Misallocation and manufacturing TFP in China and India

Chang, Tai Hsieh and Peter, J- Klenow

30 June 2007

THE
QUARTERLY JOURNAL OF ECONOMICS

Vol. CXXIV November 2009 Issue 4

MISALLOCATION AND MANUFACTURING TFP IN CHINA AND INDIA*

CHANG-TAI HSIEH AND PETER J. KLENOW

Resource misallocation can lower aggregate total factor productivity (TFP). We use microdata on manufacturing establishments to quantify the potential extent of misallocation in China and India versus the United States. We measure sizable gaps in marginal products of labor and capital across plants within narrowly defined industries in China and India compared with the United States. When capital and labor are hypothetically reallocated to equalize marginal products to the extent observed in the United States, we calculate manufacturing TFP gains of 30%–50% in China and 40%–60% in India.

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

*We are indebted to Ryoji Hiraguchi and Romans Pancs for phenomenal research assistance, and to seminar participants, referees, and the editors for comments. We gratefully acknowledge the financial support of the Kauffman Foundation. Hsieh thanks the Alfred P. Sloan Foundation and Klenow thanks SIEPR for financial support. The research in this paper on U.S. manufacturing was conducted while the authors were Special Sworn Status researchers of the U.S. Census Bureau at the California Census Research Data Center at UC Berkeley. Research results and conclusions expressed are those of the authors and do not necessarily reflect the views of the Census Bureau. This paper has been screened to ensure that no confidential data are revealed. *chsieh@chicagobooth.edu, pete@klenow.net*.

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

The Quarterly Journal of Economics, November 2009

diffusion from advanced countries to other countries. These are models of *within*-firm inefficiency, with the inefficiency varying across countries.

A recent paper by Restuccia and Rogerson (2008) takes a different approach. Instead of focusing on the efficiency of a representative firm, they suggest that misallocation of resources across firms can 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 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 to the firm with a high marginal product. The misallocation of capital results in low aggregate output per worker and TFP.

Many institutions and policies can potentially result in resource misallocation. For example, the McKinsey Global Institute (1998) argues that a key factor behind low productivity in Brazil's retail sector is labor-market regulations driving up the cost of labor for supermarkets relative to informal retailers. Despite their low productivity, the lower cost 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 potential 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 (the product of physical productivity and a firm's output price) should be equated across firms in the absence of distortions. To the extent revenue productivity differs across firms, we can use it to recover a measure of firm-level distortions.

2. In terms of the resulting size distribution, the model is a cousin to the Lucas (1978) span-of-control model.

We use this framework to measure the contribution of resource misallocation to aggregate manufacturing productivity in China and India versus the United States. 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 (ASI; 1987–1994), and the U.S. Census of Manufacturing (1977, 1982, 1987, 1992, and 1997) to measure dispersion in the marginal products of capital and labor within individual four-digit manufacturing sectors in each country. We then measure how much aggregate manufacturing output in China and India could increase if capital and labor were reallocated to equalize marginal products across plants within each four-digit sector *to the extent observed in the United States.* The United States is a critical benchmark for us, because 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 United States.

We find that moving to "U.S. efficiency" would increase TFP by 30%–50% in China and 40%–60% in India. The output gains would be roughly twice as large if capital accumulated in response to aggregate TFP gains. We find that deteriorating allocative efficiency may have shaved 2% off Indian manufacturing TFP growth from 1987 to 1994, whereas China may have boosted its TFP 2% per year over 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 United States.

Although Restuccia and Rogerson (2008) is the closest predecessor to our investigation in model and method, there are many others.[4] In addition to Restuccia and Rogerson, we build on three

3. For discussion of Chinese reforms, see Young (2000, 2003) and *The Economist* (2006b). For Indian reforms, see Kochar et al. (2006), *The Economist* (2006a), and Aghion et al. (2008). Dobson and Kashyap (2006), Farrell and Lund (2006), Allen et al. (2007), and Dollar and Wei (2007) discuss how capital continues to be misallocated in China and India.

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 (2008) model inefficiencies in the allocation of capital to managerial talent, while Guner, Ventura, and Xu (2008) model misallocation due to size restrictions. Parente and

papers in particular. First, we follow the lead of Chari, Kehoe, and McGrattan (2007) in inferring distortions from the residuals in first-order conditions. Second, the distinction between a firm's physical productivity and its revenue productivity, highlighted by Foster, Haltiwanger, and Syverson (2008), is central to our estimates of resource misallocation. Third, Banerjee and Duflo (2005) 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 that of the United States.[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 can lower 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 data sets in Section III, and present potential gains from better allocation in Section IV. In Section V we try to assess whether greater measurement error in China and India could explain away our results. In Section VI we make a first pass at relating observable policies to allocative efficiency in China and India. In Section VII we explore alternative explanations besides policy distortions and measurement error. We offer some conclusions in Section VIII.

II. 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 in their efficiency levels (as in Melitz [2003]), we assume that firms potentially face different output and capital distortions.

We assume there is a single final good Y produced by a representative firm in a perfectly competitive final output market. This firm combines the output Y_s of S manufacturing industries using

Prescott (2000) theorize that low-TFP countries are ones in which vested interests block firms from introducing better technologies.

5. See Bergoeing et al. (2002), Galindo, Schiantarelli, and Weiss (2007), Alfaro, Charlton, and Kanczuk (2008), and Bartelsman, Haltiwanger, and Scarpetta (2008) for related empirical evidence in other countries.

a Cobb-Douglas production technology:

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

Cost minimization implies

(2) $$P_s Y_s = \theta_s P Y.$$

Here, P_s refers to the price of industry output Y_S and $P \equiv \prod_{s=1}^{S} (P_s/\theta_s)^{\theta_s}$ represents the price of the final good (the final good is our numeraire, and so $P = 1$). Industry output Y_s is itself a CES aggregate of M_s differentiated products:

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

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

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

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

Because 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 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 high for firms that face government restrictions on size or high transportation costs, and low in firms that benefit from public output subsidies. In turn, we denote distortions that raise the marginal product of capital relative to labor as the capital distortion τ_K. For example, τ_K would be high for firms that do not have access to credit, but low for firms with access to cheap credit (by business groups or state-owned banks).

Profits are given by

(5) $$\pi_{si} = (1 - \tau_{Y si}) P_{si} Y_{si} - w L_{si} - (1 + \tau_{K si}) R K_{si}.$$

6. In Section VII ("Alternative Explanations"), we relax this assumption by replacing the plant-specific capital distortion with plant-specific factor shares.

Note that we assume all firms face the same wage, an issue to which we return later. Profit maximization yields the standard condition that the firm's output price is a fixed markup over its marginal cost:

$$P_{si} = \frac{\sigma}{\sigma - 1}\left(\frac{R}{\alpha_s}\right)^{\alpha_s}\left(\frac{w}{1-\alpha_s}\right)^{1-\alpha_s}\frac{(1+\tau_{Ksi})^{\alpha_s}}{A_{si}\,(1-\tau_{Ysi})}. \tag{6}$$

The capital-labor ratio, labor allocation, and output are given by

$$\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1-\alpha_s}\cdot\frac{w}{R}\cdot\frac{1}{(1+\tau_{Ksi})}, \tag{7}$$

$$L_{si} \propto \frac{A_{si}^{\sigma-1}(1-\tau_{Ysi})^{\sigma}}{(1+\tau_{Ksi})^{\alpha_s(\sigma-1)}}, \tag{8}$$

$$Y_{si} \propto \frac{A_{si}^{\sigma}(1-\tau_{Ysi})^{\sigma}}{(1+\tau_{Ksi})^{\alpha_s \sigma}}. \tag{9}$$

The allocation of resources across firms depends not only 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:

$$\mathrm{MRPL}_{si} \triangleq (1-\alpha_S)\frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{L_{si}} = w\frac{1}{1-\tau_{Ysi}}. \tag{10}$$

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

$$\mathrm{MRPK}_{si} \triangleq \alpha_S\frac{\sigma-1}{\sigma}\frac{P_{si}Y_{si}}{K_{si}} = R\frac{1+\tau_{Ksi}}{1-\tau_{Ysi}}. \tag{11}$$

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.

We are now ready to derive an expression for aggregate TFP as a function of the misallocation of capital and labor. We first solve for the equilibrium allocation of resources across sectors:[7]

$$L_s \equiv \sum_{i=1}^{M_s} L_{si} = L\frac{(1-\alpha_s)\,\theta_s/\overline{\mathrm{MRPL}}_s}{\sum_{s'=1}^{S}(1-\alpha_{s'})\,\theta_{s'}/\overline{\mathrm{MRPL}}_{s'}}, \tag{12}$$

$$K_s \equiv \sum_{i=1}^{M_s} K_{si} = K\frac{\alpha_s\,\theta_s/\overline{\mathrm{MRPK}}_s}{\sum_{s'=1}^{S}\alpha_{s'}\,\theta_{s'}/\overline{\mathrm{MRPK}}_{s'}}. \tag{13}$$

Here,

$$\overline{\mathrm{MRPL}}_s \propto \left(\sum_{i=1}^{M_s}\frac{1}{1-\tau_{Ysi}}\frac{P_{si}Y_{si}}{P_sY_s}\right),$$

$$\overline{\mathrm{MRPK}}_s \propto \left(\sum_{i=1}^{M_s}\frac{1+\tau_{Ksi}}{1-\tau_{Ysi}}\frac{P_{si}Y_{si}}{P_sY_s}\right)$$

denote the weighted average of the value of the marginal product of labor and capital in a sector, and $L \equiv \sum_{s=1}^{S} L_s$ and $K \equiv \sum_{s=1}^{S} K_s$ represent the aggregate supply of labor and capital. We can then express aggregate output as a function of K_S, L_S, and industry TFP:[8]

$$Y = \prod_{s=1}^{S}\left(\mathrm{TFP}_s \cdot K_s^{\alpha_s} \cdot L_s^{1-\alpha_s}\right)^{\theta_s}. \tag{14}$$

To determine the formula for industry productivity TFP_s, it is useful to show that 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 (2008) stress that, when industry deflators are used, differences in plant-specific prices show up in the customary measure of plant TFP. They 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.

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.

The distinction between physical and revenue productivity is vital for us too. We define these objects as follows:[9]

$$\mathrm{TFPQ}_{si} \triangleq A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s}(wL_{si})^{1-\alpha_s}}$$
$$\mathrm{TFPR}_{si} \triangleq P_{si}A_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}(wL_{si})^{1-\alpha_s}}.$$

In our simple model, TFPR does not vary across plants within an industry unless plants face capital and/or output distortions. In the absence of distortions, 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. Using (10) and (11), plant TFPR is proportional to a geometric average of the plant's marginal revenue products of capital and labor:[10]

$$\mathrm{TFPR}_{si} \propto (\mathrm{MRPK}_{si})^{\alpha_s}(\mathrm{MRPL}_{si})^{1-\alpha_s} \propto \frac{(1+\tau_{Ksi})^{\alpha_s}}{1-\tau_{Ysi}}.$$

High plant TFPR is a sign that the plant confronts barriers that raise the plant's marginal products of capital and labor, rendering the plant smaller than optimal.

With the expression for TFPR in hand, we can express industry TFP as

$$\text{(15)} \qquad \mathrm{TFP}_s = \left[\sum_{i=1}^{M_s}\left(A_{si}\cdot\frac{\overline{\mathrm{TFPR}}_s}{\mathrm{TFPR}_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}},$$

where $\overline{\mathrm{TFPR}}_s \propto (\overline{\mathrm{MRPK}}_s)^{\alpha_s}(\overline{\mathrm{MRPL}}_s)^{1-\alpha_s}$ is a geometric average of the average marginal revenue product of capital and labor in the sector.[11] If marginal products were equalized across plants, TFP would be $\bar{A}_s = (\sum_{i=1}^{M_s} A_{si}^{\sigma-1})^{\frac{1}{\sigma-1}}$. Equation (15) is the key equation we use for our empirical estimates. Appendix I shows that we would arrive at an expression similar to (15) if we assumed a Lucas span-of-control model rather than monopolistic competition.

9. To crudely control for differences in human capital we measure labor input as the wage bill, which we denote as the product of a common wage per unit of human capital w and effective labor input L_{si}.

10. $\mathrm{TFPR}_{si} = \frac{\sigma}{\sigma-1}\left(\frac{\mathrm{MRPK}_{si}}{\alpha_S}\right)^{\alpha_s}\left(\frac{\mathrm{MRPL}_{si}}{w(1-\alpha_S)}\right)^{1-\alpha_s} = \left(\frac{R}{\alpha_S}\right)^{\alpha_s}\left(\frac{1}{1-\alpha_S}\right)^{1-\alpha_s}\frac{(1+\tau_{Ksi})^{\alpha_s}}{1-\tau_{Ysi}}.$

11. $\overline{\mathrm{TFPR}}_s = \left[\frac{R}{\alpha_S}\sum_{i=1}^{M_s}\left(\frac{1+\tau_{Ksi}}{1-\tau_{Ysi}}\right)\cdot\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)\right]^{\alpha_s}\left[\frac{1}{1-\alpha_S}\sum_{i=1}^{M_s}\left(\frac{1}{1-\tau_{Ysi}}\right)\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)\right]^{1-\alpha_s}.$

When A ($\equiv$TFPQ) and TFPR are jointly lognormally distributed, there is a simple closed-form expression for aggregate TFP:

$$(16)\qquad \log \mathrm{TFP}_s = \frac{1}{\sigma - 1} \log \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right) - \frac{\sigma}{2} \mathrm{var}\,(\log \mathrm{TFPR}_{si})\,.$$

In this special case, the negative effect of distortions on aggregate TFP can be summarized by the variance of log TFPR. Intuitively, the extent of misallocation is worse when there is greater dispersion of marginal products.

We note several things about the effect of misallocation on aggregate TFP in this model. First, from (12) and (13), the shares of aggregate labor and capital in each sector are unaffected by the extent of misallocation as long as average marginal revenue products are unchanged. Our 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 later relax the Cobb-Douglas assumption to see how much it matters.

Second, we have conditioned on a fixed aggregate stock of capital. Because the rental rate rises with aggregate TFP, we would expect capital to respond to aggregate TFP (even with a fixed saving and investment rate). If we endogenize K by invoking a consumption Euler equation to pin down the long-run rental rate R, the output elasticity with respect to aggregate TFP is $1/(1 - \sum_{s=1}^{S} \alpha_S \theta_S)$. Thus 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 capital accumulation so that the output elasticity with respect to TFP is $1/(1 - \alpha)$.

Third, we 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.[12]

12. We assume entrants do not know their productivity or distortions before expending entry costs, only the joint distribution of distortions and productivity from which they will draw. We also follow Melitz (2003) and Restuccia and Rogerson (2008) in assuming exogenous exit among producers. Unlike Melitz, however,

III. Data Sets for India, China, and the United States

Our data for India are drawn from India's ASI conducted by the Indian government's Central Statistical Organisation. The ASI is a census of all registered manufacturing plants in India with more than fifty workers (one hundred if without power) and a random one-third sample of registered plants with more than ten workers (twenty if without power) but less than fifty (or one hundred) 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 (April of a given year through March of the following year). We use the ASI data from the 1987–1988 through 1994–1995 fiscal years. The raw data consist of around 40,000 plants in each year.

The variables in the ASI that we use are the plant's industry (four-digit ISIC), labor compensation, value-added, age (based on reported birth year), 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. We also have ownership information from the ASI, although the ownership classification does not distinguish between foreign-owned and domestic plants.

Our data for Chinese *firms* (not plants) are from Annual Surveys of Industrial Production from 1998 through 2005 conducted by the Chinese government's National Bureau of Statistics. The Annual Survey of Industrial Production is a census of all nonstate firms with more than 5 million yuan in revenue (about $600,000) plus all state-owned firms. The raw data consist of over 100,000 firms in 1998 and grow to over 200,000 firms in 2005. Hereafter we often refer to Chinese firms as "plants."

The information we use from the Chinese data are the plant's industry (again at the four-digit level), age (again based on

we do not have overhead costs. Because of the overhead costs in Melitz, some firms exit after spending entry costs but before commencing production, thereby creating an endogenous form of exit that truncates the left tail of the productivity distribution. We leave it as an important topic for future research to investigate the impact of distortions on aggregate productivity and welfare through endogenous entry and exit.

reported birth year), ownership, 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 report wage payments; they do not provide information on nonwage compensation. The median labor share in plant-level data is roughly 30%, which is significantly lower than the aggregate labor share in manufacturing reported in the Chinese input-output tables and the national accounts (roughly 50%). We therefore assume that nonwage 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% of aggregate value-added. We also have ownership status for the Chinese plants. Chinese manufacturing had been predominantly state run or state involved, but was principally private by the end of our sample.[13]

Our main source for U.S. data is the Census of Manufactures (CM) from 1977, 1982, 1987, 1992, and 1997 conducted by the U.S. Bureau of the Census. Befitting its name, the census covers all manufacturing plants. We drop small plants with limited production data (Administrative Records), leaving over 160,000 plants in each year. The information we use from the U.S. Census are the plant's industry (again at the four-digit level), labor compensation (wages and benefits), value-added, export revenues, and capital stock. We define the capital stock as the average of the book value of the plant's machinery and equipment and structures at the beginning and at the end of the year. The U.S. data do not provide information on plant age. We impute the plant's age by determining when the plant appears in the data for the first time.[14]

For our computations we set industry capital shares to those in the corresponding U.S. manufacturing industry. As a result, we drop nonmanufacturing plants and plants in industries without a close counterpart in the United States. We also trim the 1% tails of plant productivity and distortions in each country-year to make the results robust to outliers. Later we check robustness to adjusting the book values of capital for inflation.

13. Our data may understate the extent of privatization. Dollar and Wei (2007) conducted their own survey of Chinese firms in 2005 and found that 15% of all firms were officially classified as state owned but had in fact been privatized.

14. For plants in the Annual Survey of Manufactures (ASM), we use the annual data of the ASM (starting with the 1963 ASM) to identify the plant's birth year. For the plants that are not in the ASM, we assume the birth year is the year the plant first appears in the quinquennial CM minus three years.

IV. Potential Gains from Reallocation

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

We set the rental price of capital (excluding distortions) to $R = 0.10$. We have in mind a 5% real interest rate and a 5% depreciation rate. The actual cost of capital faced by plant i in industry s is denoted $(1 + \tau_{Ksi})R$, and so it differs from 10% if $\tau_{Ksi} \neq 0$. Because our hypothetical reforms collapse τ_{Ksi} to its average in each industry, the attendant efficiency gains do not depend on R. If we have set R incorrectly, it affects only the average capital distortion, 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, as is explicit in (16), and so we made this choice conservatively. Estimates of the substitutability of competing manufactures in the trade and industrial organization literatures typically range from three to ten (e. g., Broda and Weinstein [2006], Hendel and Nevo [2006]). Later we entertain the higher value of 5 for σ 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 1 minus the labor share in the corresponding industry in the United States. We do not set these elasticities on the basis of labor shares in the Indian and Chinese data precisely because we think distortions are potentially important in China and India. We cannot separately identify the average capital distortion and the capital production elasticity in each industry. We adopt the U.S. shares as the benchmark because we presume the United States 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, which is based on the Census and ASM. 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 two-thirds what it is in manufacturing according to the National Income and Product Accounts, which incorporate nonwage 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 U.S., Indian, and 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 therefore assume these rents show up as payments to labor (managers) and capital (owners) pro rata in each industry. In this event our assumed value of σ has no impact on our production elasticities.

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

$$1 + \tau_{Ksi} = \frac{\alpha_s}{1-\alpha_s} \frac{wL_{si}}{RK_{si}}, \tag{17}$$

$$1 - \tau_{Ysi} = \frac{\sigma}{\sigma - 1} \frac{wL_{si}}{(1-\alpha_s) P_{si} Y_{si}}, \tag{18}$$

$$A_{si} = \kappa_s \frac{(P_{si} Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}. \tag{19}$$

Equation (17) says we infer the presence of a capital distortion when the ratio of labor compensation to the capital stock is high relative to what one would expect from the output elasticities with respect to capital and labor. Recall that a high labor distortion would show up as a low capital distortion. Similarly, expression (18) says we deduce an output distortion when labor's share is low compared with what one would think from the industry elasticity of output with respect to labor (and the adjustment for rents). A critical assumption embedded in (18) is that observed value-added does *not* include any explicit output subsidies or taxes.

TFP in (19) 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, 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}. That is, we infer price vs. quantity from revenue and an assumed elasticity of demand. Equation (19) requires only our assumptions about technology and demand plus profit maximization; we need not assume anything about how inputs are determined. Third, for labor input we use the plant's wage bill rather than its employment to measure L_{si}. Earnings per worker may vary more across plants because of differences in hours worked and human capital per worker than because of worker rents. Still, as a later robustness check we measure L_{si} as employment.

Before calculating the gains from our hypothetical liberalization, we trim the 1% tails of $\log(\text{TFPR}_{si}/\overline{\text{TFPR}_s})$ and $\log(A_{si}/\bar{A}_s)$ across industries. That is, we pool all industries and trim the top and the bottom 1% of plants within each of the pools. We then recalculate wL_s, K_s, and P_sY_s as well as $\overline{\text{TFPR}}_s$ and $\bar{A}_s$. At this stage we calculate the industry shares $\theta_s = P_sY_s/Y$.

Figure I plots the distribution of TFPQ, $\log(A_{si}M_s^{\frac{1}{\sigma-1}}/\bar{A}_s)$, for the latest year in each country: India in 1994, China in 2005, and the United States in 1997. There is manifestly more TFPQ dispersion in India than in China, but this could reflect the different sampling frames (small private plants are underrepresented in the Chinese survey). The U.S. and Indian samples are more comparable. The left tail of TFPQ is far thicker in India than the United States, consistent with policies favoring the survival of inefficient plants in India relative to the United States. Table I shows that these patterns are consistent across years and several measures of dispersion of log(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 5.0 in India, 3.6 in China, and 3.2 in the United States (exponentials of the corresponding numbers in Table II). For the United States, our TFPQ differences are much larger than those documented by Foster, Haltiwanger, and Syverson (2008), who report a standard deviation of around 0.22 compared to ours of around 0.80. As we describe in Appendix II, our measure of TFPQ should reflect the quality and variety of a plant's products, not just its physical productivity. And our results cover all industries, whereas Foster, Haltiwanger, and Syverson (2008) analyze a dozen industries specifically chosen because their products are homogeneous.

Figure II plots the distribution of TFPR (specifically, $\log(\text{TFPR}_{si}/\overline{\text{TFPR}}_s)$) for the latest year in each country. There is clearly more dispersion of TFPR in India than in the United States. Even China, despite not fully sampling small private establishments, exhibits notably greater TFPR dispersion than

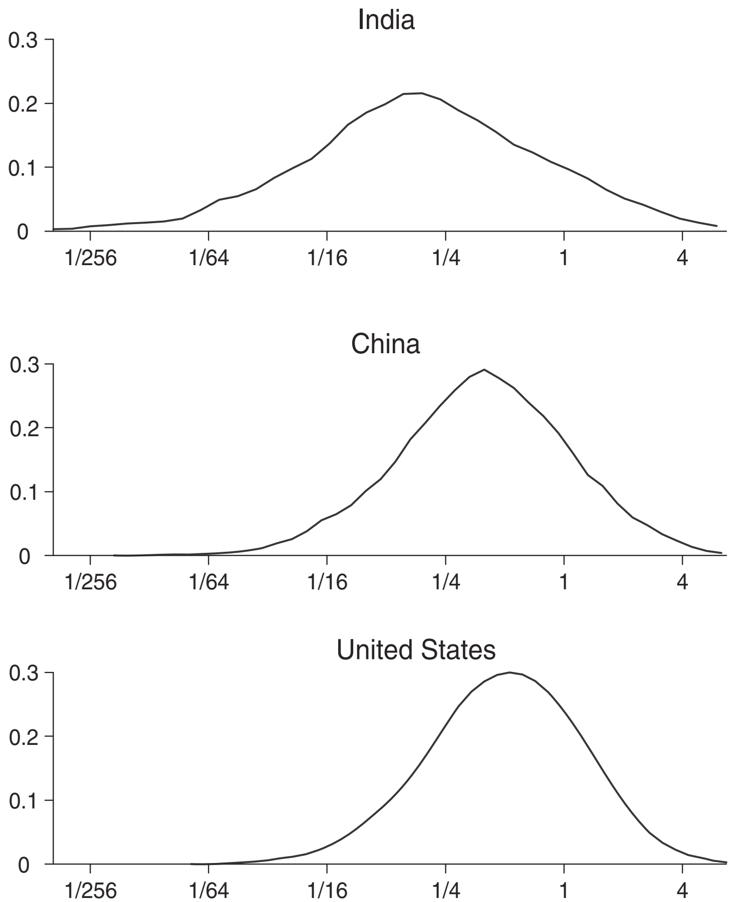

FIGURE I
Distribution of TFPQ

the United States. Table II provides TFPR dispersion statistics for a number of country-years. The ratio of 75th to 25th percentiles of TFPR in the latest year are 2.2 in India, 2.3 in China, and 1.7 in the United States. The ratios of 90th to 10th percentiles of TFPR are 5.0 in India, 4.9 in China, and 3.3 in the United States. These numbers are consistent with greater distortions in China and India than the United States.[15]

15. 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).

TABLE I
DISPERSION OF TFPQ

China	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
India	1987	1991	1994
S.D.	1.16	1.17	1.23
75 − 25	1.55	1.53	1.60
90 − 10	2.97	3.01	3.11
N	31,602	37,520	41,006
United States	1977	1987	1997
S.D.	0.85	0.79	0.84
75 − 25	1.22	1.09	1.17
90 − 10	2.22	2.05	2.18
N	164,971	173,651	194,669

Notes. For plant i in industry s, $\text{TFPQ}_{si} \equiv \frac{Y_{si}}{K_{si}^{\alpha_s}(w_{si}L_{si})^{1-\alpha_s}}$. Statistics are for deviations of log(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 II
DISPERSION OF 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.	0.69	0.67	0.67
75 − 25	0.79	0.81	0.81
90 − 10	1.73	1.64	1.60
United States	1977	1987	1997
S.D.	0.45	0.41	0.49
75 − 25	0.46	0.41	0.53
90 − 10	1.04	1.01	1.19

Notes. For plant i in industry s, $\text{TFPR}_{si} \equiv \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}(w_{si}L_{si})^{1-\alpha_s}}$. Statistics are for deviations of log(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. Number of plants is the same as in Table I.

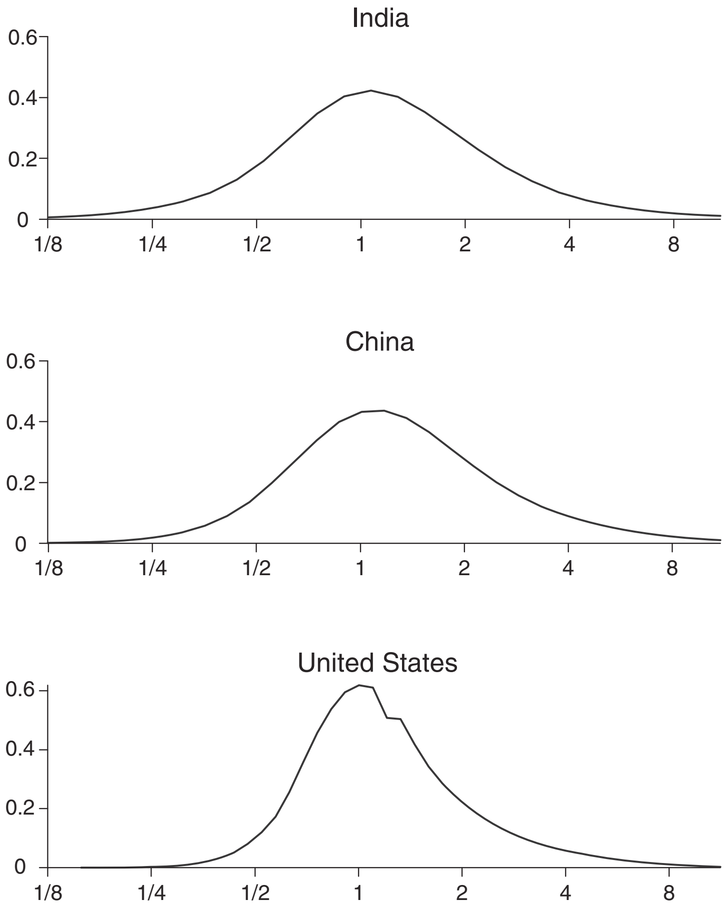

FIGURE II
Distribution of TFPR

For India and China, Table III gives the cumulative percentage of the variance of TFPR (within industry-years) explained by dummies for ownership (state ownership categories), age (quartiles), size (quartiles), and region (provinces or states). The results are pooled for all years, and are cumulative in that "age" includes dummies for both ownership and age, and so on. Ownership is less important for India (around 0.6% of the variance) than in China (over 5%). All four sets of dummies together account for less than 5% of the variance of TFPR in India and 10% of the variance of TFPR in China.

TABLE III
PERCENT SOURCES OF TFPR VARIATION WITHIN INDUSTRIES

	Ownership	Age	Size	Region
India	0.58	1.33	3.85	4.71
China	5.25	6.23	8.44	10.01

Notes. Entries are the cumulative percent of within-industry TFPR variance explained by dummies for ownership (state ownership categories), age (quartiles), size (quartiles), and region (provinces or states). The results are cumulative in that "age" includes dummies for both ownership and age, and so on.

Although it does not fit well into our monopolistically competitive framework, it is useful to ask how government-guaranteed monopoly power might show up in our measures of TFPQ and TFPR. Plants that charge high markups should evince higher TFPR levels. If they are also protected from entry of nearby competitors, they may also exhibit high TFPQ levels. Whereas we frame high TFPR plants as being held back by policy distortions, such plants may in fact be happily restricting their output. Still, such variation in TFPR is socially inefficient, and aggregate TFP would be higher if such plants expanded their output.

We next calculate "efficient" output in each country so we can compare it with actual output levels. If marginal products were equalized across plants in a given industry, then industry TFP would be $\bar{A}_s = (\sum_{i=1}^{M_s} A_{si}^{\sigma-1})^{\frac{1}{\sigma-1}}$. For each industry, we calculate the ratio of actual TFP (15) to this efficient level of TFP, and then aggregate this ratio across sectors using our Cobb-Douglas aggregator (1):

$$\frac{Y}{Y_{\text{efficient}}} = \prod_{s=1}^{S} \left[\sum_{i=1}^{M_s} \left(\frac{A_{si}}{\bar{A}_s} \frac{\overline{\text{TFPR}}_s}{\text{TFPR}_{si}} \right)^{\sigma-1} \right]^{\theta_s/(\sigma-1)}. \tag{20}$$

We freely admit this exercise heroically makes no allowance for measurement error or model misspecification. Such errors could lead us to overstate room for efficiency gains from better allocation. With these caveats firmly in mind, Table IV provides percent 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 by 86%–115% in China, 100%–128% in India, and 30%–43% in the United States. If measurement and modeling

TABLE IV
TFP GAINS FROM EQUALIZING TFPR WITHIN INDUSTRIES

China	1998	2001	2005
%	115.1	95.8	86.6
India	1987	1991	1994
%	100.4	102.1	127.5
United States	1977	1987	1997
%	36.1	30.7	42.9

Notes. Entries are $100(Y_{\text{efficient}}/Y - 1)$ where $Y/Y_{\text{efficient}} = \prod_{s=1}^{S}[\sum_{i=1}^{M_s}(\frac{A_{si}}{\bar{A}_s}\frac{\overline{\text{TFPR}}_s}{\text{TFPR}_{si}})^{\sigma-1}]^{\theta_s/(\sigma-1)}$ and $\text{TFPR}_{si} \equiv \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}(w_{si}L_{si})^{1-\alpha_s}}$.

errors are to explain these results, they clearly have to be much bigger in China and India than the United States.[16]

Figure III plots the "efficient" vs. actual size distribution of plants in the latest year. Size here is measured as plant value-added. In all three countries 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. Table V shows how the size of initially big vs. small plants would change if TFPR were equalized in each country. The entries are unweighted shares of plants. The rows are initial (actual) plant size quartiles, and the columns are bins of efficient plant size relative to actual size: 0%–50% (the plant should 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 would shrink. Thus many state-favored behemoths in China and India would be downsized. Still, initially large plants are less likely to shrink and more likely to expand in both China and India (a pattern much less pronounced in the United States). Thus TFPR increases with size more strongly in China and India than in the United States. The positive size-TFPR relation in India is consistent with Banerjee and Duflo's (2005) contention that Indian policies constrain its most efficient producers and coddle its least efficient ones.

16. In India, the variation over time is not due to the smaller, sampled plants moving in and out of the sample. When we look only at larger census plants the gains are 89%–123%.

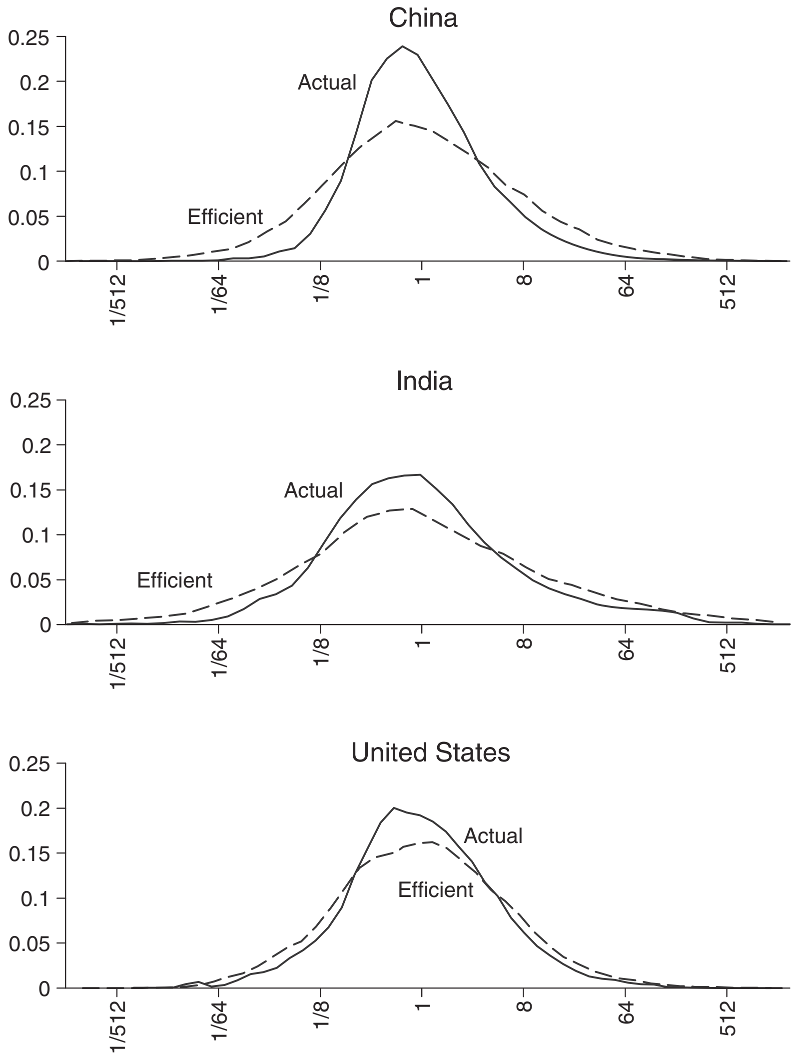

FIGURE III
Distribution of Plant Size

Although we expressed the distortions in terms of output (τ_{Ysi}) and capital relative to labor (τ_{Ksi}), in Appendix III, we show that these are equivalent to a particular combination of labor (τ^*_{Lsi}) and capital (τ^*_{Ksi}) distortions. In Appendix III, we also report that more efficient (higher TFPQ) plants appear to face bigger distortions on both capital and labor.

TABLE V

PERCENT OF PLANTS, ACTUAL SIZE VS. EFFICIENT SIZE

China 2005	0–50	50–100	100–200	200+
Top size quartile	7.0	6.1	5.4	6.6
2nd quartile	7.3	5.9	5.3	6.6
3rd quartile	8.5	6.0	5.2	5.4
Bottom quartile	10.5	5.9	4.5	4.2
India 1994	0–50	50–100	100–200	200+
Top size quartile	8.7	4.7	4.6	7.1
2nd quartile	10.7	4.6	4.1	5.7
3rd quartile	11.4	5.0	4.0	4.7
Bottom quartile	13.8	3.9	3.3	3.8
United States 1997	0–50	50–100	100–200	200+
Top size quartile	4.4	10.0	6.7	3.9
2nd quartile	4.4	9.6	5.8	5.1
3rd quartile	4.5	9.8	5.4	5.4
Bottom quartile	4.7	12.0	4.3	4.1

Notes. 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 percent 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 VI

TFP GAINS FROM EQUALIZING TFPR RELATIVE TO 1997 U.S. GAINS

China	1998	2001	2005
%	50.5	37.0	30.5
India	1987	1991	1994
%	40.2	41.4	59.2

Notes. For each country-year, we calculated $Y_{\text{efficient}}/Y$ using $Y/Y_{\text{efficient}} = \prod_{s=1}^{S}\left[\sum_{i=1}^{M_s}\left(\frac{A_{si}}{\bar{A}_s}\frac{\overline{\text{TFPR}}_s}{\text{TFPR}_{si}}\right)^{\sigma-1}\right]^{\theta_s/(\sigma-1)}$ and $\text{TFPR}_{si} \equiv \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}(w_{si}L_{si})^{1-\alpha_s}}$.

We then took the ratio of $Y_{\text{efficient}}/Y$ to the U.S. ratio in 1997, subtracted 1, and multiplied by 100 to yield the entries above.

In Table VI we report the percent TFP gains in China and India *relative to those in the United States* in 1997 (a conservative point of comparison because U.S. gains are largest in 1997). For China, hypothetically moving to "U.S. efficiency" might have boosted TFP by 50% in 1998, 37% in 2001, and 30% in 2005. Compared to the 1997 U.S. benchmark, Chinese allocative efficiency improved 15% (1.5/1.3) from 1998 to 2005, or 2.0% per year. For

India, meanwhile, hypothetically moving to U.S. efficiency might have raised TFP around 40% in 1987 or 1991, and 59% in 1994. Thus we find no evidence of improving allocations in India over 1987 to 1994. The implied decline in allocative efficiency of 12%, or 1.8% per year from 1987 to 1994, is surprising given that many Indian reforms began in the late 1980s.

How do these implied TFP gains from reallocation compare with the actual TFP growth observed in China and India? For the latter, the closest estimates we could find are by Bosworth and Collins (2007). They report Chinese industry TFP growth of 6.2% per year from 1993 to 2004 and Indian industry TFP growth of 0.3% per year from 1978 to 1993. Thus, our point estimate for China (2% per year) would suggest that perhaps one-third of its TFP growth could be attributed to better allocation of resources. For India, our evidence for worsening allocations might help to explain its minimal TFP growth.

A related question is how our estimates of TFP losses from TFPR dispersion compare with actual, observed TFP differences between China or India and the United States. We crudely estimate that U.S. manufacturing TFP in 1997 was 130% higher than China's in 1998, and 160% higher than India's in 1994.[17] Therefore, our estimates suggest that resource misallocation might be responsible for roughly 49% (log(1.5)/log(2.3)) of the TFP gap between the United States and China and 35% (log(1.4)/log(2.6)) of the TFP gap between the United States and India.

So far, our calculations of hypothetical output gains from TFPR equalization assume a fixed aggregate capital stock. As discussed above, output gains are amplified when capital accumulates to keep the rental price of capital constant. In India's case the average capital share was 50% in 1994–1995, and so the TFP gains are roughly squared. The same goes for China, because its average capital share was 49% in 2005. Thus a 30% TFP gain in China could yield a 67% long-run gain in manufacturing output, whereas a 59% TFP gain in India could ultimately boost its manufacturing output by 153%.

17. We use the aggregate price of tradable goods between India and the United States in 1985 (from the benchmark data in the Penn World Tables) to deflate Indian prices to U.S. prices. Because 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 and Lee [2000]) assuming a 10% Mincerian return.

We now provide a number of robustness checks on our baseline Table VI calculations of hypothetical efficiency gains from liberalization in China and India relative to the United States. We first adjust the book values of capital using a capital deflator for each country combined with the plant's age. We assume that a plant's current investment rate applies to all previous years of its life so that we can infer the age distribution of its capital stock. The resulting "current-market-value" capital stocks suggest very similar room for TFP gains in China vs. the United States (29.8% vs. 30.5% baseline) and India vs. the United States (59.9% vs. 59.2% baseline).

In our baseline calculations we also measured plant labor input using its wage bill. Our logic was that wages per worker adjust for plant differences in hours worked per worker and worker skills. However, wages could also reflect rent sharing between the plant and its workers. If so, we might be understating differences in TFPR across plants because the most profitable plants have to pay higher wages. We therefore recalculate the gains from equalizing TFPR in China and India (relative to the United States) using simply employment as our measure of plant labor input. Surprisingly, the reallocation gains are smaller in both China (25.6% vs. 30.5% baseline) and India (57.4% vs. 59.2% baseline) when we measure labor input using employment. Thus wage differences appear to amplify TFPR differences rather than limit them.

We have assumed an elasticity of substitution within industries (σ) of 3, conservatively at the low end of empirical estimates. Our estimated gains are highly sensitive to this elasticity. China's hypothetical TFP gain in 2005 soars from 87% under $\sigma = 3$ to 184% with $\sigma = 5$, and India's in 1994 from 128% to 230%. These are gains from fully equalizing TFPR levels. Our intuition is as follows: 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.

Our results are not nearly as sensitive to our assumption of a unitary elasticity of substitution between sectors. Cobb-Douglas aggregation across sectors means that TFPR equalization does not affect the allocation of inputs across sectors; the rise in a sector's productivity is exactly offset by the fall in its price index. Suppose instead that final output is a CES aggregate of sector outputs:

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

First consider the case wherein 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 (108% vs. 128% in 1994). The gains shrink because $\phi < 1$ means sectors with larger increases in productivity shed inputs. Next consider a case in which sector outputs are more substitutable ($\phi = 2$). In this case, the gains from liberalization are modestly larger in China (90% vs. 87%) and larger in India (142% vs. 128%). When sector outputs are better substitutes, inputs are reallocated toward sectors with bigger productivity gains so that aggregate TFP increases more.

V. 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. We cannot rule out arbitrary measurement error, but we can try to gauge whether our results can be attributable to specific forms of measurement error. One form is simply recording errors that create extreme outliers. For our baseline estimates (Table VI) we trimmed the 1% tails of TFPR (actually, in the output and capital distortions separately) and TFPQ—up to 6% of observations. When we trim 2% tails (up to 12% of observations) the hypothetical TFP gains fall from 87% to 69% for China in 2005, and from 128% to 106% for India in 1994. Thus, measurement error in the remaining 1% tails could well be important, but does not come close to accounting for the big gains from equalizing TFPR.

Of course, measurement error could be important in the interior of the TFPR distribution, too. Suppose measurement error is classical in the sense of being orthogonal to the truth and to other reported variables. Then we would not expect plant TFPR to be related to plant ownership. Table VII shows that, in fact, TFPR is systematically related to ownership in mostly reassuring ways in China and India. The table presents results of regressing TFPR and TFPQ (relative to industry means) on ownership type in China and India. All years are pooled and year fixed effects are included. The omitted group for China is privately owned domestic plants, whereas in India it is privately owned plants because we lack information on foreign ownership in India. In China, state-owned plants exhibit 41% lower TFPR, as if they received subsidies to continue operating despite low profitability.[18] Perhaps

18. Dollar and Wei (2007) likewise find lower productivity at state-owned firms in China.

TABLE VII
TFP BY OWNERSHIP

	TFPR	TFPQ
China		
State	−0.415	−0.144
	(0.023)	(0.090)
Collective	0.114	0.047
	(0.010)	(0.013)
Foreign	−0.129	0.228
	(0.024)	(0.040)
India		
State (central)	−0.285	0.717
	(0.082)	(0.295)
State (local)	−0.081	0.425
	(0.063)	(0.103)
Joint public/private	−0.162	0.671
	(0.037)	(0.085)

Notes. The dependent variable is the deviation of log TFPR or log TFPQ from the industry mean. The independent variables for China are dummies for state-owned plants, collective-owned plants (plants jointly owned by local governments and private parties), and foreign-owned plants. The omitted group is domestic private plants. The independent variables for India are dummies for a plant owned by the central government, a plant owned by a local government, and a plant jointly owned by the government (either central or local) and by private individuals. The omitted group is a privately owned plant (both domestic and foreign). Regressions are weighted least squares with industry value-added shares as weights. Entries are the dummy coefficients, with standard errors in parentheses. Results are pooled for all years.

surprisingly, collectively owned (part private, part local government) plants have 11% higher TFPR. Foreign-owned plants have 23% higher TFPQ on average, but 13% lower TFPR. The latter could reflect better access to credit or preferential treatment in export processing zones. Consistent with this interpretation, *exporting* plants have 46% higher TFPQ but 14% lower TFPR. In the United States, exporters have a similar TFPQ advantage (50%) but display higher rather than lower TFPR (+6% on average).[19]

In India, all types of plants with public involvement exhibit lower TFPR: 29% lower for plants owned by the central government, 8% lower for those owned by local governments, and 16% lower for joint public-private plants. Public involvement also goes along with 40%–70% higher TFPQ, although this might reflect monopoly rights that guarantee demand.

We next look at the correlation of TFPR with plant exit. One would expect true TFPR to be lower for exiters. If TFPR is measured with more error in China and India, the coefficient from a regression of plant exit on TFPR should be biased downward.

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

TABLE VIII
REGRESSIONS OF EXIT ON TFPR, TFPQ

China	
Exit on TFPR	−0.011
	(0.003)
Exit on TFPQ	−0.050
	(0.002)
India	
Exit on TFPR	−0.019
	(0.005)
Exit on TFPQ	−0.027
	(0.004)
United States	
Exit on TFPR	−0.011
	(0.003)
Exit on TFPQ	−0.039
	(0.002)

Notes. The dependent variables are dummies for exiting plants. The independent variables are the deviation of log(TFPR) or log(TFPQ) from the industry mean. Regressions are weighted least squares with the weights being industry value-added shares. Entries above are the coefficients on log(TFPR) or log(TFPQ), with standard errors shown in parentheses. Regressions also include a quartic function of plant age. Results are pooled for all years.

Table VIII shows that lower TFPR is associated with a higher probability of plant exit in all three countries. A 1-log-point decrease in TFPR is associated with a 1.1% higher exit probability in China and a 1.9% higher exit probability in India, compared to 1.1% higher exit probability in the United States. Low TFPR firms disproportionately exit in China and India, suggesting TFPR is a strong signal of profitability. Of course, government subsidies might allow many unprofitable plants to continue rather than exit. However, that is not what Table VIII shows, perhaps because of the reforms under way in both countries. The Chinese results partly reflect that state-owned plants are less profitable and are more likely to exit. However, the relationship between exit and TFPR is still significantly negative (−0.8% with a standard error of 0.3%) when a dummy for SOEs is included.

We can also look at the correlation of TFPQ with exit, because measurement error in TFPR should also show up as measurement error in TFPQ. (Recall that log TFPR is log revenues – log inputs, and log TFPQ is $\sigma/(\sigma - 1)$ log revenues – log inputs.) Table VIII shows that lower TFPQ is associated with higher exit probabilities, with a stronger relationship in China and a weaker relationship in India when compared with the United States. If the true

TABLE IX
REGRESSIONS OF INPUTS ON REVENUE, REVENUE ON INPUTS

	China	India	United States
Inputs on revenue	0.98	0.96	1.01
Revenue on inputs	0.82	0.90	0.82

Notes. Entries are the coefficients from regressions of $\log P_{si}Y_{si}$ on $\log K_{si}^{\alpha_s}(wL_{si})^{1-\alpha_s}$ (revenue on inputs) and $\log K_{si}^{\alpha_s}(wL_{si})^{1-\alpha_s}$ on $\log P_{si}Y_{si}$ (inputs on revenue). All variables are measured relative to the industry mean, with industries weighted by value-added shares. Results are pooled for all years.

relationship between TFPQ and plant exit is the same in the three countries, then this evidence suggests *less* measurement error in China, but more measurement error in India when compared with the United States.

We can also directly assess the extent of classical measurement error in plant revenue and inputs. If the percent errors in revenue and inputs are uncorrelated with each other, and true elasticities are the same in all countries, then we expect lower coefficients in China and India when we regress log revenue on log inputs or vice versa. We present such regressions in Table IX, pooling all years for a given country and measuring variables relative to industry means. The elasticity of inputs with respect to revenue is 0.96 in India and 0.98 in China, vs. 1.01 in the United States. These coefficients suggest greater classical measurement error might be adding 5% to the variance of log revenue in India and 3% to the variance in China. The elasticity of revenue with respect to inputs is 0.82 in China, 0.90 in India, and 0.82 in the United States. These coefficients suggest classical measurement error has the same effect on the variance of log inputs in China as in the United States, but actually lowers the variance in India by 10% relative to the United States. Putting the two-way regressions together, greater classical measurement could contribute to the higher variance of TFPR in China, but not in India. This evidence is not conclusive because the true elasticities could be lower in China and India than the United States, but it does provide mixed evidence on whether there is greater measurement error in China and India relative to the United States.

Suppose further that, for a given plant, measurement error is less serially correlated than true revenue and inputs, and that the true serial correlations are the same for all countries. Then we would expect the growth rates of revenue and inputs to vary more across plants in China and India than the United States.

TABLE X
DISPERSION OF INPUT AND REVENUE GROWTH

	Inputs	Revenue
China		
S.D.	0.45	1.00
75 − 25	0.34	0.93
India		
S.D.	0.28	0.70
75 − 25	0.24	0.60
United States		
S.D.	0.68	0.43
75 − 25	0.43	0.32

Notes. Entries are the standard deviation (S.D.) and interquartile range (75 − 25) of $d\log P_{si}Y_{si}$ and $d\log K_{si}^{\alpha_s}(w_{si}L_{si})^{1-\alpha_s}$. All variables are measured relative to the industry mean, and with industries weighted by their value-added shares. Entries are pooled for all years.

Table X presents the relevant statistics.[20] Input growth actually varies much less across plants in China and India than the United States. Revenue growth, however, varies a lot more in China and India than the United States. So the growth rates, too, provide mixed evidence on whether TFPR is noisier in China and India. Of course, true dispersion of input growth could be lower in China and India.

Finally, if measurement error is less persistent than true variables, then "instrumenting" with lagged variables should shrink efficiency gains more in China and India than in the United States. The TFP gain from fully equalizing TFPR levels falls from 87% under "OLS" to 72% under "IV" in 2005 China, from 127% to 108% in 1994 India, and from 43% to 26% in the 1997 United States. By this metric, measurement error accounts for a bigger fraction of the gains in the United States than in China or India. Of course, it could instead be that measurement error is more persistent than true TFPR.

To recap, the statistics in this subsection are inconclusive. They do not provide clear evidence that the signal-to-noise ratio for TFPR is higher in the United States than in China and India, but neither do they entirely rule out the possibility. In addition, we cannot rule out nonclassical measurement error across plants as the source of greater TFPR dispersion in China and India.

20. For this and all other U.S. calculations requiring a panel, we use the ASM rather than just the CM. We measure input growth as the growth rate of $K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}$.

TABLE XI
OWNERSHIP OF INDIAN AND CHINESE PLANTS

China	1998	2001	2005
Private domestic	15.9	37.4	62.5
Private foreign	20.0	21.7	21.9
State	29.0	18.5	8.1
Collective	35.1	22.4	7.5
India	1987	1991	2004
Private	87.7	88.4	92.4
State (central gov.)	3.3	3.3	2.4
State (local gov.)	3.9	3.0	2.8
Joint public/private	5.1	5.4	2.4

Notes. Entries are the percent of plants in each ownership category in the sector, where each sector is weighted by the value-added share of the sector. Each column adds to 100.

TABLE XII
REGRESSIONS OF SECTOR TFPR DISPERSION ON STATE OWNERSHIP IN CHINA

	1998	2001	2005	1998–2005
State ownership share	0.766 (0.165)	0.659 (0.153)	0.025 (0.213)	0.300 (0.080)
Year F.E.	NO	NO	NO	YES
Sector F.E.	NO	NO	NO	YES
N	406	403	407	3,237

Note. Entries are coefficients from regressions of the variance of log TFPR in sector s on the variance in sector s of an indicator variable for a state-owned plant. All regressions are weighted by the value-added weights of the sector. Standard errors are clustered by sector in the last column.

VI. POLICIES AND MISALLOCATION

If TFPR dispersion is real rather than a by-product of measurement error, then we should be able to relate TFPR gaps to explicit government policies. In this section we relate TFPR dispersion in China to state ownership of plants, and TFPR dispersion in India to licensing and size restrictions.

Table XI gives the percentage of plants that are state owned in China: 29% in 1998, 19% in 2001, and 8% in 2005. (In India the share of state-affiliated plants fell less dramatically, from 12% of plants in 1987 to 8% in 1994.) Now, in Table VII we documented roughly 40% lower TFPR at state-owned plants vs. private domestic plants in China. This raises the question of how much of China's TFPR dispersion can be accounted for by state ownership. In Table XII, we examine this relationship across the 400 or

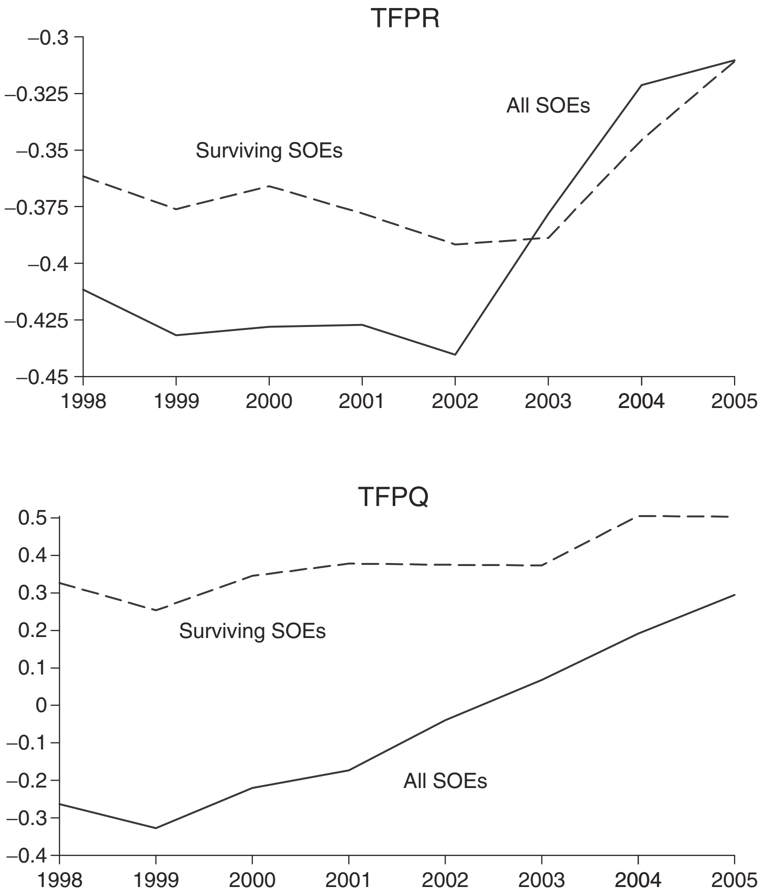

FIGURE IV
TFPR and TFPQ of Chinese State-Owned Firms

so four-digit industries in China. We regress the industry variance of log TFPR on the industry share of plants owned by the state. The relationship is positive and significant in both 1998 and 2001, with a 1% higher state share of plants associated with about 0.7% higher TFPR dispersion. The relationship is no longer significant by 2005, and Figure IV shows why. State-owned plants have much higher relative TFPR in 2005 than in 2001; some of this is due to exit of the least productive state plants, but the figure shows a sizable increase in the relative TFPR of surviving plants as well.[21]

21. Among state-owned plants in 1998, those privatized by 2005 had 11% higher TFPR (and 26% higher TFPQ) than state-owned plants exiting by 2005.

TABLE XIII
REGRESSION OF SECTOR TFPR DISPERSION ON DELICENSING AND SIZE RESTRICTIONS IN INDIA

	(1)	(2)	(3)
Delicensed 1991	−0.298		−0.298
	(0.117)		(0.117)
Delicensed 1991 × post-1991	0.032		−0.056
	(0.036)		(0.040)
Size restriction		0.368	
		(0.173)	
Delicensed 1991 ×			0.415
post 1991 × size restriction			(0.120)

Notes. The dependent variable is the variance of log TFPR in sector s in year t. Entries are coefficients on the following independent variables: (1) delicensed 1991: indicator for whether industry was delicensed in 1991; (2) delicensed 1991 × post 1991: product of an indicator for an industry delicensed in 1991 and an indicator for observations after 1991; (3) size restriction: % of value-added of an industry subject to reservations for small firms and; (4) delicensed 1991 × post 1991 × size restriction: product of size restriction, indicator variable for observations after 1991, and a dummy variable for industries delicensed after 1991. All regressions include indicator variables for year (1987 through 1994) and are weighted by the value-added share of the sector. Regressions (1) and (3) also include a dummy for industries delicensed in 1985. The omitted group consists of industries not delicensed in either 1985 or 1991. Standard errors are clustered by sector. Number of observations = 2,644.

When we equalize TFPR only within ownership categories, the gains are 8.2% lower in 1998 and 2.4% lower in 2005. Therefore, of the 15% reduction in potential gains from reallocation in China from 1998 to 2005, we calculate that 39% (5.8/15.0) comes from the shrinking TFPR gap between SOEs and other plants.

In India, misallocation within industries has often been attributed to licensing and size restrictions, among other government policies (see, e. g., Kochar et al. [2006]). These distortions may prevent efficient plants from achieving optimal scale and keep inefficient plants from contracting or exiting. The Indian government delicensed many industries in 1985 (about 40% of industries by value-added share) and in 1991 (about 42% of industries by value-added share).[22] India lifted its size restrictions much more recently (1997–2005), which unfortunately we are unable to analyze because our data end in 1994–1995. Across industries during our sample, the mean share of industry value-added subject to size restrictions was 21% with a standard deviation of 16%.[23]

In Table XIII we relate the dispersion of industry TFPR to whether the industry was delicensed in 1991 and to whether the

22. Based on three-digit data in Aghion et al. (2008).
23. The list of industries subject to size restrictions is from Mohan (2002).

industry faced size restrictions. (We also include a dummy for industries delicensed in 1985; the omitted group consists of industries not delicensed in either 1985 or 1991.) The first column shows that industries delicensed in 1991 exhibited less dispersion of TFPR, but *not* in particular for 1991 onward. It is as if licensed industries had lower TFPR dispersion despite their licensing restrictions, and the delicensing did not affect this. The reason may be that many of the delicensed industries were still subject to size restrictions. The second column of Table XIII indicates that the variance of log TFPR is greater within industries subject to size restrictions. We interact delicensing with size restrictions and years after 1991 in the third column, and find that industries delicensed in 1991 who face size restrictions do indeed display more TFPR dispersion from 1991 onward. Delicensed industries not facing size restrictions did exhibit lower TFPR from 1991, but not significantly so.

India's licensing restrictions might particularly restrict the ability of plants to acquire inputs when their efficiency rises. If so, then we would expect plants with rising TFPQ to have higher TFPR, but more so before delicensing than afterward. For Indian industries delicensed in 1991, Figure V plots average log TFPR against percentiles of plant TFPQ growth, with both variables relative to industry means. As predicted, the relationship is positive but notably flatter after delicensing. Whereas TFPR differed by 1.2 log points across the 90th vs. 10th percentile TFPQ growth before delicensing, it differed by 0.6 log points after delicensing.

We find little evidence that TFPR dispersion is correlated with measures of geography, industry concentration, and (in India) labor-market regulation. Average TFPR levels differ modestly (within 10%) across Chinese provinces and Indian states, so that the overwhelming majority of our TFPR differences are within industry regions. Within industry regions we tried without success to relate TFPR dispersion to industry concentration using a Herfindahl index. For India we experimented with an index of labor regulation for each industry, calculated as a weighted average of the cumulative index of labor regulation in Besley and Burgess (2004) in each state, with weights equal to value-added shares of each industry in each state. This index was not significantly related to the variance of log TFPR across industries, whether interacting with or controlling for delicensing and 1991 onward.

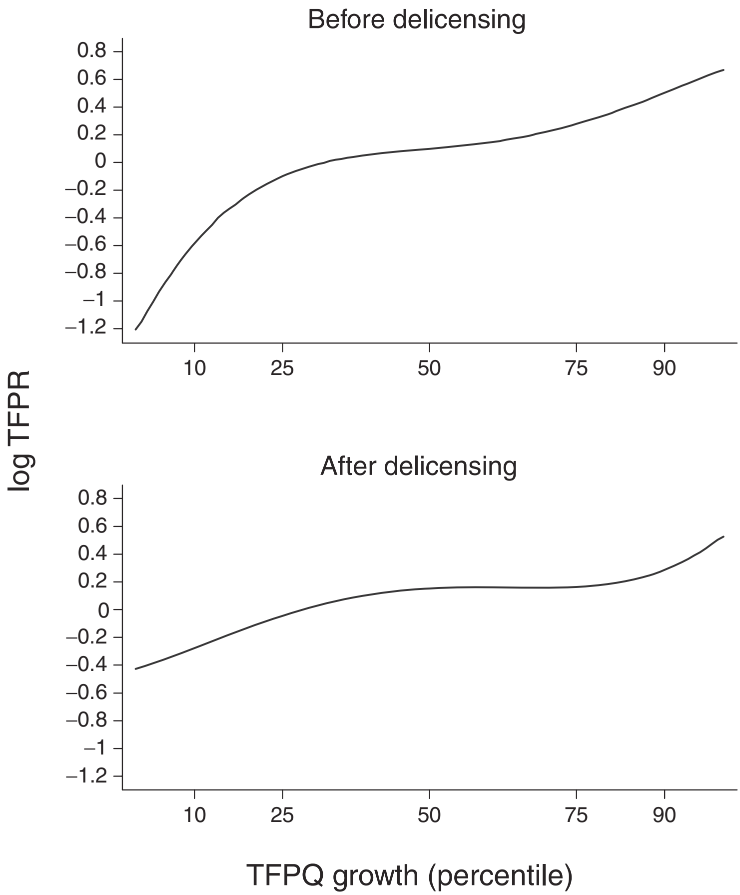

FIGURE V
TFPR and TFPQ Growth in Delicensed Sectors in India

VII. ALTERNATIVE EXPLANATIONS

We now entertain alternative explanations for TFPR dispersion besides policy distortions and measurement error. Specifically, we briefly examine varying markups with plant size, adjustment costs, unobserved investments (such as R&D), and varying capital elasticities within industries. All of these surely contribute to TFPR dispersion in all three countries, but our question is whether they might explain the *wider* TFPR dispersion in China and India than in the United States.

VII.A. Varying Markups with Plant Size

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 bigger plants, and there may be greater size dispersion in our Chinese and Indian data than in the U.S. data. Markups are distortions too, of course, but their dispersion may not wholly reflect policy differences between the countries. Melitz and Ottaviano (2008) analyze the case of linear demand, under which the elasticity of demand is falling (and the markup increasing) with size. Figure VI shows why we did not go this route. Whereas TFPR is strongly increasing in percentiles of plant size (value added) in India and mostly increasing in plant size in China, if anything TFPR decreases with plant size in the United States. If linear demand applied everywhere, then TFPR should increase with size in the United States, too. The fact that China and India differ not only quantitatively but qualitatively from the United States suggests more than just amplification of usual U.S. forces.

VII.B. Adjustment Costs

Young plants might have higher TFPR on average due to adjustment costs. If Chinese and Indian plants also differ in age more than U.S. plants do, differences in adjustment costs by age could contribute to wider TFPR dispersion in China and India. Figure VII plots average log TFPR (relative to industry means) by percentile of plant age in each country. TFPR steadily increases with plant age in India, contrary to this story. In China, TFPR rises through the youngest decile, then is flat or mildly decreasing in the interdecile range before falling for the oldest decile. Only the United States exhibits the predicted pattern of steadily falling TFPR with age.

More generally, growing plants might have higher TFPR than shrinking plants because of adjustment costs. And input growth rates may vary more in China and India, because of their reforms, than in the United States with its more stable policy environment. Figure VIII plots average TFPR by percentile of plant input growth. TFPR is increasing in input growth in all three countries, as predicted, but the United States exhibits more variation in TFPR associated with input growth than do China and India. Related, recall from Table X that input growth actually varies more across U.S. plants than across plants in China or India. The United States displays more churning, and so, if anything, should

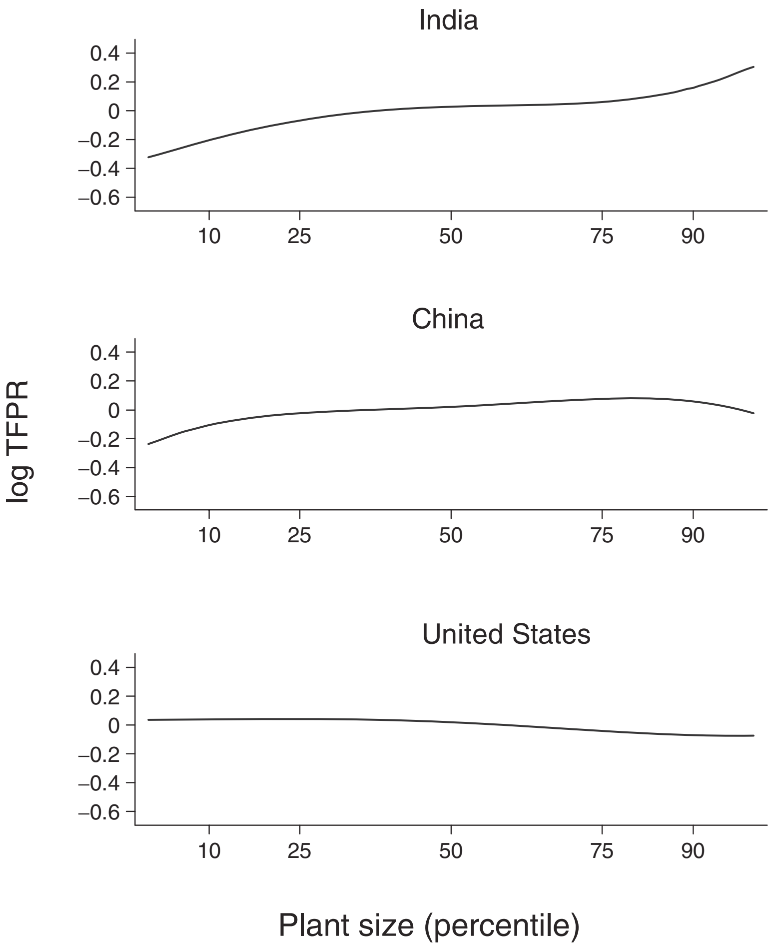

FIGURE VI
TFPR and Size

have more TFPR variation because of convex adjustment costs in input growth.[24]

Input growth may vary less in China and India because their plants are hit with less volatile idiosyncratic shocks and/or because they face higher adjustment costs. Cooper and Haltiwanger (2006) estimate idiosyncratic profitability shocks in a panel of U.S.

24. Another interpretation of Figure VIII is in terms of whether inputs are being reallocated to plants with higher TFPR. The answer is yes in all three countries, but more so in the United States. This is consistent with more efficient resource allocation in the United States.

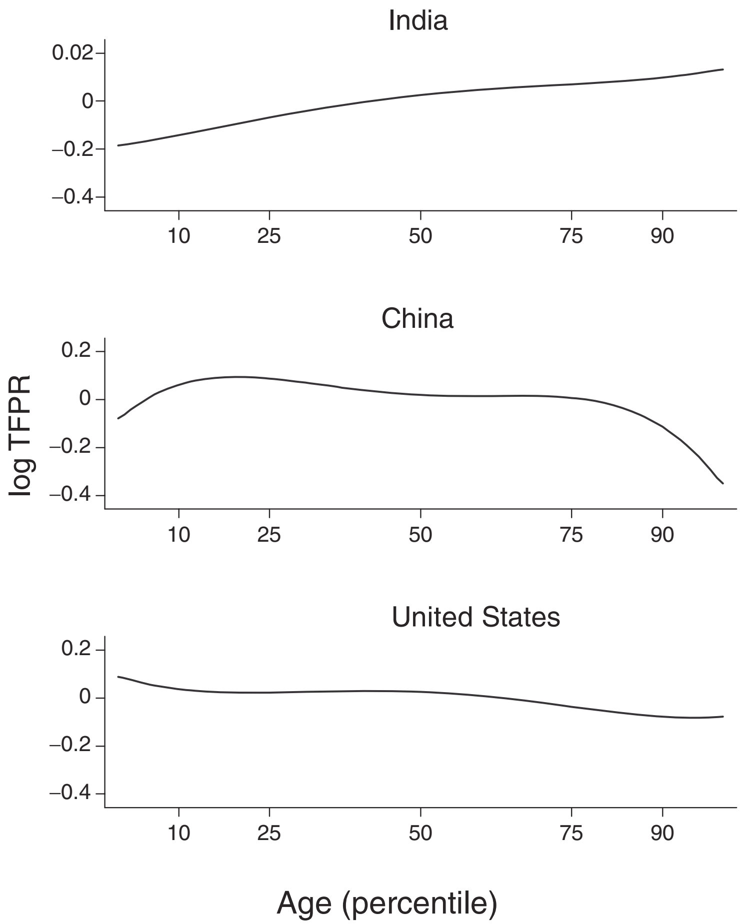

FIGURE VII
TFPR and Age

plants based on regressions of log profits (actually log revenue minus (roughly) 0.5 log capital) on its lagged value and year dummies. When we repeat their estimation for all three countries, we obtain similar estimates for the United States (serial correlation 0.81, innovation standard deviation 0.56), China (0.79 and 0.59) and India (0.84 and 0.57). The overall standard deviation is 1% higher for China than the United States and 10% higher for India than the United States. By comparison, in Table II the standard deviations of TFPR are over 50% higher for China and India than the United States. Thus it would seem that plants in China and

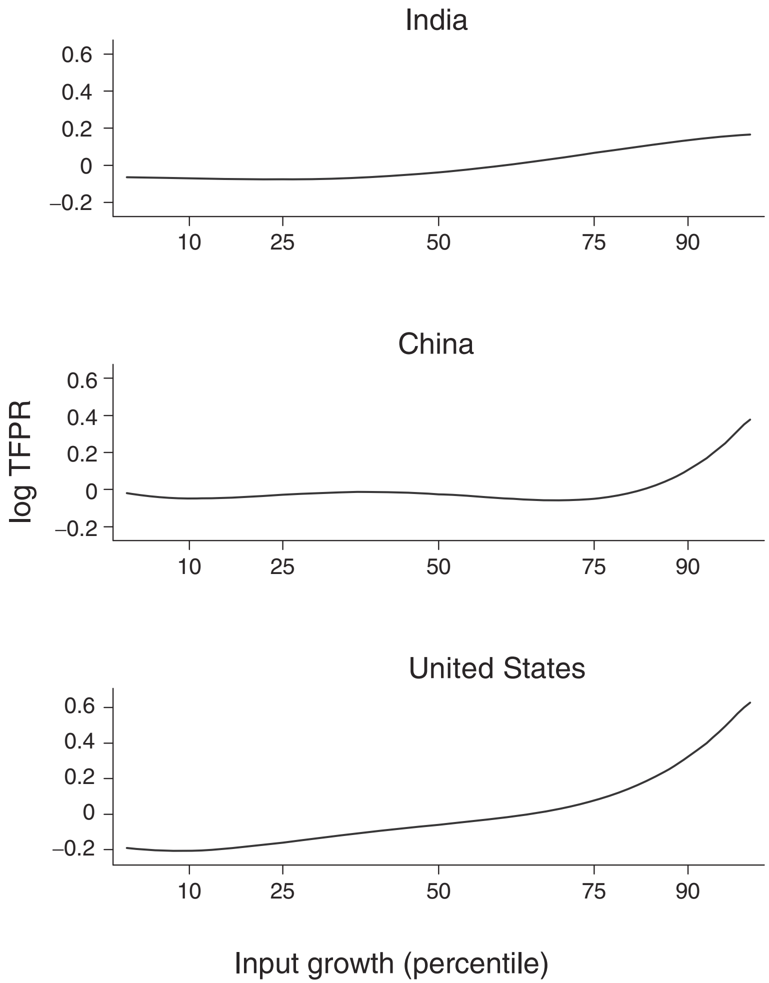

FIGURE VIII
TFPR and Input Growth

India face greater barriers to reallocation as opposed to bigger shocks with the same costs of reallocation.

Figure VII related *average* TFPR to plant age. A related hypothesis is that young (or small) plants display greater dispersion of TFPR. If plants in China or India are younger or smaller than U.S. plants, therefore, then one might expect them to display more variable TFPR. Table XIV provides the age of the 25th, 50th, and 75th percentile plants in each country. Chinese plants

TABLE XIV
DISTRIBUTION OF PLANT AGE (PERCENTILES)

	25th	50th	75th
China	2	5	22
India	6	12	22
United States	5	10	25

Notes. Entries are the 25th, 50th, and 75th percentile distribution of plant age in a sector, where each sector is weighted by the value-added share of the sector.

(median age five years) are younger than U.S. plants (median age ten years), but Indian plants are older (median age twelve years). Figure IX plots the size (employment) distribution of plants in all three countries. Indian plants (median size 33 employees) are smaller than U.S. plants (median size 47 employees), but Chinese plants (median size 160 employees) are much larger than U.S. plants. When we split plants into quartiles of size and age (respectively) and equalize TFPR only within quartiles, the gains are about 5% lower for both China and India. Thus variation in TFPR by size and age explains only a modest amount of the overall dispersion in TFPR (see Table III).

VII.C. 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 X displays precisely this pattern in the United States, but the opposite pattern in China and India. Thus it is far from obvious that unobserved plant investments vary more in China and India than in the United States. If TFPQ growth does proxy for unobserved investments, then Figure X suggests that such investments may mitigate TFPR differences in China and India.

Perhaps related, TFPR differences are more transitory in the United States than in China and India (see the "IV" results discussed near the end of Section V). U.S. TFPR differences may largely reflect temporary differences in investments and adjustment costs, whereas TFPR differences in China and India may reflect more persistent, perhaps policy-related gaps that are not as reliably closed with subsequent input reallocation and TFPQ growth.

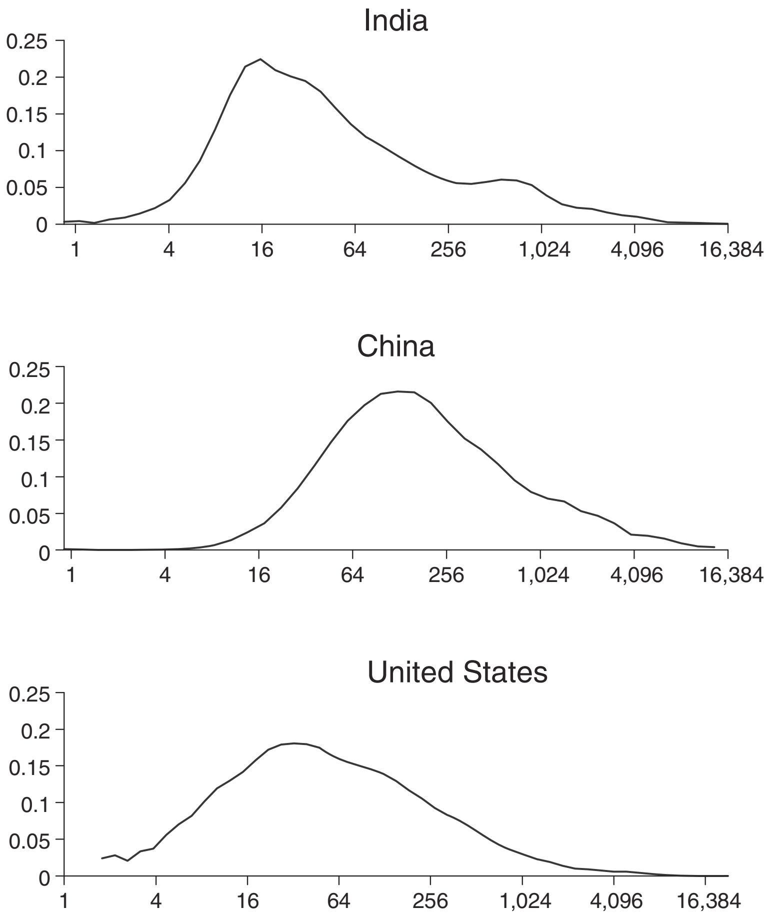

FIGURE IX
Distribution of Number of Workers

VII.D. Varying Capital Shares within Industries

Our baseline estimates in Table VI assumed the same capital elasticity for all plants within a four-digit industry. We inferred relative distortions from variation in capital-labor ratios within industries. At the other extreme, one could attribute all variation in these ratios within industries to plant-specific capital shares. Doing so and recalculating the TFP gains, we find the majority of the gains in China and India relative to the United States stem from output distortions. With plant-specific capital shares, TFP

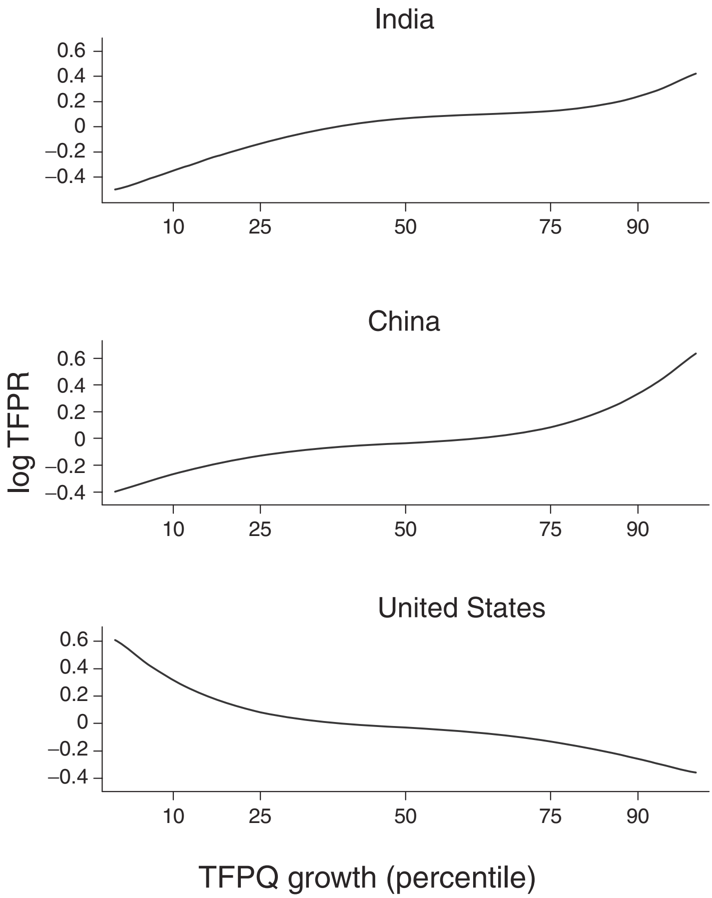

FIGURE X
TFPR and TFPQ Growth

gains are still 23%–45% (vs. 30%–50% baseline) for China and 32%–39% (vs. 40%–60% baseline) for India.

VIII. CONCLUSION

A long stream of papers has stressed that misallocation of inputs across firms can reduce aggregate TFP in a country. We used microdata on manufacturing plants to investigate the possible role of such misallocation in China (1998–2005) and India (1987–1994) compared with the United States (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 United States. We then entertained a counterfactual move by China and India to the U.S. dispersion of marginal products. We found that this would boost TFP by 30%–50% in China and by 40%–60% in India. Room for reallocation gains shrank about 2% 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 well 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 poor approximation of all three countries. Although we provided reassuring evidence on 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 plant productivity to observable policy distortions much more than we have. Finally, we neglected the potential impact of distortions on plant entry and exit, an important topic for future research.

APPENDIX I: LUCAS SPAN-OF-CONTROL VERSION

In the main text we modeled manufacturing plants as monopolistic competitors, and related the elasticity of substitution between varieties to a large empirical literature. However, many modelers, such as Restuccia and Rogerson (2008), follow Lucas (1978) in positing diminishing returns in production rather than utility. Here we show how the two formulations are isomorphic for aggregate TFP for a given number of plants and aggregate labor input.

Suppose labor is the sole input and there is a single sector. The equations for aggregate output, firm output, and firm profits for each variety are

$$
\begin{aligned}
Y &= \sum_{i=1}^{M} Y_i, \\
Y_i &= A_i L_i^{\gamma}, \\
\pi_i &= (1-\tau_i) P Y_i - w L_i.
\end{aligned}
$$

Returns to scale equal γ, and P is the price of homogeneous output. TFP ($=Y/L$ here) is

$$\text{TFP} = \left[\sum_{i=1}^{M}\left(\text{TFPQ}_i\left(\frac{\overline{\text{TFPR}}}{\text{TFPR}_i}\right)\right)^{\frac{1}{1-\gamma}}\right]^{1-\gamma} \Bigg/ L^{1-\gamma}.$$

Here $\text{TFPQ}_i = A_i$ and $\text{TFPR}_i = 1/(1-\tau_i)$. This is the same as our expression in the main text, except for two differences. First, $1/(1-\gamma)$ takes the place of $(\sigma-1)$. Diminishing returns in production ($\gamma < 1$) play the same role as diminishing returns in utility ($\sigma < \infty$). Second, aggregate TFP is now decreasing in aggregate labor input. If the number of plants is proportional to labor input, then such aggregate decreasing returns disappear. Of course, a variety benefit would then exist in the CES formulation. In terms of our calibration, our conservative choice of $\sigma = 3$ corresponds to $\gamma = 0.5$. This is quite low, even compared to studies such as Atkeson and Kehoe (2005), who chose $\gamma \geq 0.8$ based on diminishing returns in both production and utility.

Appendix II: Generalizing TFPQ for Quality and Variety

Here we sketch how our measure of TFPQ should capture not only process efficiency but also firm differences in quality and variety (equivalently, idiosyncratic demand). For simplicity, suppose labor is the sole input and there is a single sector. The equations for aggregate output, firm output, and firm profits for each variety are

$$\begin{aligned} Y &= \left[\sum_{i=1}^{M} N_i\,(Q_i\,Y_i/N_i)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \\ Y_i &= A_i\,L_i, \\ \pi_i &= (1-\tau_i)P_iY_i - wL_i. \end{aligned}$$

Here N_i is the number of symmetric varieties the firm produces, Q_i is the symmetric quality of each of its varieties, A_i is its process efficiency, Y_i/N_i is the symmetric quantity it produces of each variety, and P_i is the symmetric price of each variety. For this economy, our method of measuring TFPQ yields

$$\text{TFPQ}_i = \frac{(P_iY_i)^{\frac{\sigma}{\sigma-1}}/L_i}{Y^{\frac{1}{\sigma-1}}\,P^{\frac{\sigma}{\sigma-1}}} = A_i\,Q_i\,N_i^{\frac{1}{\sigma-1}}.$$

Measured TFPQ is a composite of process efficiency and idiosyncratic demand terms coming from quality and variety. Aggregate TFP ($=Y/L$ here) is identical to the case in which firms vary only in process efficiency, only with the above measure of TFPQ:

$$\mathrm{TFP} = \overline{\mathrm{TFPQ}} = \left\{ \sum_{i=1}^{M} \left[\mathrm{TFPQ}_i \left(\frac{\overline{\mathrm{TFPR}}}{\mathrm{TFPR}_i} \right) \right]^{\sigma-1} \right\}^{\frac{1}{\sigma-1}}.$$

TFPR is as in the main text, only here it reduces to the single distortion, $\mathrm{TFPR}_i = 1/(1 - \tau_i)$. Note that aggregate TFP (effective output per worker) is also synonymous with welfare.

APPENDIX III: LABOR AND CAPITAL DISTORTIONS

In the main text we estimated distortions to output (τ_{Ysi}) and to capital *relative* to labor (τ_{Ksi}), respectively. An observationally equivalent characterization is in terms of distortions to the *absolute* levels of capital and labor. Denote level distortions as τ^*_{Lsi} and τ^*_{Ksi}, and profits as $\pi_{si} = P_{si}Y_{si} - (1+\tau^*_{Lsi})wL_{si} - (1+\tau^*_{Ksi})RK_{si}$. The firm's first-order conditions are identical to those with $\{\tau_{Ysi},\ \tau_{Ksi}\}$ assuming $1-\tau_{Ysi} = 1/(1+\tau^*_{Lsi})$ and $1+\tau_{Ksi} = (1+\tau^*_{Ksi})/(1+\tau^*_{Lsi})$. Sectoral TFP is identical under these conditions as well.

We denote deviations of plant variables from industry-weighted means as

$$\Delta A_{si} = \ln \frac{A_{si}}{\bar{A}_s},\ \Delta\tau^*_{Lsi} = \ln \frac{1+\tau^*_{Lsi}}{1+\bar{\tau}^*_{Ls}},\ \Delta\tau^*_{Ksi} = \ln \frac{1+\tau^*_{Ksi}}{1+\bar{\tau}^*_{Ks}},$$
$$\Delta L_{si} = \ln \frac{wL_{si}}{\sum_{i=1}^{M_s} wL_{si}/M_s}.$$

For the latest years in China and India, the correlation matrices of these variables are shown in Table A.1. Not surprisingly, plants with high TFPQ tend to have high labor input. More interesting, plants with high TFPQ typically face higher "taxes" on both capital and labor. The distortions discourage labor input, but not strongly, because, again, the distortions tend to be high when TFPQ would dictate high labor input. Labor and capital wedges are positively correlated across plants, but only modestly so.

Here we can entertain the thought experiment of eliminating variation in the capital or labor distortion individually. For the latest year in China, the TFP gains from eliminating the capital

TABLE A.1

	China 2005			India 1994		
	ΔA_{si}	$\Delta\tau^*_{Lsi}$	$\Delta\tau^*_{Ksi}$	ΔA_{si}	$\Delta\tau^*_{Lsi}$	$\Delta\tau^*_{Ksi}$
ΔL_{si}	0.518	−0.202	−0.074	0.690	0.010	−0.038
$\Delta\tau^*_{Lsi}$	0.532	1	0.201	0.538	1	0.004
$\Delta\tau^*_{Ksi}$	0.592	0.201	1	0.398	0.004	1

(labor) distortion alone are 60% (24%) compared to 87% from eliminating both distortions. In India, the gains from eliminating the capital (labor) distortion alone are 78% (33%) compared to 128% from eliminating both distortions.

University of Chicago Booth School of Business and NBER
Stanford University, SIEPR, SCID, and NBER

References

Aghion, Philippe, Robin Burgess, Stephen Redding, and Fabrizio Zilibotti, “The Unequal Effects of Liberalization: Evidence from Dismantling the License Raj in India,” *American Economic Review*, 98 (2008), 1397–1412.

Alfaro, Laura, Andrew Charlton, and Fabio Kanczuk, “Plant-Size Distribution and Cross-Country Income Differences,” NBER Working Paper No. w14060, 2008.

Allen, Franklin, Rajesh Chakrabarti, Sankar De, Jun “QJ” Qian, and Meijun Qian, Financing Firms in India, manuscript, University of Pennsylvania, 2007.

Atkeson, Andrew G., and Patrick J. Kehoe, “Modeling and Measuring Organizational Capital,” *Journal of Political Economy*, 113 (2005), 1026–1053.

Banerjee, Abhijit, and Esther Duflo, “Growth Theory through the Lens of Development Economics,” in *Handbook of Economic Growth,* Vol. 1 A, P. Aghion and S. Durlauf, eds. (Amsterdam: Elsevier, 2005, Chap. 7).

Barro, Robert, J., and Jong-Wha Lee, “International Data on Educational Attainment: Updates and Implications,” NBER Working Paper No. w7911, 2000.

Bartelsman, Eric, John Haltiwanger, and Stefano Scarpetta, Cross-Country Differences in Productivity: The Role of Allocative Efficiency, manuscript,University of Maryland, 2008.

Bergoeing, Raphael, Patrick J. Kehoe, Timothy J. Kehoe, and Raimundo Soto, *Review of Economic Dynamics*, 5 (2002), 166–205.

Besley, Timothy, and Robin Burgess, “Can Labor Regulation Hinder Economic Performance? Evidence from India,” *Quarterly Journal of Economics*, 119 (2004), 91–134.

Bosworth, Barry, and Susan M. Collins, “Accounting for Growth: Comparing China and India,” NBER Working Paper No. w12943, 2007.

Broda, Christian, and David E. Weinstein, “Globalization and the Gains from Variety,” *Quarterly Journal of Economics*, 121 (2006), 541–585.

Buera, Francisco, and Yongseok Shin, Financial Frictions and the Persistence of History: A Quantitative Exploration, manuscript, University of California, Los Angeles, 2008.

Caselli, Francesco, “Accounting for Income Differences across Countries,” in *Handbook of Economic Growth,* Vol. 1 A, P. Aghion and S. Durlauf, eds. (Amsterdam: Elsevier, 2005, Chap. 9).

Caselli, Francesco, and Nicola Gennaioli, "Dynastic Management," NBER Working Paper No. w9442, 2003.
Chari, V. V., Patrick J. Kehoe, and Ellen C. McGrattan, "Business Cycle Accounting," *Econometrica*, 75 (2007), 781–836.
Cooper, Russell W., and John C. Haltiwanger, "On the Nature of Capital Adjustment Costs," *Review of Economic Studies*, 73 (2006), 611–633.
Dobson, Wendy, and Anil K. Kashyap, "The Contradiction in China's Gradualist Banking Reforms," *Brooking Papers on Economic Activity*, 2 (2006), 103–148.
Dollar, David, and Shang-jin Wei, "Das (Wasted) Kapital: Firm Ownership and Investment Efficiency in China," NBER Working Paper No. w13103, 2007.
The Economist, "Survey: Business in India," June 3, 2006a. Available online at http://www.economist.com/surveys/displayStory.cfm?story_id=6969740.
——, "Survey: China," May 23, 2006b. Available online at http://www.economist.com/surveys/displayStory.cfm?story_id=5623226.
Farrell, Diana, and Susan Lund, "China's and India's Financial Systems: A Barrier to Growth," *McKinsey Quarterly*, November (2006), 1–12.
Foster, Lucia, John Haltiwanger, and Chad Syverson, "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98 (2008), 394–425.
Galindo, Arturo, Fabio Schiantarelli, and Andrew Weiss, "Does Financial Liberalization Improve the Allocation of Investment? Micro-Evidence from Developing Countries," *Journal of Development Economics*, 83 (2007), 562–587.
Guner, Nezih, Gustavo Ventura, and Yi Xu, "Macroeconomic Implications of Size-Dependent Policies," *Review of Economic Dynamics*, 11 (2008), 721–744.
Hall, Robert E., and Charles I. Jones, "Why Do Some Countries Produce So Much More Output per Worker Than Others?" *Quarterly Journal of Economics*, 114 (1999), 83–116.
Hallward-Driemeier, Mary, Giuseppe Iarossi, and Kenneth L. Sokoloff, "Exports and Manufacturing Productivity in East Asia: A Comparative Analysis with Firm-Level Data," NBER Working Paper No. w8894, 2002.
Hendel, Igal, and Aviv Nevo, "Measuring the Implications of Consumer Inventory Behavior," *Econometrica*, 74 (2006), 1637–1673.
Hopenhayn, Hugo, and Richard Rogerson, "Job Turnover and Policy Evaluation: A General Equilibrium Analysis," *Journal of Political Economy,* 101 (1993), 915–938.
Howitt, Peter, "Endogenous Growth and Cross-Country Income Differences," *American Economic Review*, 90 (2000), 829–846.
Klenow, Peter J., and Andrés Rodríguez-Clare, "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" in *NBER Macroeconomics Annual,* B. Bernanke and J. Rotemberg, eds. (Cambridge, MA: MIT Press, 1997).
——, "Externalities and Economic Growth," in *Handbook of Economic Growth,* Vol. 1 A, P. Aghion and S. Durlauf, eds. (Amsterdam: Elsevier, 2005, Chap. 11).
Kochar, Kalpana, Utsav Kumar, Raghuram Rajan, Arvind Subramanian, and Ioannis Tokatlidis, "India's Pattern of Development: What Happened, What Follows," NBER Working Paper No. w12023, 2006.
Lagos, Ricardo, "A Model of TFP," *Review of Economic Studies*, 73 (2006), 983–1007.
Lewis, William W., *The Power of Productivity: Wealth, Poverty, and the Threat to Global Stability* (Chicago: University of Chicago Press, 2004).
Lucas, Robert E., Jr., "On the Size Distribution of Business Firms," *Bell Journal of Economics*, 9 (1978), 508–523.
McKinsey Global Institute, *Productivity: The Key to an Accelerated Development Path for Brazil* (Washington, DC: McKinsey Global Institute, 1998).
Melitz, Marc J., "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71 (2003), 1695–1725.
Melitz, Marc J., and Gianmarco I. P. Ottaviano, "Market Size, Trade, and Productivity," *Review of Economic Studies*, 75 (2008), 295–316.
Mohan, Rakesh, "Small Scale Industry in India: A Critical Evaluation," in *Economic Policy Reforms and the Indian Economy*, Anne Krueger, ed. (Chicago: University of Chicago Press, 2002).
Parente, Stephen L., and Edward C. Prescott, *Barriers to Riches* (Cambridge, MA: MIT Press, 2000).

Restuccia, Diego, and Richard Rogerson, "Policy Distortions and Aggregate Productivity with Heterogeneous Plants," *Review of Economic Dynamics*, 11 (2008), 707–720.

Young, Alwyn, "The Razor's Edge: Distortions and Incremental Reform in the People's Republic of China," *Quarterly Journal of Economics*, 115 (2000), 1091–1135.

——, "Gold into Base Metals: Productivity Growth in the People's Republic of China during the Reform Period," *Journal of Political Economy*, 111 (2003), 1220–1261.