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Resource Misallocation and Aggregate Productivity in Punjab

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Preface

The Centre for Research in Economics and Business (CREB) was established in 2007 to conduct policy-oriented research with a rigorous academic perspective on key development issues facing Pakistan. In addition, CREB (i) facilitates and coordinates research by faculty at the Lahore School of Economics, (ii) hosts visiting international scholars undertaking research on Pakistan, and (iii) administers the Lahore School's postgraduate program leading to the MPhil and PhD degrees.

An important goal of CREB is to promote public debate on policy issues through conferences, seminars, and publications. In this connection, CREB organizes the Lahore School's Annual Conference on the Management of the Pakistan Economy, the proceedings of which are published in a special issue of the *Lahore Journal of Economics*.

The CREB Working Paper Series was initiated in 2008 to bring to a wider audience the research being carried out at the Centre. It is hoped that these papers will promote discussion on the subject and contribute to a better understanding of economic and business processes and development issues in Pakistan. Comments and feedback on these papers are welcome.

Abstract

This paper follows Hsieh and Klenow's (2009) study in examining the role of misallocation in aggregate productivity for manufacturing plants in Punjab, Pakistan. Using data on manufacturing plants in Punjab from the Census of Manufacturing Industries for 2000/01 and 2005/06, we look at the extent to which marginal products differ across firms within each industry. We then simulate a liberalization setting by allowing the marginal product to equalize across plants in each industry, and find relatively more productivity dispersion in Punjab than Hsieh and Klenow do for India and China. We also find that moving to the US efficiency level boosts manufacturing total factor productivity in Punjab by 23.61 percent and 47.40 percent for 2000/01 and 2005/06, respectively. Finally, the paper explores potential sources of productivity dispersion for manufacturing plants in Punjab.

Resource Misallocation and Aggregate Productivity in Punjab

1. Introduction

Total factor productivity (TFP) is that fraction of a country's economic growth that is unexplained by the conventional input factors, capital and labor. It indicates the efficiency of a production system in translating inputs into outputs.

In his pioneering contribution to the productivity literature, Solow (1957) laid down the basis for growth accounting using an aggregate economy-wide production function to separate out the role of the factors of production—capital and labor—and residual (TFP) in economic growth. In order to determine the residual, he subtracted the weighted average growth of capital and labor from overall output growth. He carried out this exercise for US data for the period 1909–49 and found that TFP growth was the key factor responsible for the remarkable economic growth that had taken place.

Solow's work was followed by a number of studies in which TFP became the center of discussion. The evolution of productivity measures along with the availability of broad datasets allowed cross-country comparisons of TFP. Many studies found that the key distinction between rich and poor countries lay in their productivity differences. Klenow and Rodríguez-Clare (1997) argued that TFP growth explained 90 percent of the cross-country differences in output growth. Hall and Jones (1999) studied the role of social infrastructure in explaining the large cross-country differences in productivity.

In recent years, the increasing availability of plant-level data has provided a valuable micro-foundation for understanding aggregate productivity. This stream of research uses a plant-level production function to compute an individual firm productivity measure. Plant-level productivity is then aggregated to yield an expression for economy-wide productivity. Productivity dynamics at the micro-level have unveiled key sources of change in aggregate productivity. These studies look mainly at the importance of the entry and exit dynamics of firms, the movement of individual plants in productivity cohorts, and the allocation of resources across plants in explaining changes in aggregate productivity.

Productivity is often measured as the ratio of output to inputs. The literature classifies productivity measures into two broad categories: single-factor productivity measures and multifactor productivity measures. Single-factor productivity measures signify the efficiency of a single input factor, such as capital or labor, in producing output. Any change in single-factor productivity measures can represent both embodied and disembodied technical change. Any change in productivity that is not captured by factor inputs falls under disembodied technical change. For example, a change in labor productivity can be attributed to a change in capital or any other input factor (embodied technical change) or it can be attributed to a shift in technical efficiency (disembodied technical change). On the other hand, multifactor productivity measures usually take into account all input factors and thus represent only disembodied technical change.

There is a broad body of literature that provides evidence for sources of disembodied technical change. Factors such as managerial practice, organizational technique, research and development, learning by doing, and productivity spillovers are some important sources of disembodied technical change (see Syverson, 2011, for further discussion).

Recently, a number of studies have adopted a separate approach and studied the role of policy distortions in aggregate productivity (see, for example, Melitz, 2003; Restuccia & Rogerson, 2008; Hsieh & Klenow, 2009). They have argued that any policy distortion that can potentially misallocate resources across firms in an industry can have significant consequences for aggregate productivity.

Such policies impose taxes or subsidies on output or factor inputs. For example, polices that impose restrictions on the size of a firm or provide subsidized loans to firms for noneconomic reasons can create plant-level distortions in the allocation of resources. The latter operates through the misallocation of capital across plants. Profit maximization implies that any firm benefitting from subsidized loans will equate its marginal product of capital to a lower interest rate compared to a firm without a subsidized loan. This plant-level misallocation has important implications for aggregate TFP.

This paper follows Hsieh and Klenow (2009) and studies the role of misallocation in aggregate TFP for manufacturing plants in Punjab. Our objective is twofold: first, we study the productivity distribution of manufacturing plants in Punjab; and second, we estimate the gains in aggregate TFP as a result of removing the misallocation across plants. The data for manufacturing plants in Punjab is drawn from the Census of Manufacturing Industries (CMI) for 2000/01 and 2005/06. We find relatively more productivity dispersion in Punjab than Hsieh and Klenow do for India and China. We also find that moving to the US efficiency level boosts manufacturing TFP in Punjab by 22.33 percent and 55.83 percent for 2000/01 and 2005/06, respectively.

The rest of the paper is organized as follows. Section 2 reviews the literature on productivity dynamics and resource misallocation. Section 3 lay out the theoretical model developed by Hsieh and Klenow (2009). Section 4 explains the estimation strategy and data sources used. Finally, Sections 5 and 6 present the study's results and conclusions.

2. Literature Review

This section reviews the literature on productivity dynamics and resource misallocation. It examines the literature on productivity dynamics and the size distribution of firms, followed by resource misallocation and its impact on TFP.

In recent years, the availability of micro-level data has allowed researchers to study the dynamics of productivity in detail. This has shifted the focus onto important questions such as the evolution and survival of the firm, sources of productivity variation, the role of productivity in the size distribution of firms, and the role of resource misallocation in TFP.

Jovanovic (1982) provides a theoretical basis for firm selection in an industry where each firm follows a particular productivity shock. In his model, each entrant receives a random draw from the industry's productivity distribution. A valuable draw will help the firm to survive and grow; an unfavorable draw is more likely to cause it to decline and exit. Equilibrium is achieved where the net value of entry becomes zero. Therefore, the selection of the firm in equilibrium is determined by the firm-specific productivity shock. Small firms have a variable and higher growth rate and are also more likely to leave the industry. Hopenhayn (1992) uses the same framework and develops conditions for a steady-state equilibrium. In his model, firms enter and exit in equilibrium. In the steady state, the entry and exit rates are equal and the firm size distribution is stationary.

Other researchers have used these models to study the dynamics of productivity with micro-level datasets. An important study by Olley and Pakes (1996) examines the evolution of establishment-level productivity in the American telecommunication equipment industry: its primary aim is to measure the impact of technological change and deregulation on productivity. (During the 1970s and 1980s, the telecommunication industry in the US underwent major restructuring due to rapid technological development and the liberalization of the regulatory environment.) The authors find two sources of bias in estimating the production function parameters required for productivity estimations. The first arises due to the simultaneity between productivity and input choices. The second arises because the authors observe a higher rate of entry and exit during the restructuring period: this high iteration can cause selection bias in the estimation.

Olley and Pakes (1996) use structural techniques to establish a proxy variable for the unobserved productivity variable. They apply the assumption that investment is a strictly increasing function of firm productivity, and that the inverse of the investment function can, therefore, be used for the identification. They find that aggregate productivity—measured as the output share-weighted average of individual plant productivity—increases significantly following the restructuring of the telecommunication equipment industry. On decomposing the results, they find that the primary source of productivity gain is the reallocation of capital toward more productive plants rather than the increase in average productivity.

Bartelsman and Dhrymes (1998) use micro-level data on US manufacturing firms in high-tech industries to study the dynamics of productivity in detail. They use several measures of TFP and find that aggregate productivity followed a sustained decline from 1972 to 1984 and then experienced a sharp increase after 1984. They attribute this TFP gain to a reallocation of resources from less productive firms to more productive firms. The authors also use transition probabilities, based on estimated productivity, to study the movements of plants within productivity cohorts and find a high level of uncertainty in the survival of entrant firms. Another interesting observation is that new firms enter at the upper levels of productivity cohorts. The authors also find that larger firms sustain their productivity ranking and are less likely to fail than smaller firms. However, these findings are highly sensitive to the measure of productivity used.

An important finding of the micro-level productivity literature concerns the significant heterogeneity among firms' productivity levels. Syverson (2004) employs several measures of productivity to compute the productivity distribution of four-digit US manufacturing industries. He finds that the average difference in TFP between firms in the 90th percentile (efficient firms) and 10th percentile (inefficient firms) is between 1.91 and 2.68. This enormous range of difference is robust to the different measures of productivity used.

Syverson (2004) also studies the role of product substitutability in limiting the dispersion of productivity within an industry. In a perfect product substitutability setting, efficient firms are capable of capturing the entire product demand in the market, thus driving out less efficient firms. He tests this theory for the US manufacturing industry and finds a negative relationship between product substitutability and productivity dispersion.

Evidence for these enormous productivity differences has motivated researchers to study the sources of heterogeneity among plants. The recent literature has documented the role of factors such as technology, research and development, competition, and market structure in explaining productivity dispersion.[1]

Another branch of the productivity literature deals with the role of resource misallocation caused by policy distortions that inhibit TFP growth. These studies incorporate both specific and generic policy distortions at the plant level to study their impact on TFP.

Hopenhayn and Rogerson (1993) document the long-run impact of policies related to severance pay on employment and average productivity. Policies that restrict firms from firing employees create distortions that promote less efficient use of resources. The authors

[1] See Syverson (2011) for a detailed discussion on factors affecting productivity growth.

extend the model developed in Hopenhayn (1992) and introduce a policy distortion (fixed payment for each job destroyed) using an adjustment cost function. They calibrate the model with plant-level data on manufacturing firms in the US to carry out policy experiments. They find that moving from a zero tax on dismissal (benchmark model) to a 20 percent tax on job destruction decreases employment by 2.5 percent. Apart from this, an equivalent severance pay policy reduces average labor productivity by 2.1 percent. These numbers demonstrate that such policies have a significant impact on the aggregate economy.

Melitz (2003) studies the impact of exposure to trade on the measures of TFP. He starts by developing a closed economy model based on Hopenhayn's (1992) framework. In moving from the state of being a closed economy to an open economy, he introduces trade friction in the form of variable and fixed trading costs; this friction separates exporting from nonexporting firms. After observing their productivity, firms decide whether to incur trading costs and participate in trade. Trade offers relatively profitable prospects and therefore encourages productive firms to enter the market. This process continues until the zero profit condition is achieved once again. Therefore, exposure to trade leads to the reallocation of resources among firms and drives out less efficient firms from the market. This reallocation of resources toward more efficient firms has a positive effect on aggregate TFP. Another important finding of the study is that increased exposure to trade leads to a welfare gain.

Parente and Prescott (1999) develop a game-theoretic framework in which monopoly rights restrict firms from entering an industry. The government may choose to protect a group of factor suppliers by imposing a set of laws that prohibit other firms from adjusting certain work practices. Some examples include regulations such as severance pay, restrictions on firm entry and expansion, and limits on adopting new technology. Entrants have to invest heavily to overcome these restrictions. At each stage of the game, entrants decide whether to overcome or enter the coalition. The authors illustrate that, for a sufficiently large coalition, it is not feasible for entrants to overcome the restriction. Further, they carry out a thought experiment to estimate the impact of moving from the monopoly setting to free enterprise arrangements on productivity. Eradicating monopoly rights, they find, increases TFP by a factor of 2.72—a significant figure.

Schmitz (2001) studies the impact of policies that restrict private firms from entering or expanding in an industry on aggregate labor productivity. He models an economy where the government, rather than private firms, produces investment goods. The intuition is that government production, being less efficient, will have a negative effect on aggregate productivity. The government sector receives a subsidy that is financed by a tax on the private sector. Schmitz calibrates this setting with data from the US and Egypt, the purpose being to compare an economy with excessive government involvement in the production of investment goods (Egypt) with one with almost negligible government involvement in production (the US). He finds that such polices explained about 30 percent of the aggregate labor productivity gap between the US and Egypt in the 1960s.

Bergoeing, Kehoe, Kehoe, and Soto (2002) study the role of policy distortions in Chile and Mexico following the severe economic crisis of the 1980s. They find that Chile's relatively fast recovery is attributable to the difference in TFP rather than capital accumulation. Further examination reveals that the divergence in TFP growth between the two countries was an outcome of differences in policy reforms. Mexico's banking and bankruptcy laws created distortions in the market that led to lower aggregate TFP. Its banking system, which remained nationalized until the 1990s, provided subsidized loans to certain sectors; these subsidies distorted the efficient allocation of capital among firms. Likewise, the bankruptcy law protected poorly performing (inefficient) firms—who did not exit the industry as they might otherwise have been forced to do—while preventing efficient firms from entering the market. Bergoeing et al. incorporate these policy distortions in their model to explain the relatively lower aggregate TFP in Mexico.

Restuccia and Rogerson (2008) build on Hopenhayn's (1992) model to examine the impact of policies that create a misallocation of resources on TFP. They argue that settings in which the government or private sector institutions favor individual firms create distortions in the efficient allocation of resources. They present the firm's optimization problem within a single-good industry model in an entry and exit framework where policy distortions are introduced as a tax or subsidy on output. The consumer's optimization problem determines the equilibrium rental rate of capital, which, along with the zero-profit condition for firm entry, establishes the model's steady-state equilibrium.

The authors calibrate this model with plant-level data for US manufacturing firms. Based on different assumptions and parameters, they estimate the benchmark case for no distortion and then use different distortion parameters to mimic an economy in which individual firms face heterogeneous prices. They find that, in settings that subsidize inefficient firms, an output subsidy of 40 percent can reduce TFP by the considerable amount of 31 percent. This drop in TFP is sensitive to the number of inefficient firms in the market. If just 10 percent of the firms are subsidized and 90 percent are taxed—as opposed to 50 percent in the benchmark case—then the drop in TFP is 49 percent.

Hsieh and Klenow (2009) follow Restuccia and Rogerson's (2008) approach in comparing policy distortions in the US with those in India and China. They develop a monopolistic competition model under which individual firms face idiosyncratic policy distortions; they consider two separate distortion parameters: output distortion and capital distortion. An output distortion affects the marginal products of capital and labor in the same proportion. A capital distortion, on the other hand, increases or decreases the marginal product of capital relative to the marginal product of labor. The authors introduce these distortions into the firm optimization framework to capture the potential loss in aggregate productivity.

Hsieh and Klenow (2009) calibrate their model with plant-level data on India, China, and the US. The first set of estimations includes a comparison of the dispersion in TFP in each country. They find that the productivity distribution in India and China is more widely dispersed, consistent with the conjecture of relatively more policy distortions in both countries. The thicker tail of the productivity distribution in India, relative to the US, also gives evidence for the survival of inefficient firms. Additionally, the authors estimate the potential sources of TFP variation by regressing it on a set of age, ownership, size, and region dummies. In China's case, they find that ownership is a relatively important factor in explaining TFP variation.

Hsieh and Klenow's (2009) second set of estimations determines the effects of liberalization on TFP. They simulate a liberalization setting by allowing the marginal product to equalize across plants in each industry, and find that liberalization provides relative TFP gains of 86 percent in China, 127 percent in India, and almost 43 percent in the US for the latest year in each country's sample. They also find that the size distribution of firms for the full liberalization case is far more dispersed for each country. For size measured as value added, this illustrates that both small and large plants should produce more than they are at present.

In their final set of estimations, the authors perform a thought experiment in which they compute the relative TFP gains in India and China for the US's efficiency level in 1997. If China and India were to move to the US's efficiency level for that year, the two countries would gain 30–50 percent and 40–59 percent in TFP, respectively. Interestingly, the authors find that India's TFP levels did not improve over the period 1987–1994.

Following Foster, Haltiwanger, and Syverson (2008), we will also make an important distinction between revenue-based and physical quantity-based productivity measures in this working paper. Foster et al. employ a rare set of plant-level data where producer-level prices were observed separately. They use information on 11 homogenous product manufacturers in the US to study the role of producer-level prices on productivity measures. The intuition is that, if prices reflect idiosyncratic demand shifts, then revenue-based productivity measures will yield biased estimates.

Foster et al. find that physical output-based productivity distribution is much more dispersed than revenue-based productivity distribution. This implies that physical quantity-based productivity is negatively correlated with producer-level prices, while revenue-based productivity is positively related to prices. The authors observe that the primary reason for this discrepancy lies in the different price-setting behaviors of young and incumbent producers. Even though entrants are more productive than incumbent firms, young producers charge relatively low prices compared to incumbents. When productivity is measured with revenue, this price-setting behavior eradicates the differences in productivity between young and mature firms.

As mentioned earlier, we will follow Hsieh and Klenow's (2009) approach to studying the role of policy distortions in Pakistan. Khwaja and Mian (2005) have found that such distortions are widespread in the country's banking sector. They use loan-level data to estimate the extent of political rents in the sector, and identify firms' political connections by matching the data to national and state-level election results. They note that public sector banks tend to favor politically connected firms: even though such firms show a 50 percent higher default rate, the loans they are extended constitute a lending volume 45 percent larger than that given to other firms.

3. Theoretical Framework

This section presents a brief version of the monopolistic competition model incorporating heterogeneous firms, developed by Hsieh and Klenow (2009). The authors use an optimization framework to model the effect of policy distortions on the firm-level marginal products of capital and labor. They subsequently derive an expression for industry-level TFP as a function of resource misallocation.

In this framework, a representative firm produces a single final good Y in a perfectly competitive market. The firm uses S different intermediate goods and a Cobb-Douglas production technology. Intermediate goods are produced by S different manufacturing industries, each producing output Y_S:

$$Y = \prod_{S=1}^{S} Y_S^{\theta_s} \tag{1}$$

Industry output Y_S combines M_S differentiated products with a constant elasticity of substitution:

$$Y_S = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

Each differentiated product is produced according to the following firm-level production function:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \tag{3}$$

Here, A_{si} represents TFP, and K_{si} and L_{si} represent capital and labor, respectively. It is important to note that the capital and labor shares are the same across all firms in an industry.

Hsieh and Klenow (2009) employ two separate distortion factors: output distortion and capital distortion. Any distortion that has the same magnitude of impact on both the marginal products of capital and labor is an output distortion. For example, policies that impose an output tax or subsidy on an establishment affect the marginal products of capital and labor by the same amount.

The second factor covers all those distortions that affect the marginal product of capital relative to the marginal product of labor. Examples are policies that provide subsidized loans for noneconomic reasons that decrease the marginal product of capital relative to the marginal product of labor. The extent of the policy distortion will be reflected in the marginal product of labor and capital heterogeneity across establishments. If τ_y and τ_k represent the output and capital distortions, respectively, then profits are given by the following function:

$$\pi_{si} = (1-\tau_{Y_{si}})P_{si}Y_{si} - wL_{si} - (1+\tau_{K_{si}})RK_{si} \tag{4}$$

Profit maximization implies:

$$\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1-\alpha_s}.\frac{w}{R}.\frac{1}{1+\tau_{K_{si}}} \tag{5}$$

$$L_{si} \propto \frac{A_{si}^{\sigma-1}(1-\tau_{Y_{si}})^{\sigma}}{(1+\tau_{K_{si}})^{\alpha_S(\sigma-1)}} \tag{6}$$

$$Y_{si} \propto \frac{A_{si}^{\sigma}(1-\tau_{Y_{si}})^{\sigma}}{(1+\tau_{K_{si}})^{\alpha_S\sigma}} \tag{7}$$

The marginal revenue products of capital and labor are given by:

$$MRPL_{si} = \frac{w}{(1-\tau_{Y_{si}})} \tag{8}$$

$$MRPK_{si} = R\frac{(1+\tau_{K_{si}})}{(1-\tau_{Y_{si}})} \tag{9}$$

The weighted average marginal revenue products of capital and labor for a sector can be expressed as:

$$\overline{MRPL_S} \stackrel{\Delta}{=} \frac{w}{\Sigma_{i=1}^{M_s}(1-\tau_{si})\frac{P_{si}Y_{si}}{P_sY_s}} \tag{10}$$

$$\overline{MRPK_S} \stackrel{\Delta}{=} \frac{R}{\Sigma_{i=1}^{M_S}\left(\frac{1-\tau_{Y_{si}}}{1+\tau_{K_{si}}}\right)\frac{P_{si}Y_{si}}{P_sY_s}} \tag{11}$$

Following Foster et al. (2008), revenue-based productivity (*TFPR*) and physical output-based productivity (*TFPQ*) are defined as:

$$TFPQ_{si} \stackrel{\Delta}{=} A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}} \tag{12}$$

$$TFPR_{si} \stackrel{\Delta}{=} P_{si}A_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}} \tag{13}$$

The establishment-level *TFPR*is proportional to the geometric mean of the plant's marginal products of capital and labor:[2]

$$TFPR_{si} \propto (MRPK_{si})^{\alpha_s}(MRPL_{si})^{1-\alpha_s} \tag{14}$$

Intuitively, in the no-distortion case, revenue-based productivity should equalize across establishments. Large and efficient establishments, with

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[2] A similar exercise with aggregate marginal revenue products of capital and labour will yield an expression for $TFPR_S$.

a higher *TFPQ*, will have a higher level of output and a relatively smaller price level. Therefore, more resources will be allocated toward the efficient producer until *TFPR* equalizes across firms. This distinction implies the following expression for industry-level TFP:[3]

$$A_s = \left[\sum_{i=1}^{M_s} \left(A_{si} \frac{\overline{TFPR_s}}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{15}$$

where A_{si} and $TFPR_{si}$ are defined in (12) and (14), respectively.

In the no-distortion case, the marginal products of capital and labor should equalize across establishments. In this scenario, each establishment will have the same *TFPR* and expression (15) will become:

$$\overline{A_s} = \left[\sum_{i=1}^{M_s} \left(A_{si} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{16}$$

These two expressions will be used to carry out the liberalization experiments. Expression (15) implies that the greater the difference between the sector average and the individual plant-level *TFPR*, the lower will be the industry TFP.

4. Data Description

The plant-level data for Punjab has been drawn from the CMI for 2000/01 and 2005/06. The CMI is conducted every five years and is intended to cover all registered manufacturing firms in Pakistan that employ 10 or more workers. The province of Punjab is covered by the Punjab Directorate of Industries. The CMI for 2005/06 contains information on 6,417 manufacturing establishments all over Pakistan, of which the Punjab-level census includes data on only 3,528 manufacturing plants. The CMI for 2000/01 covers 4,809 establishments at the national level, of which 2,357 are based in Punjab.

[3] Please refer to Hsieh and Klenow (2009) for the detailed derivations.

The coverage of firms was improved in the 2005/06 CMI by enhancing the survey frame. The 2000/01 census only covered firms listed in the industrial directory whereas, in 2005/06, more firms were added to the frame by consulting the results of the economic census for 2001. There are nearly 50 percent more firms in the 2005/06 sample compared to the 2000/01 sample. This does not only reflect the growth of firms—it could also be a sign of better coverage and a smaller nonresponse rate.

Looking at firms' registration dates seems to indicate significant growth in this period. In the CMI for 2005/06, only 39 percent of firms reported their registration date; out of these, 5.6 percent were established after 2001. The following calculation helps put things into perspective: if we take the ratio of this number to the total number of establishments given in the CMI 2000/01, we find that the addition of at least 7.7 percent of firms in the CMI 2005/06 was due solely to new firms.[4]

We use the following variables from the two datasets: labor compensation, nominal output (revenue), expenditure on input materials, energy cost, the book value of capital, date of registration (to compute the age of the firm), and form of ownership.

One of the major industries in Punjab is cotton ginning. However, according to the International Standard Industrial Classification (Rev. 3.1), it is no longer considered a manufacturing activity, and is, therefore, excluded from our analysis. Following this, 221 (9.3 percent) and 455 (12.9 percent) firms are dropped from the CMI 2000/01 and 2005/06, respectively.

We also exclude all those firms that yield either missing or negative values for capital stock, labor compensation, and value added. This is mainly because much of our analysis uses expressions with logarithmic transformations. We drop 109 (4.6 percent) and 159 (4.5 percent) firms from the CMI 2000/01 and 2005/06, respectively.

Finally, we trim the outliers from each industry to ensure that our estimations are robust. We pool both years and trim the tails of the

[4] This analysis includes only those firms that were established after 2000/01. We want to look at the growth of firms that took place due to the addition of new firms between 2000/01 and 2005/06. We use the registration date of a firm to determine its birth year. Since this information was not available for all firms, we could only perform the exercise for a fraction of the 2005/06 firms.

capital and output distortions: $\log(TFPR_{si}/\overline{TFPR_s})$ and $\log(A_{si}/\overline{A_s})$. Following this, we drop a total of 302 firms (6.1 percent of the cleaned dataset) in both years.[5]

After cleaning the data, we are left with 1,941 establishments from the CMI 2000/01 and 2,698 from the CMI 2005/06 (see the Appendix for information on the distribution of firms for both years).

We also borrow an important piece of information from Camacho and Conover (2010). In order to calculate the distortion parameters, we require undistorted capital and labor shares. Hsieh and Klenow (2009) assume that labor and capital shares are comparatively undistorted in the US, and therefore use US labor and capital shares for India and China. Camacho and Conover (2010) provide US labor shares for three-digit industries.

5. Estimations

This section presents our estimations of productivity measures, distribution, and variations, and simulates a liberalization setting to determine its impact on TFP.

5.1. Productivity Measures

Our estimations are based primarily on calculations of the following four productivity measures:

$$TFPR_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \tag{17}$$

$$A_{si} = \kappa_s \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \tag{18}$$

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[5] In order to keep our estimations consistent, we have followed Hsieh and Klenow (2009) in identifying outliers. In this exercise, we flag all those firms that fall within 1–2 percent of the top and bottom extremes based on the four different variables discussed above. We then drop each firm that is identified as an outlier in the first step. Therefore, a drop of 6.1 percent is a combined trimming of four different measures.

where $\kappa_s = \frac{(P_s Y_s)^{-\frac{1}{\sigma-1}}}{P_s}$

$$\overline{TFPR}_s = \frac{\sigma}{\sigma-1}\left(\frac{\overline{MRPK_s}}{\alpha_s}\right)^{\alpha_s}\left(\frac{\overline{MRPL_s}}{1-\alpha_s}\right)^{1-\alpha_s} \tag{19}$$

where $\overline{MRPK_s} = \frac{R}{\sum_{i=1}^{M_s}\frac{\left(1-\tau_{Y_{si}}\right)}{\left(1+\tau_{K_{si}}\right)}\frac{P_{si}Y_{si}}{P_s Y_s}}$

and $\overline{MRPL_s} = \frac{w}{\sum_{i=1}^{M_s}\left(1-\tau_{Y_{si}}\right)\frac{P_{si}Y_{si}}{P_s Y_s}}$

$$A_s = \left[\sum_{i=1}^{M_s}\left(A_{si}\frac{\overline{TFPR_s}}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \tag{20}$$

The first expression, (17), measures plant-level total factor revenue productivity (*TFPR*). Expression (18) measures plant-level *TFPQ* with nominal output $P_{si}Y_{si}$. In the datasets, plant-level real output is unobserved. Therefore, observed nominal output is raised to the power $\frac{\sigma}{\sigma-1}$ to calculate the real output Y_{si}. This exercise uses a scalar, κ_s, which is unobserved and therefore assumed to be $\kappa_s = 1$. This assumption does not affect our calculations for relative productivities. Expression (19) is a measure of industry-level TFPR. This expression is derived by taking the geometric mean of industry-level $\overline{MRPK}$ and $\overline{MRPL}$. Finally, the last productivity measure, (20), is industry-level *TFPQ*.

In order to compute $\overline{MRPK}$ and $\overline{MRPL}$, we need information on plant-level distortions. Hsieh and Klenow (2009) calculate the distortion parameters as follows:

$$\tau_{K_{si}} = \frac{\alpha_s}{(1-\alpha_s)} \frac{wL_{si}}{RK_{si}} - 1 \tag{21}$$

$$\tau_{Y_{si}} = \frac{\sigma}{(\sigma-1)} \frac{wL_{si}}{(1-\alpha_s)P_{si}Y_{si}} - 1 \tag{22}$$

Expression (21) implies that a capital distortion is observed where the ratio of a plant's wage bill to its capital stock is different from the ratio of the respective output elasticities. Expression (22) implies that an output distortion is observed where the labor share is different from the elasticity of output with respect to labor. In both cases, we are comparing undistorted US labor and capital shares with the respective observed information for Punjab to infer the distortions present.

This exercise requires the following key parameters: labor and capital shares (α_s), the elasticity of substitution between plants (σ), the rental price of capital (R), and industry output share (θ_s). We follow the same conventions to maintain the comparability of our results with Hsieh and Klenow's (2009) analysis.

Since the elasticity of substitution between plants is positively correlated with liberalization gains, we take the modest estimate of $\sigma = 3$ to avoid exaggerated results. The undistorted rental price of capital is taken as R. However, the effective cost of capital will differ for each firm based on idiosyncratic capital distortions. Furthermore, since we are using relative productivity measures, the choice of this parameter will not affect our liberalization experiment. Finally, each industry's output share is taken as the ratio of the aggregate industry's value-added to the aggregate economy-wide value-added: $\theta_s = \frac{P_s Y_s}{Y}$.

5.2. Productivity Distribution

In Figure 1, we use $\log(A_{si} M_s^{\frac{1}{\sigma-1}} / \overline{A_s})$ to plot the TFPQ distribution for each year. These distributions show roughly the same magnitude of dispersion across time. The stretched left tail for the year 2000/01 represents the survival of less productive firms.

Figure 1: TFPQ distribution

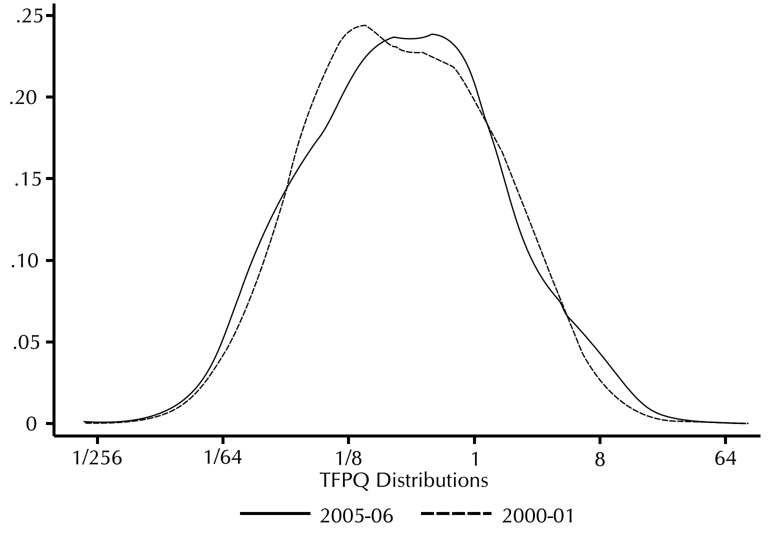


Table 1 presents several dispersion measures for log (TFPQ). The first measure is an intra-industry standard deviation (SD) weighted by the value-added share of each industry. It shows that there is a little more dispersion in 2005/06 than in 2000/01. Next, we find the intra-industry difference between the 75th and 25th percentiles weighted by the value-added share of each industry. The numbers given in Table 1 are calculated on a logarithmic scale, and can be converted into more meaningful values using exponential functions. For example, in 2000/01, firms in the 75th percentile were 7.8 times more productive than firms in the 25th percentile;[6] this difference is even higher in 2005/06. Across the measures, there is slightly greater dispersion in 2005/06.

[6] This value corresponds to an exponential of 2.06.

Table 1: TFPQ dispersion

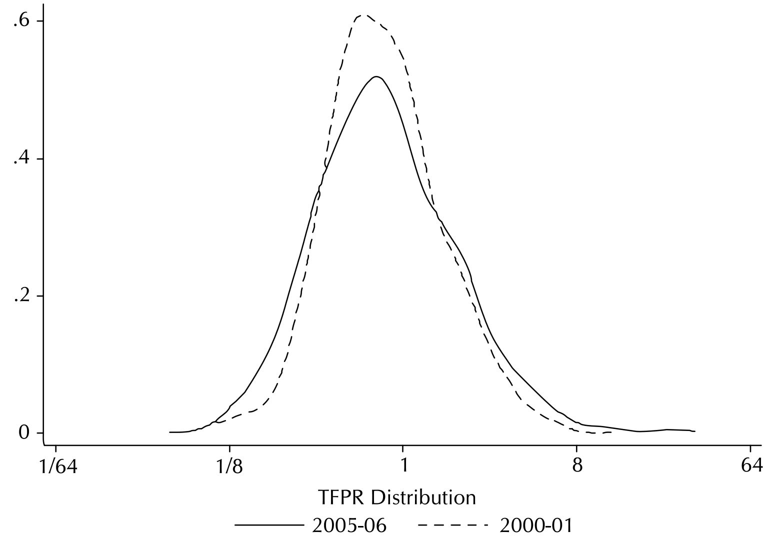
Punjab [a]	**2001**	**2005**	
SD	1.52	1.59	
Percentile 75–25	2.06	2.36	
Percentile 90–10	3.98	4.16	
N	1,941	2,698	
China [b]	**1998**	**2001**	**2005**
SD	1.06	0.99	0.95
Percentile 75–25	1.41	1.34	1.28
Percentile 90–10	2.72	2.54	2.44
N	95,980	108,702	211,304
India [b]	**1987**	**1991**	**1994**
SD	1.16	1.17	1.23
Percentile 75–25	1.55	1.53	1.60
Percentile 90–10	2.97	3.01	3.11
N	31,602	37,520	41,006
US [b]	**1977**	**1987**	**1997**
SD	0.85	0.79	0.84
Percentile 75–25	1.22	1.09	1.17
Percentile 90–10	2.22	2.05	2.18
N	164,971	173,651	194,669

Sources: a = author's calculations, b = calculations from Hsieh and Klenow (2009).

The table also gives Hsieh and Klenow's (2009) calculations for India, China, and the US at different points in time in each case. As the figures indicate, there is a relatively high level of dispersion in Punjab compared to China and the US.

In Figure 2, we use $\log(TFPR_{si} / \overline{TFPR_s})$ to plot the TFPR distribution for each year. Comparing physical output-based productivity (TFPQ) and revenue-based productivity (TFPR) reveals similar results to Foster et al. (2008)—the TFPQ distribution is relatively more dispersed than the TFPR distribution. This validates the negative correlation between TFPQ and producer-level prices.

Figure 2: TFPR dispersion



Comparing TFPR distributions across time indicates greater dispersion in 2005/06 than in 2000/01. Table 2 presents the TFPR dispersion statistics for each year. All three measures show relatively more intra-industry productivity spread in 2005/06. In 2000/01, firms in the 75th percentile were almost 2.5 times more productive than firms in the 25th percentile; this difference increases to 2.7 in 2005/06. Similarly, in 2000/01, firms in the 90th percentile were almost five times more productive than firms in the 25th percentile; this difference increases to a massive 7.2 in 2005/06.

Table 2: TFPR dispersion

Punjab [a]	**2001**	**2005**	
SD	0.66	0.77	
Percentile 75–25	0.90	1.00	
Percentile 90–10	1.61	1.98	
N	1,941	2,698	
China [b]	**1998**	**2001**	**2005**
SD	0.74	0.68	0.63
Percentile 75–25	0.97	0.88	0.82
Percentile 90–10	1.87	1.71	1.59
N	95,980	108,702	211,304
India [b]	**1987**	**1991**	**1994**
SD	0.68	0.67	0.67
Percentile 75–25	0.79	0.81	0.81
Percentile 90–10	1.73	1.64	1.60
N	31,602	37,520	41,006
US [b]	**1977**	**1987**	**1997**
SD	0.45	0.41	0.49
Percentile 75–25	0.46	0.41	0.53
Percentile 90–10	1.04	1.01	1.19
N	164,971	173,651	194,669

***Sources*:** a = author's calculations, b = calculations from Hsieh and Klenow (2009).

Comparing these statistics with Hsieh and Klenow's (2009) calculations indicates similar revenue-based productivity dispersion in both Punjab and China in 2000/01. However, in 2005/06, Punjab shows relatively more productivity dispersion than China. When comparing Punjab with India and the US, it is important to note that Hsieh and Klenow's estimations for these countries are for different time periods. We find that, in all three years, India is almost as dispersed as Punjab in 2000/01. Finally, the US is far less dispersed than any other country at any point in time.

This analysis points to an important shift in productivity dispersion during these five years, for which there are two possible explanations. First, as discussed above, the coverage of firms was much better in the CMI 2005/06. Therefore, these differences could simply be due to the more representative frame used in 2005/06. Second, policy distortions could be an important explanation for this shift (see also Section 5.4).

5.3. Productivity Variation Explained

This section uses regression analysis to study the sources of intra-industry productivity variation. We analyze four possible explanations of variation: (i) region, (ii) size, (iii) ownership type, and (iv) age. In each regression, we run the following specification:

$$\log TFPR_{si} - \log \overline{TFPR_s} = \beta_0 + \beta_1 X_{si} + \beta_2 YEAR + \varepsilon_{si}$$

The dependent variable is the deviation of plant-level TFPR from its industry average in each year. X_{si} is a vector of dummies, representing region, size, ownership type, or the age of the firm in the respective regressions below. For each regression, we pool the data for both years and weight the regression by the industry value-added share to control for the industry's size effect. When interpreting the coefficients of these regressions, one should remain aware of the potential endogeneity bias of some of the independent variables. However, we are interested primarily in the share of total TFPR variation explained by each category.

Table 3 presents a set of regressions for the pooled dataset. Another set of dummies is added to each regression to study the cumulative explanation of TFPR dispersion. In the first regression, dummy variables representing ownership type are listed on the right-hand side. "Domestic private firms" is an omitted category. Ownership type does not appear to be an important determinant of intra-industry productivity variation in Punjab because it accounts for negligible variation in TFPR.

In the second regression, we add firm-size quartiles to the right-hand side. Size is measured as firm value-added and the "bottom size quartile" is the omitted category. The estimated regression now explains a substantial 19.4 percent of the variation in TFPR.

Finally, we add dummies representing the four regions of Punjab,[7] taking "central Punjab" as the omitted category. The results indicate that region accounts for very little of the variation in TFPR.

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[7] Northern Punjab includes Rawalpindi, Attock, Jhelum, and Chakwal; southern Punjab includes Bahawalpur, Bahawalnagar, Rahimyar Khan, Multan, Khanewal, Lodhran, and Vehari; western Punjab includes Dera Ghazi Khan, Layyah, Muzaffargarh, Bhakkar, Khushab, Rajanpur, and Mianwali; and central Punjab includes Faisalabad, Jhang, Toba Tek Singh, Nankana Sahib, Gujranwala, Gujrat, Mandi Bahauddin, Hafizabad, Sialkot, Narowal, Sheikhupura, Kasur, Okara, Sahiwal, Pakpattan, Sargodha, and Lahore.

Table 3: TFPR variation explained by ownership, size, and region

Variable	(1)	(2)	(3)
Public	0.0293	-0.171***	-0.159***
	(0.541)	(-3.463)	(-3.220)
Foreign	0.319	0.0305	0.0366
	(1.267)	(0.135)	(0.164)
Collaboration	0.0558	-0.101	-0.152**
	(0.661)	(-1.330)	(-2.016)
First size quartile		-0.940***	-0.949***
		(-31.76)	(-32.31)
Second size quartile		-0.411***	-0.417***
		(-15.67)	(-16.04)
Third size quartile		-0.119***	-0.122***
		(-4.651)	(-4.777)
Northern Punjab			0.0203***
			(4.232)
Southern Punjab			0.339***
			(10.05)
Western Punjab			0.0333
			(0.663)
Constant	-0.243***	0.0450***	0.00827
	(-21.75)	(2.635)	(0.470)
N	4,639	4,639	4,639
Adjusted R-sq.	Ø[Ŧ]	0.194	0.213

Notes: t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; [Ŧ] = adjusted R-sq. near 0.
***Source*:** Author's calculations.

Since the CMI 2000/01 does not provide firms' registration dates, Table 4 reports the results of another set of regressions that include only this information. The "bottom age quartile" is the omitted category. The results show that age does not explain any significant variation in TFPR.

Table 4: TFPR variation explained by ownership, age, size, and region

Variable	(1)	(2)	(3)	(4)
Public	-0.0220	0.00765	-0.115*	-0.110
	(-0.315)	(0.108)	(-1.683)	(-1.567)
Foreign	-0.0072	-0.0620	-0.251	-0.254
	(-0.0174)	(-0.139)	(-0.600)	(-0.608)
Collaboration	-0.0342	-0.00790	-0.141	-0.143
	(-0.226)	(-0.0521)	(-0.984)	(-0.999)
First age quartile		0.0969	0.191***	0.194***
		(1.521)	(3.167)	(3.190)
Second age quartile		0.140**	0.158**	0.169***
		(2.123)	(2.551)	(2.708)
Third age quartile		0.0853	0.00842	0.0105
		(1.387)	(0.145)	(0.180)
First size quartile			-0.937***	-0.935***
			(-10.56)	(-10.52)
Second size quartile			-0.476***	-0.480***
			(-7.672)	(-7.706)
Third size quartile			-0.0720	-0.0742
			(-1.405)	(-1.441)
Northern Punjab				0.110
				(1.074)
Southern Punjab				0.172*
				(1.771)
Western Punjab				0.00196
				(0.0215)
N	1,061	1,061	1,061	1,061
Adjusted R-sq.	Ø[Ŧ]	Ø[Ŧ]	0.121	0.122

Notes: t-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; [Ŧ] = adjusted R-sq. near 0.
***Source*:** Author's calculations.

Collectively, these three categories explain 21.3 percent of the intra-industry TFPR variation in Punjab. In contrast, in Hsieh and Klenow's (2009) analysis, all four categories explain 4.7 percent and 10 percent of the intra-industry TFPR variance in India and China, respectively. Our analysis finds that size is the most important driver of TFPR variation in

Punjab. Hsieh and Klenow's study yields similar results for India and China, but of a relatively small magnitude. While ownership is the key driver in China's intra-industry productivity dispersion, it is relatively less important in Punjab's case.

The last column of Table 3 shows that public firms' TFPR values are, on average, 15.9 percent smaller than those of private firms, whereas Hsieh and Klenow (2009) find relatively large differences for India (28.5 percent) and China (41.5 percent). Moreover, we find no difference between foreign and domestic private firms after controlling for size. One important explanation for this result could be the very low statistical power assigned to foreign private firms.

Firms in the bottom size quartile have a much higher TFPR than other firms, which is clear evidence of economies of scale. These results are statistically highly significant, and imply that a firm's growth and TFPR have an important relationship. Additionally, firms in southern Punjab have a higher TFPR, on average, than firms in central Punjab, although there are no differences between the other two regions. One possible reason for this result could be the relatively small statistical power used to compute regional variations since, in the final sample, more than 85 percent of firms fall under central Punjab. On average, TFPR is higher in 2005/06 than in 2000/01—this result is consistent across all three specifications in Table 3. Finally, the last column of Table 4 shows that younger firms have a higher TFPR than older firms.

This analysis underscores the very important relationship between the size of a firm and TFPR in the case of manufacturing industries in Punjab. Section 5.5 studies this relationship in more detail by comparing the efficient (hypothetical) and actual size distributions of firms. In the next section, we carry out a liberalization experiment for Punjab.

5.4. Liberalization Experiment

The firm's TFP function we derived was:

$$A_s = \left[\sum_{i=1}^{M_s} \left(A_{si} \frac{\overline{TFPR_s}}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{23}$$

In their liberalization experiment, Hsieh and Klenow (2009) argue that, if marginal products were to equalize across plants in an industry, then one would observe the same (revenue-based) TFPR in each plant within an industry. This is because firms with greater (output-based) TFPQ are more likely to charge lower prices in order to gain a larger market share. Following this intuition, under perfect efficiency conditions, the TFP function would be:

$$\overline{A_s} = \left[\sum_{i=1}^{M_s} \left(A_{si} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}} \tag{24}$$

Combining equations (23) and (24) and making use of the constant elasticity of substitution and Cobb-Douglas aggregator, the economy-wide change in output due to the equalization of marginal products across plants becomes:

$$\frac{Y}{Y_{efficient}} = \prod_{s=1}^{s} \left[\sum_{i=1}^{M_s} \left(\frac{A_{si}}{\overline{A_s}} \frac{\overline{TFPR_s}}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}} \tag{25}$$

Table 5 reports the percentage gain in total output for Punjab and the corresponding estimates given by Hsieh and Klenow (2009) for China, India, and the US. These statistics were computed by estimating equation (25), taking its reciprocal to arrive at the ratio of efficient to actual output, subtracting 1 from it, and then multiplying the result by 100.

Table 5: Gains under full liberalization (%)

Punjab [a]	
2005/06	**2000/01**
100.61	68.24
India [b]	
100.40-127.00	
China [b]	
86.60-115.10	
US [b]	
36.10-42.90	

***Sources*:** a = author's calculations, b = calculations from Hsieh and Klenow (2009).

The results suggest that fully equalizing TFPR within Punjab's industries would yield a 68.24 percent and 100.61 percent gain in aggregate manufacturing TFP for 2000/01 and 2005/06, respectively. Interestingly, the results also indicate a higher level of policy distortion in Punjab for the latter year; this is consistent with the findings of higher TFPR variation for 2005/06. Comparing these estimates with Hsieh and Klenow's (2009) calculations reveals that, on average, Punjab is relatively less subject to policy distortions than India and China. Similar to Punjab, India also shows higher aggregate TFP gains in the latter years. Finally, the US is far less subject to policy distortions than the other three countries.

Comparing these results to the US efficient output level allows us to determine if Punjab is likely to gain in aggregate productivity if it moves to the US efficiency level. Following Hsieh and Klenow (2009), we choose the year 1997 to avoid exaggerated results (the period during which the US's aggregate TFP gains were highest).

Table 6 reports these estimates, along with Hsieh and Klenow's estimates for India and China. For each year, we calculate the efficient-to-actual output ratio for Punjab, compute the same ratio for the US in 1997, and then divide these two ratios to find the aggregate TFP gains for Punjab relative to the US. The results indicate that moving to US efficiency levels would raise aggregate TFP in Punjab by 23.61 percent and 47.40 percent in 2000/01 and 2005/06, respectively. Once again, these statistics verify the presence of relatively large distortions in 2005/06 for Punjab. The same pattern is evident for India and China.

Table 6: TFP gains relative to the US (%)

Punjab [a]	
2005/06	**2000/01**
47.40	23.61
India [b]	
40.20-59.20	
China [b]	
30.50-50.50	

***Sources*:** a = author's calculations, b = calculations from Hsieh and Klenow (2009).

In order to verify the consistency of our results with Hsieh and Klenow's (2009) analysis, we perform the same robustness check by varying the elasticity of substitution. The results vary substantially when σ is set to 5 rather than 3. Hsieh and Klenow report similar results for China and India.

While Pakistan has introduced a number of liberalization polices for the manufacturing sector, this analysis indicates that allocative efficiency in Punjab's manufacturing sector was less in 2005/06 than in 2000/01. However, as noted earlier, the coverage of firms is significantly higher in the 2005/06 dataset, and so it is difficult to interpret this as a true decline.

5.5. Size Distribution of Firms

In our previous set of estimations, we compared the actual and efficient distribution of firms by size in Punjab, measuring the firm's size by its value-addition. Both these expressions were computed as the deviation from the industry mean on a logarithmic scale, and also accounted for the number of firms in an industry.

In this section, actual size is calculated using the following expression:

$$Actualva_{si} = PS_{si} * M_s^{\frac{1}{\sigma-1}}$$

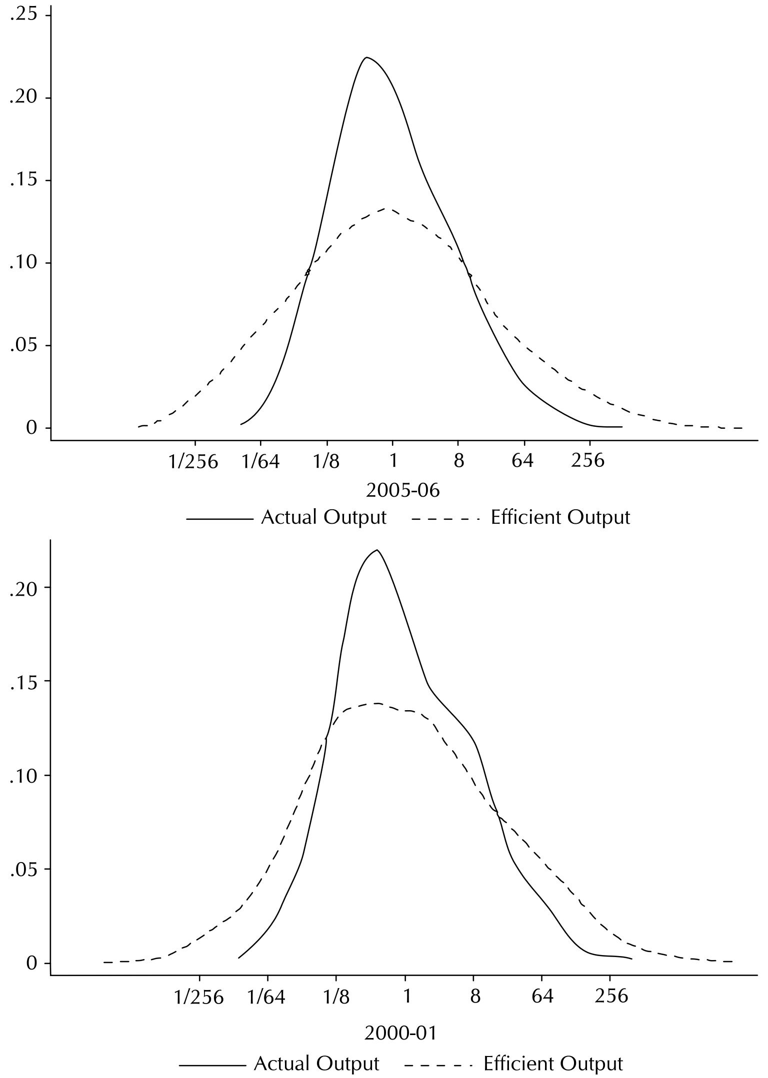
PS_{si} is the firm's value added and $M_s^{\frac{1}{\sigma-1}}$ is an adjustment factor for the number of industries in a sector.

We calculate efficient size by decomposing expression (25) to obtain plant-level efficient output:

$$Efficientva_{si} = \left[\frac{A_{si}}{A_s}\frac{TFPR_s}{TFPR_{si}}\right]^{\sigma-1} \times M_s^{\frac{1}{\sigma-1}} = \left[\frac{A_{si}}{A_s}\right]^{\sigma-1} \times M_s^{\frac{1}{\sigma-1}}$$

Figure 3 illustrates the efficient and actual distributions using $\log\frac{Actualva_{si}}{Actualva_s}$ and $\log\frac{Efficientva_{si}}{Efficientva_s}$, respectively. In both years, the hypothetical distribution is much more dispersed than the actual distribution, indicating that there should be fewer medium-size firms and more small and large firms. Hsieh and Klenow (2009) find similar patterns for India and China.

Figure 3: Efficient vs. actual output



6. Conclusion

This paper has used Hsieh and Klenow's (2009) methodology to analyze firm-level data on Pakistan. Specifically, it has used information from the CMI 2000/01 and 2005/06 to study productivity dispersion and policy distortions in Punjab.

Our results indicate that productivity dispersion, measured by TFPQ, is higher in Punjab than in India and China. However, these differences become smaller if productivity is measured by TFPR. Moreover, when comparing Punjab across time, we find relatively more dispersion in 2005/06, although this may be a product of the greater coverage of firms in the more recent dataset.

The next set of estimations use regression analysis to study the potential sources of variation in TFPR—ownership type, size, and region explain nearly 21.3 percent of this variation. This figure is large compared to Hsieh and Klenow's (2009) calculations for India and China. The results also indicate that firm size, measured by its value added, is the major driver of TFPR variation.

Generally, firms with public ownership have a much lower TFPR than private domestic firms, although this difference is still greater in China. There is also clear evidence of economies of scale: firms in the bottom size quartile are found to have a much higher TFPR than larger firms. Finally, younger firms have a higher TFPR than older firms.

A liberalization experiment carried out to compare "efficient" output with actual output reveals that moving to absolute efficiency levels boosts manufacturing TFP in Punjab by 68.24 percent and 100.61 percent for 2000/01 and 2005/06, respectively. Likewise, moving to the US's efficiency level increases manufacturing TFP by 23.61 percent and 47.40 percent for 2000/01 and 2005/06, respectively. On average, these gains are smaller than Hsieh and Klenow's (2009) estimates for India and China, indicating relatively less policy distortion in Punjab.

The results are, however, subject to certain potential limitations. First, in both years a number of firms did not respond to the survey, thus questioning the representativeness of the datasets. However, the coverage of firms improved in 2005/06, which can be said to portray a relatively true picture of Punjab's manufacturing sector. Second, the exact magnitude of the measurement errors in the CMI for both years is not certain. Despite these limitations, this study offers interesting empirical insights into the extent and sources of misallocation and fills an important gap in the literature on the productivity of manufacturing firms in Pakistan.

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Appendix

Distribution of firms

No.	Manufacturing industry	ISIC (Rev. 2) code	CMI 2005/06 (frequency of firms)	CMI 2000/01 (frequency of firms)	US labor share (%)
1	Food	311	541	296	52
2	Food	312	26	33	36
3	Beverages	313	15	15	42
4	Tobacco	314	0	0	22
5	Textiles	321	655	435	76
6	Apparel	322	91	163	75
7	Leather and leather products	323	116	45	74
8	Footwear	324	25	0	74
9	Wood and wood products	331	22	17	77
10	Furniture and fixtures	332	0	8	76
11	Paper and paper products	341	56	38	66
12	Printing, publishing, and assoc. industries	342	0	26	67
13	Industrial chemicals	351	44	41	42
14	Other chemical products	352	140	114	34
15	Petroleum refineries	353	0	0	33
16	Petroleum products	354	0	0	49
17	Rubber products	355	17	19	73
18	Plastic products	356	48	25	65
19	Pottery, china, and earthenware	361	88	24	79
20	Glass and glass products	362	10	0	62
21	Other nonmetallic mineral products	369	18	30	62
22	Iron and steel-based industries	371	163	97	76
23	Nonferrous metal basic industries	372	20	8	53
24	Fabricated metal products	381	84	116	74
25	Machinery, except electrical	382	139	128	73
26	Electrical machinery apparatus	383	182	96	70
27	Transport equipment	384	77	66	59
28	Scientific equipment	385	73	47	64
29	Other manufacturing industries	390	48	54	67

Note: Frequency of firms is generated after cleaning the data.
***Sources*:** Census of Manufacturing Industries 2000/01 and 2005/06. US labor shares taken from Camacho and Conover (2010).

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