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Misallocation or Misspecification? The Effect of “Average” Distortions on TFP Gains Estimations*

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Abstract

In recent years a vast literature has been devoted to estimate the degree of misallocation in different countries, sectors and time periods using Hsieh & Klenow (2009) -henceforth HK- framework. Even if we take the HK model at face value, such estimations still depend (heavily) on the assumed production technologies and elasticity of substitution. How much of the estimated TFP gain from eliminating distortions is due to actual TFPR dispersion among firms and how much is related to the specific parameterization of the model? We propose a decomposition of the inferred distortions that allows us to isolate the effect of “average” distortions (which depend on the parameterization and are defined at the industry level) from that of “dispersion” distortions (which are unaffected by the parameters and operate at the firm level). Using a newly available administrative dataset with the universe of Chilean firms between 1999 and 2015, we show that TFP gains from eliminating misallocations using the standard HK parameterization are 58% in the manufacturing sector (68% for the entire economy), but are reduced to 28% (44%) once the “mean” components of the distortions are removed. We find that the fraction of TFP gains explained by ”average” distortions increased significantly in Chile between 2000 and 2013, which is mainly explained by a sustained increase in average markups. We verify the robustness of our results using different datasets from Chile and Colombia.

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Resumen

En años recientes, basándose en el marco teórico propuesto por Hsieh y Klenow (2009) –en adelante HK–, una parte importante de la literatura se ha dedicado a analizar el grado en el que los factores productivos están mal asignados (*misallocated*) en diferentes países, sectores económicos y periodos de tiempo. Tales estimaciones de mala asignación de los recursos bajo este modelo dependen (fuertemente) de la función de producción y de la elasticidad de sustitución asumidas. ¿Cuánto de las ganancias en Productividad Total de Factores (PTF) que se obtienen al eliminar las distorsiones se debe a la dispersión en PTFR entre las firmas, y cuánto se relaciona con la parametrización específica del modelo? Proponemos una descomposición de las distorsiones que nos permite diferenciar el efecto del "promedio" de las distorsiones (que depende de la parametrización y está definido a nivel de la industria o sector económico) del efecto de la "dispersión" de las distorsiones (que no es afectada por los parámetros del modelo y opera al nivel de las firmas). Utilizando una nueva base de datos administrativa para el universo de empresas en Chile entre 1999 y 2015, encontramos que las ganancias de PTF de eliminar completamente la mala asignación usando la parametrización estándar de HK son de 58% para el sector manufacturero (68% para la economía en general), pero son reducidas a 28% (44%) una vez que el componente "promedio" de las distorsiones es removido. Encontramos que la fracción de ganancias en TFP explicada por el componente "promedio" de las distorsiones se ha incrementado significantemente entre 2000 y 2013, lo que es explicado por un incremento sostenido en los márgenes (*markup*) de las empresas. Verificamos la robustez de los resultados utilizando otras bases de datos para Chile y Colombia.

1 Introduction

The widespread availability of large firm-level databases in recent years has prompted the study of misallocation as a main cause of TFP differences across countries and over time. In this growing literature, the framework proposed by Hsieh & Klenow (2009) (henceforth, HK) "has become the standard methodology for analysis of misallocations" (Haltiwanger *et al.*, 2018). In their framework, dispersion in revenue productivity reflects distortions and, therefore, is associated with the extent to which resources are misallocated in the economy. Based on this insight, a vast literature has been devoted to assess the degree of misallocation in different countries, sectors and time periods.[1]

Surely, the methodology has not been free from critics, as some authors have recently questioned the extent to which the conditions in the HK model hold[2] and, in particular, the assumptions made about production technologies and structure of demand.[3] Though recognizing the value of the HK framework as a starting point for analyzing misallocations, these authors stress that "*the condition in the HK model that maps from observed production behaviors to the misallocative wedges/distortions holds in a single theoretical case, with strict assumptions required on both the demand and supply side*"(Haltiwanger *et al.*, 2018, p.1).

It is interesting, however, that despite the critics about the empirical validity of model, little has been said about the extent to which the results of HK depend on the particular parameterization of the model. That is, even if we take the HK model at face value, the estimations on the degree of misallocation still depend (heavily) on key parameters, such as the output-factor elasticities or the elasticity of demand. How much of the estimated gain from eliminating distortions is due to actual dispersion among firms and how much is related to the specific parameterization of the model? Though most papers in this literature recognize the dependence of their estimations on the chosen parameterization, it is still unclear the extent to which their conclusions are affected by it. This is, precisely, the focus of this paper.

Arguing that the U.S. is relatively undistorted, HK (as well as most of the papers based on their framework) use the U.S. economy as a benchmark[4] for their comparative analysis of the Chinese, Indian, and U.S. manufacturing sectors. The authors define two types of "distortions": (1) the difference between the firm's ratio of factor shares and the ratio of assumed output-factor elasticities, and

[1] By the time of this writing, there were more than 3,200 references to the HK paper.

[2] See, for example, Foster *et al.* (2016) and Haltiwanger *et al.* (2018).

[3] HK assume Cobb-Douglas technology with constant returns to scale, isoelastic demand, and unit output-productivity elasticity.

[4] HK use the U.S. labor shares from the NBER Productivity Database and, based on the literature, assume a common (across industries) elasticity of demand of 3 (i.e. a markup of 1.5).

(2) the difference between the firm's observed markup and the assumed markup. Defined in this way, we propose a decomposition of such "distortions" into two different and well defined components: First, the "dispersion" component, defined as the difference between the firm's ratio of factor shares (or markup) and the industry mean and, second, the "mean" (or average) component, defined as the difference between the industry mean and the benchmark. The first component is defined at the firm level and is invariant to the parameterization of the model. The second component, on the other hand, is defined at the industry level and depends on the distance between the industry's technology (or markup) and the assumed parameterization. This distinction is important, in particular because the typical exercises that eliminate misallocations actually remove both types of distortions simultaneously (i.e. they (a) remove the dispersion across firms, and (b) move the industry's technology and markup to the benchmark). Yet, the estimated TFP gains from such exercises are usually associated with the elimination of the dispersion.

In this paper, we investigate the extent to which the estimated output and TFP gains that arise when distortions are eliminated correspond to the "dispersion" or the "mean" components, respectively. Using newly available administrative data for the universe of Chilean firms between 1999 and 2015, we begin by applying HK's standard methodology (which uses the U.S. economy as a benchmark) to identify distortions and estimate the potential gains from their elimination. Then, we change the parameterization of the model so that the "mean" and "dispersion" components of distortions are removed separately (i.e. we repeat the exercise, but using Chile as a benchmark for production technologies and markups). We verify the robustness of our results replicating our analysis with data from two different datasets (ENIA, from Chile, and EAM from Colombia), for which we find remarkably similar results.

Our results show, first, that average TFP gains from eliminating misallocations for the period using the standard HK parameterization are 58% in the manufacturing sector (68% for the entire economy), but are reduced to 28% (44% for the entire economy) when Chilean markups and technology are used as a benchmark, implying that almost half of the estimated gains in the standard exercise correspond to adjustments in the "mean" component of distortions. Interestingly, the estimated gains for the Chilean manufacturing sector using Chile as a benchmark are comparable to the gains reported by HK in the U.S. manufacturing sector, which suggests that the effect of the "dispersion" components of distortions is similar in both countries. Second, we find that the fraction of TFP gains explained by "average" distortions increased significantly in the Chilean manufacturing sector between 2000 and 2013, a phenomenon that is mainly explained by a sustained increase in average markups.

In recent years we have seen an explosion of studies using the HK methodology for the analysis of misallocations in different settings. Most of these papers use the standard HK parameterization. Busso *et al.* (2013), for example, estimate TFP gains from the elimination of misallocation in 10 Latin American countries (mainly manufacturing sectors). Ziebarth (2013) studies misallocation in the United States in the 19th century. For Chile, Oberfield (2013) estimates that output gains from removing distortions of 100% in manufacturing sector in 1982. Using the same dataset, Chen & Irarrazabal (2015) estimate output gains of 76.1% in 1983 and around 45% in the 1989-1996 period. Dias *et al.* (2016) estimate TFP gains of 48% to 79% in different sectors of the Portuguese economy between 1996 and 2011. García-Santana *et al.* (2016) and Gopinath *et al.* (2017) extend the analysis for different sectors of Spain. Our results suggest that the estimations in these papers might be (seriously) affected by the fact that they use U.S. technologies and markups as benchmarks. On the other hand, our results are very similar to the findings of Rossbach & Asturias (2017) who, using industry-specific markups and production technologies estimated from the data, find TFP gains of 30% from removing misallocations in the Chilean manufacturing sector[5].

The rest of the paper is organized as follows: Section 2 summarizes the HK model and presents the proposed decomposition of distortions. Section 3 describes de data. Section 4 presents the estimations, and section 5 concludes.

2 The HK Model

We begin this section by describing the model presented in Hsieh & Klenow (2009) (including the corrections made by the same authors in Hsieh & Klenow, 2013), and the definition of distortions and TFP gains. Then, we describe our proposed decomposition of such distortions.

The model assumes there is a single final good Y, produced by a representative firm in a perfectly competitive final output market, that combines the output Y_s of S industries using a Cobb-Douglas production technology:

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

[5]Rossbach & Asturias (2017) focus is different to ours, though. They show that, accounting for the presence multiple production technologies (and, thus, using a more appropriate benchmark technologies and markups of specific groups of firms) within the different industries in the Chilean manufacturing sector reduces the estimated TFP gains from eliminating misallocations from 30.9% to 24.3%.

Industry output Y_s is a CES aggregate of M_s differentiated products:

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

The production function for each differentiated product is given by a Cobb-Douglas on firm TFP, capital, and labor:

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

Firms are assumed to face two types of distortions: *scale* distortions (τ_Y), that increase proportionally marginal products of capital and labor, and *capital* distortions (τ_K), that increase the marginal product of capital relative to labor. Profits are given by

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

where the rental rate of capital (R) and wages (w) are assumed constant across firms. From the firms' profit maximization, we obtain

$$P_{si} = \frac{\sigma}{\sigma - 1} \frac{1}{A_{si}} \left(\frac{R}{\alpha_s} \right)^{\alpha_s} \left(\frac{w}{1 - \alpha_s} \right)^{1-\alpha_s} \frac{(1 + \tau_{Ksi})^{\alpha_s}}{1 - \tau_{Ysi}}. \tag{5}$$

That is, firms charge a constant markup $\frac{\sigma}{\sigma-1}$ over their marginal cost which, in turn, is being affected by the presence of distortions.

TFP *revenue* is defined as

$$TFPR_{si} \triangleq P_{si} A_{si} = \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}, \tag{6}$$

and "Industry" TFP *revenue* (defined as a geometric average of the average marginal revenue product of capital and labor in the industry), can be written as

$$\overline{TFPR}_s = \frac{P_s Y_s}{\left(\sum_{i=1}^{M_s} K_{si} \right)^{\alpha_s} \left(\sum_{i=1}^{M_s} wL_{si} \right)^{1-\alpha_s}}, \tag{7}$$

from which $TFPR_{si}$ relative to the industry's average is written as

$$\frac{TFPR_{si}}{\overline{TFPR}_s} = \frac{\frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} (wL_{si})^{1-\alpha_s}}}{\frac{P_s Y_s}{\left(\sum_{i=1}^{M_s} K_{si} \right)^{\alpha_s} \left(\sum_{i=1}^{M_s} wL_{si} \right)^{1-\alpha_s}}}. \tag{8}$$

Expression (8) implies that the dispersion of $TFPR_{si}$ around the industry's mean is only affected by parameter α_s, and not by σ.

TFP is defined as $A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s}(wL_{si})^{1-\alpha_s}}$, and is computed as

$$A_{si} = \kappa_s \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s}(wL_{si})^{1-\alpha_s}}, \tag{9}$$

where κ_s is a constant at the industry level.

"Industry" TFP is written as

$$\bar{A}_s = \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}. \tag{10}$$

Finally, combining expressions (6), (7), (9) and (10), the ratio of actual TFP to the "efficient" level of TFP at the industry level is computed as

$$\frac{Y_s}{Y_s^{ef}} = \left[\sum_{i=1}^{M_s}\left(\frac{A_{si}}{\bar{A}_s}\frac{\overline{TFPR}_s}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}} \tag{11}$$

which can be rewritten as

$$\frac{Y_s}{Y_s^{ef}} = \frac{\frac{\left(\sum_{i=1}^{M_s} P_{si}Y_{si}\right)^{\frac{\sigma}{\sigma-1}}}{\left(\sum_{i=1}^{M_s} K_{si}\right)^{\alpha_s}\left(\sum_{i=1}^{M_s} wL_{si}\right)^{1-\alpha_s}}}{\left[\sum_{i=1}^{M_s}\left(\frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s}(wL_{si})^{1-\alpha_s}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}} \tag{12}$$

Expression (12) is the one used to estimate TFP gains associated with the elimination of distortions.

2.1 A Decomposition of the Distortions

It is clear from expression (12) that the estimated TFP gains from the elimination of distortions depend on parameters α_s and σ, which is why we should be very thoughtful about the chosen parameterization.

What are the "appropriate" values for α_s and σ? One alternative is to estimate them from the data: α_s, representing the (undistorted) elasticity of output to capital if industry s, should be equal to the firms' capital-expenditure share; and σ, representing the elasticity of substitution between differentiated goods in the industry could, in principle, be inferred from the firms' markups. The problem with this alternative is that, as HK point out, if there are indeed distortions, the observed factor shares and markups are affected by them. Another alternative is simply to pick values for α_s

and σ from somewhere else. This is the approached followed by HK in their estimations for China and India: assuming that the U.S. economy is "comparatively undistorted", they use the parameters estimated for the U.S. economy as a benchmark[6]. Such parameterization has been used extensively in the literature for the estimation of potential gains from the elimination of misallocations in different countries, sectors and periods.

To use the U.S. parameterization as a benchmark is, of course, a valid and informative exercise. But we must understand the potential (qualitative and quantitative) implications of such choice on our estimations, if we do not want to misinterpret our results. What we do here is, precisely, to propose a decomposition of the distortions that helps us understand the effect of a particular parameterization on the estimated TFP gains.

As HK explain, *capital* distortions are inferred as

$$1 + \tau_{Ksi} = \frac{\alpha_s}{1-\alpha_s} \frac{wL_{si}}{RK_{si}}, \tag{13}$$

to which the authors add "*...we infer the presence of a capital distortion when the ratio of labor compensation to the capital stock is high relative to what one would expect from the output elasticities with respect to capital and labor.*"[7] That is, distortions are inferred when the ratio $\frac{wL_{si}}{RK_{si}}$ is high relative to ratio of assumed factor shares $\frac{1-\alpha_s}{\alpha_s}$. Such distortions can be decomposed as

$$1 + \tau_{Ksi} = \frac{\alpha_s}{1-\alpha_s} \overline{\frac{wL_s}{RK_s}} \frac{\frac{wL_{si}}{RK_{si}}}{\overline{\frac{wL_s}{RK_s}}} = (1 + \bar{\tau}_{Ks})(1 + \tilde{\tau}_{Ksi}), \tag{14}$$

where $\overline{\frac{wL_s}{RK_s}}$ is the mean[8] of the ratio $\frac{wL_{si}}{RK_{si}}$ at the industry level (which, in turn, is equal to the average of the ratio of factor shares $\frac{wL_{si}/(wL_{si}+RK_{si})}{wL_{si}/(wL_{si}+RK_{si})}$).

The term $1 + \bar{\tau}_{Ks} \triangleq \frac{\alpha_s}{1-\alpha_s}\overline{\frac{wL_s}{RK_s}}$ is what we call the "mean" component of capital distortions, and captures the *average* capital distortion. Intuitively, $\bar{\tau}_{Ks}$ reflects the extent to which the firms' average ratio of factor shares $\overline{\frac{wL_s}{RK_s}}$ differs from the *assumed* ratio of factor shares $\frac{1-\alpha_s}{\alpha_s}$. It is, therefore, a measure of how the assumed production technology fits the data, on average.

[6]Specifically, HK use capital factor shares from the NBER Productivity Database, which are based on the Census of Manufactures and the Annual Survey of Manufactures (they set the elasticity of output with respect to capital in each industry -α_s- to be 1 minus the labor share -scaled up by 3/2- in the corresponding industry in the United States) and, based on other studies, they set the elasticity of substitution between plant value added to $\sigma = 3$.

[7]Hsieh & Klenow (2009, p. 1415).

[8]In our exercises, we define $\overline{\frac{wL_s}{RK_s}}$ as the *weighted* average of the ratio $\frac{wL_{si}}{RK_{si}}$, where each firm's weight is its share of value added in the industry. Similarly, $\overline{\frac{wL_s}{PY_s}}$ is the *weighted* average of the ratio $\frac{wL_{si}}{P_{si}Y_{si}}$.

The term $1+\tilde{\tau}_{Ks} \triangleq \frac{wL_{si}}{RK_{si}} / \overline{\frac{wL_s}{RK_s}}$, on the other hand, is what we call the "dispersion" component of capital distortions, and is a measure of the firms' capital distortion *relative* to the industry. Defined in this way, the *dispersion* component is independent of the assumed parameterization.

Similarly, *scale* distortions are inferred as

$$1+\tau_{Ysi} = \frac{\sigma}{\sigma-1}\frac{1}{1-\alpha_s}\frac{wL_{si}}{P_{si}Y_{si}} = \frac{\left.\frac{\sigma}{\sigma-1}\right\} \text{Assumed Markup}}{\left.\frac{1-\alpha_s}{\frac{wL_{si}}{P_{si}Y_{si}}}\right\} \text{Firm's Markup}} \tag{15}$$

which can be expressed as the ratio between the assumed markup $\sigma/(\sigma-1)$ and the (empirically estimated) markup that, as De Loecker & Warzynski (2012) show, can be estimated as $(1-\alpha_s)/\left(\frac{wL_{si}}{P_{si}Y_{si}}\right)$[9]. That is, we infer *scale* distortions when a firm's *empirical* markup differs from the *assumed* markup.

Scale distortions can be decomposed as

$$1+\tau_{Ysi} = \frac{\sigma}{\sigma-1}\frac{1}{1-\alpha_s}\overline{\frac{wL_s}{PY_s}}\frac{\frac{wL_{si}}{P_{si}Y_{si}}}{\overline{\frac{wL_s}{PY_s}}} = (1+\bar{\tau}_{Ys})(1+\tilde{\tau}_{Ysi}) \tag{16}$$

where $\overline{\frac{wL_s}{PY_s}}$ is the average of the ratio $\frac{wL_{si}}{P_{si}Y_{si}}$ at the industry level.

The term $1+\bar{\tau}_{Ys} \triangleq \frac{\sigma}{\sigma-1}\frac{1}{1-\alpha_s}\overline{\frac{wL_s}{PY_s}}$ is what we call the "mean" component of the scale distortion, and captures the average scale distortion. Intuitively, it reflects how the firms' average markup $(1-\alpha_s)/\overline{\frac{wL_s}{PY_s}}$ differs from the *assumed* markup $\sigma/(\sigma-1)$. It is, therefore, a measure of how the assumed markup fits, on average, the observed markups (which, in turn, depend on the assumed elasticity $1-\alpha_s$).

The term $1+\tilde{\tau}_{Ysi} \triangleq \frac{wL_{si}}{P_{si}Y_{si}}/\overline{\frac{wL_s}{PY_s}}$, on the other hand, is the "dispersion" component of the scale distortions, and is a measure of the firms' scale distortion *relative* to the industry. Intuitively, is the ratio between the industry's (average) markup $(1-\alpha_s)/\overline{\frac{wL_s}{PY_s}}$ and the firm's markup $(1-\alpha_s)/\left(\frac{wL_{si}}{P_{si}Y_{si}}\right)$ (where the elasticity $1-\alpha_s$ cancels out). Defined in this way, $1+\tilde{\tau}_{Ysi}$ is independent of the assumed parameterization.

This decomposition of distortions allows us to distinguish between two qualitatively different types of distortions. On the one hand, $\tilde{\tau}_{Ksi}$ and $\tilde{\tau}_{Ysi}$ identify distortions defined at the firm level that manifest themselves in the form of dispersion of factor shares and markups across firms within industry. On the other hand, $\bar{\tau}_{Ks}$ and $\bar{\tau}_{Ys}$ represent distortions defined at the industry (or sector, or

[9] De Loecker & Warzynski (2012) show that, if the output-labor elasticity is $1-\alpha_s$, cost minimization implies that the firm's markup is equal to $(1-\alpha_s)/\left(\frac{wL_{si}}{P_{si}Y_{si}}\right)$.

economy) level that manifest themselves as systematic deviations of the industry's factor shares and markups from their assumed values.

2.2 Misallocation or Misspecification?

We could question whether the mean components of the distortions $\bar{\tau}_{Ks}$ and $\bar{\tau}_{Ys}$ indeed represent average distortions or they simply reflect the extent to which the model is misparameterized. The answer, of course, depends on how confident we are that the assumed parameters properly represent both, the production technologies used by firms and the elasticity of demand. With an appropriate parameterization (something that we cannot be sure of), the value of $\bar{\tau}_{Ks}$ informs about the magnitude and sign of systematic inefficiencies (at the industry level) in the way firms combine capital and labor given the used technology; and the value of $\bar{\tau}_{Ys}$ informs about the magnitude and sign of the deviation of the industry average markup with respect to the efficient level. However, and on the other extreme, even in the absence of average distortions, if the model is improperly parameterized, $\bar{\tau}_{Ks}$ and $\bar{\tau}_{Ys}$ would reflect how far the benchmark is from the true underlying parameters. We are not fully able to distinguish whether the *mean* components of distortions represent misallocation or misparameterization (or both) but, as we explain below, at least we are able to distinguish their effect from that of the *dispersion* components in the estimated gains from eliminating misallocations.

Based on the fact that we cannot distinguish empirically whether the parameterization is correct or not, the literature has systematically opted for using the standard HK specification, which takes industry factor shares from the U.S. and sets $\sigma = 3$. Thus, the reported gains from eliminating distortions are the cumulative gains from removing, simultaneously, the mean and the dispersion components of both capital and scale distortions. Such exercises, though informative, do not allow us to identify how much of those potential TFP gains correspond to the removal of each type of distortions and/or their components. Our empirical exercises consist, precisely, in computing the TFP gains from removing the different distortions and their components sequentially, which allows us to separately quantify their effects.

3 Data

We use three different datasets for our empirical exercises. We use administrative data from Chile's Internal Revenue Service for our baseline analysis, which is complemented with survey data from Chile and Colombia.

Our baseline analysis is performed with a newly available dataset from Chiles tax collection agency (*Servicio de Impuestos Internos* - SII), which includes all formal firms in the Chilean economy between 1999 and 2015 (firms' identifiers are anonymized to guarantee confidentiality). We use information contained in the income tax form (F22), which is submitted annually by firms. Importantly, this dataset only considers *firms* (as opposed to *plants*), and includes and tracks overtime all formal firms in the Chilean economy, including firms of all sizes and sectors. Additionally, and in order to make our results comparable to the literature, we use data from the Annual National Industrial Survey (Encuesta Nacional de Industria Anual-ENIA) collected by Chile's National Statistical Office (INE), which covers all active manufacturing plants with 10 or more employees, for the period 1995-2007. Finally, and in order to verify the robustness of our results, we use data from the Colombian Annual Manufacturing Survey (EAM) from 1995 to 2015, collected by Colombia's National Administrative Department of Statistics (DANE). This survey covers all manufacturing plants belonging to firms with 10 or more employees.

Using the IRS data, we get information on sales (S), intermediate materials (M), capital stock (immobile assets, K) and wage bill (wL), and define *value added* as sales minus materials ($VA = S - M$). When we use ENIA and EAM, we use the *value added* reported in the survey.[10] We eliminate observations with missing or negative values for any of the variables, as well as firms/plants that are active only for one year in the database.

In order to make our results robust to outliers, we trim the 1% tails of the distributions of the ratios of capital to revenue, wage bill to revenue and material to revenue[11], and the 1 and 98 percentile of the revenue to total cost ratio[12] in each dataset.

The original IRS and ENIA datasets are under the (adapted to Chile) ISIC Rev. 4 and 3 classifications, respectively, and the EAM dataset is under the (adapted to Colombia) ISIC Rev. 4, all of them at the four-digit level. In order to perform our exercises using the U.S. as a benchmark we match our data to the NAICS classification. As a result, we drop firms in industries without a close counterpart in the U.S. Our final IRS dataset consists of around 55,000 firms per year for the whole economy, and 11,000 firms for the manufacturing sector. Table A.1 in the appendix presents some descriptive statistics of the final samples of each of the datasets.

[10]Our baseline estimations are performed year by year, and do not require deflated variables. When deflated variables are necessary (e.g. when we estimate a common σ and set of α_s for all the years), each of these variables is deflated (1) using specific price deflators computed by the National Accounts office of the Central Bank of Chile, in the case of the IRS Dataset and, (2) with the CPI in the case of ENIA and EAM.

[11]Defined as wL/S, K/S, M/S, respectively

[12]Defined as $S/(wL + RK + M)$, respectively, where the rental rate of capital is $R = 0.1$ (as in HK).

4 Estimations

In this section we present our estimations of TFP gains from eliminating misallocations. We follow HK and compute, for each year and industry[13], the ratio of actual TFP to its efficient level using expression (11). Then, we aggregate this ratio at the sector level using the Cobb-Douglas aggregator of expression (1), where each industry is weighted with its share of value added in the sector (θ_s). Finally, potential TFP gains at the sector level in a given year are computed as $(Y^{Eff}/Y - 1) * 100$.

In order to make our results comparable to those of HK (and to most estimations in this literature), Table 1 presents TFP gain estimations for the manufacturing sector in Chile and Colombia, using different datasets and samples (rows), and different parameterizations of the model (columns (1)-(4)). Figures in the table correspond to average TFP gains from eliminating distortions for the period 1999-2015 (Panel A) and 1999-2007 (Panel B). In column (1), we apply the standard HK parameterization and set (a) the elasticity of output with respect to capital in each industry (α_s) to be 1 minus the labor share in the corresponding industry in the United States[14], and (b) $\sigma = 3$. In column (2), we set the elasticity of output with respect to capital in each industry and year so that the mean component of *capital* distortions is eliminated (i.e. we set α_s so that $\bar{\tau}_{Ks} = 0$ for all s in each year), and keep $\sigma = 3$. In column (3) of the table, we keep the α_s from the corresponding industries in the United States (as in column (1), but set σ in each industry and year so that mean component of *scale* distortions is eliminated (i.e. we set σ so that $\bar{\tau}_{Ys} = 0$ for all s in each year). Finally, in column (4) we remove simultaneously the mean components of both types of distortions, setting α_s so that $\bar{\tau}_{Ks} = 0$ and σ so that $\bar{\tau}_{Ys} = 0$ for all s in each year. Thus, while TFP gains reported in column (1) include the gains from eliminating the mean and dispersion components of both types of distortions, the ones reported in column (4) correspond only to the elimination of the dispersion components. The difference between TFP gains in columns (1) and (4) captures the impact of mean components of distortions (i.e. "average" distortions) in the standard (HK) TFP gains estimation.

How do we interpret the figures? The difference between column (1) and (2) informs us about the effect of modifying α_s so that $\bar{\tau}_{Ks} = 1$. But we must be careful when interpreting the figure, given that changing α_s implies changing the average markup $(1 - \alpha_s)/\overline{\frac{wL_s}{PY_s}}\,\bar{\tau}_{Ys}$, and, therefore, changing the mean component of *scale* distortions $\bar{\tau}_{Ys}$. On the other hand, given that $\bar{\tau}_{Ks}$ does not depend on σ, the difference between the estimations in columns (1) and (3) is more straightforward and informs

[13] Our exercises with Chile's IRS data include 120 4-digit level industries in the manufacturing sector.

[14] Using data from the United States Bureau of Labor Statistics (BLS) Multifactor Productivity Tables, we compute the labor shares as the average share of Labor Factor Share between 1999 and 2015 at 3 digit industry classification level.

us about the effect of $\bar{\tau}_{Ys}$ (assuming elasticities of output with respect to capital similar to those in the U.S.) on our original TFP gains estimations. Such effect might be positive (as is the case in all the samples in Table 1) of negative, depending on whether the initially assumed markup $\sigma/(\sigma-1)$ is lower or higher than the industry's (average) markup $(1-\alpha_s)/\overline{\frac{wL_s}{PY_s}}$. Similarly, the difference between columns (2) and (4) is informative about the effect of removing $\bar{\tau}_{Ys}$ when the elasticities of output with respect to capital are estimated from the data. Finally, the difference between columns (3) and (4) is the result of (a) modifying α_s so that $\bar{\tau}_{Ks}$ is set to 1 and, (b) modifying σ so that we keep $\bar{\tau}_{Ys}=1$ (which, otherwise, changes as a consequence of changing α_s). Given these difficulties, we prefer to focus on estimations in columns (1) and (4), which are easier to interpret.

[Table 1 here]

In the first row of Table 1 we report average TFP gains in the Chilean manufacturing sector from 1995 to 2015 using data from the IRS. The estimation includes more than 10 thousand firms per year. Using the standard HK parameterization (column (1)), average TFP gains for the period are 57.6%. This figure is in line with the numbers reported by Chen & Irarrazabal (2015) who use data from ENIA but the same parameterization. In similar exercises, HK report TFP gains of 86.6% for China in 2005, 127.5% for India in 1994, and 42.9% for the U.S. in 2005 (our estimation for Chile in 2005 is 56.1%), which implies that, based on this metric, misallocation in Chile is higher than in the U.S. but lower than in China and India. When we only remove the mean component of *capital* distortions (column (2), first row) average TFP gains are reduced to 48.0%, and when we only remove mean component of *scale* distortions (column (3)) estimated TFP gains are 46.6%. Finally, when we remove the effect of $\bar{\tau}_{Ks}$ and $\bar{\tau}_{Ys}$ simultaneously (column (4)), TFP gains from the elimination of distortions are 28.5%, which implies that more than half of the initial TFP gains in column (1) are explained by "average" distortions, and are not related to the dispersion components.

[Figure 1 here]

Figure 1 plots the evolution of TFP gains estimations with the four different parameterizations, for the manufacturing sector in Chile between from 1999 to 2015. Interestingly, the estimations not only differ in their average levels, but also in their trends. Following the standard HK parameterization (1), we would conclude that misallocation increased significantly during the period, with TFP gains going from 50% in 1999 to approximately 65% by 2015. However, if we look at estimation (4) (that excludes the mean components of distortions), we have a different story: misallocation due to idiosyncratic differences in TFPR across firms within industries has indeed declined, so that TFP gains from their elimination has gone from about 38% in 1999 to 23% in 2005.

How do we explain the differences in levels and trends between estimations (1) and (4) in Figure 1? As mentioned above, the difference between (1) and (4) captures the impact of ”average” distortions which, in turn, can be explained by either true aggregate (industry, sector, or economy-level) distortions that affect average factor intensities and markups, or simply misparameterization of the model, which could be exacerbated if the true underlying parameters that represent the economy change over time. We cannot distinguish between the possible explanations, but we can at least analyze the relative impact of $\bar{\tau}_{Ks}$ and $\bar{\tau}_{Ys}$ over time. Averaging the differences between (1) and (2) and between (3) and (4), we can have a rough idea of the impact of $\bar{\tau}_{Ks}$, and averaging the differences between (1) and (3) and between (2) and (4), we estimate the average effect of $\bar{\tau}_{Ks}$. Figure 2 decompose the total contribution of mean components to the standard HK TFP gain estimation (computed as the difference between TFP gains estimations (1) and (4)), into the average mean components of *capital* and *scale* distortions. As can be seen from the figure, TFP gains explained by mean *capital* distortions are relatively stable over time, and range between 8 and 18%. On the other hand, TFP gains explained by mean *scale* distortions increase over time and range from 0% (in 2000) to 32% (in 2015), suggesting that an increasing gap between the initially assumed markup $(3/(3-1) = 1.5)$ and the empirically observed (average) markups plays an important role in explaining the standard HK TFP gains estimation. The intuition is confirmed by the dotted line in 2, which plots the implicit median (across industries) markup that result from the estimation (4) in figure 1. Markups increased significantly between 2000 and 2013[15], and so did standard TFP gains estimations.

[Figure 2 here]

4.1 Robustness Checks

In this section we assess the robustness of the results from our baseline exercise (using data on manufacturing firms from Chile’s IRS).

In the second row of Table 1 we replicate the previous analysis but restrict our sample to large manufacturing firms, defined as those with annual sales above 100,000*UF* (which, in real terms, is equivalent to about US$4.2 million in 2018 prices). There are, on average, slightly more than one thousand of such firms in our database. As the table shows, the results are similar, with TFP gains

[15]Similarly, our estimations using data for plants from ENIA, median markups increase by more than 12% from 1999 to 2006.

going from 50.2% in the standard HK estimation (column (1)) to 23.8% when both mean components of distortions are removed (column (4)).

In Panel B of Table 1 we extend the analysis to different datasets and periods. In order to make the estimations comparable, we restrict the estimations to the period 1999-2007, which is common to the three datasets. In row 4 we estimate TFP gains from eliminating restrictions under the four parameterizations for *plants* (10+ employees) from ENIA, and in row 5 we do the same with Colombian manufacturing plants (10+ employees) from EAM. The results are remarkable similar to our baseline estimations, in particular when comparing standard HK TFP gains estimations in column (1) and the estimations when the mean components of both types of distortions are removed (column (4)).

Additionally, in Table A.2 in the Appendix we include a series of regressions similar to those of Hsieh & Klenow (2009, Table VIII), in which we asses that extent to which the *TFPR* and *TFPQ* measures that result from each of these parameterizations predict the firm's (plant's) exit in future periods.

4.2 TFP gains by Sector

Our analysis so far has been restricted to the manufacturing sector. We now extend our analysis to the main sectors of the economy. In Table 2 we present TPF gains estimations from eliminating distortions using the four different parameterizations, first, for all sectors[16], and then disaggregated in 5 main groups.[17]

[Table 2 here]

As Table 2 shows, there is substantial variation across sectors in the potential gains from eliminating distortions. Again, when comparing figures in columns (1) and (4), both for all as well as for large firms, we verify that "average" distortions explain a significant fraction of the standard HK TFP gain estimations. The exception is the group conformed by Construction, Utilities and Other Industrial Activities, for which the effects of both mean components of distortions offset each other.

[16] The IRS database does not include section T (Activities of households as employers, etc.) of the ISIC Rev. 4 classification. Additionally, we exclude from our analysis sections A (Agriculture, forestry and fishing), O (Public administration and defence; compulsory social security), and U (Activities of extraterritorial organizations and bodies).

[17] In order to match the U.S. NAICS classification with disaggregate the sectors at the three-digit level.

5 Concluding Remarks

In this paper, we investigate the extent to which estimated output and TFP gains that arise when distortions are eliminated correspond “average” distortions (defined at the industry, sector, or economy-level), as opposed to idiosyncratic distortions (defined at the firm level). We propose a decomposition of standard TFP gains estimations based on the parameterization used by Hsieh & Klenow (2009) into two different components: the “mean” component, which is defined at the industry level and depends on the parameterization, and the “dispersion” component, which is defined at the firm (or plant) level and is independent of the adopted parameterization. Using newly available administrative data for the universe of Chilean firms between 1999 and 2015, we begin by applying HK’s standard methodology (which uses the U.S. economy as a benchmark) to identify distortions and estimate the potential gains from their elimination. Then, we change the parameterization of the model so that the “mean” and “dispersion” components of distortions are removed separately (i.e. we repeat the exercise, but using Chile as a benchmark for production technologies and markups). We verify the robustness of our results replicating our analysis with data from two different datasets (ENIA, from Chile, and EAM from Colombia), for which we find remarkably similar results.

Our results show, first, that average TFP gains from eliminating misallocations for the period using the standard HK parameterization are 58% in the manufacturing sector (68% for the entire economy), but are reduced to 28% (44% for the entire economy) when Chilean markups and technology are used as a benchmark, implying that almost half of the estimated gains in the standard exercise correspond to adjustments in the “mean” component of distortions. Interestingly, the estimated gains for the Chilean manufacturing sector using Chile as a benchmark are comparable to the gains reported by HK in the U.S. manufacturing sector, which suggests that the effect of the “dispersion” components of distortions is similar in both countries. Second, we find that the fraction of TFP gains explained by ”average” distortions increased significantly in the Chilean manufacturing sector between 2000 and 2013, a phenomenon that is mainly explained by a sustained increase in average markups.

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Table 1: TFP Gains - Manufacturing Sector (%)
ISIC 4-digit Classification

	(1)	(2)	(3)	(4)	Average
α_s:	U.S.	$\bar{\tau}_{Ks} = 0$	U.S.	$\bar{\tau}_{Ks} = 0$	Firms/Plants
σ:	3	3	$\bar{\tau}_{Ys} = 0$	$\bar{\tau}_{Ys} = 0$	per year
			A. 1999-2015 - Chile - IRS Data		
All Firms	57.6	48.0	46.6	28.5	10,363
Large Firms	50.2	41.8	36.4	23.8	1,023
			B. 1999-2007		
Chile - IRS (firms)	52.1	43.9	49.4	31.1	9,190
Chile - ENIA (plants)	58.9	53.1	36.0	29.8	4,580
Colombia - EAM (plants)	58.7	56.9	18.1	26.4	6,633

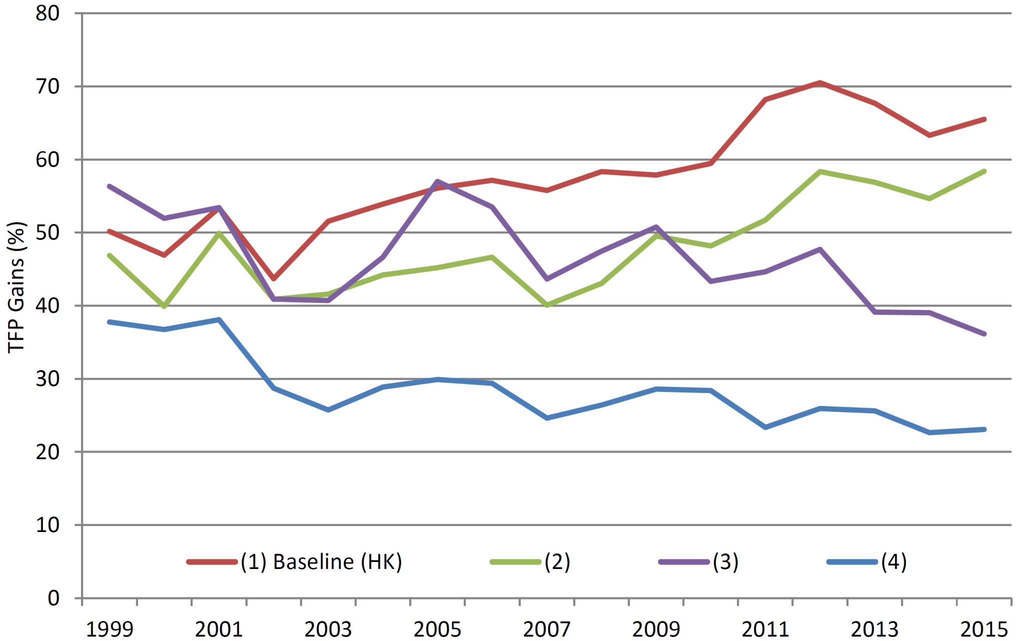
Notes: Annual averages of potential TFP gains from eliminating distortions, estimated, in each case, with expression (11) at the ISIC 4-digit level. The parameterization used in column (1) is similar to that of HK. In column (2), α_s is set so that $\bar{\tau}_{Ks} = 0$ for each industry s and year; in column (3), σ is set so that $\bar{\tau}_{Ys} = 0$ for each industry s and year; and in column (4) α_s and σ are set so that both $\bar{\tau}_{Ks} = 0$ and $\bar{\tau}_{Ys} = 0$ simultaneously for each industry s and year. We follow Chile's IRS size classification and define *Large Firms* as those with annual sales above 100,000*UF* (about US\$4.2 Million in 2018 prices).

Table 2: TFP Gains in Chile, by Sector - 1999-2015 (%)
IRS Data - ISIC 3-digit Classification

	(1)	(2)	(3)	(4)	Avg.
α_s:	U.S.	$\bar{\tau}_{Ks} = 0$	U.S.	$\bar{\tau}_{Ks} = 0$	Firms
σ:	3	3	$\bar{\tau}_{Ys} = 0$	$\bar{\tau}_{Ys} = 0$	per year
		A. All Firms			
All Sectors	68.3	64.6	57.0	44.1	52,435
Mining	77.6	67.8	138.0	38.5	348
Manufacturing	57.9	47.5	47.8	27.5	10,666
Construction, Utilities, Other Indust.	85.7	95.5	62.7	81.1	10,203
Commerce, Hotels & Restaurants	65.9	60.9	46.6	36.7	23,208
Other Services	67.2	61.5	83.5	48.1	8,010
		B. Large Firms			
All Sectors	58.7	56.1	46.5	38.5	3,459
Mining	71.8	64.5	116.1	36.1	62
Manufacturing	51.0	41.5	37.4	23.0	1,011
Construction, Utilities, Other Indust.	77.1	87.5	54.7	77.2	737
Commerce, Hotels & Restaurants	54.8	52.6	37.6	32.4	1,313
Services	51.1	44.9	63.9	35.8	336

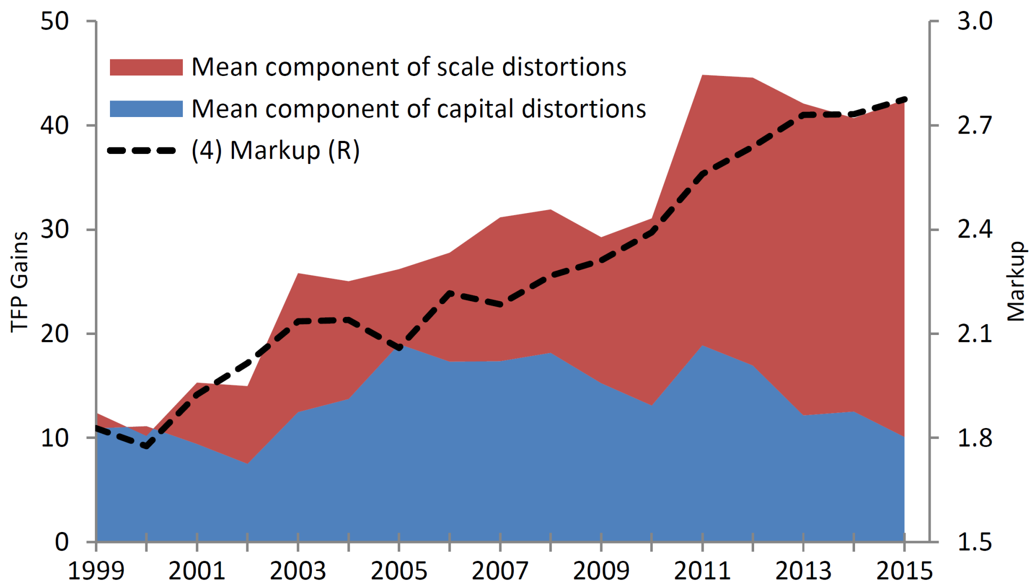
Notes: Annual averages of potential TFP gains from eliminating distortions, estimated, in each case, with expression (11) at the ISIC 3-digit level. The parameterization used in column (1) is similar to that of HK. In column (2), α_s is set so that $\bar{\tau}_{Ks} = 0$ for each industry s and year; in column (3), σ is set so that $\bar{\tau}_{Ys} = 0$ for each industry s and year; and in column (4) α_s and σ are set so that both $\bar{\tau}_{Ks} = 0$ and $\bar{\tau}_{Ys} = 0$ simultaneously for each industry s and year. We follow Chile's IRS size classification and define *Large Firms* as those with annual sales above 100,000*UF* (about $US\$4.2$ Million in 2018 prices).

Figure 1: TFP Gains, 1999-2015 - Different Parameterizations
Chile, Manufacturing Sector - All Firms



Notes: Potential TFP gains from eliminating distortions, estimated, in each case, with expression (11) using IRS data at the ISIC 4-digit level. The parameterization used in (1) is similar to that of HK. In (2), α_s is set so that $\bar{\tau}_{Ks} = 0$ in each year; in (3), σ is set, in each year, so that $\bar{\tau}_{Ys} = 0$; and in (4) α_s and σ are set so that both $\bar{\tau}_{Ks} = 0$ and $\bar{\tau}_{Ys} = 0$ simultaneously in each year.

Figure 2: Effect of "Mean" Components on TFP Gains Est. & Implicit Median Markups 1999-2015 Chile, Manufacturing Sector - All Firms



Notes: Potential TFP gains from eliminating the mean components of *capital* and *scale* distortions (i.e. $\bar{\tau}_{Ks}$ and $\bar{\tau}_{Ys}$). The sum is equal to the difference between the standard HK estimation (1) and estimation (4) in Figure 1. Implicit median industry markup (estimation (4)) is displayed in the right axis.

A Appendix

Table A.1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	P50	P90	P10
Panel A: IRS Database						
Value Added	176,169	833.45	7193.40	66.55	907.65	6.55
Capital	176,169	915.52	13389.42	26.45	637.58	2.10
Labor	176,169	228.86	1371.46	25.39	344.68	2.21
Panel B: ENIA Database						
Value Added	61,136	2.53	18.81	0.32	4.06	0.06
Capital	61,136	2.96	31.12	0.16	3.48	0.01
Labor	61,136	0.55	2.19	0.12	1.20	0.03
Panel C: EAM Database						
Value Added	157,935	5.65	34.09	0.64	10.25	0.08
Capital	157,935	8.78	51.82	0.56	13.71	0.05
Labor	157,935	0.74	1.94	0.18	1.66	0.03
Panel D: IRS Economy Database						
Value Added	891,395	594.77	8689.77	48.89	555.56	4.01
Capital	891,395	722.70	18242.35	18.47	338.69	1.30
Labor	891,395	182.50	1878.52	17.10	219.79	1.29

Table A.2: TFP Measures & Exit Probability
Linear Probability Model

	(1)	(2)	(3)	(4)
α_s:	U.S.	$\bar{\tau}_{Ks} = 0$	U.S.	$\bar{\tau}_{Ks} = 0$
σ:	3	$\bar{\tau}_{Ys} = 0$	3	$\bar{\tau}_{Ys} = 0$
A. Manuf., 2000-2014 - Chile IRS				
TFPR	-0.0139***	-0.0110***	-0.0331***	-0.0277***
Adj. R-Sq	(0.041)	(0.041)	(0.181)	(0.180)
TFPQ	-0.0456***	-0.0160***	-0.0554***	-0.0326***
Adj. R-Sq	(0.067)	(0.068)	(0.191)	(0.201)
B. Manuf., 1996-2006 - Chile ENIA				
TFPR	-0.00737**	-0.0137***	-0.00962**	-0.00978**
Adj. R-Sq	(0.050)	(0.051)	(0.222)	(0.221)
TFPQ	-0.00670***	0.000759	-0.0150***	0.00196*
Adj. R-Sq	(0.051)	(0.050)	(0.223)	(0.221)
C. Manuf., 1996-2014 - Colombia EAM				
TFPR	-0.0144***	-0.0135***	-0.0119***	-0.0147***
Adj. R-Sq	(0.012)	(0.012)	(0.199)	(0.199)
TFPQ	-0.0131***	-0.00344***	-0.0133***	-0.00496***
Adj. R-Sq	(0.017)	(0.017)	(0.201)	(0.203)
Age FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes

Notes: The dependent variable is, for each firm/plant and year, an indicator variable for exiting plants in the following year. Independent variables of interest are log TFPR or log TFPQ deviated from industry-year means. Fixed effect regressions weighted by industry value-added share, as in Hsieh & Klenow (2009, Table VIII). Adjusted R-Squared in parentheses. Regressions include year fixed effects and cubic age function in columns (1) and (2), and firm fixed effect in columns (3) and (4).

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