The Role of Allocative Efficiency in a Decade of Recovery*

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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) in 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 40 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' implicit output subsidies is the most important reason for the reduction in resource misallocation during this period. Our evidence suggests that Chile's banking reform during the early and mid-1980s is likely to have played an important role in the observed improvement in allocation.

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1 Introduction

Since the 2008 financial crisis has grown into a persistent recession across the Western economies, there has been rising concern that the global economy might stagnate as Japan did in the 1990s.[1]

Historical experience provides both positive and negative answers to this cautionary tale. Chile and Mexico provide two comparative cases, as in 1982 both countries experienced a financial crisis as a consequence of sharply rising world interest rates and negative terms-of-trade shocks. As shown by Panel (a) of Figure 1, after a declining by more than 20 percent relative to the trend level, Chile's real GDP per working-age population (15–64) started to recover in the mid-1980s and by 1996 was 20 percent above the trend.[2] In sharp contrast, between 1982 and 1995 Mexico experienced zero economic growth and has grown only modestly since then. A similar dichotomy is found when comparing Japan and Finland, which both suffered a financial crisis in the early 1990s. While Japan's economy has stagnated since then, the Finnish economy recovered and has grown spectacularly. As many researchers have found, total factor productivity (TFP) is one key factor explaining the divergent post-crisis paths among the above economies. Chile and Finland experienced fast growth in aggregate TFP after their financial crises, while Mexico and Japan did not.[3] Therefore, understanding the evolution of aggregate productivity and the potential policies that may influence its dynamics sheds light on how the Western economies may emerge from the current recession, as Chile and Finland did from theirs.[4]

Chile's manufacturing TFP dynamics offers a useful lens to understanding how its macroeconomy recovered from the financial crisis. Similar to the pattern seen in its aggregate economy, a takeoff occurred in the Chilean manufacturing sector after the 1982 crisis. Specifically, in the late 1980s the manufacturing sector began a rapid increase in value-added. As shown in Panel (b), aggregate TFP in the manufacturing sector closely tracked manufacturing value-added 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 for the aggregate manufacturing output during the recovery.

This paper studies the role of resource reallocation in the recovery of Chilean manufacturing TFP after the 1982 crisis. We use establishment-level data from the Chilean manufacturing census to address these three questions: How important is an 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 this improvement in allocative efficiency? What Chilean policy reforms might be potentially important in explaining

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

[2] We assume that the trend level of real GDP per working-age person is 2 percent per year.

[3] See, for example, Bergoeing, Kehoe, Kehoe, and Soto (2007) for a comparison between Chile and Mexico; Conesa, Kehoe, Ruhl (2007) for Finland; and Hayashi and Prescott (2002) for Japan.

[4] Ohanian (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.

the improvement in allocative efficiency? To these ends, we employ the framework used in Hsieh and Klenow (2009) to obtain plant-specific output and capital distortions (wedges), as well as physical and revenue productivity measures (TFPQ and TFPR), for each year between 1980 and 1996.

Our results show that between 1983 and 1996, an improvement in allocative efficiency accounted for about 40 percent of the observed aggregate manufacturing TFP growth. Specifically, allocative efficiency improved by 19 percent during this period, or 1.46 percent per year, contributing to a 3.68 percent annual growth rate in aggregate manufacturing TFP. The key factor behind this improvement is a reduction in the cross-sectional dispersion in output distortions, which accounts for essentially all the reduction in the cross-sectional dispersion of revenue productivity during this period. Moreover, the cross-sectional correlation of physical and revenue productivity shows a similar decline to the cross-sectional dispersion of revenue productivity, suggesting an improvement in resource allocation among plants with different productivity. We then quantify the improvement in allocative efficiency among plants with different levels of productivity. We group plants into quintiles based on their current year physical productivity and decompose the cross-sectional dispersion of revenue productivity and output distortion into two components: between-group and within-group variances. We find that the between-group variance explains more than 60 percent of the decline in the overall dispersion of revenue productivity and output distortion. Furthermore, a reduction in the least productive group's implicit output subsidy 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.

It has been argued that the prevalance of self-loans by Chilean banks toward affiliated firms within the business groups led to credit misallocation and the 1982–1983 financial crisis[5]. We therefore make a first pass to assess the role that Chile's banking reforms during the early and middle 1980s played in the observed improvement in allocative efficiency. Our regression results suggest that in the early 1980s, Chilean plants with higher implicit output subsidy and thus lower revenue productivity had, on average, a higher liability-asset ratio, suggesting that these firms had preferential access to credit. Moreover, industries with a higher average liability-asset ratio in the early 1980s enjoyed a faster improvement in allocative efficiency since 1983, with a correlation coefficient of 0.53. Such evidence suggests that Chile's banking reforms during the early and mid-1980s, which largely restricted making self-loans within business groups, are likely important factors in reducing the resource misallocation between business group-affiliated and independent firms.

Our work complements Petrin and Levinsohn (2012) and Oberfield (2013), two recent pa-

[5]See, for example, Diaz-Alejandro (1985), Harberger (1985), Galvez and Tybout (1985), Tybout (1986), Edwards and Edwards (1991), McKinnon (1991), de la Cuadra and Valdes (1992), and Akerlof and Romer (1993).

pers that use the same manufacturing census data to examine the sources of Chilean aggregate productivity changes between 1980 and 1995. Specifically, in Petrin and Levinsohn (2012), misallocation of each input is implicitly captured by the gap between its value of marginal product and its marginal cost. Accordingly, the reallocation term is measured by the weighted average of changes in factor inputs across plants, with weights in the above-mentioned gaps for individual plants. Hence, this approach ignores the change in the allocative efficiency when a plant's physical output changes, but inputs do not. Hsieh and Klenow, by contrast, measure specific distortions based on a plant's first-order conditions. As a result, Hsieh and Klenow's decomposition incorporates changes in allocative efficiency due to changes in both factor inputs and physical productivity. Oberfield (2013) obtains measures of both within- and across-industry allocative efficiency by extending Hsieh and Klenow's approach. Our results are consistent with Oberfield (2013), which finds that within-industry misallocation did not contribute much to the fall in output during Chile's 1982 recession. Our decomposition not only confirms this result, but also finds that the role of allocative efficiency becomes more important in the post-crisis recovery phase. Moreover, to the best of our knowledge we are the first to link changes in policy distortions as a result of banking reforms in Chile to the improvements in allocative efficiency achieved after the financial crisis.

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 eliminating misallocation. For example, these studies found that Argentina could increase its TFP by 50–60 percent (Neumeyer and Sandleris, 2010), 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 during the period following the financial crisis and the potential policies contributing to such a change.

Our findings provide empirical support for Buera and Shin (2010)'s argument that a reduction in idiosyncratic distortions preceded domestic financial market development in emerging economies. In their theoretical framework, economic reforms occur in two stages: in the first, idiosyncratic output distortions are removed; in the second stage, borrowing constraints are relaxed. As a consequence, massive capital outflows accompany TFP growth during the first stage of reform. Consistent with Buera and Shin (2010), our evidence shows that a reduction in output distortion, rather than the capital distortion, is the key to explain the improvement in Chilean manufacturing TFP between 1983 and 1996. Furthermore, we show that for the case of Chile output distortions may result from preferential credit policy, which is widely available in emerging countries. Consequently, banking reforms by restricting prefential credit policy are likely to play important roles in reducing output distortion.

The rest of the paper proceeds as follows: in section 2, we briefly describe the monopolistic competition model of Hsieh and Klenow (2009) used to measure the effect of distortion on productivity. In section 3, we describe the dataset used in the analysis and how we compute idiosyncratic distortions at the plant level. In section 4, we present our empirical findings. In section 5, we present the Chilean economy's institutional background for the period examined. In addition, we assess the importance of the banking reforms in the improvement of resource allocation. Section 6 concludes. The appendix describes the data construction, provides the derivation of aggregate TFP using plant-specific wedges and its decomposition, and presents a simple model to capture the effect of banking reforms on allocative efficiency.

2 Theoretical Framework

This section describes the linkage between an economy's aggregate productivity and resource misallocation resulting from firm-level distortions by 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 with share θ_s. We set final output as the 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 with elasticity parameter δ. The production function for each differentiated product, Y_{si} is given by a Cobb-Douglas function of firm-level productivity A_{si}, capital K_{si} and labor L_{si} with labor share α_s. Capital elasticity across firms within a given industry is assumed to be the same as α_s. Following HK (2009), 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.[6] The problem of a firm i in industry s is described below

$$\max_{P_{si},K_{si},L_{si}} (1-\tau_{ysi})\, P_{si} \underbrace{A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}_{Y_{si}} - W L_{si} - (1+\tau_{ksi})\, R K_{si}$$

$$st: Y_{si} = Y_s \left[\frac{P_s}{P_{si}}\right]^{\sigma},$$

where W is the wage rate and R is the gross interest rate. As shown in HK (2009) the output distortion affects the marginal revenue product of both factors in a symmetric manner 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.

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

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

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

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

2.1 Aggregate TFP

We measure TFP in 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 7.2, we show that TFP_s can be expressed as

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

where M_s is the number of firms in industry s. Note that if we eliminate all the idiosyncratic distortions, i.e., $1-\tau_{ysi} = 1+\tau_{ksi} = 1$, we obtain the efficient TFP, which we denoted as $\overline{A}_s = \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$. It is easy to show that the manufacturing TFP at each sector can be rewritten as

$$TFP_s = \left(\sum_{i=1}^{Ms}\left\{A_{si}\frac{\overline{TFPR_s}}{TFPR_{si}}\right\}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}, \tag{2}$$

where $\overline{TFPR_s} = \frac{\sigma}{\sigma-1}\left[(1-\alpha_s)\sum_{i=1}^{M_s}(1-\tau_{ysi})\frac{P_{si}Y_{si}}{P_SY_S}/W\right]^{\alpha_s-1}\left[\alpha_s\sum_{i=1}^{M_s}\frac{(1-\tau_{ysi})}{1+\tau_{ksi}}\frac{P_{si}Y_{si}}{P_SY_S}/R\right]^{-\alpha_s}$. For each manufacturing sector, we calculate the ratio of actual TFP to the efficient TFP and aggregate this ratio across all sectors using the Cobb-Douglas aggregator,

$$\frac{Y}{Y^e} = \prod_{s=1}^{S}\left(\sum_{i=1}^{Ms}\left\{\frac{A_{si}}{\overline{A}_s}\frac{\overline{TFPR_s}}{TFPR_{si}}\right\}^{\sigma-1}\right)^{\frac{\theta_s}{\sigma-1}}.$$

2.2 Log-Normal Case

We want to understand the forces driving aggregate TFP by decomposing it into different components. To this end, we assume that A_{si}, $(1-\tau_{ysi})$, and $(1+\tau_{ksi})$ follow a joint log normal distribution. Using the Central Limit Theorem and assuming $M_s \to \infty$, we obtain the following decomposition for aggregate TFP (see Appendix 7.3 for details):

$$\log TFP_s = \log TFP_s^e - \frac{\sigma}{2} var\left(\log TFPR_{si}\right) - \frac{\alpha_s(1-\alpha_s)}{2} var \log\left(1+\tau_{ksi}\right). \tag{3}$$

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

In order to further understand the driving forces of the time variation in the TFPR dispersion, we decompose $var\left(\log TFPR_{si}\right)$ as

$$\begin{aligned} var\left(\log TFPR_{si}\right) = {} & var\left[\log\left(1-\tau_{ysi}\right)\right] + \alpha_s^2 var \log\left(1+\tau_{ksi}\right) \\ & - 2\alpha_s cov\left[\log\left(1-\tau_{ysi}\right), \log\left(1+\tau_{ksi}\right)\right]. \end{aligned} \tag{4}$$

The first term on the right side of equation (4) captures the resource misallocation due to output distortion, while the second term describes capital-specific distortion.

2.3 Size Distribution

Resource misallocation also influences the distribution of plant size, measured as individual plants' value added. In our model, the dispersion of firm size translates into a dispersion of firm output,

$$P_{si}Y_{si} = Y_{si}^{1-\frac{1}{\sigma}} P_s Y_s^{\frac{1}{\sigma}}. \tag{5}$$

Since $\sigma \geq 1$, equation (5) implies that larger firms should have higher output. Moreover,

$$Y_{si} = \frac{A_{si}^{\sigma}\left(1-\tau_{ysi}\right)^{\sigma}}{\left(1+\tau_{ksi}\right)^{\alpha_s\sigma}} \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{\alpha_s}{R}\right)^{\alpha_s\sigma} \left(\frac{1-\alpha_s}{W}\right)^{\sigma(1-\alpha_s)} Y_s. \tag{6}$$

Combining equations (5) and (6), we have

$$P_{si}Y_{si} \propto \left[\frac{A_{si}\left(1-\tau_{ysi}\right)}{\left(1+\tau_{ki}\right)^{\alpha_s}}\right]^{\sigma-1}. \tag{7}$$

Absent distortions, more productive firms tend to be larger. If A_{si} and $1-\tau_{ysi}$ are negatively correlated (or A_{si} and $1+\tau_{ksi}$ are positively correlated), more (less) productive firms tend to be smaller (larger) than the efficient size. As a result, the size dispersion becomes smaller. This implies that when there are frictions, the efficient size distribution is more dispersed than is the actual size distribution.

In reality, apart from idiosyncratic distortions, the dispersion of revenue productivity may result from other frictions, such as overhead labor, quasi-fixed capital, idiosyncratic demand and cost factors. Therefore, we also examine an alternative measure of resource misallocation:

the covariance between TFPQ and physical output, as implied by equation (6).[7] Intuitively, in the absence of distortions, more productive firms will produce more. This prediction is robust to a wide range of models. The presence of idiosyncratic output or capital wedges essentially adds noise to the profitability of plants, thus reducing such a correlation. It is easy to show that the covariance between physical output and TFPQ is linked to the covariance between physical and revenue productivity.

$$\frac{cov\left(\log Y_{si},\log A_{si}\right)}{\sigma var\left(\log A_{si}\right)}=1-\frac{cov\left(\log TFPR_{si},\log A_{si}\right)}{\sigma var\left(\log A_{si}\right)} \tag{8}$$

Equation (8) implies that there is a one-to-one mapping between the covariance using TFPQ and physical output and the covariance between physical and revenue productivity, both normalized by the dispersion of physical productivity.[8] For example, without idiosyncratic distortions, the left side of equation (8) is simply the correlation between TFPQ and physical output, $corr\left(\log Y_{si},\log A_{si}\right)$, and equal to one, which implies $cov\left(\log TFPR_{si},\log A_{si}\right)=0$. Such a relationship allows us to proxy the covariance between physical productivity and physical output with the covariance between physical and revenue productivity. We can further decompose this covariance as

$$cov\left(\log A_{si},\log TFPR_{si}\right)=corr\left(\log A_{si},\log TFPR_{si}\right)std\left(\log A_{si}\right)std\left(\log TFPR_{si}\right). \tag{9}$$

Accordingly, a decrease in the dispersion of TFPR will increase the covariance of physical and revenue productivity and such an effect would be larger, the larger is the correlation between physical and revenue productivity.

3 Empirical Implementation

This section describes the empirical implementation of our theoretical model. We first describe the data. We then introduce how to measure various distortions using plant-level information.

3.1 The Data

We use Chilean manufacturing census data from 1980 to 1996. The census is an annual survey of manufacturing plants, collected by the ENIA, which covers firms employing at least 10 workers.[9] The data contain information on plant balance sheets at the 4-digit level of aggregation. The survey reports data on value added, employment, wages, materials, investments, liabilities, assets, and capitals in different categories. Most of the variables are recorded in nominal terms.

[7] See Bartlesman, Haltiwanger, and Scarpetta (2013).

[8] In addition, the covariance between TFPQ and physical output is linked to the covariance between TFPQ and employment $\frac{cov(\log Y_{si},\log A_{si})}{var(\log A_{si})}=1+\frac{cov(\log L_{si},\log A_{si})}{var(\log A_{si})}-\frac{\alpha_s cov(\log 1+\tau_{ksi},\log A_{si})}{var(\log A_{si})}$. Due to the possible movement of the covariance of TFPQ and capital wedge, we prefer using the covariance of TFPQ and TFPR as proxy for the covariance between physical output and TFPQ.

[9] ENIA stands for Encuesta Nacional Industrial Annual (Annual National Industrial Survey).

We employ different deflators, collected from Liu (1990), to compute for real values with 1980 as base year. These deflators include output price deflator, price deflators for different capital goods, intermediate material input price deflator, etc. The appendix 7.1 describes the procedure to construct plant level capital stock and our data sampling.

We use a plant's employment numbers as measurement of plant labor input.[10] During our sample period, Chile experienced a dramatic change in labor unions' bargaining power. According to Edwards and Edwards (2000), the 1980 labor market reform allowed union affiliation to be voluntary. It also decentralized collective bargaining to the firm-level. For example, the revised labor law stipulated that in the absence of a new collective agreement, the old contract would continue to be in effect while the negotiations proceeded. As a result, the employers' new contract offer would have to contain a wage adjustment that matched accumulated inflation. Along with the decentralization of collective bargaining, some firm-level unions bargained more successfully than others.[11] The heterogeneity of union bargaining power at the firm level motivates us to use the employment as our measure of plant labor input. A robustness check using the wage bill as measure of plant labor input is provided in Section 4.5.2.

Given that our focus is on tracking the dynamic changes in measures of allocative efficiency, we eliminate plants with incomplete data from the sample.[12] Most of our analysis will focus on the subsample labeled "unbalanced panel," which contains plants for which we have full information (value-added, labor, capital, and wages) for all years. In other words, we omit the plants from the database that systematically reported negative and zero value added, as well as those that reported having no employees, no fixed assets, and no wages in some year. We also omit plants at the top and bottom 0.2 percent of the wage distribution of wage in each year (see Appendix 7.1 for details). After deleting these plants, we arrived at an average number of 1,437 plants per year. For comparison, we also computed the corresponding statistics for a balanced panel, that is, the plants that survived from 1980 to 1996.

Table 1 compares the number of plants, the employment distribution and the employment share by subgroups in 1983 between the unbalanced panel and the entire sample. As shown by the share of plants in each subgroup, our screening strategy somewhat over-samples the plants with few employees. For example, the share of plants with fewer than 50 employees is 76.8 and 80.6 percent, in the full sample and in the unbalanced panel respectively. In Section 4.5.3, we perform robustness checks using the balanced panel.

3.2 Computing Distortions

To calculate distortions, we set the ratio of the rental price-to-capital to 10 percent and the elasticity of substitution, σ, to 3. The capital share in sector s, α_s, corresponds to the U.S.

[10] See also Bartlesman, Haltiwanger and Scarpetta (2013) and Petrin and Levinsohn (2012).

[11] According to Table 1 in Palacio (2006), between 1990 and 2004, in Chile unions negotiated 64 percent of the collective contracts and represented 72 percent of the number of workers who engaged in collective bargaining.

[12] We will perform several robustness checks to test the impact of this cleaning procedure.

capital shares, as in Hsieh and Klenow (2009), that are taken from the NBER productivity database.

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

$$1+\tau_{ksi} = \frac{\alpha}{1-\alpha}\frac{WL_{si}}{RK_{si}} \tag{10}$$

$$1-\tau_{ysi} = \frac{\sigma}{\sigma-1}\frac{WL_{si}}{(1-\alpha)\,P_{si}Y_{si}} \tag{11}$$

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

where $\kappa_s = (P_sY_s)^{-\frac{1}{\sigma-1}}/P_s$. Although we do not observe κ_s, relative productivity—and, hence, reallocation gains—are unaffected by setting $\kappa_s = 1$ for each industry s.[13]

We then use measured A_{si} to construct

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

We follow HK and drop 1 percent of the tails of the distributions of TFPR, $\log\left(TFPR_{si}/\overline{TFPR}_s\right)$, and TFPQ, $\log\left(A_{si}M_s^{\frac{1}{\sigma-1}}/\overline{A}_s\right)$, for each year and recalculate the firm's wage bill, capital, and revenue, as well as physical and revenue productivity. At this stage, we calculate the industry shares $\theta_s = P_sY_s/Y$.

4 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. After this, we explore the resource misallocation and reallocation of factor inputs among plants with different productivity. Finally, we conduct a robustness check of our main results.

4.1 Productivity Dispersion

For the rest of section 4, we choose two years, 1983 and 1996, to characterize the dynamics of productivity and plant-size distributions. The initial year 1983, corresponds to the peak of the financial crisis, while 1996 is the last year in our sample. Panel (a) of Figure 2 plots the distribution of TFPQ, $\log\left(A_{si}M_s^{\frac{1}{\sigma-1}}/\overline{A}_s\right)$, for 1983 and 1996. The distribution of TFPQ in 1983 has a fat left tail, which is consistent with policies in place during 1983 that favored the survival of (relatively) less efficient plants. Over time, the TFPQ dispersion became narrower, indicating that these inefficient plants either exited the sample or increased their physical productivity

[13] Since the level of aggregate TFP in each period influences the growth rate of TFP, we multiply the TFP calculated under the assumption $\kappa_s = 1$ by $(P_sY_s)^{-\frac{1}{\sigma-1}}/P_s$ to obtain the actual TFP in each period.

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 1.454 to 1.332 between 1983 and 1996; the ratio of the 75th to the 25th percentile of TFPQ dropped from 2.135 to 1.912; and the ratio of the 90th to the 10th percentiles dropped from 3.805 to 3.553.[14]

Panel (b) of Figure 2 plots the distribution of TFPR, $\log\left(TFPR_{si}/\overline{TFPR}_s\right)$, for the same two years. Similar to that of physical productivity, the distribution of revenue productivity is less dispersed in 1996 than 1983, reflecting an improvement in allocative efficiency since 1983. Moreover, the left tail has become significantly thinner, implying that the less-productive plants' revenue productivity became closer to the industry mean. Again, Table 2 suggests that this pattern is consistent across different measures of the dispersion in revenue productivity. Note that, consistent with our model, revenue productivity is less dispersed than physical productivity, as our model predicts that prices and physical productivity 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 0.58, much larger than the level of the United States in 1998, which was 0.45.

To explore the resource misallocation among firms of different physical productivity, and how the degree of resource allocation changes over time, we compute the correlation between physical and revenue productivity. Table 2 shows that physical and revenue productivity are positively correlated. For example, in 1983 the correlation between physical and revenue was 0.694. The key reason for this positive correlation, as suggested by the negative correlation between physical productivity 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. A potential explanation, as Table 3 suggests, is that the correlation between physical productivity and $1 - \tau_y$ increased from –0.755 in 1983 to –0.703 in 1996. A simultaneous decline in the dispersion of distortions and the correlation between physical and revenue productivity leads to a fall in its covariance, as shown in Panel (c) of Figure 2.[15] This suggests that over time, more productive firms tend to produce more. This fact provides additional evidence in favor of an improvement in resource allocation.

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 versus actual plant size distribution in both 1983 and 1996. Consistent with the distribution of physical productivity, the efficient plant size distribution became less dispersed and by 1996 had a thinner left tail. The actual plant size distributions in both years are less dispersed than their corresponding efficient size distribution,

[14] With plant labor input measured as wage bills, between 1983 and 1996 for physical productivity, the standard deviation fell from 1.21 to 1.073; the ratio of the 75th to the 25th percentile dropped from 1.639 to 1.329; and the ratio of the 90th to the 10th percentiles dropped from 3.134 to 2.778. These measures of Chilean physical productivity dispersion in 1996 are higher than their U.S. counterparts in 1998, which are 0.85, 1.22 and 2.22, respectively (see Hsieh and Klenow, 2009).

[15] Consistent with the dynamics of covariance of physical and revenue productivity, we find the covariance between physical productivity and employment increased steadily during the 1980s and leveled off in the 1990s.

especially on the left tail. This suggests that many small plants were implicitly subsidized and produced more than their counterparts that did not receive implicit subsidies. Following the approach of Hsieh and Klenow (2009), in Table 3 we show how the initial relative size of big versus small plants would change if there were no idiosyncratic distortions within each industry. The rows are the 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 column with the most plants is the 0-50 percent for every initial size quantile. In particular, most small plants (those in the bottom quantile) should have shrunk by half or more compared to their actual size in 1983. The actual plant-size distribution in 1996 is closer to its efficient distribution than it was in 1983, especially on the left tail. In 1996, the fraction of small plants that should shrink by at least 50 percent has dropped to 19.3 percent. This pattern is consistent with the fact that, over time, the correlation between physical productivity and $1-\tau_{ysi}$ increases. Accordingly, less productive plants were subsidized less and thus were downsized, while more productive 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.

4.2 Decomposition of Aggregate Productivity Growth

We now decompose aggregate TFP growth to explore the contribution of different components. Table 4 provides the percentage TFP gains from removing idiosyncratic distortions in each industry. In 1983, the aggregate manufacturing TFP would gain 60.2 percent by moving to efficient allocation in each industry. However, the magnitude of TFP gains has a downward trend over time. By 1996, TFP gains dropped to around 35.2 percent. Therefore, allocative efficiency improved by 19 percent (1.60/1.35-1) between 1983 and 1996, or 1.46 percent per year. The aggregate manufacturing TFP grew at an annual rate of 3.68 percent per year between 1983 and 1996. Thus, our results suggest that about 39.7 percent (1.46/3.68) of aggregate manufacturing TFP growth during this period may be attributed to better resource allocation.

An alternative approach to examine the contribution of improved in allocative efficiency to the within-industry manufacturing TFP growth is to run a panel regression of the log difference in aggregate TFP against the log difference in our measured allocative efficiency, $\frac{TFP_{s,t}}{TFP^e_{s,t}}$. The regression includes year dummies to capture the aggregate shocks, while a constant is included to capture the trend growth rate. The empirical specification is as follows

$$\Delta \log TFP_{s,t} = \alpha + \beta \Delta \log \left(\frac{TFP_{s,t}}{TFP^e_{s,t}} \right) + \gamma_t + \varepsilon_{s,t}.$$

The estimated $\beta = 0.606$, and is statistically significant at 1 percent. This implies that in 1983 and 1996, a 1 percentage increase in allocative efficiency would, on average, contribute to 0.6

percent increase in aggregate TFP[16].

To what extent is the improvement in allocative efficiency attributable to the change in the variance of revenue productivity, as opposed to a change in the capital-specific distortion? To answer this question, we re-order equation (3) as follows:

$$\log TFP^e - \log TFP = \frac{\sigma}{2} var\left(\log TFPR_i\right) + \frac{\alpha(1-\alpha)}{2} var \log\left(1+\tau_{ki}\right). \tag{13}$$

Accordingly, total allocative efficiency can be decomposed into two components as captured by the right side of equation (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, as both measures decline steadily since 1983. By contrast, the capital-specific distortion barely changed. Panel (b) of Figure 3 plots the secular movement in $var\left(\log TFPR\right)$ and its different components in equation (4). It is clear that almost all the decline in the dispersion of revenue productivity can be accounted for by the decline in the dispersion of the output distortion. Therefore, from here on we focus on the variations in dispersion in revenue productivity and the output distortion.

4.3 Misallocation across Plants of Different Productivity

In this section, we quantify the improvement of resource allocation among firms with different levels of physical productivity. To this end, we classify firms into quintiles based on their physical productivity in each year. We then decompose the variance of log TFPR into between- and within-group variation as follows:

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

where $\log TFPR_{sqi}$ is the log of TFPR for plant i that belongs to quintile q in the s industry; $\overline{\log TFPR_s}$ is the mean of $\log TFPR$ for industry s; and $\overline{\log TFPR_{sq}}$ is the mean of $\log TFPR$ for quintile q within industry s.

The between-group component captures the dispersion of revenue productivity across groups of firms with different physical productivity. By definition, this component eliminates the idiosyncratic factors that may potentially drive the dispersion of revenue productivity (e.g. a reduction of measurement error over time or volatility of idiosyncratic demand shocks) and provides a clear picture of the degree of resource misallocation across different productivity

[16] We thank one of the anonymous referees for suggesting this empirical formulation.

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 revenue productivity since 1983 is mostly accounted for by the between-group variance, which is responsible for 64.3 percent of the decline in the variance of revenue productivity.[17] This finding suggests that improvements in resource allocation across firms of different productivity, rather than a reduction in the measurement error or volatility of idiosyncratic shocks, played a crucial role in driving the decline of the dispersion in revenue productivity.

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.[18] This result implies that the main reason for the decline in the between-group variance is that the average revenue productivity of the bottom and top quintiles converged to the mean. Moreover, given the positive correlation between physical and revenue productivity in 1983, the convergence of both the bottom and top quintiles of revenue productivity to the mean implies that the revenue productivity of the least (most) productive plants became larger (smaller).[19]

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. Accordingly, we decompose the variance of output distortion into between- and within-group components in a similar fashion as what we did for the variance of log TFPR. This variance is computed as follows:

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

Panel (c) of Figure 4 shows that the between-group variance still plays a dominant role in the decline of the dispersion in output distortion. The contribution of the between-group

[17] We 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 $\frac{\Delta\frac{1}{N}\sum_{q}^{Q}N_q\left(\overline{\log TFPR_q}-\overline{\log TFPR}\right)^2}{\Delta Var(\log TFPR)}$, where $\Delta x = x_{1996} - x_{1983}$.

[18] Again, for each quintile q, we calculate its contribution to the overall change in between-group component as $\frac{\Delta\frac{N_q}{N}\left(\overline{\log TFPR_q}-\overline{\log TFPR}\right)^2}{\Delta between-group\ component}$. The measured contribution of the bottom and top quintiles to the between-group component are 64.8 and 31.2 percent, respectively.

[19] In 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.

variance to the decline in the variance of total output distortion is 61.4 percent[20]. As suggested by Panel (d), this decline is mainly driven by the convergence of the output distortion of the bottom quintile to the industry mean, followed by that of the top quintile.[21] Such a change in output distortions would naturally trigger resource reallocation across firms with different productivity, as we examine in the next section.

4.4 Reallocation of Factors

We now provide additional evidence that capital and labor were reallocated across firms of different productivity. We first examine the distribution of capital and labor between 1983 and 1996, plotted in the top two panels of Figure 5. Over time, the distribution of both capital and labor became more dispersed. In particular, the density of small plants in terms of capital and labor increased significantly. This result is consistent with the above finding that the implicit subsidization of less-productive plants 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 down. The corresponding changes in capital stock exhibit a similar pattern, though this process accelerated in the late 1980s.

A decline in capital and labor of plants in the bottom quintile results from a decline in the idiosyncratic distortions they face relative to TFPQ.[22] This is because an increase in the relative TFPQ of plants in the bottom quintile, as we found previously, tends to increase the bottom quintile's demand for capital and labor. Therefore, it is interesting to ask to what extent the increase of revenue productivity of plants in the bottom quintile relative to the industry mean is attributable to changes in TFPQ of the bottom quintile (holding constant the relationship between TFPQ and idiosyncratic distortions) and to the change in idiosyncratic distortions relative to TFPQ. Appendix 7.2 shows that the relative change in TFPR of the *qth* TFPQ quintile can be decomposed into two components:

$$\begin{aligned}\Delta\left[\overline{\log TFPR_{sq}}-\overline{\log TFPR_{s}}\right] &= \left(1-\frac{1}{\sigma}\right)\Delta\left[\overline{\log A_{si}}\mid_q-\overline{\log A_s}\right] \\ &\quad -\frac{1}{\sigma}\left[\alpha_s\Delta\left(\overline{\log K_{si}}\mid_q-\Delta\overline{\log K_s}\right)+\left(1-\alpha_s\right)\Delta\left(\overline{\log L_{si}}\mid_q-\overline{\log L_s}\right)\right],\end{aligned} \tag{14}$$

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

[21]We compute the contribution of each quintile q to the changes in between-group variance as $\dfrac{\frac{N_q}{M_s}\left(\overline{\log\left(1-\tau_y\right)}_q-\overline{\log\left(1-\tau_y\right)}\right)^2}{\frac{1}{M_s}\sum_q^Q N_q\left(\overline{\log\left(1-\tau_y\right)}_q-\overline{\log\left(1-\tau_y\right)}\right)^2}$. Accordingly, the contributions of the bottom and top quintiles are 58.6 and 38.3 percent, respectively.

[22]See equations (21) and (22) in Appendix 7.2.

where $\overline{\log X_{si}} \mid_q = \left(\sum_{i=1}^{N_q} \log X_{si}\right)/N_q$, $\overline{\log X_s} = \left(\sum_{i=1}^{N} \log X_{si}\right)/N$ for $X = A$, K or L. The first argument on the right side of equation (14) denotes the change in TFPQ (holding constant the relationship between TFPQ and idiosyncratic distortions) and the second shows the change in idiosyncratic distortions relative to TFPQ. We find that around 40 percent of the increase in the average TFPR of plants in the bottom quintile is attributable to a faster decline of their implicit distortions relative to their TFPQ, which, despite an increase in their TFPQ, led to the decline in both capital and labor of those least productive plants.

To summarize, our evidence suggests that between 1983 and 1996, around 40 percent of Chile's aggregate manufacturing TFP growth is attributable to the improvement in allocative efficiency, shown as a fall in the dispersion of revenue productivity. Among those wedges, the reduction in the dispersion of output distortions plays a dominant role in the reduction of the revenue productivity dispersion. In particular, a reduction in the least-productive plants' implicit output subsidy and, to a lesser degree, the most-productive plants' implicit output tax constitutes the most important factors that explain the reduction in resource misallocation during this period.

4.5 Robustness Checks

In this section, we conduct robustness checks for our main findings. We first vary the elasticity of substitution among differentiated goods. We then measure plant labor input as wage bills. After that, we restrict our sample to a balanced panel of plants. Finally, we link revenue productivity with a plant's exit probability to shed light on the main source of revenue productivity variation in our sample.

4.5.1 Elasticity of Substitution

We check the sensitivity of the TFP gains resulting from removing idiosyncratic distortions to alternative values of the elasticity of substitution of differentiated goods. Table 5 reports the TFP gains by removing idiosyncratic distortions within-industry for $\sigma = 3$ and $\sigma = 5$. As expected, TFP gains increase for all years when $\sigma = 5$. Between 1983 and 1996, the allocative efficiency increased by 12.9 percent (1.66/1.47-1), or a gain of 0.99 percent per year. This increase is less than its counterpart (19 percent or 1.46 percent per year) under $\sigma = 3$. Intuitively, when σ is larger, TFPR gaps close more slowly in response to a reallocation of inputs from low to high TFPR plants.

4.5.2 Labor Input Measured by the Wage Bill

In our baseline calculations, we use employment to measure plant labor input. Our logic is that in the presence of collective bargaining, wage bills would conflate the quantity of labor with idiosyncratic wage rates at the plant level. However, plants may differ in hours worked or worker skills, which could mean that wages per worker are a better measure of the plant labor input. In this section, we examine the robustness of our main results by using the wage bill as the measure of plant labor input.

Table 7 reports the TFP gains of moving to efficient allocation across years. It is noted that the TFP gains are larger than their counterparts in the baseline calculation, suggesting that the wage difference tends to amplify TFPR difference. For example, in 1996, the TFP gains from removing idiosyncratic distortions are 40.3 percent, as compared with 35.2 percent in the baseline calculation.[23] In terms of the growth of the allocative efficiency between 1983 and 1996, the allocative efficiency improved by 21 percent, or 1.64 percent per year, which is larger than the growth rate of allocative efficiency (1.46 percent per year) under our baseline calculation.[24] Therefore, we conclude that our main results are robust to alternative measures of plant labor input.

4.5.3 Balanced versus Unbalanced Panel

In our benchmark sample, a plant could enter or exit at any time. To examine the quantitative importance of the extensive margin versus the intensive margin in terms of allocative efficiency and its improvement over time, we now restrict the sample to plants that survived the whole period (1980–1996), which we denote as the balanced panel. The total number of observations for the whole sample period is now 9,129, with 537 in each year.

The right column of Table 5 reports the TFP gains of moving to efficient allocation under the balanced panel. Compared with the benchmark case, under the balanced panel the TFP gains are now smaller, suggesting that part of the resource misallocation comes from the extensive margin. Over time, TFP gains also decline. Between 1983 and 1996, Chilean allocative efficiency increased by 12.5 percent, or 0.96 percent per year. These numbers are again smaller than their counterparts in the benchmark case (19 percent and 1.46 percent), suggesting that about one-third of the overall improvement in resource allocation comes from the extensive margin. Aggregate manufacturing TFP for the balanced panel grew by 2.89 percent per year. Therefore, an improvement in allocative efficiency contributed to about 33.2 percent (0.96/2.89) of the total TFP growth in Chile that took place between 1983 and 1996, a magnitude closer to the benchmark case (39.7 percent).

Another margin we examine is whether changes in the distribution of physical productivity between 1983 and 1986 originate from the extensive or intensive margin. Intuitively, both the exit of less productive plants and their faster growth of physical productivity than the industry average would lead to a thinner left tail. To this end, we plot the distribution of physical productivity for the balanced panel in Figure 6. We find that changes in distribution of physical

[23] Using the wage bill as the measure of plant labor input, Hsieh and Klenow (2009) report a value of 36.1 percent of TFP gains in 1998 for U.S. manufacturing plants moving to efficient resource allocation within industries.

[24] Moreover, the dominant role of the decline in the variance of TFPR and output wedge in the improvement of allocative efficiency is robust to the measure of plant labor input as wage bills.

productivity share a similar pattern with the unbalanced panel, that is, over time the left tail of physical productivity became much thinner. This indicates that firms with different physical productivity initially in 1983 had a different growth rate for physical productivity between 1983 and 1996. To confirm this conjecture, we classify firms in the balanced panel into quintiles accordingly to their physical productivity in 1983. We then compute the average growth rate of physical productivity between 1983 and 1996 for each quintile. Consistent with Figure 6, plants with lower initial physical productivity had enjoyed faster growth in TFPQ during our sample period (Table 6). This suggests that between 1983 and 1996, changes in idiosyncratic distortions, especially on the initially low TFPQ plants, not only contributed to an improvement of resource allocation among incumbent firms, but also to their faster productivity growth.

Finally, for the unbalanced panel the positive correlation between TFPQ and TFPR in the data may be driven by selection effects, as firms with high implicit taxes are induced to exit unless they also have high TFPQ. Hence, even if plant-level efficiency and idiosyncratic distortions are uncorrelated, the observed plant-level frictions and efficiency could potentially exhibit positive correlation due to selection. As a result, the fall the positive correlation in the data may simple reflect the selection effect. As a robustness check we compute the covariance and correlation between physical and revenue productivity using the balanced panel. We find a similar magnitude in the decline for correlation and covariance of physical and revenue productivity. This result suggests that the main driving force for the observed decline in covariance of physical and revenue productivity is a fall in the underlying correlation between efficiency and micro-distortions.

4.5.4 Selection and Revenue Productivity

Our model assumes homogeneous markup across firms. Accordingly, revenue productivity dispersion reflects the dispersion of idiosyncratic distortions. In reality, however, within-industry dispersion in revenue productivity or prices may reflect idiosyncratic demand shift or market power variations (see Foster, Haltiwanger, and Syverson 2008). To distinguish the source of TFPR dispersion, we next look at the correlation of TFPR with plant exit.

To this end, we define exit as $\xi_{ijt} = 1$ if plant i in industry j at year t exit at $t+1$. We then run the following pooled Probit regression[25] (with industry and time dummies)

$$\Pr(\xi_{ijt} = 1) = F(\beta_0^R + \beta_1^R \log(TFPR_{ijt}) + \beta_1^Q \log(TFPQ_{ijt})).$$

If the revenue productivity dispersion is mainly driven by idiosyncratic distortions, the estimated coefficient for TFPR tends to be positive, $\beta_1^R > 0$, suggesting that low TFPR firms are less likely to exit. If, instead, variations in market power dominate revenue productivity dispersions, then

[25] We thank one of the anonymous referees for suggesting this analysis. See Hsieh and Klenow (2009) and Yang (2012) for a similar test.

the estimated coefficient for TFPR tends to be negatively, since low TFPR firms tend to have less market power and thus are more likely to exit.

Table 8 shows that lower revenue productivity is associated with a lower probability of exit. A one-log-point decrease in TFPR is associated with 22.9 percent lower probability of exit. On the other hand, lower physical productivity is associated with higher probability of exit, consistent with the prediction of the standard model. The fact that a lower TFPR plants have a lower probability of exit suggests that the main driving force of revenue productivity dispersion across Chilean manufacturing plants is idiosyncratic distortions.

5 Banking Reforms and Changes in Allocative Efficiency

What are the potential sources of resource misallocation among Chilean manufacturing plants and what policies might have led to an improvement of allocative efficiency observed during the 1980s? It has been argued in the literature that in Chile the presence of business groups (so called "grupo") might have distorted the allocation of bank credit between firms owned or controlled by business groups and independent firms before and during the financial crisis. It is also noteworthy that Chile conducted a series of banking reforms in the 1980s. Therefore, we make a first pass in linking the preferential credit policy by Chilean banks to our measured idiosyncratic distortions and assess the potential roles that Chile's banking reforms might have played in the observed improvement of resource allocation after the 1982 financial crisis.

5.1 Preferential Credit Policy and Distortions

In this section, we first document the widespread presence of preferential credit policy among Chilean banks towards the affiliated firms to motivate our following empirical exercises. We then characterize the link between our measures of idiosyncratic distortions and a plant's leverage position and the link between the degree of resource misallocation and an industry's leverage position.

5.1.1 Preferential Bank Loan towards Affiliated Firms

Before the banking reform occurred during the early and mid-1980s, all the major business groups in Chile were organized around one or more banks, which were used to channel credit to the firms they owned or controlled. For example, in 1979 business groups directly controlled 10 major banks, whose equity represented more than 80 percent of all private bank equity. Accordingly, firms in business groups were in a relatively favored financial position.[26] This is evident in the rates of debt growth. In 1980 and 1981, independent firms absorbed debt at a

[26] According to Tybout (1986), in 1978, when Chile's capital accounts was still relatively closed, group-affiliated firms enjoyed financial costs that average 14 percent a year, while independent firms were paying an average of 22 percent.

real rate that exceeded their operating earnings rate by only a few percentage points. Yet, the group-affiliated firms absorbed debt at rates that exceeded their returns on equity by close to 30 percent over the two-year period (Galvez and Tybout, 1985). In late 1982, the proportion of credit that banks had granted to the firms directly related to the controlling business groups became alarmingly high. In fact, some of the banks had granted almost half of their loans to the controlling grupos (Table 4-2 of Edwards and Edwards, 1987).

The preferential credit access by group-affiliated firms is reflected by the drastically different investment growth that occurred in 1981 in the presence of high interest rates. According to Galvez and Tybout (1985), in 1981 independent firms reduced the rate of fixed capital investment from 7 percent in 1980 to –6 percent. By contrast, group-affiliated firms reduced the rate of fixed capital investment from 11 percent in 1980 to 8 percent in 1981, suggesting these firms adjusted their investment plan by too little in reaction to rising interest rates and financed the continuing expansion with additional debt.

Another potential channel for preferential access to bank loans by group-affiliated Chilean firms to translate into output distortion is through working capital used to finance the purchase of intermediate inputs. Edwards and Edwards (1987, pp.65) argue that in late 1970s there was a strong credit demand, by all sorts of firms, to finance working capital. Also, according to Corbo and Sanchez (1985), all the firms in their survey ranked the increasing cost to finance working capital as the number one negative shock during the 1981–1983 financial crisis, suggesting the major role bank loans played in funding of working capital. In addition, the findings of Oberfield (2013) suggest that during Chilean financial crisis, deteriorating financing conditions increased the cost of working capital required to purchase imported intermediates inputs.

5.1.2 Leverage Position and Distortions

Even though in our data it is not possible to identify which plants belong to the business groups, in this section we make a first pass of relating a plant's leverage position to measured distortions. Intuitively, group-affiliated firms had a larger leverage position. To establish the linkage between leverage and distortions, we regress TFPR, different wedges, and TFPQ on the liability-asset ratio, $\frac{\text{total liability}}{\text{total assets}}$, with sectoral fixed effects. For example, for TFPR, we specify

$$\log \frac{TFPR_{si}}{\overline{TFPR}_s} = \beta_0 + \beta_1 \log \left(\frac{\text{total liability}}{\text{total assets}} \right) + \varepsilon_{si}.$$

If the preferential credit access by group-affiliated firms is the main distortion driving our results, we should observe that firms with a higher liability-asset ratio have lower revenue productivity and a higher output wedge, $1 - \tau_{Y_{si}}$. Table 9 reports estimates of β_1 for different measures of distortions. We see that for both 1980 and 1981 plants with a higher liability-asset ratio had a higher output subsidy and a lower $\frac{TFPR}{\overline{TFPR}}$. Moreover, these plants tended to have lower physical productivity. Thus, our finding points to preferential credit policy as one plausible source of the observed idiosyncratic distortions.

Similarly, if group-affiliated firms are disproportionally represented by some particular industries, we should observe that those industries tend to be subject to greater resource misallocation before the banking reform, assuming that the preferential credit policy is the main policy distortion. We therefore check the cross-industry correlation between an industry's median liability-asset ratio and the different measures of its misallocation. Table 10 shows that in both 1980 and 1981, industries with a larger median liability-asset ratio had a larger variance of revenue productivity, output distortions and physical productivity. This positive correlation got strengthen as Chilean economy moved towards the financial crisis. Therefore, our evidence suggests that before the banking reforms, bank's preferential credit policy towards affiliated firms were likely to be an important driver for resource misallocation among Chilean manufacturing plants.

5.2 Banking Reforms and Changes in Distortions

Is it possible that banking reforms in Chile played a role in the observed improvement of allocative efficiency? In this section, we first document Chile's banking reforms that took place in the early and middle 1980s and their impact on the banks' self-loans. We then assess the role of banking reforms by examining at the industry level the relationship between the industry's initial leverage position and the change in the allocative efficiency since 1983.

5.2.1 Chile's Banking Reforms

In response to the alarmingly large share of bank loans made to affiliated firms, Chile conducted a series of banking reforms started in the middle of a banking crisis. In the late 1981, the Superintendency of Banks adopted measures that limited the amount of bank exposure to a single enterprise and to a bank's own subsidiaries. But it was not until 1982 that a set of comprehensive measures were approved that tightened bank supervision. The regulation included a more precise definition of the limit on loans to a single enterprise that took into account the interlocking ownership of firms. In June 1982, the Superintendency of Banks announced a new self-loan limit of 5 percent of a bank's total loans, meaning a 100 percent of a bank's equity. Two weeks later, the target was changed to a complete ban on self-loans to shell companies, and the limit on self-loans to productive companies was reduced to 2.5 percent of total loans.

Meanwhile, for the first time in the early 1980s, the Superintendency attempted to classify loans on a risk scale. In April 1981, its required the classification of the 300 largest debtors. However, it turned out that as of June 1982, when the overall result of the classification procedure was published, only 6 percent of loans were considered to be at risk. According to Held (1989), the Superintendency of Banks did not review the classification of loans made by at least some important banks, and self-loans among the business groups comprising the respective banks had simply not been classified.

Chile's new banking legislation was enacted in 1986 (Law No. 18,756) and supplemented in 1988 (Law No. 18707) and 1989 (Law No. 18818). A major issue in the new banking law was the establishment of stringent restrictions on the power of banks to do business with related parties. The various loans granted to firms owned by the same group of shareholders were viewed as a single individual loan subject to relevant loan limitation —5 percent or 25 percent of the bank's equity, depending on whether valid guarantees were involved (Article 84, No. 2). In addition, the agreed-upon terms for such debt had to be made at market value. The Superintendency of Banks was also legally empowered to object to various kinds of contracts executed by the bank and the related parties (Article 19 bis).

Following the series of banking reforms, the preferential credit access by group-affiliated firms in Chile was largely eliminated. Figure 7, which replicates Figure 7 of Held and Jimenez (1999), illustrates the substantial reduction of self-loan between June 1982 and 1998, both as a proportion of bank's equity and as a proportion of banks' total loans. The ratio of self-loans to banks' equity dropped from 160 percent in 1983 to about 20 percent in 1986 and has remained at that level since then. Similarly, the share of self-loans in banks' total loan portfolio declined from 16 percent in 1983 to around 2 percent by 1988. Such an outcome suggests that the Superintendency of Banks succeeded in preventing business groups from advancing preferential credit access to their affiliated firms.

In addition, the reorganization of the banking sector led to a severe curtailing of banking cartels. Between 1982 and 1985, the government intervened in 21 financial institutions; 14 were liquidated and the rest were rehabilitated and privatized. A vigorous bank recapitalization program was carried out in 1985 and 1986, based on selling stocks in those banks to small-scale stockholders. In the late 1986, the Herfindahl concentration index for Chile's banking sector was 0.102, compared to 0.082 in late 1988. During the same period, the share of the five main institutions in total loans fell from 61 percent to 55 percent.

5.2.2 Leverage Position and Improved Allocation

To assess the contribution of banking reforms to improved allocation, we explore the link between the magnitudes of different measures of an industry's improvement in allocation and its initial leverage position during 1980–1982. Our evidence suggests that plants with initially higher liability-asset ratios had lower physical and revenue productivity initially. Accordingly, industries with higher liability-asset ratios before the banking reforms are likely to be subject to more severe resource misallocation due to the presence of self-loans. Therefore, if the banking reforms were important for the allocative efficiency gain in Chile after the financial crisis, we should observe a larger improvement in allocation for industries with higher initial liability-asset ratio.

Table 11 reports the cross-industry correlation of the initial liability-asset ratio during 1980-1982 with the allocative efficiency gain between 1983 and 1996, and changes in dispersion of physical and revenue productivity. We use the industry's value-added shares in the manufacturing sector as weights when computing correlation coefficients. The correlation of the initial leverage position with the allocative efficiency gain during this period is 0.53, and its correlation with the decline in the dispersion of TFPR is 0.47. This suggests that the banking reforms in Chile are likely to be important in the resource reallocation via the stringent restrictions on the power of banks to do business with related parties.

Another interesting finding is that industries with a higher initial liability-asset ratio in 1980–1982 also experienced a faster decline in the dispersion of TFPQ between 1983 and 1996, with a weighted correlation coefficient of 0.42. A possible explanation is that according to the new banking law, the Superintendency of Banks requires all banks to rate the quality of all loans above a certain size according to their risks. In addition, the Superintendency receives this information monthly and can compare risk ratings given by different banks to the same companies. This reform would tend to increase banks' incentive to monitor and screen the business groups' self-loans, raising the intermediation cost for business-affiliated firms. Accordingly, managers in group-affiliated firms would exert more effort to increase their plants' productive efficiency by, for example, better inventory management, streamlining production lines, closing inefficient plants, and reassigning workers. All these process innovations would likely contribute to an increase in TFPQ.

A positive relationship between the industry's initial leverage position and improvements in allocative efficiency is puzzling from the perspective of standard models of financial frictions (e.g. Buera and Shin, 2010 and Moll, 2010). According to these models, an *increase* in an economy's overall leverage ratio implies an improvement in resource allocation. In Appendix 7.4, we develop a simple model to formalize the idea that the banking reform leads to both an improvement in resource allocation and a lower overall leverage position of an economy. The key ingredient in the model is the heterogeneity of entrepreneurs: a fraction of them own both a bank and a project while the remaining entrepreneurs only own a project. Accordingly, the collateral constraint on the project belonging to the entrepreneur who also owns a bank is essentially not binding, while it is binding for a project belonging to the independent entrepreneur. This creates idiosyncratic distortions that resemble output distortion. And banking reforms, by restricting the share of self-loans in the net worth of the entrepreneur who owns a bank, leads to a decline in the dispersion of TFPR.

Apart from the banking reforms, other policy reforms Chile implemented during this period might also have contributed to the allocative efficiency gain established in this paper. For example, the 1984 corporate tax reform lowered the tax on retained earnings and eliminated the preferential treatment of a firm's debt liabilities. By eliminating the taxation of retained profits, this policy reform might have allowed larger and more productive firms to accumulate more internal funds for further investment, rather than to distribute these funds as dividends from retained earnings. As a result, larger firms expanded their production scales. The contribution of corporate tax reforms to better resource allocation in Chile is clearly an interesting issue for future research.

6 Conclusion

Chile's aggregate TFP grew spectacularly and became the country's engine of output growth in the decade following its 1982 financial crisis. In this paper, we use micro data on manufacturing firms to assess the role that resource reallocation played in aggregate productivity growth during this period. We find that the cross-sectional allocative efficiency significantly improved and contributed to about 40 percent of the aggregate TFP growth between 1983 and 1996. Moreover, this improvement in allocative efficiency was essentially driven by a reduction in the cross-sectional dispersion of output distortion. Interestingly, a reduction in the least productive plants' implicit output subsidy and the corresponding increase in their average revenue productivity were the most important reasons for the reduction in resource misallocation during this period. Consequently, factor inputs were reallocated from the least productive plants toward more productive ones.

We have provided a first pass in linking a series of Chile's banking reforms during the early and mid-1980s to the observed improvement in resource allocation. The regression results suggest that in the early 1980s, Chilean plants with higher implicit output subsidy and thus lower revenue productivity had, on average, a higher liability-asset ratio, suggesting preference credit access by these firms. Moreover, industries with a higher average liability-asset ratio in the early 1980s enjoyed a faster improvement in allocative efficiency since 1983, with a correlation coefficient of 0.53. Such evidence suggests that Chile's banking reforms during the early and mid-1980s, which largely restricted self-loans within business groups, were likely important factors in reducing the resource misallocation between business group-affiliated and independent firms.

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 reducing such distortions?[27] 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 for shedding light on how Western economies can emerge from their current recession as Chile did in the mid-1980s. We address some of these issues in our ongoing research.

[27] To 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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7 Appendix

In this appendix, we first describe the procedure for data construction and sampling. We then derive the agregate TFP and decompose it into various components. Finally, we present a simple model to capture the idea that banking reforms, by restricting self-loans, contribute to the improvement in allocative efficiency.

7.1 Data Construction and Sampling

The construction of capital series follows Liu (1990). There are five categories of capital good: buildings, machines, vehicles, furniture and others. First, we deflate investment and capital for each category using category-specific deflators. Most plants have capital stock available for two years 1980 and 1981. However, some plants may have missing capital information later in the sample. For plants having capital available in 1980, we use the perpetual inventory method to update forward the capital using real investment following the law of motion for capital. For the plants without capital in 1980, we generate their capital backward starting from the year when capital and investment information is available. We assume a depreciation rate of 5 percent for building, 10 percent for machines and 20 percent for vehicles, and zero for furniture and others. Finally, the aggregate real capital series for the manufacturing sector is the sum of capital stock for each category using the 1980 base series. For those plants where the 1980 capital information is missing, we aggregate using the 1981 based series.

We clean the dataset in the following steps. First, we keep the plants which enter/exit at maximum twice, and those that stay in the sample at least for five consecutive years. We drop the plant in all years with the top 0.1 percent of investment and firms in all years with missing and negative observations in investment, number of labor, capital, value added and wage. In the original data, we find plants with at least 10 workers. We drop plants in all years with 0.2 percent tail of wage in each year.

7.2 Derivation of Aggregate TFP

In this section, we derive (1) and (3). Again, we use the growth accounting $TFP_s = \frac{Y_s}{K_s^{\alpha_s} L_s^{1-\alpha_s}}$. The first-order conditions of a firm i in industry s imply

$$MRPL_{si} = W/\left(1-\tau_{ysi}\right) \tag{15}$$

$$MRPK_{si} = R\left(1+\tau_{ksi}\right)/\left(1-\tau_{ysi}\right), \tag{16}$$

From the first-order conditions, we obtain

$$\frac{K_{si}}{L_{si}} = \frac{W}{R}\frac{\alpha_s}{1-\alpha_s}\frac{1}{1+\tau_{ksi}}. \tag{17}$$

We can express L_{si} and K_{si} as functions of Y_s. Equation (16) implies

$$\alpha_s \left[\left(1-\tau_{ysi}\right) P_{si}\right] \frac{\sigma}{\sigma-1} A_{si} \left(\frac{K_{si}}{L_{si}}\right)^{\alpha_s-1} = \left(1+\tau_{ksi}\right) R. \tag{18}$$

Note also:

$$P_{si} = \left(\frac{Y_{si}}{Y_s}\right)^{-\frac{1}{\sigma}} P_s = \left(\frac{A_{si} K_{si}^{\alpha} L_{si}^{1-\alpha}}{Y_s}\right)^{-\frac{1}{\sigma}} P = \left(\frac{A_{si}\left(K_{si}/L_{si}\right)^{\alpha} L_{si}}{Y_s}\right)^{-\frac{1}{\sigma}} P_s \tag{19}$$

$$= \left(\frac{A_{si}\left(K_{si}/L_{i}\right)^{\alpha_s-1} K_{si}}{Y_s}\right)^{-\frac{1}{\sigma}} P_s. \tag{20}$$

Plugging (19) into (18) and using (17), we get

$$L_{si} = \frac{A_{si}^{\sigma-1}\left(1-\tau_{ysi}\right)^{\sigma}}{\left(1+\tau_{ksi}\right)^{\alpha_s(\sigma-1)}} \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{R}{\alpha}\right)^{\alpha_s(1-\sigma)} \left(\frac{W}{1-\alpha_s}\right)^{\alpha_s(\sigma-1)-\sigma} Y_s. \tag{21}$$

Plugging (20) into (18) and using (17), we get

$$K_{si} = \frac{A_{si}^{\sigma-1}\left(1-\tau_{ysi}\right)^{\sigma}}{\left(1+\tau_{ksi}\right)^{\alpha_s(\sigma-1)+1}} \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{R}{\alpha_s}\right)^{\alpha_s(1-\sigma)-1} \left(\frac{W}{1-\alpha_s}\right)^{(\alpha_s-1)(\sigma-1)} Y_s. \tag{22}$$

We now compute Y_{si}

$$\begin{aligned} Y_{si} &= A_{si}\left(\frac{K_{si}}{L_{si}}\right)^{\alpha_s} L_{si} \\ &= A_{si}\left[\frac{W_{si}}{R}\frac{\alpha_s}{1-\alpha_s}\frac{1}{1+\tau_{ksi}}\right]^{\alpha_s} L_{si} \\ &= \frac{A_{si}^{\sigma}\left(1-\tau_{ysi}\right)^{\sigma}}{\left(1+\tau_{ksi}\right)^{\alpha_s\sigma}} \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{\alpha_s}{R}\right)^{\alpha\sigma} \left(\frac{1-\alpha_s}{W}\right)^{\sigma(1-\alpha_s)} Y_s. \end{aligned} \tag{23}$$

Using (21) and (22), we can rewrite L and K as

$$L_s = \sum_{i=1}^{M_s} L_{si} = Y_s \sum_{i=1}^{M_s} \frac{A_{si}^{\sigma-1}\left(1-\tau_{ysi}\right)^{\sigma}}{\left(1+\tau_{ksi}\right)^{\alpha_s(\sigma-1)}} \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{R}{\alpha_s}\right)^{\alpha_s(1-\sigma)} \left(\frac{W}{1-\alpha_s}\right)^{\alpha_s(\sigma-1)-\sigma}, \tag{24}$$

$$K_s = \sum_{i=1}^{M_s} K_{si} = Y_s \sum_{i=1}^{M_s} \frac{A_{si}^{\sigma-1}\left(1-\tau_{ysi}\right)^{\sigma}}{\left(1+\tau_{ki}\right)^{\alpha_s(\sigma-1)+1}} \left(\frac{\sigma-1}{\sigma}\right)^{\sigma} \left(\frac{R}{\alpha_s}\right)^{\alpha_s(1-\sigma)-1} \left(\frac{W}{1-\alpha_s}\right)^{(\alpha_s-1)(\sigma-1)}. \tag{25}$$

Plugging (24) and(25) into the definition of TFP, we get

$$TFP_s = \frac{1}{\left[\left(\sum_{i=1}^{M_s}\frac{A_{si}^{\sigma-1}(1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)+1}}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{R}{\alpha_s}\right)^{\alpha_s(1-\sigma)-1}\left(\frac{W}{1-\alpha_s}\right)^{(\alpha_s-1)(\sigma-1)}\right)\right]^{\alpha_s}}$$
$$\frac{1}{\left[\sum_{i=1}^{M_s}\frac{A_{si}^{\sigma-1}(1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)}}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{R}{\alpha_s}\right)^{\alpha_s(1-\sigma)}\left(\frac{W}{1-\alpha_s}\right)^{\alpha_s(\sigma-1)-\sigma}\right]^{1-\alpha_s}}$$
$$= \frac{\left[\frac{\sigma}{\sigma-1}\left(\frac{W}{1-\alpha_s}\right)^{1-\alpha_s}\left(\frac{R}{\alpha_s}\right)^{\alpha_s}\right]^{\sigma}}{\left[\sum_{i=1}^{M_s}\frac{A_{si}^{\sigma-1}(1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)+1}}\right]^{\alpha_s}\left[\sum_{i=1}^{M_s}\frac{A_{si}^{\sigma-1}(1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)}}\right]^{1-\alpha_s}}. \tag{26}$$

Finally, using (23), we have

$$Y_s = \left[\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$
$$= \left[\sum_{i=1}^{M_s}\left(\frac{A_{si}^{\sigma}(1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s\sigma}}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma}\left(\frac{\alpha_s}{R}\right)^{\alpha_s\sigma}\left(\frac{1-\alpha_s}{W}\right)^{\sigma(1-\alpha_s)}Y_s\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$
$$= Y_s\left[\frac{\sigma-1}{\sigma}\left(\frac{\alpha_s}{R}\right)^{\alpha_s}\left(\frac{1-\alpha_s}{W}\right)^{(1-\alpha_s)}\right]^{\sigma}\left[\sum_{i=1}^{Ms}\left(A_{si}\frac{(1-\tau_{ysi})}{(1+\tau_{ksi})^{\alpha_s}}\right)^{\sigma-1}\right]^{\frac{\sigma}{\sigma-1}},$$

which gives

$$\frac{\sigma}{\sigma-1}\left(\frac{W}{1-\alpha_s}\right)^{1-\alpha_s}\left(\frac{R}{\alpha_s}\right)^{\alpha_s} = \left[\sum_{i=1}^{Ms}\left(A_{si}\frac{(1-\tau_{ysi})}{(1+\tau_{ksi})^{\alpha_s}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}. \tag{27}$$

Substituting (27) 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 (26), we get equation (1).

To derive equation (14), we rewritte TFPR for an individual plant as

$$TFPR_{si} = A_{si}^{1-\frac{1}{\sigma}}\left(K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}\right)^{-\frac{1}{\sigma}}P_sY_s^{\frac{1}{\sigma}} \tag{28}$$
$$= A_{si}^{1-\frac{1}{\sigma}}A_{si}^{\frac{1}{\sigma}-1}\frac{(1+\tau_{ksi})^{\alpha_s}}{1-\tau_{ysi}}\frac{\sigma}{\sigma-1}\left(\frac{R}{\alpha_s}\right)^{\alpha_s}\left(\frac{W}{1-\alpha_s}\right)^{1-\alpha_s}. \tag{29}$$

Equation (29) implies that if an increase in $\frac{(1+\tau_{ksi})^{\alpha_s}}{1-\tau_{ysi}}$ is accompanied by a proportional increase in $A_{si}^{1-\frac{1}{\sigma}}$, then changes in TFPR show up as an increase in TFPQ (holding constant the relationship between TFPQ and TFPR). On the other hand, when $\frac{(1+\tau_{ksi})^{\alpha_s}}{1-\tau_{ysi}}$ increases while A_{si} stays unchanged, then the relationship between TFPQ and idiosyncratic distortions (TFPR) changes. Taking log difference to (28), we have

$$\Delta \log TFPR_{si} = \left(1 - \frac{1}{\sigma}\right) \Delta \log A_{si} - \frac{1}{\sigma} \left[\alpha_s \Delta \log K_{si} + (1-\alpha_s) \Delta \log L_{si}\right] + \Delta \log P_s Y_s^{\frac{1}{\sigma}}. \quad (30)$$

Taking average of both sides of (30) across all firms for the qth quintile and across all firms in the industry s, respectively, and subtracting each other, we obtain equation (14).

7.3 Decomposition of Aggregate TFP

Under the central limit theorem, as $M^s \to \infty$, equation (1) becomes

$$\begin{aligned} \log TFP_s = {} & \frac{\sigma}{\sigma-1} \log \int \left(A_{si} \frac{(1-\tau_{ysi})}{(1+\tau_{ksi})^{\alpha_s}} \right)^{\sigma-1} \\ & - \alpha_s \log \int \frac{A_{si}^{\sigma-1} (1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)+1}} - (1-\alpha_s) \log \int \frac{A_{si}^{\sigma-1} (1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)}}. \end{aligned} \quad (31)$$

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

$$\begin{aligned} & \log \int \left(A_{si} \frac{(1-\tau_{ysi})}{(1+\tau_{ksi})^{\alpha_s}} \right)^{\sigma-1} \\ & = (\sigma-1) E[\log A] + \frac{(\sigma-1)^2}{2} var[\log A] + (\sigma-1) E[\log(1-\tau_{ysi})] + \frac{(\sigma-1)^2}{2} var[\log(1-\tau_{ysi})] \\ & - \alpha_s (\sigma-1) E[\log(1+\tau_{ksi})] + \frac{(\sigma-1)^2 \alpha_s^2}{2} var[\log(1+\tau_{ksi})] \\ & + (\sigma-1)^2 cov[\log A_{si}, \log(1-\tau_{ysi})] \\ & - \alpha_s (\sigma-1)^2 cov[\log A_{si}, \log(1+\tau_{ksi})] - \alpha_s (\sigma-1)^2 cov[\log(1-\tau_{ysi}), \log(1+\tau_{ksi})]. \end{aligned} \quad (32)$$

$$\begin{aligned} & \log \int \frac{A_{si}^{\sigma-1} (1-\tau_{ysi})^{\sigma}}{(1+\tau_{ksi})^{\alpha_s(\sigma-1)+1}} \quad (33) \\ & = (\sigma-1) E[\log A] + \frac{(\sigma-1)^2}{2} var[\log A] + \sigma E[\log(1-\tau_{ysi})] + \frac{\sigma^2}{2} [var \log(1-\tau_{ysi})] \\ & - [1+\alpha_s(\sigma-1)] E[\log(1+\tau_{ksi})] + \frac{[1+\alpha_s(\sigma-1)]^2}{2} var \log(1+\tau_{ksi}) \\ & + (\sigma-1) \sigma cov[\log A, \log(1-\tau_{ysi})] \\ & - (\sigma-1)[1+\alpha_s(\sigma-1)] cov[\log A, \log(1+\tau_{ksi})] \\ & - \sigma [1+\alpha_s(\sigma-1)] cov[\log(1-\tau_{ysi}), \log(1+\tau_{ksi})]. \end{aligned}$$

$$
\begin{aligned}
\log \int \frac{A_{si}^{\sigma-1}\left(1-\tau_{ysi}\right)^{\sigma}}{\left(1+\tau_{ksi}\right)^{\alpha_s(\sigma-1)}} = & \left(\sigma-1\right) E\left[\log A\right] + \frac{\left(\sigma-1\right)^2}{2} var \log A + \sigma E\left[\log\left(1-\tau_{ysi}\right)\right] \\
& + \frac{\sigma^2}{2} var\left[\log\left(1-\tau_{ysi}\right)\right] - \alpha_s\left(\sigma-1\right) E\left[\log\left(1+\tau_{ksi}\right)\right] \\
& + \frac{\left[\alpha_s\left(\sigma-1\right)\right]^2}{2} var\left[\log\left(1+\tau_{ksi}\right)\right] \\
& + \left(\sigma-1\right)\sigma cov\left[\log A, \log\left(1-\tau_{ysi}\right)\right] \\
& - \left(\sigma-1\right)\alpha_s\left(\sigma-1\right) cov\left[\log A, \log\left(1+\tau_{ksi}\right)\right] \\
& - \sigma\alpha_s\left(\sigma-1\right) cov\left[\log\left(1-\tau_{ysi}\right), \log\left(1+\tau_{ksi}\right)\right]. \qquad (34)
\end{aligned}
$$

Plugging (32), (33) and (34) into (31) and rearranging, we have

$$
\begin{aligned}
& \log TFP_s \\
& = E\log A_{si} + \frac{\sigma-1}{2} var \log A_{si} \\
& - \frac{\sigma}{2} var\left[\log\left(1-\tau_{ysi}\right)\right] - \frac{\alpha_s + \alpha_s^2\left(\sigma-1\right)}{2} var\left[\log\left(1+\tau_{ksi}\right)\right] \\
& + \alpha_s\sigma cov\left[\log\left(1-\tau_{ysi}\right), \log\left(1+\tau_{ksi}\right)\right]. \qquad (35)
\end{aligned}
$$

To see the relationship between equations (3) and (35), note that in (3), the first two arguments are

$$
\frac{1}{\sigma-1}\log\sum A_i^{\sigma-1} = E\left[\log A\right] + \frac{\sigma-1}{2} var\left[\log A\right]. \qquad (36)
$$

$$
\begin{aligned}
& var\left(\log TFPR_{si}\right) \\
& = var\left(\log\frac{\left(1+\tau_{ksi}\right)^{\alpha_s}}{1-\tau_{ysi}}\right) \\
& = \alpha_s^2 var\left[\log\left(1+\tau_{ksi}\right)\right] + var\left[\log\left(1-\tau_{ysi}\right)\right] \qquad (37) \\
& - 2\alpha_s cov\left[\log\left(1-\tau_{ysi}\right), \log\left(1+\tau_{ksi}\right)\right]
\end{aligned}
$$

Plugging equations (36) and (37) into (3), we have

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

which is the same as (35).

7.4 A Simple Model of Banking Reforms

In this section, we develop a simple model to formalize the idea that the preferential bank loan access by group-affiliated firms creates idiosyncratic distortions that resemble output distortion. The model abstracts from many ingredients such as the entrepreneurial saving decision and the household's problem to highlight the asymmetric access to bank loan by different types of firms and the effects of banking reforms on such asymmetry.[28] In particular, we want our model to match the following facts:

1. Before the banking reform, firms having a higher implicit output subsidy, $1-\tau_y$ were less productive in terms of physical productivity and had a higher debt-to-asset ratio.
2. The banking reform, which had restricted the ratio of self-loans in the bank equity, has led to a decline in $1-\tau_y$ for firms with low physical productivity (and initially higher $1-\tau_y$).
3. After the banking reform, the variance of output distortion and, thus, revenue productivity , declined steadily, while the covariance between physical and revenue productivity declined.

Consider an economy with a continuum of entrepreneurs with unit mass. Entrepreneurs have access to the technology of operating projects and are residual claimants on the profits. Each entrepreneur can operate only one project.

Entrepreneurs are classified into two types, type-E and type-F, with share η and $1-\eta$, respectively. A type-F (financially integrated) entrepreneur owns a bank, while a type-E (independent) entrepreneur does not.

7.4.1 Technology

The revenue function of a type-j project is given by

$$y_t^j = A_t^j \left[\left(k_t^j\right)^{\alpha} \left(l_t^j\right)^{1-\alpha} \right]^{\mu}, \; j = E \text{ or } F.$$

where y_t^j, k_t^j, and l_t^j denote the output, capital stock, and labor of a type-j project, respectively. For simplicity, we assume away the within-group heterogeneity and time variation in physical productivity , i.e. $A_t^E = \chi^E$, $A_t^F = \chi^F$, where $0 < \chi^F < \chi^E$ reflecting that the technology of a type-E project is more efficient than that of a type-F project.[29]

[28] A fully fledged model is available upon request.

[29] In an appendix, available upon request, we extend the model to allow for entrepreneurial effort choices and the fixed banking intermediation costs, thus endogenizing a project's mean TFPQ. The banking reform forces the bank to exert more strict screening or monitoring on a self-loan. This would incur a fixed intermediation cost to type-F entrepreneurs. With a negative wealth effect, type-F entrepreneurs would exert more effort, which enhances their TFPQ.

7.4.2 Working Capital Finance

Both types of projects need to advance working capital before production takes place. Entrepreneurs finance working capital with their net worth or a bank loan. A type-E entrepreneur has only limited access to bank lending due to limited enforcement of debt repayment. By contrast, a type-F entrepreneur can borrow freely from the bank, reflecting the preferential policy of Chilean bank loans toward affiliated enterprises. Accordingly, credit is misallocated between the two types of entrepreneurs.

7.4.3 The Type-j Entrepreneur's Problem

At time t, a type-j entrepreneur with net worth s_{t-1}^j solves

$$\pi_t^j\left(s_{t-1}^j\right) = \max_{l_t^j,k_t^j,b_t^j} A_t^j\left[\left(k_t^j\right)^\alpha\left(l_t^j\right)^{1-\alpha}\right]^\mu - b_t^j\left(1+i_t\right) \tag{38}$$

subject to

$$\left(W_t l_t^j + R_t k_t^j\right)\left(1+i_t\right) \leq b_t^j, \tag{39}$$

$$b_t^j \leq \eta_t^j s_{t-1}^E,\ \eta_t^j \geq 1. \tag{40}$$

(39) is the working capital constraint in that the size for working capital is constrained by the value of bank loan. (40) is the borrowing constraint, stating that the bank loan is constrained to be a fraction η_t^j of entrepreneur's net worth. η_t^j is a choice variable by the bank, as will be specified below. $\eta_t^j = 1$ implies that the project is self-financing. Implicitly, entrepreneurs have incentive to default on the factor payment. Accordingly, the size of their working capital loans is constrained to be proportional to the individual entrepreneur's net worth, which serve as the collateral for bank loan. It is easy to see that the working capital constraint (39) is binding. Accordingly, the entrepreneur's problem can be rewritten as

$$\pi_t^j\left(s_{t-1}^j\right) = \max_{l_t^j,k_t^j} A_t^j\left[\left(k_t^j\right)^\alpha\left(l_t^j\right)^{1-\alpha}\right]^\mu - \left(W_t l_t^j + R_t k_t^j\right)\left(1+i_t\right)$$

subject to

$$\left(W_t l_t^j + R_t k_t^j\right)\left(1+i_t\right) \leq \eta_t^j s_{t-1}^j,\ \eta_t^j \geq 1. \tag{41}$$

The first-order conditions for labor and capital are

$$MRPL_t^j \equiv \left(1-\alpha\right)\mu A_t^j\left(k_t^j\right)^{\alpha\mu}\left(l_t^j\right)^{(1-\alpha)\mu-1} = \left(1+i_t\right)\left[1+\lambda_t^j\right]W_t, \tag{42}$$

$$MRPK_t^j \equiv \alpha\mu A_t^j\left(k_t^j\right)^{\alpha\mu-1}\left(l_t^j\right)^{(1-\alpha)\mu} = \left(1+i_t\right)\left[1+\lambda_t^j\right]R_t, \tag{43}$$

where λ_t^j is the Lagrangian multiplier associated with (41). Moreover, consistent with (11), we can define the output distortion as

$$1-\tau_{yt}^j \equiv \frac{W_t l_t^j}{(1-\alpha)\mu y_t^j} = \frac{1}{(1+i_t)\left(1+\lambda_t^j\right)},\ j=E \text{ or } F. \tag{44}$$

Similarly, we define the capital wedge as $1+\tau_{k,t}^j \equiv \frac{\alpha\mu}{1-\alpha}\frac{W_t l_t^j}{R_t k_t^j}$, and revenue productivity as $TFPR_t^j \equiv \frac{y_t^j}{\left(k_t^j\right)^\alpha \left(l_t^j\right)^{1-\alpha}}$. Equations (42) and (43) implies that $1+\tau_{k,t}^j=1$, $j=E$ or F. The revenue productivity can be expressed as

$$TFPR_t^j = \frac{1}{\mu\left(1-\tau_{yt}^j\right)}\left(\frac{R_t}{\alpha}\right)^\alpha \left(\frac{W_t}{1-\alpha}\right)^{1-\alpha}.$$

The dispersion of TFPR can be proxied by the ratio of TFPR between the two groups of entrepreneurs

$$\frac{TFPR_t^E}{TFPR_t^F} = \frac{1-\tau_{yt}^F}{1-\tau_{yt}^E} = \frac{1+\lambda_t^E}{1+\lambda_t^F},$$

which implies $var\left[\log TFPR_t^j\right] = var\left[\log\left(1-\tau_{yt}^j\right)\right] = var\left[\log\left(1+\lambda_t^j\right)\right]$. Finally, the covariance between physical and revenue productivity is

$$cov\left(\log TFPQ, \log TFPR\right) = \eta\left(1-\eta\right)\left(\chi^E-\chi^F\right)\log\frac{1+\lambda_t^E}{1+\lambda_t^F}.$$

Note that the fact that more productive projects (type-E projects) are more likely to be financially constrained implies a positive covariance between physical and revenue productivity.

7.4.4 The Bank's Problem

Each period, the bank draws deposits d_t, which is the sum of deposits from type-E entrepreneur, s_t^E and from the foreign lender, s_t^I. The bank promises to pay a deposit rate $1+i_{t+1}$ at period $t+1$. The bank's assets, which are the sum of the bank's deposit and its net worth (s_t^F), are then lent to each type of entrepreneur at an lending rate $1+i_{t+1}^l$. For expositional simplicity, the lending rate for both types of firms is the same. Moreover, we assume that banks commit to repay all the deposit. The bank solves a two-stage problem: in the first, it chooses the amount of deposit.

$$\pi_{t+1}^B \equiv \max_{d_t}\left(1+i_{t+1}^l\right)\left(d_t+s_t^F\right)-\left(1+i_{t+1}\right)d_t$$

where d_t is bank demand for deposits. It is easy to see that the first-order condition implies that the equilibrium deposit rate equals the lending rate, that is $1+i_{t+1}^l = 1+i_{t+1}$. As a result, the bank profit is $\pi_{t+1}^B = \left(1+i_{t+1}\right)s_t^F$.[30]

[30]Note that in equilibrium i_{t+1}^l is such that the bank loan market clears

$$s_t^E + s_t^F + s_t^I = b_{t+1}^E + b_{t+1}^F.$$

Given the bank's demand for deposit, d_t, the bank sets a financial contract with each type of projects. For a type-F project, since the bank and the project are owned by the same entrepreneur, there is no conflict of interest. This implies that the bank would like to set η_t^F sufficiently large to maximize the type-F project's profit. Without tight banking regulation, as was the case in Chile before the banking reform, the bank simply sets η_t^F such that the borrowing constraint (40) is essentially not binding. By contrast, a type-E entrepreneur, since it does not own the bank, has incentive to default on the bank loan. As a consequence, the bank would advance the loan based on the collateral of the type-E entrepreneurs, that is, their bank deposit. The optimal contract per Hart and Moore (1994), determines η_t^E, which implicitly is positively related to the recovery rate of the collateral value. Assuming that the constraint (41) is binding ONLY for a type-E project, we have $\lambda_t^E > \lambda_t^F = 0$, which implies that $\tau_{yt}^E > \tau_{yt}^F$.

A banking reform sets the self-loan to be a fraction of the bank's (the type-F entrepreneur's) net worth. In other words, the banking reform places an upper bound on the bank's leverage ratio, $\eta_t^F \leq \overline{\eta}^F$. This is captured in our model by a decrease in η_t^F, such that the type-F projects are subject to a binding borrowing constraint. Accordingly, the Lagrangian multiplier associated with working capital constraint becomes positive, $\lambda_t^F > 0$. This implies that $1 - \tau_t^F = \frac{1-i_t}{1+\lambda_t^F}$ will fall. Since the working capital constraint for a type-E project is unaffected by the banking law's restriction on self-loans, the leverage ratio for the type-E entrepreneur, η_t^E will not change. This implies that the overall leverage ratio of the economy will decline as a result of banking reform. Accordingly, the dispersion of output distortion and TFPR, as measured by $\frac{1+\lambda_t^E}{1+\lambda_t^F}$ will decline. Correspondingly, the covariance between physical and revenue productivity also declines.

Table 1: Number of Plants and Employees by Subgroups (1983)

Number of Employees	All plants (shares) #plants	Share of Total (%)	Labor (%)	Unbalanced panel (shares) #plants	Share of Total (%)	Labor (%)
10–19	1720	41.7	10.7	768	44.3	14.0
20–49	1447	35.1	19.5	629	36.3	24.0
50–99	491	11.9	15.6	179	10.3	16.9
100–249	314	7.6	22.7	119	6.9	25.1
250–499	96	2.3	14.7	30	1.7	13.4
500–999	36	0.9	11.2	8	0.5	6.5
>=1000	24	0.6	5.7	0	0	0

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

	$\log TFPQ_{si}$	$\log TFPR_{si}$	$\log(1-\tau_{ysi})$	$\log(1+\tau_{ksi})$
		1983		
SD	1.454	0.720	0.743	1.306
90–10	3.805	1.791	1.874	3.166
75–25	2.135	0.880	0.987	1.685
Correlation with A_{si}	1	0.694	-0.755	-0.169
		1996		
SD	1.332	0.577	0.575	1.345
90–10	3.553	1.437	1.368	3.442
75–25	1.912	0.769	0.745	1.744
Correlation with A_{si}	1	0.445	-0.703	-0.285

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. The first column is based on HK (2009)'s table I and II.

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

1983	0–50	50–100	100–200	200+
Top size quartile	9.7	7.0	5.1	3.2
2nd quartile	17.1	4.4	2.4	1.1
3rd quartile	22.1	2.0	0.5	0.4
Bottom quartile	24.5	0.4	0.1	0.1
1996	0–50	50–100	100–200	200+
Top size quartile	8.4	7.4	6.6	2.6
2nd quartile	13.0	6.0	3.5	2.6
3rd quartile	15.1	4.3	3.4	2.1
Bottom quartile	19.3	3.0	1.3	1.4

Notes: In each year, plants are put into quantiles 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 idiosyncratic distortions are removed. 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%. This table is based on HK (2009)'s table V.

Table 4: TFP Gains from Removing Idiosyncratic Distortions within Industries

Year	1983	1984	1985	1986	1987	1988	1989
TFP gains	60.2	47.4	51.1	41.0	33.6	39.9	32.7
Year	1990	1991	1992	1993	1994	1995	1996
TFP gains	28.5	34.3	33.3	37.2	35.0	34.5	35.2

Notes: Entries are $(Y^e/Y - 1) \times 100$, where $Y/Y^e = \Pi_{s=1}^{S}\left(\Sigma_{i=1}^{M_s}\left\{\frac{A_{si}}{\overline{A}_s}\frac{\overline{TFPR_s}}{TFPR_{si}}\right\}^{\sigma-1}\right)^{\frac{\theta_s}{\sigma-1}}$. $TFPR_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}$. This table is based on HK (2009)'s table IV.

Table 5: Sensitivity Analysis: TFP Gains from Removing Idiosyncratic Distortions within Industries

	TFP Gain		
	$\sigma = 3$, Unbalanced Panel	$\sigma = 5$, Unbalanced Panel	$\sigma = 3$, Balanced Panel
1983	60.2	66.0	44.4
1984	47.4	66.8	34.5
1985	51.1	76.0	36.1
1986	41.0	51.1	25.9
1987	33.6	55.2	23.8
1988	39.9	53.9	33.3
1989	32.7	54.4	23.1
1990	28.5	43.9	22.8
1991	34.3	45.0	25.3
1992	33.3	52.3	28.2
1993	37.2	51.6	28.4
1994	35.0	44.8	27.6
1995	34.5	49.1	27.3
1996	35.2	46.9	27.5

Notes: See notes in Table 4.

Table 6: Average Growth Rate of TFPQ by Quantitles of TFPQ in 1983

Quintile of TFPQ (in 1983)	$gTFP_q$ mean of y-by-y growth 83-96
1	0.179
2	0.086
3	0.080
4	0.045
5	−0.004

Table 7: TFP Gain by Removing Idiosyncratic Distortions (L= Wage Bill)

Year	1983	1984	1985	1986	1987	1988	1989
TFP gains	70.2	58.0	55.6	50.9	44.7	50.4	45.4
Year	1990	1991	1992	1993	1994	1995	1996
TFP gains	34.3	40.0	37.2	39.3	38.2	38.5	40.3

Notes: See notes in Table 4.

Table 8: Regression of Exit on TFPR and TFPQ

	w/o. Time Dummy	w. Time Dummy
exit on TFPR	0.229***	0.227***
	(0.037)	(0.042)
exit on TFPQ	−0.292***	−0.329***
	(0.017)	(0.023)

Notes: The dependent variables are dummies for exiting plants. The independent variables are the deviation of log(TFPR) and log(TFPQ) from their industry means. Entries above are the estimated coefficients on log(TFPR) and log(TFPQ), with standard errors in parentheses. Regressions also include sector dummies and, for the right column, time dummies. Results are pooled for all years between 1983 and 1995. This table is based on HK(2009)'s table VIII.

Table 9: Regression of TFPQ and TFPR with Liability-Asset Ratio (OLS)

	$\log \frac{TFPR}{\overline{TFPR}}$	$\log(1-\tau_Y)$	$\log(1+\tau_K)$	$\log(A_{si})$
	β_1	β_1	β_1	β_1
1980	-0.601^{***}	0.383^{**}	-0.613^{***}	-0.225
	(0.106)	(0.103)	(0.165)	(0.191)
1981	-0.550^{***}	0.555^{***}	-0.040	-0.512^{**}
	(0.117)	(0.111)	(0.105)	(0.255)

Notes: Robust Standard error in brackets. *** if significant at 1%; ** if significant at 5%; * if significant at 10%. The 3-digit sectoral fixed effects are included in each regression.

Table 10: Cross-Industry Correlation of Liability-Asset Ratio with Measures of Distortions

	1980	1981
$\log\left(\frac{TFP_s^e}{TFP_s}\right)$	0.152	0.580
$var_s(\log TFPR)$	0.254	0.590
$var_s(\log(1-\tau_Y))$	0.410	0.496
$var_s(\log TFPQ)$	0.154	0.341

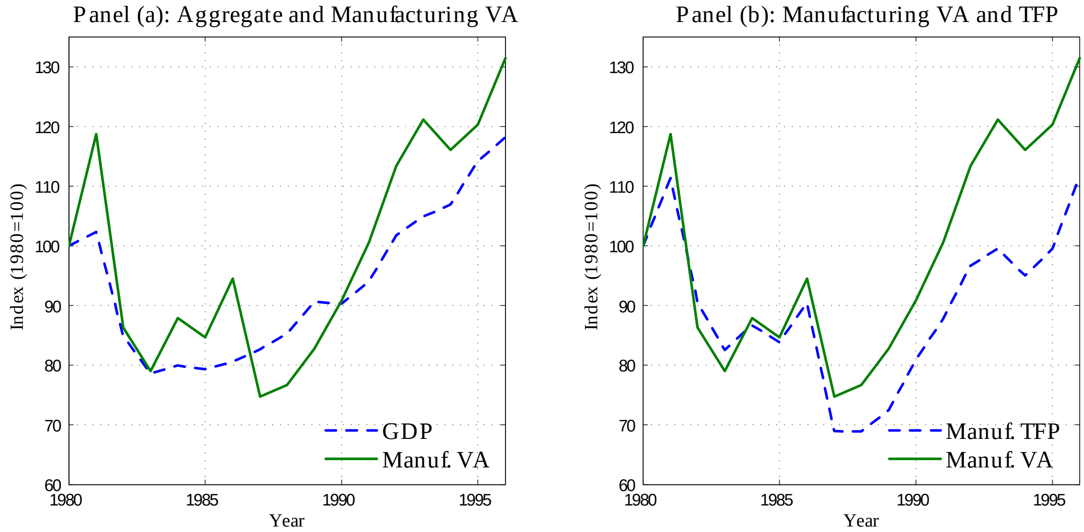
Note: Entries are cross-industry weighted correlations between industry median liability-asset ratios and different measures of resource misallocation.

Table 11: Cross-Industry Correlation of Liability-Asset Ratio (1980–1982) with Changes in Allocative Efficiency

	Correlation
$\Delta\log\left(\frac{TFP_s^e}{TFP_s}\right)$	0.529
$\Delta var_s(\log TFPR)$	0.473
$\Delta var_s(\log(1-\tau_Y))$	0.212
$\Delta var_s(\log TFPQ)$	0.424

Note: Entries are weighted correlations between the industry's median liability-asset ratio in 1980–1982 and changes in various moments during 1983–1996. For each industry, the liability-asset ratio is computed as the simple average of the median liability-asset ratios across 1980-1982. Δ for each moment in the left column denotes its 1983 value minus its 1996 value. The weighted correlation is computed using industry value-added shares as weights.

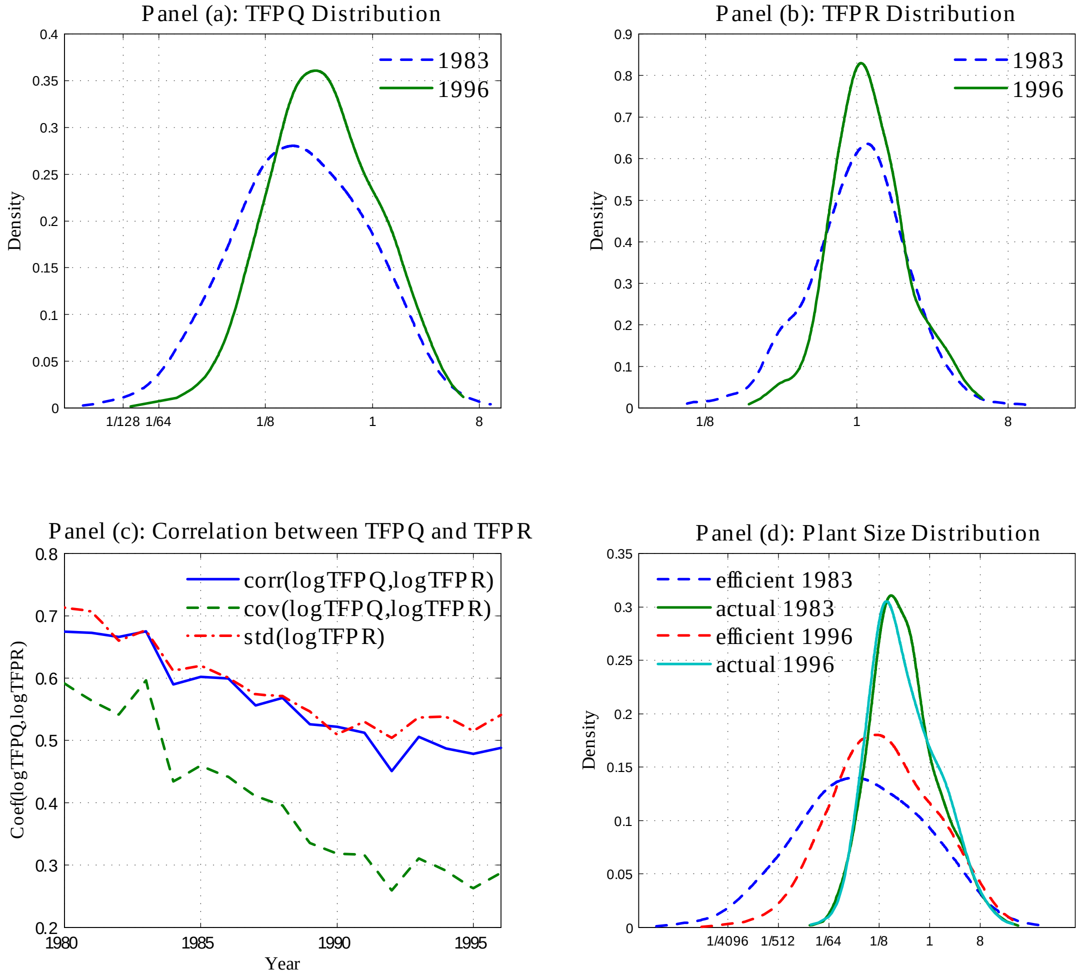
Figure 1: Chilean Manufacturing Value-Added and TFP



Note: Panel (a) shows Chilean GDP and value-added (referred to as "VA") 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 percent per year and normalized such that their 1980 values equal to 100. The manufacturing TFP is detrended by 1.4 percent per year and normalized in a similar way.

Source: authors' calculations.

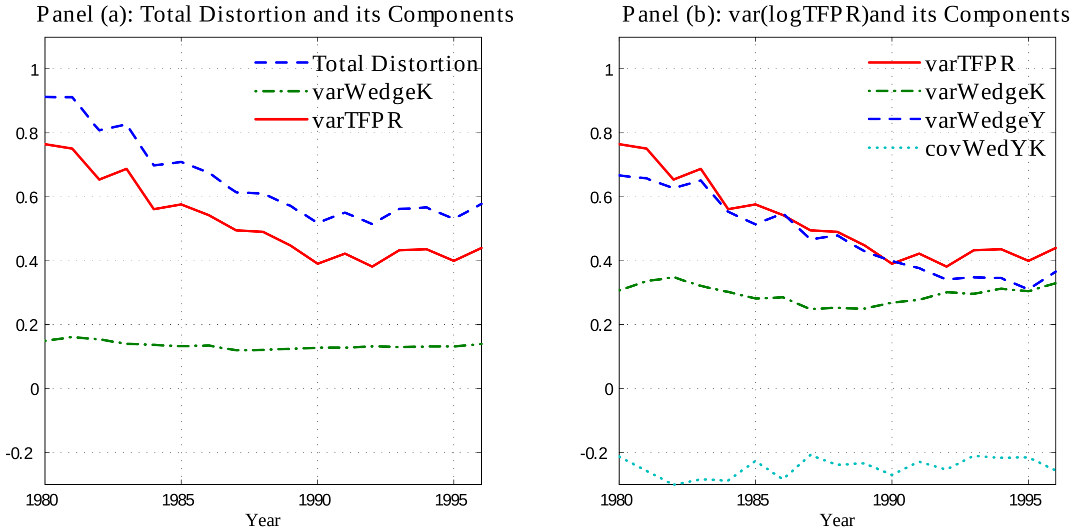
Figure 2: Distribution of Productivity and Plant Size



Note: Panel (a) plots the distribution of TFPQ, $\log\left(A_{si}M_s^{\frac{1}{\sigma-1}}/\overline{A}_s\right)$, while panel (b) plots the distribution of TFPR, $\log\left(TFPR_{si}/\overline{TFPR}_s\right)$, both for 1983 and 1996. Panel (c) plots the time-series of correlation between logTFPQ and logTFPR. Value added share is used as the weight for computing the industry mean. Panel (d) plots the efficient and actual plant size distribution, $\log\left(P_{si}Y_{si}/\overline{P_sY_s}\right)$, where $\overline{P_sY_s}$ refers to the mean value-added of industry s.

Source: authors' calculations.

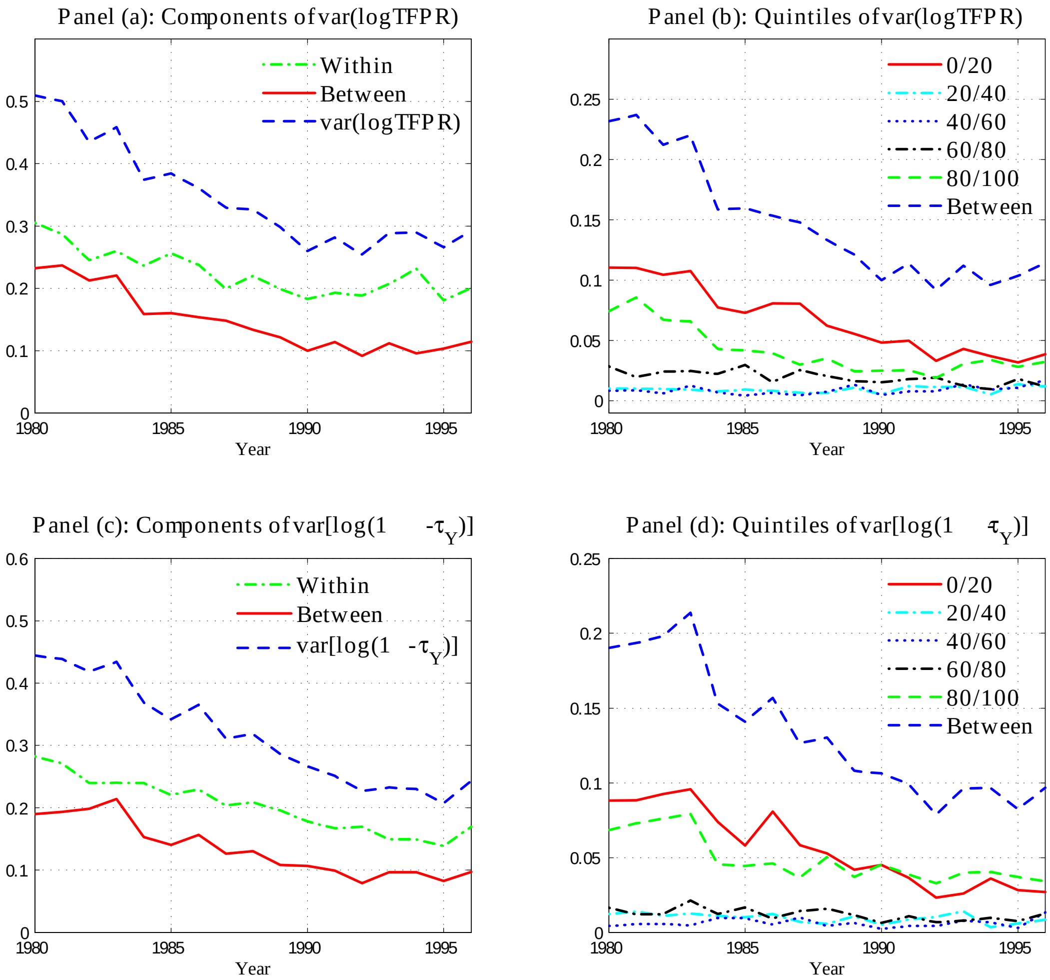
Figure 3: Decomposition of Resource Misallocation



Note: Panel (a) plots total misallocation and its two components, variance of TFPR, measured as $\frac{\sigma}{2} var\left(\log TFPR_i\right)$, and the dispersion on plant-specific distortion to capital-labor ratio, as captured by $\frac{\alpha(1-\alpha)}{2} var\left[\log\left(1+\tau_{ki}\right)\right]$. Panel (b) plots variance of TFPR and its various components between 1980 and 1996. Variances and components plot in the graphs are the weighted mean across sectors. Value-added share, θ_s, is used as the weight for computing the mean, and $\alpha = \sum_{s=1}^{S} \theta_s \alpha_s$.

Source: authors' calculations.

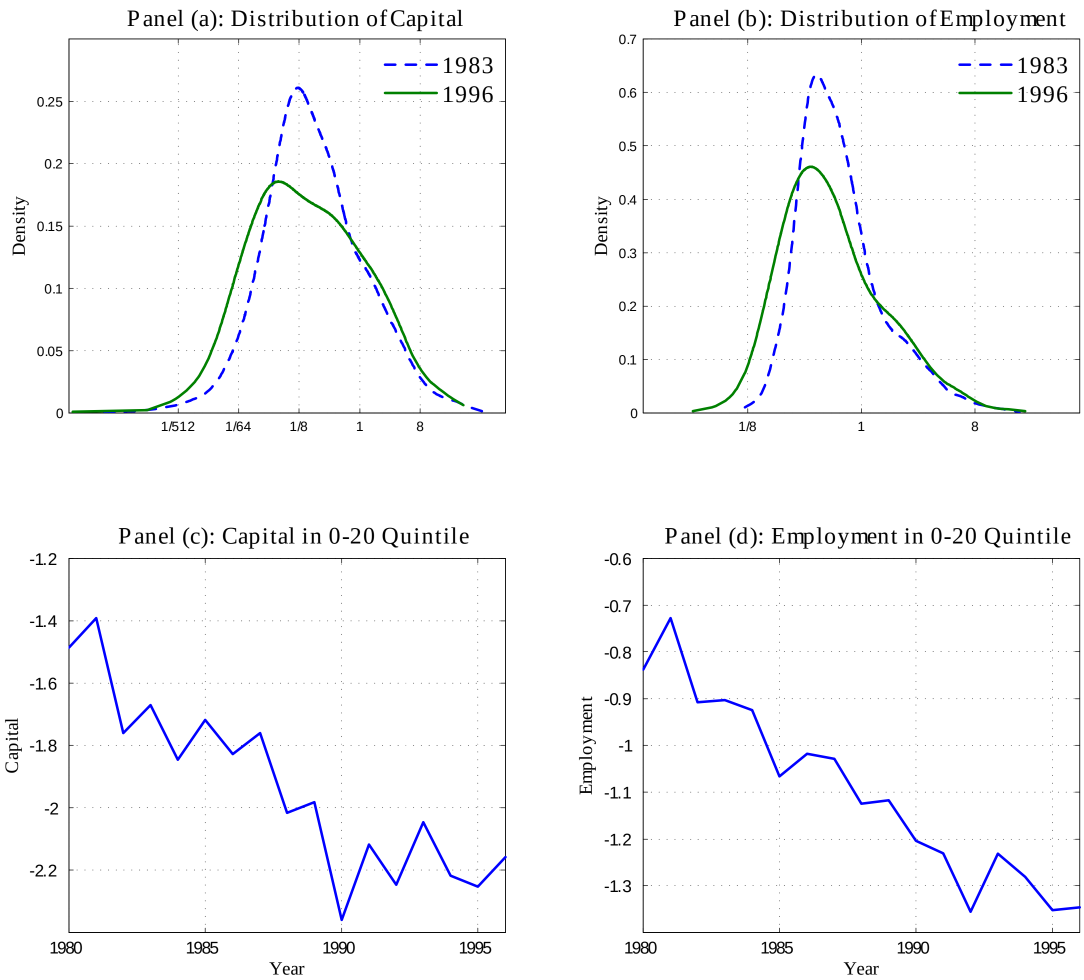
Figure 4: Quantile Analysis of Dispersion in TFPR and Output Distortion



Note: Panel (a) plots TFPR dispersion, $var\left(\log TFPR_{si}\right)$, and its within-group and between-group components. Panel (b) plots the quintiles average of $var\left(\log TFPR_{si}\right)$, together with its between-group component. Panel (c) plots the dispersion of output distortion, $var\left[\log\left(1-\tau_{ysi}\right)\right]$, and its within-group and between-group components, while panel (d) plots quintile averages of dispersion of output, together with its between-group component. Variances and components plot in the graphs are the weighted mean across sectors. Value-added share, θ_s,is used as the weight for computing the mean.

Source: authors' calculations.

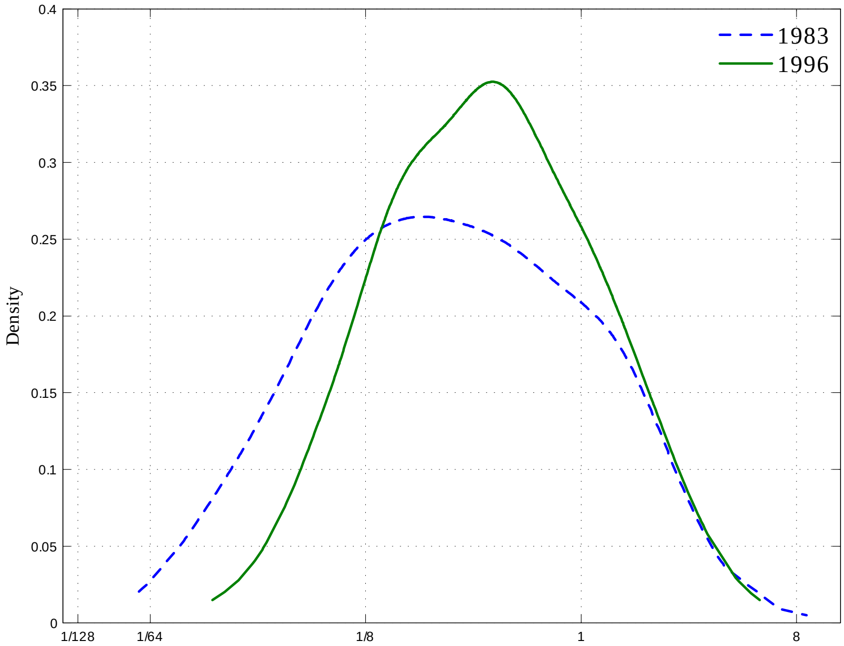
Figure 5: Capital and Labor Allocation over Time



Note: Panel (a) and (b) plot the distribution of capital and labor, measured by $\log\left(K_{si}/\overline{K}_s\right)$ and $\log\left(L_{si}/\overline{L}_s\right)$ for 1983 and 1996. Panel (c) and (d) plot the time series of capital and labor in the bottom quintile, measured by as $\log\left(\overline{K}_s\mid_1/\overline{K}_s\right)$ and $\log\left(\overline{L}_s\mid_1/\overline{L}_s\right)$. $\overline{K}_s$ denotes the mean of capital for s industry. $\overline{K}_s\mid_1$ denotes the mean of capital for the bottom quintile of s industry. Similar definition applies to labor.

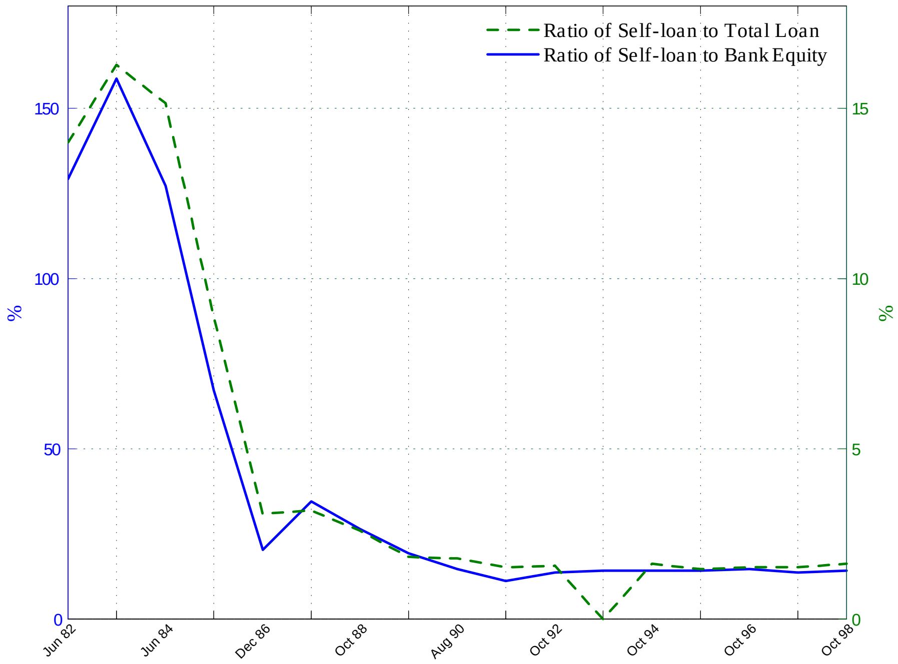
Source: authors' calculations.

Figure 6: Distribution of TFPQ in the Balanced Panel



Notes: The figure plots the distribution of TFPQ, $\log\left(A_{si} M_s^{\frac{1}{\sigma-1}} / \overline{A}_s\right)$, for the balanced panel.

Figure 7: Self-Loan as a Fraction of Banks' Equity and Total Loans



Note: The dash circle line refers to the ratio of self-loan to banks' equity; the dash dot line refers to the ratio of self-loan to the banks' total loan. The data comes from Held and Jimenez (1999).