Misallocation and Manufacturing TFP in China and India*

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Resource misallocation can lower aggregate total factor productivity (TFP). We use micro data on manufacturing establishments to quantify the extent of this misallocation in China and India in recent years. In each country, we measure sizable gaps in marginal products of labor and capital across plants within narrowly-defined industries. When capital and labor are hypothetically reallocated to equalize the marginal products, we calculate manufacturing TFP gains on the order of a factor of 2. Output gains are nearly a factor of 4 if physical capital accumulates to restore the original average marginal product of capital.

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I. Introduction

It is well established that most of the large differences in output per worker between rich and poor countries can be attributed to large differences in Total Factor Productivity (Hall and Jones 1999, Klenow and Rodríguez-Clare 1997). 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 Keller (2004) show how large TFP differences can emerge in a world with slow technology diffusion from advanced countries to other countries. To take another example, Parente and Prescott (2000) theorize that low TFP countries are ones in which vested interests block the introduction of better technologies to all firms. In these models, the inefficiencies preventing low TFP countries from reaching the frontier are internal to firms. In other words, they are models of within-firm inefficiency, with the inefficiency varying across countries.

A recent paper by Restuccia and Rogerson (2003) takes a different approach. Instead of focusing on the efficiency of a representative firm, they suggest that the misallocation of resources across firms can potentially have important effects on aggregate TFP. For example, imagine an economy with two firms that have identical technologies but in which the firm with political connections benefits from subsidized credit (say from a state-owned bank) and the other firm (without political connections) can only borrow at high interest rates from informal financial markets. Assuming that both firms equate the marginal product of capital with the interest rate, the marginal product of capital of the firm with access to subsidized credit will be lower than the marginal product of capital of the firm that only has access to informal financial markets. Clearly, capital is misallocated in this economy: aggregate output would be higher if capital was reallocated from the firm with a low marginal product of capital to the firm with a high marginal product of capital. The misallocation of capital results in low aggregate output per worker and TFP. Banerjee and Duflo (2005) argue that gaps in marginal products of capital could play a large role in the low manufacturing TFP in India relative to the U.S., and Bergoeing et al. (2002) that it explains the divergent growth paths of Chile and Mexico in recent decades.
More broadly, there are many institutions and policies that will potentially result in a misallocation of resources across firms. For example, the McKinsey Global Institute (1998) argues that a key factor behind low productivity in the retail sector in Brazil is that labor market regulations drive up the cost of labor for supermarkets, but do not affect retailers in the informal sector. Therefore, despite their low productivity, the lower cost 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. To take another example, Svensson (2003) shows that profitable firms in Uganda are solicited for bribes, whereas less profitable firms manage to slip under the radar screen of government officials.

Our goal in this paper is to provide quantitative evidence on the impact of resource misallocation on aggregate TFP. We use a standard model of monopolistic competition with heterogeneous firms, as in Hopenhayn (1982) and Melitz (2003), to show how distortions that result in a dispersion in the marginal product of capital and labor across firms will lower aggregate TFP. In addition, we show that different types of distortions will have different effects on the distribution of firm size, productivity, and capital intensity. For example, suppose that some firms are solicited for bribes while others are not. This will tend to increase the dispersion of firm size and firm productivity in the sector. However, since this distortion has the same effect on the marginal products of capital and labor, it will not affect the dispersion of firm capital-labor ratios. On the other hand, the credit market distortion discussed above will increase the dispersion of firm capital-labor ratios, as well as the dispersion of firm size and productivity.

We use this framework to measure the contribution of resource misallocation to aggregate manufacturing productivity in China and India. We think these countries are of particular interest because they have carried out reforms that may have contributed to their more rapid growth in recent years. Specifically, we use plant-level data from the Chinese and Indian manufacturing censuses to measure the dispersion in the marginal products of capital and labor within individual 4-digit manufacturing sectors in the two countries. We then measure how much aggregate manufacturing output in China and

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India would increase if capital and labor were to be reallocated to equalize the marginal products of capital and labor across plants within each 4-digit sector. We find that TFP would roughly double in both countries. We find little evidence that Indian reaped efficiency gains in 1994-1995 relative to 1989-1990. But China appears to have boosted its TFP by 2% per year from 1998-2003 by winnowing its distortions. In both countries in all years, the largest plants within industries have higher TFP and should expand at the expense of smaller plants. Also in both countries, the gains from partial liberalizations – such as eliminating output subsidies and restrictions but not capital market distortions – are notably smaller. But the output gains are larger if capital accumulates in response to aggregate TFP gains.

The rest of the paper proceeds as follows. We sketch a model of monopolistic competition with heterogeneous firms to show how the misallocation of capital and labor lowers aggregate TFP. We then take this model to the Chinese and Indian manufacturing censuses to quantify the contribution of factor misallocation to aggregate TFP in the manufacturing sectors in China and India. We lay out the model in section II, describe the datasets in section III, and present empirical results in section IV. In section V we carry out a number of robustness checks, and we offer some tentative conclusions in section VI. [Sections V and VI to be completed.]

II. Resource Misallocation and TFP

This section sketches out a standard model of monopolistic competition with heterogeneous firms to illustrate the effect of resource misallocation on aggregate productivity. What is different is that, in addition to differing by their level of efficiencies (as in Melitz, 2003), we also assume that firms potentially face different output and capital taxes (or subsidies). To develop intuition, we will first sketch out a minimalist model where there is one sector, a single distortion (to output), and in which labor is the only factor of production. We will then introduce a more complicated model with several sectors, two factors of production (physical capital, variously fixed or endogenous, and labor), and two distortions (a capital market distortion and an output distortion.)
One Factor and One Distortion

Suppose that aggregate output is a C.E.S aggregate of $M$ differentiated goods indexed by $i$:

\[
Y = \left( \frac{1}{\sigma-1} \right)^{\frac{\sigma}{\sigma-1}} \left( \sum_{i=1}^{M} Y_i^\sigma \right)^{\frac{\sigma-1}{\sigma}}.
\]

The demand for good $i$ is given by

\[
Y_i = Y \left( \frac{P_i}{P} \right)^{-\sigma}.
\]

Here, $P_i$ refers to the price of good $i$ and $P \equiv \left( \sum_{i=1}^{M} P_i^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$ to the price of aggregate output.

The production function of each differentiated product is given by:

\[
Y_i = A_i L_i
\]

Here, $A_i$ represents the TFP of firm $i$, and $L_i$ the labor it employs. In addition, suppose that there is an output distortion $\tau_{yi}$ that differs across firms. This output distortion can represent factors such as government restrictions on size, public subsidies to preferential firms, or high transportation costs. The profit of firm $i$ is then given by:

\[
\pi_i = (1 - \tau_{yi}) P_i Y_i - W L_i
\]

In sum, we assume that firms differ by TFP and by the output distortion faced.
Assuming that firms maximize profits (equation (2.4)) subject to the demand curve (equation (2.2)), we get the standard condition that price is set at a fixed markup over marginal cost:

\[
P_i = \frac{\sigma}{\sigma - 1} \frac{W}{A_i (1 - \tau_{yi})}.
\]

(2.5)

From substituting this pricing equation into the demand curve (equation (2.2)) and the production function (equation (2.3)), we obtain the following expression for the allocation of labor

\[
L_i = \lambda A_i^{\sigma - 1} (1 - \tau_{yi})^\sigma
\]

(2.6)

and firm output

\[
Y_i = \lambda A_i^\sigma (1 - \tau_{yi})^\sigma.
\]

(2.7)

Here, \( \lambda \equiv \left( \frac{\sigma - 1}{\sigma} \right)^\sigma \frac{Y}{W^\sigma} \) is a scalar common to all firms. As can be seen, the amount of labor employed by a firm will not only depend on its productivity, but also on the output distortion. In turn, the marginal revenue product of labor of a firm is its revenue per worker:

\[
MRPL = \frac{W}{1 - \tau_{yi}} = \frac{P_i Y_i}{L_i}
\]

(2.8)

Intuitively, the marginal revenue product of labor is high in firms that are small because they face large output disincentives, but low in firms that benefit from output subsidies. If labor were allocated efficiently across firms, a firm’s size would only depend on its TFP, and the marginal revenue product of labor would be the same across firms. Clearly, to the extent that the output distortion differs across firms, the misallocation of labor
lowers aggregate output and TFP: aggregate output would increase if labor were to be reallocated from firms that benefit from output subsidies to firms that face large output distortions.

Two Factors and Two Distortions

Although the one-sector one-factor model illustrates the basic idea that misallocation can lower aggregate TFP, it is much too simple to take seriously to the data. Therefore, we now introduce a more complicated model that features multiple sectors, two factors of production, and two distortions. This will be the model that we actually take to the data.

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

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

Expenditure minimization implies:

$$ P_s Y_s = \theta_s P Y $$

Here, $P_s$ is the price index of industry $s$ output and $P$ is the price of the final good:

$$ P = \prod_{s=1}^{S} \left( \frac{P_s}{\theta_s} \right)^{\theta_s} . $$

We set the final output good as the numeraire, so $P=1$.

The aggregate output of industry $s$ is a C.E.S. aggregate of $M_s$ differentiated products:
The demand curve for each differentiated product is:

\[ Y_{si} = Y_s \left( \frac{P_{si}}{P_s} \right)^{-\sigma} \]  

Here, \( P_{si} \) denotes the price of firm \( i \) in sector \( s \) and \( P_s \) is defined as:

\[ P_s = \left( \sum_{i=1}^{M_s} P_{si}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \]

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

\[ Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \]

Note that capital and labor shares are allowed to differ across industries (but not across firms within an industry). As in the one-sector model, each firm faces a firm-specific output distortion \( \tau_y \). However, we will now also allow for a firm-specific capital market distortion \( \tau_k \). This can represent factors such as the lack of access to credit by some firms and access to cheap credit (by business groups or state-owned banks) by other firms. Firm i’s profits are now given by:

\[ \pi_{si} = (1 - \tau_{Ysi}) P_{si} Y_{si} - W L_{si} - (1 + \tau_{Ksi}) R K_{si} \]
To be clear, TFP is allowed to vary across firms (\( A_{si} \)), as are the distortions to output and capital (\( \tau_{ysi} \) and \( \tau_{ksi} \)).

The solution to the firm’s problem implies the standard equation where price is set at a fixed markup over marginal cost

\[
(2.17) \quad P_{si} = \frac{\sigma}{\sigma - 1} \left( \frac{W}{1 - \alpha_s} \right)^{1 - \alpha_s} \left( \frac{R}{\alpha_s} \right)^{\alpha_s} \frac{(1 + \tau_{ksi})^{\alpha_s}}{A_{si} \cdot (1 - \tau_{ysi})},
\]

and the following expression for the firm’s capital-labor ratio:

\[
(2.18) \quad \frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1 - \alpha_s} \cdot \frac{W}{R} \cdot \frac{1}{(1 + \tau_{ksi})}.
\]

Substituting (2.17) into (2.15) and (2.18) into (2.13), we get

\[
(2.19) \quad L_{si} = \mu_s \frac{A_{si}^{\sigma - 1} (1 - \tau_{ysi})^\sigma}{(1 + \tau_{ksi})^{\alpha_s (\sigma - 1)}}.
\]

where \( \mu_s \equiv Y_s \left( \frac{\sigma - 1}{\sigma} \right)^\sigma \left( \frac{\alpha_s}{R} \right)^{\alpha_s (\sigma - 1)} (1 - \alpha_s)^{(1 - \alpha_s)\sigma + \alpha_s} \). Finally, substituting (2.19) and (2.18) into the production function (equation (2.15)), we get the following expression for firm output:

\[
(2.20) \quad Y_{si} = \delta_s \frac{A_{si}^{\sigma} (1 - \tau_{ysi})^\sigma}{(1 + \tau_{ksi})^{\alpha_s \sigma}}.
\]

where \( \delta_s \equiv Y_s \left( \frac{\sigma - 1}{\sigma} \right)^\sigma \left( \frac{\alpha_s}{R} \right)^{\alpha_s (\sigma)} (1 - \alpha_s)^{(1 - \alpha_s)\sigma} \). As can be seen, the allocation of resources across firms will not only depend on the distribution of firm TFP, but also on the distribution of the distortions. The resulting misallocation of resources is reflected in
the dispersion of the marginal products of labor and capital. Specifically, the marginal revenue product of labor is proportional to revenue per worker

\[ MRPL = \frac{W}{1 - \tau_{Ysi}} \frac{\alpha_{P_{si}Y_{si}}}{L_{si}}. \]

and the marginal revenue product of capital is proportional to the firm’s revenue-capital ratio

\[ MRPK = R \cdot \frac{1 + \tau_{Ksi}}{1 - \tau_{Ysi}} \frac{\alpha_{P_{si}Y_{si}}}{K_{si}}. \]

Intuitively, since all firms face the same labor cost, the marginal product of labor in firms that face large output distortions is higher than in firms that benefit from output subsidies. Similarly, the marginal product of capital will be low in firms that benefit from access to cheap capital and high in firms that have difficulty accessing capital.

How much lower is aggregate output due to the misallocation? To answer this question, we proceed as follows. First, we aggregate the demand for capital and labor (equations (2.19) and (2.18)) across firms in a given industry:

\[ wL_s = \frac{\sigma}{\sigma - 1} (1 - \alpha_s)(1 - \tau_{Ys})P_s Y_s \]

\[ RK_s = \frac{\sigma}{\sigma - 1} \alpha_s \frac{1 - \tau_{Ys}}{1 + \tau_{Ks}} P_s Y_s \]

Here, \( \tau_{Ys} \) and \( \tau_{Ks} \) denote the average output and capital distortion in a sector:

\[ \bar{\tau}_{Ys} = \frac{\sum_{i=1}^{M_s} \tau_{Ysi}P_{si}Y_{si}}{P_s Y_s} \quad \text{and} \quad \bar{\tau}_{Ks} = \frac{\sum_{i=1}^{M_s} \tau_{Ksi}K_{si}}{K_s} \]

Equations (2.23), (2.24), and (2.10) pin down the allocation of resources across sectors:
We can now solve for aggregate output as a function of the resources employed in each sector. Specifically, we combine equations (2.17), (2.14), (2.11), (2.23), and (2.24) to obtain

\begin{align*}
Y &= \prod_{s=1}^{S} \left[ \sum_{i=1}^{M_{s}} A_{si} \left( \frac{1 - \tau_{ysi}}{1 - \bar{\tau}_{ys}} \right) \left( \frac{1 + \tau_{ksi}}{1 + \bar{\tau}_{ks}} \right)^{-\alpha_{s}} \right] \left( \frac{1}{\sigma^{-1}} \right)^{1 - \alpha_{s}} \theta_{s} K_{s}^{\alpha_{s}} L_{s}^{1 - \alpha_{s}} \\
\end{align*}

where $K_{s}$ is given by (2.26) and $L_{s}$ by (2.25). Intuitively, the term multiplying $K_{s}^{\alpha_{s}} L_{s}^{1 - \alpha_{s}}$ is aggregate TFP of sector $s$, which depends on the joint distribution of firm TFP and the distortions.

We are now ready to characterize the effect of the misallocation within sectors on aggregate TFP. We consider a reform that leaves each industry’s average output and capital distortion in place, but eliminates dispersion around those averages. Specifically, if we set $\tau_{ysi} = \bar{\tau}_{ys}$ and $\tau_{ksi} = \bar{\tau}_{ks}$ for all firms in each industry, aggregate output will be:

\begin{align*}
Y_{\text{efficient}} &= \prod_{s=1}^{S} \left[ A_{si} K_{s}^{\alpha_{s}} L_{s}^{1 - \alpha_{s}} \theta_{s} \right] \\
\end{align*}
Here, \( \bar{A}_s \equiv \left( \frac{1}{M_s} \sum_{j=1}^{M_s} A_{sj}^{\sigma-1} \right)^{1/(\sigma-1)} \) is a weighted average of firm TFP in sector \( s \). The ratio of the actual level of aggregate output to hypothetical level under our reform scenario ("efficient" output) is then:

\[
\frac{Y}{Y_{efficient}} = \prod_{s=1}^{S} \left[ \frac{1}{M_s} \sum_{i=1}^{M_s} \left( \frac{A_{si}}{\bar{A}_s} \right)^{\frac{1-\tau_{ysi}}{1-\tau_{ysi}} \left(1+\tau_{Ksi}\right)^{-\alpha_s}} \right]^{\sigma^{-1}/\sigma-1} \theta_s
\]

The fraction of actual to distortion-free output is small when the summand within brackets is small. The summand is small when more productive plants \((\text{high } A_{si}/\bar{A}_s)\) confront relatively large output distortions \((\text{small } (1-\tau_{ysi})/(1-\tau_{ysi}))\) and relatively large capital distortions \((\text{large } (1+\tau_{Ksi})/(1+\tau_{Ksi}))\). The potential gains from liberalization are larger when more efficient plants face bigger distortions.

We note several things about this hypothetical liberalization. First, from (2.25) and (2.26), the share of aggregate labor and capital devoted to a given sector does not change as a result of the reform. Our assumption of a Cobb-Douglas aggregator of sector outputs, with its unit elastic demand, is responsible for this property (an industry that is 1% more efficient has a 1% lower price index and 1% higher demand, which can be accommodated without adding or shedding inputs). We will relax this assumption in section V.

Second, we conditioned on a fixed aggregate stock of capital. Because the rental rate rises with liberalization, we would expect capital to accumulate (even with a fixed saving and investment rate). If we endogenize K by invoking an Euler equation to pin down the rental rate \( R \), there is a simple relationship between the gains from liberalization when the aggregate capital stock is fixed \((Y_{efficient}/Y)\) and the gains when capital is accumulated endogenously \((Y_{efficient}/Y)\) endogenous \( K \):
Here, $\bar{\alpha} = \sum_{s=1}^{S} \alpha_s \theta_s$ is a weighted average of industry elasticities of output with respect to capital. Thus, a higher average elasticity leads to greater gains from liberalization when capital accumulates relative to when it is fixed. This property is reminiscent of a one sector neoclassical growth model, wherein increases in TFP are amplified by the capital accumulation they induce so that the output elasticity with respect to TFP is $1/(1-\alpha)$.

Third, we held the number of firms in each industry fixed in the wake of liberalization. In an Appendix (available upon request) we show that this will occur in a model of endogenous entry in which entry costs take the form of a fixed amount of labor.²

III. Datasets for India and China

Our data for India are drawn from India’s Annual Survey of Industries (ASI) conducted by the Indian government’s Central Statistical Organisation (CSO). The ASI is a census of all registered manufacturing plants in India with more than 100 workers and a random one-third sample of registered plants with more than 20 workers but less than 100 workers. The survey has been conducted since the early 1970s and provides information on plant characteristics over the fiscal year (July of a given year through June of the following year). We use the ASI data from the 1989-1990 and 1994-1995 fiscal years. The raw data consists of over 41,000 plants in 1989-1990 and 49,000 in 1994-1995. For our computations we set industry capital shares to those in the corresponding U.S. manufacturing industry. As a result, we drop non-manufacturing plants and plants in industries without a close counterpart in the U.S. We also trim the 1% tails for plant productivity and implied distortions. For our baseline calculations, we end up with over

² A critical assumption we make is that an entrant does not know its productivity or distortions ex ante. These are only known ex post, i.e., after expending entry costs. Ex ante a potential entrant knows only that they will receive a random draw from the existing joint distribution of distortions and productivity.
35,000 Indian plants in 1989-1990 and over 41,000 in 1994-1995. We retain a little over 84% of the value added in the original data in each year. Table 1 summarizes the raw and selected sample sizes for China in each year.

<table>
<thead>
<tr>
<th>Raw # of plants</th>
<th>Selected # of plants</th>
<th>Selected % of VA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989-1990</td>
<td>41,680</td>
<td>35,094</td>
</tr>
<tr>
<td>1994-1995</td>
<td>49,394</td>
<td>41,580</td>
</tr>
</tbody>
</table>

Of particular interest to us, plants in the ASI report their industry (4-digit ISIC), geographic location, ownership, labor compensation, value-added, and the book value of their 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. The dataset also reports the ownership type for each plant, which we summarize in Table 2. Upwards of 90% of Indian plants are wholly private, but the state-owned plants are larger and comprise 16-22% of value added. The share of value added in wholly private plants rose from 66% to 76% over the two years.

<table>
<thead>
<tr>
<th>% of plants</th>
<th>% of value added</th>
</tr>
</thead>
<tbody>
<tr>
<td>Government</td>
<td>Mixed</td>
</tr>
<tr>
<td>1989-1990</td>
<td>4.4</td>
</tr>
<tr>
<td>1994-1995</td>
<td>3.6</td>
</tr>
</tbody>
</table>

Our data for Chinese plants are from the 1995 Manufacturing Census and the Annual Survey of Industrial Production from 1998 through 2003 conducted by the Chinese government’s National Bureau of Statistics (NBS). The 1995 Manufacturing Census is a census of all manufacturing establishments in China. The Annual Survey of
Industrial Production is a census of all non-state plants with more than 5 million yuan in revenue plus all state-owned plants. The raw data consists of over 330,000 plants in 1995, and from 119,000 to 169,000 in 1998-2003. To make the sample in 1995 more consistent with the later samples, we drop all plants with revenue less than 5 million yuan in all years. Also, because we set industry capital shares to those in the corresponding U.S. manufacturing industry, we exclude non-manufacturing plants and plants in industries without a close counterpart in the U.S. Finally, we trim the 1% tails for plant productivity and implied distortions. For our baseline calculations, we end up with between 98,000 and 141,000 plants, depending on the year. Our sample covers over 60% of the value added in the original data in each year (the bulk of this reduction owing to plants not being in manufacturing). Table 3 summarizes the raw and selected sample sizes for China in each year.
Table 3: Chinese Samples

<table>
<thead>
<tr>
<th>Year</th>
<th>Raw # of plants</th>
<th>Selected # of plants</th>
<th>Selected % of VA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>339,703</td>
<td>98,456</td>
<td>59.9</td>
</tr>
<tr>
<td>1998</td>
<td>119,709</td>
<td>96,589</td>
<td>61.8</td>
</tr>
<tr>
<td>1999</td>
<td>119,756</td>
<td>96,422</td>
<td>63.5</td>
</tr>
<tr>
<td>2000</td>
<td>125,194</td>
<td>100,671</td>
<td>60.8</td>
</tr>
<tr>
<td>2001</td>
<td>133,282</td>
<td>108,869</td>
<td>60.9</td>
</tr>
<tr>
<td>2002</td>
<td>147,057</td>
<td>120,547</td>
<td>60.5</td>
</tr>
<tr>
<td>2003</td>
<td>168,463</td>
<td>140,143</td>
<td>63.2</td>
</tr>
</tbody>
</table>

The specific information we use from the two Chinese datasets are the plant’s industry (again at the 4-digit level), geographic location, ownership, wage payments, value-added, monetary subsidies, and capital stock. In particular, we define the capital stock as the book value of fixed capital net of depreciation. As for labor compensation, the Chinese data only reports wage payments; it does not provide information on non-wage compensation. The median labor share in plant-level data is roughly 30 percent, which is significantly lower than the aggregate labor share in manufacturing reported in the Chinese input-output tables and the national accounts (roughly 50 percent). We therefore assume that non-wage benefits are a constant fraction of a plant’s wage compensation, where the adjustment factor is calculated such that the sum of imputed benefits and wages across all plants equals 50 percent of aggregate value-added. We also have ownership status for the Chinese plants, and Table 4 breaks this down by year. The years from 1995 to 2003 transformed Chinese manufacturing from being predominantly state-run or state-involved in 1995 (73% of value added) to principally private in 2003 (72% of value added). This privatization may have brought with it a rationalization of government policies, with reduced subsidies and subsidized loans for the formerly state-affiliated plants.
Table 4: Ownership of Chinese Plants

<table>
<thead>
<tr>
<th></th>
<th>State</th>
<th>Collective</th>
<th>Private</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>45.8</td>
<td>37.7</td>
<td>16.5</td>
</tr>
<tr>
<td></td>
<td>56.4</td>
<td>20.9</td>
<td>22.7</td>
</tr>
<tr>
<td>1998</td>
<td>27.3</td>
<td>37.8</td>
<td>34.9</td>
</tr>
<tr>
<td></td>
<td>40.7</td>
<td>20.2</td>
<td>39.1</td>
</tr>
<tr>
<td>1999</td>
<td>24.5</td>
<td>35.0</td>
<td>40.5</td>
</tr>
<tr>
<td></td>
<td>38.8</td>
<td>17.6</td>
<td>43.6</td>
</tr>
<tr>
<td>2000</td>
<td>19.7</td>
<td>31.1</td>
<td>49.2</td>
</tr>
<tr>
<td></td>
<td>32.8</td>
<td>15.8</td>
<td>51.4</td>
</tr>
<tr>
<td>2001</td>
<td>14.2</td>
<td>24.8</td>
<td>61.0</td>
</tr>
<tr>
<td></td>
<td>27.1</td>
<td>12.4</td>
<td>60.5</td>
</tr>
<tr>
<td>2002</td>
<td>11.5</td>
<td>20.2</td>
<td>68.3</td>
</tr>
<tr>
<td></td>
<td>24.1</td>
<td>10.5</td>
<td>65.4</td>
</tr>
<tr>
<td>2003</td>
<td>7.9</td>
<td>15.8</td>
<td>76.3</td>
</tr>
<tr>
<td></td>
<td>20.4</td>
<td>8.0</td>
<td>71.6</td>
</tr>
</tbody>
</table>

IV. Empirical Results

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

We set the rental price of capital (before reforms and excluding distortions) to \( R = 0.10 \). We have in mind a 5% real interest rate and a 5% depreciation rate. The cost of capital faced by plant \( i \) in industry \( s \) differs from 10% if \( \tau_{ksi} \neq 0 \). Specifically, it is \((1 + \tau_{ksi})R\). Because our reforms collapse \( \tau_{ksi} \) to \( \bar{\tau}_{ks} \) in each industry, the attendant efficiency gains do not depend on \( R \). If we have set \( R \) incorrectly, it affects only the \( \bar{\tau}_{ks} \) values, not the liberalization experiment. This does make us reluctant, however, to emphasize the average level of \( \bar{\tau}_{ks} \) in any given country-year.

We set the elasticity of substitution between plant value added to \( \sigma = 3 \). The gains from liberalization are increasing in \( \sigma \), so we made this choice conservatively. Estimates of the substitutability of competing manufactures in the trade and industrial organization literatures are typically 3 to 7. We also entertained the higher value of \( \sigma = 5 \) as a robustness check.
As mentioned, we set the elasticity of output with respect to capital in each industry \((\alpha_i)\) to be one minus the labor share in the corresponding industry in the U.S. We do not set these elasticities based on labor shares in the Indian and Chinese data precisely because we think distortions are potentially important in the latter. We cannot separately identify the average output distortion and the production elasticity in each industry. We adopt the U.S. shares as the benchmark because we presume the U.S. is comparatively undistorted (both across plants and, more to the point here, across industries). Our source for the U.S. shares is the NBER Productivity Database, based on the Census and Annual Survey of Manufactures. One well-known issue with this data is that payments to labor omit fringe benefits and employer Social Security contributions. The CM/ASM manufacturing labor share is about 2/3 what it is in manufacturing according to the National Income and Product Accounts, which incorporates non-wage forms of compensation. We therefore scale up each industry’s CM/ASM labor share by 3/2 to arrive at the labor elasticity we assume for the corresponding Indian or Chinese industry.

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

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

\[
1 + \tau_{K_{si}} = \frac{\alpha_s}{1 - \alpha_s} \frac{wL_{si}}{RK_{si}} \tag{4.1}
\]

\[
1 - \tau_{Y_{si}} = \frac{\sigma}{\sigma - 1} \frac{wL_{si}}{1 - \alpha_s (P_{si} Y_{si})} \tag{4.2}
\]

\[
A_{si} = \kappa_{si} \frac{(P_{si} Y_{si})^{\sigma - 1}}{K_{si} L_{si}^{1-\alpha_s}} \tag{4.3}
\]
Equation (4.1) says we infer the presence of a capital distortion (subsidy) when the ratio of labor compensation to the capital stock is high (low) relative to what one would expect from the output elasticities with respect to capital and labor. Similarly, expression (4.2) says we deduce an output distortion (subsidy) when labor’s share is low (high) compared to what one would think from the industry elasticity of output with respect to labor (and the adjustment for rents).

TFP in (4.3) warrants more explanation. First, the scalar is \( \kappa_s = \left( \frac{1}{s^{\alpha_k}} \right)^{\frac{1}{\sigma}} \). Although we do not observe \( \kappa_s \), the 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 \( P_s Y_{si} \). However, plants with high real output (relative to what one would expect from \( \kappa_s \)) must charge a lower price to explain why buyers would demand the higher output. We therefore raise \( P_s Y_{si} \) to the power \( \sigma / (\sigma - 1) \) to arrive at \( Y_{si} \). Third, for labor input we use the plant’s wage bill rather than its employment to measure its \( L_{si} \). We think earnings per worker probably vary more across plants because of differences in hours worked and human capital per worker than because of an omitted labor distortion.

It is typical in the productivity literature to have industry deflators but not plant-specific deflators. Foster, Haltiwanger and Syverson (2005) stress that, when industry deflators are used, differences in plant-specific prices show up in the customary measure of plant TFP. They therefore stress the distinction between “physical productivity”, which they denote TFPQ, and “revenue productivity”, which they call TFPR. The use of a plant-specific deflator yields TFPQ, whereas using an industry deflator gives TFPR. This distinction is vital for us too. We get

\[
\text{TFPQ}_{si} \equiv A_{si} \equiv \frac{Y_{si}}{K_{si}^{\alpha_k} (wL_{si})^{1-\alpha_k}},
\]

and

\[
\text{TFPR}_{si} \equiv P_{si} A_{si} \equiv \frac{P_{si} Y_{si}}{K_{si}^{\alpha_k} (wL_{si})^{1-\alpha_k}} \propto \frac{(1 + \tau_{Ki})^{\alpha_s}}{1 - \tau_{yi}}.
\]
Unlike TFPQ, TFPR does not vary across plants within an industry unless the plant faces capital and/or output distortions. Just as revenue per worker should be the same across plants in the one factor model, it is efficient to equalize TFPR across plants in this two factor model. More capital and labor should be allocated to plants with higher TFPQ to the point that their higher output results in a lower price and the same TFPR as at smaller plants. High plant TFPR within an industry is a sign that the plant confronts capital and output barriers that make it smaller than optimal. In the distorted equilibrium labor input in plant \( i \) in section \( s \) is

\[
L_{si} \propto A_{si}^{\sigma-1} (1 - \tau_{ysi})^\sigma (1 + \tau_{Ksi})^{-\alpha,(\sigma-1)}.
\]

With no distortions, labor is allocated solely based on the each plant’s TFPQ. Otherwise plants subject to output restrictions (subsidies) and/or high (low) borrowing costs are employ less (more) labor.

Before calculating the gains from our hypothetical liberalization, we trim the 1% tails from the distributions of

\[
\Delta \tau_{Ksi} \equiv \ln \left( \frac{1 + \tau_{Ksi}}{1 + \tau_{Ks}} \right), \\
\Delta \tau_{ysi} \equiv -\ln \left( \frac{1 + \tau_{ysi}}{1 + \tau_{ys}} \right), \\
\Delta A_{si} \equiv \ln \left( \frac{A_{si}}{\bar{A}_s} \right)
\]

across industries. That is, we pool all industries and trim the top and the bottom 1% of plants within each of the three pools. We then recalculate \( wL_s, K_s, \) and \( P_sY_s \) as well as \( \tau_{Ks}, \tau_{ys}, \) and \( \bar{A}_s \). At this stage we calculate the industry shares \( \theta_s = P_sY_s/(PY) \).

Figure 1 plots the resulting distributions of TFP (\( \Delta A_{si} \)), the output distortion (\( \tau_{ysi} - \tau_{ys} \)), and the capital distortion (\( \tau_{Ksi} - \tau_{Ks} \)) for India in 1994 and China in 2003. Both countries exhibit left-skewed TFP distributions, but India more so. Still, the bulk of
the distribution is within +/− two log points of zero (the industry average). The output distortion is also left-skewed in both countries, suggesting more plants are heavily subsidized than are heavily restricted. The capital wedge is right-skewed in China and India alike: more plants face exceedingly high costs of capital than enjoy cheap financing. Recall that the capital distortion applies to $RK$ (where $K$ is 0.10), so a capital distortion of “5” corresponds to a 50% rental price of capital.³

³ In India, the median output (capital) distortion is 23% (27%) in 1989-1990 and 37% (1%) in 1994-1995. In China, the median output (capital) distortion is -2% (112%) in 1998 and -1% (197%) in 1994-1995. The median capital distortions in China translate to rental prices of 21% (2.112*0.10) and 30% (2.97*0.10).
Distribution of Plant TFP, Output Distortion, and Capital Distortion

TFP

Output Distortion

Capital Distortion
Table 5 presents the efficiency gains (i.e., the proportional increases in output and TFP) from setting all plant distortions to industry averages in India. The relevant formula for efficiency gains is equation (4.4). For India the gains are just over 2 in our baseline case of \( \sigma = 3 \) (elasticity of substitution between different manufacturing intermediates) and \( \varepsilon = 0.01 \) (trimming of 1\% from the tails of TFP and each distortion in each country-year). i.e., according to the model India could double its manufacturing TFP by leveling its treatment of plants within industries. This constitutes a sizable chunk of the TFP differences typically found between the U.S. and India of a factor of 4 or so (see, for example, Hall and Jones, 1999). Perhaps surprisingly, the potential gains edged up from 1989-1990 to 1994-1995 – a time when reforms were being implemented – although the increase is a modest 2\%. Table 5 shows bigger gains (a factor of around 3 instead of 2) if \( \sigma = 5 \) instead of 3, so that there are greater gains from piling labor and capital inputs onto the most productive plants. The Table shows smaller gains (a factor of 1.6 or so vs. 2.1 in the baseline) when we trim 5\% from each variable’s tail rather than 1\%.

Table 5: Efficiency gains in India (Fixed Capital)

<table>
<thead>
<tr>
<th></th>
<th>( \sigma = 3 )</th>
<th>( \sigma = 5 )</th>
<th>( \sigma = 3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \varepsilon = 0.01 )</td>
<td>2.12</td>
<td>2.85</td>
<td>1.59</td>
</tr>
<tr>
<td>( \varepsilon = 0.05 )</td>
<td>1.94</td>
<td>2.55</td>
<td>1.29</td>
</tr>
</tbody>
</table>

Table 6 provides the same statistics for China. The baseline gains are around 2, just as for India. The potential gains rose from 1.92 to 2.06 from 1995 to 1998, but this could reflect a difference in sampling methodology between the 1995 Census and the 1998-2003 Surveys. If we focus on the Survey period, the room for gains falls around 10\% from 1998 to 2003, consistent with reallocation gains of about 2\% per year. This pattern (a step up in 1998 vs. 1995, then down 1998 to 2003) holds for the other two cases – of higher elasticity of substitution and more aggressive trimming of outliers – as

---

4 Rodrik and Subramanian (2004)
5 Young (2000) does estimate, however, that between-region distortions worsened in the 1978-1998 period in China, including in the manufacturing sector.
well. With $\sigma = 5$ instead of 3, the potential gains are a factor of 3 rather than 2 (again, similar to India). And with trimming of 5% from each tail there would still appear to be room for boosting TFP by a factor of 1.5.

Table 6: Efficiency gains in China (Fixed Capital)

<table>
<thead>
<tr>
<th></th>
<th>$\sigma = 3$</th>
<th>$\sigma = 5$</th>
<th>$\sigma = 3$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\varepsilon = 0.01$</td>
<td>$\varepsilon = 0.01$</td>
<td>$\varepsilon = 0.05$</td>
</tr>
<tr>
<td>1995</td>
<td>1.92</td>
<td>3.25</td>
<td>1.50</td>
</tr>
<tr>
<td>1998</td>
<td>2.06</td>
<td>3.37</td>
<td>1.59</td>
</tr>
<tr>
<td>1999</td>
<td>1.96</td>
<td>3.14</td>
<td>1.55</td>
</tr>
<tr>
<td>2000</td>
<td>1.94</td>
<td>3.06</td>
<td>1.52</td>
</tr>
<tr>
<td>2001</td>
<td>1.91</td>
<td>3.04</td>
<td>1.53</td>
</tr>
<tr>
<td>2002</td>
<td>1.92</td>
<td>3.07</td>
<td>1.51</td>
</tr>
<tr>
<td>2003</td>
<td>1.86</td>
<td>2.98</td>
<td>1.48</td>
</tr>
</tbody>
</table>

We next ask how reforms might affect the size distribution of plants. Equivalently, we want to know whether large or small plants appear to receive favorable treatment in terms of output subsidies and cheap financing. Figure 2 plots the distribution of log plant value added before (“actual”) and after (“efficient”) our hypothetical liberalizations. In all four cases shown – India in 1989-1990 and 1994-1995 and China in 1998 and 2003 – the efficient distribution involves fewer midsize plants and more small plants. Thus small plants appear to receive special treatment, coinciding with many discussions of the “license raj” in India and promotion of local state-owned enterprises in China. Less transparent from the plots, the largest establishments should comprise bigger share of value added. The median share of the top 10 plants in industry value added should rise from around 72% to 80% in India (whose industries average about 1,000 plants), and from around 35% to 45% in China (whose industries average closer to 3,000 plants).
Tables 7 and 8 consider “partial” liberalizations, i.e., eliminating the dispersion of either the output distortion or the capital distortion individually in India and China. The first column in each table reproduces the baseline efficiency gains of around 100%. The next columns show the effect of eliminating the output distortion and capital distortion, respectively. The results illustrate that wholesale reforms raise TFP more than the product of the gains from piecemeal reforms. Removing a single distortion boosts TFP, but by 23% or less in 16 of the 18 cases (the exceptions being 34% and 35% gains from eliminating output distortions in China in 1995 and 1998). The product of the gains is between 28% and 58%, vs. the combined gains of 86% to 117%. We think this finding stems from the negative correlation between distortions (about 0.50 in all country-years): plants facing bigger output restrictions tend to exhibit lower costs of capital. This might reflect that more efficient plants are larger, albeit not as large as if the government did not constrain them, yet their greater size affords better access to capital (either political connections to state-owned banks or lesser capital market imperfections).

Table 7: Gains from Partial Liberalizations in India (Fixed Capital)

<table>
<thead>
<tr>
<th></th>
<th>Removing Both Distortions</th>
<th>Removing only the Output Distortion</th>
<th>Removing only the Capital Distortion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989-1990</td>
<td>2.12</td>
<td>1.20</td>
<td>1.17</td>
</tr>
<tr>
<td>1994-1995</td>
<td>2.17</td>
<td>1.20</td>
<td>1.07</td>
</tr>
</tbody>
</table>

Table 8: Gains from Partial Liberalizations in China (Fixed Capital)

<table>
<thead>
<tr>
<th></th>
<th>Removing Both Distortions</th>
<th>Removing only the Output Distortion</th>
<th>Removing only the Capital Distortion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>1.92</td>
<td>1.35</td>
<td>1.12</td>
</tr>
<tr>
<td>1998</td>
<td>2.06</td>
<td>1.34</td>
<td>1.18</td>
</tr>
<tr>
<td>1999</td>
<td>1.96</td>
<td>1.18</td>
<td>1.19</td>
</tr>
<tr>
<td>2000</td>
<td>1.94</td>
<td>1.22</td>
<td>1.19</td>
</tr>
<tr>
<td>2001</td>
<td>1.91</td>
<td>1.22</td>
<td>1.22</td>
</tr>
<tr>
<td>2002</td>
<td>1.92</td>
<td>1.23</td>
<td>1.23</td>
</tr>
<tr>
<td>2003</td>
<td>1.86</td>
<td>1.15</td>
<td>1.22</td>
</tr>
</tbody>
</table>
One reason reforms are more than the sum of their parts could be that the distortions correlate positively across plants, so that plants facing output restrictions also face high costs of capital. That turns out not to be true. The correlation of industry deviations $\Delta \tau_{yi}$ and $\Delta \tau_{ki}$ across plants in India is -0.43 in 1989-1990 and -0.52 in 1994-1995, and across plants in China it ranges from -0.32 to -0.38. The reason the two are so much more damaging together must be convexity of efficiency costs in the level of distortions. Interestingly, more efficient plants (higher $A_{yi}$) do not face systematically higher costs of capital (correlation around 0.07 in both countries), but they do seem restrained by output barriers (correlation around 0.45 in India and 0.55 in China). Perhaps more efficient plants are larger and size confers an advantage in obtaining financing that offsets state-imposed financing barriers. More efficient establishments do tend to be larger, obviously in terms of value added but also including labor inputs (correlations around 0.55). Plants with more labor face nothing unusual in terms of their cost of capital, but do face lesser output restrictions (correlations around -0.25).

V. Robustness Checks

In this section, we conduct a series of robustness checks designed to probe the sensitivity of our estimates.

Endogenous Capital

We have so far assumed that the capital stock is fixed in our estimates of the gain from liberalization. However, as shown in equation (2.30), TFP gains are amplified by an exponent equal to the inverse of one minus capital’s share (more accurately, the elasticity of output with respect to capital) when capital accumulates to keep the rental price of capital constant. In India’s case the average capital share is 50.8% in 1989-1990 and 50.4% in 1994-1995, so the TFP gains are roughly squared. The result is more than a four-fold increase in manufacturing output. In the case of China, both the capital shares (47.4% to 49.3% across years) and the TFP gains (a little less than 2 rather than a little
greater than 2) are modestly lower. Therefore, manufacturing output in China would jump by a factor of 3 or more due to the capital accumulation and TFP increases together.

C.E.S Aggregator of Sectoral Output

We now consider the consequence of relaxing the assumption that the elasticity of substitution between output of the different sectors is one. Specifically, suppose that aggregate output is a C.E.S. aggregate of sectoral outputs:

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

When \( \phi = 1 \), aggregate output is a Cobb-Douglas aggregate of sectoral outputs (equation (2.9)) and the gain from liberalization thus given by, the output gain from removing distortions around the industry mean is given by:

\[
\frac{Y_{actual}}{Y_{efficient}} = \left( \sum_{s=1}^{S} \frac{P_s Y_s}{Y} \frac{1}{M_s} \sum_{i=1}^{M_s} \left\{ \frac{A_{si}}{A_s} \left( \frac{1 - \tau_{ysi}}{1 - \tau_{ysi}} \right) \left( \frac{1 + \tau_{Ksi}}{1 + \tau_{Ksi}} \right)^{-\alpha_s} \right\} \right)^{\phi-1} \phi \phi
\]

Since we can observe \( \frac{P_s Y_s}{Y} \), equation (4.6) allows us to examine the sensitivity of estimates to different values of \( \phi \). [to be completed.]

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\( ^6 \) Details on the derivation of equation (4.6) are provided in the appendix.
References


