Misallocation and the Recovery of Manufacturing TFP after a Financial Crisis

Kaiji Chen*  Alfonso Irarrazabal†

February 2012

Abstract

The Chilean economy experienced a decade-long spectacular growth in aggregate output and productivity after the 1982 financial crisis. This paper analyzes the effects of resource misallocation on Chilean total factor productivity (TFP) 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 more than sixty percent of the growth in manufacturing TFP between 1986 and 1996. The improvement in allocative efficiency, moreover, is essentially driven by a reduction in the cross-sectional dispersion of output distortion. In particular, a reduction in the least productive plants’ output subsidies and the corresponding increase their average $TFPR$ constitute the most important reason for the reduction in resource misallocation during this period.

JEL Classification: O11, O47.

Keywords: Misallocation, TFP, Crisis, Recovery.

*Emory University, Department of Economics, Atlanta, GA 30322. Email: kaiji.chen@emory.edu.
†Norges Bank, Norway. Email: alfonso.irarrazabal@norges-bank.no
1 Introduction

As the financial crisis in 2008 evolved into a deep recession across the Western economies, there is growing concern over whether the world economy could enter a stagnation like that of the 1990s for Japan.\footnote{See, for example, “Japanisation is the new word of fear,” in Financial Times, August 20/21, 2011.}

The historical experience provides both the positive and negative answers to the above question. As a comparison, in 1982, both Chile and Mexico experienced a financial crisis as a consequence of sharp rising world interest rates and negative terms-of-trade shocks. After a sharp fall in real GDP in 1982 and 1983, the Chilean economy started to grow in 1984, and Chile has been the fastest-growing country in Latin America since then. By contrast, between 1982 and 1995, Mexico experienced no economic growth and has grown only modestly since then (Bergoeing, Kehoe, Kehoe and Soto, 2001). Similar contrast could be found between Japan and Finland, both of which suffered a financial crisis in the early 1990s. While Japan’s economy has stagnated, the Finnish economy has grown spectacularly since then. The key factor explaining the divergent post-crisis paths among the above economies, as many researchers have found, have not been in employment and investment, but in productivity: Chile and Finland have experienced fast growth in aggregate Total Factor Productivity after the financial crisis, while Mexico and Japan have not.\footnote{See, for example, Bergoeing, Kehoe, Kehoe, Soto (2001) for a comparison between Chile and Mexico, Conesa, Kehoe, Ruhl (2001) for Finland and Hayashi and Prescott (1999) for Japan.}

Understanding the evolution of aggregate productivity and the potential policies that may influence its dynamics, therefore, shed light on how the Western economies could emerge from the current crisis as Chile and Finland did from theirs.\footnote{Ohanian (2010) finds that during the Great Recession, Total Factor Productivity dropped by an average 7.1 percent for G7 countries other than the United States.}

This paper studies the role of resource misallocation in the recovery of Chilean manufacturing TFP after its 1982 crisis. We use establishment data from Chilean manufacturing census to address three questions: How important is improvement in the allocative efficiency in accounting for the fast growth in Chilean manufacturing TFP after the crisis? What are the key distortions that have contributed to the improvement in the allocative efficiency? How was resource (i.e. capital and labor) reallocated across plants as a result of changes in the plant-level distortions? To this end, we employ Hsieh and Klenow (2009) framework to obtain the plant-specific output and capital distortion (wedges), as well as the physical and revenue TFP measures ($TPPQ$ and $TPPR$).
Our results show that between 1986 and 1996, an improvement in the allocative efficiency accounts for more than one third of the observed aggregate manufacturing TFP growth. The efficiency gain by equalizing $TFPR$ fell from 80% to 65% during this period. The key driving force of the improvement in the allocative efficiency is a reduction in the cross-sectional dispersion in output distortion, which accounts for essentially all the reduction in the cross-sectional dispersion of $TFPR$ during this period. Moreover, the cross-sectional correlation of $TFPQ$ and $TFPR$ shares a similar declining pattern to the cross-sectional dispersion of $TFPR$, suggesting an improvement of resource allocation among plants of different productivity.

We then ask how important is the improvement of allocative efficiency among plants of different productivity in driving the decline in $TFPR$ dispersion. To this end, we group plants into quintiles based on their current year $TFPQ$. We then decompose the cross-sectional dispersion of $TFPR$ and output distortion into two components: between-group and within-group variances. By construction, average $TFPR$ or output distortion for each quintile washes out the measurement error within each quintile. Accordingly, between-group variance allows us to better isolate the impact of resource misallocation on measured cross-sectional dispersions. We find that the between-group dispersion plays dominant roles in driving down the overall dispersion of both $TFPR$ and output distortion, suggesting the key role of improvement in the resource allocation across plants of different productivity in driving the dispersion of $TFPR$. Interestingly, changes in both ends (first and fifth quintiles) of the distribution are the main factor explaining the fall of the between-group dispersion. In particular, a reduction in the least productive group’s output subsidies and the corresponding increase in this group’s average $TFPR$, constitute the most important reason for the decrease in between-group dispersion.

We then provide direct evidence of resource reallocation across plants of different productivity and changes in the firm size distribution. Consistent with the time variation in distortions, our evidence shows that over time the most productive plants’ capital and labor share increases while the corresponding share for least productive plants declines. Accordingly, the distribution of plant size (measured as revenue) became more dispersed and skewed to the left. Intuitively, the least productive plants downsized as the their subsidies dropped.

This study is closest in spirit 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 empirical literature that use micro-data to measure the extent
of micro-level misallocation. Following the methodology of Hsieh and Klenow (2009), this literature consistently finds large potential aggregate TFP gains from removing misallocation: Argentina could increase its TFP by 50-60% (Neumeyer and Sandleris, 2009), Bolivia by 52-70% (Machicado and Birbuet, 2011), Colombia by 50% (Camacho and Conover, 2010), and Uruguay by 50-60% (Casacuberta and Gandelman, 2009). This paper focus on the dynamics of Chilean manufacturing TFP and, in particular, the period after the financial crisis.

Our findings provides empirical support for the argument of Buera and Shin (2010) that a reduction of idiosyncratic distortions preceded domestic financial market reforms for developing countries. In their theoretical framework, economic reforms take two stages: in the first stage, idiosyncratic output distortions were removed; in the second, borrowing constraints were relaxed. As a consequence, massive capital outflows accompany TFP growth during the first stage of reform. Consistent with their argument, our evidence shows that a reduction in the output distortion, rather than capital distortion is key to explain the improvement in Chilean manufacturing TFP between 1986 and 1996.

The rest of the paper proceeds as follows: in Section 2, we present the background of Chilean economy for the period of study. In section 2, we present the monopolistic competition model of Hsieh and Klenow (2009) to measure the effect of distortion on productivity. In Section 4, we describe the panel data set used in the analysis. In Section 5, we present our empirical findings. Section 6 does the robustness check. Section 7 concludes.

2 Recovery and Reforms in Chile after the 1982 Crisis

2.1 Recovery

The Chilean economy experienced a large recession in 1982, but a sustained recovery since 1984. The left panel of Figure 1 shows that between 1982 and 1984, real GDP per working age (15-64) person declined by more than twenty percent relative to the trend level. From the mid 1980s, however, GDP per capita started to recover and, by 1996, was twenty percent above the trend. As argued by Bergoeing, Kehoe, Kehoe, and Soto (2007), most of the change in GDP can be accounted for by fluctuations in aggregate TFP during this period. This is evidenced by the right panel of Figure 1, which shows that aggregate TFP bears a similar pattern for aggregate output. Therefore, understanding aggregate TFP dynamics is crucial to understand the recovery of Chilean economy after the financial crisis.

---

4We assume that the trend level of real GDP per working age person grows at two percent per year.
In this paper, we explore the dynamics of Chilean TFP from the lens of manufacturing sector. The left panel of Figure 2 shows that a similar takeoff of aggregate output happened in the manufacturing sector after the 1982 crisis. In particular, aggregate manufacturing output had experienced a fast increases since the late 1980s. Aggregate manufacturing TFP, as shown in the right panel, tracked manufacturing output closely during both the recession and the recovery. In particular, aggregate manufacturing TFP increased by forty percent relative to the trend level, providing a strong driving force of aggregate manufacturing output during the recovery. Therefore, Chilean manufacturing TFP dynamics provides a lens for us to understand the dynamics of aggregate TFP.

2.2 Reforms

Massive policy intervention occurred during the banking crisis. Between 1982-1985, the Chilean government intervened 21 financial institutions, 14 were liquidated and the rest were rehabilitated and privatized. The state rehabilitated the banks by allowing them to recapitalize and issue long term debt, which the Central Bank bought, to replace their existing non-performing assets. As a result, the state became the manager and main creditor of rescued banks. More importantly, the state reinstated financial controls such as “suggested”
Figure 2: Chilean Manufacturing Output and TFP

The financial reforms take two stages. In the first stage (1985-1990), the state reversed the protective measures imposed during the crisis. The controls on interest rates were eliminated in 1985 and a new banking law was enacted. The new banking law included (i) limits on the debt-to-capital ratio and reserve requirements related to the leverage position of the bank, (ii) incentives for private monitoring of banks through both a public guarantee on deposits and the mandatory information disclosure to the public, and (iii) separation between the core business of the bank and that of its subsidiaries.

In addition to the banking reforms, other reforms were also implemented during this period. For example, a new bankruptcy law that clarified the extent of private sector responsibility in failing enterprises was implemented. Also, the tax reform of 1984 eliminated the preferential treatment of debt liabilities by the firms.

Important financial market reforms did not occur until the start of the 1990s. During the 1990s, the stock market and other financial markets experienced a striking development. Firms with good credit rating were allowed to issue bonds and shares in external markets. Institutional investors, such as banks pension fund managers and insurance companies, were allowed to hold external assets. Meanwhile, there was significant rise in the stock market efficiency, as measured by the stock market traded value to GDP and the turnover ratio.
3 Theoretical Framework

This section describes the linkage between aggregate productivity and resource misallocation that results from firm-level distortions in a theoretical framework proposed by Hsieh and Klenow (2009, “HK” hereafter). The key difference between our model and that of Hsieh and Klenow (2009) is that our model incorporates firm-specific wage rates, a new channel to distort the allocation of labor across plants.

The economy consists of monopolistic competitive firms. The production function for each differentiated product is given by Cobb-Douglas function of firm-level TFP, capital and labor. In our benchmark case, capital elasticity across industries are assumed to be the same. In our robustness check, we allow for sector-specific capital elasticity. Following HK, we introduce two types of distortions: an output distortion that takes the forms of a tax on revenues, and a capital distortion takes the forms of a tax on capital services. The problem of a firm \( i \) is

\[
\max_{P_i, K_i, L_i} (1 - \tau_{yi}) P_i A_i K_i^\alpha L_i^{1-\alpha} - W_i L_i - (1 + \tau_{ki}) R K_i
\]

\[st: Y_i = Y \left( \frac{P_i}{P} \right) \]

Without loss of generality, we assume that aggregate price \( P = 1 \). The first-order conditions are

\[
MRPL_i \equiv (1 - \alpha) \frac{\sigma - 1}{\sigma} P_i Y_i / L_i = W_i / (1 - \tau_{ysi})
\]

\[
MRPK_i \equiv \alpha \frac{\sigma - 1}{\sigma} P_i Y_i / K_i = R (1 + \tau_{ki}) / (1 - \tau_{ysi})
\]

where \( W_i \) is one specific type of labor distortion. From the first order conditions, which obtain

\[
\frac{K_i}{L_i} = \frac{1}{R} \frac{\alpha}{1 - \alpha} \frac{W_i}{1 + \tau_{ki}}
\]

Notice that the output distortion affects the marginal revenue product of both factors in a symmetric way and thus does not distort the capital-labor ratio. On the other hand, a capital distortion, \( 1 + \tau_{ki} \), makes capital services more costly to labor services, distorting the capital-labor ratio away from the first-best level.

Following Foster, Haltiwanger and Syverson (2008), we define revenue-based TFP as

\[
TFPR_i = \frac{P_i Y_i}{K_i^\alpha L_i^{1-\alpha}} = P_i A_i
\]

It is easy to show that \( TFPR_i \) follows

\[
TFPR_i = \frac{\sigma}{\sigma - 1} \left( \frac{MRPK_i}{\alpha} \right)^\alpha \left( \frac{MRPL_i}{1 - \alpha} \right)^{1-\alpha}
\]

\[= \frac{\sigma}{\sigma - 1} \left( \frac{R}{\alpha} \right)^\alpha \left( \frac{W_i}{1 - \alpha} \right)^{1-\alpha} \left( \frac{(1 + \tau_{ki})^\alpha}{1 - \tau_{ysi}} \right)
\]
The higher is $1 + \tau_{ki}$ and $W_i$ and the lower $1 - \tau_{yi}$ is, the lower is the output relative to the first best. Accordingly, the price $P_i$ and thus $TFPR_i$ is above the first-best level. Recall that without distortions, $TFPR_i$ should be equalized across plants. This is because more resources are allocated to plants with higher $TFPQ_i = A_i$, leading to higher output, and lower price, which lowers $P_i A_i$.

### 3.1 Aggregate TFP

Aggregate TFP can be expressed as

$$TFP = \frac{Y}{K^{\alpha} L^{1-\alpha}}$$

$$= \left[ \frac{\sum_{i=1}^{M} A_i^{(1-\tau_{yi})^{\alpha}} W_i^{(\sigma-1)}}{(1+\tau_{ki})^{\sigma-1}} \right]^{-\frac{\sigma}{\sigma-1}}$$

where $M$ is the number of firms.\footnote{Since the data does not have separate information for the price of goods at firm level, we use value-added, instead of output, in our measure of TFP, i.e., $TFP = \frac{PY}{K^{\alpha} L^{1-\alpha}}$.}

Note that if we shut down all the idiosyncratic distortions, i.e. $1 - \tau_{yi} = 1 + \tau_{ki} = 1$ and $W_i = W$, then we obtain the efficient level TFP, denoted as $TFP^e = \left( \sum_{i=1}^{M} A_i^{\sigma-1} \right)^{-\frac{1}{\sigma-1}}$.

We would like to understand the driving forces of aggregate TFP by decomposing it into different components. To this end, we assume that $A_i$, $1 - \tau_{yi}$, $1 + \tau_{ki}$ and $W_i$ are joint log normal. Using the Central Limit Theorem and assuming $M \to \infty$, we have

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

\hspace{1cm} \text{(2)}

$\text{var} \left( \log TFPR_i \right)$ captures the distortions on resource allocation across firms. where $\text{var} \left[ \log \left( \frac{1+\tau_{ki}}{W_i} \right) \right]$ captures the distortions that drives the capital-labor ratio, $\frac{K}{L}$, away from the first best. Note that the right hand side ("RHS" hereafter) of equation 2 may not be equal to $\log TFP$ computed according to equation 1. To check the lognormal assumption, in Section 6.2 we will compare $\log TFP$ computed using equation 1 and its counterpart using equation 2. We show that the approximated TFP share very similar dynamics as the actual TFP.

In order to further understand the driving forces of the time variation in the $TFPR$ dispersion, we decompose $\text{var} \left( \log TFPR_i \right)$ as...
\[ \text{var} (\log TFPR_i) = \text{var} \left[ \log \left( W_i^{1-\alpha} \frac{(1 + \tau_{ki})^\alpha}{1 - \tau_{yi}} \right) \right] = \alpha^2 \text{var} \log (1 + \tau_{ki}) + \text{var} \log (1 - \tau_{yi}) - 2\alpha \text{cov} [\log (1 - \tau_{yi}), \log (1 + \tau_{ki})] + \text{cov} (\log W_i^{1-\alpha}, \log TFPR_i) \] (3)

### 3.2 Size Distribution

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

\[ P_i Y_i = Y_i^{1-\frac{1}{\sigma}} Y^{\frac{1}{\sigma}} \] (4)

Hence, the dispersion of firm size translates into the dispersion of firm output. Since \( \sigma \geq 1 \), equation 4 implies that larger firms (in terms of revenue) should have higher output. Moreover,

\[ Y_i = A_i \sigma (1 - \tau_{yi})^\sigma \left( \frac{\sigma - 1}{\sigma} \right)^\sigma (\alpha R) ^{\alpha \sigma} \left( \frac{1 - \alpha}{W_i} \right)^{\sigma(1 - \alpha)} Y \] (5)

Combining equation 4 and 5, we have

\[ P_i Y_i \propto \frac{A_i^{\sigma - 1} (1 - \tau_{yi})^{\sigma - 1}}{(1 + \tau_{ki})^{\alpha(\sigma - 1)}} \left( \frac{1}{W_i} \right)^{(\sigma - 1)(1 - \alpha)} \] (6)

According to our model, more productive firms produce more and are larger. If there exists size-dependent policies such that \( A_i \) and \( 1 - \tau_{yi} \) are negatively correlated (or \( A_i \) and \( 1 + \tau_{ki} \) are positively correlated), more productive firms tend to produce less and low productive firms to produce more. As a result, the size dispersion will become narrowed. This implies that the efficient size distribution is more spread out than the actual size distribution when there are frictions.

### 4 Empirical Implementation

#### 4.1 The Data

We use manufacturing Census data from 1980-1996. The Census is an annual survey of manufacturing plants covering firms with at least ten workers. The data has information on the balance sheets of the firms at 4-digit level of aggregation. Capital series are computed using simple inventory methods.
Given that our focus is to track the dynamic changes in measures of misallocation we drop firms with missing data from the sample\(^6\). Most of our analysis will focus on the sub-sample labeled unbalanced panel, which contain plants for which we have information (revenue, labor, capital) for all years. In other words, we delete from the database all the firms that systematically reported negative and zero revenue, and also those firms that report no employees and no fixed assets in some year. After deleting those firms we arrive to an average number of 1489 firms per year. For comparison, we also compute misallocation statistics for a balanced panel, that is firms who survived from 1980 to 1996.

Table 1 compares the number of plants, revenue and employment share by size class for the whole sample and the unbalanced panel in 1986. As we can see from the share of firms in each size class, our screening strategy oversamples the small plants. For example, the share of plants with fewer or equal to 100 employees is 84.7 and 86.4 percent, respectively, in the full sample and unbalanced panel respectively. In Section 6, we perform robustness checks using different samples.

### Table 1. Number of Firms and Employments by Size Class (1986)

<table>
<thead>
<tr>
<th>Firm Size (number of Employees)</th>
<th>All firms (shares)</th>
<th>Unbalanced panel (shares)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#firms</td>
<td>Share of Total (%)</td>
</tr>
<tr>
<td>0-10</td>
<td>146</td>
<td>3.5</td>
</tr>
<tr>
<td>10-20</td>
<td>1273</td>
<td>30.9</td>
</tr>
<tr>
<td>20-50</td>
<td>1468</td>
<td>35.7</td>
</tr>
<tr>
<td>50-100</td>
<td>599</td>
<td>14.6</td>
</tr>
<tr>
<td>100-250</td>
<td>409</td>
<td>9.9</td>
</tr>
<tr>
<td>250-500</td>
<td>146</td>
<td>3.5</td>
</tr>
<tr>
<td>500-1000</td>
<td>48</td>
<td>1.2</td>
</tr>
<tr>
<td>&gt;1000</td>
<td>26</td>
<td>0.6</td>
</tr>
</tbody>
</table>

### 4.2 Computing Distortions

To calculate distortions, we set rental price to capital to 10 percent and the elasticity of substitution \(\sigma\) to 3. We treat all firm as one sector and we set the capital share parameter \(\alpha\)\(^6\). We will perform several robustness checks to test the impact of this cleaning procedure.
to 0.3. In Section 6 we compute distortions using sectorial information. In that case, we use information for NBER productivity database to compute US capital shares by sectors as in Hsieh and Klenow (2009).

We compute distortions (or wedges) and productivity as follows

\[ 1 + \tau_{ki} = \frac{\alpha}{1 - \alpha} \frac{W_i L_i}{R K_i} \]  \hspace{2cm} (7)

\[ 1 - \tau_{yi} = \frac{\sigma}{\sigma - 1} \frac{W_i L_i}{(1 - \alpha) P_i Y_i} \]  \hspace{2cm} (8)

\[ A_i = \frac{Y_i}{K_i^{\alpha} L_i^{1-\alpha}} = \kappa \left( \frac{P_i Y_i}{K_i^{\alpha} L_i^{1-\alpha}} \right)^{\frac{\sigma}{\sigma - 1}} \]  \hspace{2cm} (9)

where \( \kappa = (PY)^{\frac{1}{\sigma - 1}} / P \). We then use measured \( A_i \) to construct \( TFP^e = \left( \sum_{i=1}^{M} A_i^{\sigma - 1} \right)^{\frac{1}{1-\sigma}} \).

As contrast to HK and other studies, we have labor, instead of wage bills, in our definition of \( A_i \). We follow HK and winsorize data by dropping 1 percent of the tails of \( TFP_R \) and \( TFP_Q \) each year and recalculate the wage bill, capital and revenue as well as \( TFP_R \) and \( TFP_Q \).

5 Resource Allocation, Wedges and Productivity in Chile: 1986-1996

5.1 Aggregate TFP Evolution and Decomposition

Table 2 illustrates the potential gain in terms of aggregate TFP of equalizing \( TFP_R \) over time. We choose 1986, when Chilean manufacturing TFP took off, as the initial year of our analysis. In 1986, the potential gain by eliminating distortions on resource misallocation is about 80%. Since then, the allocative efficiency of the Chilean economy has improved significantly. By 1996, the potential gain has dropped by 15 percent to 65%. The fact that actual TFP grew at a faster rate than the efficient TFP suggests that resource reallocation contributes positively to aggregate manufacturing TFP growth.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>( 100(TFP^e_t/TFP_t - 1) )</td>
<td>80.4</td>
<td>66.5</td>
<td>65.0</td>
</tr>
</tbody>
</table>

11
To understand the contribution of different components of aggregate TFP in equation 2 to the observed TFP growth, we decompose the growth rate of TFP according to the RHS of equation 2. We freely admit that this exercise make no allowance for measurement error and model mis-specification.

\[ \Delta \log TFP = \Delta \log TFP^e - \Delta \frac{\sigma}{2} \text{var} (\log TFPR_i) - \Delta \frac{\alpha(1-\alpha)}{2} \text{var} \log \left( \frac{1+\tau_{ki}}{W_i} \right) \] (10)

Table 3 reports the average growth rate of different components and their contribution to aggregate TFP growth. The upper panel shows that during this period, aggregate manufacturing TFP grew at rate of 4.11 percent. The lower panel shows that improvement in allocative efficiency contributes to more than sixty percent of the aggregate TFP growth. Interestingly, the improvement of allocative efficiency can be fully attributed to variations in the dispersion of \( TFPR \). The distortions affecting capital-labor ratio, on the other hand, became more severe and contributed negatively to the TFP growth.

<table>
<thead>
<tr>
<th>Table 3. Accounting for Aggregate TFP Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Growth Rate in %</td>
</tr>
<tr>
<td>( TFP )</td>
</tr>
<tr>
<td>( TFP^e )</td>
</tr>
<tr>
<td>(- \frac{\sigma}{2} \text{var} (\log TFPR_i))</td>
</tr>
<tr>
<td>(- \frac{\alpha(1-\alpha)}{2} \text{var} \log \left( \frac{1+\tau_{ki}}{W_i} \right))</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Contribution to TFP Growth</th>
<th>Share of Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>( TFP^e )</td>
<td>0.398</td>
</tr>
<tr>
<td>(- \frac{\sigma}{2} \text{var} (\log TFPR_i))</td>
<td>0.663</td>
</tr>
<tr>
<td>(- \frac{\alpha(1-\alpha)}{2} \text{var} \log \left( \frac{1+\tau_{ki}}{W_i} \right))</td>
<td>-0.061</td>
</tr>
<tr>
<td>Total allocative efficiency</td>
<td>0.602</td>
</tr>
</tbody>
</table>

To highlight the role of changes in dispersion of \( TFPR \) in the dynamics of allocative efficiency, we plot the model-implied total distortions, \( \frac{TFP^e}{TFP} \), and its two components in Figure 3. The total distortion declined steadily between 1986 and 1994 after a temporary deterioration during the 1982 crisis. Interestingly, The dispersion of \( TFPR \) shared a very similar secular movements as the total distortion. By contrast, the capital-specific distortion barely changed and, if any, slightly increased since 1990. Therefore, we conclude that all the decline in total distortion after the crisis is accounted for by a decline in the variance of \( \log TFPR \).
5.2 The Evolution of the Dispersion of $TFPR$ and Its Components

We now go a step further to explore the dynamics of the dispersion of various wedges and productivity. Table 4 reports several measures of the dispersion: the standard deviation, the 75th minus the 25th percentiles, and the 90th minus the 10th percentiles. We see that the dispersion of $TFPQ$ fell from 1.362 to 1.217 between 1986 and 1996. This suggests that as time goes by, it is more difficult for inefficient firms to survive. Note that consistent with our model, $TFPR$ is less dispersed than $TFPQ$, as our model predicts that prices and $TFPQ$ shall be negatively correlated. The standard deviation of $TFPR$ in 1986 is 0.75, much larger than the level of United States, 0.33. The numbers in the table are consistent with greater distortions in Chile than in the United States.
Table 4: Summary Statistics for the Distribution of Wedges and Productivity

<table>
<thead>
<tr>
<th></th>
<th>log ( TFPQ_i )</th>
<th>log(1 - ( \tau_{yi} ))</th>
<th>log(1 + ( \tau_{ki} ))</th>
<th>log(( W_i ))</th>
<th>log ( TFPR_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1986</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td>1.362</td>
<td>0.672</td>
<td>1.182</td>
<td>0.550</td>
<td>0.749</td>
</tr>
<tr>
<td>90-10</td>
<td>3.521</td>
<td>1.643</td>
<td>2.745</td>
<td>1.463</td>
<td>1.903</td>
</tr>
<tr>
<td>75-25</td>
<td>1.854</td>
<td>0.752</td>
<td>1.428</td>
<td>0.723</td>
<td>0.990</td>
</tr>
<tr>
<td>Correlation with ( A_i )</td>
<td>1</td>
<td>-0.708</td>
<td>-0.073</td>
<td>0.649</td>
<td>0.914</td>
</tr>
<tr>
<td></td>
<td>1994</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td>1.135</td>
<td>0.520</td>
<td>1.190</td>
<td>0.481</td>
<td>0.5869</td>
</tr>
<tr>
<td>90-10</td>
<td>2.915</td>
<td>1.241</td>
<td>2.982</td>
<td>1.290</td>
<td>1.459</td>
</tr>
<tr>
<td>75-25</td>
<td>1.570</td>
<td>0.636</td>
<td>1.585</td>
<td>0.693</td>
<td>0.766</td>
</tr>
<tr>
<td>Correlation with ( A_i )</td>
<td>1</td>
<td>-0.620</td>
<td>-0.120</td>
<td>0.650</td>
<td>0.825</td>
</tr>
<tr>
<td></td>
<td>1996</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td>1.217</td>
<td>0.549</td>
<td>1.245</td>
<td>0.482</td>
<td>0.616</td>
</tr>
<tr>
<td>90-10</td>
<td>3.129</td>
<td>1.415</td>
<td>3.246</td>
<td>1.238</td>
<td>1.571</td>
</tr>
<tr>
<td>75-25</td>
<td>1.685</td>
<td>0.673</td>
<td>1.527</td>
<td>0.717</td>
<td>0.829</td>
</tr>
<tr>
<td>Correlation with ( A_i )</td>
<td>1</td>
<td>-0.680</td>
<td>-0.166</td>
<td>0.673</td>
<td>0.847</td>
</tr>
</tbody>
</table>

Turning to the evolution of the three wedges, Table 4 shows that the dispersion of both output distortion and wages declined over time, while the dispersion of capital distortion slightly increased during the same period. Figure 4 plots secular movement in \( \text{var} (\log TFPR) \) and its different components in equation 3. It is clear that almost all the decline in the dispersion of \( TFPR \) can be accounted for by the decline in the dispersion of the output distortion. To explore the resource misallocation among firms of different \( TFPQ \) and how the degree of resource allocation changes over time, we explore the correlation between \( TFPQ \) and different wedges and \( TFPR \). As shown by both Table 4 and Figure 5, \( TFPR \) and \( TFPQ \) are positively correlated. For example, in 1986 the correlation between \( TFPQ \) and \( TFPR \) is 0.914. The key reason, as suggested by the negative correlation between \( TFPQ \) and \( 1 - \tau_y \), is that firms with higher productivity are subject to larger idiosyncratic distortions. This correlation increased from -0.708 in 1986 to -0.620 in 1994. This suggests that distortions on high productivity firms and subsidies on low productivity firms were gradually removed over time.
Figure 4: Decomposition of Variance of $TFPR$

Figure 5: Correlation between $TFPQ$ and $TFPR$
5.3 Misallocation across Plants of Different Productivity

Our key question is how important is the improvement of resource allocation among firms of different productivity (measured in $\text{TFPQ}$) in driving the decline in the dispersion of $\text{TFPR}$ against other factors.

To this end, we decompose the variance of log $\text{TFPR}$ into between- and within-group variation using:

\[
\text{Var}(\log \text{TFPR}) = \frac{1}{N} \sum_{q} Q \sum_{i} N_{q} (\log \text{TFPR}_{qi} - \overline{\log \text{TFPR}})^{2}
\]

\[
= \frac{1}{N} \sum_{q} N_{q} \text{Var}(\log \text{TFPR})_{q} + \frac{1}{N} \sum_{q} N_{q} (\log \text{TFPR}_{q} - \overline{\log \text{TFPR}})^{2}
\]

The between-group component captures the dispersion of $\text{TFPR}$ across groups of different $\text{TFPQ}$. By definition, it washes out idiosyncratic factors that may potentially drive the dispersion of $\text{TFPR}$ (e.g. a reduction of measurement error over time or volatility of idiosyncratic demand shocks) and provide a clear picture of the degree of resource misallocation across different productivity groups. On the other hand, while the within-group component may still capture the degree of resource misallocation within each group, it may also be driven by other idiosyncratic factors.

We now decompose the change in the dispersion of $\text{TFPR}$ into the between-group and within-group variances. Since the purpose of this exercise is to isolate the importance of variations in resource allocation across different productivity levels from other factors in explaining declining in dispersion of $\text{TFPR}$, we classify firms into quintiles based on their $\text{TFPQ}$ in each year. Interestingly, Figure 6 shows that all the decline in dispersion of $\text{TFPR}$ since 1986 is accounted for by the between-group variance. This suggests improvement in resource allocation across firms of different productivity play crucial roles in driving the decline of dispersion of $\text{TFPR}$.

To further show the direction of resource reallocation, we plot the different elements of between- and within-group variances in Figure 7. As shown by the left panel, the average
Components of \( \text{var(lnTFPR)} \): Within & Between Group

<table>
<thead>
<tr>
<th>Year</th>
<th>Within</th>
<th>Between</th>
<th>( \text{var(lnTFPR)} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>80</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>82</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>84</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>86</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>88</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>90</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>92</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>94</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>96</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 6: Quantile Analysis for the Variance of TFPR

The TFPR of the bottom quintile experienced the fastest convergence to the mean, followed by that of the top quintile. This implies that the main reason for the decline in the between-group variance is that the average TFPR of the bottom and top quintiles converges to the mean. Moreover, given the positive correlation between \( TFPQ \) and TFPR in 1986, the convergence of TFPR for both the bottom and top quintiles to the mean implies that the TFPR of least productive plant becomes larger and the TFPR of the most productive firms is smaller.

To further support the quantitative importance of resource reallocation, the right panel of Figure 7 plots the within-group variance and its different elements. In contrast to the pattern of between-group variances, elements of within-group variance across all quintiles follow similar dynamics since 1986. This suggests that the reduction in the dispersion of TFPR is NOT caused by a reduction in the measurement error or volatility of idiosyncratic shocks.

Finally, we decompose the variance of output distortion into between- and within-group components. Our purpose again is to see to what extent the decline in the dispersion of output distortion is attributed to the changes in the distribution of idiosyncratic distortion among plants of different TFPQ. The left panel of Figure 8 shows that the between-group variance still plays the dominant role in the decline of the dispersion of output distortion. The
main driving force of the decline, as suggested by the right panel, again, is the convergence of the output distortion of the bottom quintile to its economic-wide mean. Overall, Figure 8 suggests that over time plants with lower (higher) $\text{TFPQ}$ are associated with less output subsidy (distortion).

### 5.4 Size Distribution

Another way to examine how variations in distortions have improved resource allocation in Chilean economy after the crisis is to explore changes in the size distribution over time. Our measure of plant size is the value-added. To remove the impacts of changes in the mean plant size on the size distribution, we plot the demeaned size distribution. Figure 9 shows that firm size distribution skews to the left, consistent with the view that small plants constitutes the majority of the plants. Over time, firm size distribution become more dispersed: the density of both large and small plants increases while that for the middle-size plants declines. In particular, the density of small plants increased significantly. This is consistent with the fact that over time, low $\text{TFPQ}$ plants became less subsidized and thus downsized, while high $\text{TFPQ}$ plants became less distorted and thus produced more.
Figure 8: Decomposition of the Dispersion of Output Distortion

Figure 9: Plant Size Distribution
5.5 Resource Reallocation

The evidence so far suggests that a reduction in distortions causes resource reallocated among plants of different productivity, which translates into less dispersion in \( TFPR \). We now provide direct evidence of resource allocation among different \( TFPQ \) quintiles. To tease out the impacts of trend growth on capital and labor deployed across plants, we demean the capital and labor for each group. Figure 10 shows that over time the top quintile gain more share in both capital and labor. By contrast, the bottom two quintiles lose shares of both capital and labor.\(^7\)

Resource reallocation also shifted the distribution of capital and labor, as evidenced by Figure 11. The left panel shows that over time, distribution of physical capital become more dispersed. There are fewer mid-size plants and more small and large plants. This is consistent with the above evidence that high \( TFPQ \) plants gained more capital stock, whereas the low \( TFPQ \) plants downsized. Similarly, the right panel shows that the distribution of labor also became more dispersed, in the sense that there are more large and small plants, but fewer

---

\(^7\)The increase in capital share for the top quantile accelerated in the 1990s. This may be explained by the fact that the 1990s is a period of significantly higher financial development than before.
mid-sized plants.

To summarize, our evidence suggests that between 1986 and 1996, more than sixty percent of aggregate manufacturing TFP growth is attributed to the improvement of allocative efficiency, shown up as a shrinkage of dispersion of $TFPR$. Among those wedges, the reduction in the dispersion of output distortions plays the dominant role in the reduction of $TFPR$ dispersion. In particular, a reduction in the least productive plants’ output subsidies and the corresponding increase their average $TFPR$ constitute the most important reason for the reduction in resource misallocation during this period.

6 Robustness Checks

6.1 Balanced versus Unbalanced Panel

In our benchmark case, we delete any firm (for all years) with negative investment, value added, and zero or missing wages the labor. Therefore, a firm can still enter or exit at any time in our sample. To examine the quantitative importance of extensive margin versus intensive margin in contributing to aggregate TFP dynamics, we now restrict the sample for
firms that survive the whole period (1980-1996), which is a balanced panel.

Figure 12 shows that aggregate manufacturing TFP follows similar pattern for both balanced and unbalanced panel. That is, after a sharp decline during the 1982 and 1983 crisis, the manufacturing TFP started to take off in the late 1980s. If any, the TFP for unbalanced panel recovered at a rate slightly faster than that of balanced panel. This is consistent with the view that entry of more productive firms and exit of least productive firms contributed positively to aggregate TFP grow. Quantitatively, however, such a difference is small relative to the overall increase of manufacturing TFP during this period. This suggests that resource reallocation along the intensive margin still plays dominant roles in the increases in TFP due to resource allocation.

6.2 TFP Approximation under Log Normal Assumption

Our decomposition methodology of TFP relies on the assumption of joint log normal distribution for $1 + \tau_{ki}$ and $W_i, 1 - \tau_{yi}$. We now check this assumption. We compute aggregate manufacturing TFP from the data using equation 1. We then compute aggregate TFP using the RHS of equation 2, which equal to the data under the log normal distribution. The gap between these two series, on the other hand, might be due to measurement error or model
mis-specification. As can be seen from Figure 13, the two series track each other closely across our sample years, both starting to recover in the late 1980s. Since the focus of this paper is to explore the time variation in TFP, we argue that the assumption of lognormal distribution is suitable for our analysis.

6.3 Materials in Production Function

In our benchmark case, we assume that only capital and labor are factor inputs and ignore the information on materials to measure the distortions. Now we assume materials are part of factor inputs. Specifically, for each producer $i$, the production technology is Cobb-Douglas in capital labor and materials

$$Y_i = A_i K_i^{\alpha_K} L_i^{\alpha_L} M_i^{1-\alpha_K-\alpha_L} \quad (11)$$

To back out the plant-specific distortions, we assume that the rental price of materials, denoted as $r^m$, is not distorted and measure capital and labor distortions using the relative input demands. The first-order conditions of the firm allow us to retrieve the wedges$^8$ as

---

$^8$Details can be found in the appendix.
We would like to examine the robustness of the potential TFP gain by eliminating distortions. To this end, Table 5 reports the TFP gains from equalizing TFPR under different robustness checks. We see that with materials in the production function, the magnitude of potential TFP gains reduces by around 5-8 percent. Over time, however, the decrease in such efficient gain (13.7 percent) is only slightly smaller than its counterpart in the benchmark case (15.4 percent).

Table 5: Robustness Check: TFP Gains from Equalizing TFPR

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark</td>
<td>80.4</td>
<td>66.5</td>
<td>65.0</td>
</tr>
<tr>
<td>Materials</td>
<td>74.0</td>
<td>58.0</td>
<td>60.3</td>
</tr>
<tr>
<td>Sector-specific $\alpha_K$</td>
<td>63.4</td>
<td>49.9</td>
<td>51.9</td>
</tr>
</tbody>
</table>

Table 6 reports the robustness check for contribution of various elements to aggregate manufacturing TFP growth between 1986 and 1996. Comparing the first and third columns, we see that with materials in production, the contribution of improvement in allocative efficiency increases slightly to 62.7%, whereas the contribution of efficiency TFP drops. Among the two components of allocative efficiency, the introduction of materials reduces the negative impact of capital distortion on TFP growth by 5%. But still, the change in the dispersion of TFPR is the only factor that contribute positively to an improvement in allocative efficiency.

Table 6: Robustness Check: Contribution to TFP Growth (1986-1996)

<table>
<thead>
<tr>
<th>Contribution to TFP Growth</th>
<th>Materials</th>
<th>Sector-specific $\alpha_K$</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>$TFP^e$</td>
<td>0.373</td>
<td>0.456</td>
<td>0.398</td>
</tr>
<tr>
<td>$-\frac{\varphi}{2} \text{var} (\log TFPR_i)$</td>
<td>0.639</td>
<td>0.553</td>
<td>0.663</td>
</tr>
<tr>
<td>$-\frac{\alpha(1-\alpha)}{2} \text{var} \log \left(\frac{1+\tau_{L_i}}{W_i}\right)$</td>
<td>-0.011</td>
<td>-0.009</td>
<td>-0.061</td>
</tr>
<tr>
<td>Total allocative efficiency</td>
<td>0.627</td>
<td>0.544</td>
<td>0.602</td>
</tr>
</tbody>
</table>
6.4 Sector-specific Capital Shares

So far we have not used information by sectors when calculating wedges and TFPR. Now we relax this assumption and compute distortions using sector-specific capital shares. We use information on labor shares from the US. The last row of Table 5 shows that the potential gain from equalizing TFPR becomes smaller in magnitude compared with the benchmark case. This suggests that the assumption of common capital share may exaggerate the capital-specific distortion. Between 1986 and 1996, the potential gain of eliminating misallocation dropped by 11.5 percent.

Table 6 shows that with sector-specific capital shares, the contribution of total allocative efficiency to aggregate manufacturing TFP growth is 54.4 percent. In particular, changes in the dispersion of TFPR still plays dominant roles in the improvement of allocative efficiency. Therefore, the quantitative important of the improvement in allocative efficiency in aggregate manufacturing TFP growth is robust to sector-specific capital shares.

7 Conclusion

The Chilean aggregate TFP has grown spectacularly and become the engine of output growth in the decade following the 1982 financial crisis. In this paper, we use micro data on manufacturing firms to assess the role of resource misallocation in aggregate productivity growth during this period. We find that the cross-sectional allocation of resources has significantly improved and contributed to more than sixty percent of the aggregate TFP growth. Moreover, the improvement in allocative efficiency is essentially driven by a reduction in the cross-sectional dispersion of output distortion. Interestingly, a reduction in the least productive plants’ output subsidies and the corresponding increase their average TFPR constitute the most important reason for the reduction in resource misallocation during this period. Consequently, factor inputs are reallocated away from the least productive plants toward more productive ones.

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 are the quantitative importance of various policy reforms in Chile in reducing such distortions.\footnote{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.} A related issue is
why similar reforms have not happened in other countries after a financial crisis, for example, in Japan and Mexico. Answers to these questions are important to shed light on how western economies can emerge from the current recession as Chile did in the mid 1980s. These are our ongoing research.
References


