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Abstract

Using administrative tax records for all formal Chilean firms, we compute and characterize the evolution and distribution of total factor productivity at the firm level. With data on labor, capital, and value-added, we compute TFPR measures for individual firms between 2006 and 2015, allowing for differences in factor intensities across economic sectors. Our results show that factor reallocation plays a relevant role in explaining the evolution of aggregate TFP in Chile over the last decade. Firms with higher TFPR hire more workers, have stronger capital growth, and have a larger probability of survival. However, the extent of reallocation does not prevent a large, persistent dispersion in TFPR among firms. The magnitude of this dispersion suggests that further reallocation could bring up first-order gains in aggregate productivity and output. Our results also suggest that misallocation comes mainly from distortions on the firms´ overall scale, rather than from distortions on the relative use of capital and labor.

Resumen

En base a registros administrativos de un censo de la población de firmas chilenas, este artículo calcula y caracteriza la evolución y distribución de la productividad total de factores (PTF) a nivel de firmas entre 2006 y 2015, utilizando distintas estrategias empíricas y permitiendo diferencias en la intensidad de uso de factores entre sectores. Los resultados muestran que la reasignación de factores juega un rol relevante en la evolución de la PTF agregada en la última década. Empresas con mayor PTF (medida como PTF-Recaudación) contratan más trabajadores, acumulan más capital y tienen una mayor probabilidad de supervivencia. Sin embargo, este proceso de reasignación no impide que persista un grado importante de dispersión en la PTF-R entre empresas, asociada a diferencias en la productividad marginal de los factores. La magnitud de esta dispersión sugiere que una mejora en la asignación podría tener consecuencias de primer orden en productividad agregada y el PIB. El análisis también apunta a que los problemas de asignación vienen principalmente de distorsiones de la escala óptima de las empresas, más que de distorsiones en la utilización relativa de capital y trabajo.

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1. Introduction

Total factor productivity (TFP) plays a crucial role in explaining income differences across countries, and its evolution over time is a key element underlying growth dynamics. Development accounting exercises show that physical and human capital typically explain less than 40% of the cross-country differences in per capita income (Hall and Jones, 1999; Caselli, 2005), implying that more than half of those differences are explained by different unobservables that fall under the banner of TFP. The result is qualitatively robust to different methodologies to adjust for the quality of human and physical capital.

For economists, the importance of TFP in explaining income differences is a failure as well as a challenge. A failure, because TFP is a residual in estimated production functions. In that sense, it provides a "measure of our ignorance" (Caselli, 2005) that highlights the limitations of the standard growth framework. A challenge, because the lack of a widely accepted explanation of the determinants of TFP provides a research opportunity for theoretical and empirical analysis.

The more literal interpretation of TFP, technology, does not appear to be the main driving force for income differences, as evidence suggests that countries can imitate or directly import frontier technologies at a reasonable cost.[1] Thus, differences in TFP seem to reflect differences in the efficiency with which production factors are allocated. Hence, for a given set of aggregate factors, differences in the allocation of those factors across firms lead to significant differences in aggregate output.

The implication of this finding is strong and surprising: even if poor countries had workers with the same level of education as rich countries, a similar stock of machinery, equipment, and infrastructure, and access to the same technologies, they would still produce significantly less. These differences persist even when accounting for differences in sectoral composition across countries, such as the larger importance of agriculture -a low-productivity sector- in poorer countries. In fact, TFP differences in agriculture between rich and poor countries are even larger than in other sectors (Adamopoulos and Restuccia, 2014).

Thus, it seems that differences in aggregate TFP largely depend in the microstructure of factor allocation. Accordingly, over the last decade theoretical and empirical research has focused intensively on growth determinants at the micro-level. This development has gone together with the growing availability of micro-level data for both developed and developing countries. Consequently, a long list of papers published in the past decade attempt to measure and understand TFP directly using individual firm-level data.

This paper provides evidence on total factor productivity at the firm level in Chile between 2005 and 2015, using census data from administrative tax records provided by the Chilean Internal Revenue Service (IRS). Given its nature, the census covers all sectors in the economy, and firms of all ages and sizes. This extends the previous literature for Chile on the microstructure of productivity, which was, as much of the international literature, limited to firms in manufacturing, and allows us to provide novel statistics of the distribution and dynamics of TFP. Using this data, the paper characterizes the dynamics of TFP growth in Chile, the role of factor reallocation, and the extent of misallocation that persists across time and sectors. The stylized facts documented in the

[1] Another interpretation is that while the technology of wealthier countries— understood as specialized machinery, software, corporate administration models, etc.—is readily available for adoption by poorer countries, the return on that technology can be lower due to differences in the composition of human capital in the different countries (see, for example, Caselli and Coleman, 2006).

paper generate multiple research questions, and provide a starting point for subsequent projects that can address these issues.

The main conclusions of our analysis are the following. First, and consistent with the international literature, aggregate TFP growth in Chile between 2005 and 2015 can be explained by productivity gains at the level of individual firms (intensive margin) and by reallocation of production factors towards more efficient firms (extensive margin). This result is robust to different estimation methodologies, and highlights the importance of factor markets as growth engines by reallocating capital and labor to more productive uses. Second, and in line with the previous result, more productive firms hire more workers, have stronger capital growth, and have a lower hazard rate, which relates directly to the reallocation of factors towards more productive firms. Third, despite the previous results, the extent of reallocation is insufficient to prevent large, persistent dispersion in TFPR across firms. This implies that there are significant differences in the marginal product of both capital and labor across firms. This result, which holds for all sectors, is consistent with the literature on misallocation started by Hsieh and Klenow (2009) and suggests that there are large unexploited gains in aggregate TFP. Reallocation that reduces the gap in the marginal product of factors could significantly increase aggregate efficiency and output for the same aggregate endowment.

The rest of the paper is organized as follows. Section 2 summarizes the data and the methodology to calculate productivity measures. Section 3 presents a decomposition of aggregate TFP dynamics between TFP growth in individual firms, reallocation, and firm creation and destruction. Section 4 studies the reallocation process in more detail. Section 5 characterizes the dispersion of TFPR as a proxy of the extent of misallocation and computes the potential output gains of reducing dispersion. Finally, Section 6 concludes with a review of the major results and questions for future research.

2. Data Sources

All our data comes from Chile's Servicio de Impuestos Internos (SII), the country's tax collection agency. The SII dataset has unique identifiers for both workers and companies, allowing us to track individuals and firms over time. Identifiers are anonymized to guarantee confidentiality. All formal firms in the country are included in the data.

Specifically, we use information contained in two different tax forms, namely:

- Form 22: A statement of annual income presented by companies and individuals for tax purposes, which is compulsory for all companies and workers that received any non-exempt taxable income during the fiscal year. This form also shows the net income of companies that can be subject to capital taxation, based on current or accrued revenues. From this statement, we get information on sales, intermediate costs, and capital stock (immobile assets).

- Form 1887: An annual statement reported by all natural or juridical entities that develop an entrepreneurial activity and pay taxable income to their workers (according to the 42nd Article Nr 1 of the Law of Taxable Income) which includes wages, overtime wages, labor earnings and any other similar income (excluding disability, pensions and retirement payments). From this form, we obtain the firm´s wage bill, which we use as a proxy for quality-adjusted labor.[2]

Combining this information, we build a panel with annual frequency data over the period 2005-2015, with all variables expressed in nominal terms (current prices). We deflate the capital stock series with a capital stock deflator built from series on nominal and real aggregate capital stock. The wage bill is deflated with an aggregate labor cost index (ICMO). In order to deflate sales and the cost of intermediate goods we construct deflators at a 3–digit level for 111 economic sectors. Table 1 presents a summary of all variables and sources.

The data presents a number of missing observations and potential mistakes/misreporting that lead to implausible figures. In order to deal with these issues, we proceed to: first, eliminate firms with obvious misreporting issues such as missing variables or negative values in variables like sales or wage bill. We also exclude firms that have gaps in their annual reports. [3] Second, we exclude from the sample firms that only operate with one worker over the whole period. Third, we eliminate firms with extremely volatile rates of growth of capital stock or value added. Specifically, we compute the distributions of the standard deviation of the growth rates of capital and value added, and eliminate the firms above the 90th percentile. Fourth, we drop firms with implausible reversions in the growth rates of capital (labor)[4] and firms with implausible ratios of sales to labor and sales to capital.[5] Finally, after computing the TFP (defined below), we trim the distribution at the 1th and 99th percentile. Additionally, and as discussed later in more detail, we exclude economic sectors for which the assumed production technology might not be representative, such as Public Administration, Mining, and Utilities. The table in Appendix C describes the effect of these changes.

As we discuss in Section 5, we can distinguish at least two measures of firm productivity: total factor productivity based on quantities (TFPQ) and total factor productivity based on revenue (TFPR).[6] While TFPQ is a physical (unobserved) productivity measure, TFPR is the product of physical productivity and the output price of firms. Because our databases do not contain information on prices at the firm level, we cannot directly obtain measures of output from sales. Therefore, measures of productivity (TFP) throughout the paper are specifically measures of TFPR.

3. A decomposition of aggregate TFP growth

A large literature[7] has decomposed the growth of aggregate TFP measures (typically at the sectoral level) between changes in TFP measures at the firm level (the *intensive* margin) and the reallocation of capital and labor across firms (the *extensive* margin). Additionally, depending on the available

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[2] The F22 Form also collects data on workers´ remuneration. However, we find that data is more reliable for the sub-sample of firms that report both, the F22 Form and the F1887 Statement.

[3] We eliminate firms with missing data since this complicates the interpretation of the different components of productivity growth, and poses some doubt on the reliability and quality of their report. These gaps in the tax report do not correspond to seasonality of firm's dynamics but to firms that, for any reason, do not complete the tax reports for at least a year and then send again their complete tax reports. As we exclude these firms for all years, this does not affect whether the panel is balanced. In fact, the panel is not balanced as the data allows for firm entry and exit during the period of analysis

[4] This is, firms with very large increases (decreases) in capital or labor in a given year that are reversed in the following year.

[5] Firms that report very small (large) sales but very high (low) levels of capital and labor.

[6] See Foster et al. (2001) for a more detailed discussion on the differences between these two productivity measures.

[7] See, for example, Foster et al. (2001), Syverson (2011) and Melitz and Polanec (2015).

data, some papers also include in the extensive margin the impact of firm entry and exit. While there is large variation in specifications and methodologies across these exercises, a common finding has been that factor reallocation plays an important role in explaining the evolution of aggregate TFP measures. TFP growth comes not only from efficiency/technology improvements at the firm level, but also from factors that on average move towards more productive firms. For Chile, several studies that use data on manufacturing firms reach similar conclusions.[8]

We contribute to this literature by taking advantage of the fact that our data includes firms of all sizes and economic sectors, which allows us to build a proxy of aggregate TFP that approximates the productivity measures typically used in macro papers. We use the census data to build a proxy of GDP by summing up value added across all firms, as well as measures of aggregate factors. We then calculate a measure of aggregate TFP that is a weighted average of productivity measures at the firm level.[9] As mentioned earlier, our data also accounts for the effects of firm entry and exit.

We assume that GDP can be expressed as a standard Cobb-Douglas production function with constant returns to scale in capital and labor in any given year:

$$Y_t = A_t L_t^{\beta} K_t^{1-\beta}$$

Where Y_t is total value added, A_t is total factor productivity (TFP), L_t is labor, K_t is the capital stock, and β is the labor share.

Similarly, we assume that the value added of firm i in sector j can be expressed as:

$$Y_{it} = A_{it} L_{it}^{\alpha_j} K_{it}^{\beta j}$$

where α_j and β_j measure factor (labor and capital, respectively) intensities in sector j. This is, we assume that, for each sector, factor intensities across all firms and years are identical. As mentioned earlier, the production function does not impose constant returns to scale at the firm level.

As the sum of value added across all firms is a measure of GDP, aggregate TFP can be written as a weighted average of individual firm TFPs:

$$A_t = \sum_{i=1}^{Nt} \omega_{it} A_{it}$$

where the weight ω_{it} measures firm i´s combined used of factors, relative to the economy´s combined aggregate endowments:[10]

$$\omega_{it} = L_{it}^{\alpha j} K_{it}^{\beta j} / (L_t^{\beta} K_t^{1-\beta})$$

[8] See Busso et al. (2013); Bergoeing et al. (2010); Chen and Irarrázabal (2015); Micco and Repetto (2012).

[9] Conceptually, GDP is the sum of value added across all firms in the economy and, in principle, we can construct it directly from data on tax records. However, the actual calculation of GDP in national accounts uses information from various sources besides tax records, such as direct surveys, and therefore, by construction, it is not identical to our proxy measure.

[10] In most of the literature, aggregate TFP measures in decomposition exercises are lineal averages of individual TFPs, using shares of sales or employment as weights. In our case, the weights are non-linear, and might not add up to one.

From there, the absolute change in aggregate TFP in two consecutive years can be written as:

$$A_t - A_{t-1} = \sum_{i=1}^{Nt} \omega_{it} A_{it} - \sum_{i=1}^{Nt-1} \omega_{it-1} A_{it-1}$$

Additionally, as entry and exit decisions change the set of operating firms over time, we can rewrite the change in aggregate TFP as:

$$A_t - A_{t-1} = \sum_{i \in C} \omega_{it} A_{it} - \sum_{i \in C} \omega_{it-1} A_{it-1} + \sum_{i \in E} \omega_{it} A_{it} - \sum_{i \in S} \omega_{it-1} A_{it-1}$$

where C are *continuing* firms (that operate in both periods, $t-1$ and t), E are firms that *enter* in period t, and S are the firms that *exit* after period $t-1$.

There are several ways to decompose aggregate TFP growth over different components using the last expression.[11] They are all based on the general idea that changes in aggregate productivity are explained at the firm level by movements along the intensive and extensive margins. We adapt two of these decompositions and use them to characterize the evolution of TFP growth in Chile between 2006 and 2015.

The first decomposition, based on Grilliches and Regev (1995) (Method 1), expresses TFP growth as:

$$\Delta\%A_t = \sum_{i \in C} \Delta\%A_{it} \widetilde{\omega_t} \frac{A_{it-1}}{\widetilde{A_t}} + \sum_{i \in C} \Delta\omega_{it} \frac{\widetilde{A_{it}}}{\widetilde{A_t}} + \left[\sum_{i \in E} \omega_{it} \frac{A_{it}}{\widetilde{A_t}} - \sum_{i \in S} \omega_{it-1} \frac{A_{it-1}}{\widetilde{A_t}} \right]$$

Where $\widetilde{\omega_t} = \frac{1}{2}(\omega_t + \omega_{t-1})$, $\widetilde{A_t} = \frac{1}{2}(A_t + A_{t-1})$, y . $\widetilde{A_{it}} = \frac{1}{2}(A_{it} + A_{it-1})$

In this decomposition, the 2-year averages (over periods $t-1$ and t) of weights and productivities are taken as references. The first term is the weighted average of the percentage change in the productivity of each individual firm, where firms are weighted by their average factor participation and its productivity relative to aggregate TFP. This can be seen as the *intensive margin* (or *within* firm effect), showing the impact of individual TFP changes for a given allocation of factors. The second term is the weighted average of the change in total factor use for each firm, where firms are weighted by their average productivity. This term represents the *extensive margin* (or *between* firms effect), and is a measure of factor reallocation. For a given distribution of productivity, aggregate TFP will increase if more productive firms become relatively larger. The third term (in brackets) is the net effect of entry and exit on aggregate productivity. This represents the *extensive margin* associated to the creation and destruction of firms.

Alternatively, we also adapt the methodology devised by Foster, Haltiwanger and Krizan (2001) (Method 2), according to which aggregate TFP growth is expressed as:

$$\Delta\%A_t = \sum_{i \in C} \Delta\%A_{it} \omega_{it-1} \frac{A_{it-1}}{\widetilde{A_t}} + \sum_{i \in C} \Delta\omega_{it} \frac{A_{it-1}}{\widetilde{A_t}} + \sum_{i \in C} \Delta\%A_{it} \frac{A_{it-1}}{\widetilde{A_t}} \Delta\omega_{it} + \left[\sum_{i \in E} \omega_{it} \frac{A_{it}}{\widetilde{A_t}} - \sum_{i \in S} \omega_{it-1} \frac{A_{it-1}}{\widetilde{A_t}} \right]$$

[11] See, for example, Foster, Haltiwanger, and Krizan (2001), and Melitz and Polanec (2015).

This decomposition has two main differences with the first method. First, instead of weighting each continuing firm by the average productivity ($\widetilde{A_{it}}$) or average factor weight ($\widetilde{\omega_{it}}$) the initial values for both variables (A_{it-1} and ω_{it-1}, respectively) are now used . Second, and as a result, there is an additional term that captures the covariance between changes in productivity and changes in factor use. The entry and exit terms are identical to the previous method. Netting out the effect of the covariance provides a cleaner interpretation of the *within* and *between* firms effects. However, and as acknowledged by Foster, Haltiwanger y Krizan (2001), this second decomposition is more sensitive to measurement error in the data.

These decomposition exercises are analytically useful, as they identify distinct channels through which aggregate TFP changes, and provide a quantitative measure of their relative importance. However, and similarly to growth accounting exercises, a correct interpretation of the results must acknowledge that these channels do not operate independently, but closely interact in a dynamic context. For example, the entry margin can allow for the appearance of innovative firms, whose productivity grows over time, which in turn increases their factor utilization.

Table 2 presents both decompositions for the average growth in aggregate TFP average in Chile between 2005 and 2015, estimating production function parameters following the methodology in Levinsohn and Petrin (2003).[12] As the analytical setup does not adequately describe the technological or institutional setup of some sectors, we exclude from the sample firms in Mining, Utilities, Public Administration, and Residential Services.

The average annual growth of the measure of aggregate TFP derived from the micro data is 0.97%, very close to the figure obtained from a standard growth accounting exercise using sectoral data from national accounts. This provides a validation for the macroeconomic implications of the analysis using micro data, and allows us to interpret our results with greater confidence.

In line with the international literature, the contribution of the intensive margin is greater than that of the extensive margin, but of the same order of magnitude. This is, aggregate TFP growth is partially driven by efficiency gains at the firm level, and partly by reallocation of capital and labor toward more productive units. While there is large literature that focuses on the determinants of the intensive margin (such as R&D or the firm's organizational structure), in the rest of the paper we focus our attention on the reallocation channel. First, we look at the reallocation channel in more detail, looking at the response of individual firms hiring and investments decisions to productivity, and the effect of productivity on hazard rates. Second, we argue that, while reallocation has been important for TFP growth, it has been insufficient to dampen the large and persistent dispersion in the marginal product of factors across firms. As mentioned in the introduction, one of the paper's main conclusions is that the potential contribution of the extensive margin is an order of magnitude greater than the actual contribution observed in the data.

A final, somehow surprising result that emerges from both decompositions is that the impact of the entry/exit margin is negative. This result implies that, on average, the net effect of firm creation and destruction dynamics is detrimental to productivity growth: aggregate TFP is lower because of firm turnover. Here, the caveat of the interpretation of these channels as independent processes becomes crucial, so one should be very careful when analyzing the marginal impact on any given channel. In equilibrium, channels interact, and changes on the underlying determinants of any given channel are likely to have a significant effect on the others.

[12] As a robustness exercise, other estimations are presented in the Appendix.

In fact, the negative effect of firm turnover does not imply that restrictions on firm creation and destruction would enhance productivity growth. First, the result does not mean that entering firms are less productive than exiting firms but, that these firms are smaller. In fact, new firms are, on average, 10% more productive than exiting firms, but they are 20% smaller. Hence, the negative effect is not the result of a reduction on average (unweighted) productivity, but due to scale differences that affect average weighted productivity. Turnover is efficient in the sense that firms that are more productive are replacing less productive firms. Second, the entry/exit margin only reflects the impact of firm turnover in the year it occurs. Thus, it does not take into account the dynamic consequences of turnover, to the extent that the firms that enter— and survive—increase their productivity over time and grow in scale. These longer-term effects of turnover show up in the measurement of the first two margins, so restrictions on entry and exit would affect the intensive and extensive margins over time. Alternatively, one could run the same decomposition, but focusing on productivity changes over periods longer than one year. In that exercise, the turnover margin would measure the accumulated contribution of firms that enter the market between t and $t + n$, with n being the period length. This is, the intensive and extensive margins of all firms that entered in that period would be now accounted by entry/exit. In the limit, with a sufficiently large n, firm creation would fully explain productivity growth, as all firms operating in the economy at any given moment were entrants at some point in the past.

Table 3 decomposes TFP growth over larger time windows, up to the maximum length allowed by the data (2005–2015 period). The choice of window length does not affect average productivity growth, but the identification and interpretation of the different margins. As expected, the turnover margin becomes less negative over a longer horizon, although the panel is not sufficiently large for it to become positive. The reallocation margin becomes relatively less important, which reflects the growth of successful new firms that are now accounted in the turnover margin.

4. A closer look at reallocation

The previous section highlighted that factor reallocation plays a significant role in explaining the evolution of aggregate TFP. This section looks at that process in detail, characterizing the speed and magnitude of the reallocation process. In particular, we address three questions. How do labor and capital react to a firm's productivity? How does productivity relate to the probability that a firm shuts down? Are these effects related to firm size?

Table 4 presents the estimations of regressions of the annual change in the firms' employment level (columns 1 and 2) and capital stock (columns 3 and 4) on the firm's productivity level in the previous year, as in Haltiwanger et al (2018b). While using productivity lags might partially address endogeneity concerns, identifying causality is still troublesome, so results are best seen as suggestive correlations. All specifications include firm, sector-year[13], and age[14] fixed effects, but they use different firm size controls. While columns (1) and (3) only include controls for the

[13] We include sector-year fixed effects to control for the possibility of different technologies between all the sectors we observe in the data. However, results are robust to this variable.

[14] The evolution of employment might differ between young -fast growing firms and old-slow growing firms (Evans, 1987). However, excluding age effects from the estimation has no impact on the estimated effects of productivity.

initial level of employment and capital in each firm, regressions (2) and (4) include, additionally, a set of firm-size dummies and their interaction with initial TFP. As expected from the decomposition analysis, column (1) shows that employment grows faster in firms with higher initial productivity. In addition, column (2) shows that the sensitivity of employment growth to initial TFP is smaller in larger firms, which seems consistent with the presence of some degree of concavity in scale. On average, a 10% increase in TFPR generates increases employment close to 3%. Consistent with decreasing marginal returns and factor complementarities, employment growth is slower in firms that start off with more labor and faster in firms with more capital. The results for capital (columns 3 and 4) are qualitatively similar, although the elasticity of capital to productivity is smaller than the elasticity of labor. A 10% increase in TFP leads to a 2.2% increase in capital, which implies that the capital/labor ratio of a firm falls modestly as productivity increases, at least on the margin. Explaining these differences across factors is a question for future research, but a possible explanation relates to differences in adjustment costs and the presence of financial constraints.

Table 5 applies a similar analysis to the probability that the firm exits in the next period. Results are consistent with reallocation at the firm turnover margin, as the hazard rate of a firm decreases with its productivity level. This is, the destruction process is not random, but relates to productivity, with low productivity firms closing down with more likelihood. Column (2) shows that the exit probability of larger firms is less sensitive to productivity, which makes sense as these firms have probably stronger buffers to survive temporary adverse shocks, and productivity in a given year might be less revealing of the firm's long-term characteristics. Smaller firms, on the other hand, have smaller buffers, and productivity realizations might be more revealing of their true type, as they are typically younger. Therefore, their productivity level in a given year has a stronger effect on their exit probability.

In sum, as suggested by the growth decomposition exercise, the reallocation margin works in the right direction, with high-TFPR firms accumulating more factors. The turnover margin is also qualitatively efficient, in that lower-TFPR firms are more likely to exit the market. However, and as discussed in the next section, the strength and speed of reallocation are insufficient to prevent large and persistent factor misallocation across firms.

5. The myth of reallocation? The persistence of misallocation

5.1 Productivity dispersion: Consequences and explanations

The previous sections emphasize that reallocation plays a significant role in explaining the evolution of aggregate TFP. However, reallocation flows do not necessarily indicate that the economy is close to efficiency. Reallocation, while important, might be insufficient and unable to reduce aggregate misallocation. Thus, aggregate TFP, while growing, might lag significantly below its potential.

How do we define misallocation? Conceptually, factors are misallocated if they are not assigned toward their more productive uses. In the absence of frictions, in an efficient allocation marginal products of all factors are equalized across all firms.

In an efficient allocation, different firms can have different levels of *physical* productivity—henceforth, TFPQ, where Q represents quantity. This measure captures total factor productivity, defined in constant prices. In the absence of frictions in factor utilization, firms with a higher TFPQ should have a larger scale. In practice, the firm's size is limited by the existence of diminishing marginal returns—for example, if the production function has decreasing returns to scale—or, alternatively, if the firm has some degree of market power and must lower its prices if it wants to increase sales. The optimal firm size is determined when the marginal cost of adding more factors—determined, in turn, by wages and capital rental rates—is equal to the marginal revenue generated by those factors. If all firms meet this optimality condition in equilibrium, the value of TFPR must be equalized acrossr all firms.[15]

Thus, while the distribution of TFPQ by itself has no direct relation to efficiency, the distribution of TFPR, if correctly measured, provides a measure on how the current allocation of production factors compares to the optimal allocation – or, at least, to the optimal allocation *in a frictionless world*. As mentioned earlier, measuring TFPQ directly requires data on the specific prices charged by each firm for their products, as well as on the firm-specific factor allocations to each of the firms' products. Most measures of productivity in firms, including those used for Chile (both the data from the National Industrial Survey and the IRS data used in this paper), are based on firms' total sales and value added, so they are measures of TFPR. [16][17]

Hsieh and Klenow (2009) develop this idea and show how dispersion in TFPR across firms is associated with first-order efficiency losses relative to an optimal allocation. In their paper, a hypothetical reallocation of resources that eliminates TFPR dispersion among firms would increase the aggregate TFP of India by around 100–130%. That is, India could, in principle, double its aggregate TFP level if it could redistribute the factors that it already has. For China, the estimated gains are similar in magnitude, in the range of 86–110%.[18] TFPR dispersion – and thus, potential productivity gains – is large even in the US. Given the fact, as discussed below, that zero dispersion might not be efficient or desirable, a more conservative exercise is to take actual dispersion on the US as a benchmark, on the basis that it reflects fundamental factors rather than distortions. In that case, the potential gains from China and India of converging to the US are still large, at 30–60% of aggregate TFP.

Nonetheless, it is important to highlight that Hsieh and Klenow (2009) develop a model where misallocation explains all the dispersion in TFPR, a strong assumption that simplifies reality to emphasize the role of misallocation. For example, and as pointed out by Bagger, Christensen and Mortensen (2014), it could be the case that the dispersion in TFPR is increased because the model assumes homogeneous input factors instead of heterogeneous ones, therefore attributing more relevance to misallocation by simply ruling out dispersion attributable to heterogeneous input factors. Another caveat to consider is the assumption made by the authors of constant markup (across countries, firms and years), which could lead to dispersion of TFPR that is not necessarily associated with resource misallocation. However, despite these and other possible caveats of the specific methodology proposed by Hsieh and Klenow (2009), there is broad consensus in the literature in that misallocation is one of the most important factors explaining the high dispersion in TFPR.

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[15] The TFPR level also depends on the production function, in particular on the capital and labor exponents, their shares in returns in a Cobb-Douglas function. Therefore, the TFPR equality condition should be tested on subsectors that operate with a fairly uniform technology.

[16] For example, Busso et al. (2013) and Bergoeing et al. (2010).

[17] TFPQ can be inferred from TFPR based on a series of functional assumptions. For a detailed discussion of the differences between these data-derived productivity measures, see Foster et al. (2017).

[18] The last year in Hsieh and Klenow's (2009) estimates is 2005 for China, 1994 for India, and 1997 for the United States.

A large literature has followed Hsieh and Klenow (2009), pointing at inefficiencies in factor allocation as the main culprit in explaining TFP differences across countries.[19] Under the same logic, several empirical studies have identified reductions in TFPR dispersion as an important determinant of real aggregate TFP growth.[20] For Chile, studies using data for the manufacturing sector through the mid-2000s highlight the importance of reallocation in the growth process, as well as the existence of a persistent wide dispersion in TFPR.[21]

What explains TFPR dispersion among firms?[22] A first explanation is that it does not reflect an economic phenomenon, but simply reflects measurement error. Estimating productivity requires correctly computing (i) the value added of each firm, (ii) its labor utilization (adjusted by some sort of quality indicator, such as wages), and (iii) its capital stock. There are numerous possible errors and omissions in the imputation of each of these variables, in both surveys and administrative data, which could exaggerate TFPR differences among firms. Several studies have evaluated the possible quantitative impacts of these errors, and proposed more robust measurement methodologies.[23] The general conclusion is that the main results are robust to different measurement strategies.

A second explanation is that firms with high marginal productivity might not immediately adjust factors for technological reasons, or might optimally choose a partial adjustment due to adjustment costs. For example, search frictions in the labor market imply that finding and hiring adequate workers takes time. Analogously, capital adjustment costs might lead firms to adopt gradual increases. However, methodologies that explicitly control for adjustment costs find that they only explain a small fraction of the TFPR dispersion observed in the cross-sectional data.[24]

A related explanation is that the low elasticity of factor adjustments to TFPR might reflect uncertainty over the persistence of productivity. However, micro studies based on panels typically find that differences in TFPR at the individual firm level tend to be highly persistent over time.

Other potential culprits for TFPR dispersion are imperfections that restrict the operation of factor markets, but that are not directly associated with regulations or political distortions, such as financial constraints. Relatively young firms or firms with little collateral might find it difficult to hire more factors if they are unable to get credit.[25]

Finally, there can be distortions to firm decisions related to the legal and regulatory environment. For example, several studies show how the effects of labor legislation can vary among firms with different characteristics. Although regulatory requirements regarding social security contributions or severance payments can be identical for all firms, they can have a bigger impact on larger firms if, for example, they are subject to stricter oversight and enforcement. This is just one

[19] Alfaro et al. (2008), Hsieh and Klenow (2009), Kalemli-Özcan and Sorensen (2016), and Busso et al. (2013), among others.

[20] Ziebarth (2013) for the United States; Fuji and Nowaza (2013) for Japan; Gopinath et al. (2017) for Eastern European economies; Reis (2013) for Portugal; and Calligaris (2015) for Italy.

[21] Busso et al. (2013); Bergoeing et al. (2010).

[22] For a more general perspective, see the reviews in Hopenhayn (2014) and Restuccia and Rogerson (2017).

[23] See, for example, Hsieh and Klenow (2009) and Bils et al. (2017).

[24] Midrigan and Xu (2014) and David and Venkateswaran (2017). However, Asker et al. (2014) present results indicating that adjustment costs are more important, especially in developing countries.

[25] Buera et al. (2011), Greenwood et al. (2013), Midrigan and Xu (2014) and Moll (2014).

example of the many types of size-dependent policies that generate the so-called "correlated distortions": firms that are more productive face *de facto* larger distortions.[26]

An important aspect of this analysis is that, by construction, typical dispersion measures are only available for firms that effectively choose to operate at a given point in time. However, the same distortions that generate productivity dispersion can also affect entry and exit decisions, as well as the incentives for firms to invest in technology that improves productivity. While the quantitative impact of these margins cannot be measured directly in the data, it is possible to combine the data with structural dynamic decision models to estimate the possible quantitative effects on aggregate efficiency. In this line, Bento and Restuccia (2017) calibrate a model with these characteristics for a large sample of countries and find that the quantitative effects on aggregate TFP can be substantial. Furthermore, they argue that this type of distortion can explain the large observed differences in the size distribution of firms among countries. In particular, the existence of more small and medium-sized firms in poorer countries and more large firms in developed countries.

5.2 Evidence for Chile

5.2.1 Dispersion

In the first empirical exercise we calculate the cross-sectional TFPR dispersion of firms following the methodology used by Hsieh and Klenow (2009).[27] As mentioned, since data on prices is not available, TFP is computed using Levinsohn and Petrin's (2003) approach, which corresponds to a measure of TFPR. Thus, the resulting dispersion provides information on the degree of efficiency of the resource allocation in the Chilean economy.

Hsieh and Klenow (2009) show that, based on their model specifications, a firm's TFPR is an increasing function of the marginal product of its factors. Using their terminology,

$$TFPR_{si} \propto \left(\frac{VMPK_{si}}{\beta_s}\right)^{\beta_s} \left(\frac{VMPL_{si}}{\alpha_s}\right)^{\alpha_s}$$

Where $VMPK_{si}$ and $VMPL_{si}$ are, respectively, firm's i value of marginal product of capital and labor, and α_s and β_s are the sectorial labor and capital shares in its (Cobb-Douglas) production function.

The expression implies that TFPR dispersion is directly (proportionally) related to differences in the marginal productivity of factors among firms. Conceptually, TFPR dispersion derives from two types of distortions: scale distortions and distortions on the relative costs of capital and labor.

Following Hsieh and Klenow (2009) (and the corrections made by the same authors in Hsieh and Klenow, 2013), we calculate the degree of TFPR dispersion for our data (Table 6). Dispersion is defined as the ratio between the productivity of the firms in the 90th (75th) and 10th (25th) percentiles. The exercise is carried out for three samples: all firms in the economy; firms in the

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[26] Restuccia and Rogerson (2013), Restuccia (2013), and Hopenhayn (2014).

[27] Crucially, we follow the equations in the correction appendix (2013) to the original article. The equations in the original version of the paper have typos that have a significant effect on calculations of dispersion and productivity gains. While Hsieh and Klenow argue that the codes used in calculating the results in their paper used the correct equations instead of the published ones, it is likely that several papers that followed the original paper inadvertently miscalculated some of their results.

manufacturing sector; and large firms in the manufacturing sector. The last sample is closest to the ones used by Hsieh and Klenow (2009) in their calculations for China, India, and the United States, and to the samples used in most of the international literature. In any case, cross-country comparisons are difficult due to differences in the period of analysis, the type of firms (or plants) included, and the estimation methodology for factor shares.

Table 6 shows that dispersion is larger in the whole economy than in the manufacturing sector, and smaller among large manufacturing firms, possibly due to greater homogeneity in production processes. Second, dispersion has not changed significantly in the last decade, although it did increase recently after a mild reduction. This result suggests that overall efficiency in factor allocation in Chile did not change to a relevant extent between 2005 and 2015 despite the active reallocation process described in previous sections. Third, dispersion is large, with firms in the 90th percentile of the sample of large manufacturing companies being up to five times more productive than those in the 10th percentile.[28]

Extending the exercise to other sectors, as well as disaggregating the manufacturing sector, reveals substantial heterogeneity, with higher dispersion in sectors like Agriculture, Fishing, and Financial services and, lower dispersion in manufacturing subsectors such as Cellulose and Paper and Chemicals (Table 7). In general terms, wide dispersion in marginal productivities is prevalent across all sectors.[29]

As discussed above, dispersion might not be a serious concern if the TFPR of individual firms is not serially correlated. If a large part of the cross-sectional variance in TFPR comes from measurement errors that reverse over time, or from fundamental disturbances that are not persistent, the efficiency costs of high dispersion in a given year could be minor, as temporary movements in TFPR might not require adjustments in scale and hiring. The data shows that this is not the case (Table 8). First, TFPR levels are highly persistent at the firm level, such that the unrealized gains of a better allocation do not disappear over time (Table 8, panel A). Second, the dispersion is similar if it is calculated using average TFPR for several years, instead of TFPR in a given year (Table 8, panel B).

5.2.2 TFPR and Firm Size

How does TFPR correlate with size? Under the hypothesis of *correlated distortions*, larger firms, which should be firms with higher TFPQ, face de facto tighter restrictions (for example, have a higher probability of being inspected and audited). In consequence, they might be further away from their optimal size than small firms, and thus have a higher TFPR. However, an alternative, non/exclusive hypothesis, such a credit constraints, suggests that small firms, which are more likely to be constrained, might have a larger TFPR as financial constraints limits their scale relative to larger firms.

[28] These results are qualitatively similar to the findings of Busso et al. (2013) and Micco and Repetto (2012) based on ENIA data on the manufacturing sector for the mid-1990s and mid-2000s.

[29] Of course, sectoral comparisons of dispersion must be taken with care, as differences in technological characteristics and competitive structure can explain some of the observed differences.

The relationship between size and TFPR[30] is explored in Table 12, where the first column shows the number of firms by size category and the next three columns presents the mean[31], standard deviation, and p90-over-p10 ratio of the log TFPR (demeaned by sector-year). The results suggest that larger firms are more productive in the margin, as the mean is monotonically higher as size increases. In addition, we find more dispersion within the smallest group of firms, which suggests that misallocation is relatively more severe among smaller firms.

Figure 1 depicts the relation between size and TFPR within each size category.[32] It is clear that, within the set of largest firms, TFPR and size move together. Due to their relative size, large firms have a very significant effect on aggregate TFP. Hence, distortions in this margin can have significant consequences on the aggregate.

5.2.3 Which factor drives TFPR dispersion?

What is the relative importance of the allocation of capital and labor to explain the dispersion of TFPR? Are differences across firms driven by the marginal productivity for one of the two factors? Figure 2 presents the variance decomposition of $TFPR_i = \left(\frac{VMPK_i}{\beta_i}\right)^{\beta_i}\left(\frac{VMPL_i}{\alpha_i}\right)^{\alpha_i}$ for the manufacturing sector, but similar results are found for the economy and for the large manufacturing sector. The contribution of both factors is relatively similar, although capital has become relatively more important over recent years. The covariance term is positive, suggesting that firms with a larger marginal productivity of capital also have a relatively large marginal productivity of labor. This fact implies that distortions are not associated to a specific factor, but rather to overall scale. Figure 3 depicts the relation between size and the marginal productivity of capital and labor. As the figure shows, the marginal revenue productivity of labor decreases with size within each size category, while the reverse holds true for capital. This is a somehow counterintuitive result, which seems to go both against the notion that small firms are specially constrained in capital and larger firms are specially constrained by labor regulations. Further research on this topic might provide a clearer answer.

5.2.4 Gains from reducing dispersion

What are the costs of TFPR dispersion? A reduction in the differences in TFPR among firms generates efficiency gains by reducing gaps in the marginal productivity of factors. That is, the dispersion disappears because implicitly factors are reallocated away from firms with low TFPR (where marginal productivity of factors is low) toward firms with higher TFPR. The new allocation would be more efficient and, therefore, would be associated with a higher aggregate TFP.[33] The economy would produce more with the same amount of factors.

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[30] In this exercise, firm ln TFPR is computed net of sector-year fixed effects to avoid sectorial heterogeneity across firm size distributions.

[31] By construction, since ln TFPR is demeaned by sector-year, the unconditional mean of ln TFPR is 0. The mean conditional on a firm size category represent the percent difference between the productivity of the average firm in the specific size category, and the average firm, within sector-year.

[32] Again, here we use ln TFPR net of sector-year fixed effects.

[33] In Section 3 aggregate TFP was defined as the weighted average of individual firm TFPs, where the weights are a function of the firms' relative use of factors. Intuitively, the reallocation process increases the relative "weights" of more productive firms, therefore increasing aggregate TFP.

Making several assumptions on the functional form and structure of supply and demand, Hsieh and Klenow (2009) propose a methodology to quantify the potential gains in aggregate TFP associated with reductions in TFPR dispersion. This methodology, while not immune to criticism, provides a good approximation of the order of magnitude of the potential gains associated with a more efficient factor allocation process. Tables Table 9 and Table 10 replicate the baseline exercise in Hsieh and Klenow (2009) and calculate the hypothetical impact of eliminating TFPR dispersion for different sectors. Consistent with the findings in the international literature, the estimated gains are large in magnitude, given the high TFPR dispersion observed in the data. For the aggregate economy (Table 9), the TFP gains are 90%, on average, enough to close the gap between productivity in Chile and productivity in the developed world. For the manufacturing sector, given the lower relative dispersion, the estimated gains are around 50%, which is in line with the findings of Busso et al. (2013) based on data from the National Industrial Survey (ENIA) for 1996 and 2006.

The analysis of the sectoral gains (Table 10) is, of course, a mirror of TFPR dispersion: the sectors with the largest gains are those with the largest dispersion. The estimated gains are very large (over 100%) in sectors such as Textiles, and more moderate in sectors such as Oil and Chemicals (below 30%, on average).

Table 11 complements this analysis with a breakdown of the potential TFP gain between two distortion margins identified by Hsieh and Klenow (2009): scale distortions, and labor and capital-labor ratio distortions (defined by the authors as a distortion in the relative cost of capital). The exercise illustrates the gains associated with incremental reductions in one of the distortions, for a given reduction in the other. As the table shows, even modest reductions in distortions in any of the margins (for example, of around 20%) generate significant gains in TFP (of about 12 to 25%). The scale distortion appears to be more important, since its (marginal) reduction has a much larger impact on aggregate TFP.[34] This result suggest that, though distortions in the relative use of capital and labor might be important for the Chilean firms, they seem to be more affected by the fact that they operate at a suboptimal scale.

To conclude, one must remember that there are several reasons to take these results with caution, although the qualitative implications – there are large potential gains from reallocation that remain unexploited – are robust. First, the complete elimination of dispersion, implicit in the calculation of the potential gains in the baseline exercise, might not be conceptually desirable. As discussed above, some degree of dispersion might be the efficient response by firms to technological factors such as adjustment costs. Consequently, forcing complete equalization of TFPR across firms might not be efficient. In that context, the estimated gains would represent an upper limit for the true potential gains, and the gains from partial reductions would provide a better approximation. Second, and in contrast to the previous caveat, the estimated values represent a measure of the static gains, without considering the potential dynamic gains that could be associated with the elimination of distortions that discourage firm-level productivity growth or aggregate factor accumulation (Bento and Restuccia, 2017). Third, the potential gains from reallocation come from the assumptions in the model of Hsieh and Klenow (2009). However, this theoretical framework, as any other one, is sensitive to model misspecification (Haltiwanger et al, 2018a), specially for sectors that are more heterogeneous in terms of the type of goods or services produced.

[34] A counterintuitive result in this exercise is that the progressive elimination of distortions to capital does not always have a monotonic impact on aggregate TFP. This is probably due to the fact that the production function factor shares are estimated with the original data, which is affected by the distortions.

6. Conclusions

In this paper, we compute and characterize the evolution and distribution of total factor productivity at the firm level for Chile. Using recently available data from Chile´s tax agency on the universe of firms and workers in the formal economy, we compute TFPR measures for individual firms following the Levinsohn and Petrin (2003) methodology. We then compute aggregate TFP indices, and decompose aggregate productivity growth into gains from firm´s individual productivity, gains from factor reallocation, and gains from the firms´ entry and exit process. We characterize the distribution and dispersion of TFPR for aggregate economy and for different sectors and groups of firms. Finally, we estimate the potential TFP gains associated with the elimination of resource misallocation (based on the methodology proposed by Hsieh and Klenow, 2009), and analyze the effects of removing different types of distortions separately.

Our results suggest the existence of a positive relationship between TFPR and firm´s performance. Firms with higher TFPR hire more workers, have stronger capital growth, and have a higher probability of survival. At the aggregate level, factor reallocation across firms is an important source of aggregate productivity growth in Chile over the past decade. However, high and persistent dispersion of marginal productivities across firms, suggest that there are still significant *potential* productivity gains from factor reallocation. Particularly, distortions associated to the firms' scale of operation seem to be more relevant than distortions on the relative use of capital and labor. Several exercises suggest our results are robust to using different methodologies.

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Table 1: Data Definitions and Sources.

Variable	Definitions	Data Source
Sales	Accrued and realized revenue.	Chile´s Internal Revenue Service, 2005-2015.
Intermediate goods	Cost of goods and services.	Chile´s Internal Revenue Service, 2005-2015.
Capital stock	Fixed assets.	Chile´s Internal Revenue Service, 2005-2015.
Labor	Remunerations.	Chile´s Internal Revenue Service, 2005-2015.
Aggregate and sectoral labor share	Worker´s remuneration of the corporate sector (financial and non-financial) and aggregate value net of taxes, average 2008-2014. Worker´s remunerations in aggregate value added of each economic sector.	Albagli et al., (2015) and Corbo and Gonzalez (2012) from National accounts data, Central Bank of Chile. Reference 2008 and 2003.
Sales deflator	Producer price index. We match 111 economic sectors from the input-output matrix, with data from the CPI, PPI and sectoral GDP deflators. We use E-views to obtain monthly series from quarterly frequency deflators.	National accounts, Central Bank of Chile.
Intermediate goods deflator	Intermediate materials price index, for 111 economic sectors from the input-output matrix. We weight production prices of each economic activity by its weight in the input-output matrix. To consider imported goods, we add the intermediate goods Import Unit Values Index weighted by total import expenses. We use E-views to obtain monthly series from quarterly data.	National accounts, Central Bank of Chile.
Remuneration deflator	Labor cost index. To construct annual deflators we take a 12 months average.	National Statistics Institute.
Capital stock deflator	Capital stock at current prices over capital stock at constant prices.	National accounts, Central Bank of Chile. Reference 2008.
GDP deflator	GDP deflator by economic activity.	National accounts, Central Bank of Chile. Reference 2008.

Table 2: Average Productivity Growth Decomposition, 2006-2015.

Panel A: Method 1	
Aggregate TFP Growth	**0.97%**
Intensive margin	1.23%
Extensive margin	1.03%
Net entry - exit	-1.30%
Panel B: Method 2	
Aggregate TFP Growth	**0.97%**
Intensive margin	1.67%
Extensive margin	1.47%
Covariance term	-0.87%
Net entry - exit	-1.30%

Note: Annual average aggregate TFP growth between 2006 and 2015. Productivity estimated with Levinsohn and Petrin (2003) methodology. Method 1 is based on Grilliches and Regev (1995), where intensive margin refers to the impact of firm TFP changes for a given allocation of factors, extensive margin refers to the reallocation of factors and net entry and exit refers to the creation and destruction of firms. Method 2 is based in Foster, Haltiwanger and Krizan (2001), where the covariance term provides a cleaner interpretation of the intensive and extensive margins.

Table 3: Average TFP Growth Decomposition - Different Time Windows, 2006-2015.

Panel A: Method 1	*(1)*	*(2)*	*(3)*	*(4)*
	1 year	*2 years*	*5 years*	*10 years*
Aggregate TFP Growth	**0.97%**	**0.97%**	**0.97%**	**0.97%**
Intensive margin	1.23%	1.33%	1.18%	1.04%
Extensive margin	1.03%	0.63%	0.43%	0.28%
Net entry - exit	-1.30%	-0.99%	-0.64%	-0.35%
Panel B: Method 2				
Aggregate TFP Growth	**0.97%**	**0.97%**	**0.97%**	**0.97%**
Intensive margin	1.67%	1.63%	1.37%	1.08%
Extensive margin	1.47%	0.93%	0.62%	0.32%
Covariance term	-0.87%	-0.61%	-0.38%	-0.08%
Net entry - exit	-1.30%	-0.99%	-0.64%	-0.35%

Note: Annual average aggregate TFP growth between 2006 and 2015. Productivity estimated following Levinsohn and Petrin (2003) methodology. Method 1 is based on Grilliches and Regev (1995), where intensive margin refers to the impact of firm TFP changes for a given allocation of factors, extensive margin refers to the reallocation of factors and net entry and exit refers to the creation and destruction of firms. Method 2 is based in Foster, Haltiwanger and Krizan (2001), where the covariance term provides a cleaner interpretation of the intensive and extensive margins.

Table 4: TFPR and Factor Accumulation

	Employment Growth		Capital Growth	
	(1)	(2)	(3)	(4)
Employment (ln)	-0.27***	-0.27***	0.25***	0.27***
	(0.004)	(0.005)	(0.004)	(0.004)
Capital (ln)	0.22***	0.22***	-0.18***	-0.18***
	(0.003)	(0.003)	(0.003)	(0.003)
TFPR (ln)	0.28***		0.22***	
	(0.004)		(0.003)	
Micro		0.31***		0.24***
		(0.004)		(0.004)
Small		0.19***		0.16***
		(0.007)		(0.007)
Medium		0.16***		0.14***
		(0.012)		(0.012)
Large		0.16***		0.14***
		(0.018)		(0.018)
Obs	334,424	334,424	334,424	334,424
R-squared (Overall)	0.451	0.452	0.420	0.421
Sector-Year FE	X	X	X	X
Firm age FE	X	X	X	X
Firm size FE	-	X	-	X
Firm FE	X	X	X	X
Number of firms	72,446	72,446	72,446	72,446

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5: TFPR and Probability of Exit – Linear Probability Model

Dep. Var.: 1 if the firm exits in period $t+1$, and 0 otherwise

	(1)	(2)
Employment (ln)	-0.11***	-0.12***
	(0.002)	(0.002)
Capital (ln)	-0.08***	-0.08***
	(0.001)	(0.001)
TFPR (ln)	-0.10***	
	(0.002)	
Micro		-0.11***
		(0.002)
Small		-0.06***
		(0.003)
Medium		-0.05***
		(0.005)
Large		-0.05***
		(0.008)
Obs	334,424	334,424
R-squared (Overall)	0.396	0.397
Sector-Year FE	X	X
Firm age FE	X	X
Firm size FE	-	X
Firm FE	X	X
Number of firms	72,446	72,446

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6: TFPR Dispersion

	All firms			Manufactures			Large Manufactures		
Year	**Std. Dev**	**p90/p10**	**p75/p25**	**Std. Dev**	**p90/p10**	**p75/p25**	**Std. Dev**	**p90/p10**	**p75/p25**
2005	0.91	7.84	2.76	0.82	6.41	2.53	0.64	4.60	2.14
2006	0.85	7.13	2.61	0.82	6.41	2.53	0.60	4.16	2.11
2007	0.85	7.10	2.61	0.77	5.80	2.41	0.60	4.21	2.00
2008	0.83	6.91	2.59	0.75	5.64	2.39	0.61	4.17	2.04
2009	0.82	6.67	2.57	0.73	5.42	2.30	0.62	4.44	2.07
2010	0.82	6.93	2.64	0.77	5.57	2.31	0.61	4.20	2.08
2011	0.81	6.69	2.62	0.74	5.72	2.34	0.61	4.31	2.08
2012	0.82	6.80	2.65	0.73	5.66	2.31	0.65	4.92	2.21
2013	0.82	6.98	2.66	0.75	5.95	2.44	0.66	4.70	2.24
2014	0.84	7.13	2.71	0.77	6.00	2.54	0.71	5.02	2.29
2015	0.88	7.80	2.85	0.85	6.62	2.63	0.68	4.84	2.21
Total	**0.84**	**7.09**	**2.66**	**0.77**	**5.93**	**2.43**	**0.64**	**4.51**	**2.13**

Table 7: TFPR Dispersion by Sector

	All firms			Large Manufactures		
Sector	**Std. Dev**	**P90 / P10**	**P75 / P25**	**Std. Dev**	**P90 / P10**	**P75 / P25**
Agriculture	1.10	11.34	3.27			
Fishing	1.06	12.27	3.46			
Food and beverages	0.79	6.12	2.40	0.72	5.07	2.22
Textile industries	0.86	7.34	2.76	0.78	4.98	2.22
Wood and furniture	0.80	6.32	2.52	0.72	4.69	2.17
Paper and paper products	0.74	5.94	2.45	0.66	3.99	1.99
Chemicals and petroleum	0.65	4.23	2.06	0.57	3.49	1.89
Other non-mineral products	0.84	7.13	2.67	0.55	4.28	2.37
Metal products	0.77	6.08	2.47	0.68	4.44	2.12
Construction	0.83	6.88	2.59			
Wholesale and Retail trade	0.82	6.83	2.62			
Transport	0.85	7.31	2.72			
Communications	0.91	8.26	2.88			
Financial services	0.95	9.30	3.02			
Personal services	0.79	6.14	2.62			

Table 8: TFPR Persistence

Panel A: TFPR explained by it lags

	TFPR	
L.TFPR	0.561***	0.564***
	(0.0124)	(0.00710)
L2.TFPR	0.140***	0.166***
	(0.0123)	(0.00636)
L3.TFPR	0.0676***	
	(0.0114)	
L4.TFPR	0.0908***	
	(0.0112)	
L5.TFPR	0.0816***	
	(0.00886)	

Panel B: mean TFPR by year windows

Year Window	**Manufactures**		**Large Manufactures**	
	Mean	**Std. Dev**	**Mean**	**Std. Dev**
1	1.23	1.28	1.09	1.07
10	1.10	1.17	1.01	0.83

Note: Panel A corresponds to a panel regression where TFPR is explained in function of its lags. Panel B shows the average of TFPR statistics in 1 and 10 years average. As the table shows, the mean and the standard deviation decrease with larger time spans, but there still exists high persistence and dispersion of TFPR.

Table 9: TFP Gains from Equalizing TFPR within Industries.

Year	(1) All firms	(2) Manufactures	(3) Large Manufactures
2005	91.7	53.0	42.8
2006	78.8	40.9	36.0
2007	77.4	40.9	36.7
2008	76.7	40.3	37.4
2009	80.5	52.0	49.0
2010	86.0	49.1	45.6
2011	88.8	52.3	48.9
2012	100.2	60.4	56.6
2013	97.4	54.5	50.5
2014	108.9	55.7	50.8
2015	111.9	59.7	49.5
Average	**90.7**	**50.8**	**45.8**

Note: TFP gains calculated as Hsieh and Klenow (2009). Productivity estimated with Levinsohn and Petrin (2003) methodology at 91 desegregated sectors for "All firms". "Average" refers to the linear years mean.

Table 10: TFP Gains from Equalizing TFPR by sector.

Year	(1) Food and Beverages	(2) Textil	(3) Woods and Furniture	(4) Cellulose and paper	(5) Chemicals and Oil	(6) Non-metalic minerals	(7) Metalic Products	(8) Construction	(9) Commerce and hotels	(10) Transport	(11) Communications	(12) Financial Services	(13) Personal Services
05	41.2	122.5	74.3	31.5	31.4	59.7	79.2	146.1	105.1	134.9	50.1	102.9	61.7
2006	32.0	98.5	55.6	23.7	25.4	43.8	63.1	118.3	93.1	120.2	60.3	90.4	62.7
2007	39.9	98.3	71.0	13.7	26.3	75.2	54.5	125.6	87.0	105.0	32.7	100.8	62.7
2008	38.7	90.5	54.3	16.1	23.4	78.9	58.9	104.3	84.0	111.9	26.9	105.2	65.1
2009	42.2	107.8	52.1	65.1	26.2	120.8	74.2	116.4	88.8	109.7	35.8	94.9	55.4
2010	45.0	119.3	43.6	40.5	29.7	89.5	71.2	123.1	97.7	114.6	30.9	109.1	56.7
2011	60.2	93.2	45.2	37.8	24.9	89.1	60.7	110.4	109.5	109.7	102.0	101.4	54.4
2012	56.1	88.7	51.1	58.0	26.9	110.1	90.4	154.9	111.7	109.4	79.6	129.3	60.2
2013	52.6	101.9	44.7	39.6	27.7	117.2	85.9	160.0	105.4	113.6	98.0	129.5	58.3
2014	48.5	92.1	42.9	48.0	31.6	144.0	102.0	215.6	124.6	123.3	54.3	148.8	63.0
2015	49.7	135.3	55.3	41.5	36.7	154.4	124.5	181.8	112.1	138.0	126.3	176.0	68.6
Average	**46.0**	**104.4**	**53.6**	**37.8**	**28.2**	**98.4**	**78.6**	**141.5**	**101.7**	**117.3**	**63.4**	**117.1**	**60.8**

Table 11: Average TFP Gains from Reducing Distortions

Panel A: All firms					
Reducion in Scale Distortions	**Reduction in Capital Distortions**				
	0%	10%	20%	30%	100%
0%	-	12.1	13.2	13.7	12.3
10%	5.3	17.4	18.3	18.8	16.5
20%	12.3	24.7	25.6	26.0	22.6
30%	19.0	32.2	33.1	33.5	29.1
100%	60.2	85.1	88.2	89.9	90.7

Panel B: Manufactures					
	Reduction in Capital Distortion				
Reduc. in Scale Distortion	0%	10%	20%	30%	100%
0%	-	8.6	9.5	9.9	9.4
10%	2.2	10.7	11.5	11.9	11.0
20%	5.4	14.2	15.1	15.5	14.4
30%	8.7	18.2	19.1	19.6	18.4
100%	30.3	46.3	48.1	49.0	50.8

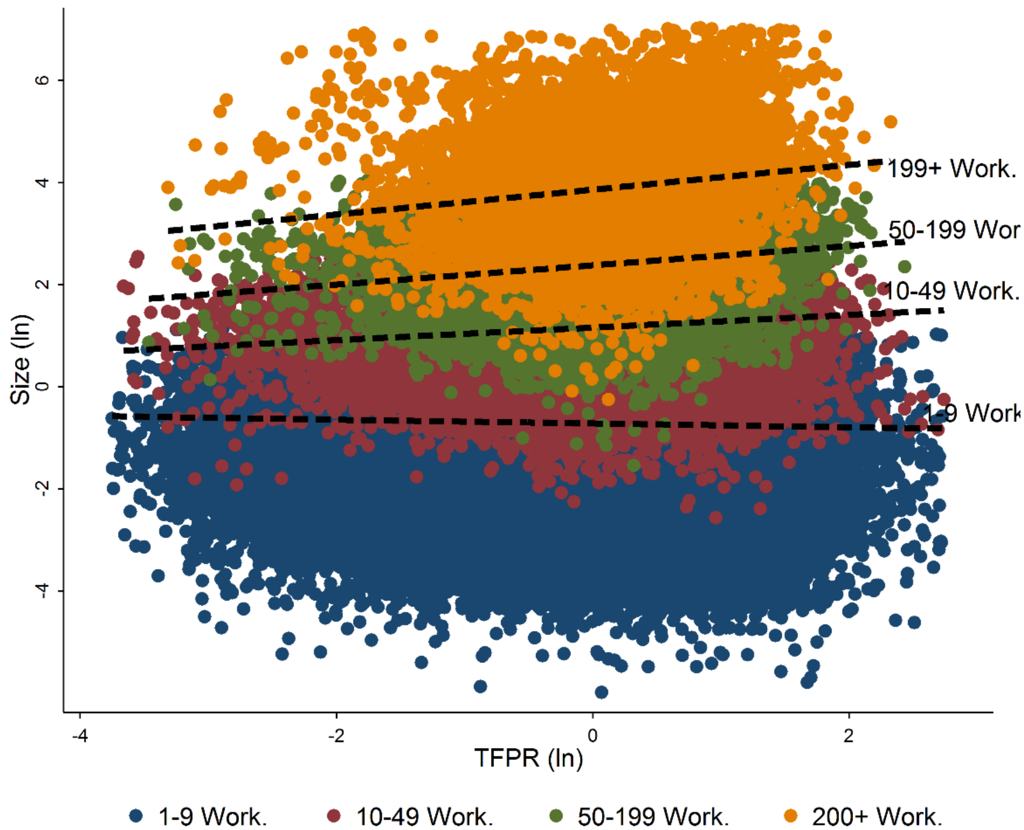
Note: TFP gains from reducing the capital and/or scale distortions by a given factor. The columns shows a decrease in capital distortions, while the rows for the scale distortions.

Table 12: Size and TFPR

Number of workers	Number of firms	TFPR (ln)		
		Mean	Std. Dev	p90-p10 Ratio
1-9	303,361	-0.03	0.77	6.68
10-49	99,927	0.06	0.58	3.87
50-199	26,784	0.12	0.57	3.79
200+	9,405	0.15	0.65	4.82
All firms	**439,477**	**0.00**	**0.72**	**5.70**

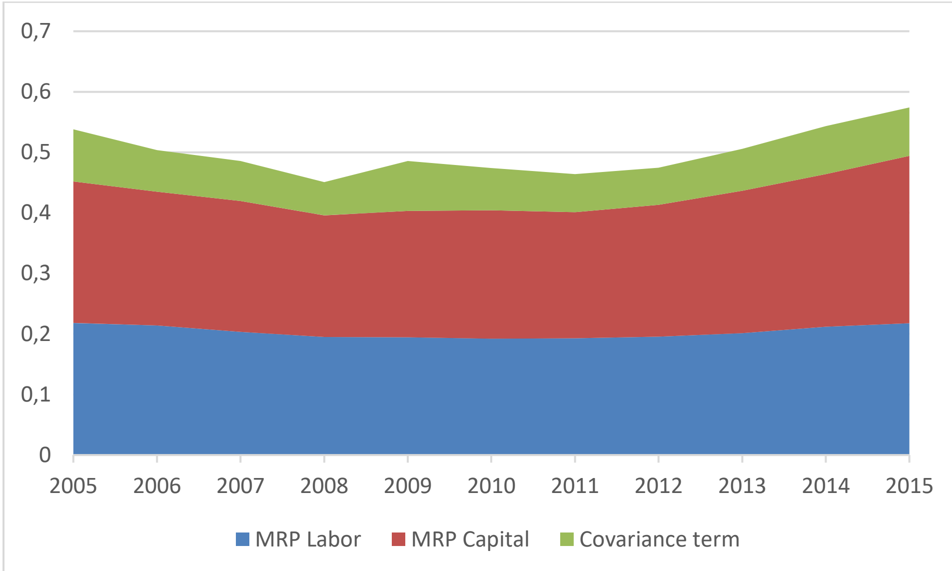
Note: TFPR net of sector-year fixed effects, descriptive statistics.

Figure 1: Size and TFPR



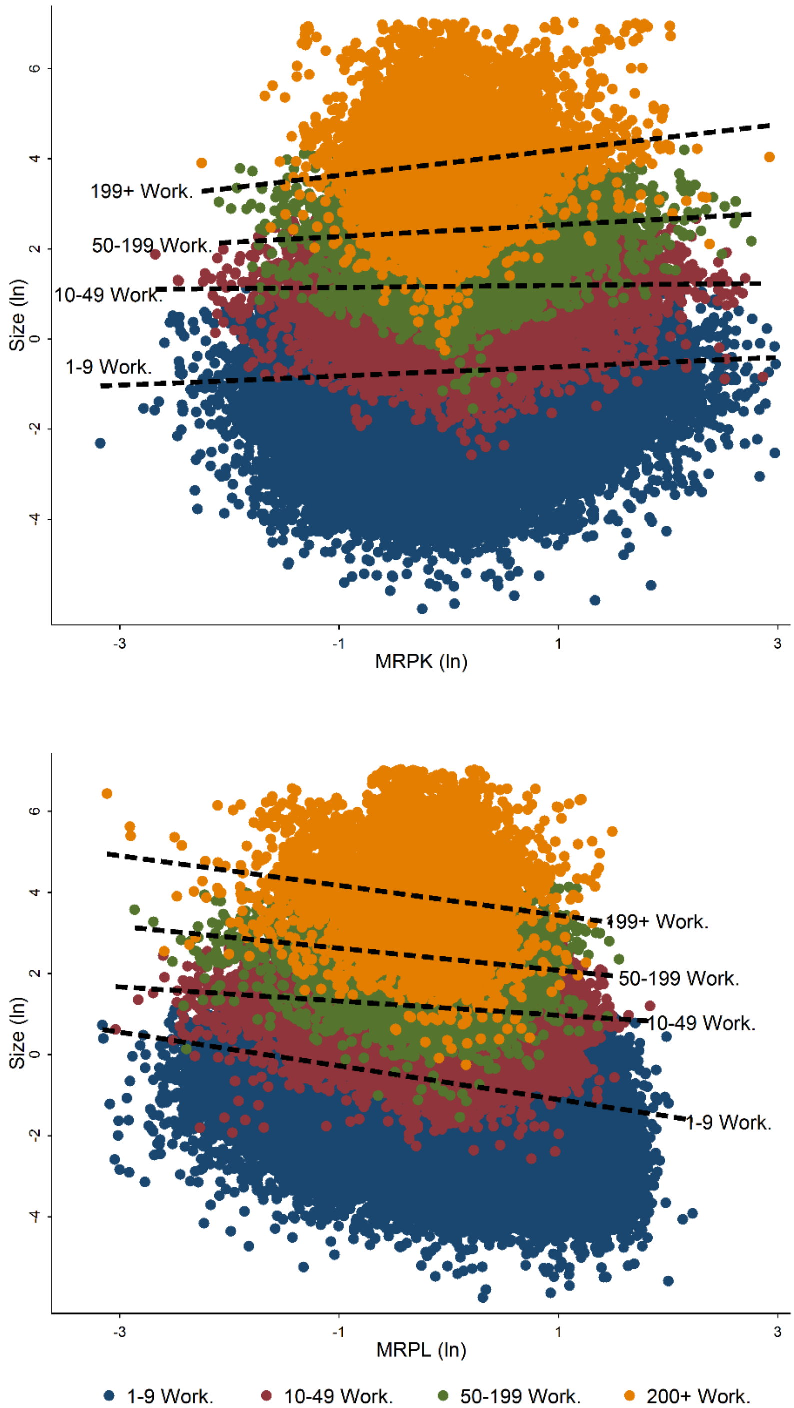
Note: Size measured as the log number of workers in the firm, net of sector-year fixed effects. TFPR measured as the log TFPR net of sector-year fixed effects. Dashed lines represents the linear tendency within each size group.

Figure 2: Variance decomposition of log TFPR, manufacturing sector.



Note: Variance decomposition of log TFPR net of sector-year fixed effects within the manufacturing sector as the variance of the Marginal Revenue Productivity of Capital, Marginal Revenue Productivity of Labor and the covariance of this last two terms. The Marginal Revenue Productivity of Capital (Labor) is calculated as $\left(\frac{VMPK_i}{\beta_i}\right)^{\beta_i}$, where $VMPK_i$ is the Value of the Marginal Productivity of Capital (Labor) divided by its shares (β_i) and raised to its shares power, net of sector-year fixed effects.

Figure 3: Size and Marginal Revenue Productivity of Capital and Labor



Note: Size and Marginal Revenue Productivity of Capital and Labor measured as the log net of sector-year fixed effects.

Appendix A

Table A1: Average Productivity Growth decomposition, 2006-2015, different methods.

Panel A: Method 1	*(1)* **LevPet**	*(2)* **Factor Share**	*(3)* **Corbo**
Aggregate TFP Growth	**0.97%**	**0.97%**	**0.97%**
Intensive margin	1.23%	2.28%	1.92%
Extensive margin	1.03%	-0.01%	0.35%
Net entry - exit	-1.30%	-1.30%	-1.30%

Panel B: Method 2			
Aggregate TFP Growth	**0.97%**	**0.97%**	**0.97%**
Intensive margin	1.67%	4.48%	3.54%
Extensive margin	1.47%	2.19%	1.96%
Covariance term	-0.87%	-4.40%	-3.23%
Net entry - exit	-1.30%	-1.30%	-1.30%

Note: Annual average aggregate TFP growth between 2006 and 2015. Productivity estimated following Levinsohn and Petrin (2003) methodology. Method 1 is based on Grilliches and Regev (1995), where intensive margin refers to the impact of firm TFP changes for a given allocation of factors, extensive margin refers to the reallocation of factors and net entry and exit refers to the creation and destruction of firms. Method 2 is based in Foster, Haltiwanger and Krizan (2001), where the covariance term provides a cleaner interpretation of the intensive and extensive margins.

Table A2: Average TFP Growth decomposition, different windows, 2006-2015.

	(1)	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
	LevPet				**Factor Shares**				**Corbo**			
	1 year	*2 years*	*5 years*	*10 years*	*1 year*	*2 years*	*5 years*	*10 years*	*1 year*	*2 years*	*5 years*	*10 years*
Panel A: Method 1												
Aggregate TFP Growth	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**
Intensive margin	1.23%	1.33%	1.18%	1.04%	2.28%	2.00%	1.65%	1.40%	1.92%	1.77%	1.48%	1.28%
Extensive margin	1.03%	0.63%	0.43%	0.28%	-0.01%	-0.04%	-0.03%	-0.08%	0.35%	0.19%	0.14%	0.04%
Net entry - exit	-1.30%	-0.99%	-0.64%	-0.35%	-1.30%	-0.99%	-0.64%	-0.35%	-1.30%	-0.99%	-0.64%	-0.35%
Panel B: Method 2												
Aggregate TFP Growth	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**0.97%**
Intensive margin	1.67%	1.63%	1.37%	1.08%	4.48%	3.73%	2.98%	2.19%	3.54%	3.07%	2.39%	1.85%
Extensive margin	1.47%	0.93%	0.62%	0.32%	2.19%	1.69%	1.30%	0.71%	1.96%	1.49%	1.05%	0.61%
Covariance term	-0.87%	-0.61%	-0.38%	-0.08%	-4.40%	-3.47%	-2.67%	-1.57%	-3.23%	-2.61%	-1.83%	-1.14%
Net entry - exit	-1.30%	-0.99%	-0.64%	-0.35%	-1.30%	-0.99%	-0.64%	-0.35%	-1.30%	-0.99%	-0.64%	-0.35%

Note: Annual average aggregate TFP growth between 2006 and 2015. Productivity estimated following Levinsohn and Petrin (2003) methodology. Method 1 is based on Grilliches and Regev (1995), where intensive margin refers to the impact of firm TFP changes for a given allocation of factors, extensive margin refers to the reallocation of factors and net entry and exit refers to the creation and destruction of firms. Method 2 is based in Foster, Haltiwanger and Krizan (2001), where the covariance term provides a cleaner interpretation of the intensive and extensive margins.

Appendix B

Table B1: Average Productivity Growth decomposition, 2006-2015, different methods.

Panel A: Method 1	*(1)*	*(2)*	*(3)*
	LevPet	**Factor Share**	**Corbo**
Aggregate TFP Growth	**0.97%**	**1.17%**	**1.30%**
Intensive margin	1.23%	2.50%	2.26%
Extensive margin	1.03%	0.30%	0.53%
Net entry - exit	-1.30%	-1.62%	-1.50%
Panel B: Method 2			
Aggregate TFP Growth	**0.97%**	**1.17%**	**1.30%**
Intensive margin	1.67%	4.66%	3.85%
Extensive margin	1.47%	2.45%	2.13%
Covariance term	-0.87%	-4.32%	-3.18%
Net entry - exit	-1.30%	-1.62%	-1.50%

Note: Annual average aggregate TFP growth between 2006 and 2015. Productivity estimated following Levinsohn and Petrin (2003) methodology. Method 1 is based on Grilliches and Regev (1995), where intensive margin refers to the impact of firm TFP changes for a given allocation of factors, extensive margin refers to the reallocation of factors and net entry and exit refers to the creation and destruction of firms. Method 2 is based in Foster, Haltiwanger and Krizan (2001), where the covariance term provides a cleaner interpretation of the intensive and extensive margins.

Table B2: Average TFP Growth decomposition, different windows, 2006-2015.

	(1)	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*	*(1)*	*(2)*	*(3)*	*(4)*
	LevPet				**Factor Shares**				**Corbo**			
	1 year	*2 years*	*5 years*	*10 years*	*1 year*	*2 years*	*5 years*	*10 years*	*1 year*	*2 years*	*5 years*	*10 years*
Panel A: Method 1												
Aggregate TFP Growth	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**1.17%**	**1.17%**	**1.17%**	**1.18%**	**1.30%**	**1.30%**	**1.30%**	**1.30%**
Intensive margin	1.23%	1.33%	1.18%	1.04%	2.50%	2.22%	1.95%	1.66%	2.26%	2.08%	1.76%	1.57%
Extensive margin	1.03%	0.63%	0.43%	0.28%	0.30%	0.24%	0.12%	0.04%	0.53%	0.36%	0.27%	0.13%
Net entry - exit	-1.30%	-0.99%	-0.64%	-0.35%	-1.62%	-1.29%	-0.89%	-0.53%	-1.50%	-1.14%	-0.74%	-0.41%
Panel B: Method 2												
Aggregate TFP Growth	**0.97%**	**0.97%**	**0.97%**	**0.97%**	**1.17%**	**1.17%**	**1.17%**	**1.18%**	**1.30%**	**1.30%**	**1.30%**	**1.30%**
Intensive margin	1.67%	1.63%	1.37%	1.08%	4.66%	3.93%	3.28%	2.51%	3.85%	3.38%	2.67%	2.22%
Extensive margin	1.47%	0.93%	0.62%	0.32%	2.45%	1.95%	1.45%	0.88%	2.13%	1.66%	1.17%	0.77%
Covariance term	-0.87%	-0.61%	-0.38%	-0.08%	-4.32%	-3.43%	-2.66%	-1.69%	-3.18%	-2.61%	-1.81%	-1.28%
Net entry - exit	-1.30%	-0.99%	-0.64%	-0.35%	-1.62%	-1.29%	-0.89%	-0.53%	-1.50%	-1.14%	-0.74%	-0.41%

Note: Annual average aggregate TFP growth between 2006 and 2015. Productivity estimated following Levinsohn and Petrin (2003) methodology. Method 1 is based on Grilliches and Regev (1995), where intensive margin refers to the impact of firm TFP changes for a given allocation of factors, extensive margin refers to the reallocation of factors and net entry and exit refers to the creation and destruction of firms. Method 2 is based in Foster, Haltiwanger and Krizan (2001), where the covariance term provides a cleaner interpretation of the intensive and extensive margins.

Appendix C

Table C1: Number of Observations and Firms obtained after eliminating missing observations and mistakes in reporting.

Filtros	Nr Observations	Nr Firms
F22 and F1887 Forms are merged.	2.603.778	578.806
Dropping firms with missing or negative data.	1.196.713	290.133
Dropping sectors.	1.186.069	287.363
Dropping firms with gaps in reports.	775.263	213.208
Capital and value added growth with standard deviation above the 90th percentile.	785.149*	194.144
Dropping firms with extreme reversions in labor growth in consecutive years and, firms that continue operations, 2 years after labor growth decreases by almost 100%.	775.561	192.812
Dropping firms with extreme values of capital growth.	626.928	170.970
Dropping firms with extreme values of labor growth.	609.068	166.901
Dropping firms which ratio of factor of production to value added takes extreme values.	580.598	158.015
Trimming productivity at the 1th and 99th percentile.	555.520	151.507

* The increased number of observations after the filter is due to adding an exit moment for each firm (in the year after which the firm is no longer observed in the data). This does not modify the number of firms, only the number of observations in the database.

Appendix D: Sensitivity to the 2009 Recession

Since productivity closely relates to the business cycle, periods of turbulence such as the 2008-09 financial crisis could affect our results. Although the impact of the 2008-09 financial crisis in Chile was relatively modest, with a mild recession in 2009, we compute our results for the years 2008-2009 and compare them the rest of the sample. The tables and figures on this appendix suggest that the recession has no effect on the results and conclusions mentioned above.

Table D.1 shows the decomposition of aggregate TFP growth excluding the years 2008-09. Even though aggregate productivity growth is slightly smaller (0.52% versus 0.97%), our main conclusions are the same: reallocation of productive factors (the extensive margin) plays a significant role in aggregate productivity growth.

Table D.1: Average Productivity Growth Decomposition, 2006-2007 and 2010-2015.

Panel A: Method 1	
Aggregate TFP Growth	**0.52%**
Intensive margin	0.85%
Extensive margin	0.49%
Net entry - exit	-0.82%
Panel B: Method 2	
Aggregate TFP Growth	**0.52%**
Intensive margin	1.30%
Extensive margin	0.94%
Covariance term	-0.90%
Net entry - exit	-0.82%

Note: Annual average aggregate TFP growth between 2006-07 and 2010-15. Productivity estimated with Levinsohn and Petrin (2003) methodology. Method 1 is based on Grilliches and Regev (1995), where intensive margin refers to the impact of firm TFP changes for a given allocation of factors, extensive margin refers to the reallocation of factors and net entry and exit refers to the creation and destruction of firms. Method 2 is based in Foster, Haltiwanger and Krizan (2001), where the covariance term provides a cleaner interpretation of the intensive and extensive margins.

If we check the sensitivity of tables 4 (TFPR and Factor Accumulation) and 5 (TFPR and Probability of Exit), we find our results are robust to excluding the financial crisis. In fact, the results from table D.2 show that during the financial crisis, capital growth was more sensitive to capital and employment levels, but that the sensitivity of capital growth to TFPR is very similar.

The results of employment growth from table D.3 shows that the sensitivity to TFPR was larger in 2008-09.

Also, from table D.4 we can observe that our measure of TFPR is a robust predictor of the exit of the firm, with similar coefficients for both periods. However, during the financial crisis the exit probability increases more with lower employment and capital levels.

Table D.2: TFPR and Capital Growth, crisis and no crisis periods

	Crisis		No Crisis	
	(1)	(2)	(3)	(4)
Employment (ln)	0.36***	0.38***	0.24***	0.25***
	(0.014)	(0.015)	(0.004)	(0.004)
Capital (ln)	-0.72***	-0.72***	-0.18***	-0.18***
	(0.015)	(0.015)	(0.004)	(0.004)
TFPR (ln)	0.18***		0.21***	
	(0.012)		(0.004)	
Micro		0.21***		0.23***
		(0.013)		(0.004)
Small		0.10***		0.16***
		(0.019)		(0.008)
Medium		0.07**		0.14***
		(0.031)		(0.014)
Large		0.13**		0.14***
		(0.052)		(0.021)
Obs	53,848	53,848	266,622	266,622
R-squared	0.634	0.634	0.450	0.450
Sector-Year FE	X	X	X	X
Firm age FE	X	X	X	X
Firm size FE	-	X	-	X
Firm FE	X	X	X	X
Number of firms	26924	26924	66766	66766

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table D.3: TFPR and Employment Growth, crisis and no crisis periods

	Crisis		No Crisis	
	(1)	(2)	(3)	(4)
Employment (ln)	-0.58***	-0.56***	-0.28***	-0.29***
	(0.015)	(0.016)	(0.005)	(0.005)
Capital (ln)	0.26***	0.26***	0.21***	0.21***
	(0.013)	(0.013)	(0.004)	(0.004)
TFPR (ln)	0.20***		0.27***	
	(0.012)		(0.004)	
Micro		0.24***		0.29***
		(0.014)		(0.005)
Small		0.10***		0.19***
		(0.019)		(0.008)
Medium		0.08**		0.16***
		(0.030)		(0.013)
Large		0.09*		0.16***
		(0.049)		(0.020)
Obs	53,848	53,848	266,622	266,622
R-squared	0.658	0.659	0.482	0.483
Sector-Year FE	X	X	X	X
Firm age FE	X	X	X	X
Firm size FE	-	X	-	X
Firm FE	X	X	X	X
Number of firms	26924	26924	66766	66766

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table D.4: TFPR and Probability of Exit, crisis and no crisis period

	Crisis		No Crisis	
	(1)	(2)	(3)	(4)
Employment (ln)	-0.16***	-0.17***	-0.10***	-0.11***
	(0.007)	(0.007)	(0.002)	(0.002)
Capital (ln)	-0.10***	-0.10***	-0.07***	-0.07***
	(0.006)	(0.006)	(0.002)	(0.002)
TFPR (ln)	-0.08***		-0.09***	
	(0.006)		(0.002)	
Micro		-0.10***		-0.10***
		(0.007)		(0.002)
Small		-0.03***		-0.06***
		(0.009)		(0.003)
Medium		-0.03**		-0.05***
		(0.013)		(0.006)
Large		-0.04*		-0.04***
		(0.023)		(0.009)
Obs	53,848	53,848	266,622	266,622
R-squared (Overall)	0.581	0.582	0.426	0.427
Sector-Year FE	X	X	X	X
Firm age FE	X	X	X	X
Firm size FE	-	X	-	X
Firm FE	X	X	X	X
Number of firms	26924	26924	66766	66766

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

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