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Misallocation and Manufacturing TFP in Colombia

RESEARCH

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ABSTRACT

Following Hsieh and Klenow (2009) this paper studies productivity dispersion in Colombian industrial establishments using the Colombian Annual Manufacturing Survey (AMS) from 1982 to 1998. We consider how much a hypothetical removal of firm-level distortions would increase manufacturing productivity in Colombia and compare it with the United States. We find that such a reallocation would increase manufacturing Total Factor Productivity (TFP) in Colombia around 15% more than in the United States in our baseline calibration. We find that distortions have been increasing over time. Productivity gains are larger if we use Colombia's higher estimated elasticity of output with respect to capital. Furthermore we show that TFP is positively correlated with exporting status, age, size, and location in the Oriental region and the capital of the country.

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1 INTRODUCTION

Colombia is a middle-income country whose Total Factor Productivity (TFP) is far below the leading international economies (Restuccia 2013). A reason why TFP is lower could be factor misallocation, a situation where inputs are not allocated where they are most productive. We study the role of factor misallocation in lowering productivity in Colombian manufacturing, applying the Hsieh and Klenow (2009) approach to establishment data from the Annual Manufacturing Survey (AMS) from 1982 to 1998.

Hsieh and Klenow (2009) develop a monopolistic competition model with heterogeneous firms to show the effect of resource misallocation on aggregate productivity. With establishment-level data, they estimate productivity losses of 30–50% in China and 40–60% in India due to misallocation beyond the level present in the United States. We find that revenue TFP is a little more variable in Colombia than in the United States. Consequently, we find that the degree of misallocation in Colombia is not as large as in India or China, and is around 15% greater than in the United States. Colombia's lagging productivity, when compared with the United States, does not appear to be mostly due to misallocation among manufacturing firms. This is different from Hsieh and Klenow (2009), who find that a substantial fraction of the manufacturing productivity gap between the United States and China and India is due to misallocation.

In our baseline specification, and depending on the year in question, the aggregate TFP gains that would result from our hypothetical reallocation are generally around 45–60%. Hsieh and Klenow report that similar exercises in US data result in productivity improvements around 36%, implying reallocation gains for Colombia 10% to 20% larger than for the United States.[1] We consider how the distribution of firm size—measured by output—would change if all within-industry misallocation were eliminated and find that Colombia should have fewer mid-size plants and more small and large ones.[2]

We conduct several robustness checks by varying the elasticity of substitution between plant value added and the assumed labor and industry shares. Using Colombian capital shares suggests larger productivity gains from reallocation, as does a larger elasticity of substitution between varieties of goods produced within the industry. The estimated gains are not sensitive to the relative sizes of industries within Colombia. We also examine correlates of productivity measures (both TFPQ and TFPR) across firms. Firm level regressions show that physical TFP (TFPQ) is positively associated with exporting status, age, size, and location in the central region of the country, where the capital is located. In addition, the variability of revenue TFP (TFPR) is larger among smaller firms.

Colombian productivity growth in the 1980s and 1990s was poor. According to data from the Penn World Tables 10.0, Colombia's total factor productivity went from 90% of U.S. TFP in 1980 to 70% in 1990 and 53% in 2000 (see Feenstra et al. 2015). We find some evidence that labor and capital became less efficiently allocated across firms over this period, but not enough to explain the overall decline in TFP.

The rest of the paper is structured as follows: Section 2 summarizes recent literature related to our paper. Section 3 we provide background information on trade, labor market, and financial reforms that took place during the period we study. Section 4 describes the panel dataset used in the analysis for Colombia and the NBER-CES Manufacturing Industry Database used to calculate the US labor shares. Section 5 provides details about the methodology used to derive the empirical results. Section 6 starts with descriptive statistics, then provides the empirical findings with robustness checks. It includes an assessment of the possibility of measurement error in the plant revenue and inputs variables and a discussion of the firm-level correlates of TFPQ and TFPR. In section 7 we suggest potential explanations as to why misallocation increased in spite of reforms. Section 8 summarizes the main findings and concludes.

1 Table IV in Hsieh and Klenow (2009) reports productivity gains of 36.1% for the United States in 1998, the final year of our sample, 30.7% in 2001, and 42.9% in 2005, so 36.1% is the median value they report. Note that Bils et al. (2021) suggest that the perceived decline in US allocative efficiency could be driven by measurement error becoming worse over time. We similarly find a trend of declining allocative efficiency in Colombia.

2 The data we use is restricted to firms with ten or more employees. It is possible that many excluded small firms ought to be larger. Our result and conclusions should be applied to the group of firms we study.

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2 RELATED LITERATURE

Studies of factor misallocation are part of a larger literature examining large productivity differences across countries (Hsieh and Klenow 2010). Economists have long pondered how efficiently resources are allocated among firms. For example, Harberger (1959) and Dougherty and Selowsky (1973) consider this question, focusing on Latin American economies. The more recent literature on productivity and misallocation has grown much since Hsieh and Klenow (2009).[3] Restuccia and Rogerson (2008) demonstrate that idiosyncratic, firm-level distortions can reduce productivity because of the misallocation of inputs across firms with heterogeneous productivity. By contrast with Hsieh and Klenow, Restuccia and Rogerson's model is dynamic, with firms exiting or choosing to enter. The possibility of entry and the investment choice that affects firm productivity are important elements that shape the long-run distribution of firms and the steady-state level of productivity.

Related to Restuccia and Rogerson's (2008) discussion, several studies focus on size-dependent policies (see, for example, Guner et al. 2008; Restuccia 2013). Size-dependent policies can be problematic since they reduce the covariance between firm size and productivity (see Bartelsman et al. 2013). Smaller firms might find it easier to avoid paying taxes, or larger firms might have to comply with additional labor regulations. This tends to reduce the size of larger firms—that have high productivity—and to increase the size and number of small firms. In a related contribution, Hsieh and Klenow (2014) point out that the relationship between firm size and age is much steeper in the United States than in Mexico and especially India. One interpretation is that size-related frictions reduce the incentive of existing Indian (and Mexican) firms to invest in technological upgrades as they age.

Some of the policy changes in Colombia over the period we study could have had a differential effect on larger firms. Mondragón-Vélez et al. (2010) highlight growth in the informal sector in Colombia during the 1990s, attributing a large part of this growth to labor market regulations that are not enforced on informal workers who are typically at smaller firms. Some of Colombia's major economic reforms during the period we study focused on financial market regulation, so could plausibly have induced changes in the efficiency with which capital was allocated. Another strand of the literature provides a wide range of estimates regarding the importance of financial frictions for distorting capital allocation and productivity. Banerjee and Duflo (2005) survey evidence suggesting substantial dispersion of marginal products of capital across firms and Buera et al. (2011) argue that financial frictions can explain a large part of the aggregate TFP differences across countries, with more capital intensive industries struggling to operate successfully in financially underdeveloped settings.[4] Midrigan and Xu (2014) and Moll (2014) argue that self-financing can overcome productivity losses due to misallocation from financing constraints.[5]

Beyond financial market imperfections, David et al. (2016) suggest that misallocation could arise from firms' uncertainty about their productivity and demand conditions, and that greater uncertainty in China and India could lead to more misallocation. Asker et al. (2014) argue that adjustment costs can lead to variation in static marginal products but that these productivity variations are not a form of misallocation and will get eliminated over time as firms gradually adjust their input levels.[6] Haltiwanger et al. (2018) also dispute the importance of Hsieh and Klenow's findings, arguing that the measured distortions are sensitive to model misspecification.

3 See Hopenhayn (2014) and Restuccia and Rogerson (2017) for reviews. As Restuccia and Rogerson (2017) note, there are many possible reasons for resources to be misallocated among firms and the discussion here is not meant to be exhaustive.

4 See also Gopinath et al. (2017) and Rajan and Zingales (1998).

5 Moll (2014) and Banerjee and Moll (2010) suggest that financing frictions could have substantial effects on the transition dynamics of an economy even if they have minor effects on the steady state.

6 Though note David and Venkateswaran's (2019) argument that what Asker et al. (2014) interpret as an artefact of adjustment costs could also be persistent misallocation. In a model where both distortions and adjustment costs are present, they find that measures of misallocation are more driven by distortions than by adjustment costs.

A different perspective on input misallocation focuses on international trade, an area where Colombia had significant policy changes during the 1980s and 1990s. Melitz (2003) shows how a reduction in trade barriers can lead to a reallocation of inputs away from unproductive firms (that shrink or exit) toward more productive firms (that grow), supporting a higher level of overall productivity even in the absence of changing productivity at any single firm. Edmond et al. (2015) argue that trade openings can stimulate productivity through reallocation, especially when markups are variable and trade is procompetitive. Beyond reallocation effects, opening to international trade could increase productivity through faster productivity growth among incumbents, as discussed in Eslava et al. (2013).[7]

While the literature has largely focused on manufacturing, there are also some studies that look at other sectors, typically finding substantial misallocation. Adamopoulos and Restuccia (2014) study agricultural misallocation with a focus on explaining the farm size distribution. Adamopoulos et al. (2022), Chen et al. (2022), and Chen et al. (2017) identify substantial resource misallocation in agriculture in China, Ethiopia, and Malawi respectively. For Latin America, de Vries (2014) argues that misallocation is significant in Brazil's retail sector, and Busso et al. (2013) refers to large possible gains from reallocation in other Latin American economies' retail sectors.

Our paper examines the manufacturing sector in Colombia. We apply the Hsieh and Klenow (2009) method for measuring the extent of factor misallocation within sectors. Despite substantial reforms in trade, financial, and labor markets, we find that the extent of misallocation grew during the 1980s and 1990s, is greater than in the United States, and smaller than other developing countries. We find that the distortions across firms tend to compress the firm size distribution. An efficient reallocation would see two-thirds of firms become smaller, though the tendency for firms to become smaller is much greater among already small firms.

3 BACKGROUND

In Colombia in the early 1980s there were several trade reforms that increased effective protection.[8] The tendency toward greater protection was reversed in the latter 1980s and early 1990s. Goldberg and Pavcnik (2005) report that the average tariff rate in manufacturing rose to 50% in 1984 but subsequently was reduced, with substantial reductions in tariff rates in 1985 and again between 1990 and 1992. Effective protection rates fell from 62.5% to 26.6% between 1990 and 1991 (Edwards 2001). Between 1991 and 1992 the average tariff level was 11% (Ocampo and Villar 1992).[9]

The 1990s saw a series of major reforms in both governance and safety nets such as public health insurance. In 1991 a new Constitution gave independence to the central bank, and introduced municipal decentralization. One of the most important reforms of that decade took place in 1993, when *Law 100* reformed health and retirement income provision. The pension system added individual accounts with defined contributions while retaining the preexisting, pay-as-you-go public pensions (see, for example, Kugler and Kugler 2009; Cárdenas et al. 2008). The law also created a contributive health insurance regime, increasing contributions for health and pensions through employment by 10 percentage points from 1992 to 1996.

In the early nineties Colombia started a broad process of economic and political reforms in areas including employment policies, social security, financial markets, and trade. A main goal of the reforms was to achieve greater flexibility in the labor market. *Law 50* of December 1990 modified severance payments savings accounts, and reduced dismissal costs between 60% and 80% (see, for example, Kugler 1999; 2005). During the same year *Law 45* eliminated interest rate ceilings,

7 See also Bond et al. (2013) for a study of tariffs and misallocation in the United States in the 1930s.

8 See Garay et al. (1998) for a detailed description of trade policies from 1983 to 1985. Eslava et al. (2013) report variation in tariffs across industries in the early 1980s.

9 Bond et al. (2013) use a model with misallocation to argue that the output effect of higher levels of protection depends not only on how much stronger trade protections are but also on how variable tariff rates are across sectors and products.

requirements to invest in government securities, and lowered reserve requirements. Additional financial sector reforms took place in 1991. First, *Law 9* abolished exchange controls. Second, financial markets were reinforced according to the Basel Accords. Finally, *Resolution 49* eliminated restrictions on foreign direct investment (see, for example, Kugler 2006). A result of these financial reforms was an increase in capital inflows, which benefited the economy as a whole and especially the financial sector.

In summary, the period we study featured substantial liberalizing reforms. Labor costs were initially reduced in 1990 by the changes introduced with *Law 50*, but were later increased with the reforms of the health and pension systems as dictated by *Law 100* of December 1993. Frictions in financial markets were substantially lowered in 1990 and 1991 by *Law 45*, *Law 9,* and *Resolution 49*. Trade protection was high in the mid-1980s, but by 1990 and 1991 liberalization had greatly reduced trade barriers. Our study looks for evidence that these regulatory changes have affected productivity via reducing misallocation in Colombian manufacturing. We explore whether the degree of misallocation, or the wedges we measure, have declined over time, as one might expect if the liberalizations have leveled the playing field among firms within industries. We also infer a measures of productivity for firms and explore the extent to which they vary with firm characteristics.

4 DATA

4.1 ANNUAL MANUFACTURING SURVEY IN COLOMBIA 1982–1998

We use the panel of manufacturing firms created by Eslava et al. (2004) in collaboration with the National Statistical Agency (Departamento Administrativo Nacional de Estadísticas, DANE).[10] The panel uses the Colombian Annual Manufacturing Survey (AMS) conducted by DANE from 1982 until 1998. The AMS is a census of industrial plants with more than ten employees, or annual production above 115.5 million pesos (measured in 2005 prices).[11]

For the analysis we use plant information at the four-digit International Standard Industrial Classification (ISIC) level on: employees (production and non-production personnel); output (at constant 1982 prices) and a price index used to recover the nominal values[12]; capital stock (buildings, structures, machinery and equipment); and intermediate consumption (at constant 1982 prices and using the price index from Eslava et al. (2004)).

The 1998 panel does not include all the variables necessary to replicate Hsieh and Klenow (2009), so we use the 2004 panel to get additional information on total wage and benefit payments. Major differences in the original and updated panel correspond to the way deflators are constructed. We merge both panels using information that does not involve prices (four-digit level ISIC, production and non-production personnel, year, energy consumption). We use price indices to reconstruct nominal output and materials, and take the difference to get nominal value added.

As documented by Eslava et al. (2004), the plant capital stock is constructed recursively by depreciating the capital stock in the previous year and adding deflated investment. The deflator for investments calculated at the three-digit ISIC code level corresponds to the implicit deflator for capital formation from the input-output matrices for 1991–94, and from the output utilization matrices for later years. Pombo (1999) calculates different three-digit ISIC code level depreciation rates for buildings and structures, and machinery and equipment. We use these rates of depreciation and investment deflators to calculate the nominal capital stock variable.

10 Eslava et al. (2004) use this dataset to study productivity and resource allocation in a period of structural reforms in Colombia.

11 This value is adjusted every year using the Producer Price Index. The 115.5 million peso threshold corresponds to approximately $60,000 US.

12 See Eslava et al. (2004) for details on the construction of price index.

To avoid losing firms due to missing values and the recursive method used to construct capital stocks, we impute values for machinery and equipment and/or buildings and structures when there are positive values for capital stock in previous and subsequent years for a specific firm.

We keep plants that have positive value added, labor compensation, and capital stock. We analyze plants with ten or more employees, since the AMS is designed to study only these firms. We conduct the analysis with an unbalanced panel of 76,853 plant-year observations for the period between 1982 and 1998.

4.2 NBER-CES MANUFACTURING INDUSTRY DATABASE

We take the key production function elasticities from US data, since we presume that the factor shares in Colombian data correspond less closely to output elasticities of capital and labor due to the presence of distortions. We calculate labor shares for US industries from the National Bureau of Economic Research (NBER) and from the US Census Bureau Center for Economic Studies Manufacturing Industry Database (CES). We set the elasticity of output with respect to capital in each industry, α_s, as one minus the labor share in the corresponding industry in the US.

To assign US labor shares to Colombian plants within four-digit level ISIC sectors, we match usSIC codes to the ISIC Revision 2 codes (Colombian industrial codes). For the ISIC codes with more than one corresponding usSIC, we added the payroll and value added, then we calculated the labor shares. We have US data from 1982 to 1997 and use it to calculate these labor shares.

Using the ISIC three-digit classification for the industries in the analysis, US capital shares have a mean value of 0.39, a minimum of 0.16 (Manufacture of invalid carriages, not motorized) and a maximum of 0.78 (Manufacture of tobacco products).[13] We also estimate capital shares from within the Colombian data. Our data indicate very high capital shares, even if we make a casual correction scaling up labor compensation for unmeasured benefits by 50% as in the United States.[14] We report the output and labor shares for Colombia and the US in Appendix Table A.1.

5 ANALYTICS OF MISALLOCATION

5.1 ECONOMIC STRUCTURE

The economy is composed of many industries. The economy's final output, *Y*, is an aggregate of output from *S* separate industries, where each industry is indexed by *s*

$$Y = \Pi_{s=1}^{S} Y_s^{\theta_s}, \quad \Sigma_s \theta_s = 1 \tag{1}$$

and these industry-level outputs are supplied competitively. Final output is the numeraire good, so all other prices are relative to this final output.

Within an industry *s,* there are M_s firms that produce differentiated products and compete monopolistically. The industry-level output is given by

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

The production function of each firm *i* in sector *s* is Cobb-Douglas

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

13 When computing the α's we replaced negative values for one sector (Manufacture of engines and turbines for marine propulsion) with the minimum value among other sectors. The treatment of this sector has a trivial effect on our overall results, which are very similar if we replace this elasticity with the mean from other sectors, the maximum from other sectors, or simply drop the sector.

14 Gollin (2002), Bernanke and Gürkaynak (2001), and Izyumov and Vahaly (2015) each find capital shares for Colombia to be higher than for the United States, though not as high as implied by the manufacturing panel we work with. We do not subtract indirect taxes from value added, nor do we account for proprietor income, both of which would tend to inflate the capital share as we measure it.

with sector specific elasticities of output with respect to capital, α_s. Within a sector, plants face the same production function except for plant-specific total factor productivity, A_{si}. Each firm sets its own price, P_{si}.

The firm's profit function is

$$(1-\tau_{Ysi})P_{is}Y_{is}-(1+\tau_{Ksi})RK_{si}-wL_{si}. \tag{4}$$

where R and w are factor prices. Firm-specific capital distortions means the cost of capital varies across firms according to $(1+\tau_{Ksi})R$, where τ_{Ksi} are distortions that increase the marginal product of capital relative to the marginal product of labor. The overall distortion, τ_{Ysi}, can be thought of as distorting capital and labor demand equally, or distorting the overall size of the firm.

5.2 FIRM BEHAVIOR AND AGGREGATE OUTCOMES

When final output is made up of a cost-minimizing bundle of intermediate aggregates, the share of spending on output from each sector will equal θ_s

$$\frac{P_sY_s}{\sum_{s=1}^{S}P_sY_s}=\theta_s \tag{5}$$

where P_s is the price of a unit of the intermediate aggregate. Competitive supply of final output means that

$$\sum_{s=1}^{S}P_sY_s=PY=Y \tag{6}$$

since we normalize the price level of final output $P = 1$.

The price level of the intermediate aggregate P_s is the cost of a cost-minimizing bundle of output from individual firms in industry s. This price level is equal to

$$P_s=\left(\sum_{i=1}^{M_s}P_{si}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{7}$$

The cost minimization in sourcing output from the individual firms leads to the standard demand function

$$Y_{si}=Y_s\left(\frac{P_{si}}{P_s}\right)^{-\sigma}. \tag{8}$$

Individual firms maximize profits, taking the demand curve above as given. They set a price and choose capital and labor inputs. The first-order conditions for the firm problem imply, as in Hsieh and Klenow (2009),

$$P_{si}=\frac{\sigma}{\sigma-1}\left(\frac{w}{1-\alpha_s}\right)^{1-\alpha_s}\left(\frac{R}{\alpha_s}\right)^{\alpha_s}\frac{(1+\tau_{Ksi})^{\alpha_s}}{A_{si}(1-\tau_{Ysi})} \tag{9}$$

$$1+\tau_{Ksi}=\frac{\alpha_s}{1-\alpha_s}\frac{wL_{si}}{RK_{si}} \tag{10}$$

$$1-\tau_{Ysi}=\frac{\sigma}{\sigma-1}\frac{wL_{si}}{(1-\alpha_s)P_{si}Y_{si}} \tag{11}$$

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

The sector-specific factor κ_s is given by

$$(P_sY_s)^{-\frac{1}{\sigma-1}}P_s^{-1}. \tag{13}$$

Given the price set by an individual firm and the formula for the industry-level price, we can define $\chi_{si} = \frac{(1+\tau_{Ksi})^{\alpha_s}}{A_{si}(1-\tau_{Ysi})}$ and express the relative price as

$$\frac{P_{si}}{P_s} = \frac{\chi_{si}}{\left(\sum_{i=1}^{M_s} \chi_{si}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}}, \tag{14}$$

the firm's value-added share in the industry is given by

$$\frac{P_{si}Y_{si}}{P_sY_s} = \left(\frac{P_{si}}{P_s}\right)^{1-\sigma} = \frac{\chi_{si}^{1-\sigma}}{\left(\sum_{i=1}^{M_s} \chi_{si}^{1-\sigma}\right)}, \tag{15}$$

and the output of the firm relative to the industry is

$$\frac{Y_{si}}{Y_s} = \left(\frac{P_{si}}{P_s}\right)^{-\sigma} = \frac{\chi_{si}^{-\sigma}}{\left(\sum_{i=1}^{M_s} \chi_{si}^{1-\sigma}\right)^{-\frac{\sigma}{1-\sigma}}}, \tag{16}$$

so that the firm's relative price, relative value-added and relative output are all determined by the term χ and its distribution within the industry.

5.3 PRODUCTIVITY MEASURES AND REALLOCATION

We consider now different measures of productivity in this economy. The physical total factor productivity (TFPQ) for a firm is $A_{si} = Y_{si}/(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s})$. Since many firm-level datasets do not distinguish nominal value added from physical quantity produced, studies frequently refer to revenue productivity (Foster et al. 2008). Revenue total factor productivity for a firm is

$$TFPR_{si} = P_{si}A_{si} \tag{17}$$

so that TFPR is not directly proportional to TFPQ since as A_{si} rises the price charged by the firm falls. As in Hsieh and Klenow (2009), we can express TFPR in terms of marginal revenue products:

$$TFPR_{si} = \frac{\sigma}{\sigma-1}\left(\frac{MRPK_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{MRPL_{si}}{1-\alpha_s}\right)^{1-\alpha_s} \tag{18}$$

where the marginal revenue products of capital and labor are the amount of additional pre-tax revenue the firm generates when using one additional unit of the input. If each firm in an industry faces the same distortions, then each will have the same TFPR. The variation of TFPR and its covariation with physical productivity determine the extent of misallocation.

At the industry level, Hsieh and Klenow (2009) show that total factor productivity is

$$TFP_s = \left(\sum_{i=1}^{M_s}\left(A_{si}\frac{\overline{TFPR}_s}{TFPR_{si}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \tag{19}$$

where the average TFPR is defined as P_sTFP_s and can be expressed as

$$\overline{TFPR}_s = \frac{\sigma}{\sigma-1}\left[\frac{\overline{MRPK}_s}{\alpha_s}\right]^{\alpha_s}\left[\frac{\overline{MRPL}_s}{1-\alpha_s}\right]^{1-\alpha_s} \tag{20}$$

where $\overline{MRPK}_s$ and $\overline{MRPL}_s$ are industry-level measures of distortions, calculated as weighted harmonic means of firm-level distortions, with weights equal to nominal value-added shares. Specifically,

$$\overline{MRPK}_s = \frac{1}{\sum_i \frac{1}{MRPK_{si}}\frac{P_{si}Y_{si}}{P_sY_s}} \tag{21}$$

and

$$\overline{MRPL}_s = \frac{1}{\sum_i \frac{1}{MRPL_{si}} \frac{P_{si}Y_{si}}{P_s Y_s}}. \tag{22}$$

We consider hypothetical scenarios in which the distortions faced by firms are identical within the industry. Therefore each firm has the same marginal revenue products and TFPR. We assume that these new distortions are set so that the capital and labor used in the industry do not change. In this case, using * to denote the outcome without idiosyncratic distortions, the industry TFP becomes

$$TFP_s^* = \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{23}$$

which is also called $\overline{A}_s$ in Hsieh and Klenow.

6 RESULTS

6.1 PRELIMINARIES

In constructing our measures of productivity and misallocation for Colombia, we follow Hsieh and Klenow (2009) in calibrating various parameters. Given that labor is heterogeneous, we use the wage bill as our measure of the labor input, rather than the number of workers, which implies the normalization $w = 1$. We assume a rental price of capital, R, of 10%. We assume an elasticity of substitution between plant value added of $\sigma = 3$ in our baseline analysis. This value corresponds closely to the Broda et al. (2006) estimate of $\sigma = 2.9$ for Colombia.

We remove outliers in the distributions of plant productivity and distortions by trimming values below the 1st percentile and above the 99th percentile of the distribution of $\log(\frac{TFPR_{si}}{\overline{TFPR}_s})$ and $\log(\frac{A_{si}}{\overline{A}_s} M_s^{\frac{1}{\sigma-1}})$ for each year, where M_s is the number of firms in sector s. In our baseline analysis, this corresponds to excluding approximately 12% of production.[15] Then we recalculate $\overline{A}_s$ and $\overline{TFPR}_s$ using this trimmed sample.

6.2 DESCRIPTIVE STATISTICS

The last column of Table 1 shows the number of plants by year and two-digit sector. On average there are approximately 4,500 plants per year, though there is a trend decline in the number of firms present. Of the sectors represented, "Textile, apparel and leather industries" is the largest sector, followed by the "Food, beverages and tobacco" and "Fabricated Metal Products" sectors. "Basic metal industries" and "Other manufacturing industries" have the smallest share of firms in the panel. Though there are fluctuations in the number of firms over time, the distribution of firms across sectors remains relatively stable. Each industry exhibits a decline in the number of firms between the sample's beginning and end. While the number of firms declined over this period, the average number of employees per firm increased so that manufacturing employment fell in Colombia, but by a smaller proportion than the number of firms.

Table 2 shows the number of firms that enter and exit the panel over time, with the last column indicating the net entry. We define entry as a firm that appears in the dataset and is not observed in the previous year. Exit corresponds to a firm previously observed that is not observed the next year in the dataset. Net entry is calculated as the difference between firms that enter in year t and firms that exit in year t-1. Thus a particular firm can be counted both in the entry and the exit column (though not in the same year). About 500 firms enter each year, while 600 exit. This corresponds to average annual entry and exit rates of approximately 11% and 13% respectively of the plants observed in the panel.

15 We lose a lot of the measured production since we trim out the firms that appear to be most productive.

YEAR	FOOD, BEVERAGES AND TOBACCO	TEXTILE, APPAREL AND LEATHER INDUSTRIES	WOOD PRODUCTS AND WOOD	PAPER PRODUCTS AND PAPER	CHEMICALS, OIL, COAL AND PLASTIC PRODUCTS	NON-METALLIC MINERAL PRODUCTS	BASIC METAL INDUSTRIES	FABRICATED METAL PRODUCTS	OTHER MANUFACTURING INDUSTRIES	TOTAL
1982	1,002	1,408	301	386	652	330	68	1,085	117	5,349
1983	1,007	1,446	304	368	613	305	69	1,018	115	5,245
1984	981	1,447	287	363	615	278	67	952	111	5,101
1985	975	1,466	269	347	622	260	66	948	101	5,054
1986	991	1,490	279	340	630	251	68	946	101	5,096
1987	1,009	1,478	295	336	639	255	67	946	99	5,124
1988	998	1,418	296	327	655	228	66	959	105	5,052
1989	999	1,377	306	338	658	225	65	950	102	5,020
1990	977	1,319	290	317	641	212	65	914	99	4,834
1991	934	1,209	261	302	616	195	61	850	83	4,511
1992	869	976	241	282	581	173	53	756	78	4,009
1993	859	926	218	273	577	167	53	758	78	3,909
1994	847	898	217	269	562	157	48	699	71	3,768
1995	888	889	224	273	570	171	45	727	82	3,869
1996	877	850	212	260	572	172	44	708	80	3,775
1997	898	835	204	253	559	170	39	674	74	3,706
1998	865	758	172	236	535	155	36	603	71	3,431
Total	15,976	20,190	4,376	5,270	10,297	3,704	980	14,493	1,567	76,853

Table 1 Firms by Sector over Time.

Source: AMS and authors' calculations.

YEAR	EXIT	ENTRY	NET ENTRY
1983	760	656	–104
1984	677	533	–144
1985	606	559	–47
1986	513	555	42
1987	495	523	28
1988	541	469	–72
1989	517	485	–32
1990	474	288	–186
1991	552	229	–323
1992	811	309	–502
1993	464	364	–100
1994	560	419	–141
1995	490	591	101
1996	482	388	–94
1997	444	375	–69
1998	539	264	–275

Table 2 Entry and Exit over Time.

Source: AMS and authors' calculations.

As reported in the last column of Table 2 from year-to-year the number of plants declines slightly, with a more noticeable fall from 1991 to 1992, possibly due to a change in plant identifiers.[16] An additional explanation for the drop in number of firms is the aggregate economic cycle. Figure 1 reports the GDP growth rate and the net entry of firms. The values for this figure are taken from the final column in Table 2. The figure shows a correlation between the decline in GDP growth during the late 1980s and a decline in the net number of manufacturing firms getting started. This pattern is reversed when the economy recovers in the early 1990s, and on net there is a higher number of firms getting started.

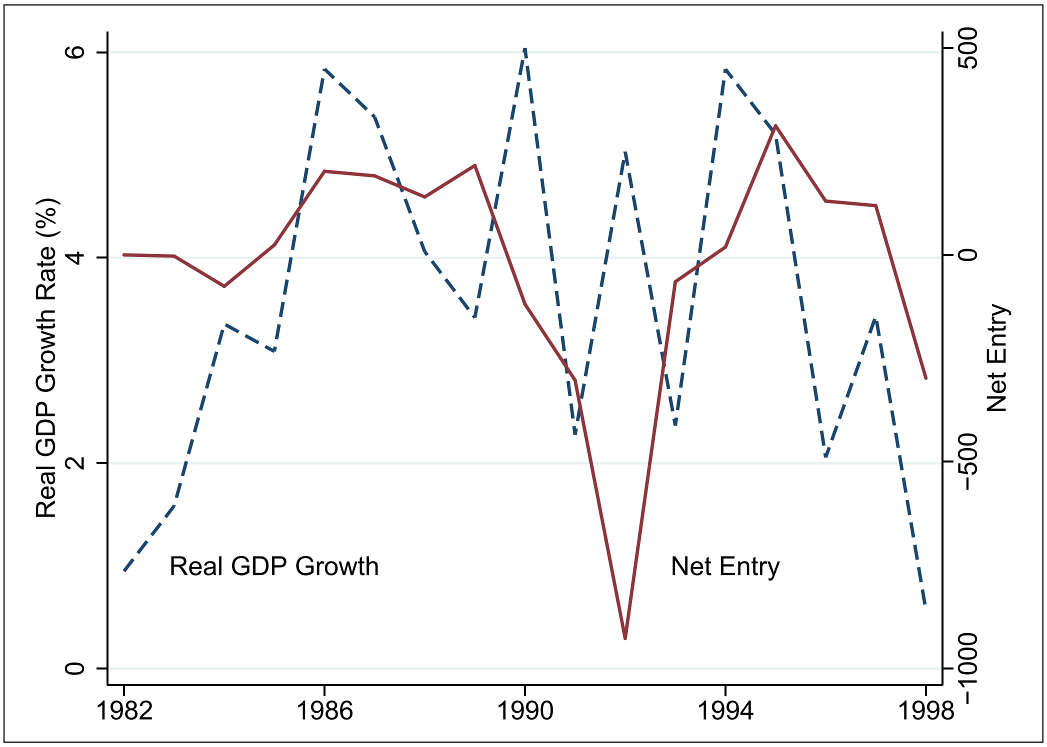

Figure 1 Net Entry and GDP Growth.

Source: DANE, AMS and authors' calculations.

Table 3 shows the number of plants by size categories (measured by the number of employees) in 1998. This table omits plants with fewer than ten employees, as we do not use them in our main analyses. In this selection of firms, the typical pattern is that firm size distribution has a density that declines in the firm size, and small firms are extremely common. In our data, the most common firm size is ten employees. The median firm has 34 employees and the median worker is employed at a plant with a little more than 200 employees.

Table 3 Firm Size Distribution.

Source: AMS and authors' calculations.

	FIRMS				EMPLOYMENT			
FIRM SIZE (EMPLOYEES)	NUMBER OF FIRMS	CUMULATIVE FIRMS	SHARE	CUMULATIVE SHARE	NUMBER OF EMPLOYEES	CUMULATIVE EMPLOYEES	SHARE	CUMULATIVE SHARE
Size 10–19	990	990	28.9%	28.9%	13,856	13,856	4.5%	4.5%
Size 20–49	1,088	2,078	31.7%	60.6%	33,608	47,464	10.9%	15.4%
Size 50–99	612	2,690	17.8%	78.4%	43,026	90,490	14.0%	29.4%
Size 100–249	469	3,159	13.7%	92.1%	72,619	163,109	23.6%	53.0%
Size 250–499	180	3,339	5.2%	97.3%	61,780	224,889	20.1%	73.1%
Size 500–999	65	3,404	1.9%	99.2%	45,035	269,924	14.6%	87.8%
Size 1000–	27	3,431	0.8%	100.0%	37,579	307,503	12.2%	100.0%

16 We are able to match most of the new and old firm identifiers with a dictionary. However despite the dictionary, there were some plants that do not match.

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6.3 EMPIRICAL RESULTS

6.3.1 Distribution of TFPQ

Figure 2 plots the distribution of the plant TFPQ relative to the industry's potential TFPQ for 1998. It is calculated as

$$\log\left(\frac{A_{si}}{\bar{A}_s}\right)M_s^{\frac{1}{\sigma-1}}. \tag{24}$$

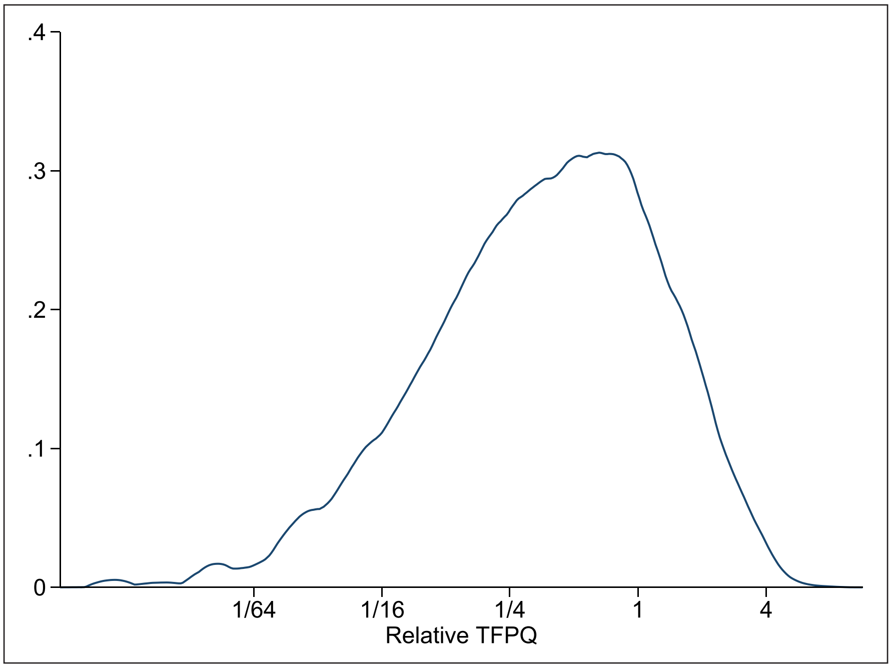

Figure 2 Distribution of TFPQ in Colombia, 1998.

Source: AMS and authors' calculations.

This distribution is weighted by the value added share of the industry relative to the economy, divided by the number of firms in the specific sector. Colombia's TFPQ dispersion is wider than in the US, slightly smaller than in China and substantially narrower than in India as reported by Hsieh and Klenow (2009), and the left tail is thicker.

Figure 3 plots the distribution of plant TFPQ relative to industry TFPQ for selected years. The most noticeable feature of the distribution is that it has spread out over time. The 1982 distribution is much more concentrated around the average, with less mass in the tails. As the years progress, there is an increasing tendency for firms to have either very low or very high physical productivity relative to their industry, perhaps suggesting a reduced propensity of low productivity firms to exit. The analysis we conduct focuses on misallocation of resources among incumbent firms, but the evidence on TFPQ dispersion suggests possible changes over time in the process by why low productivity firms enter or exit. This could be good if the low productivity firms are supplying a market niche, but it could be bad if these firms are mainly competing for inputs that could be used more productively elsewhere.

The left panel of Table 4 shows the standard deviation (SD), the interquartile range (IQR, difference between the 75th and 25th percentile) and the interdecile range (difference between the 90th and 10th percentiles) of plant TFPQ relative to the industry TFPQ levels, weighted by the importance of each sectors' firms in the overall economy. The table shows that, across years, several measures of dispersion of TFPQ are wider in Colombia than those reported by Hsieh and Klenow (2009) for the United States. The US standard deviation ranges from 0.79 to 0.85; the 75–25 percentile comparison from 1.09 to 1.22; and the 90–10 percentile comparison from 2.05 to 2.22. For Colombia these numbers are 1.11 to 1.48 for the standard deviation range; the 75–25 percentile comparison from 1.58 to 1.89; and the 90–10 percentile comparison from 3.04 to 3.82. For comparison, Hsieh and Klenow report a standard deviation of TFPQ around 1 for China and close to 1.2 for India. Therefore, the distribution of physical productivity is more dispersed in the Colombian data.

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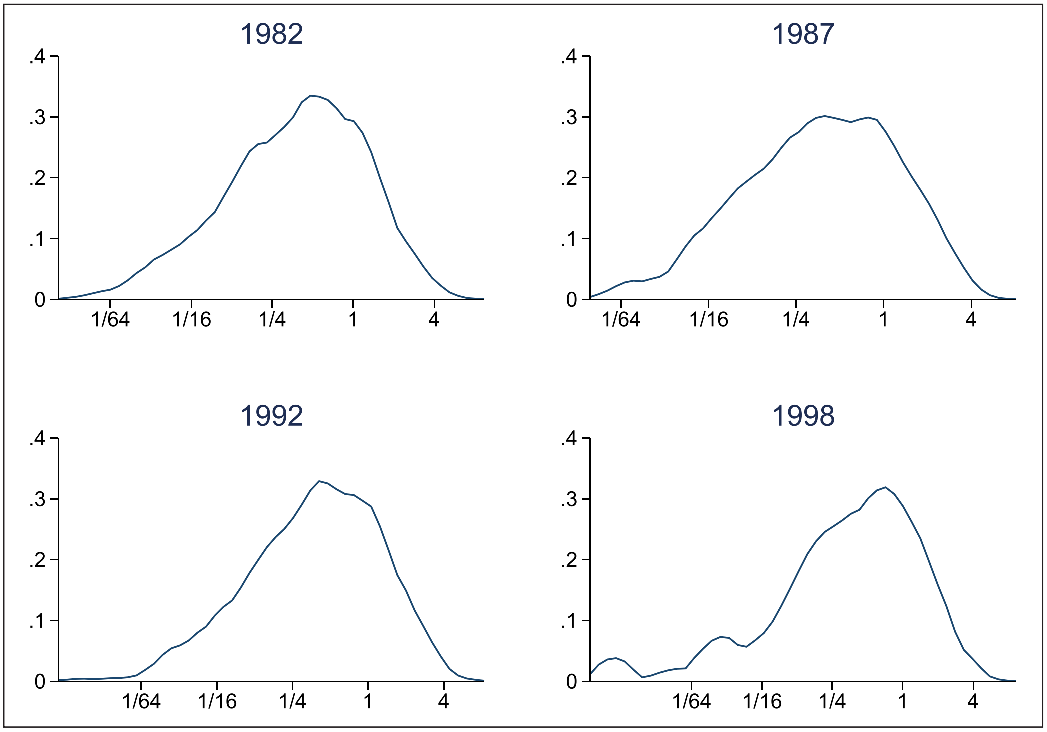

Figure 3 Distribution of TFPQ, Select Years.

Source: AMS and authors' calculations.

Table 4 Dispersion of TFPQ and TFPR.

Source: AMS and authors' calculations.

	ln(TFPQ)			ln(TFPR)		
YEAR	**SD**	**IQR**	**90–10**	**SD**	**IQR**	**90–10**
1982	1.19	1.69	3.06	0.64	0.74	1.59
1983	1.24	1.72	3.30	0.65	0.73	1.61
1984	1.13	1.58	3.04	0.61	0.74	1.50
1985	1.19	1.61	3.10	0.62	0.68	1.53
1986	1.25	1.72	3.27	0.65	0.72	1.63
1987	1.21	1.74	3.21	0.64	0.80	1.58
1988	1.21	1.79	3.27	0.64	0.82	1.63
1989	1.23	1.78	3.27	0.63	0.77	1.58
1990	1.16	1.69	3.05	0.60	0.72	1.48
1991	1.11	1.65	3.02	0.59	0.75	1.43
1992	1.21	1.68	3.12	0.65	0.77	1.56
1993	1.26	1.78	3.27	0.68	0.77	1.65
1994	1.25	1.77	3.23	0.67	0.74	1.61
1995	1.32	1.89	3.54	0.77	0.83	1.89
1996	1.44	1.79	3.65	0.84	0.82	1.89
1997	1.38	1.84	3.57	0.81	0.87	1.99
1998	1.48	1.80	3.82	0.88	0.80	2.02

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6.3.2 Distribution of TFPR

Figure 4 plots the distribution of plant TFPR relative to industry TFPR for 1998. It is calculated as

$$\log\left(\frac{TFPR_{si}}{TFPR_s}\right). \quad (25)$$

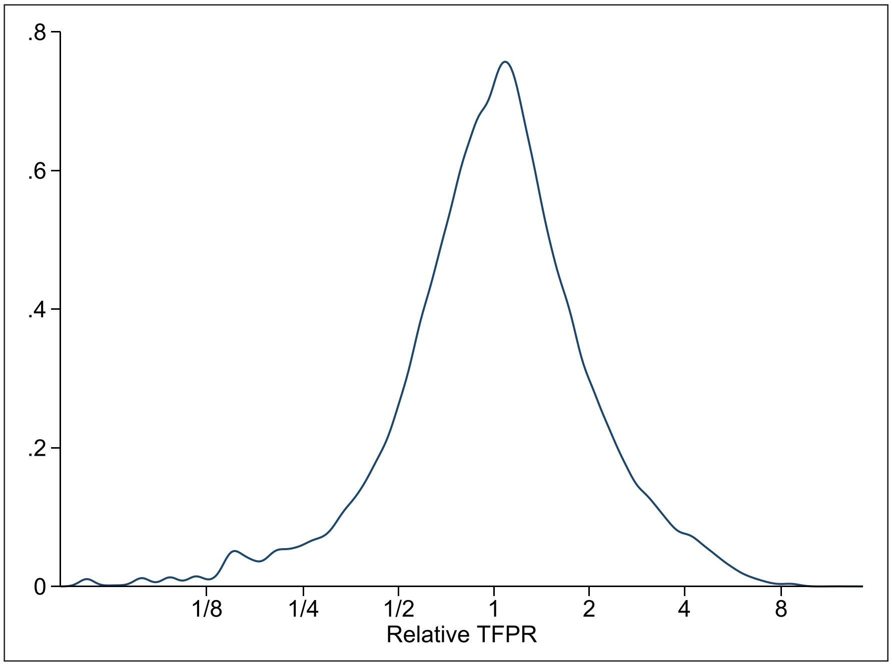

Figure 4 Distribution of TFPR in Colombia, 1998.

Source: AMS and authors' calculations.

This distribution is weighted by the value added share of the industry relative to the economy, divided by the number of firms in 1998 in the specific sector. Despite having lower overall manufacturing productivity, we measure Colombian TFPR dispersion as similar to the United States. Figure 5 provides more detail by plotting the distribution of the plant TFPR relative to the industry TFPR by year. The dispersion in plant TFPR gradually increased between 1982 and 1998. See also Figure 6.

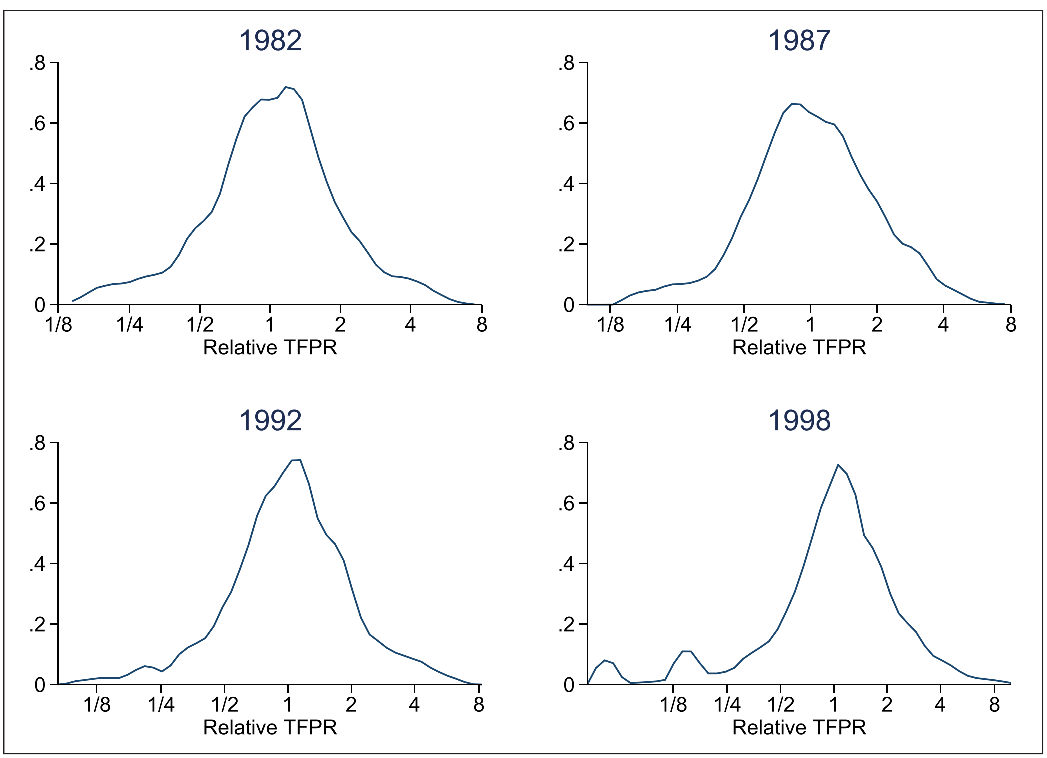

Figure 5 Distribution of TFPR in Colombia by Year.

Source: AMS and authors' calculations.

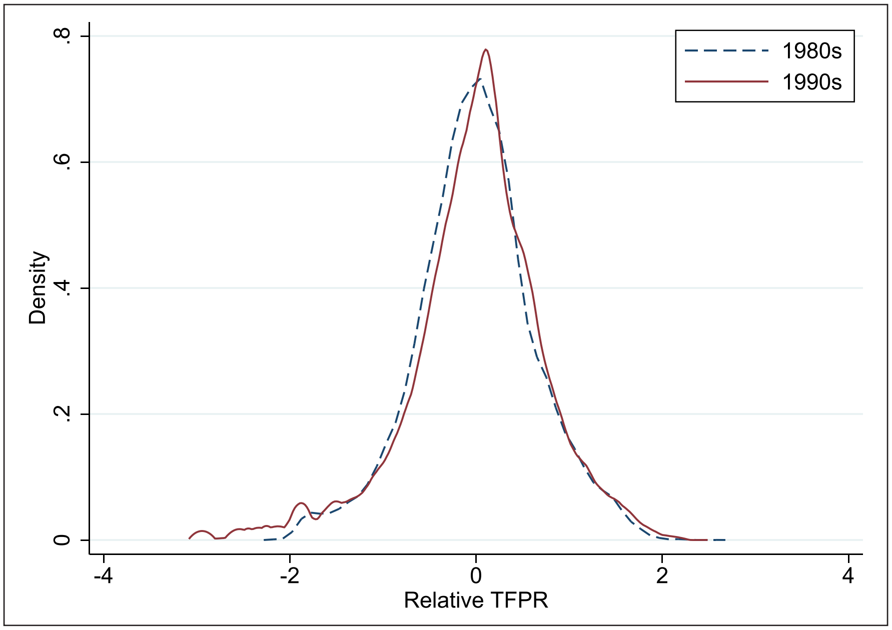

Figure 6 Distribution of TFPR in Colombia by Decade.

Note: The two distributions are for 1982–1989 and 1990–1998. Source: AMS and authors' calculations.

The right panel of Table 4 shows the standard deviation, the interquartile range and interdecile range of plant TFPR relative to the industry TFPR levels, weighted by share of value added of the industry with respect to the economy, divided by the number of firms in that specific year and sector. The US values reported by Hsieh and Klenow (2009) for the standard deviation of TFPR range from 0.41 to 0.49. The corresponding values for Colombia are from 0.59 to 0.88. Since the dispersion of TFPR we find in Colombia is larger than that in the United States, we find greater possible gains from reallocating resources in Colombia. This is the major finding of our paper.

For India and China, as shown in Hsieh and Klenow (2009), the dispersion of TFPR is very wide. The standard deviation of TFPR in each country is around 0.68, above the values we find generally find for Colombia, though below the values we find toward the end of the sample period. This means resource allocation is less efficient than in the United States, implying large productivity gains if distortions are reduced in those countries.

6.3.3 Gains from Reallocation

Table 5 shows the TFP gains (in percentage terms) from equalizing TFPR across plants within industries as:

$$100\left(\tfrac{Y^*}{Y}-1\right) \tag{26}$$

where

$$\frac{Y}{Y^*}=\prod_{s=1}^{S}\left(\sum_{i=1}^{M_s}\left(\frac{A_{si}\overline{TFPR}_s}{\bar{A}_s TFPR_{si}}\right)^{\sigma-1}\right)^{\frac{\theta_s}{\sigma-1}}. \tag{27}$$

To ensure that $\sum_s \theta_s = 1$ we calculate θ_s as the industry's share of value added. In our baseline calibration, using US labor shares $(1-\alpha_s)$ (θ_s), column (1) in Table 5 shows that aggregate manufacturing TFP would increase by 45–60% with full liberalization.

The measured misallocation is not driven by the industrial composition of Colombia's manufacturing sector. Measured misallocation is slightly smaller if we use US industry shares (θ) instead of the Colombian shares in computing the possible TFP gains. (See column (2).)

	(1)	(2)	(3)	(4)
	$\sigma = 3$	$\sigma = 3$	$\sigma = 3$	$\sigma = 5$
	α_s: U.S.	α_s: U.S.	α_s: Col.	α_s: U.S.
YEAR	θ_s: Col.	θ_s: U.S.	θ_s: Col.	θ_s: Col.
1982	48.8	43.4	96.7	74.6
1983	46.1	43.0	87.9	64.3
1984	45.5	43.4	95.4	71.0
1985	47.6	40.3	89.5	73.8
1986	48.2	41.1	99.8	72.7
1987	48.1	41.1	82.5	68.9
1988	58.2	46.6	116.9	92.8
1989	50.5	41.8	87.5	75.1
1990	47.5	41.3	77.9	75.1
1991	45.2	38.8	81.8	72.1
1992	47.3	47.2	75.4	73.8
1993	51.3	51.4	90.2	80.2
1994	56.9	55.2	94.5	88.2
1995	60.0	52.4	97.5	96.1
1996	49.5	49.9	81.2	77.3
1997	52.2	52.8	87.6	80.8
1998	53.9	59.0	80.6	86.2

Table 5 TFP Gains from Equalizing TFPR within Industries.

Source: AMS and authors' calculations.

By contrast, if we use the capital elasticities (α_s) derived from Colombian data within each manufacturing sector the estimated productivity gains generally range between 75–100%, as shown in column (3). This is about thirty-five percentage points larger than the estimated gains when using US capital elasticities. Capital elasticities estimated from the Colombian data are generally larger than implied by US data, though the measures from our data probably overstate the capital income shares, and therefore the capital elasticity. (See footnote 14 for more discussion.) As such, the estimates in column (3) probably overstate potential gains from resource reallocation.

Similarly, the estimated gains are larger with higher values of σ, the elasticity of substitution between varieties within an industry. Hsieh and Klenow find that the estimated gains in China and India are more sensitive to σ than we find for Colombia. It is worth noting that Broda et al. (2006) report estimates of the elasticity of substitution among different varieties of a good to be equal to 2.9 in Colombia.

6.3.4 Comparison with Other Countries

We find that Colombia's within-industry allocative efficiency is lower than the United States. We estimate possible gains from efficiently reallocating inputs that are typically around 45% to 60%, whereas Hsieh and Klenow estimate that productivity in the United States would increase around 35% to 40% with fully efficient reallocation. We find no evidence that allocative efficiency increased in Colombia from 1982 to 1998, in contrast to what Hsieh and Klenow find for India. The implied decline in allocative efficiency is around 4% or 0.2% per year, on average, from 1982 to 1998. Hsieh and Klenow also find a slight decline in the allocative efficiency of production in the United States between 1977 and 2005. Bils et al. (2021) consider whether this is an artifact of increasing measurement error.

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The worsening of measured allocative efficiency in Colombian manufacturing is modest when compared with the decline in overall total factor productivity in Colombia relative to the United States. While we find a modest excess of within-industry misallocation in Colombia relative to the United States, it is also possible that there are differences in between-industry misallocation which we do not study here. In the next subsections we consider how a hypothetical reallocation of resources would change firm sizes and we also estimate the persistence of distortions.

6.3.5 Actual and Efficient Firm Size

We consider how a reallocation of resources within sectors would affect the size distribution of firms. We can measure the size of firms either by value added or by physical output. Furthermore, we can measure the firm's efficient size relative to its original size or relative to its industry's average size.

Table 6 shows how firms' sizes, measured as value added, would change if TFPR were equalized. The rows are actual plant size quartiles (within industry), and the columns correspond to the ratio of efficient plant size relative to original size. From this efficient-to-actual size ratio we create four categories: 0–50% (the plant should reduce its size at least by 50%), 50–100%, 100–200%, and more than 200% (the plant should increase in size by at least doubling). Generally, small firms should be relatively smaller. Many large firms should shrink too. However, large firms are more likely to be inefficiently small than small firms are. Overall, a reallocation that equalizes TFPR would spread out the distribution of firm size substantially.

Table 6 Changes in Firm Size under Efficient Reallocation.

Note: The rows are for separate quartiles of the within-industry observed distribution of value added. The columns show the fraction of firms whose size relative to the industry aggregate becomes less than 50%, 50% to 100%, 100% to 200%, and more than 200% of the original. Source: AMS and authors' calculations.

	VALUE ADDED, RELATIVE TO INDUSTRY				
	0–50%	50–100%	100–200%	200+%	TOTAL
Bottom Quartile	17.0	4.0	2.2	1.8	25.0
2nd Quartile	14.0	6.2	2.9	1.9	25.0
3rd Quartile	11.2	7.0	4.2	2.6	25.0
Fourth Quartile	8.4	8.0	5.7	2.9	25.0
Total	50.6	25.1	15.1	9.2	100.0

The basic pattern in Table 6 is replicated if we consider physical output relative to the industry. Firms that increase value added do so by increasing output even more (offsetting the decline in prices they charge).

Figure 7 plots the efficient and the actual size distribution of plants in 1998. The size of plants is measured by value added. As Hsieh and Klenow (2009) find for the United States, China, and India, the efficient distribution is more dispersed than the actual distribution. In particular it

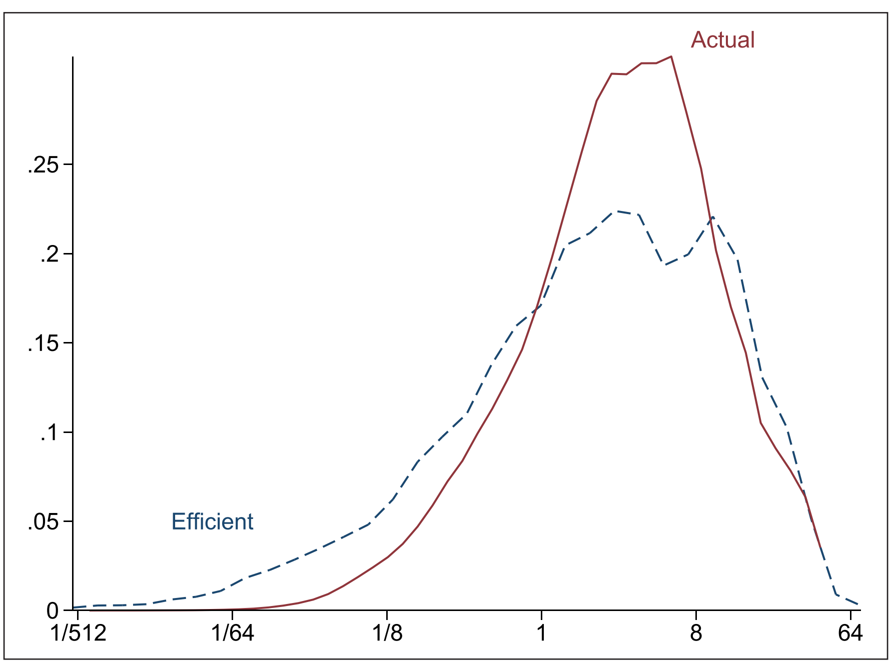

Figure 7 Distribution of Plant Value Added Relative to Industry, Actual vs. Efficient, 1998.

Source: AMS and authors' calculations.

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shows a larger concentration of firms in the left and right tails. This indicates that there should be fewer mid-sized plants and more small and large ones.[17] This result—that the efficient firm-size distribution has a larger variance than the actual distribution—is consistent across years, as depicted in Figure 8.

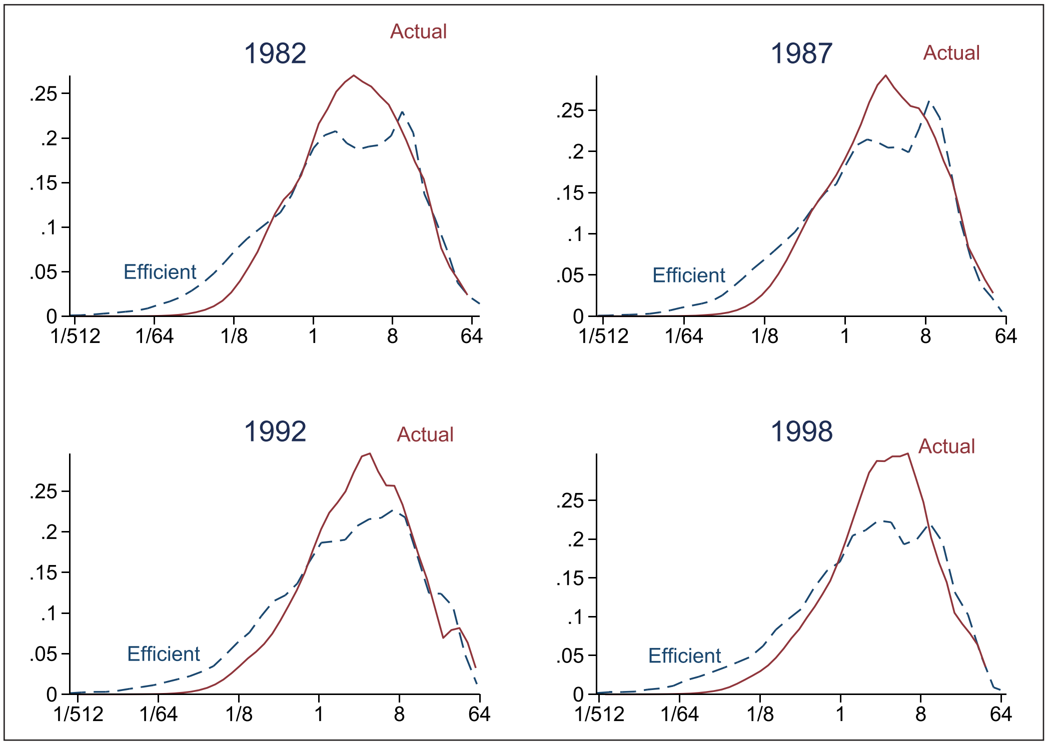

Figure 8 Distribution of Plant Value Added Relative to Industry, Actual vs. Efficient, Multiple Years.

Source: AMS and authors' calculations.

6.3.6 Distortion Dynamics

Some important contributions to the recent literature on misallocation emphasize dynamic aspects of resource allocation, for example Asker et al. (2014) and David and Venkateswaran (2019). Since we have data on plants observed annually for nearly twenty years, we can examine the dynamics of the measured distortions. We consider three variables: the logs of $(1+\tau_{Ksi}),(1-\tau_{Ysi})$ and A_{si} relative to an industry-year reference. We examine whether firms with advantageous distortions are likely to see those advantages persist into the following year or whether these boosts are simply transitory. Table 7 reports estimated coefficients when regressing one of these distortions on lags of all three.[18] We find that distortions and TFP are very persistent over time. The measured capital distortion and TFP are highly persistent, with autoregressive coefficients above 0.9. The output distortion does not have such a high autoregressive coefficient (in a univariate autoregression the coefficient is around 0.6). The two distortion series we measure are largely independent of each other. A firm's TFP does not help much to predict future distortions, but the current output distortion predicts future productivity (See Banerjee and Moll (2010), David and Venkateswaran (2019) and David et al. (2021) for further discussion of persistent distortions and their causes).

17 However, it is important to keep in mind the sample restrictions in the panel which exclude most plants with less than ten employees. The efficient firm sizes we compute would leave many firms below our ten-employee cutoff. In practice, some of these firms would become sufficiently small in this counterfactual that they would presumably exit.

18 Note that we do not use firm fixed effects as we are measuring the overall degree of persistence in the distortions. Adding firm fixed effects would account for some of the persistence.

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	(1)	(2)	(3)
	$\log(\tau_{Ksi,t})$	$\log(\tau_{Ysi,t})$	$\log(A_{si,t})$
$\log(\tau_{Ksi,t-1})$	0.905***	0.0529***	–0.0954***
	(0.00236)	(0.00158)	(0.00247)
$\log(\tau_{Ysi,t-1})$	–0.109***	0.577***	0.449***
	(0.00799)	(0.00537)	(0.00838)
$\log(A_{si,t-1})$	–0.0995***	–0.0599***	0.988***
	(0.00390)	(0.00262)	(0.00409)
Observations	61608	61608	61608
R-squared	0.771	0.474	0.646

Table 7 Dynamics of Distortions and Productivity.

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6.4 CHANGING DISTORTIONS AND MISALLOCATION

Our estimates in Table 5 show that the degree of misallocation has grown slightly in Colombia over time (see also Figure 9). Table 4 shows there is a simultaneous rise in the variability of TFPR. Underlying the increasing TFPR variation are changing distortions. Table 8 shows that variation in the capital distortion, $\log((1+\tau_{Ksi})/(1+\tau_{Ks}))$, has been relatively stable—the standard deviation is around 1.25 early in the sample and also at the end of the period. The output distortion, $\log((1+\tau_{Ysi})/(1+\tau_{Ys}))$ has become more variable over time, with a standard deviation increasing from around 0.6 in the mid-1980s to 0.8 in the late 1990s.[19] Figure 10 shows dispersions of τ_{Ksi} and τ_{Ysi}. While the dispersion of τ_{Ksi} is relatively stable over time, the output distortion, τ_{Ysi}, is becoming more dispersed, explaining why our estimates suggest there are greater potential gains from reallocation toward the end of the sample.

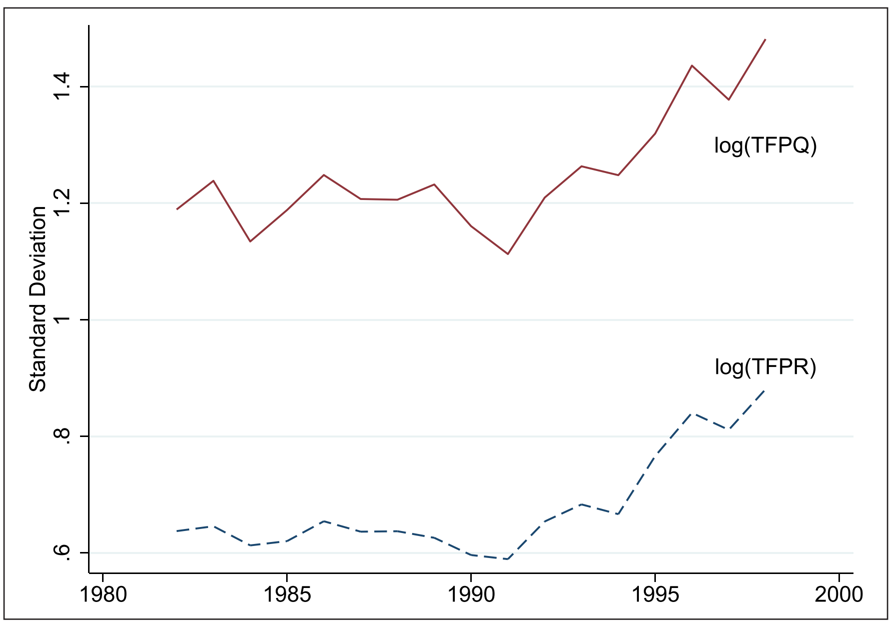

Figure 9 Dispersion of TFPQ and TFPR over Time.

Source: AMS and authors' calculations.

The growing output losses due to misallocation are related to the increasing elasticity of TFPR with respect to TFPQ. Bento and Restuccia (2017) emphasize this elasticity as a summary of the implications of distortions for misallocation. Figure 11 shows that this elasticity has increased in Colombia over time. It was relatively stable in the 1980s but increased in the 1990s. The elasticities we estimate for Colombia are generally similar to what Fattal-Jaef (2022) reports (noting that his estimates are reported as a difference from the US figure). Bento and Restuccia (2017) report a range of elasticities using World Bank Enterprise Surveys data, finding an average elasticity of 0.56, somewhat higher than our estimates for Colombia.

19 Note that the output and capital distortions do not have a structural interpretation. An alternative specification to the model would apply the relative input distortion to the labor input rather than capital. This would imply a different output distortion but no difference in firms' choices or the degree of misallocation.

As noted earlier, the Colombian economy was subject to many liberalizing reforms during the period we study. Since these reforms apply to all sectors simultaneously it is difficult to take a program evaluation approach to estimating their effects on misallocation. We might expect more capital intensive industries to be more affected by financial reforms, or import intensive industries to be more affected by tariff reductions. However, when splitting the sample according to whether the industry is relatively capital intensive, we find that the more capital intensive industries show a greater increase in the elasticity of TFPR with respect to TFPQ after the financial market liberalizations. If anything, the degree of misallocation grew more in capital intensive industries than in non-capital intensive industries.

Table 8 Dispersion of $\tau_{K\,si}$ and $\tau_{Y\,si}$.

Source: AMS and authors' calculations.

	$\ln(1+\tau_K)$			$\ln(1-\tau_Y)$		
YEAR	SD	IQR	90–10	SD	IQR	90–10
1982	1.22	1.49	3.10	0.54	0.63	1.27
1983	1.26	1.47	3.06	0.61	0.65	1.39
1984	1.28	1.48	3.24	0.56	0.64	1.27
1985	1.25	1.48	3.07	0.60	0.69	1.41
1986	1.23	1.50	3.10	0.63	0.75	1.40
1987	1.27	1.58	3.16	0.63	0.77	1.50
1988	1.26	1.58	3.15	0.65	0.84	1.55
1989	1.25	1.58	3.04	0.67	0.85	1.64
1990	1.28	1.57	3.06	0.65	0.79	1.57
1991	1.22	1.54	3.05	0.58	0.79	1.47
1992	1.22	1.52	3.01	0.62	0.75	1.50
1993	1.19	1.48	2.93	0.66	0.79	1.58
1994	1.19	1.45	2.93	0.64	0.75	1.50
1995	1.26	1.56	3.13	0.74	0.83	1.71
1996	1.22	1.56	3.07	0.84	0.84	1.86
1997	1.26	1.69	3.02	0.80	0.84	1.79
1998	1.26	1.70	3.04	0.92	0.87	2.01

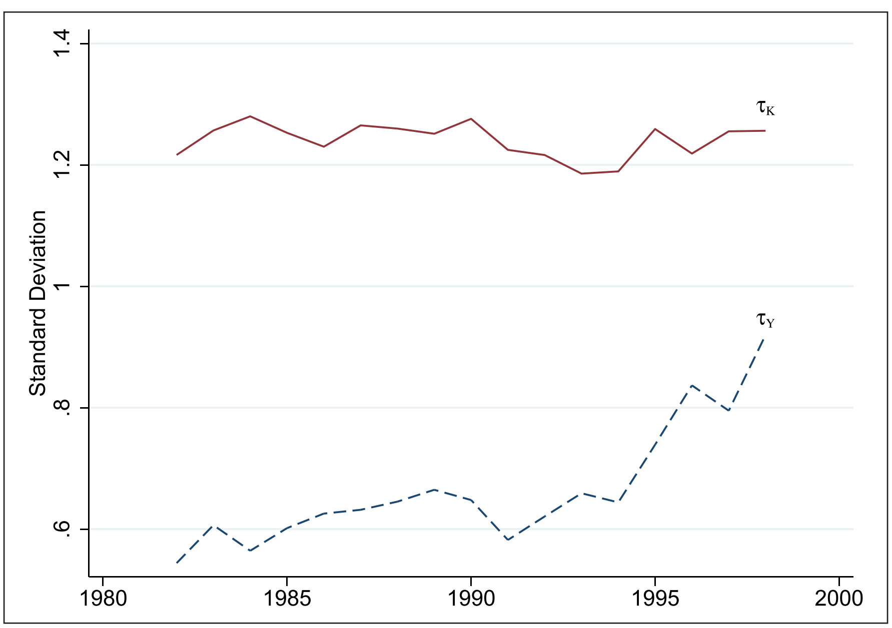

Figure 10 Dispersion of τ_Y *and* τ_K over Time.

Source: AMS and authors' calculations.

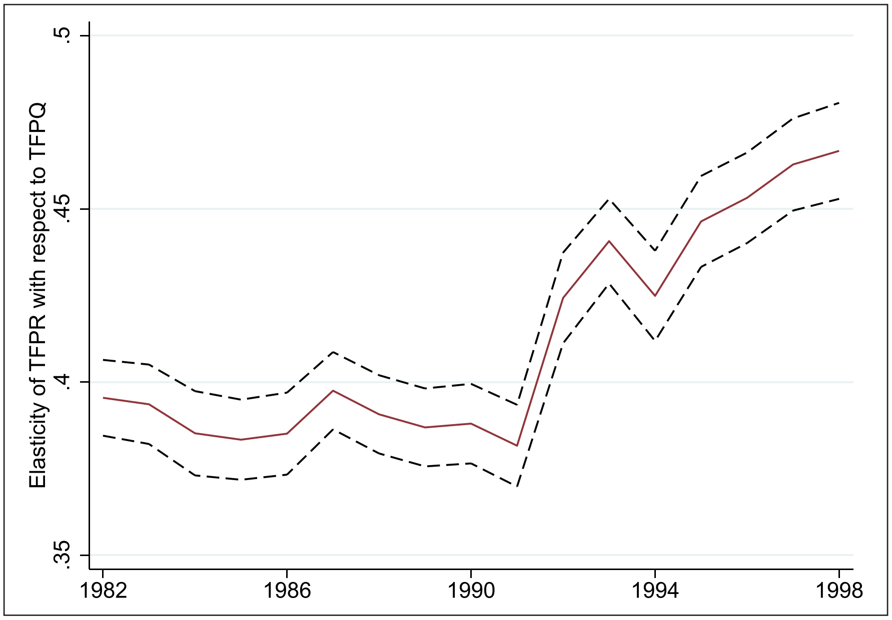

Figure 11 Elasticity of TFPR with respect to TFPQ over Time.

Source: AMS and authors' calculations. Dashed lines indicate 95% confidence intervals.

6.5 ASSESSMENT OF MEASUREMENT ERROR

To explore the impact that classical measurement error in plant revenue and inputs may have in the Colombian estimates, we regress revenues on inputs as:

$$\log\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)=\beta_0+\beta_1\log\left(\frac{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}{K_s^{\alpha_s}L_s^{1-\alpha_s}}\right)+\epsilon_{si} \tag{28}$$

We also regress inputs on revenues as:

$$\log\left(\frac{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}}{K_s^{\alpha_s}L_s^{1-\alpha_s}}\right)=\delta_0+\delta_1\log\left(\frac{P_{si}Y_{si}}{P_sY_s}\right)+\nu_{si} \tag{29}$$

Each regression includes weights derived from the share of value added of the industry over the whole economy, divided by the number of firms in that specific year and sector. Results are reported in Table 9. The table shows that the elasticity of inputs with respect to revenue is 0.86 in Colombia, relative to 1.01 in the US. Assuming that the true elasticities are the same in all countries, the results suggest that classical measurement error might add 18% of the variance of log revenue in Colombia, relative to the United States. The table also shows that the elasticity of revenue with respect to inputs is 0.65 in Colombia, and Hsieh and Klenow (2009) report that the corresponding US elasticity is 0.82, indicating that classical measurement error increases the variance of inputs in Colombia by around 21% relative to the United States.

	COLOMBIA	U.S.A.
Inputs on Revenue	0.86	1.01
Revenue on Inputs	0.65	0.82

Table 9 Regressions of Inputs on Revenue, Revenue on Inputs.

Source: AMS and authors' calculations.

If, like Hsieh and Klenow, we assume that the serial correlation in measurement error for a given plant is lower than the true correlation for revenue and inputs, and that the true correlations are the same across countries, then we should find that the growth rates in revenue and inputs varies more in Colombian plants than in US plants. In Table 10 we test whether growth rates of revenue and inputs vary more across plants in Colombia than in the United States. First, we create the percentage growth of the firm value added, and the percentage growth of the sector value added. Then we compare the difference in variation of the firm with respect to the industry. This calculation is weighted by the share of value added of the industry over the whole economy, divided by the number of firms in that specific year and sector. Table 10 shows that the variation

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in revenue and input growth in Colombia appears quite high. Year-to-year variation is smaller, but the statistics Hsieh and Klenow report are for changes over longer periods. When we look at Colombian input and revenue growth over eight-year periods, the variability is substantially higher. This higher variability in the Colombian firms could be an indicator of noisier data, but these could also be legitimate changes in economic activity.

Table 10 Dispersion of Input and Revenue Growth.

Source: AMS, authors' calculations, and Hsieh and Klenow (2009).

	COLOMBIA, ANNUAL		COLOMBIA, OCTENNIAL		U.S.A.	
	SD	IQR	SD	IQR	SD	IQR
Inputs	0.33	0.30	0.74	0.89	0.68	0.43
Revenue	0.49	0.44	0.73	0.83	0.43	0.32

As an alternative approach to dealing with measurement error, we apply the method of Bils et al. (2021). Note that we do not follow Bils et al. exactly, using value added as our output, rather than gross output, for example. We do not find the same kind of inverse relationship between TFPR and the elasticity of measured revenue with respect to measured inputs. This finding would suggest less substantial measurement error in the Colombian data than in the Longitudinal Business Database that Bils et al. use for the United States. On the other hand, it implies that Colombian manufacturing actually does have more to gain from an efficient reallocation than the US economy does.

To summarize, the results in this section test for evidence of classical measurement error in plant revenue and inputs in Colombia. Under the assumptions that the elasticities in revenue and inputs are the same across countries, and that measurement error is likely to have less serial correlation than the true values, we find some tentative evidence that measurement error could be driving the higher TFPR variance observed in Colombia relative to the United States.

6.6 ADDITIONAL RESULTS: CORRELATES OF PRODUCTIVITY AND MISALLOCATION

Tables 11 and 12 provide some evidence on the correlates of productivity and the dispersion of productivity. In Column (1) of Table 11 we regress the firm's TFPQ on an indicator of whether the firm exports. The results shown in column (1) are positive and significant, indicating that firms that export are more productive than firms that do not. Column (2) shows that older firms are more productive (with age measured from the first time the firm appears in the panel dataset).[20] Column (3) indicates that productivity increases with firm size (measured by the number of employees). Column (4) shows that, relative to the Atlantic region, firms in the Central region and in Bogotá are more productive, while firms in the Orinoquía and Amazonía are less productive.[21] Conditional on firm size, age is negatively associated with TFPQ, and exporter status is not as strongly associated with productivity. The last four columns of the table show the same analysis, but using TFPR instead of TFPQ as the outcome. The most interesting finding here is that larger firms tend to have lower values for TFPR.

Table 12 shows how the variability of TFP, especially for TFPR, is systematically related to firm characteristics. In particular, the variability of TFPR within a sector and year declines with the size of the firm. Among smaller firms there is a more dispersed distribution of TFPR and hence more misallocation. Whether the costs of this TFPR dispersion are great depends on the tendency of the distortions or the firms to disappear over time (Buera et al. 2013; Hsieh and Klenow 2014).

20 Given that we do not know the firm's age when the panel begins in 1982 we assume that any firm appearing in 1982 is one year old.

21 For the Orinoquía and Amazonía region there are fewer than 25 firm-year observations in the dataset. The number of plant-year observations for the other regions are between around 6,000 (Atlantic) and 21,000 (Bogotá).

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	log (TFPQ)				log (TFPR)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exporter	1.027***			0.444***	0.121***			0.139***
	(0.0279)			(0.0380)	(0.0163)			(0.0228)
Age 6–10		0.114**		–0.0834*		–0.00947		–0.0199
		(0.0381)		(0.0362)		(0.0236)		(0.0221)
Age 11–		0.317***		–0.125**		0.0114		–0.0119
		(0.0426)		(0.0380)		(0.0241)		(0.0235)
Size 20–49			0.416***	0.395***			–0.0201	–0.0289*
			(0.0197)	(0.0198)			(0.0134)	(0.0136)
Size 50–99			0.979***	0.935***			0.0475**	0.0294
			(0.0272)	(0.0282)			(0.0181)	(0.0189)
Size 100–249			1.363***	1.304***			0.0546	0.0294
			(0.0505)	(0.0459)			(0.0323)	(0.0307)
Size 250–499			1.569***	1.473***			–0.0112	–0.0491
			(0.122)	(0.115)			(0.0672)	(0.0657)
Size 500–999			2.016***	1.788***			0.0217	–0.0554
			(0.0477)	(0.0520)			(0.0262)	(0.0296)
Size 1000–			2.243***	2.052***			–0.0225	–0.0940**
			(0.0509)	(0.0564)			(0.0300)	(0.0327)
Oriental				–0.119				–0.0160
				(0.0779)				(0.0476)
Central				0.0790*				0.0342
				(0.0353)				(0.0217)
Pacifica				0.0207				0.0248
				(0.0412)				(0.0247)
Bogotá				0.172***				0.0713***
				(0.0350)				(0.0216)
Orinoquía y Amazonía				–0.627***				–0.334*
				(0.180)				(0.167)
Observations	72256	72256	72256	72256	72256	72256	72256	72256
R-squared	0.121	0.011	0.282	0.308	0.006	0.000	0.002	0.011

Table 11 Regressions of TFPQ and TFPR on Firm Characteristics.

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: AMS and authors' calculations.

7 DISCUSSION

We might expect the reforms of the 1980s and 1990s to have improved the allocation of resources in Colombia. However, using the Hsieh-Klenow approach, we find that misallocation has increased during the 1990s. Why, in spite of reforms, has misallocation increased? We consider several possible reasons.

One possibility is that the reforms have been overstated. For example, the labor market reforms with *Law 50* of 1990, reduced firing costs by between 60% and 80% (Kugler 1999, 2005), which should make for a more efficient allocation of workers. On the other hand, significant increases in

	log (TFPQ) squared				log (TFPR) squared			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exporter	–2.073***			–1.010***	–0.185***			–0.133**
	(0.102)			(0.173)	(0.0274)			(0.0440)
Age 6–10		–0.136		0.297		0.0454		0.0580
		(0.165)		(0.153)		(0.0431)		(0.0380)
Age 11–		–0.582**		0.350		0.0290		0.0708
		(0.195)		(0.183)		(0.0509)		(0.0470)
Size 20–49			–1.412***	–1.357***			–0.0309*	–0.0190
			(0.0906)	(0.0903)			(0.0141)	(0.0145)
Size 50–99			–2.781***	–2.694***			–0.0315	–0.0209
			(0.107)	(0.111)			(0.0207)	(0.0222)
Size 100–249			–3.466***	–3.379***			–0.0663	–0.0693
			(0.214)	(0.197)			(0.0572)	(0.0528)
Size 250–499			–2.707***	–2.595***			0.156	0.141
			(0.595)	(0.566)			(0.149)	(0.142)
Size 500–999			–4.241***	–3.744***			–0.310***	–0.240***
			(0.0972)	(0.148)			(0.0226)	(0.0359)
Size 1000–			–4.299***	–4.037***			–0.382***	–0.413***
			(0.0940)	(0.134)			(0.0245)	(0.0375)
Oriental				0.680				0.191*
				(0.347)				(0.0898)
Central				–0.370***				–0.152***
				(0.0970)				(0.0225)
Pacifica				0.121				–0.0604*
				(0.126)				(0.0272)
Bogotá				–0.465***				–0.117***
				(0.0960)				(0.0223)
Orinoquía y Amazonía				1.966**				0.142
				(0.669)				(0.168)
Observations	72256	72256	72256	72256	72256	72256	72256	72256
R-squared	0.048	0.004	0.118	0.140	0.009	0.001	0.018	0.043

Table 12 Regressions of TFPQ and TFPR Squared on Firm Characteristics.

Standard errors in parentheses.

*$p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Source: AMS and authors' calculations.

social security contributions with *Law 100* of 1993 made it more costly for firms to take on labor, since this law introduced an increase for mandatory health and pension contributions of which 75% was paid by employers (Burki and Perry 1997). In fact, Kugler and Kugler (2009) document that from 1989 to 1996 payroll tax rates increased from 39.4% to 51.5% of wages. Similarly, while the financial market reforms, such as *Law 9* of 1991 and Resolution 49 of 1991, should have reduced borrowing costs (Eslava et al. 2010), the 1990s were characterized by continued high real interest rates and high interest rate spread in the banking sector (Banco de la República 2000a, b). Indeed, as Eslava et al. (2004) point out, it is possible that the reforms did not go as far as expected, as the election of a new president in 1994 brought the momentum of market-oriented reforms to a halt. This government was unsuccessful in dismantling existing reforms, but it also did not seek to continue or expand what had been started in the early 1990s.

Another possibility is that the reforms reduced industry-wide average distortions but not within-industry relative distortions that drive our measures of misallocation. A change in the output wedge or capital wedge that applies equally to all firms does not change the degree of misallocation in the model. What matters is the relative output wedge and the relative capital wedge. It is possible that the reforms reduced distortions among firms but only in a broad way that does not show up as reduced misallocation when looking within sectors.

A further possibility is that there was substantial uncertainty regarding how to take advantage of the opportunities opened up by the reforms, particularly the trade reforms. For example, Eslava et al. (2004) find that there is substantial churn in firms in the 1990s. Many firms enter but then exit soon after, while entrants that survive show more learning by doing after the reforms. The initial entry of many firms could mean there are many unproductive firms that are using up resources. This would appear to be misallocation in our measurements but could be an important aspect of economic adjustment to the different patterns of tariffs.

Finally, perhaps allocative efficiency actually improved over this period, and the Hsieh-Klenow model is not well-suited to detect this improvement (Haltiwanger et al. 2018). Some prior work has found evidence that productivity in Colombia grew through this period, including due to reallocation of inputs toward more productive firms (Eslava et al. 2004). Hsieh and Klenow (2017), focusing on the United States, argue that such reallocation could move resources from low to high average product firms but that what matters for overall output is the relative marginal products of firms among which the reallocation happens, thus possibly explaining the different results obtained by both models.

8 SUMMARY AND CONCLUSION

In this paper we use a monopolistic competition model of industry structure with firm-specific distortions (Hsieh and Klenow 2009) to measure misallocation and plant-level manufacturing productivity in Colombia. We use a panel dataset with approximately 65,000 plant-year observations for industrial establishments. The period that we study goes from 1982 to 1998, a period of many trade, financial and social program reforms. We find that plants in Colombia have a somewhat greater TFPR dispersion than the U.S. indicating more resource misallocation across plants within industries.

We hypothetically reallocate resources by equalizing TFPR across plants and within industries. The aggregate TFP gains that would result range between 45% and 60%, depending on the year. This suggests that a reduction in misallocation to the level found in the United States would lead to productivity improvements of around 15%. The degree of misallocation in Colombia has increased over time, despite economic reforms of this period. Comparing actual firm sizes to the size observed if TFPR were equalized, we find that in Colombia there should be fewer mid-size plants and more small and large ones. In particular, we find that medium and large firms should increase their plant size. These results are consistent across years.

We assess the robustness of our results by changing the elasticity of substitution between plant value added and the source of the labor and output shares. We find that using Colombian labor shares increases the estimated gains from equalizing TFPR within industries. Using US labor and industry shares reduces the gains from equalizing TFPR within industries. As with other studies, a higher elasticity of substitution between varieties increases the gains from reallocation, though there is no evidence these gains would be any larger for Colombia than for other countries, such as the United States.

The period of time our study covers saw substantial deterioration in Colombia's total factor productivity relative to other countries. Our results suggest that some of this decline could be attributed to a worsening of within-industry allocative efficiency.

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APPENDIX

	COL. OUTPUT SHARE (%)	U.S. OUTPUT SHARE (%)	COL. LABOR SHARE (%)	U.S. LABOR SHARE (%)
311. Food manufacturing	17.2	7.4	25.1	52.4
312. Food manufacturing	3.3	1.1	26.7	36.0
313. Beverage industries	14.0	1.7	11.4	42.2
314. Tobacco manufacturing	0.8	1.5	12.5	22.4
321. Manuf. of textiles	4.7	2.6	42.9	76.0
322. Manuf. of wearing apparel, except footwear	2.3	1.6	42.3	74.6
323. Manuf. of leather products of leather, substitutes and fur	0.5	0.2	43.2	74.4
324. Manuf. of footwear, except vulcanized or rubber or plastic footwear	0.8	0.1	37.6	74.2
331. Manuf. of wood and wood and cork products, except furniture	0.2	1.5	57.2	76.5
332. Manuf. of furniture and fixtures, except primarily of metal	0.4	1.8	53.4	76.3
341. Manuf. of paper and paper products	4.1	4.3	28.2	66.0
342. Printing, publishing and allied industries	2.3	7.8	37.0	67.4
351. Manuf. of industrial chemicals	3.9	3.2	19.2	42.0
352. Manuf. of other chemical products	10.8	8.3	25.9	34.4
353. Petroleum refineries	9.8	1.5	6.8	33.4
354. Manuf. of miscellaneous products of petroleum and coal	0.6	0.3	12.4	48.9
355. Manuf. of rubber products	1.2	1.1	40.8	72.6
356. Manuf. of plastic products not elsewhere classified	4.6	3.3	32.7	64.8
361. Manuf. of pottery, china and earthenware	1.5	0.2	31.0	79.2
362. Manuf. of glass and glass products	1.8	0.6	28.2	62.4
369. Manuf. of other non-metallic mineral products	3.8	1.5	20.0	62.2
371. Iron and steel basic industries	0.9	2.3	40.6	75.5
372. Non-ferrous metal basic industries	0.5	0.2	20.4	53.5
381. Manuf. of fabricated metal products, except machinery and equipment	2.6	7.1	37.9	74.4
382. Manuf. of machinery except electrical	1.7	6.0	42.5	73.2
383. Manuf. of electrical machinery apparatus, appliances and supplies	2.1	15.8	44.3	69.8
384. Manuf. of transport equipment	2.5	10.8	36.8	60.4
385. Manuf. of professional and scientific equipment not elsewhere classified	0.3	4.4	32.7	64.1
390. Other Manufacturing Industries	0.9	1.6	32.5	66.9

Table A.1 US and Colombian Output and Labor Shares for 1998 by Industry.

Source: AMS and authors' calculations, and NBER-CES.

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COMPETING INTERESTS

The authors have no competing interests to declare.

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