

The Role of Allocative Efficiency in A Decade of Recovery*

Kaiji Chen[†]

Alfonso Irarrazabal[‡]

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Abstract

The Chilean economy experienced a decade of sustained growth in aggregate output and productivity after the 1982 financial crisis. This paper analyzes the role of resource allocative efficiency on total factor productivity (TFP) of the manufacturing sector by applying the methodology of Hsieh and Klenow (2009) to the establishment data from the Chilean manufacturing census. We find that a reduction in resource misallocation accounts for about 46 percent of the growth in manufacturing TFP between 1983 and 1996. The improvement in allocative efficiency, moreover, is essentially driven by a reduction in the cross-sectional dispersion of output distortion. In particular, a reduction in the least productive plants' output subsidies is the most important reason for the reduction in resource misallocation during this period.

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[†]Emory University, Department of Economics, Atlanta, GA 30322. Email: kaiji.chen@emory.edu.

[‡]Norges Bank, Norway. Email: alfonso.irarrazabal@norges-bank.no

1 Introduction

As the 2008 financial crisis has evolved into a deep recession across the Western economies, there has been growing concern that the world economy can enter stagnation like Japan in the 1990s.¹

Historical experience provides both positive and negative answers to the above question. As a comparison, in 1982 both Chile and Mexico experienced financial crises as a consequence of sharply rising world interest rates and negative terms-of-trade shocks. After a sharp fall in real GDP in 1982 and 1983, the Chilean economy started to grow in 1984, and Chile has been the fastest-growing country in Latin America since then. By contrast, between 1982 and 1995 Mexico experienced no economic growth and has grown only modestly since then. A similar contrast can be found between Japan and Finland, both of which suffered financial crisis in the early 1990s. While Japan's economy has stagnated, the Finnish economy has grown spectacularly since then. One key factor explaining the divergent post-crisis paths among the above economies, as many researchers have found, is productivity: Chile and Finland have experienced fast growth in aggregate total factor productivity after their financial crises, while Mexico and Japan have not.² Understanding the evolution of aggregate productivity and the potential policies that may influence its dynamics, therefore, shed light on how the Western economies could emerge from the current recession, as Chile and Finland did from theirs.³

This paper studies the role of resource misallocation in the recovery of Chilean manufacturing TFP after the 1982 crisis. We use establishment data from the Chilean manufacturing census to address three questions: How important is the improvement in allocative efficiency in accounting for the fast growth in Chilean manufacturing TFP after the crisis? What are the key distortions that have mitigated and, thus, contributed to the improvement in allocative efficiency? What policy reforms in Chile might be potentially important in explaining the improvement in allocative efficiency? To this end, we employ the Hsieh and Klenow (2009) framework to obtain plant-specific output and capital distortions (wedges), as well as physical and revenue-based TFP measures ($TFPQ$ and $TFPR$), for each year between 1980 and 1996.

Our results show that between 1983 and 1996, an improvement in allocative efficiency

¹See, for example, "Japanisation is the new word of fear," in *Financial Times*, August 20/21, 2011.

²See, for example, Bergoeing, Kehoe, Kehoe, and Soto (2007) for a comparison between Chile and Mexico; Conesa, Kehoe, Ruhl (2001) for Finland; and Hayashi and Prescott (1999) for Japan.

³Ohanian (2010) finds that during the Great Recession, Total Factor Productivity dropped by an average of 7.1 percent for G7 countries other than the United States.

accounted for about 46 percent of the observed aggregate manufacturing TFP growth. The efficiency gain by equalizing $TFPR$ fell from 85 percent to 51 percent during this period. The key factor is a reduction in the cross-sectional dispersion in output distortions, which accounts for essentially all the reduction in the cross-sectional dispersion of $TFPR$ during this period. Moreover, the cross-sectional correlation of $TFPQ$ and $TFPR$ shows a similar decline in relation to the cross-sectional dispersion of $TFPR$, suggesting an improvement in resource allocation among plants of different productivity.

We then quantify the improvement in allocative efficiency among plants of different productivity. We group plants into quintiles based on their current year $TFPQ$ and decompose the cross-sectional dispersion of $TFPR$ and output distortion into two components: between-group and within-group variances. We find that the between-group variance explains more than 80 (70) percent of the decline in the overall dispersion of $TFPR$ (output distortion). Furthermore, a reduction in the least productive group's output distortions accounts for more than half of the decrease in the between-group dispersion. Consistent with this evidence, over time, the least productive plants' capital and labor shares exhibit a significant decline.

Finally, we discuss the policy reforms in Chile that may potentially lead to the above-mentioned improvement in allocative efficiency. Our regression results suggest that the least productive plants in Chile are small plants on average. We argue that the elimination of interest rate controls and the banking reform in Chile during the mid 1980s are likely to be important in reducing the output subsidies of the least productive plants.

Our work complements two recent papers that use the same manufacturing census data to examine the sources of Chilean aggregate productivity changes between 1980 and 1995 (Petrin and Levinsohn, 2012 and Oberfield, 2013). However, the methods to decompose aggregate productivity growth by both Petrin and Levinsohn and Oberfield are very different from that of Hsieh and Klenow, which we adopt in this paper. Specifically, Petrin and Levinsohn's method does not rely on the assumption of market structures or the measurement of wedges and, thus, serves as an important first step in measuring the contribution of technical efficiency and resource reallocation to aggregate productivity growth. Oberfield measures labor and capital wedges in a reduced-form way, without any assumption on factor market structure and, thus, plant's choice of capital and labor. Hsieh and Klenow, by contrast, rely on the explicit assumption of market structure and the measurement of specific wedges based on plant's first-order conditions.⁴ More-

⁴Interestingly, our paper obtains an average contribution of changes in allocative efficiency to aggregate productivity growth close to the counterpart in their paper for the same sample period.

over, the approach to decompose aggregate productivity into allocational efficiency and technological efficiency are vastly different between Hsieh and Klenow and the above two papers. Oberfield (2013) decomposes what he called “appropriate” Solow residual, instead of standard solow residual as Hsieh and Klenow did. In our paper, Hsieh and Klenow’s methodology allows us to explore the quantitative importance of different types of distortions to changes in allocative efficiency and the potential policy reforms contributing to changes in allocative efficiencies.

This study is related to a rapidly expanding recent literature on the importance of micro-distortions for aggregate productivity (Restuccia and Rogerson, 2008; Guner, Ventura and Xu, 2008; Buera and Shin, 2008; Buera, Kaboski and Shin, 2011; Midrigan and Xu, 2010; Moll, 2010). It is also part of the empirical literature that uses micro-data to measure the extent of micro-level misallocation. Following the methodology of Hsieh and Klenow (2009), this literature consistently finds large potential aggregate TFP gains from removing misallocation. For example, these studies found that Argentina could increase its TFP by 50-60 percent (Neumeyer and Sandleris, 2009), Bolivia by 52-70 percent (Machicado and Birbuet, 2011), Colombia by 50 percent (Camacho and Conover, 2010), and Uruguay by 50-60 percent (Casacuberta and Gandelman, 2009). Our paper focuses on the dynamics of Chilean manufacturing TFP and, in particular, the period after the financial crisis.⁵

Our findings provide empirical support for Buera and Shin (2010)’s argument that a reduction in idiosyncratic distortions preceded domestic financial market reforms in developing countries. In their theoretical framework, economic reforms consist of two stages: in the first stage, idiosyncratic output distortions are removed; in the second, borrowing constraints are relaxed. As a consequence, massive capital outflows accompany TFP growth during the first stage of reform. Consistent with their argument, our evidence shows that a reduction in the output distortion, rather than capital distortion, is key to explaining the improvement in Chilean manufacturing TFP between 1983 and 1996. Our results are also consistent with Oberfield (2012)’s findings. He finds, that misallocation did not contributed much to the fall in output during the recession. Our decomposition also confirm this, but finds that misallocation becomes more important in the recovery phase after the crisis.

The rest of the paper proceeds as follows: In section 2, we present the background of the Chilean economy for the period examined in this paper. In section 3, we present

⁵Oberfeld (2011) in a preliminary work also establishes a fall in resource misallocation for Chile after the financial crisis.

the monopolistic competition model of Hsieh and Klenow (2009) to measure the effect of distortion on productivity. In section 4, we describe the panel data set used in the analysis. In section 5, we present our empirical findings. Section 6 discusses the policy reforms in Chile that may be potentially important for the improvement in resource allocation. Section 7 concludes. The appendix provides the derivation of aggregate TFP using plant-specific wedges and its decomposition.

2 Recovery and Reforms in Chile after the 1982 Crisis

2.1 The recovery period

The Chilean economy experienced a large recession in 1982, but has been in a sustained recovery since 1984. Panel (a) of Figure 1 shows that between 1982 and 1984, real GDP per working-age (15-64) person declined by more than 20 percent relative to the trend level.⁶ From the mid-1980s, however, GDP per capita started to recover and, by 1996, was 20 percent above the trend. A similar takeoff of value added happened in the manufacturing sector after the 1982 crisis. In particular, value added of manufacturing sector began a rapid increase in the late 1980s. As shown in Panel (b), aggregate TFP in manufacturing sector tracked manufacturing value added closely during both the recession and the recovery. In particular, aggregate manufacturing TFP, relative to the trend level, increased by more than 20 percent between 1983 and 1996, providing a strong driving force of aggregate manufacturing output during the recovery. Understanding aggregate manufacturing TFP dynamics, therefore, provides a useful lens for us to understand the recovery of the aggregate economy after the financial crisis.

2.2 Reforms

Policy interventions intensified during the banking crisis. Between 1982 and 1985, the government intervened in 21 financial institutions; 14 were liquidated and the rest were rehabilitated and privatized. The state rehabilitated the banks by allowing them to re-capitalize and issue long-term debt, which the Central Bank bought, to replace their existing non-performing assets. As a result, the state became the manager and main creditor of rescued banks. More importantly, the state reinstated financial controls, such as “suggested” interest rates by the Central Bank (Gallego and Loyaza, 2000).

⁶We assume that the trend level of real GDP per working-age person is at two percent per year.

The financial reforms were implemented in two stages. In the first stage (1985-1990), the state reversed the protective measures imposed during the crisis. The controls on interest rates were eliminated in 1985 and a new banking law was enacted. The new banking law included: (i) limits on the debt-to-capital ratio and reserve requirements related to the leverage position of the bank; (ii) incentives for private monitoring of banks through both a public guarantee on deposits and mandatory information disclosure to the public; and (iii) separation between the core business of the bank and that of its subsidiaries. According to Hsieh and Parker (Figure 7, 2007), these restrictions caused bank credit to fall from 60 percent of GDP in 1986 to roughly 40 percent in 1987, and it remained there until the start of the 1990s.

In addition to the banking reforms, other reforms were also implemented during this period. For example, the corporate tax reform of 1984 lowered the tax on retained earnings and eliminated the preferential treatment of firm's debt liabilities. This tax reform, according to Hsieh and Parker (2007), was the main driving force for the investment boom in Chile between 1984 and 1989.

The second wave of financial market reforms did not occur until the start of the 1990s. During the 1990s, the stock market and other financial markets experienced important developments. Firms with a good credit rating were allowed to issue bonds and shares in external markets. Institutional investors, such as banks, pension funds and insurance companies, were allowed to hold external assets. Meanwhile, there was a significant rise in the stock market efficiency, as measured by the stock market's traded value to GDP and the turnover ratio.

3 Theoretical Framework

This section describes the linkage between aggregate productivity and resource misallocation that results from firm-level distortions, using a theoretical framework proposed by Hsieh and Klenow (2009, "HK" hereafter). A representative final good producer faces perfectly competitive output and input markets. The final good producer combines the output Y_s of S manufacturing industries using a Cobb-Douglas production technology

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

We set the final output as numeraire such that its price $P = 1$. In turn, each industry output Y_s is produced by combining M_s differentiated goods Y_{si} produced by individual

firms using a CES technology

$$Y_s = \left[\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

The production function for each differentiated product Y_{si} is given by a Cobb-Douglas function of firm-level TFP A_{si} , capital K_{si} and labor L_{si} .

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

Capital elasticity across firms within a given industry is assumed to be the same as α_s . Following HK, we introduce two types of distortions: an output distortion that takes the form of a tax on revenues, and a capital distortion that takes the form of a tax on capital services.⁷ The problem of a firm i in industry s is

$$\begin{aligned} \max_{P_{si}, K_{si}, L_{si}} \quad & (1 - \tau_{ysi}) P_{si} \underbrace{A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}_{Y_{si}} - W_{si} L_{si} - (1 + \tau_{ksi}) R K_{si} \\ \text{st : } & Y_{si} = Y_s \left[\frac{P_s}{P_{si}} \right]^\sigma \end{aligned}$$

The first-order conditions imply

$$MRPL_{si} = W_{si} / (1 - \tau_{ysi}) \quad (1)$$

$$MRPK_{si} = R (1 + \tau_{ksi}) / (1 - \tau_{ysi}), \quad (2)$$

where W_{si} is the firm-specific wage rate. From the first-order conditions, we obtain

$$\frac{K_{si}}{L_{si}} = \frac{1}{R} \frac{\alpha_s}{1 - \alpha_s} \frac{W_{si}}{1 + \tau_{ksi}}. \quad (3)$$

Notice that the output distortion affects the marginal revenue product of both factors in a symmetric way and, thus, does not distort the capital-labor ratio. By contrast, a capital distortion, $1 + \tau_{ksi}$, makes capital services more costly relative to labor services, distorting the capital-labor ratio below the first-best level.

Following Foster, Haltiwanger and Syverson (2008), we define revenue-based TFP as $TFPR_{si} = \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} = P_{si} A_{si}$ and quantity-based TFP as $TFPQ_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} = A_{si}$. It is easy to show that $TFPR_{si}$ follows

$$TFPR_{si} = \frac{\sigma}{\sigma - 1} \left(\frac{R}{\alpha_s} \right)^\alpha \left(\frac{W_{si}}{1 - \alpha_s} \right)^{1-\alpha_s} \frac{(1 + \tau_{ksi})^{\alpha_s}}{(1 - \tau_{ysi})}.$$

⁷In an appendix, available upon request, we consider the effect of labor-specific distortions by augmenting the production function with materials as input.

Intuitively, the higher is $1 + \tau_{ksi}$ and W_{si} , and the lower is $1 - \tau_{ysi}$, the lower is the output relative to the first best. Accordingly, the price P_{si} and, thus, $TFPR_{si}$ are above the first-best level. Recall that without distortions, $TFPR_i$ should be equalized across plants. This is because more resources are allocated to plants with higher $TFPQ_{si}$, leading to higher output and lower prices, which lower $TFPR_{si}$.

3.1 Aggregate TFP

We measure TFP at each industry s as $TFP_s \equiv \frac{Y_s}{K_s^{\alpha_s} L_s^{1-\alpha_s}}$, where $K_s = \sum_{i=1}^{M_s} K_{si}$ and $L_s = \sum_{i=1}^{M_s} L_{si}$. In Appendix 8.1, we show that TFP_s can be expressed as

$$TFP_s = \frac{\left[\sum_{i=1}^{M_s} \left(A_{si} \frac{(1-\tau_{ysi})W_{si}^{\alpha_s-1}}{(1+\tau_{ksi})^{\alpha_s}} \right)^{\sigma-1} \right]^{\frac{\sigma}{\sigma-1}}}{\left[\sum_{i=1}^{M_s} \frac{A_{si}^{\sigma-1}(1-\tau_{ysi})^{\sigma} W_{si}^{(\alpha_s-1)(\sigma-1)}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)+1}} \right]^{\alpha_s} \left[\sum_{i=1}^{M_s} \frac{A_{si}^{\sigma-1}(1-\tau_{ysi})^{\sigma} W_{si}^{\alpha_s(\sigma-1)-\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)}} \right]^{1-\alpha_s}} \quad (4)$$

where M_s is the number of firms in industry s . Note that if we shut down all the idiosyncratic distortions—i.e. $1 - \tau_{ysi} = 1 + \tau_{ksi} = 1$ and $W_{si} = W_s$ —then we obtain the efficient TFP, denoted as

$$\bar{A}_s \equiv \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \quad (5)$$

Given the assumed aggregate production function, aggregate manufacturing TFP can be expressed as

$$TFP = \prod_{s=1}^S TFP_s^{\theta_s} = \prod_{s=1}^S \left(\sum_{i=1}^{M_s} \left\{ A_{si} \frac{\overline{TFPR}_s}{TFPR_{si}} \right\}^{\sigma-1} \right)^{\frac{\theta_s}{\sigma-1}}$$

where

$$\overline{TFPR}_s \equiv \frac{\sigma}{\sigma-1} \left(\frac{W_s}{(1-\alpha_s) \sum_{i=1}^{M_s} (1-\tau_{ysi}) \frac{P_{si}Y_{si}}{P_sY_s}} \right)^{1-\alpha_s} \left(\frac{R}{\alpha_s \sum_{i=1}^{M_s} \frac{(1-\tau_{ysi})}{1+\tau_{ksi}} \frac{P_{si}Y_{si}}{P_sY_s}} \right)^{\alpha_s}$$

The gap between aggregate efficient TFP, denoted as TFP^e , and actual level of TFP can be shown to be

$$\frac{TFP}{TFP^e} = \prod_{s=1}^S \left(\sum_{i=1}^{M_s} \left\{ \frac{A_{si}}{\bar{A}_s} \frac{\overline{TFPR}_s}{TFPR_{si}} \right\}^{\sigma-1} \right)^{\frac{\theta_s}{\sigma-1}}$$

3.2 Log-normal case

We would like to understand the driving forces of aggregate TFP by decomposing it into different components. To this end, we assume that A_{si} , $(1 - \tau_{ysi})$, $(1 + \tau_{ksi})$ and W_{si} follow a joint log normal distribution. Using the Central Limit Theorem and assuming $M_s \rightarrow \infty$, we have the following decomposition for aggregate TFP (see Appendix 8.2 for details)

$$\log TFP_s = \log TFP_s^e - \frac{\sigma}{2} \text{var}(\log TFP R_{si}) - \frac{\alpha_s(1 - \alpha_s)}{2} \text{var} \left(\log \frac{1 + \tau_{ksi}}{W_{si}} \right) \quad (6)$$

The term $\text{var}(\log TFP R_{si})$ captures the distortions on resource allocation across firms, and $\text{var} \left(\log \frac{1 + \tau_{ksi}}{W_{si}} \right)$ captures the distortions that drive the capital-labor ratio, $\frac{K_{si}}{L_{si}}$, away from the first best.

In order to further understand the driving forces of the time variation in the $TFPR$ dispersion, we decompose $\text{var}(\log TFP R_i)$ as

$$\begin{aligned} \text{var}(\log TFP R_{si}) &= \text{var}[\log(1 - \tau_{ysi})] + \alpha_s^2 \text{var} \log(1 + \tau_{ksi}) \\ &\quad - 2\alpha_s \text{cov}[\log(1 - \tau_{ysi}), \log(1 + \tau_{ksi})] \\ &\quad + \text{cov}(\log W_{si}^{1-\alpha_s}, \log TFP R_{si}) \end{aligned} \quad (7)$$

The first term on the right-hand-side of (7) captures the resource misallocation due to output distortion, while the second term is capital-specific distortion.

3.3 Size Distribution

Resource misallocation also influences the distribution of plant size, measured as the value-added of plants.

$$P_{si} Y_{si} = Y_{si}^{1-\frac{1}{\sigma}} P_s Y_s^{\frac{1}{\sigma}} \quad (8)$$

Hence, the dispersion of firm size translates into a dispersion of firm output. Since $\sigma \geq 1$, equation (8) implies that larger firms (in terms of revenue) should have higher output. Moreover,

$$Y_{si} = \frac{A_{si}^\sigma (1 - \tau_{ysi})^\sigma}{(1 + \tau_{ksi})^{\alpha_s \sigma}} \left(\frac{\sigma - 1}{\sigma} \right)^\sigma \left(\frac{\alpha_s}{R} \right)^{\alpha_s \sigma} \left(\frac{1 - \alpha_s}{W_{si}} \right)^{\sigma(1-\alpha_s)} Y_s. \quad (9)$$

Combining equations (8) and (9), we have

$$P_{si} Y_{si} \propto \left[\frac{A_{si} (1 - \tau_{ysi})}{(1 + \tau_{ki})^{\alpha_s}} \left(\frac{1}{W_{si}} \right)^{1-\alpha_s} \right]^{\sigma-1}.$$

According to our model, more productive firms produce more and are larger. If there exist size-dependent policies such that A_{si} and $1 - \tau_{ysi}$ are negatively correlated (or A_{si} and $1 + \tau_{ksi}$ are positively correlated), more productive firms tend to produce less and less productive firms to produce more. As a result, the size dispersion becomes smaller. This implies that the efficient size distribution is more spread out than the actual size distribution when there are frictions.

4 Empirical Implementation

4.1 The Data

We use manufacturing Census data from 1980 to 1996. The Census is an annual survey of manufacturing plants collected by the ENIA covering firms with at least ten workers. The data contain information on the balance sheets of the firms at the 4-digit level of aggregation. Capital series are computed using perpetual inventory methods. Capital goods are divided in four categories: buildings, machinery, equipment and vehicles. The dataset contain information on depreciation and investment for each category. Then, we generate for each firm and category next period capital as depreciated capital previous period (using category specific depreciation) plus investment.

Given that our focus is on tracking the dynamic changes in measures of misallocation, we drop firms with missing data from the sample.⁸ Most of our analysis will focus on the sub-sample labeled “unbalanced panel” which contains plants for which we have information (revenue, labor, capital) for all years. In other words, we delete from the database all the firms that systematically report negative and zero revenue, as well as those that report no employees and no fixed assets in some year. After deleting those firms, we arrive at an average number of 1489 firms per year. For comparison, we also compute misallocation statistics for a balanced panel—that is, firms that survived from 1980 to 1996.

Table 1 compares the number of plants, firm-size distribution and employment share by size class for the whole sample and the unbalanced panel in 1983. As we can see from the share of firms in each size class, our screening strategy somewhat over-samples the small plants. For example, the share of plants with fewer than 50 employees is 76.8 and 80 percent, in the full sample and the unbalanced panel, respectively. In Section 6, we perform robustness checks using the balanced panel.

⁸We will perform several robustness checks to test the impact of this cleaning procedure.

4.2 Computing Distortions

To calculate distortions, we set the rental price to capital to ten percent and the elasticity of substitution σ to three. The capital share in sector s , α_s corresponds to the U.S. capital shares, as in Hsieh and Klenow (2009), which is from the NBER productivity database.

We compute distortions (or wedges) and productivity as follows:

$$1 + \tau_{ksi} = \frac{\alpha}{1 - \alpha} \frac{W_{si} L_{si}}{R K_{si}} \quad (10)$$

$$1 - \tau_{ysi} = \frac{\sigma}{\sigma - 1} \frac{W_{si} L_{si}}{(1 - \alpha) P_{si} Y_{si}} \quad (11)$$

$$A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} = \kappa \frac{(P_{si} Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}, \quad (12)$$

where $\kappa_s = (P_s Y_s)^{-\frac{1}{\sigma-1}} / P_s$. Although we do not observe κ_s , relative productivities—and, hence, reallocation gains—are unaffected by setting $\kappa_s = 1$ for each industry s .

We then use measured A_{si} to construct

$$TFP_s^e = \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}} = \kappa_s \left(\sum_{i=1}^{M_s} \left(\frac{(P_{si} Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$$

In contrast to HK and other studies, we use labor instead of the wage bill, in our definition of A_i ⁹. We follow HK and drop one percent of the tails of the distributions of $TFPR$ ($\log TFPR_{si} / \overline{TFPR_s}$) and $TFPQ$ ($\log \left(\frac{A_{si} M_s^{\frac{1}{\sigma-1}}}{A_s} \right)$) each year and recalculate the wage bill, capital and revenue, as well as $TFPR$ and $TFPQ$. At this stage, we calculate the industry shares $\theta_s = P_s Y_s / Y$.

5 Main Results

In this section, we first describe the evolution of various measures of productivity dispersion and plant-size distribution over time. We then decompose the aggregate TFP growth. Finally, we explore the resource misallocation among plants of different productivity.

5.1 Productivity Dispersion

In what follows, we choose two years, 1983 and 1996, to characterize the dynamics of the distributions. The initial year, 1983, corresponds to the peak of the financial crisis, and

⁹This allows us to account for changes in the dispersion of wages over time. Chile experienced a consistent decline in wage dispersion over the period of study (cites here!)

1996 is the last year in our sample. Panel (a) of Figure 2 plots the distribution of $TFPQ$, $\log\left(\frac{A_{si}M_s^{\frac{1}{\sigma-1}}}{A_s}\right)$ for 1983 and 1996. The distribution of $TFPQ$ in 1983 has a fat left tail. This is consistent with policies favoring the survival of (relatively) less efficient plants in 1983. Over time, $TFPQ$ dispersion became smaller, indicating that these inefficient plants either exited the sample or increased their $TFPQ$ faster than the industry average. Table 2 shows that this pattern is consistent across several measures of dispersion: The standard deviation of $TFPQ$ fell from 1.370 to 1.217 between 1983 and 1996; the ratio of the 75th to the 25th percentile of $TFPQ$ dropped from 1.912 to 1.685; and the ratio of the 90th to the 10th percentiles dropped from 3.612 to 3.129.

Panel (b) of Figure 2 plots the distribution of $TFPR$ ($\log TFPR_{si}/\sqrt{TFPR_s}$) for the same two years. Similar to that of $TFPQ$, the distribution of $TFPR$ is less dispersed in 1996 than 1983, reflecting an improvement of allocative efficiency between the two years. Moreover, the left tail has become significantly thinner, implying downsizing of the less-productive plants, which pushes up their $TFPR$ toward the mean. Again, Table 2 suggests that this pattern is consistent across different measures of the dispersion in $TFPR$. Note that, consistent with our model, $TFPR$ is less dispersed than $TFPQ$, as our model predicts that prices and $TFPQ$ are negatively correlated. The numbers in Table 2 are also consistent with greater distortions in Chile than in the United States. The standard deviation of $TFPR$ in 1996 is 0.62, much larger than the level of the United States, in 1987, which was 0.41.

To explore the resource misallocation among firms of different $TFPQ$, and how the degree of resource allocation changes over time, we explore the correlation between $TFPQ$ and $TFPR$. Table 2 shows that $TFPR$ and $TFPQ$ are positively correlated. For example, in 1983 the correlation between $TFPQ$ and $TFPR$ was 0.924. The key reason for this positive correlation, as suggested by the negative correlation between $TFPQ$ and $1 - \tau_y$, is that firms with higher productivity are subject to larger idiosyncratic distortions. Panel (c) of Figure 2 shows that since 1983, this positive correlation declined steadily until the early 1990s, when it levelled off. A potential explanation, as Table 2 suggests, is that the correlation between $TFPQ$ and $1 - \tau_y$ increased from -0.752 in 1983 to -0.680 in 1996.

The improvement in allocative efficiency led to changes in the size distribution after the crisis. In Panel (d) of Figure 2, we plot the efficient vs actual firm size distribution in both 1983 and 1996. Consistent with the distribution of $TFPQ$, the efficient firm size distribution became less dispersed with a thinner left tail in 1996. The actual firm size distributions in both years are less dispersed than their corresponding efficient size

distribution, especially on the left tail. This suggests that many small firms are subsidized and produce more than their counterparts without subsidy. Table 3 shows how the initial relative size of big versus small plants would change if $TFPR$ were equalized in each industry. The rows are initial (actual) plant size quantiles, and the columns are bins of efficient plant size relative to actual size: 0–50 percent (the plant should shrink in size by one half or more), 50–100 percent, 100–200 percent, and 200+ percent (the plant should at least double in size). We see that the most populous column is the 0–50 percent for every initial size quantile. In particular, most small plants (those in the bottom quartile) should shrink by one half or more in 1983. The actual firm-size distribution in 1996 is closer to its efficient distribution than its counterpart in 1983, especially on the left tail. In 1996, the fraction of small plants that should shrink by at least one half has dropped to 19 percent. This pattern is consistent with the fact that, over time, the correlation between $TFPQ$ and $1 - \tau_{ysi}$ increases. Accordingly, low $TFPQ$ plants became less subsidized and, thus, downsized, while high $TFPQ$ plants became less distorted and, thus, produced more. Also note that the size distribution moves further to the left, implying an increase in the proportion of small plants.

5.2 Decomposition of Aggregate Productivity Growth

We now decompose aggregate TFP growth to explore the contribution of different elements. We first compute TFP gain by fully equalizing $TFPR$ across plants within an industry. Table 4 provides percent TFP gains from fully equalizing $TFPR$ across plants in each industry. In 1983, TFP gains explain an increase in aggregate manufacturing TFP of 85 percent. However, the magnitude of TFP gains has a downward trend over time. By 1996, TFP gains have dropped to around 51 percent. Therefore, allocative efficiency improves by 22 percent ($1.85/1.51$) between 1983 and 1996, or 1.54 percent per year. The aggregate manufacturing TFP grows at 3.36 percent per year between 1983 and 1996. Thus, our results suggest that about 45.8 percent of aggregate manufacturing TFP growth during this period could be attributed to better allocation of resources. This number is consistent with what Petrin and Levinsohn (2012) find for the contribution of resource reallocation to aggregate productivity growth during the same period using a different approach.¹⁰

To what extent is the improvement in allocative efficiency attributable to the change

¹⁰ According to Table 2 of Petrin and Levinsohn (2012), between 1983 and 1995, resource reallocation contributes to about half of aggregate productivity growth.

in the variance of $TFPR$, as opposed to a change in the capital-specific distortion? To answer this question, we re-order equation (6) as follows:

$$\log TFP^e - \log TFP = \frac{\sigma}{2} \text{var}(\log TFP R_i) + \frac{\alpha(1-\alpha)}{2} \text{var}\left(\log \frac{1+\tau_{ki}}{W_i}\right) \quad (13)$$

Accordingly, total allocative efficiency can be decomposed into two components as captured by the right-hand side of (13). Panel (a) of Figure 3 plots the evolution of these two factors over time. Clearly, the dispersion of $TFPR$ tracks the total resource misallocation closely, both peaking at 1983 and then declining afterwards. By contrast, the capital-specific distortion barely changed and, if at all, slightly increased after 1990. Panel (b) of Figure 3 plots secular movement in $\text{var}(\log TFP R)$ and its different components in equation (7). It is clear that almost all the decline in the dispersion of $TFPR$ can be accounted for by the decline in the dispersion of the output distortion. Therefore, from now on, we focus on the variations in dispersion in $TFPR$ and the output distortion.

5.3 Misallocation across Plants of Different Productivity

In this section, we quantify the improvement of resource allocation among firms of different productivity (measured in $TFPQ$). To this end, we classify firms into quintiles based on their $TFPQ$ in each year. We then decompose the variance of $\log TFP R$ into between- and within-group variation as follows

$$\begin{aligned} \text{Var}(\log TFP R_{si}) &= \underbrace{\frac{1}{M_s} \sum_q^Q \sum_i^{N_q} (\log TFP R_{sqi} - \overline{\log TFP R_s})^2}_{\text{overall variation}} \\ &= \underbrace{\frac{1}{M_s} \sum_q^Q N_q \text{Var}(\log TFP R_{si})_q}_{\text{within-group component}} + \underbrace{\frac{1}{M_s} \sum_q^Q N_q (\overline{\log TFP R_{sq}} - \overline{\log TFP R_s})^2}_{\text{between-group component}}, \end{aligned}$$

where $\log TFP R_{sqi}$ is log of $TFPR$ for firm i that belongs to quintile q in the s industry; $\overline{\log TFP R_s}$ is the mean of $\log TFP R$ for industry s ; and $\overline{\log TFP R_{sq}}$ is the mean of $\log TFP R$ for quintile q within industry s .

The between-group component captures the dispersion of $TFPR$ across groups of different $TFPQ$. By definition, it washes out idiosyncratic factors that may potentially drive the dispersion of $TFPR$ (e.g. a reduction of measurement error over time or volatility of idiosyncratic demand shocks) and provide a clear picture of the degree of resource misallocation across different productivity groups. By contrast, while the within-group

component may still capture the degree of resource misallocation within each quintile, it may be driven by other idiosyncratic factors.

Panel (a) of Figure 4 shows that the decline in the variance of $TFPR$ since 1983 is mostly accounted for by the between-group variance. The contribution of the between-group variance to the decline in the variance of $TFPR$ is 83.5 percent.¹¹ This suggests that improvements in resource allocation across firms of different productivities, rather than a reduction in the measurement error or volatility of idiosyncratic shocks, play a crucial role in driving the decline of the dispersion in $TFPR$.

To further show the direction of resource reallocation, we plot the different elements of the between-group variance in Panel (b) of Figure 4. The average $TFPR$ of the bottom quintile experienced the fastest convergence to the mean, followed by the top quintile.¹² This implies that the main reason for the decline in the between-group variance is that the average $TFPR$ of the bottom and top quintiles converges to the mean. Moreover, given the positive correlation between $TFPQ$ and $TFPR$ in 1983, the convergence of $TFPR$ for both the bottom and top quintiles to the mean implies that the $TFPR$ of the least-productive plants becomes larger and the $TFPR$ of the most-productive ones smaller.¹³

We would like to measure the extent to which the decline in the dispersion of output distortions is attributed to the changes in the distribution of idiosyncratic distortions among plants of different $TFPQ$. In a similar vein, we decompose the variance of output distortion into between- and within-group components in a similar fashion to what we did for the variance of $\log TFPR$.

¹¹We compute the contribution of the changes in the between-group component between 1983 and 1986 in changes in variance of $TFPR$ of the same period as
$$\frac{\Delta \frac{1}{N} \sum_q N_q (\log TFPR_q - \log TFPR)^2}{\Delta Var(\log TFPR)},$$
 where $\Delta x = x_{1996} - x_{1983}$.

¹²Again, for each quintile q , we calculate its contribution to the overall change in between-group component as $\frac{\Delta \frac{N_q}{N} (\log TFPR_q - \log TFPR)^2}{\Delta_{between-group\ component}}$. The measured contribution of the bottom and top quintiles to the between-group component are 64.2 and 29.7 percent, respectively.

¹³In contrast to the pattern of between-group variances, elements of within-group variance across all quintiles follow similar dynamics. The results are available upon request.

$$\begin{aligned}
var [\log (1 - \tau_{ysi})] &= \underbrace{\frac{1}{M_s} \sum_q^Q \sum_i^{N_q} \left(\log (1 - \tau_{yqi}) - \overline{\log (1 - \tau_y)} \right)^2}_{\text{overall variation}} \\
&= \underbrace{\frac{1}{M_s} \sum_q^Q N_q Var \log (1 - \tau_{yi})_q}_{\text{within-group component}} + \underbrace{\frac{1}{M_s} \sum_q^Q N_q \left(\overline{\log (1 - \tau_y)}_q - \overline{\log (1 - \tau_y)} \right)^2}_{\text{between-group component}}
\end{aligned}$$

Panel (c) of Figure 4 shows that the between-group variance still play a dominant role in the decline of the dispersion in output distortion. The contribution of the between-group variance to the decline in the variance of total output distortion is 71.2 percent.¹⁴ The main driving force of this decline, as suggested by Panel (d), is as before the convergence of the output distortion of the bottom quintile to its economic-wide mean, followed by that of the top quintile.¹⁵ Overall, our analysis suggests that a reduction in the least-productive plants' output subsidies and the most-productive plants' output distortion constitute the most important reason for the reduction in resource misallocation during this period.

5.4 Reallocation of Factor Inputs

We now provide additional evidence of reallocation of capital and labor across firms. We first examine the distribution of capital and labor between 1983 and 1996, which are plotted in the top two panels of Figure 5. Over time, the distributions of both capital and labor became more dispersed. In particular, the density of small plants in terms of capital and labor has increased significantly. This is consistent with the above finding that the subsidy of less-productive plants has decreased significantly over time.

The bottom two panels of Figure 5 plot the dynamics of capital and labor, respectively, for the bottom *TFPQ* quintiles. Between 1983 and 1990, the bottom quintile's labor input declined significantly relative to the industry mean, while after 1990, this process slowed

¹⁴We compute the contribution of between-group variance to the decline in total output distortion as $\frac{\Delta \frac{1}{M_s} \sum_q^Q N_q \left(\overline{\log (1 - \tau_y)}_q - \overline{\log (1 - \tau_y)} \right)^2}{\Delta var \log (1 - \tau_{yi})}$.

¹⁵We compute the contribution of each quintile q to the changes in between-group variance as $\frac{\frac{N_q}{M_s} \left(\overline{\log (1 - \tau_y)}_q - \overline{\log (1 - \tau_y)} \right)^2}{\frac{1}{M_s} \sum_q^Q N_q \left(\overline{\log (1 - \tau_y)}_q - \overline{\log (1 - \tau_y)} \right)^2}$. Accordingly, the contributions of the bottom and top quintiles are 55.6 and 34.1 percent, respectively.

down. The corresponding changes in capital stock exhibit a similar pattern, though this process started in 1985.

To summarize, our evidence suggests that between 1983 and 1996, more than 40 percent of aggregate manufacturing TFP growth is attributed to the improvement in allocative efficiency, shown as a fall in the dispersion of $TFPR$. Among those wedges, the reduction in the dispersion of output distortions plays a dominant role in the reduction of the $TFPR$ dispersion. In particular, a reduction in the least-productive plants' output subsidies, followed by a reduction in the most-productive plants' output distortion constitute the most important factors to explain the reduction in resource misallocation during this period.

5.5 Robustness Checks

In this section, we conduct a sensitivity analysis of the estimates of potential TFP gains by equalizing $TFPR$ within industries. In particular, we vary the elasticity of substitution among differentiated goods. We then check the robustness of our results when we consider a balanced panel of firms.

5.5.1 Elasticity of Substitution

We check the sensitivity of the TFP gains from equalizing $TFPR$ to alternative values of the elasticity of substitution of differentiated goods. Table 4 reports the TFP gains by equalizing $TFPR$ within industry for $\sigma = 3$ and $\sigma = 5$. As expected, $TFPR$ gains increase for all years when $\sigma = 5$. Between 1983 and 1996, the allocative efficiency increased by 19.6 percent, or 1.39 percent per year. This is smaller than its counterpart (22 percent or 1.54 percent per year) under $\sigma = 3$. Intuitively, when σ is larger, $TFPR$ gaps are closed more slowly in response to reallocation of inputs from low to high $TFPR$ plants. Given an average growth rate in aggregate manufacturing TFP of 3.43 percent between 1983 and 1996, about 44.9 percent of the TFP growth during this period could be attributed to a better allocation of resources.

5.5.2 Balanced versus Unbalanced Panel

In our benchmark sample, a firm can still enter or exit at any time. To examine the quantitative importance of the extensive margin versus the intensive margin in terms of resource misallocation and its change over time, we now restrict the sample to firms that

survive the whole period (1980-1996), which we denote as the balanced panel. The total number of observations for the whole sample period is now 8483, with 499 in each year.

The right column of Table 4 reports the TFP gains of equalizing $TFPR$ under the balanced panel. Compared with the benchmark case, the TFP gain under the balanced panel is now smaller, suggesting that part of the resource misallocation comes from the extensive margin. Over time, TFP gains also decline over time. Between 1983 and 1996, Chilean allocative efficiency increased by 14 percent, or 1 percent per year. These numbers are again smaller than their counterparts in the benchmark case (22 percent and 1.54 percent), suggesting that about one third of overall improvement in resource allocation comes from the extensive margin. Aggregate manufacturing TFP for the balanced panel grows by 2.63 percent per year. Therefore, improvement in resource reallocation contributes to about 38 percent of total TFP growth in Chile, a magnitude closer to the benchmark case (45.8 percent).

6 Discussion: Misallocation and Policies

What policies potentially contributed to the improvement of resource allocation among plants of different $TFPQ$? To address this question, we first characterize the link between firm size and our measures of productivity. We then discuss policies that potentially contributed to the observed improvement in allocation of resources after the financial crisis.

6.1 Productivity and Firm Characteristics

We would like to determine the relationship between $TFPQ$ and different firm characteristics. To this end, we run a simple OLS regression of $TFPQ$ (specifically, $\log\left(\frac{A_{si}M_s^{\frac{1}{\sigma-1}}}{A_s}\right)$) and $TFPR$ ($\log TFPR_{si}/\overline{TFPR_s}$) separately against firm-size dummies. In the regressions, there are four size dummies, for firms belonging to the $[20, 49]$, $[50, 99]$, $[100, 249]$ and $[250, \infty]$ size (numbers of employees) classifications.

As expected, productivity measured as $TFPQ$ is positively correlated with plant size. In both 1983 and 1996, the estimated coefficients on plant-size dummies increase with firm size, suggesting that larger firms are more productive. More specifically, compared to manufacturing plants employing 10-19 workers, manufacturing plants in the 20-49 range are more than 50 percent more productive. Productivity in plants of more than

100 workers is about 200 percent higher than for firms in the 10-19 category. Over time, however, the gap of $TFPQ$ between large and small plants becomes smaller, consistent with a reduction in $TFPQ$ dispersion from 1983 and 1996.

An interesting pattern is apparent in the distribution of $TFPR$. In 1983, $TFPR$ of median and large firms (except for those larger than 250) is larger than those of small firms. This pattern, however, had largely disappeared by 1996. This is consistent with the fact that more capital and labor are reallocated from low- $TFPQ$ to high- $TFPQ$ plants, which are indeed larger.

6.2 Policy Reforms and Changes in Distortion

Note that small firms are more likely to be financially constrained and depend more heavily on bank credit. Hence, changes in bank credits due to policy reforms are more likely to exert a negative impact on them. For example, eliminating interest rate controls in 1985 and establishing a new banking law in 1986 would restrict small plants' access to bank credit and have a negative impact on their production scale. By contrast, large and more-productive plants are not likely to be directly affected by such reforms, as they can rely more on internal funds to finance production. As a result, small firms downsize and free up resources to larger and more productive plants.

Another potentially important policy contributing to the resource reallocation in Chile during the 1980s is the 1984 corporate tax reform. This policy reform, by eliminating taxation of retained profit, allowed the productive (larger) firms to accumulate more internal funds and encouraged them to invest, rather than to distribute as dividends the retained earnings. As a result, their production scales expanded. This leads, again, to resources being reallocated away from the less productive plants towards more productive ones. Hsieh and Parker (2007) find that the investment boom during the late 1980s is consistent with increased funds available from internal sources allowing plants with profitable investment opportunities to invest substantially more. Meanwhile, they also find that the ratio of interest payments to capital does not rise for their measured "constrained" firms relative to the "unconstrained" firms. Nor is there an increase in available debt instruments and access to credit for constrained plants. This evidence is consistent with the above mentioned prudent financial regulation after the financial crisis.

The experience in Chile is in sharp contrast to the conventional argument that developments in financial markets improve resource reallocation via facilitating small and more-productive firms to obtain external finance. The improvement in resource allocation

took place during the 1980s, but aggregate bank credit did not increase over this period. Similarly, the equity market did not develop significantly until the 1990s. Rather, Chile’s experience suggests that prudence in financial regulation after a financial crisis might be the key to improving allocative efficiency by restricting access to credit.

7 Conclusion

The Chilean aggregate TFP grew spectacularly and became the engine of output growth in the decade following the 1982 financial crisis. In this paper, we use micro data on manufacturing firms to assess the role of resource misallocation in aggregate productivity growth during this period. We find that the cross-sectional allocation of resources has significantly improved and contributed to about 46 percent of the aggregate TFP growth. Moreover, the improvement in allocative efficiency is driven essentially by a reduction in the cross-sectional dispersion of output distortion. Interestingly, a reduction in the least productive plants’ output subsidies and the corresponding increase in their average *TFPR* was the most important reason for the reduction in resource misallocation during this period. Consequently, factor inputs were reallocated away from the least productive plants toward more productive ones. Our results suggest that the elimination of interest-rate controls and the enactment of the banking law that occurred in 1985 may be important for the observed improvement in allocative efficiency in Chile since then.

Given the importance of output distortions in the improvement of resource allocation, the next question is: What are the origins of these distortions, and what is the quantitative importance of various policy reforms in Chile in reducing such distortions?¹⁶ A related issue is why similar reforms have not happened in other countries after a financial crisis—for example, in Japan and Mexico. Answers to these questions are important to shed light on how Western economies can emerge from the current recession as Chile did in the mid-1980s. We address some of these issues in our ongoing research.

¹⁶To our knowledge, Buera, Moll and Shin (2011) is the first attempt to provide a theory for idiosyncratic distortions. They show that well-intended policy intervention during a period of market failure may evolve into idiosyncratic distortions.

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8 Technical Appendix

8.1 Derivation of Aggregate TFP

In this section, we derive (4) and (6). Again, we use the growth accounting $TFP_s = \frac{Y_s}{K_s^{\alpha_s} L_s^{1-\alpha_s}}$.

We can express L_{si} and K_{si} as functions of Y_s . equation (2) implies

$$\alpha_s [(1 - \tau_{ysi}) P_{si}] \frac{\sigma}{\sigma - 1} A_{si} \left(\frac{K_{si}}{L_{si}} \right)^{\alpha_s - 1} = (1 + \tau_{ksi}) R. \quad (14)$$

Note also:

$$P_{si} = \left(\frac{Y_{si}}{Y_s} \right)^{-\frac{1}{\sigma}} P_s = \left(\frac{A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}{Y_s} \right)^{-\frac{1}{\sigma}} P_s = \left(\frac{A_{si} (K_{si}/L_{si})^{\alpha_s} L_{si}}{Y_s} \right)^{-\frac{1}{\sigma}} P_s \quad (15)$$

$$= \left(\frac{A_{si} (K_{si}/L_{si})^{\alpha_s - 1} K_{si}}{Y_s} \right)^{-\frac{1}{\sigma}} P_s. \quad (16)$$

Plugging (15) into (14) and using (3), we get

$$L_{si} = \frac{A_{si}^{\sigma-1} (1 - \tau_{ysi})^{\sigma}}{(1 + \tau_{ksi})^{\alpha_s(\sigma-1)}} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} \left(\frac{R}{\alpha_s} \right)^{\alpha_s(1-\sigma)} \left(\frac{W_{si}}{1 - \alpha_s} \right)^{\alpha_s(\sigma-1)-\sigma} Y_s. \quad (17)$$

Plugging (16) into (14) and using (3), we get

$$K_{si} = \frac{A_{si}^{\sigma-1} (1 - \tau_{ysi})^{\sigma}}{(1 + \tau_{ksi})^{\alpha_s(\sigma-1)+1}} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} \left(\frac{R}{\alpha_s} \right)^{\alpha_s(1-\sigma)-1} \left(\frac{W_{si}}{1 - \alpha_s} \right)^{(\alpha_s-1)(\sigma-1)} Y_s. \quad (18)$$

We now compute Y_{si}

$$\begin{aligned} Y_{si} &= A_{si} \left(\frac{K_{si}}{L_{si}} \right)^{\alpha_s} L_{si} \\ &= A_{si} \left[\frac{W_{si}}{R} \frac{\alpha_s}{1 - \alpha_s} \frac{1}{1 + \tau_{ksi}} \right]^{\alpha_s} L_{si} \\ &= \frac{A_{si}^{\sigma} (1 - \tau_{ysi})^{\sigma}}{(1 + \tau_{ksi})^{\alpha_s \sigma}} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} \left(\frac{\alpha_s}{R} \right)^{\alpha_s \sigma} \left(\frac{1 - \alpha_s}{W_{si}} \right)^{\sigma(1-\alpha_s)} Y_s. \end{aligned} \quad (19)$$

Using (17) and (18), we can rewrite L and K as

$$L_s = \sum_{i=1}^{M_s} L_{si} = Y_s \sum_{i=1}^{M_s} \frac{A_{si}^{\sigma-1} (1 - \tau_{ysi})^{\sigma}}{(1 + \tau_{ksi})^{\alpha_s(\sigma-1)}} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} \left(\frac{R}{\alpha_s} \right)^{\alpha_s(1-\sigma)} \left(\frac{W}{1 - \alpha_s} \right)^{\alpha_s(\sigma-1)-\sigma} \quad (20)$$

$$K_s = \sum_{i=1}^{M_s} K_{si} = Y_s \sum_{i=1}^{M_s} \frac{A_{si}^{\sigma-1} (1 - \tau_{ysi})^{\sigma}}{(1 + \tau_{ki})^{\alpha_s(\sigma-1)+1}} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} \left(\frac{R}{\alpha_s} \right)^{\alpha_s(1-\sigma)-1} \left(\frac{W}{1 - \alpha_s} \right)^{(\alpha_s-1)(\sigma-1)} \quad (21)$$

Plugging (20) and (21) into the definition of TFP, we get

$$\begin{aligned}
TFP_s &= \frac{1}{\left[\left(\sum_{i=1}^{M_s} \frac{A_{si}^{\sigma-1} (1-\tau_{ysi})^\sigma}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)+1}} \left(\frac{\sigma-1}{\sigma} \right)^\sigma \left(\frac{R}{\alpha_s} \right)^{\alpha_s(1-\sigma)-1} \left(\frac{W_i}{1-\alpha_s} \right)^{(\alpha_s-1)(\sigma-1)} \right)^{\alpha_s} \right]} \\
&\quad \frac{1}{\left[\sum_{i=1}^{M_s} \frac{A_{si}^{\sigma-1} (1-\tau_{ysi})^\sigma}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)}} \left(\frac{\sigma-1}{\sigma} \right)^\sigma \left(\frac{R}{\alpha_s} \right)^{\alpha_s(1-\sigma)} \left(\frac{W_i}{1-\alpha_s} \right)^{\alpha_s(\sigma-1)-\sigma} \right]^{1-\alpha_s}} \\
&= \frac{\left[\frac{\sigma}{\sigma-1} \left(\frac{1}{1-\alpha_s} \right)^{1-\alpha_s} \left(\frac{R}{\alpha_s} \right)^{\alpha_s} \right]^\sigma}{\left[\sum_{i=1}^{M_s} \frac{A_{si}^{\sigma-1} (1-\tau_{ysi})^\sigma W_{si}^{(\alpha_s-1)(\sigma-1)}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)+1}} \right]^{\alpha_s} \left[\sum_{i=1}^{M_s} \frac{A_{si}^{\sigma-1} (1-\tau_{ysi})^\sigma W_{si}^{\alpha_s(\sigma-1)-\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)}} \right]^{1-\alpha_s}}. \quad (22)
\end{aligned}$$

Finally, using (19), we have

$$\begin{aligned}
Y_s &= \left[\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \\
&= \left[\sum_{i=1}^{M_s} \left(\frac{A_{si}^{\sigma-1} (1-\tau_{ysi})^\sigma}{(1+\tau_{ksi})^{\alpha_s \sigma}} \left(\frac{\sigma-1}{\sigma} \right)^\sigma \left(\frac{\alpha_s}{R} \right)^{\alpha_s \sigma} \left(\frac{1-\alpha_s}{W_{si}} \right)^{\sigma(1-\alpha_s)} Y_s \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \\
&= Y_s \left[\frac{\sigma-1}{\sigma} \left(\frac{\alpha_s}{R} \right)^{\alpha_s} (1-\alpha_s)^{(1-\alpha_s)} \right]^\sigma \left[\sum_{i=1}^{M_s} \left(A_{si} \frac{(1-\tau_{ysi})}{(1+\tau_{ksi})^{\alpha_s} W_i^{(1-\alpha_s)}} \right)^{\sigma-1} \right]^{\frac{\sigma}{\sigma-1}},
\end{aligned}$$

which gives

$$\frac{\sigma}{\sigma-1} \left(\frac{1}{1-\alpha_s} \right)^{1-\alpha_s} \left(\frac{R}{\alpha_s} \right)^{\alpha_s} = \left[\sum_{i=1}^{M_s} \left(A_{si} \frac{(1-\tau_{ysi})}{(1+\tau_{ksi})^{\alpha_s} W_i^{(1-\alpha_s)}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}}. \quad (23)$$

Substituting (23) for $\frac{\sigma}{\sigma-1} \left(\frac{1}{1-\alpha_s} \right)^{1-\alpha_s} \left(\frac{R}{\alpha_s} \right)^{\alpha_s}$ in the numerator of (22), we get equation (4).

8.2 Decomposition of Aggregate TFP

Under the central limit theorem, as $M^s \rightarrow \infty$, equation (4) becomes

$$\begin{aligned}
\log TFP_s &= \frac{\sigma}{\sigma-1} \log \int \left(A_{si} \frac{(1-\tau_{ysi})}{(1+\tau_{ksi})^{\alpha_s}} \right)^{\sigma-1} \\
&\quad - \alpha_s \log \int \frac{A_{si}^{\sigma-1} (1-\tau_{ysi})^\sigma}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)+1}} - (1-\alpha_s) \log \int \frac{A_{si}^{\sigma-1} (1-\tau_{ysi})^\sigma}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)}}. \quad (24)
\end{aligned}$$

Assuming that A_{si} , $1 - \tau_{ysi}$ and $1 + \tau_{ksi}$ are joint log normal, we have

$$\begin{aligned}
& \log \int \left(A_{si} \frac{(1 - \tau_{ysi})}{(1 + \tau_{ksi})^{\alpha_s}} \right)^{\sigma-1} \\
= & (\sigma - 1) E [\log A] + \frac{(\sigma - 1)^2}{2} \text{var} [\log A] + (\sigma - 1) E [\log (1 - \tau_{ysi})] + \frac{(\sigma - 1)^2}{2} \text{var} [\log (1 - \tau_{ysi})] \\
& - \alpha_s (\sigma - 1) E [\log (1 + \tau_{ksi})] + \frac{(\sigma - 1)^2 \alpha_s^2}{2} \text{var} [\log (1 + \tau_{ksi})] \\
& + (\sigma - 1)^2 \text{cov} [\log A_{si}, \log (1 - \tau_{ysi})] \\
& - \alpha_s (\sigma - 1)^2 \text{cov} [\log A_{si}, \log (1 + \tau_{ksi})] - \alpha_s (\sigma - 1)^2 \text{cov} [\log (1 - \tau_{ysi}), \log (1 + \tau_{ksi})] \quad (25)
\end{aligned}$$

$$\begin{aligned}
& \log \int \frac{A_{si}^{\sigma-1} (1 - \tau_{ysi})^\sigma}{(1 + \tau_{ksi})^{\alpha_s(\sigma-1)+1}} \quad (26) \\
= & (\sigma - 1) E [\log A] + \frac{(\sigma - 1)^2}{2} \text{var} [\log A] + \sigma E [\log (1 - \tau_{ysi})] + \frac{\sigma^2}{2} [\text{var} \log (1 - \tau_{ysi})] \\
& - [1 + \alpha_s (\sigma - 1)] E [\log (1 + \tau_{ksi})] + \frac{[1 + \alpha_s (\sigma - 1)]^2}{2} \text{var} \log (1 + \tau_{ksi}) \\
& + (\sigma - 1) \sigma \text{cov} [\log A, \log (1 - \tau_{ysi})] \\
& - (\sigma - 1) [1 + \alpha_s (\sigma - 1)] \text{cov} [\log A, \log (1 + \tau_{ksi})] \\
& - \sigma [1 + \alpha_s (\sigma - 1)] \text{cov} [\log (1 - \tau_{ysi}), \log (1 + \tau_{ksi})]
\end{aligned}$$

$$\begin{aligned}
\log \int \frac{A_{si}^{\sigma-1} (1 - \tau_{ysi})^\sigma}{(1 + \tau_{ksi})^{\alpha_s(\sigma-1)}} &= (\sigma - 1) E [\log A] + \frac{(\sigma - 1)^2}{2} \text{var} \log A + \sigma E [\log (1 - \tau_{ysi})] \\
& + \frac{\sigma^2}{2} \text{var} [\log (1 - \tau_{ysi})] - \alpha_s (\sigma - 1) E [\log (1 + \tau_{ksi})] \\
& + \frac{[\alpha_s (\sigma - 1)]^2}{2} \text{var} [\log (1 + \tau_{ksi})] \\
& + (\sigma - 1) \sigma \text{cov} [\log A, \log (1 - \tau_{ysi})] \\
& - (\sigma - 1) \alpha_s (\sigma - 1) \text{cov} [\log A, \log (1 + \tau_{ksi})] \\
& - \sigma \alpha_s (\sigma - 1) \text{cov} [\log (1 - \tau_{ysi}), \log (1 + \tau_{ksi})] \quad (27)
\end{aligned}$$

Plugging (25), (26) and (27) into (24) and rearranging, we have

$$\begin{aligned}
& \log TFP_s \\
= & E \log A_{si} + \frac{\sigma - 1}{2} \text{var} \log A_{si} \\
& - \frac{\sigma}{2} \text{var} [\log (1 - \tau_{ysi})] - \frac{\alpha_s + \alpha_s^2 (\sigma - 1)}{2} \text{var} [\log (1 + \tau_{ksi})] \\
& + \alpha_s \sigma \text{cov} [\log (1 - \tau_{ysi}), \log (1 + \tau_{ksi})]. \quad (28)
\end{aligned}$$

To see the relationship between (6) and (28), note that in (6), the first two arguments are

$$\frac{1}{\sigma-1} \log \sum A_i^{\sigma-1} = E[\log A] + \frac{\sigma-1}{2} \text{var}[\log A] \quad (29)$$

$$\begin{aligned} & \text{var}(\log TFP_{si}) \\ = & \text{var} \left(\log \frac{(1 + \tau_{ksi})^{\alpha_s}}{1 - \tau_{ysi}} \right) \\ = & \alpha^2 \text{var}[\log(1 + \tau_{ksi})] + \text{var}[\log(1 - \tau_{ysi})] - 2\alpha_s \text{cov}[\log(1 - \tau_{ysi}), \log(1 + \tau_{ksi})] \end{aligned} \quad (30)$$

Plugging (29) and (30) into (6), we have

$$\begin{aligned} \log TFP_s &= E \log A + \frac{\sigma-1}{2} [\text{var} \log A] \\ &\quad - \frac{\sigma}{2} \text{var}[\log(1 - \tau_{ysi})] - \frac{\alpha_s + \alpha_s^2(\sigma-1)}{2} \text{var}[\log(1 + \tau_{ksi})] \\ &\quad + \alpha_s \sigma \text{cov}[\log(1 - \tau_{ysi}), \log(1 + \tau_{ksi})], \end{aligned}$$

which is the same as (28).

Table 1. Number of Firms and Employees by Size Class (1983)

Firm Size (number of Employees)	All firms (shares)			Unbalanced panel (shares)		
	#firms	Share of Total (%)	Labor (%)	#firms	Share of Total (%)	Labor (%)
10-19	1720	41.7	10.7	802	44.7	14.0
20-49	1447	35.1	19.5	641	35.7	23.5
50-99	491	11.9	15.6	188	10.5	17.1
100-249	314	7.6	22.7	123	6.9	24.8
250-499	96	2.3	14.7	32	1.8	13.6
500-999	36	0.9	11.2	9	0.5	7.0
>=1000	24	0.6	5.7	0	0	0

Table 2: Summary Statistics for the Distribution of Wedges and Productivity

	$\log TFPQ_{si}$	$\log TFPR_{si}$	$\log(1 - \tau_{ysi})$	$\log(1 + \tau_{ksi})$	$\log(W_{si})$
1983					
SD	1.370	0.792	0.723	1.256	0.527
90-10	3.612	2.054	1.842	2.824	1.402
75-25	1.912	1.004	0.903	1.435	0.690
Correlation with A_{si}	1	0.924	-0.752	-0.035	0.577
1996					
SD	1.217	0.616	0.549	1.245	0.482
90-10	3.129	1.571	1.415	3.246	1.238
75-25	1.685	0.829	0.673	1.527	0.717
Correlation with A_{si}	1	0.847	-0.680	-0.166	0.673

Notes: For each plant i , $TFPQ_{si} \equiv \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}$, $TFPR_{si} \equiv \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}$. S.D. = standard deviation, 75 - 25 is the difference between the 75th and 25th percentiles, and 90 - 10 the 90th and 10th percentiles. Industries are weighted by their value-added shares.

Table 3: Percent of Plants: Actual Size vs. Efficient Size

1983	0-50	50-100	100-200	200+
Top size quartile	10.7	6.9	4.0	3.3
2nd quartile	17.8	3.9	2.1	1.2
3rd quartile	22.5	1.6	0.5	0.3
Bottom quartile	24.4	0.3	0.2	0.2
1996	0-50	50-100	100-200	200+
Top size quartile	9.6	6.5	5.9	2.9
2nd quartile	12.7	6.1	3.5	2.8
3rd quartile	14.2	5.1	3.4	2.3
Bottom quartile	19.0	2.9	1.9	1.3

Note: In each year, plants are put into quartiles based on their actual value-added, with an equal number of plants in each quartile. The hypothetically efficient level of each plant's output is then calculated, assuming that distortions are removed so that $TFPR$ levels are equalized within industries. The entries above show the percent of plants with efficient/actual output levels in the four bins: 0%–50% (efficient output less than half of actual output), 50%–100%, 100%–200%, and 200%+ (efficient output more than double actual output). The rows add up to 25%, and the rows and columns together to 100%.

Table 4: TFP Gains from Equalizing $TFPR$ within Industries

<i>Year</i>	1983	1984	1985	1986	1987	1988	1989
TFP gains	84.7	69.3	65.3	60.3	52.2	55.0	44.3
<i>Year</i>	1990	1991	1992	1993	1994	1995	1996
TFP gains	42.7	52.9	48.1	54.6	48.6	46.1	51.3

Note: entries are $(TFP^e/TFP - 1) \times 100$, where $TFP/TFP^e = \Pi_{s=1}^S \left(\Sigma_{i=1}^{M_s} \left\{ \frac{A_{si}}{A_s} \frac{\overline{TFPR}_s}{\overline{TFPR}_{si}} \right\}^{\sigma-1} \right)^{\frac{\theta_s}{\sigma-1}}$.
 $TFPR_{si} = \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}$.

Table 5: Sensitivity Analysis: TFP Gains of Equalizing *TFPR*

Gain			
	$\sigma = 3$, Unbalanced Panel	$\sigma = 5$, Unbalanced Panel	$\sigma = 3$, Balanced Panel
1983	84.7	116.2	63.4
1984	69.3	96.6	50.8
1985	65.3	87.4	46.6
1986	60.3	82.7	43.1
1987	52.2	79.3	38.3
1988	55.0	86.5	42.8
1989	44.3	60.2	34.4
1990	42.7	60.7	36.3
1991	52.9	79.8	39.7
1992	48.1	85.1	45.2
1993	54.6	99.1	48.9
1994	48.6	80.0	43.1
1995	46.1	75.8	38.7
1996	51.3	80.7	42.7

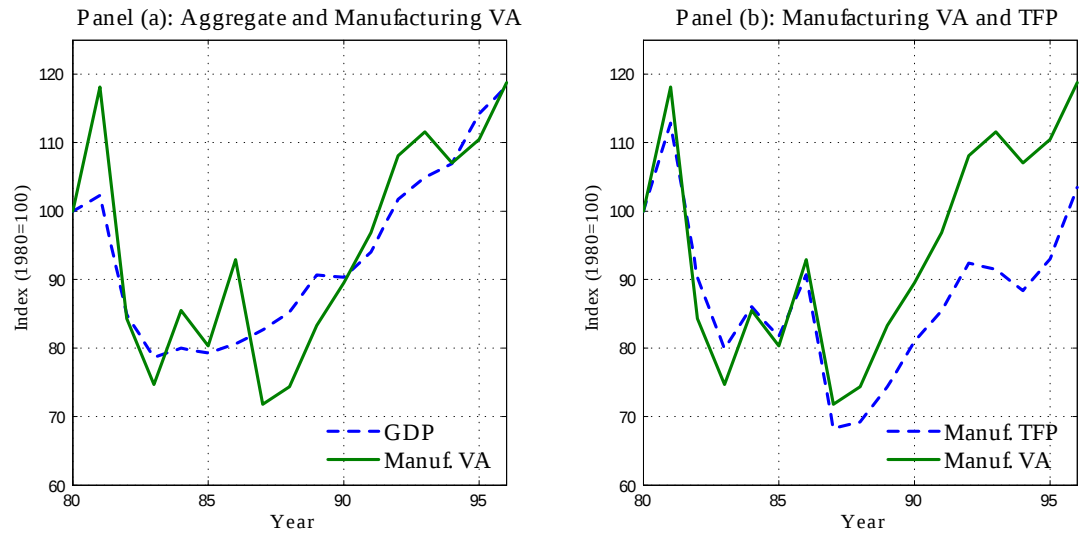
Note: See footnote of Table 3.

Table 6: *TFPQ* and *TFPR* with Multi-Covariates (OLS)

	<i>TFPQ</i>		<i>TFPR</i>	
	1983	1996	1983	1996
Employment 20-49	0.661*** (0.071)	0.406*** (0.076)	0.153*** (0.046)	-0.007 (0.052)
Employment 50-99	1.533*** (0.110)	1.123*** (0.096)	0.335*** (0.071)	0.134** (0.066)
Employment 100-249	2.020*** (0.137)	1.499*** (0.127)	0.339*** (0.089)	0.084 (0.069)
Employment ≥ 250	2.124*** (0.293)	1.947*** (0.127)	0.214 (0.190)	0.087 (0.087)
R-squares	0.233	0.352	0.026	0.009

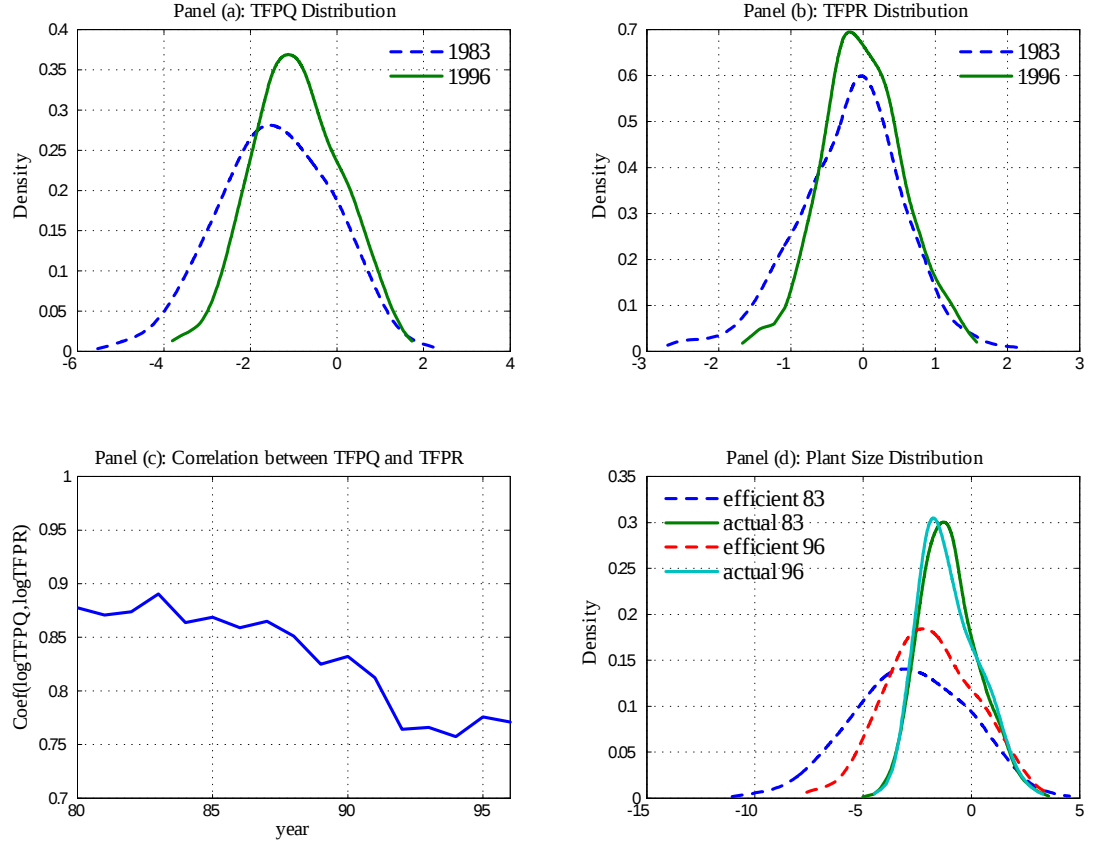
Note: Robust Standard error in brackets. *** if significant at 1%; ** if significant at 5%; * if significant at 10%.

Figure 1: Chilean Manufacturing Output and TFP



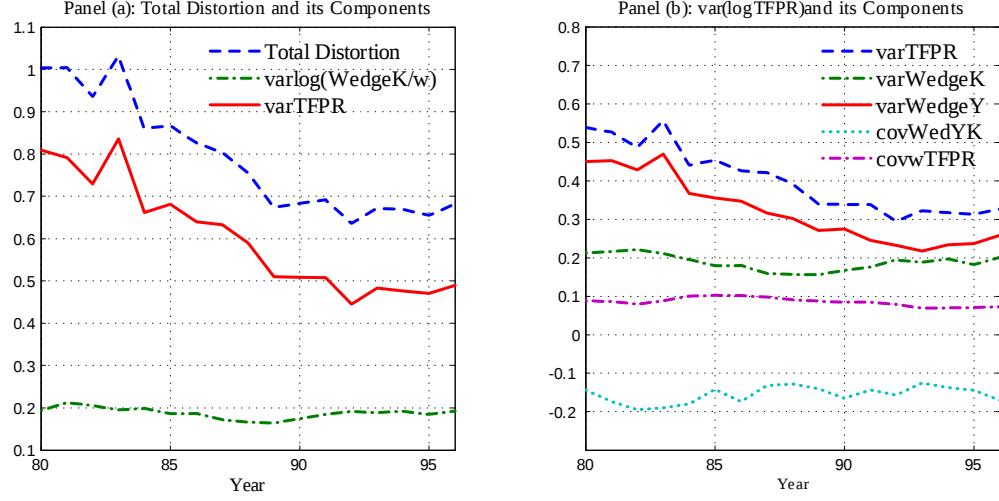
Note: Panel (a) shows Chilean GDP and value added for the manufacturing sector, while panel (b) shows value added and TFP for the manufacturing sector. Measured TFP is $\frac{VA}{K^\alpha L^{1-\alpha}}$ with $\alpha = 0.3$. Both GDP and the value added for manufacturing sector are detrended by 2% per year and normalized such that their 1980 values equal to 100. The manufacturing TFP is detrended by 1.4% per year and normalized in a similar way.

Figure 2: Distribution of Productivity and Plant Size



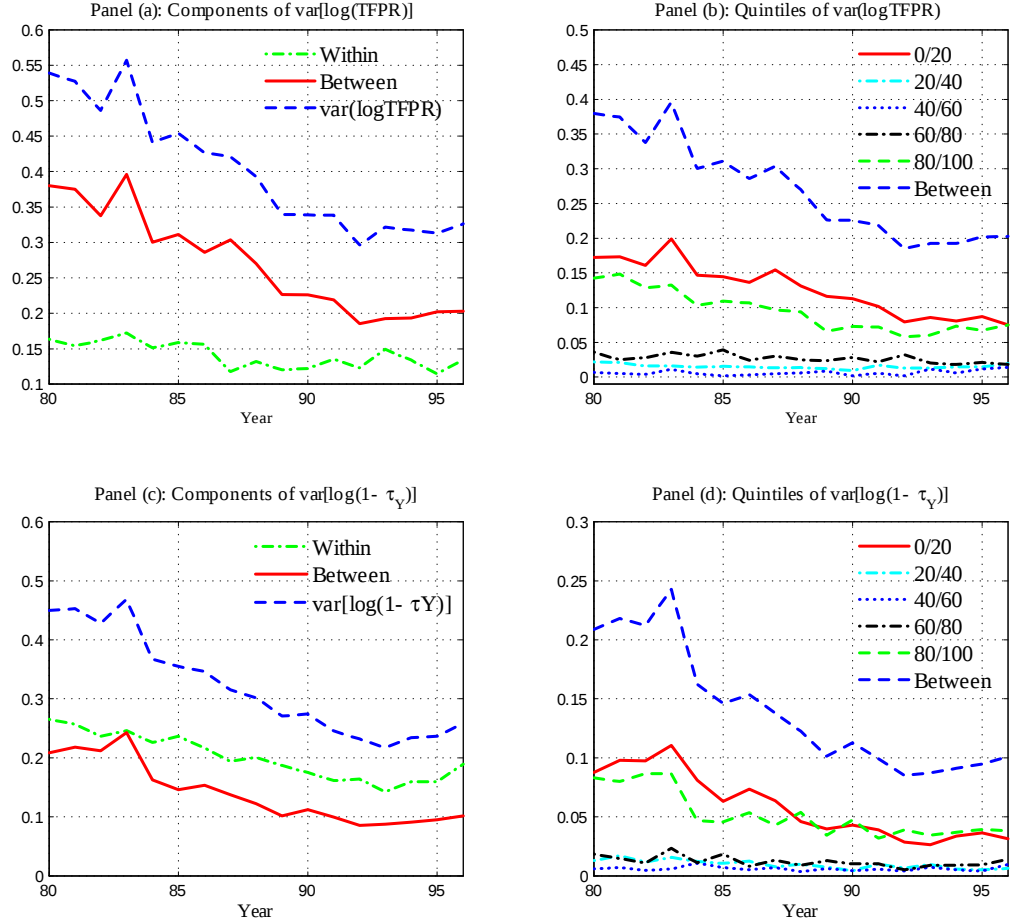
Note: Panel (a) plots the distribution of $TFPQ$, $\log \left(\frac{A_{si} M_s^{\frac{1}{\sigma-1}}}{A_s} \right)$, while panel (b) plots the distribution of $TFPR$, $\log TFPR_{si} / \overline{TFPR}_s$, both for 1983 and 1996. Panel (c) plots the time-series of correlation between $\log TFPQ$ and $\log TFPR$. Panel (d) plots the efficient and actual plant size distribution, $\log P_{si} Y_{si} - \log (mean_s (P_{si} Y_{si}))$.

Figure 3: Decomposition of Resource Misallocation



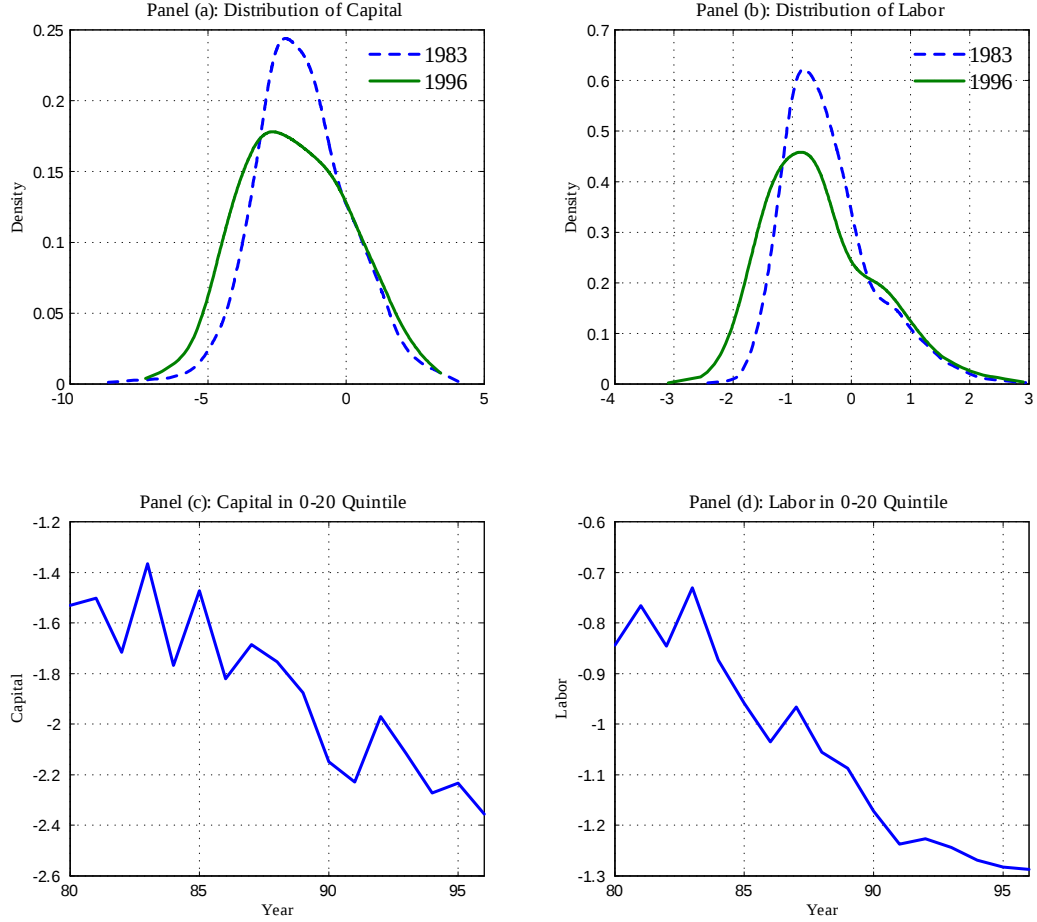
Note: Panel (a) plots total misallocation and its two components, variance of $TFPR$, measured as $\frac{\sigma}{2} \text{var}(\log TFPR_i)$, and the dispersion on plant-specific distortion to capital-labor ratio, as captured by $\frac{\alpha(1-\alpha)}{2} \text{var}\left(\log \frac{1+\tau_{ki}}{W_i}\right)$. Panel (b) plots variance of $TFPR$ and its various components between 1980 and 1996.

Figure 4: Quantile Analysis of Dispersion in $TFPR$ and Output Distortion



Note: Panel (a) plots $TFPR$ dispersion, $var(\log TFPR_i)$, and its within-group and between-group components. Panel (b) plots the quintiles average of $var(\log TFPR_i)$, together with its between-group component. Panel (c) plots the dispersion of output distortion, $var[\log(1 - \tau_{ysi})]$, and its within-group and between-group components, while panel (d) plots quintile averages of dispersion of output, together with its between-group component.

Figure 5: Capital and Labor Allocation



Note: Panel (a) and (b) plot the distribution of capital and labor, measured by $\log(K_{si}) - \log(\text{mean}_s(K_{si}))$ and $\log(L_{si}) - \log(\text{mean}_s(L_{si}))$ for 1983 and 1996. Panel (c) and (d) plot the time series of capital and labor in the bottom quintile, measured by $\log(\text{mean}_s^1(K_{si})) - \log(\text{mean}_s(K_{si}))$ and $\log(\text{mean}_s^1(L_{si})) - \log(\text{mean}_s(L_{si}))$. $\text{mean}_s(K_{si})$ denotes the mean of capital for s industry. $\text{mean}_s^1(K_{si})$ denotes the mean of capital for the bottom quintile of s industry. Similar definition applies to labor.