms will not only depend on firm TFP levels, but also on the output and capital distortions they face. To the extent resource allocation is driven by distortions rather than firm TFP, this will result in differences in the marginal revenue products of labor and capital across firms. The marginal revenue product of labor is proportional to revenue per worker:

$$(2.10) \quad MRPL_i = \frac{w}{1 - \tau_{Ysi}} \propto \frac{P_{si} Y_{si}}{L_{si}}.$$

The marginal revenue product of capital is proportional to the revenue-capital ratio:

$$(2.11) \quad MRPK_i = R \cdot \frac{1 + \tau_{Ksi}}{1 - \tau_{Ysi}} \propto \frac{P_{si} Y_{si}}{K_{si}}.$$

Intuitively, the after-tax marginal revenue products of capital and labor are equalized across firms. The before-tax marginal revenue products must be higher in firms that face disincentives, and can be lower in firms that benefit from subsidies. If labor and capital were allocated efficiently across firms, the allocation of labor and capital would only depend on firm TFP and the marginal revenue product of labor and capital would be the same for all firms.

How much lower is aggregate TFP and output due to the misallocation of capital and labor? We proceed as follows. First, we solve for the equilibrium allocation of resources across sectors:⁷

$$(2.12) \quad L_s \equiv \sum_{i=1}^{M_s} L_{si} = L \frac{(1 - \alpha_s) \theta_s (1 - \bar{\tau}_{Ys})}{\sum_{s'=1}^S (1 - \alpha_{s'}) \theta_{s'} (1 - \bar{\tau}_{Ys'})}$$

$$(2.13) \quad K_s \equiv \sum_{i=1}^S K_{si} = K \frac{\alpha_s \theta_s \frac{1 - \bar{\tau}_{Ys}}{1 + \bar{\tau}_{Ks}}}{\sum_{s'=1}^S \alpha_{s'} \theta_{s'} \frac{1 - \bar{\tau}_{Ys'}}{1 + \bar{\tau}_{Ks'}}}$$

Here, $L \equiv \sum_{s=1}^S L_s$ and $K \equiv \sum_{s=1}^S K_s$ represent the aggregate supply of labor and capital, respectively, and $\bar{\tau}_{Ys} \equiv \sum_{i=1}^{M_s} \tau_{Ysi} \left(\frac{P_{si} Y_{si}}{P_s Y_s} \right)$ and $\bar{\tau}_{Ks} \equiv \sum_{i=1}^{M_s} \tau_{Ksi} \left(\frac{K_{si}}{K_s} \right)$ denote the weighted average output and capital distortions in sector s . We can then express aggregate output as a function of K_s , L_s , and aggregate TFP in a sector:⁸

$$(2.14) \quad Y = \prod_{s=1}^S (TFP_s \cdot K_s^{\alpha_s} \cdot L_s^{1-\alpha_s})^{\theta_s},$$

where aggregate TFP in sector s is given by:

$$(2.15) \quad TFP_s = \left(\frac{1}{M_s} \sum_{i=1}^{M_s} \left\{ A_{si} \left(\frac{1 - \tau_{Ysi}}{1 - \bar{\tau}_{Ys}} \right) \left(\frac{1 + \tau_{Ksi}}{1 + \bar{\tau}_{Ks}} \right)^{-\alpha_s} \right\}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}.$$

Thus aggregate TFP in sector s is a weighted average of A_{si} , where the weights are the firm-specific distortions.

⁷ To derive K_s and L_s , we proceed as follows. First, we derive the aggregate demand for capital and labor in a sector by aggregating the firm-level demands for the two factor inputs. We then combine the aggregate demand for the factor inputs in each sector with the allocation of total expenditure across sectors.

⁸ We combine the aggregate demand for capital and labor in a sector, the expression for the price of aggregate industry output, and the expression for the price of aggregate output.

To illustrate the intuition behind the expression for aggregate TFP, it is useful to show that the firm-specific distortions can be measured by the firm's *revenue* productivity. It is typical in the productivity literature to have industry deflators but not plant-specific deflators. Foster, Haltiwanger and Syverson (2005) stress that, when industry deflators are used, differences in plant-specific prices show up in the customary measure of plant TFP. They therefore stress the distinction between “physical productivity”, which they denote TFPQ, and “revenue productivity”, which they call TFPR. The use of a plant-specific deflator yields TFPQ, whereas using an industry deflator gives TFPR.

The distinction between physical and revenue productivity is vital for us too. We get

$$TFPQ_{si} \equiv A_{si} \equiv \frac{Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}} \quad \text{and}$$

$$TFPR_{si} \equiv P_{si} A_{si} \equiv \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}} \propto \frac{(1 + \tau_{Ksi})^{\alpha_s}}{1 - \tau_{Ysi}}.$$

Unlike TFPQ, TFPR does not vary across plants within an industry unless plants face capital and/or output distortions. In this model, more capital and labor should be allocated to plants with higher TFPQ to the point where their higher output results in a lower price and the exact same TFPR as at smaller plants. To be precise, from (2.10) and (2.11), plant TFPR will be inversely proportional to a weighted average of the plant's marginal product of capital and labor:

$$TFPR_{si} \propto \frac{(1 + \tau_{Ksi})^{\alpha_s}}{1 - \tau_{Ysi}} = \left(\frac{1}{MPL_{si}} \right)^{1-\alpha_s} \left(\frac{1}{MPK_{si}} \right)^{\alpha_s}.$$

High plant TFPR within an industry is a sign that the plant confronts capital and output barriers that raises the plant's marginal product of capital and labor and thus make it smaller than optimal.

With the expression for TFPR in hand, we can rewrite aggregate TFP as:

$$(2.16) \quad TFP_s = \left(\frac{1}{M_s} \sum_{i=1}^{M_s} \left\{ A_{si} \cdot \frac{\overline{TFPR}_s}{TFPR_{si}} \right\}^{\sigma-1} \right)^{\frac{1}{\sigma-1}},$$

where $\overline{TFPR}_s \propto \frac{(1 + \bar{\tau}_{Ksi})^{\alpha_s}}{1 - \bar{\tau}_{Ysi}}$. This is the key equation we use for our empirical

estimates. Moreover, when A (\equiv TFPQ) and TFPR are jointly log-normally distributed, there is a simple closed form expression for aggregate TFP:

$$(2.17) \quad \ln TFPR_s = \frac{1}{M_s} \sum_{i=1}^{M_s} \ln A_{si} + \frac{\sigma-1}{2} \left[\text{var}(\ln A_{si}) - \text{var}(\ln TFPR_{si}) - 2 \text{cov}(\ln A_{si}, \ln TFPR_{si}) \right].$$

In this case, the negative effect of distortions on aggregate TFP can be summarized by two statistics: the variance of TFPR and the covariance of TFPR with A . Intuitively, the extent of misallocation is worse when there is greater dispersion of marginal products and when high productivity firms face greater distortions. In our empirical section below, we will estimate the joint distribution of A and TFPR in China, India and the U.S to measure the effects of misallocation.

We note several things about the effect of misallocation on aggregate TFP in this model. First, from (2.12) and (2.13), the shares of aggregate labor and capital devoted to a given sector are not affected by the extent of misallocation as long as $\bar{\tau}_{Ys}$ and $\bar{\tau}_{Ks}$ do not change. Our assumption of a Cobb-Douglas aggregator (unit elastic demand) is responsible for this property (an industry that is 1% more efficient has a 1% lower price index and 1% higher demand, which can be accommodated without adding or shedding inputs). We will relax this assumption when we do our robustness checks in section V.

Second, we conditioned on a fixed aggregate stock of capital. Because the rental rate rises with liberalization, we would expect capital to accumulate (even with a fixed saving and investment rate). If we endogenize K by invoking a consumption Euler equation to pin down the rental rate R , the output elasticity with respect to aggregate TFP

is $\frac{1}{1 - \sum_{s=1}^S \alpha_s \theta_s}$. When capital accumulates the effect of misallocation on output is

increasing in the average capital share. This property is reminiscent of a one sector neoclassical growth model, wherein increases in TFP are amplified by the capital accumulation they induce so that the output elasticity with respect to TFP is $1/(1 - \alpha)$.

Third, we will assume that the number of firms in each industry is not affected by the extent of misallocation. In an Appendix available upon request, we show that the number of firms would be unaffected by the extent of misallocation in a model of endogenous entry in which entry costs take the form of a fixed amount of labor.⁹

III. Datasets for India, China and the U.S.

Our data for India are drawn from India's Annual Survey of Industries (ASI) conducted by the Indian government's Central Statistical Organisation (CSO). The ASI is a census of all registered manufacturing plants in India with more than 100 workers and a random one-third sample of registered plants with more than 20 workers but less than 100 workers. For all calculations we apply a sampling weight so that our weighted sample reflects the population. The survey provides information on plant characteristics over the *fiscal* year (July of a given year through June of the following year). We use the ASI data from the 1987-1988 through 1994-1995 fiscal years. The raw data consists of around 40,000 plants in each year. For our computations we set industry capital shares to those in the corresponding U.S. manufacturing industry. As a result, we drop non-manufacturing plants and plants in industries without a close counterpart in the U.S. We also trim the 1% tails of both plant productivity and distortions to make the results robust to outliers.

The variables in the ASI we use are the plants' industry (4-digit ISIC), labor compensation, value-added, and book value of the fixed capital stock. Specifically, the ASI reports the plant's total wage payments, bonus payments, and the imputed value of benefits. Our measure of labor compensation is the sum of wages, bonuses, and benefits. In addition, the ASI reports the book value of fixed capital at the beginning and end of the fiscal year net of depreciation. We take the average of the net book value of fixed capital at the beginning and end of the fiscal year as our measure of the plant's capital.

⁹ A critical assumption we make is that an entrant does not know its productivity or distortions *ex ante*. These are only known *ex post*, i.e., after expending entry costs. *Ex ante* a potential entrant knows only that they will receive a random draw from the existing joint distribution of distortions and productivity. We also follow Melitz (2003) and Restuccia and Rogerson (2007) in assuming exogenous exit.

Our data for Chinese plants are from Annual Surveys of Industrial Production from 1998 through 2005 conducted by the Chinese government's National Bureau of Statistics (NBS). The Annual Survey of Industrial Production is a census of all non-state plants with more than 5 million yuan in revenue (about \$600,000) plus all state-owned plants. The raw data consists of over 100,000 plants in 1998 and grows to over 200,000 plants in 2005. Because we set industry capital shares to those in the corresponding U.S. manufacturing industry, we exclude non-manufacturing plants and plants in industries without a close counterpart in the U.S. Finally, we trim the 1% tails for plant productivity and distortions.

The information we use from the Chinese data are the plant's industry (again at the 4-digit level), wage payments, value-added, export revenues, and capital stock. We define the capital stock as the book value of fixed capital net of depreciation. As for labor compensation, the Chinese data only reports wage payments; it does not provide information on non-wage compensation. The median labor share in plant-level data is roughly 30 percent, which is significantly lower than the aggregate labor share in manufacturing reported in the Chinese input-output tables and the national accounts (roughly 50 percent). We therefore assume that non-wage benefits are a constant fraction of a plant's wage compensation, where the adjustment factor is calculated such that the sum of imputed benefits and wages across all plants equals 50 percent of aggregate value-added. We also have ownership status for the Chinese plants, and Table 1 shows this for several years.¹⁰ Chinese manufacturing had been predominantly state-run or state-involved, but was principally private by the end of our sample (around 80% of value added). This privatization may have brought a rationalization of government policies, with reduced subsidies for the formerly state-affiliated plants.

Our source for U.S. data is the Census of Manufactures in 1977, 1987 and 1997 conducted by the U.S. Bureau of the Census. Befitting their name, the Census covers all manufacturing plants regardless of size or ownership. The data consists of over 300,000 plants in each year. As with the Chinese and Indian data, we trim the 1% tails of the distributions of plant productivity and distortions. The information we use from the U.S.

¹⁰ These figures may understate the extent of privatization. Dollar and Wei (2007) conducted their own survey of Chinese firms in 2005, and found 15% of all firms were officially classified as state-owned who had in fact been privatized.

Census are the plant's industry (again at the 4-digit level), labor compensation (wages and benefits), value-added, export revenues, and capital stock. We define the capital stock as the book value of the plant's machinery and equipment and structures.

IV. Empirical Results

In order to calculate the effects of resource misallocation, we need to back out key parameters (output shares, capital shares, the firm-specific distortions) from the data. We proceed as follows:

We set the rental price of capital (before reforms and excluding distortions) to $R = 0.10$. We have in mind a 5% real interest rate and a 5% depreciation rate. The cost of capital faced by plant i in industry s is $(1 + \tau_{Ksi})R$, so it differs from 10% if $\tau_{Ksi} \neq 0$. Because our reforms collapse τ_{Ksi} to $\bar{\tau}_{Ks}$ in each industry, the attendant efficiency gains do not depend on R . If we have set R incorrectly, it affects only the $\bar{\tau}_{Ks}$ values, not the liberalization experiment.

We set the elasticity of substitution between plant value added to $\sigma = 3$. The gains from liberalization are increasing in σ , so we made this choice conservatively. Estimates of the substitutability of competing manufactures in the trade and industrial organization literatures typically range from 3 to 10 (e.g., Broda and Weinstein 2006, Hendel and Nevo 2006). Below we entertain the higher value of $\sigma = 5$ as a robustness check. Of course, the elasticity surely differs across goods (Broda and Weinstein report lower elasticities for more differentiated goods), so our single σ is a strong simplifying assumption.

As mentioned, we set the elasticity of output with respect to capital in each industry (α_s) to be one minus the labor share in the corresponding industry in the U.S. We do not set these elasticities based on labor shares in the Indian and Chinese data precisely because we think distortions are potentially important in the latter. We cannot separately identify the average output distortion and the production elasticity in each industry. We adopt the U.S. shares as the benchmark because we presume the U.S. is comparatively undistorted (both across plants and, more to the point here, across industries). Our source for the U.S. shares is the NBER Productivity Database, based on

the Census and Annual Surveys of Manufactures. One well-known issue with these data is that payments to labor omit fringe benefits and employer Social Security contributions. The CM/ASM manufacturing labor share is about 2/3 what it is in manufacturing according to the National Income and Product Accounts, which incorporates non-wage forms of compensation. We therefore scale up each industry's CM/ASM labor share by 3/2 to arrive at the labor elasticity we assume for the corresponding Indian or Chinese industry.

One issue that arises when translating factor shares into production elasticities is the division of rents from markups in these differentiated good industries. Because we assume a modest σ of 3, these rents are large. We assume that these rents show up as payments to labor (managers) and capital (owners) pro rata in each industry. As a consequence, our assumed value of σ has no impact on our production elasticities.

Based on the other parameters and the plant data, we infer the distortions and productivity for each plant in each country-year as follows:

$$(4.1) \quad 1 + \tau_{Ksi} = \frac{\alpha_s}{1 - \alpha_s} \frac{wL_{si}}{RK_{si}}$$

$$(4.2) \quad 1 - \tau_{Ysi} = \frac{\sigma}{\sigma - 1} \frac{wL_{si}}{(1 - \alpha_s) P_{si} Y_{si}}$$

$$(4.3) \quad A_{si} = \kappa_s \frac{(P_{si} Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}},$$

Equation (4.1) says we infer the presence of a capital distortion (subsidy) when the ratio of labor compensation to the capital stock is high (low) relative to what one would expect from the output elasticities with respect to capital and labor. Similarly, expression (4.2) says we deduce an output distortion (subsidy) when labor's share is low (high) compared to what one would think from the industry elasticity of output with respect to labor (and the adjustment for rents). A critical assumption embedded in (4.2) is that observed value added does *not* include any explicit output subsidies or taxes.

TFP in (4.3) warrants more explanation. First, the scalar is $\kappa_s = w^{1-\alpha_s} (P_s Y_s)^{-\frac{1}{\sigma-1}} / P_s$. Although we do not observe κ_s , relative productivities – and hence reallocation gains – are unaffected by setting $\kappa_s = 1$ for each industry s . Second and related, we do not observe each plant’s real output Y_{si} but rather its nominal output $P_{si} Y_{si}$. Plants with high real output (relative to what one would expect from κ_s), however, must have a lower price to explain why buyers would demand the higher output. We therefore raise $P_{si} Y_{si}$ to the power $\sigma/(\sigma-1)$ to arrive at Y_{si} . Third, for labor input we use the plant’s wage bill rather than its employment to measure L_{si} . We think earnings per worker probably vary more across plants because of differences in hours worked and human capital per worker than because of an omitted labor distortion.

Before calculating the gains from our hypothetical liberalization, we trim the 1% tails from the distributions of $\ln\left(\frac{1+\tau_{Ksi}}{1+\bar{\tau}_{Ks}}\right)$, $-\ln\left(\frac{1-\tau_{Ysi}}{1-\bar{\tau}_{Ys}}\right)$, and $\ln\left(\frac{A_{si}}{\bar{A}_s}\right)$ across industries. (Here, \bar{A}_s is defined as $\sum_{i=1}^{M_s} A_{si} \left(\frac{P_{si} Y_{si}}{P_s Y_s}\right)$). That is, we pool all industries and trim the top and the bottom 1% of plants within each of the three pools. We then recalculate wL_s , K_s , and $P_s Y_s$ as well as $\bar{\tau}_{Ks}$, $\bar{\tau}_{Ys}$, and \bar{A}_s . At this stage we calculate the industry shares $\theta_s = P_s Y_s / Y$.

Figure 1 plots the distribution of $\ln(\text{TFPQ})$ ($\ln A_{si}$) relative to the industry mean for the latest year in each country: India in 1994, China in 2005, and the U.S. in 1997. There is more dispersion in TFPQ in India and the U.S. than in China, but this could reflect the different sampling frames (no small private plants are covered in the Chinese survey). The left-tail of TFPQ is far thicker in India than the U.S., however, consistent with policies favoring inefficient incumbents there relative to the U.S. Table 2 shows that these patterns are consistent across years and several measures of dispersion of $\ln(\text{TFPQ})$: the standard deviation, the 75th minus the 25th percentiles, and the 90th minus the 10th percentiles. The ratio of 75th to 25th percentiles of TFPQ in the latest year are 5.7

in India, 3.6 in China, and 4.6 in the U.S. (exponentials of the corresponding numbers in Table 2).

Figure 2 plots the distribution of $\ln(\text{TFPR})$ [the log of $(1 + \tau_{Ksi})^{\alpha_s} / (1 - \tau_{Ysi})$] relative to the industry mean for the latest year in each country. There is clearly more dispersion of TFPR in India than in the U.S. Even China, despite not sampling small private establishments, exhibits notably greater TFPR dispersion than the U.S. Table 3 provides statistics of $\ln(\text{TFPR})$ for a number of country-years. The ratio of 75th to 25th percentiles of TFPR in the latest year are 2.5 in India, 2.3 in China, and 1.3 in the U.S. The ratio of 90th to 10th percentiles of TFPR are 6.7 in India, 4.9 in China and 2.4 in the U.S. in the latest year. According to Table 3, the contrast is even starker in other years. These numbers are consistent with there being greater distortions in China and India than in the U.S.¹¹

Recall from equation (2.16) that efficiency is linked to not only dispersion in TFPR but also its covariance with TFPQ. Hitting higher TFPQ plants with bigger distortions (higher TFPR) is particularly damaging to aggregate TFP. Table 4 presents regressions of $\ln(\text{TFPR})$ on $\ln(\text{TFPQ})$. The elasticities are positive in all country-years, but are two to four times larger in India and China than in the U.S. Again, these patterns suggest efficient plants may face more restrictions in India and China than in the U.S.

Table 5 presents results of regressing TFPR and TFPQ on ownership type in China in 2005. The omitted group is privately-owned domestic plants – the majority of plants and value added. State-owned plants exhibit 41% lower TFPR and 14% lower TFPQ, suggesting they enjoy preferential treatment.¹² Their exit and privatization may play an important role in improving allocations. Perhaps surprisingly, the collectively-owned (part private, part local government) plants have 11% higher TFPR and 5% higher TFPQ, as if they are both less favored and modestly more productive. Figure 4 shows that (surviving) state-owned plants have increased their relative TFPQ markedly since

¹¹ Hallward-Driemeier, Iarossi and Sokoloff (2002) similarly report more TFP variation across plants in poorer East Asian nations (Indonesia and the Philippines vs. Thailand, Malaysia and South Korea).

¹² Dollar and Wei (2007) likewise find lower (higher) productivity at state-owned (foreign-owned) firms.

1999. But they have increased their relative TFPR only modestly and only since 2002, suggesting favoritism towards them may linger.

The last portion of Table 5 indicates that foreign-owned plants are more productive (23% higher TFPQ), as one would expect, but also appear to be favored (13% lower TFPR). The latter could reflect better access to credit, but also preferential treatment if they are operating in export processing zones. Consistent with this interpretation, Table 6 reports that exporting plants have 46% higher TFPQ on average, but 14% lower TFPR. In the U.S., exporters have an even bigger TFPQ advantage (120%) but they display higher rather than lower TFPR (+19% on average).¹³

We next calculate “efficient” output in each country so we can compare it with actual output levels. That, if marginal products were equalized across plants in a given

sector, aggregate TFP in the sector would be given by $\left(\frac{1}{M_s} \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$. We calculate

the ratio of the actual level of TFP in each sector to the “efficient” level of TFP using this formula, and then aggregate this ratio across sectors using our Cobb-Douglas aggregator (equation (2.1)). We freely admit this exercise heroically makes no allowance for model misspecification or data measurement error. Such errors would lead us to overstate room for efficiency gains from better allocation. With these caveats firmly in mind, Table 7 provides the % TFP gains in each country from fully equalizing TFPR across plants in each industry. We provide three years per country. Full liberalization, by this calculation, would boost aggregate manufacturing TFP around 90% in China, around 125% in India, and around 40% in the U.S.

If measurement and modeling errors are to explain these results, they clearly have to be much bigger in China and India than the U.S. Related, Figure 3 plots the “efficient” vs. actual size distribution of plants in the most recent years. Size here is measured as plant value added. In both China and India, the hypothetical efficient distribution is more dispersed than the actual one. In particular, there should be fewer mid-sized plants and more small and large plants. In the U.S., by comparison, the efficient and actual distributions lie virtually on top of one another. The contrast suggests the U.S. may not

¹³ The high TFPQ of exporters could reflect the “demand shock” coming from accessing foreign markets, rather than just physical productivity.

distort its size distribution in the way China and India do. Although we will explore possible model and measurement errors when we do our robustness checks in section V, Table 7 and Figure 3 imply that such errors would have to be very different in China and India than the U.S.

If Figure 3 was the whole story then the hypothetical TFP gain in the U.S. would not be 40%. Table 8 shows the changes in establishment size (value added) needed to equalize TFPR in each country. The rows are unweighted shares of plants by size quartile, and the columns are bins of efficient plant size relative to actual size: 0-50% (the plant shrink by a half or more), 50-100%, 100-200%, and 200+% (the plant should at least double in size). In China and India the most populous column is 0-50% for every initial size quartile. Although average output rises substantially, many plants of all sizes should shrink. Thus there could be many state-favored behemoths in China and India that should be downsized, even if large plants should typically be larger. For the U.S., the most populous column for every size quartile is 100-200%. Still, whereas the actual and efficient size distributions are similar for the U.S. in Figure 3, many plants should become bigger or smaller within this distribution. There are TFPR gaps in the U.S., just not ones very correlated with actual size in the U.S.

It might not be desirable to equalize TFPR across all plants within a country, say because of measurement error and model misspecification. But the U.S. may represent a desirable benchmark. We next consider the efficiency gains in China and India from moving to the U.S. joint distribution of TFPR and TFPQ. As we have seen earlier, when TFPQ and TFPR are jointly log-normally distributed, the effect of misallocation on log aggregate TFP is linear in the variance of $\ln(\text{TFPR})$ and the covariance of $\ln(\text{TFPR})$ and $\ln(\text{TFPQ})$. In this case, the TFP gain from moving to the U.S. joint distribution of TFPQ and TFPR is the same as the relative gains from “full liberalization” in China or India vs. the U.S. By full liberalization we mean setting the variance of TFPR and its covariance with TFPQ to zero.¹⁴

¹⁴ We have experimented with alternative ways of altering the distribution of TFPR and TFPQ in the China and India to mimic that of the U.S.. For example, an alternative we tried is to set the elasticity of TFPR with respect to TFPQ in India and China equal to that in the U.S. data and to set the residual variance in TFPR in India and China equal to that in the U.S. This approach yielded similar results.

In Table 9 we report the % TFP gains in China and India relative to those in the U.S. in 1997 (a conservative point of comparison as U.S. gains are largest in 1997). For China, hypothetically moving to “U.S. efficiency” might have resulted in 40% higher TFP in 1998, 30% higher TFP in 2001, and 27% higher TFP in 2005. By this calculation, improved allocative efficiency may have contributed 1.4 percentage points annually to TFP growth in Chinese manufacturing from 1998 to 2005. For India, meanwhile, hypothetically moving to U.S. efficiency might have brought 53% higher TFP in 1987 or 1991, and 58% higher TFP in 1994. Thus we find no evidence of improved allocation in India from 1987 to 1994. The implied decline in allocative efficiency of almost 1% per year from 1991 to 1994 is surprising given that Indian reforms began in the early 1990s.

Our implied TFP gains in China and India from moving to U.S. efficiency are large, even when viewed as a fraction of aggregate TFP differences between China and India and the U.S. Aggregate TFP in U.S. manufacturing is 130% higher than in China and 160% higher than in India.¹⁵ Therefore, our estimates suggest that resource misallocation might be responsible for 20% of the TFP gap between the U.S. and China and 30% of the TFP gap between the U.S. and India.

V. Robustness Checks

In this section, we gauge the sensitivity of our calculated efficiency gains to various assumptions we have made.

Endogenous Capital

For our baseline estimates of output gains from liberalization we assumed a fixed aggregate capital stock. As discussed earlier, however, TFP gains are amplified by an exponent equal to the inverse of one minus capital’s share (more accurately, the elasticity of output with respect to capital) when capital accumulates to keep the rental price of

¹⁵ We use the aggregate price of tradable goods between India and the U.S. in 1985 (from the benchmark data in the Penn World Tables) to deflate Indian prices to U.S. prices. Since we do not have price deflators for Chinese manufacturing, we use the Indian price of tradable goods to convert Chinese prices at market exchange rates to PPP prices. In addition, we assume that the capital-output ratio and the average level of human capital in the manufacturing sector is the same as that in the aggregate economy. The aggregate capital-output ratio is calculated from the Penn World Tables and the average level of human capital is calculated from average years of schooling (from Barro-Lee) assuming a 10 percent Mincerian return.

capital constant. In India's case the average capital share was 50% in 1994-1995, so the TFP gains are roughly squared. The same goes for China, as its average capital share was 49% in 2005. Thus the 27% TFP gain in 2005 China could yield a 60% long run gain in manufacturing output, whereas the 58% TFP gain in 1994 India could ultimately boost manufacturing output 149%.

Alternative Elasticity of Substitution Within Sectors

In our baseline calculations, we assumed an elasticity of substitution within industries (σ) of 3, conservatively at the low end of empirical estimates. China's hypothetical TFP gain in 2005 soars from 87% with $\sigma = 3$ to 185% with $\sigma = 5$, and India's in 1994 from 132% to 237%. These are gains from fully equalizing TFPR levels. When σ is higher, TFPR gaps are closed more slowly in response to reallocation of inputs from low to high TFPR plants, enabling bigger gains from equalizing TFPR levels.

Alternative Elasticity of Substitution Between Sectors

In our baseline estimates, we assumed unitary elasticity of substitution between sectors. This implied that liberalization did not affect the allocation of inputs across sectors; the rise in sector productivity due to liberalization was exactly offset by the resulting fall in the sector's price index. We now relax this assumption. Specifically, suppose aggregate output is a CES aggregate of sector outputs:

$$Y = \left(\sum_{s=1}^S \theta_s Y_s^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}}$$

We first consider a case where sector outputs are closer complements ($\phi = 0.5$). The gains from liberalization are modestly smaller in China (82% vs. 87% in 2005) and appreciably smaller in India (112% vs. 132% in 1994). The gains shrink because $\phi < 1$ means sectors with larger increases in productivity shed inputs. Next consider a case where sector outputs are more substitutable ($\phi = 2$). In this case, the gains from liberalization are modestly larger in China (90% vs. 87%) and notably larger in India

(147% vs. 132%). When sector outputs are substitutes, inputs are reallocated toward sectors with bigger productivity gains, so aggregate TFP increases more

Varying markups

Our CES aggregation of plant value added within industries implies that all goods have the same markup within industries (not to mention across industries). Yet markups might be higher for high TFPQ plants. Such a pattern could explain the positive correlation we find between TFPR and TFPQ. Markups are a distortion too, of course, but one presumably less amenable to policy reforms. Melitz and Ottaviano (2005) analyze the case of linear demand, under which the elasticity of demand is falling with size and the markup is increasing in size. Figure 5 shows why we did not go this route. Whereas TFPR is strongly increasing in plant size in India and modestly increasing in plant size in China, it shows no clear pattern in the U.S. If linear demand applied everywhere and was responsible for the correlation of TFPR with TFPQ, we would expect TFPR to be smartly increasing in size in the U.S. It is possible that markups behave differently in China and India than in the U.S., of course.

Adjustment costs

Growing plants might have higher TFPR than shrinking plants due to adjustment costs. Related, young plants might exhibit high TFPR due to adjustment costs and/or learning about their productivity in the face of irreversible investments. Figure 6 demonstrates why we did not incorporate such forces. TFPR is steadily increasing in plant age in India, contrary to these stories. In China TFPR rises through the youngest decile, then is flat in the middle deciles before falling in the oldest decile. This is similarly inconsistent with adjustment costs. Only the U.S. exhibits the predicted pattern of high and falling TFPR for young plants (the youngest quartile), before flattening out for older plants.

Figure 7 is similarly hard to reconcile with these hypotheses. In India, TFPR is flat for the bottom half of the distribution of input growth rates before rising slowly. For China, TFPR is flat for the bottom three quartiles of input growth before rising more rapidly. In the U.S., TFPR edges down in the bottom quartile of input growth, rises

slowly in the middle quartiles, then rises more sharply in the top quartile. The U.S. data fits the adjustment cost story at least as well as the Chinese and Indian data. But perhaps input growth rates vary more in China and Indian, due to their reforms, than in the U.S. with its more stable policy environment. According to Table 10, however, input growth varies more across U.S. plants than plants in China or (especially) India. The U.S. displays more churning, so if anything should have more TFPR variation due to adjustment costs.

Unobserved investments

Low TFPR might reflect learning by doing or other unobserved investments (R&D, building a customer base) rather than distortions. If so, then we expect low TFPR plants to exhibit high subsequent TFPQ growth. Figure 8 displays precisely this pattern in the U.S., but the opposite pattern in China and India.

Measurement Error

Our potential efficiency gains could be a figment of greater measurement error in Chinese and Indian data than in the U.S. data. For our baseline estimates we trimmed the 1% outliers in TFPR (actually, in the output and capital distortions separately) and in TFPQ. When we trim 2% tails the hypothetical TFP gain falls from 87% to 69% in 2005 China, and from 132% to 110% in 1994 India. Measurement error in the remaining 1% tails therefore does not account for the big gains from equalizing TFPR.

As a way to address measurement error in the interior of the TFPR distribution, we project the log levels of each plant's value added, capital stock, and wage bill on the previous year's log levels. We then use fitted values to calculate TFPR and TFPQ. Obviously, this can be performed only on incumbent plants. If measurement error is less persistent than true variables, then this "instrumenting" should shrink efficiency gains more in China and India than in the U.S. The TFP gain from fully equalizing TFPR levels falls from 87% under "OLS" to 72% under "IV" in 2005 China, from 132% to 121% in 1994 India, and from 47% to 30% in the 1997 U.S. By this metric, measurement error accounts for a bigger fraction of the gains in the U.S. than in China or India. But it could instead be that measurement error is more persistent than true TFPR.

Finally and perhaps most compellingly, we look at the TFPR of exiters and entrants. Although our model did not feature endogenous exit, one would expect true TFPR to be lower for exiters. If TFPR is measured with greater error in the Chinese and Indian data, we expect TFPR to be more negative for U.S. exiters than for exiters in China and India. Table 11 shows that the opposite is true in these datasets: exiters average 3.4% lower TFPR in China, 11.2% lower TFPR in India, and 3.4% *higher* TFPR in the U.S. Low TFPR firms disproportionately exit in China and India, suggesting TFPR is a strong signal of profitability. Of course, government subsidies might allow unprofitable plants to continue rather than exit. But that is not what Table 11 shows, perhaps because of the reforms underway in both countries. The Table also shows that selection is much stronger on TFPQ in the U.S. But the efficiency gains revolve around TFPR differences, not TFPQ differences. For completeness the Table also shows that TFPR is higher for entrants in all three countries, and TFPQ markedly lower.¹⁶

Varying capital shares within industries

Our baseline estimates assumed the same capital elasticity for all plants within a 4-digit industry. We inferred capital-labor distortions from variation in capital-labor ratios within industries. At the other extreme, one could attribute all variation in capital-labor ratios within industries to plant-specific capital shares. Table 12 presents aggregate TFP gains for China and India relative to the U.S. with such plant-specific capital shares.¹⁷ Evidently the bulk of the baseline gains in China (25-40%) stem from output distortions, as TFP gains are 20-35% with plant-specific capital shares. Capital distortions contributed more to the baseline gains of 50-60% in India, as TFP gains fall to 32-45% with plant-specific capital shares. Even in India, however, the output distortions appear twice as important as any distortions to capital-labor ratios.

¹⁶ In China, it is also interesting to compare the TFPR and TFPQ of privatized vs. exiting state plants. Among state-owned plants in 2000, those privatized by 2005 had 11% higher TFPR and 26% higher TFPQ than plants exiting by 2005.

¹⁷ The closed form expression (2.17) does not apply with plant-specific capital shares. We had to solve for aggregate TFP gains numerically.

VI. Conclusion

A long stream of papers has stressed that misallocation of inputs across firms can reduce aggregate TFP in a country. We used micro data on manufacturing plants to investigate the possible role of such misallocation in China (1998-2005) and India (1987-1994) compared to the U.S. (1977, 1987, 1997). Viewing the data through the prism of a standard monopolistic competition model, we estimated differences in marginal products of labor and capital across plants within narrowly-defined industries. We found much bigger gaps in China and India than in the U.S. We then entertained a counterfactual move by China and India to the U.S. distribution of marginal products. We found that this would boost TFP by 25-40% in China and by 50-60% in India. Room for reallocation gains shrank about 1% per year from 1998-2005 in China, as if reforms there reaped some of the gains. In India, despite reforms in the early 1990s, we report evidence of rising misallocation from 1991 to 1994.

Our results require many caveats. There could be greater measurement error in the Chinese and Indian data than in the U.S. data. The static monopolistic competition model we deploy could be a particularly bad approximation for manufacturing in China and India in the wake of reforms there. Although we provided reassuring evidence on each of these concerns, our investigation was very much a first pass. In addition to investigating these issues more fully, future work could try to relate differences in firm productivity to observable policy distortions.

Table 1

Ownership of Chinese plants

	<u>State</u>	<u>Collective</u>	<u>Private</u>
2000	33	16	51
2002	24	11	65
2004	15	5	80

Notes: Data are from the *Chinese Annual Surveys of Industrial Production*. Collective enterprises are jointly owned by local governments and private parties.

Table 2
Dispersion of ln(TFPQ)

<u>China</u>			
	1998	2001	2005
S.D.	1.06	0.99	0.95
75-25	1.41	1.34	1.28
90-10	2.72	2.54	2.44
N	95,980	108,702	211,304
<u>India</u>			
	1987	1991	1994
S.D.	1.38	1.33	1.37
75-25	1.67	1.67	1.74
90-10	3.44	3.35	3.43
N	31,603	37,550	41,081
<u>United States</u>			
	1977	1987	1997
S.D.	1.08	1.03	1.07
75-25	1.53	1.42	1.52
90-10	2.82	2.69	2.79
N	315,737	337,137	348,859

Notes: Data are from the Chinese *Annual Surveys of Industrial Production*, the Indian *Annual Survey of Industries*, and the U.S. *Census of Manufactures*. For plant i in

industry s , $TFPQ_{si} \equiv \frac{Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}$. Statistics are for deviations of $\ln(TFPQ)$ from

industry means. S.D. = standard deviation, 75-25 is the difference between the 75th and 25th percentiles, and 90-10 the 90th vs. 10th percentiles. Industries are weighted by their value added shares. N = the number of plants.

Table 3

Dispersion of ln(TFPR)

China

	1998	2001	2005
S.D.	0.74	0.68	0.63
75-25	0.97	0.88	0.82
90-10	1.87	1.71	1.59

India

	1987	1991	1994
S.D.	0.86	0.81	0.79
75-25	0.94	0.95	0.93
90-10	2.10	1.96	1.90

United States

	1977	1987	1997
S.D.	0.39	0.33	0.42
75-25	0.26	0.18	0.24
90-10	0.79	0.68	0.86

Notes: Data are from the Chinese *Annual Surveys of Industrial Production*, the Indian *Annual Survey of Industries*, and the U.S. *Census of Manufactures*. For plant i in

industry s , $TFPR_{si} \equiv \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}$. Statistics are for deviations of ln(TFPR) from

industry means. S.D. = standard deviation, 75-25 is the difference between the 75th and 25th percentiles, and 90-10 the 90th vs. 10th percentiles. Industries are weighted by their value added shares. N = the number of plants.

Table 4
Regressing ln(TFPR) on ln(TFPQ)

<u>China</u>	1998	2001	2005
Elasticity	0.490	0.456	0.430
S.E.	0.551	0.542	0.517
 <u>India</u>	 1987	 1991	 1994
Elasticity	0.412	0.400	0.373
S.E.	0.689	0.675	0.642
 <u>U.S.</u>	 1977	 1987	 1997
Elasticity	0.137	0.103	0.179
S.E.	0.394	0.338	0.386

Notes: Data are from the Chinese *Annual Surveys of Industrial Production*, the Indian *Annual Survey of Industries*, and the U.S. *Census of Manufactures*. For plant i in industry s ,

$$TFPQ_{si} \equiv \frac{Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}} \text{ and } TFPR_{si} \equiv \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}. \text{ The dependent variable is the}$$

deviation of $\ln(TFPR)$ from the industry mean, and the independent variable is the deviation of $\ln(TFPQ)$ from its industry mean. Regression are weighted least squares, where industries are weighted by their value added shares. The Elasticity is the regression coefficient, and S.E. is its standard error.

Table 5
TFP by ownership in China

	TFPR	TFPQ
State	-0.415 (0.023)	-0.144 (0.090)
Collective	0.114 (0.010)	0.047 (0.013)
Foreign	-0.129 (0.024)	0.228 (0.040)

Notes: Data are from the *Chinese Annual Surveys of Industrial Production*. For plant i

in industry s , $TFPQ_{si} \equiv \frac{Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}$ and $TFPR_{si} \equiv \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}$. The dependent

variable is the deviation of $\ln(\text{TFPR})$ or $\ln(\text{TFPQ})$ from the industry mean. The independent variables are dummies for state-owned plants, collective-owned plants, and foreign-owned plants. The omitted group is domestic privately-owned plants. Regressions are weighted least squares with the weights being industry value added shares. Entries above are the dummy coefficients, with standard errors are in parentheses. Results are pooled for all years.

Table 6**TFP for Exporters (vs. Non-Exporters)**

	TFPR	TFPQ
China	-0.141 (0.038)	0.461 (0.051)
United States	0.194 (0.015)	1.214 (0.074)

Notes: Data are from the Chinese *Annual Surveys of Industrial Production* and the U.S.

Census of Manufactures. For plant i in industry s , $TFPQ_{si} \equiv \frac{Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}$ and

$TFPR_{si} \equiv \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}$. The dependent variable is the deviation of $\ln(TFPR)$ or $\ln(TFPQ)$

from the industry mean. The independent variable is a dummy for whether the plant exported. The omitted group is non-exporters. Regressions are weighted least squares with the weights being industry value added shares. Entries above are the dummy coefficients. Results are pooled for all years.

Table 7

TFP Gains from Equalizing TFPR Within Industries

<u>China</u>	1998	2001	2005
%	105.1	90.8	86.5
<u>India</u>	1987	1991	1994
%	125.1	125.6	132.0
<u>U.S.</u>	1977	1987	1997
%	38.6	31.6	47.0

Notes: Data are from the Chinese *Annual Surveys of Industrial Production*, the Indian *Annual Survey of Industries*, and the U.S. *Census of Manufactures*. For plant i in industry s ,

$TFPR_{si} \equiv \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}$. Entries in the Table are $100 \cdot (Y_{efficient} / Y_{data} - 1)$, where

$$Y_{efficient} = \prod_{s=1}^S \left[\frac{1}{M_s} \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}}.$$

Table 8**% of Plants, Actual Size vs. Efficient Size****China 2005**

	0-50%	50-100%	100-200%	200+%
Top Size Quartile	8.2	6.2	4.6	6.0
2nd Quartile	7.8	6.0	4.7	6.5
3rd Quartile	8.7	6.0	4.5	5.8
Bottom Quartile	10.5	5.8	4.0	4.7

India 1994

	0-50%	50-100%	100-200%	200+%
Top Size Quartile	9.4	5.2	4.2	6.2
2nd Quartile	10.6	5.4	3.5	5.6
3rd Quartile	12.3	4.9	3.2	4.7
Bottom Quartile	14.2	4.1	2.6	4.1

U.S. 1997

	0-50%	50-100%	100-200%	200+%
Top Size Quartile	4.6	6.2	9.7	4.5
2nd Quartile	4.3	4.9	11.5	4.3
3rd Quartile	1.6	3.2	16.9	3.4
Bottom Quartile	0.5	3.0	18.6	2.8

Notes: Data are from the Chinese *Annual Surveys of Industrial Production*, the Indian *Annual Survey of Industries*, and the U.S. *Census of Manufactures*. In each country-year, plants are put into quartiles based on their actual value added, with an equal number of plants in each quartile. The hypothetically efficient level of each plant's output is then calculated, assuming distortions are removed so that TFPR levels are equalized within industries. The entries above show the % of plants with efficient/actual output levels in the four bins 0-50% (efficient output less than half actual output), 50-100%, 100-200%, and 200%+ (efficient output more than double actual output). The rows add up to 25%, and the rows and columns together to 100%.

Table 9

TFP Gains from Equalizing TFPR *relative to 1997 U.S. Gains*

<u>China</u>	1998	2001	2005
%	39.6	29.8	26.9
<u>India</u>	1987	1991	1994
%	53.2	53.5	57.9

Notes: Data are from the Chinese *Annual Surveys of Industrial Production*, the Indian *Annual Survey of Industries*, and the U.S. *Census of Manufactures*. For plant i in industry s ,

$TFPR_{si} \equiv \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}$. For each country-year shown above, we calculated $Y_{efficient} / Y_{data}$

using $Y_{efficient} = \prod_{s=1}^S \left[\frac{1}{M_s} \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}}$. We then took the ratio of $Y_{efficient} / Y_{data}$ to the

U.S. ratio in 1997. Finally, we subtracted 1 and multiplied by 100 to yield the entries above.

Table 10
Dispersion of Annual Input Growth

	China	India	US
S.D.	0.47	0.28	0.54
75-25	0.39	0.25	0.55
90-10	0.93	0.58	1.15

Notes: Data are from the *Chinese Annual Surveys of Industrial Production*, the *Indian Annual Survey of Industries*, and the *U.S. Census of Manufactures*. For plant i in industry s , input growth is the log first difference of $K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}$ across successive years. S.D. is the standard deviation of input growth (vs. industry means, and with industries weighted by their value added shares), 75-25 is the 75th vs. 25th percentiles, and 90-10 is the 90th vs. 10th percentiles. Results are pooled for all years.

Table 11

Regressions of ln(TFPR), ln(TFPQ) on Exit, Entry

	Exiter TFPR	Exiter TFPQ	Entrant TFPR	Entrant TFPQ
<u>China</u>				
Elasticity	-0.034	-0.349	0.091	-0.188
S.E.	0.012	0.016	0.016	0.023
<u>India</u>				
Elasticity	-0.112	-0.428	0.172	-0.567
S.E.	0.015	0.029	0.023	0.039
<u>U.S.</u>				
Elasticity	0.034	-0.868	0.063	-0.696
S.E.	0.011	0.049	0.012	0.038

Notes: Data are from the Chinese *Annual Surveys of Industrial Production*, the Indian *Annual Survey of Industries*, and the U.S. *Census of Manufactures*. For plant i in

industry s , $TFPQ_{si} \equiv \frac{Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}$ and $TFPR_{si} \equiv \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}$. The dependent

variable is the deviation of ln(TFPR) or ln(TFPQ) from the industry mean. The independent variables are dummies for exiting plants or new plants (separate regressions). Results are pooled for all years. Regressions are weighted least squares with the weights being industry value added shares. Entries above are the dummy coefficients, with S.E. referring to their standard errors.

Table 12

% TFP Gains with Common vs. Plant-Specific Capital Shares

<u>China</u>	1998	2001	2005
Common (α_s)	39.6	29.8	26.9
Plant-specific (α_{si})	34.8	22.5	19.9
<u>India</u>	1987	1991	1994
Common (α_s)	53.2	53.5	57.9
Plant-specific (α_{si})	44.8	32.4	38.1

Notes: Data are from the Chinese *Annual Surveys of Industrial Production*, the Indian *Annual Survey of Industries*, and the U.S. *Census of Manufactures*. The entries with common capital shares are reproduced from Table 7. Also see the notes to Table 7.

Figure 1: Distribution of TFPQ

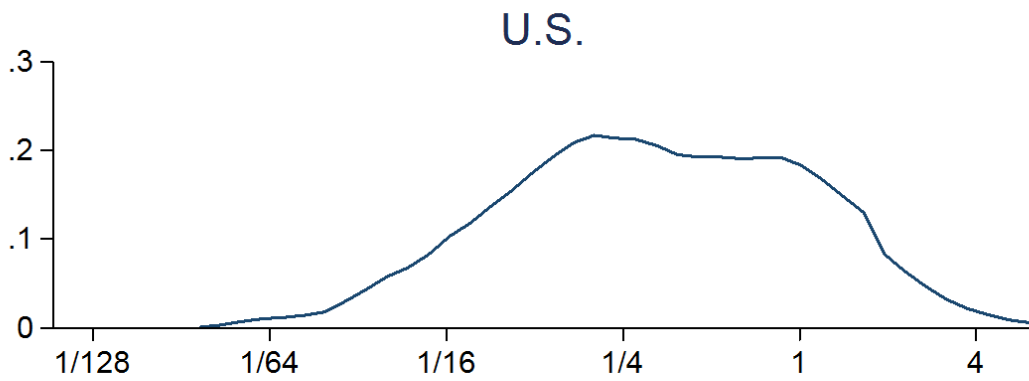
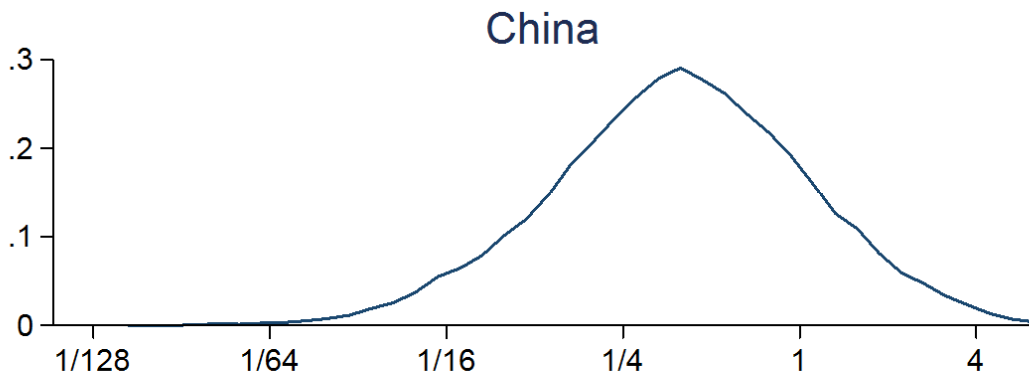
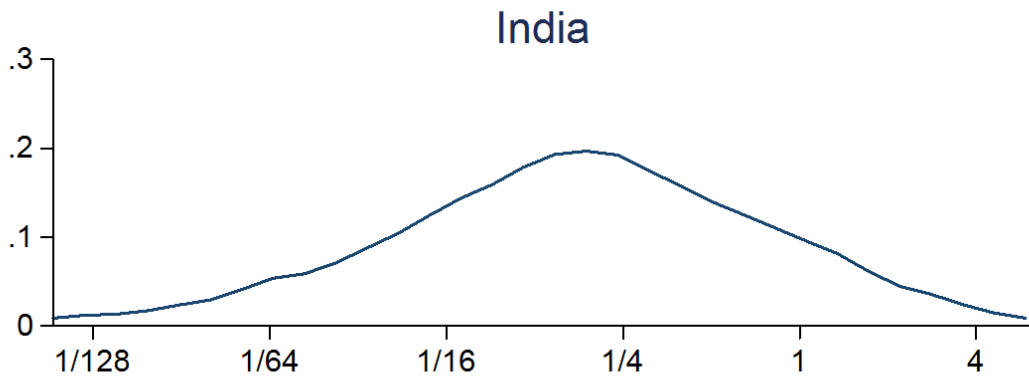


Figure 2: Distribution of TFPR

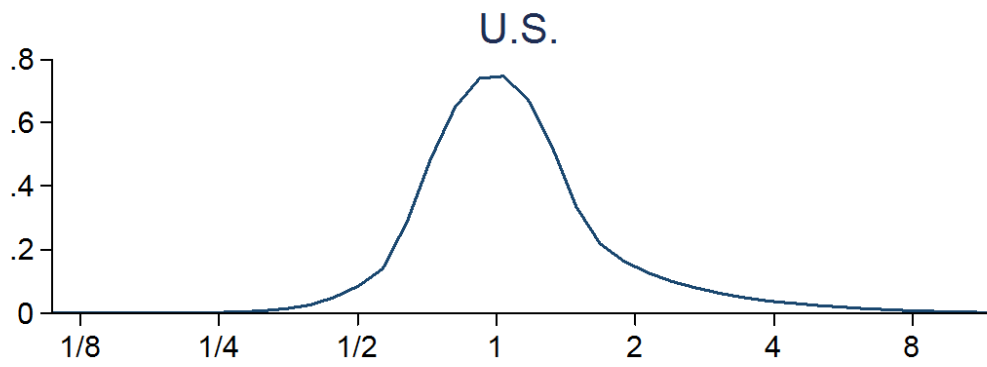
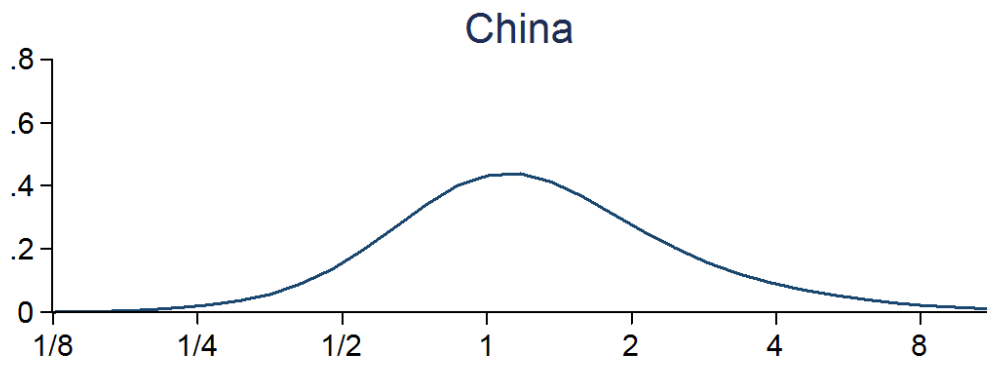
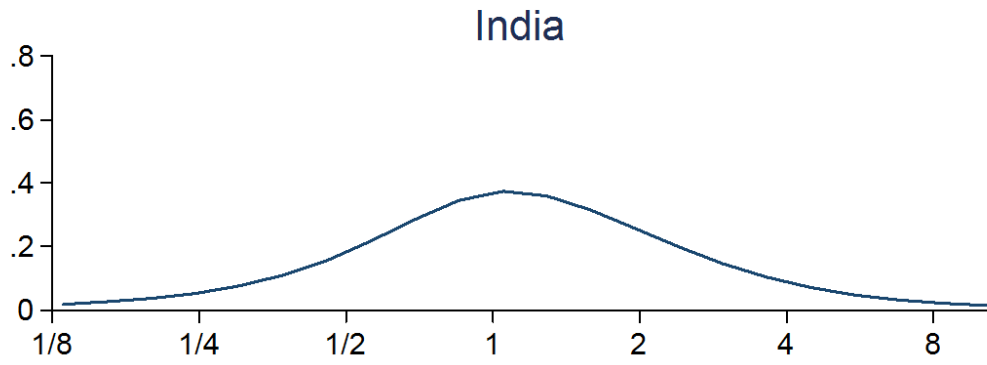


Figure 3

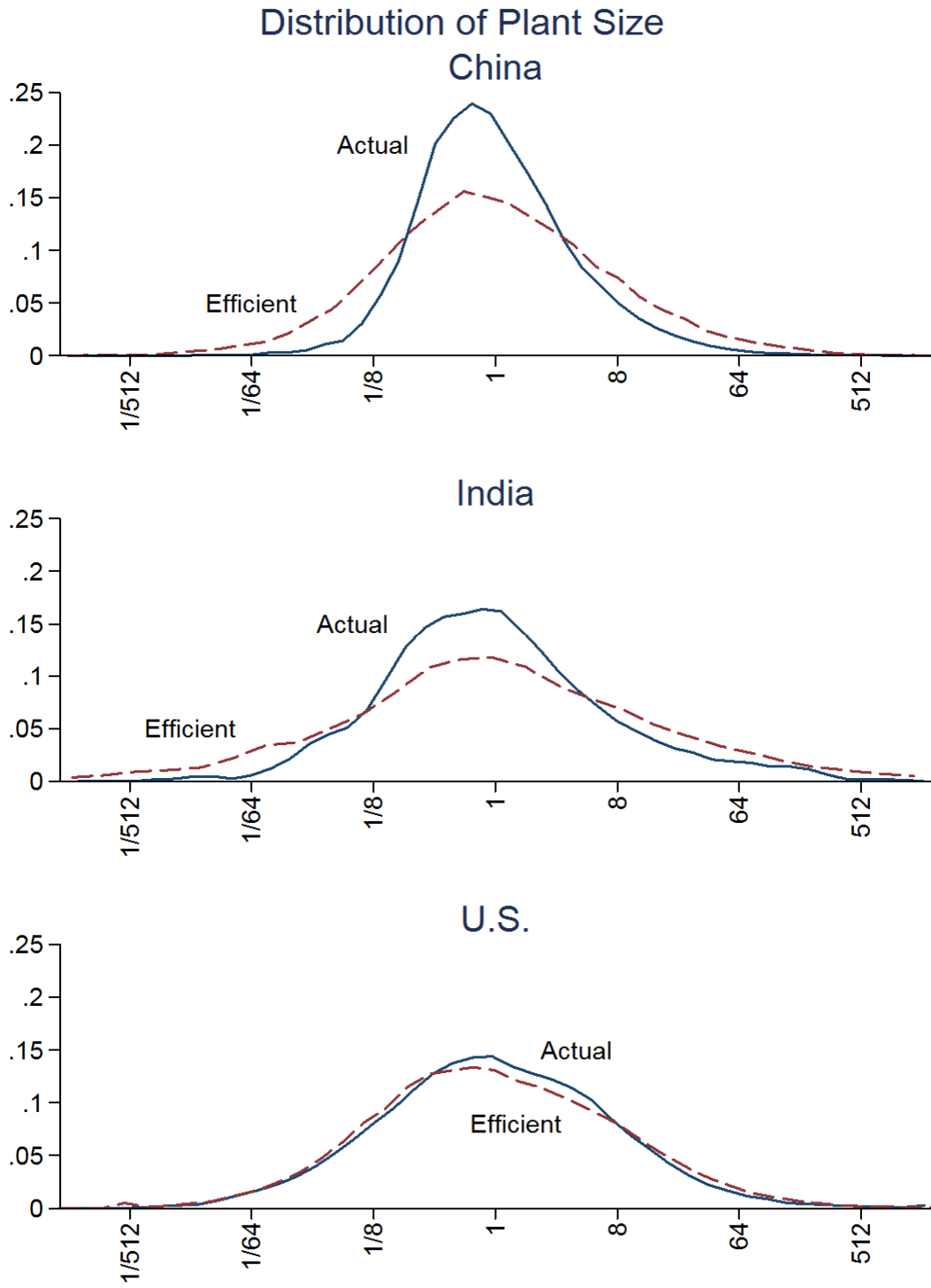


Figure 4

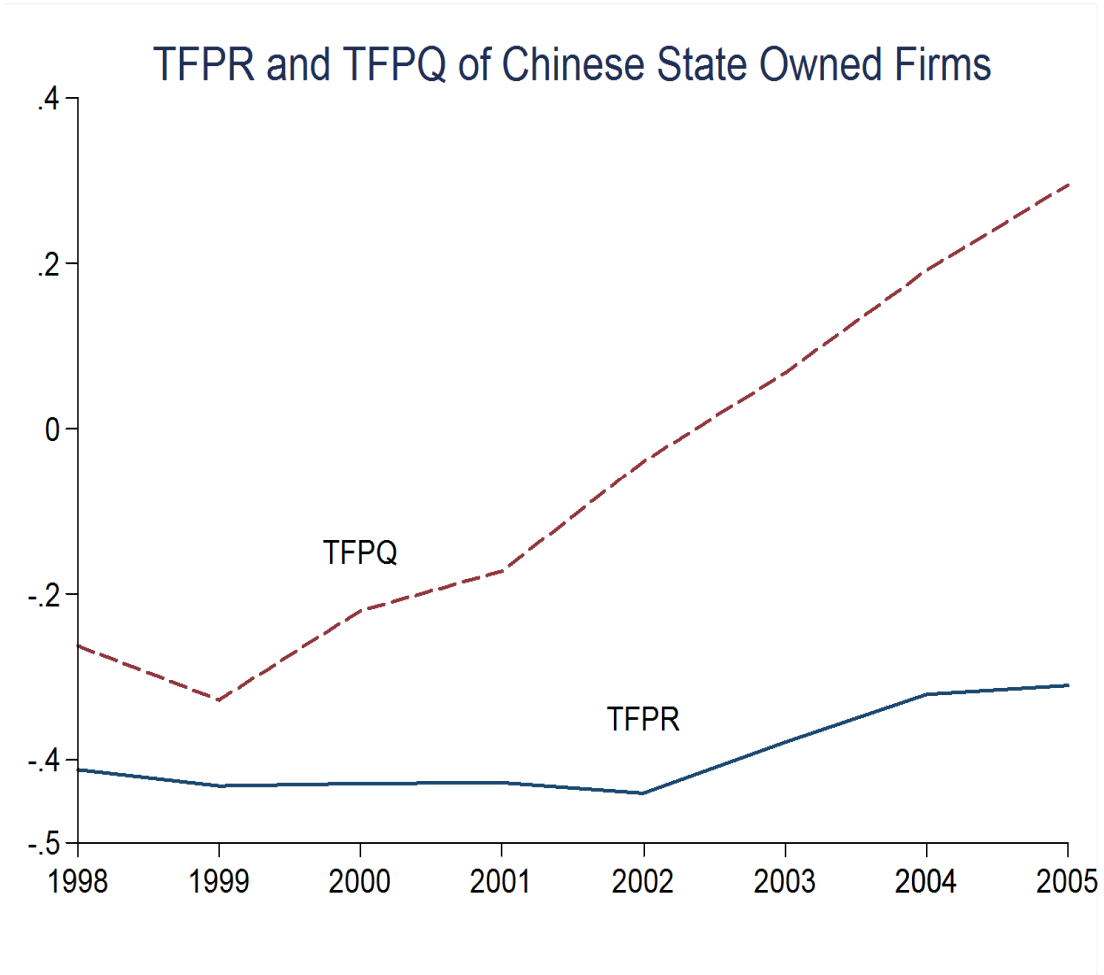


Figure 5: TFPR and Size

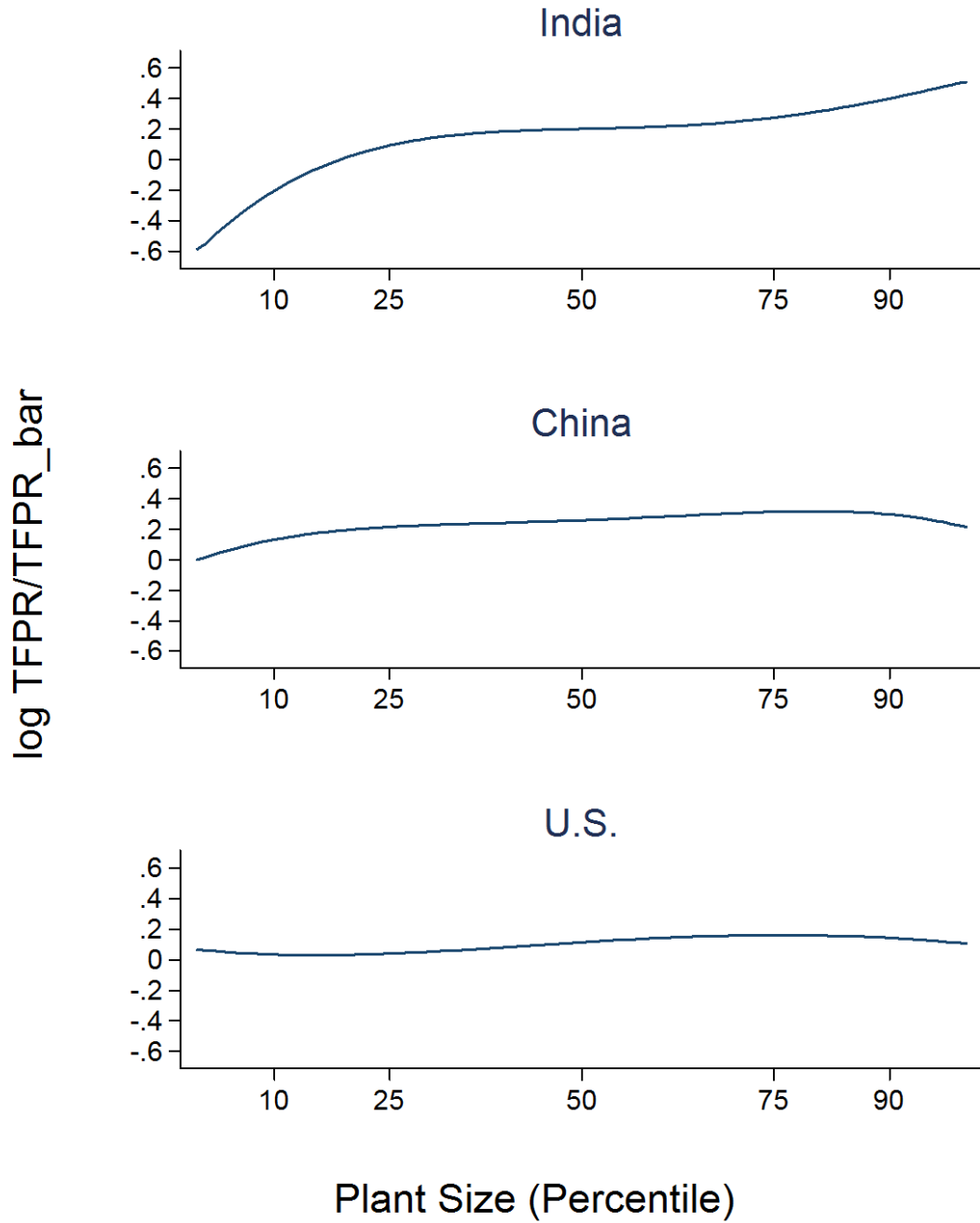


Figure 6: TFPR and Age

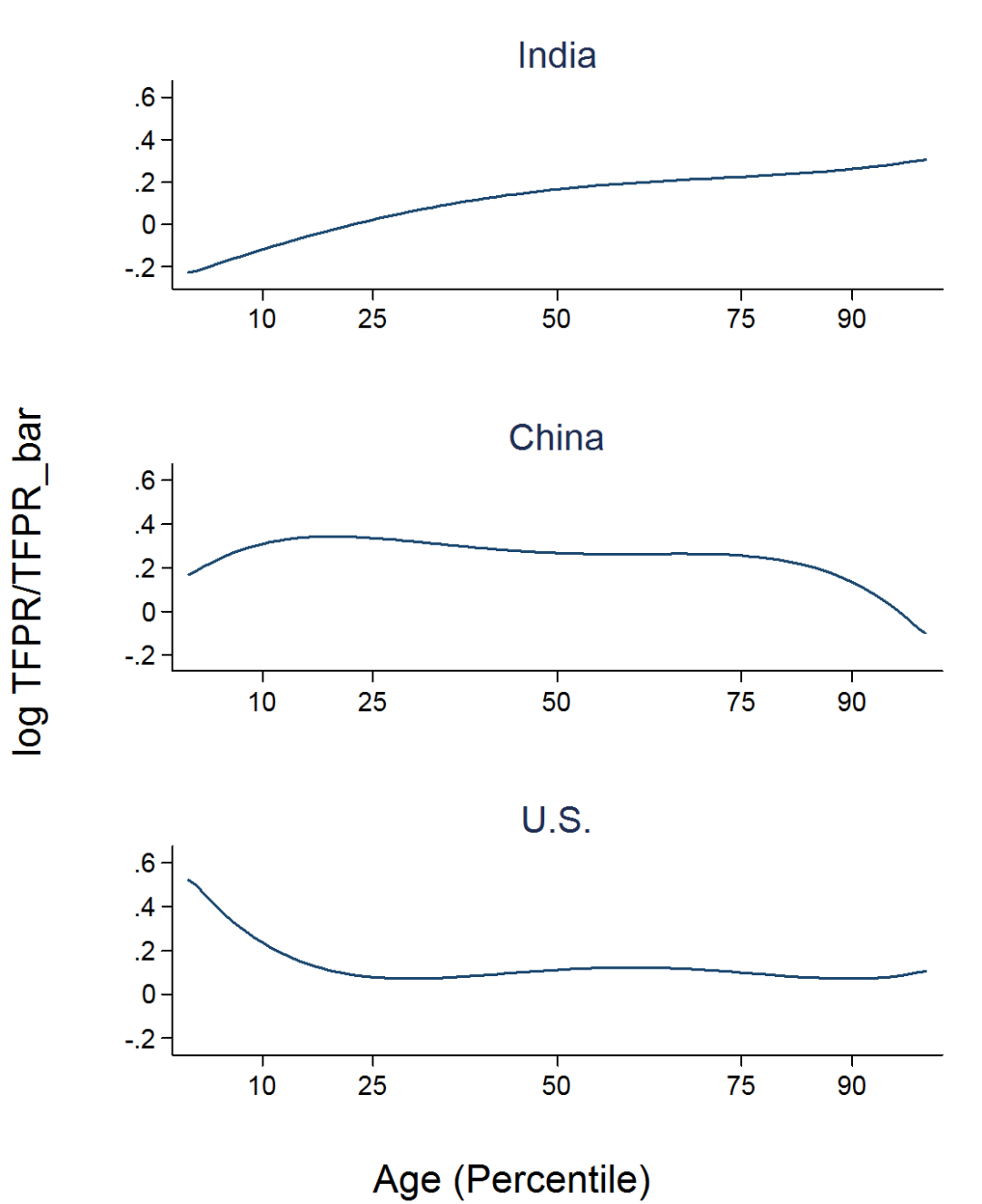


Figure 7: TFPR and Input Growth

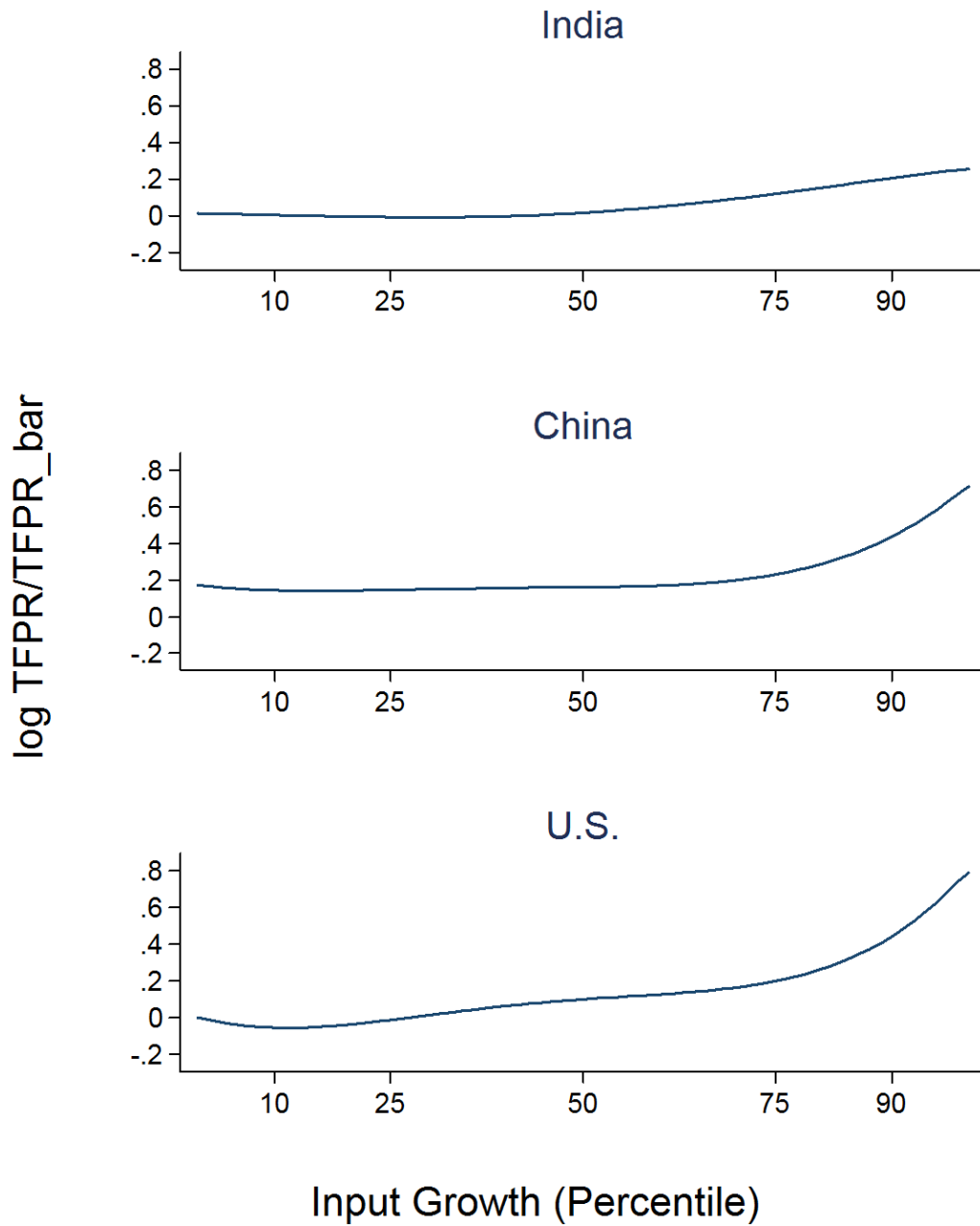
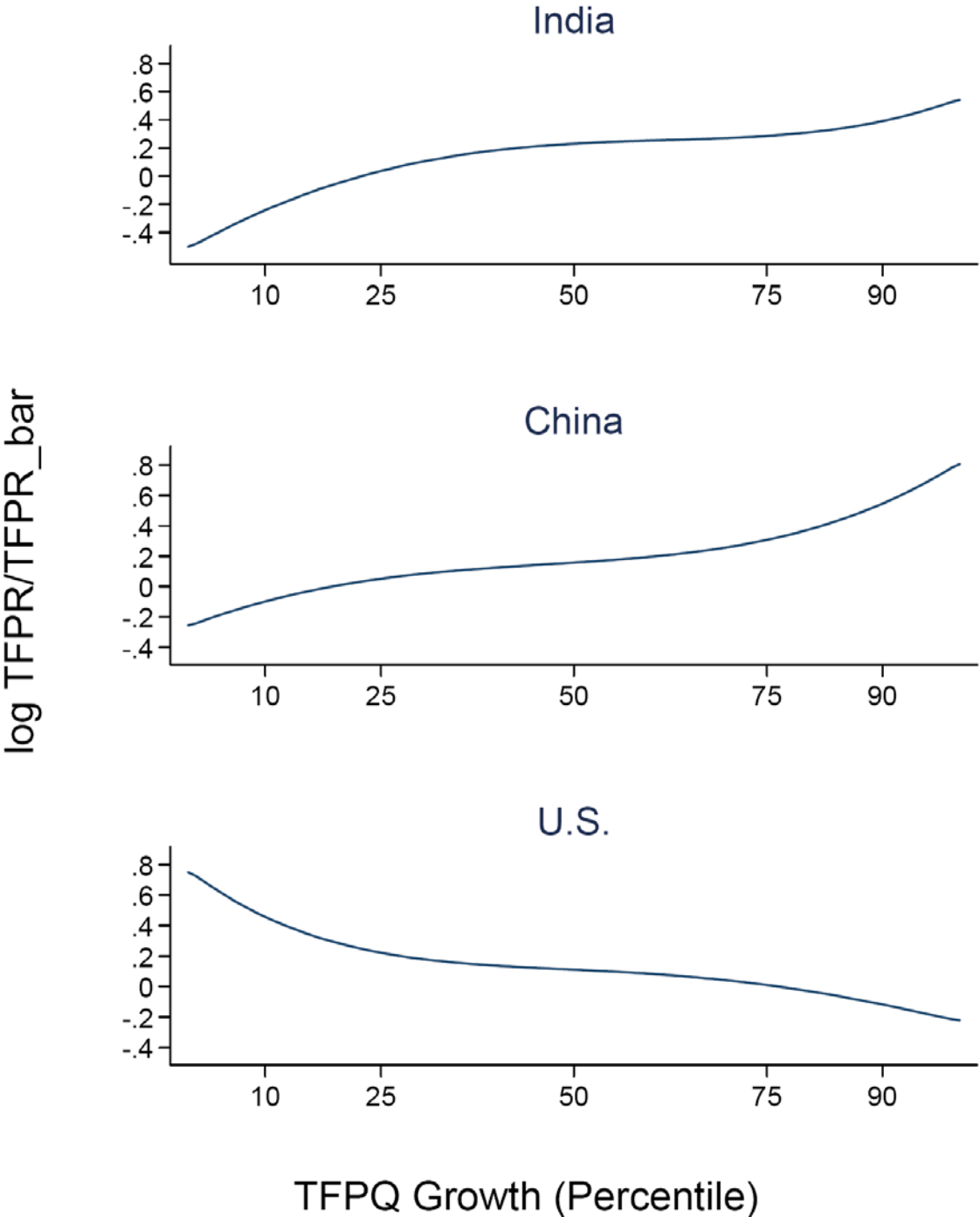


Figure 8: TFPR and TFPQ Growth



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