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Productivity and Export Market Participation: Evidence from Colombia

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Abstract:

We study the evolution of the Colombian manufacturing sector during 2005–2013. For the firms in our sample, we estimate an overall total factor productivity (TFP) cumulative growth rate of 19 percent and an average productivity premium for exporters of 53 percent. In both cases, we find large differences across sectors. We also find that productivity significantly increases a firm's probability of being an exporter. However, the data also indicate that there are significant differences between continuous exporters and occasional exporters.

JEL Classifications: F14, L22, L60

Keywords: productivity, exporters, productivity premium, openness

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1 Overview

Total factor productivity (TFP) and access to foreign markets are usually considered to be two critical ingredients driving economic growth; see, for example, Edwards (1998) and Wacziarg and Welch (2008). In this paper, we study the relationship between firms' productivity and their export market participation decisions. Understanding the link between these two variables is critical for the study and the design of policies aimed at achieving high and sustainable economic growth in the long run.

In our analysis, we combine two firm-level datasets that allow us to observe detailed data on output, inputs, and exports of Colombian manufacturers during the years 2005–2013. We proceed in two steps. First, we use the data on production and inputs to recover the firm's unobserved productivity, based on a methodology proposed by Levinsohn and Petrin (2003). Second, we combine our estimated firm-level productivity measures with customs data on firms' exporting decisions. Specifically, we link a firm's TFP level with its corresponding exporter status.

Our findings can be summarized as follows. First, we find that average TFP growth for 2005–2013 was around 19 percent for the firms in our sample, albeit with great heterogeneity across sectors.¹ At the same time, our analysis suggests that traditional (OLS) methods to estimate TFP substantially overestimate the growth rate. Second, we find that exporters have a productivity premium (that is, higher TFP) over nonexporters: on average, we estimate this premium to be 53 percent. Again, there appears to be substantial variation across sectors. Third, and consistent with the previous finding, productivity appears to be strongly associated

¹The firms included in our dataset are, in general, large manufacturers. Therefore, if larger firms are more (less) productive than smaller firms, the TFP growth of the manufacturing industry may be smaller (larger) than our estimate of 19 percent.

with a higher probability of a firm's being an exporter. Fourth, we show that there exists a productivity premium for those firms that are continuous exporters versus firms that export only occasionally. Finally, we find some evidence that future exporters may have higher productivity before exporting, and we do not find significant evidence of reverse causality in the relationship between a firm's productivity and its exporter status.

The paper is related to the literature intersecting industrial organization and international trade. Methodologically, it is related to the literature on the structural estimation of production functions and unobserved total factor productivity. Our strategy for estimating firm-level productivity relies on the work first introduced by Olley and Pakes (1996), and then modified by Levinsohn and Petrin (2003). These papers provided the groundwork to recover estimated firms' unobserved productivity while correcting for the simultaneity bias.

Our paper is also related to the vast literature that explains a firm's decision to export and, particularly, to studies of the relationship between a firm's productivity and its participation in international markets. Several studies find a positive correlation between TFP and exporting status. For instance, using data from Slovenia, DeLoecker (2007) finds that firms that decide to export become more productive. Similar results are found using data from Taiwan and Korea (Aw, Chung, and Roberts 2000), data from Chile (Pavnick 2002), and data from sub-Saharan Africa (Van Biesebroeck 2005).²

Finally, our paper also relates to a series of papers that have focused specifically on the Colombian manufacturing sector. In the case of Colombia, empirical evidence points in a direction similar to the findings for other countries mentioned

²Our focus is on studies that estimate productivity at the firm level using structural models. For an extensive review of the literature on the relationship between trade and productivity with non-structural productivity estimations, see Wagner (2007).

above. Clerides, Lach, and Tybout (1998) studies the causal relationship between a firm's productivity and its export intensity, and finds that the more efficient firms self-select into exporters. Following the model presented by Clerides, Lach, and Tybout (1998), López (2006) finds that exporters are more productive *ex ante*, and that the productivity of exporting firms increases with their exposure to international markets. Meléndez and Seim (2006) studies the impact of trade liberalization policies on productivity, and finds an increase in productivity for the manufacturing sector as a whole as a result of the reallocation of production toward firms in highly productive sectors and of the entry of new, more productive plants. Similarly, Echavarría, Arbeláez, and Rosales (2006) finds that total factor productivity increased with trade liberalization, since it allowed for the technological progress of firms participating in foreign markets. Other studies that analyze the causes of this positive relationship between productivity and export status include Fernandes and Isgut (2005), Eslava et al. (2004), and Parra (2003).

Despite the vast literature supporting the hypothesis of exporters' productivity premium, Rivers (2010) states that this premium depends on the estimation strategy followed to recover the unobservable productivity. Following the methodology proposed by Gandhi, Navarro, and Rivers (2013), he estimates the TFP of Colombian manufacturing firms in the apparel sector for the period between 1981 and 1991, and finds that, once the simultaneity and unobserved prices biases are corrected, the difference between exporters and nonexporters is not statistically different from zero. It is worth noting, however, that his estimates cover a period previous to the trade liberalization, and that his results are specific to one manufacturing sector.

The rest of the paper is organized as follows. Section 2 describes how the data

are collected and presents the basic features of our estimation sample. Section 3 presents our productivity estimation and its variation across sectors and time. Section 4 studies the relationship between a firm’s productivity and its decision to participate in the export market. Section 5 provides an assessment regarding openness to international trade and productivity. Section 6 concludes.

2 Data

2.1 Data Sources

In our analysis, we combine two different firm-level datasets: one contains detailed balance sheet and operational information, while the other has information on firms’ foreign market participation. Next, we describe each of our two datasets.

Our data on firms’ production and input consumption come from “Superintendencia de Sociedades,” the agency in charge of supervising corporations. Specifically, the data come from the “Sistema de Información y Riesgo Empresarial” (SIREM) database. The data are at an annual frequency and are self-reported by the firms. We have access to public information such as balance sheets, as well as to confidential data included in the annexes filed by the firms.³ Thus, we are able to observe a great many details about each firm that are not usually available in other datasets. These variables include the income obtained from the sales of each product, the use of raw materials, investments, and the capital stock. Additionally, we observe the number of employees and the payroll, broken down by type (executive, administrative, and production workers) and tenure (permanent or temporary). We can also distinguish whether the firm is a standalone firm, an

³We obtained access to the confidential data through the Banco de la República.

affiliate, a headquarters (HQ) with affiliates, or part of a conglomerate.⁴

The data on international trade come from the customs agency (DIAN), and the department of statistics (DANE). We access the data through a system called “Serankua” at the Banco de la República. These data, which we aggregate to the annual level, include the exporting firm’s tax identification number, the 10-digit product code (according to the Nandina classification system, based on the Harmonized System), the value exported (in U.S. dollars), and the country of destination, among other details.

2.2 Data Description

The data from SIREM include information on firms from several industries. Throughout the paper, we focus only on manufacturing firms, excluding manufacturers of coke, refined petroleum products, nuclear fuel, and basic metals (which include metals such as gold, silver, platinum, and nickel).⁵ Our data cover the period 2005–2013.

Given our focus on the manufacturing sector, the first step prior to estimation was to define precisely which firms would be considered manufacturers. This step was relevant for multi-product firms that are not limited to manufacturing. In applying this definition, we took advantage of the rich data on income, reported by firms at the product level.⁶ For our estimations, we consider as manufacturing

⁴The variables listed above are those we use in our empirical work. The dataset also includes several other variables, like detailed financial information, that we plan to use in future work.

⁵It is usual in the literature to focus on manufacturing firms since these are the ones producing noncommodities, tradable goods. We cannot consider sectors such as services and construction because (obviously) they do not have the possibility of exporting. The agricultural and mining sectors do export, but since they are commodity producers, their dynamics are probably different from those of the manufacturing firms. For this same reason, we exclude firms classified in the manufacturing sectors mentioned in the body of the text above.

⁶In the operational income annex, products are defined according to the ISIC classification (Revision 3.1), at the 4-digit level.

firms only firms that report having positive income from manufacturing products in all the years they appear in the sample.

In the presence of multi-product manufacturing firms, the second step was to decide how to allocate each firm to a specific manufacturing sector.⁷ Once again, we used the information on income by product, and we assigned each firm to the sector that includes the product that generated the most income throughout the sample period. Specifically, we added up the income per product (deflated) for 2005–2013, and assigned the firm to the manufacturing sector with the highest share.

With the subset of manufacturing firms clearly defined, the final step was to clean the data, given that the raw data from SIREM contains a large number of missing values and inconsistencies. The cleaning process included removing observations with exorbitant annual growth rates (perhaps confusing thousands with millions of Colombian pesos, or number of employees with payroll), as well as occasional value interpolation when a particular variable was missing for a single year.⁸

After dropping those observations for which we had missing values for any variable, the resulting dataset, which we call “Baseline Sample,” contains 26,165 firm-year observations. This is the sample we used in all of our estimations. Additionally, we also consider an “Alternative Sample” that contains 19,311 observations. The difference between the two samples is that, when constructing the latter, we dropped the entire firm if we had missing information for any variable. For the former, we only dropped the *observation* that was missing a variable, but

⁷By sector we mean, specifically, a 2-digit industry based on the ISIC classification. See Table 1 for the description of all manufacturing sectors considered. In the paper we use the terms ‘sector’ and ‘industry’ interchangeably.

⁸See Appendix A for details on the data cleaning process.

we kept those years for which a firm had complete data.

Table 2 presents some basic statistics of our baseline sample. In the first column we observe that, on average, we have around 2,900 manufacturing firms per year. The next column presents the share of firms that were exporters, which ranged from 46 to 52 percent. In the remaining columns we report, for the average firm in our sample, the income, capital stock, amount of raw materials used, number of workers employed, and the share of these that were production workers. Thus, the average firm had an average annual income of 29.5 million Colombian pesos of 2005, an average capital stock of 16 million, used raw materials worth 13.3 million, and employed 164 workers, of whom 55 percent were production workers.⁹

In Table 3 we present the analogous statistics, broken down by industry and averaged over time.¹⁰ From the table it is clear that there is great heterogeneity across sectors; moreover, we find no clear relationship between a sector's average income (or number of workers) and its share of exporting firms. For instance, manufacturers of food products and beverages (ISIC 15) and motor vehicles (ISIC 34) have a similar average income, but the share of exporters is twice as large in the latter industry. Further, ISIC 20 (wood products) also has around a third of its firms exporting, but this is the sector with the lowest average income. In a similar fashion, sectors ISIC 15 (foods and beverages) and ISIC 18 (apparel) have workforces of similar sizes, but, in the former, fewer than 30 percent of firms are exporters while, in the latter, exporters account for 60 percent of firms—a share similar to that in ISIC 36 (furniture), an industry that hires fewer than half the number of workers.

⁹The values for income, capital, and raw materials are expressed in millions of Colombian pesos of 2005. Each variable was deflated using a variable-specific deflator.

¹⁰There are three industries for which we only have very few observations: ISIC 16 (tobacco), ISIC 30 (office and computing), and ISIC 32 (radio, television and communication equipment). In order to avoid disclosing confidential information, we do not report statistics for these industries.

Next, we focus on the importance of exports in a firm’s total sales. In Table 4 we report the ratio of exports to total income, averaging across all exporting firms within a sector.¹¹ We see that there are sectors like ISIC 35 (manufacture of other transport equipment) for which exports are almost nil, while for sectors like ISIC 21 (paper and paper products) exports account, on average, for over a third of their sales. At the same time, sectors differ greatly in the evolution of the export shares over the period between 2005 and 2013. For instance, the share of exports remained relatively unchanged, with the exception of 2008, for ISIC 24 (chemicals and chemical products), while it more than halved for ISIC 29 (machinery and equipment) and, after the trade collapse of 2009–10, it grew steadily for ISIC 31 (electrical machinery).

2.3 Representativeness of the Data

We now benchmark our SIREM data against data from other sources in order to evaluate its representativeness. This is particularly important given the novelty of our dataset, and the fact that the data from SIREM are neither census-based nor from a random survey. Still, as we show next, we are able to capture a large share of the universe of Colombian manufacturing firms.

We compare our SIREM dataset with two alternative sources. First, we compare it with national accounts data, containing the official aggregate estimates for the manufacturing sector. Second, we compare it with the annual survey of manufactures, called EAM (“Encuesta Anual Manufacturera”), conducted by the Colombian National Administrative Department of Statistics (DANE). The EAM database contains a rich set of variables that characterize firm behavior and is, in

¹¹To aggregate the data up from the firm level, we take weighted averages, using firms’ income as weights. We use this method of aggregation throughout the paper.

practice, a truncated census since all manufacturing firms above a certain threshold are obliged to respond.¹²

In Table 5 we benchmark our data against data from these two alternative data sources.¹³ Given that each database contains a different set of variables, we can only compare the levels of (real) income and of permanent workers.¹⁴ Still, these two variables are probably the most important ones for our purposes. The upper panel compares these variables in the baseline sample, while the lower panel compares them in the alternative sample. As can be seen, with our baseline sample we cover more than half of all manufacturing income according to the national accounts, and almost two thirds of the production from EAM. Likewise, the alternative sample accounts for more than 50 percent of the production measured on the EAM. In terms of employment, for which we can only compare our SIREM data with the EAM data, the baseline sample covers on average over 90 percent of the permanent workers on the EAM, while the alternative sample covers almost 75 percent of the EAM. Thus, based on the information contained in Table 5 we conclude that our data provide a fairly comprehensive picture of the overall Colombian manufacturing sector.

¹²The downside of EAM data, for our purposes, is that they cannot be linked to the detailed data on firm export market participation.

¹³In our comparisons, we use information on all manufacturing sectors (including ISIC 23 and 27, coke, refined petroleum products, and nuclear fuel, and basic metals) because there is not a one-to-one correspondence between the ISIC codes and the sector codes used in national accounts data. Therefore, we cannot exclude only these two sectors from industry totals. When we keep firms from these sectors, our “Baseline Sample” increases to 26,923 observations (4,998 firms) and our “Alternative Sample” increases to 19,836 observations (3,518 firms).

¹⁴In the case of income, we are specifically comparing the estimated value of output of the complete manufacturing sector (national accounts), the value of output (EAM), and operational income (SIREM). In all cases, the variables are expressed in millions of pesos of 2005.

3 Productivity Estimations

The first step in estimating firm-level TFP is to estimate the firm’s production function. However, production function estimations have a fundamental difficulty: if the unobserved productivity shocks are correlated with the firm’s input choices, the OLS production function and productivity estimates will be biased. Levinsohn and Petrin (2003) proposes a method to solve this simultaneity problem. In a nutshell, it develops an estimator that uses the consumption of intermediate inputs as a proxy for the unobservable shocks. In the analysis we present below, we follow precisely this methodology.¹⁵

We estimate the following real gross output production function:

$$Y_{it} = \beta_0 + \sum_{\ell} \beta_{\ell} L_{it}^{\ell} + \beta_k K_{it} + \beta_m M_{it} + \epsilon_{it}, \quad (1)$$

where Y refers to deflated value of gross output; L^{ℓ} refers to the four types of labor we consider (permanent production workers, temporary production workers, permanent other (administrative and executive) workers, and temporary other workers); K refers to the deflated value of the capital stock (plant, property, and equipment); M refers to the deflated value of the raw materials (intermediate inputs) used; and $\epsilon (= \omega + \eta)$ is the error term, composed of productivity (ω) and an error term uncorrelated with the input choices (η).

In Table 6 we present our production function estimates; the left panel contains the estimates for our baseline sample and the right panel the estimates for the

¹⁵An alternative method, proposed by Olley and Pakes (1996), uses investment as a proxy for the unobservable shocks. However, since in our data there are a large number of observations where investment is zero (indicating that investment is lumpy), we consider the Levinsohn and Petrin (2003) methodology to be more appropriate for our case. Yet another alternative method is proposed by Gandhi, Navarro, and Rivers (2013); in future work, we plan to test the robustness of our findings using this methodology.

alternative sample discussed above. For comparison purposes, we include both Levinsohn and Petrin (LevPet) and OLS estimates. Note that all coefficients are precisely estimated. Moreover, it is clear from the table that, as the theory predicts, the OLS estimates for all variable inputs are upward biased—indeed, note that the LevPet estimates are smaller than their OLS counterparts.¹⁶ Even further, note that the largest biases (differences between LevPet and OLS) are found for the temporary workers. We find this reassuring, since the LevPet framework assumes that labor is fully flexible; however, due to institutional rigidities in the Colombian labor market, only temporary workers are really fully flexible. Overall, these results highlight the importance of estimating productivity with a method that solves the simultaneity problem.

Our next step is to use the LevPet estimates to obtain our TFP productivity measures. In Figure 1 we plot the evolution of estimated TFP for the overall manufacturing sector (solid, black line) and for those industries with the largest number of firms (thinner, dashed and dotted lines). From the firm-level estimates, we take averages, weighing by the corresponding income, in order to obtain the aggregate measures. We then normalize the resulting estimates so that the value of the TFP index for the overall manufacturing sector equals 100 in 2005. From Figure 1 we can see that overall TFP grew 19 percent between 2005 and 2013: the TFP index value for 2013 was estimated to be 118.98. Interestingly, we also find that there is great heterogeneity across sectors. For instance, the TFP values for chemicals (ISIC 24) were systematically above the overall value, while for other industries, like foods and beverages (ISIC 15), apparel (ISIC 18), and rubber and plastic products (ISIC 25), the TFP values were systematically below the overall

¹⁶The OLS coefficient on capital also seems to be biased upward. However, there is no theoretical prediction regarding the direction of the LevPet adjustment on this coefficient. Using data for Chile, Pavcnik (2002) finds the same bias for capital in three of the eight sectors considered.

level. Further, the values for furniture and other manufacturing industries not elsewhere classified (ISIC 36) started above the aggregate level in 2005 but dropped below it by the end of the period.

Table 7 presents the full list of the estimated TFP indices by sector and year.¹⁷ As can be seen, for some sectors we estimate large year-to-year variations. These jumps are mostly driven by the noise created by the entry and exit of firms from our sample. Those sectors with a relatively small number of firms are the most sensitive to the entry or exit of a single firm. In contrast, those sectors with the largest number of firms are less affected by these dynamics—in fact, note that the biggest sectors like ISIC 15, 18, 24 and 25 do not have big jumps. To check whether this is the case, we re-estimated the production function coefficients and the resulting TFP indices by year-industry using a balanced panel, with around 9,000 observations, where every firm appears in all years. We found that, indeed, the average yearly growth rate is significantly smaller when we eliminate the entry and exit of firms. While the average is roughly 9 percent when we look at the complete sample, it drops to 1 percent when we look at the balanced panel. In our estimations below, however, we do not use the balanced panel since this would reduce our sample by about two thirds and would induce a huge selection bias in our results.

Next, we compare our TFP estimates with a commonly used alternative productivity measure, namely, labor productivity (measured as income per production worker). In Figure 2, the solid, blue line plots our TFP measure based on LevPet, while the dashed, red line plots labor productivity. Both variables measure productivity for the overall manufacturing sector and are normalized to have a value

¹⁷For the reasons we explain below, we do not report the indices for those industries with a very small number of firms: ISIC 16, 30, 32, 33, and 35.

of 100 in 2005. It is interesting to note that, throughout most of our sample period, labor productivity is above TFP. That is, from the figure we find that if we were to use labor productivity instead of TFP, we would be overestimating 2005–2013 productivity growth by roughly 25 percent. Indeed, for those firms included in our sample, TFP growth during 2005–2013 was 19 percent, while labor productivity grew 24 percent during the same period. These differences in growth highlight the importance of the methodological issues discussed above.

We now turn our analysis to a firm’s decision to participate in the export market, and how this is related to its productivity level.

4 Export Market Participation

In this section, we use the TFP measures just estimated to assess the relationship between a firm’s productivity and its exporting decisions. As mentioned in the introduction, there is a vast literature that finds that exporters are indeed more productive than nonexporters. This fact can be rationalized within the context of a Melitz model of international trade, where heterogeneous firms select themselves into international markets: only those firms that are sufficiently productive expect to export an amount large enough to cover the fixed costs entailed in accessing foreign markets. Formally, it is assumed that the profits of exporting (π_x) are increasing in productivity (ω), so firm i will export if its productivity is above a certain threshold $\hat{\omega}$ defined as

$$\hat{\omega} : \pi_x(\omega) - f_x = 0, \tag{2}$$

where f_x is the fixed cost of exporting. Thus, the most productive firms self-select into the export market.

Therefore, a good starting point to check the reliability of our results so far, is to compare the estimated productivity of the exporting firms relative to that of the nonexporting firms—the so-called exporters’ productivity premium. This is what we do next.

4.1 Informal Evidence

In Figure 3 we plot the evolution of the exporters’ productivity premium, aggregated for the manufacturing firms in our sample, over the period 2005–2013.¹⁸ From the figure, it is clear that exporters have a higher level of productivity than nonexporters. Indeed, we find that, over the period considered, exporters were roughly one and a half and up to two times as productive as nonexporters, with the premium averaging 53 percent.¹⁹

In Figure 4, we exploit the cross-sectoral variation of our data, plotting the exporters’ premia across the various 2-digit manufacturing industries, after averaging over years. Interestingly, we find a very large degree of heterogeneity. While exporters are more than twice as productive as nonexporters in several industries, exporters are only slightly more productive than nonexporters in the case of manufacturing of foods and beverages (ISIC 15) and of apparel (ISIC 18), and they are

¹⁸Specifically, we compute the premium as the ratio of average TFP for exporters to average TFP of nonexporters. In Figure 3 we use weighted averages to aggregate from the firm level. The results are qualitatively similar if we use simple averages instead, although the average premium increases to 71 percent. This increase suggests that the differences in productivity are smaller for larger firms.

¹⁹These findings are in contrast to Rivers (2010), who looks at Colombian data for 1981–1991 and finds, after estimating a gross output production function, an average TFP premium of 5 percent. However, the results are not strictly comparable due to differences in the time frames considered and in the methodologies employed in the two papers.

actually less productive than nonexporters in the case of publishing and printing of recorded media (ISIC 22).

Based on the evidence presented in Figures 3 and 4, and consistent with the vast majority of the literature, we find that exporters are (unconditionally) associated with higher levels of productivity, but that there is substantial variation across sectors. Next, we examine this relationship in a more rigorous way.

4.2 Baseline Specification

In order to study in a more formal fashion the relationship between a firm’s productivity and its exporting status, we begin by defining a dummy variable, EXP_{it} , that takes a value of one if firm i exported in year t and zero otherwise. Next, we conjecture that the probability of exporting depends, among other things, on productivity. In particular, we consider the following Probit model:

$$EXP_{it} = F(\textit{productivity}_{it}, \textit{size}_{it}, \textit{age}_{it}, \textit{legal}_{it}), \quad (3)$$

where *productivity* is the log of the TFP estimated in the previous section; *size* refers to five dummy variables (*very small*, *small*, *medium*, *large*, *very large*) resulting from assigning firms to different quintiles based on their assets; *age* is the firm’s age; *legal* refers to three dummy variables, depending on whether firm i is a headquarters with affiliates, is itself an affiliate, or is part of a conglomerate. In addition, we also include year, industry, and geography (department) fixed effects.

The results are presented in Table 8, where the number of controls included in the specification increases from left to right. From the table it is clear that a higher productivity level is associated with a higher probability of being an exporter: the coefficient on productivity is estimated to be positive and significant

across all models considered. It is also worth mentioning that larger and/or older firms are also more likely to be exporters (a positive estimated coefficient for the size dummies and *age*). Similarly, firms that are HQ (that is, firms that have other firms as affiliates) are also more likely to be exporters. In contrast, being an affiliate or being part of a conglomerate has no statistical effect on the odds of exporting.

Additionally, we estimate analogous specifications using lagged productivity values. The results are presented in Table 9, and it is clear that our findings remain practically unchanged. Moreover, in Table 10 we conduct the same exercise but including as a regressor the lagged value of the dependent variable, following the methodology proposed by Arellano and Bond (1991). Given the hysteresis that usually characterizes exporting decisions, one would expect the lagged value of the exporting dummy to be the main driver of the results—and we find that this is indeed the case. Still, from Table 10 we can see that the coefficient on productivity, while not as precisely estimated, is still positive and statistically significant.²⁰

The findings from the tables just discussed are quite assertive in suggesting that firms with higher productivity are more likely to export. However, within the group of exporting firms, one can distinguish firms that are continuous exporters from those firms that export only occasionally. The rationale for exporters being more

²⁰Since the TFP we use in the right-hand-side is not observed but, rather, estimated in the first stage of our paper, one may be concerned about the so-called generated regressors problem. That is, underestimating the standard errors of the second stage by not taking into account the standard errors from the first stage (TFP) estimation. However, we are not overly concerned for two reasons. First, we re-estimated the last specification from Table 8 using a bootstrap procedure to correct the standard errors, and found that the TFP coefficient is still positive and significant. Second, according to Pagan (1984), when using a 2-step procedure there is no correction needed for the standard errors of the generated regressors. In light of this, we re-estimated Table 10 using the 2-step procedure and found that the estimates are still positive and significant (in Table 10 we use the 1-step procedure since this is the method recommended by Arellano and Bond 1991). Thus, we are confident in the results we obtain when we use our TFP estimate as a regressor.

productive expressed in equation (2) is inherently static. In contrast, in our data, a firm’s exporting status as well as our estimated TFP vary over time. It follows that the distinction between types of exporters could potentially be relevant. This is the topic of the next subsection.

4.3 Different Types of Exporters

We now introduce a distinction within the group of exporting firms. We call “continuous exporters” those firms that, once they enter the export market, continue exporting for the remainder of the sample. In contrast, we call “occasional exporters” those firms that, having exported in some year t , do not export at some point after t . In our data, we have 1,266 continuous exporters and 1,634 occasional exporters.²¹

In Figure 5 we plot the productivity premium of continuous over occasional exporters, computed as the ratio of their estimated productivities. From the figure we see that there is a clear difference between the two groups of exporters. Indeed, we find that on average continuous exporters are 36 percent more productive than occasional exporters.²²

Next, we run a multinomial logit regression where the dependent variable can take three possible values, depending on whether the firm is a nonexporter, an occasional exporter, or a continuous exporter. In order to highlight the differences between the two types of exporters, we report the marginal effects in Table 11. The upper panel of the table reports the effect that higher productivity has on

²¹We classify firms into different exporting groups using the customs data from DIAN and DANE. Since these data cover a longer period than our SIREM data (2000–2013), a firm may still be considered an occasional exporter, even if it did not export during our sample period of 2005–2013, but it exported sometime between 2000 and 2004.

²²If we aggregate without using firm weights, the average premium is 60 percent.

the probability of being a continuous exporter, and the lower panel reports the effect on the probability of being an occasional exporter. From the table it is clear that higher TFP is associated with a higher probability of being a continuous exporter, while higher TFP may reduce the odds of being an occasional exporter. These findings provide strong evidence supporting the idea that the two types of exporters are indeed quite dissimilar.

4.4 Productivity *Before* Exporting

In this subsection, we look at whether future exporters have an ex ante productivity advantage over nonexporters. That is, we study the differences in productivity between those firms that originally were not exporting and ended up becoming exporters by the end of our sample, and those firms that were always nonexporters during our sample period. We are interested in determining whether those firms that were to become exporters enjoyed some productivity advantage, relative to nonexporters, *before* (ex ante) they started exporting.²³

In Table 12 we present the results of comparing those firms that exported only in 2013 relative to those firms that never exported during our sample period.²⁴ In particular, the regressions include those firms that did not export during 2005–2012. The dependent variable is simply $EXP_{i,2013}$, while the regressors are cross-sectional after averaging over all years except 2013.²⁵ Once again, we find that productivity has a positive and (sometimes) significant effect on the probability of

²³The analysis presented in the next two tables is analogous to that of Greenaway, Guariglia, and Kneller (2007), who study the effects of financial health variables on exporting status.

²⁴Since for this particular exercise our results are qualitatively different for our two data samples (specifically, in terms of the statistical significance of the productivity coefficients), we include both sets of estimations in Table 12.

²⁵Given that the number of observations is greatly reduced for this exercise (and the one in the following section), we were unable to control with department fixed effects as in the previous specifications.

exporting.

The results from Table 12 suggest that future exporters had slightly higher productivity levels than nonexporters even *before* they became exporters; this is consistent with previous findings in the literature (Bernard and Jensen 1999; Clerides, Lach and Tybout 1998).

4.5 Productivity *After* Exporting

Finally, we consider whether exporting leads to a productivity advantage. That is, we consider the case of reverse causality, where it is the exporting status that causes firms to have higher productivity levels.

In order to address this issue, we compare those firms that only exported in 2013 with those firms that also exported in other years. Specifically, we run a cross-sectional Probit regression, where the estimated coefficient measures the ex post productivity advantage of those firms that were *early* exporters relative to those firms that started exporting in 2013.

We present the results in Table 13.²⁶ As can be seen, once we include our usual controls, the coefficients on productivity are barely significant. This suggests to us that exporter status does not seem to increase per se the productivity of a firm. In other words, this finding is evidence against the reverse causality argument.

5 Trade Openness and Productivity Growth

In the previous section we documented that those firms that have higher productivity are more likely to participate in foreign markets via exports. A very

²⁶We again include the estimates for both samples in order to make this table comparable to Table 12. In this case, however, results remain qualitatively unchanged across samples.

important policy question naturally arises: does a trade liberalization process help to increase overall TFP?²⁷ The answer is very important since higher aggregate TFP results in higher economic growth and real wages. Economic policy cannot directly affect productivity. It can, nonetheless, affect the environment in which the firms operate, and, in particular, firms' ease of access to foreign markets. Thus, we can observe the aggregate consequences of incentivizing the most productive (exporting) firms. In this section, we provide some insights into the relationship between commercial policies and productivity growth.

In recent years, Colombia has liberalized its economy. We can observe this by looking at the declining average tariffs Colombia imposes on its imports. In Figure 6 we plot Colombian tariffs averaged over all goods (dashed, blue line) and over manufactured goods only (dotted, green line). We observe that, indeed, tariffs were reduced in the latter part of the period considered. Figure 6 also plots the TFP estimated in Section 3. Interestingly, we find that tariffs and TFP are clearly negatively related—in fact, their correlation is -0.6 , implying that lower tariffs are associated with higher productivity levels.

A similar pattern emerges if, instead of looking at the tariffs imposed by Colombia, we look at the tariffs imposed on Colombian goods by its trading partners. In Figure 7, we plot TFP against the average foreign tariff faced by Colombian exporters of all goods (dashed, blue line) and by Colombian exporters of manufactures only (dotted, green line). Once again, we observe that lower foreign tariffs are associated with higher Colombian productivity levels; the correlation is around -0.4 .

²⁷There are several theoretical reasons to believe that trade liberalization policies would lead to an increase in TFP. First, within a Melitz context, lower trade costs lead to an expansion of the most productive firms via intra-industry reallocation of resources. Additionally, easier access to export markets may lead to higher TFP through a learning process. Finally, trade liberalization may also make available better (foreign) technologies, thereby increasing TFP.

Alternatively, instead of tariffs, we can look at the level of openness of the manufacturing sector. That is, the ratio of the value of total trade (exports plus imports) in manufacturing to the total value of manufacturing output. In Figure 8 we plot our measure of openness against TFP and find that the degree of openness is positively related to TFP—the correlation is 0.5—implying that as the manufacturing sector becomes more deeply interconnected with the rest of the world, there is an increase in the estimated productivity.

While by no means conclusive, these findings are consistent with the claim that the trade liberalization process resulted in an increase in the overall productivity of the manufacturing sector. Some of the possible reasons for this increase include the reallocation of resources toward the most productive firms, a broader access to better technologies, and the entry of new, more productive firms. Assessing the importance of these (and other possible) causes is beyond the scope of this paper, and is left for future research.

6 Conclusion

In this paper, we study the Colombian manufacturing sector during the period 2005–2013. We combine two firm-level data sources: operational information from SIREM and customs data from DIAN and DANE. This combination allows us to estimate firm-level total factor productivity and to link it to the firm’s exporting status.

We find that for the overall manufacturing sector TFP grew around 19 percent. However, we also find substantial differences across sectors. Moreover, based on our analysis, TFP is strongly associated with a higher probability of being an exporter. In fact, we find that exporters enjoy a productivity premium over nonexporters.

Still, we also find that there are differences between those firms that are continuous exporters and those that export only occasionally, with the former usually being the most productive firms. Further, we find no evidence of reverse causality in the relationship between productivity and exporter status. Finally, we argue that the evidence is consistent with trade liberalization and TFP being positively related.

In future work we plan to extend our analysis in several directions. First, we will test the robustness of our findings by estimating TFP with the methodology proposed by Gandhi, Navarro, and Rivers (2013), who find significantly lower productivity premia for exporters. Given this striking finding, and the fact that they use Colombian data for 1981–1991, it seems natural to test their methodology using our (more recent) data. Second, we also plan to exploit to a fuller degree the richness of the customs data. In particular, we can also assess how productivity affects the degree of internationalization of a firm; that is, we plan to not only look at the binary decision of exporting (or not), but also to characterize a firm’s behavior based on what products it exports, what markets it exports to, and in what order markets are accessed. Finally, our work could also be extended by looking not just at exports but also at the import decisions. There is evidence that most exporting firms are also importers; however, the relationship between productivity and being an importer remains to be understood.

APPENDIX

A Data Cleaning

The original SIREM dataset includes over 223,000 firm-year observations for the period 2005–2013, with an average of around 25,000 firms per year. In this appendix, we describe how we cleaned the data to construct our “Baseline” and “Alternative” datasets.

In order to select manufacturers, we started by looking at the data on income by product. Out of the 223,623 observations, 203,096 have data on income, and 43,068 report income from a manufacturing product. As mentioned in Section 2.2, we defined as manufacturers those firms with a positive income from manufacturing products for *every* year they appear in our sample. This selection criterion left us with 36,968 observations, corresponding to 5,760 firms.

Once we defined the subset of manufacturing firms clearly, we proceeded to clean the data in several steps, and reduce our sample to those firms for which we had complete, consistent information for all the variables we need for our TFP estimation (operational income, capital stock, value of the raw materials used by each firm, and number of workers).

First, we eliminated the firms for which we had no information on capital or raw materials. (Given the way we selected manufacturing firms, we had complete information for income by construction). We eliminated 2,456 observations corresponding to those firms that did not have information on raw materials throughout the sample, and 38 additional firms that did not have information on capital stock.

Next, if a firm was missing information for a single year for any variable (but not all), we filled the gaps by interpolating the information of the adjacent years.

We were able to approximate 369 missing values for raw materials, and eight for capital. Of course, this approach is not valid if we are missing values for the first or the final years of a firm. In these cases, we eliminated 2,296 observations due to missing information on raw materials, and 80 observations due to missing information on the capital stock. In addition, we dropped 359 observations for which the information gaps were longer than two years, such that we were unable to approximate the value of capital or raw materials (six were missing capital, and 409 were missing raw materials).

Next, we identified firms with exorbitant annual growth rates (500 percent or more) for variables reported in thousands of pesos. An informal look at the database suggests that, in some cases, firms might have been mixing reporting units: sometimes they report these variables in pesos or in millions of pesos, thereby introducing noise to our sample. By looking at firms with growth rates above this threshold, we were able to identify observations that seemed to mix reporting units. In these cases, we either multiplied or divided the reported value by 1,000 to make it comparable to the observations for the same firms in different years. Overall, we changed 82 income observations (from pesos to thousands of pesos), 84 raw materials observations (82 from pesos and two from millions to thousands of pesos), and 79 capital observations (from pesos to thousands of pesos). In addition to these fixes, we identified three firms with inexplicably high growth rates for some variable, but for which it was not clear that there is a problem with the reporting unit. We dropped the corresponding nine observations.

The calculation of growth rates for the number of employees allowed us to identify a different kind of mix-up for labor variables: in some cases, number of employees and wages seemed to be transposed. We identified 151 observations

for which this seemed to be a problem, and interchanged the values manually. We did this for every category (male/female, permanent/temporary, and production/administrative/executive workers). For some of these 151 observations, we had to fix more than one labor variable.

After cleaning labor variables, we calculated the total number of employees per firm-year, and eliminated those observations with zero workers. We did not attempt to fill one-year gaps by interpolating this variable, since we do not have a clear way of distributing employees into the different categories used in our estimations. In this step, we eliminated 4,751 observations.

This cleaning process left us with 26,923 observations, corresponding to 4,998 firms. If we eliminate all the observations from firms classified as manufacturers of coke, refined petroleum products, and nuclear fuel (ISIC 23), or as manufacturers of basic metals (ISIC 27), we are left with 26,165 observations, corresponding to 4,861 firms. This is what we call our “Baseline Sample.” If, in addition, we drop all the observations from a firm for which we eliminated *any* year, we are left with 19,311 observations, corresponding to 3,427 firms. This is our “Alternative Sample.”

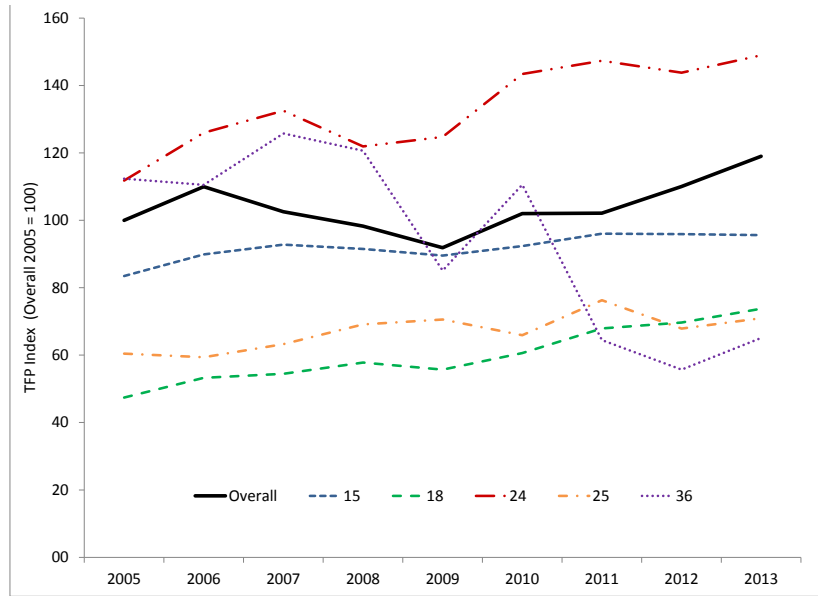
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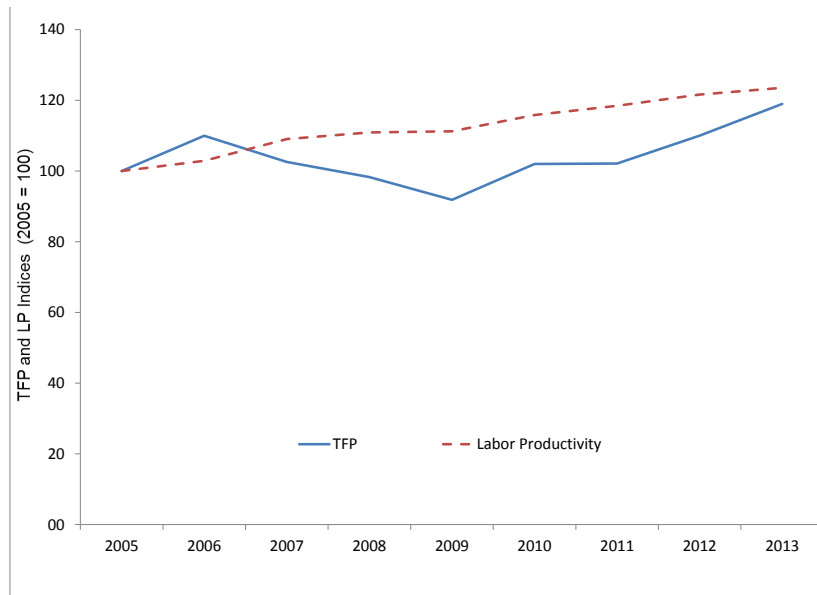
Figure 1: TFP: Overall Manufacturing and Selected Industries



Source: Authors' calculations based on data from SIREM.

Notes: The graph plots the estimated TFP following the methodology by Levinsohn and Petrin (2003). The thick, solid line measures TFP for the overall manufacturing sector. Each of the thinner lines plots TFP for a selected industry. See Table 1 for the corresponding industry codes. The data were normalized to have the overall TFP index equal to 100 in 2005 .

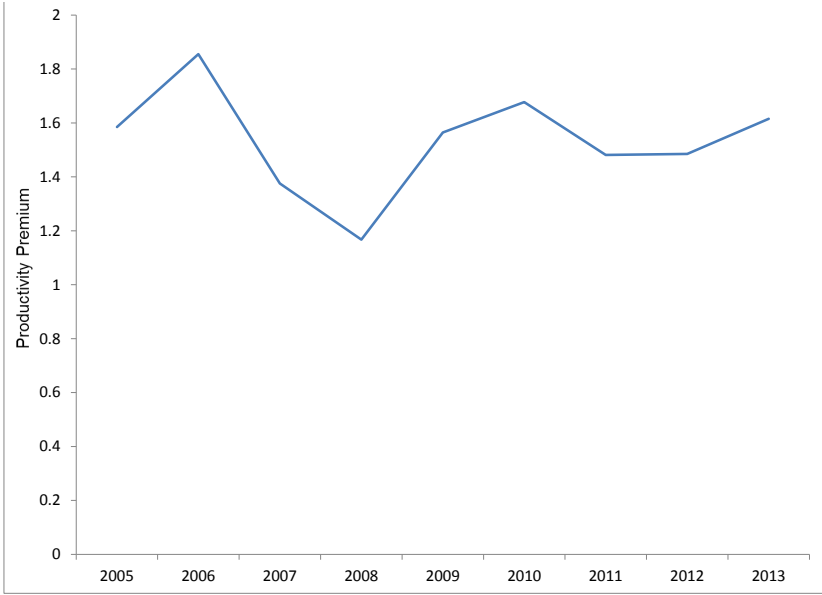
Figure 2: TFP vs. Labor Productivity



Source: Authors' calculations based on data from SIREM.

Notes: The solid, blue line measures total factor productivity (TFP) using the methodology proposed by Levinsohn and Petrin (2003). The dashed, red line plots labor productivity measured as total income divided by the number of production workers. The data include firms from all manufacturing sectors, except ISIC 23 (manufacture of coke, refined petroleum products, and nuclear fuel) and ISIC 27 (manufacture of basic metals). Both variables are re-scaled so that their level equals 100 in 2005.

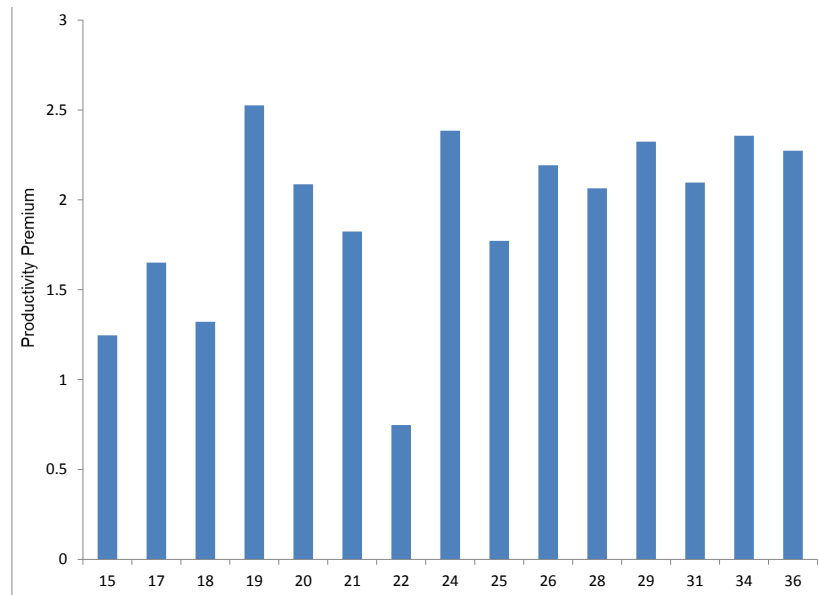
Figure 3: Exporters' Productivity Premium



Source: Authors' calculations based on data from SIREM and DIAN/DANE.

Notes: The blue line measures the productivity premium experienced by exporters over firms selling only in the domestic market. The data include firms from all manufacturing sectors, except ISIC 23 (manufacture of coke, refined petroleum products, and nuclear fuel) and ISIC 27 (manufacture of basic metals).

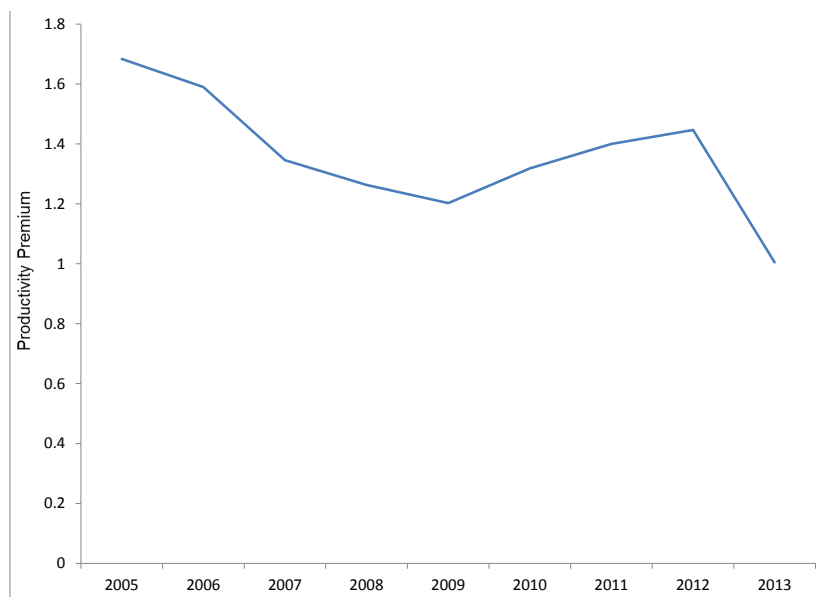
Figure 4: Exporters' Productivity Premium, by Sector



Source: Authors' calculations based on data from SIREM and DIAN/DANE.

Notes: The vertical axis measures the productivity premium experienced by exporters over firms selling only in the domestic market. The horizontal axis indexes the different manufacturing sectors. The data were averaged over 2005–2013.

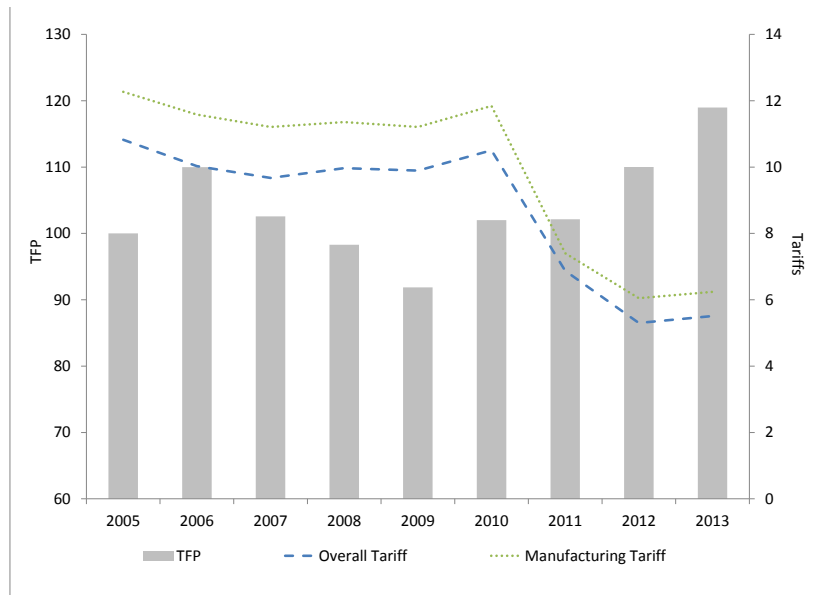
Figure 5: Productivity Premium: Continuous vs. Occasional Exporters



Source: Authors' calculations based on data from SIREM and DIAN/DANE.

Notes: The blue line measures the productivity premium experienced by continuous exporters over occasional exporters. The data include firms from all manufacturing sectors, except ISIC 23 (manufacture of coke, refined petroleum products, and nuclear fuel) and ISIC 27 (manufacture of basic metals).

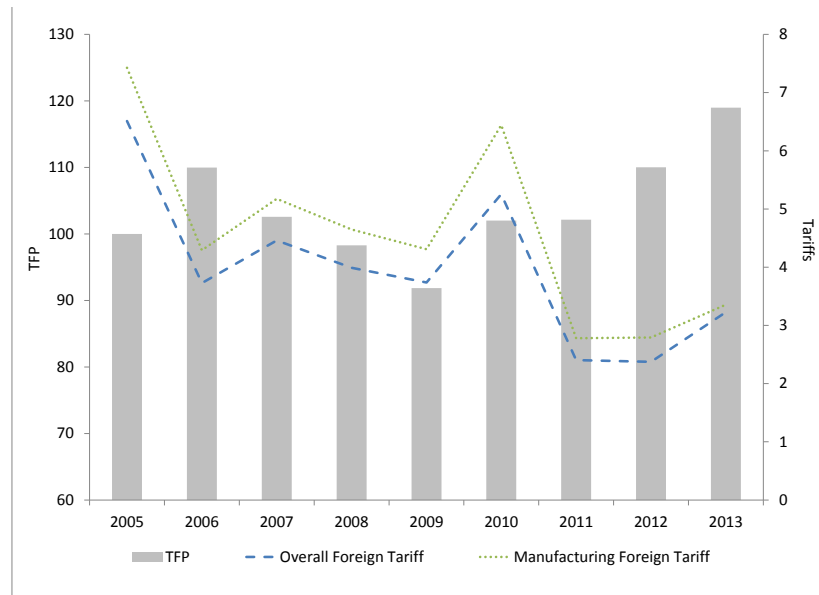
Figure 6: Tariffs and Productivity



Source: Authors' calculations based on data from SIREM and TRAINS.

Notes: "TFP" stands for total factor productivity, calculated at the firm level and aggregated using firms' income as weights. "Overall Tariff" stands for the average tariff imposed on all imported goods by Colombia. "Manufacturing Tariff" refers to the average tariff imposed by Colombia on manufactured goods.

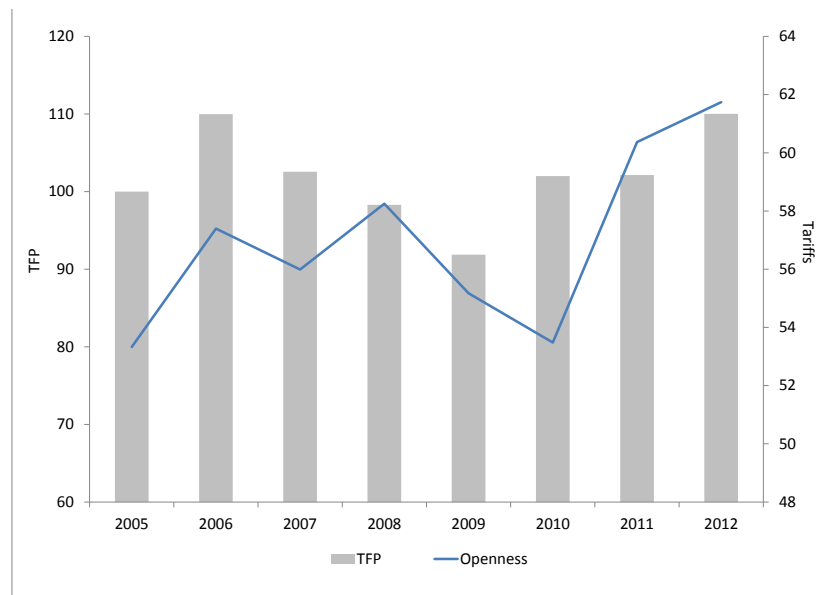
Figure 7: Foreign Tariffs and Productivity



Source: Authors' calculations based on data from SIREM and TRAINS.

Notes: "TFP" stands for total factor productivity, calculated at the firm level and aggregated using firms' income as weights. "Overall Foreign Tariff" stands for the average tariff imposed by the rest of the world on all goods exported by Colombia. "Manufacturing Foreign Tariff" refers to the average tariff imposed by the rest of the world on Colombia's exports of manufactured goods.

Figure 8: Openness and Productivity



Source: Authors' calculations based on data from SIREM and DANE.

Notes: "TFP" stands for total factor productivity calculated at the firm level and aggregated using firms' income as weights. "Openness" refers to the ratio of the value of manufacturing trade (imports plus exports) to the value of manufacturing production.

Table 1: Industry (ISIC Rev. 3.1) Codes

Code	Description
15	Manufacture of food products and beverages
16	Manufacture of tobacco products
17	Manufacture of textiles
18	Manufacture of wearing apparel; dressing and dyeing of fur
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
21	Manufacture of paper and paper products
22	Publishing, printing and reproduction of recorded media
23	Manufacture of coke, refined petroleum products and nuclear fuel
24	Manufacture of chemicals and chemical products
25	Manufacture of rubber and plastics products
26	Manufacture of other non-metallic mineral products
27	Manufacture of basic metals
28	Manufacture of fabricated metal products, except machinery and equipment
29	Manufacture of machinery and equipment n.e.c.
30	Manufacture of office, accounting and computing machinery
31	Manufacture of electrical machinery and apparatus n.e.c.
32	Manufacture of radio, television and communication equipment and apparatus
33	Manufacture of medical, precision and optical instruments, watches and clocks
34	Manufacture of motor vehicles, trailers and semi-trailers
35	Manufacture of other transport equipment
36	Manufacture of furniture; manufacturing n.e.c.

Table 2: Basic Statistics: Overall Manufacturing

	Firms (#)	Exporters (%)	Income (\$)	Capital (\$)	Materials (\$)	All Wkrs. (#)	Pdn Wkrs. (%)
2005	2,836	51.6%	25.5	11.4	12.0	147.2	58.9%
2006	3,277	49.8%	25.3	10.7	11.8	163.8	51.1%
2007	2,861	51.1%	30.1	14.6	13.8	162.8	57.8%
2008	2,807	51.3%	29.9	16.3	14.5	168.0	54.7%
2009	3,004	48.2%	27.0	15.4	12.3	156.4	52.9%
2010	2,892	48.6%	29.2	17.6	12.8	155.4	55.2%
2011	2,982	46.2%	30.3	17.9	13.2	160.4	54.3%
2012	2,852	46.9%	32.2	18.9	13.7	171.5	52.5%
2013	2,654	48.2%	36.0	21.3	15.3	187.3	53.0%
Average	2,907	49.1%	29.5	16.0	13.3	163.6	54.5%

Source: Authors' calculations based on data from SIREM and DIAN/DANE.

Notes: Manufacturers of coke, refined petroleum products, nuclear fuel and basic metals are not included. The sign '\$' corresponds to millions of Colombian pesos of 2005.

Table 3: Basic Statistics, by Sector

Sector:	15	16	17	18	19	20	21	22	24	25
Firms (#)	501	2	154	253	76	44	61	220	350	330
Exporters (%)	27.3%	-	54.8%	59.9%	64.3%	33.1%	62.0%	38.3%	55.6%	55.0%
Income (\$)	50.9	-	17.8	14.1	12.2	6.7	64.0	13.8	49.4	16.9
Capital (\$)	29.0	-	11.3	5.1	3.6	6.8	52.9	9.0	22.9	11.4
Raw Materials (\$)	26.8	-	6.6	3.9	3.5	1.9	27.1	3.4	19.5	6.8
All Workers (#)	226.5	-	170.2	224.8	156.3	81.5	227.8	117.0	168.8	114.0
Production Workers (%)	51.7%	-	71.0%	55.9%	62.5%	65.9%	57.4%	36.6%	39.0%	64.9%

Sector:	26	28	29	30	31	32	33	34	35	36
Firms (#)	137	239	94	3	53	2	15	105	11	257
Exporters (%)	38.5%	49.3%	69.4%	-	63.0%	-	51.4%	66.2%	56.2%	53.1%
Income (\$)	30.7	17.1	20.0	-	30.6	-	8.4	51.6	161.3	14.4
Capital (\$)	34.9	9.0	7.8	-	11.5	-	7.3	10.7	25.2	5.8
Raw Materials (\$)	8.4	9.5	8.3	-	11.4	-	2.4	26.5	53.1	6.5
All Workers (#)	186.1	100.5	152.1	-	173.9	-	108.6	182.7	493.1	102.5
Production Workers (%)	65.4%	63.1%	64.5%	-	50.4%	-	66.8%	69.3%	45.4%	56.2%

Source: Authors' calculations based on data from SIREM and DIAN/DANE.
Notes: The sign '\$' corresponds to millions of Colombian pesos of 2005.

Table 4: Share of Exports in Total Sales of Exporting Firms (%)

Sector	2005	2006	2007	2008	2009	2010	2011	2012	2013
15	14.1	13.2	12.6	13.5	9.7	9.4	8.0	9.6	9.5
17	24.4	21.1	25.0	16.4	27.0	19.8	21.0	20.7	19.7
18	44.5	41.7	35.2	36.9	25.1	22.1	19.5	17.5	14.5
19	26.1	27.4	32.1	23.3	16.5	15.6	11.0	14.0	11.0
20	24.9	21.1	17.5	15.5	16.8	13.8	7.8	10.4	10.6
21	37.1	41.1	38.6	38.0	41.3	32.7	36.5	21.4	19.0
22	14.7	12.5	11.7	6.2	11.7	7.9	8.2	5.9	5.2
24	18.9	18.6	12.7	10.5	19.0	19.8	20.7	20.9	22.0
25	18.5	19.8	20.1	12.9	24.7	5.6	20.7	19.6	21.7
26	15.7	14.5	11.5	10.3	11.4	9.3	13.0	16.2	10.9
28	25.3	27.7	7.8	15.0	25.2	20.0	18.9	19.0	16.4
29	27.4	25.0	28.1	7.1	22.4	15.3	14.0	15.3	12.3
31	19.3	20.4	29.6	21.3	28.0	9.5	12.4	15.9	24.3
33	33.9	35.4	44.6	42.3	41.3	35.1	40.9	40.6	33.4
34	24.7	22.5	32.3	20.1	13.9	13.3	13.2	11.0	20.4
35	7.5	7.9	8.6	6.7	8.9	3.0	3.4	2.3	1.0
36	31.4	39.6	42.3	13.7	22.1	17.4	23.8	20.1	19.1
Overall	21.7	21.9	17.9	14.0	18.3	13.3	15.5	15.4	15.6

Source: Authors' calculations based on data from SIREM and DIAN/DANE.

Table 5: SIREM vs. Alternative Data Sources

	Baseline Sample			Permanent Workers		
	Sample (\$)	% Nat. Acc.	% EAM	Sample (#)	% EAM	
2005	75,700,424.8	49.7%	64.1%	283,846	86.8%	
2006	87,488,066.8	53.9%	68.5%	318,303	95.6%	
2007	89,466,052.7	51.4%	65.7%	341,140	97.8%	
2008	90,306,212.7	51.6%	67.0%	341,412	93.9%	
2009	86,668,065.2	52.0%	65.9%	354,285	96.0%	
2010	90,231,015.3	52.8%	65.3%	322,404	85.2%	
2011	97,506,545.5	54.1%	59.9%	343,663	89.0%	
2012	98,548,279.2	54.5%	61.1%	374,776	96.8%	

	Alternative Sample			Permanent Workers		
	Sample (\$)	% Nat. Acc.	% EAM	Sample (#)	% EAM	
2005	62,455,446.4	41.0%	52.9%	228,328	69.8%	
2006	72,833,594.4	44.8%	57.0%	251,728	75.6%	
2007	77,617,609.2	44.6%	57.0%	266,366	76.4%	
2008	78,469,338.1	44.8%	58.2%	277,531	76.4%	
2009	74,352,339.7	44.6%	56.5%	294,300	79.7%	
2010	78,239,507.2	45.8%	56.6%	266,521	70.5%	
2011	85,529,785.1	47.5%	52.5%	285,273	73.9%	
2012	82,832,820.8	45.8%	51.4%	293,387	75.8%	

Source: Authors' calculations based on data from SIREM and DIAN/DANE.
Notes: In order to have comparable samples, data include firms manufacturing coke, refined petroleum products, nuclear fuel and basic metals. The sign '\$' corresponds to millions of Colombian pesos of 2005.

Table 6: Production Function Estimations

	Baseline LevPet	Sample OLS	Alternative LevPet	Sample OLS
Production Permanent	0.0494*** (0.0040)	0.0516*** (0.0049)	0.0453*** (0.0044)	0.0440*** (0.0060)
Production Temporary	0.0350*** (0.0033)	0.0473*** (0.0039)	0.0297*** (0.0039)	0.0411*** (0.0045)
Other Permanent	0.231*** (0.0071)	0.255*** (0.0089)	0.242*** (0.0094)	0.263*** (0.0109)
Other Temporary	0.0637*** (0.0042)	0.0694*** (0.0051)	0.0597*** (0.0053)	0.0631*** (0.0059)
Raw Materials	0.277*** 0.0447)	0.456*** (0.0109)	0.266*** (0.0538)	0.458*** (0.0133)
Property, Plant & Equipment	0.0897*** (0.0309)	0.206*** (0.0081)	0.0744* (0.0402)	0.208*** (0.0097)
OLS Constant		3.447*** (0.0639)		3.411*** (0.0742)
Observations	26,165	26,165	19,311	19,311
R-squared		0.90		0.91

Notes: Standard errors in parenthesis. ‘***’, ‘**’ and ‘*’ refer to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Estimated Productivity Index by Sector

Sector	2005	2006	2007	2008	2009	2010	2011	2012	2013
15	83.5	89.9	92.8	91.5	89.5	92.4	96.0	95.9	95.6
17	60.2	64.5	75.0	74.0	67.0	71.6	76.9	72.1	71.4
18	47.4	53.3	54.5	57.8	55.7	60.6	67.9	69.7	73.8
19	41.7	45.1	47.1	53.6	49.5	57.7	72.8	56.4	72.1
20	43.0	45.6	47.6	44.5	38.6	39.3	41.9	39.2	29.1
21	87.1	83.2	92.7	95.9	82.4	75.0	90.8	91.3	101.3
22	62.7	67.6	75.8	76.3	75.7	93.6	79.0	96.7	80.7
24	111.8	126.0	132.5	121.9	124.8	143.4	147.3	143.8	149.0
25	60.4	59.4	63.2	69.1	70.6	65.9	76.3	67.9	71.0
26	104.9	131.9	121.2	121.9	115.7	110.7	118.9	114.8	97.8
28	63.6	92.9	75.6	83.3	63.8	64.7	68.9	69.8	72.0
29	62.7	65.6	82.9	85.5	71.9	148.6	73.3	75.3	59.0
31	85.5	98.1	64.7	103.1	87.6	92.4	78.1	75.0	77.4
34	244.3	262.6	177.6	151.3	103.6	135.4	130.0	247.1	234.2
36	112.3	110.5	125.8	120.6	85.1	110.5	64.4	55.7	65.1
Overall	100.0	110.0	102.6	98.3	91.9	102.0	102.1	110.0	119.0

Notes: To construct overall and sector-specific TFP indexes, we aggregate firm-level estimates weighting by income, and then normalize the aggregate estimates so that the value of the TFP index for the overall manufacturing industry equals 100 in 2005. The TFP for the overall manufacturing industry includes firms from all manufacturing sectors, except ISC 23 (manufacture of coke, refined petroleum products, and nuclear fuel) and ISIC 27 (manufacture of basic metals). We do not report individual indices for the smallest industries (ISICs 16, 30, 32, 33 and 35), since these can be greatly affected by changes in single firms, and therefore can exhibit implausible jumps over time.

Table 8: Exporter Status and Productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Productivity	0.614*** (0.0247)	0.622*** (0.0249)	0.202*** (0.0307)	0.257*** (0.0328)	0.277*** (0.0331)	0.276*** (0.0334)	0.270*** (0.0337)
Small			0.478*** (0.0499)	0.516*** (0.0521)	0.485*** (0.0524)	0.487*** (0.0524)	0.498*** (0.0526)
Medium			0.751*** (0.0567)	0.823*** (0.0586)	0.755*** (0.0594)	0.758*** (0.0594)	0.778*** (0.0595)
Large			1.001*** (0.0641)	1.108*** (0.0664)	0.997*** (0.0673)	1.002*** (0.0673)	1.035*** (0.0681)
Very Large			1.301*** (0.0780)	1.521*** (0.0825)	1.329*** (0.0855)	1.338*** (0.0872)	1.393*** (0.0892)
Age					0.0116*** (0.00144)	0.0114*** (0.00144)	0.00973*** (0.00148)
HQ						0.222*** (0.0712)	0.202*** (0.0726)
Affiliate						-0.0317 (0.0732)	-0.0126 (0.0737)
Conglomerate						-0.0940 (0.0658)	-0.0763 (0.0661)
Year		x	x	x	x	x	x
Size			x	x	x	x	x
Sector				x	x	x	x
Age					x	x	x
Legal						x	x
Department							x
Observations	26,165	26,165	26,165	26,165	26,165	26,165	26,067

Notes: Standard errors (in parenthesis) clustered by firm. ‘***’, ‘**’, and ‘*’ refer to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Exporter Status and Lagged Productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Productivity _(t-1)	0.624*** (0.0285)	0.631*** (0.0288)	0.184*** (0.0372)	0.254*** (0.0401)	0.270*** (0.0404)	0.266*** (0.0407)	0.258*** (0.0410)
Small			0.475*** (0.0584)	0.506*** (0.0610)	0.478*** (0.0614)	0.482*** (0.0615)	0.493*** (0.0617)
Medium			0.758*** (0.0657)	0.819*** (0.0683)	0.756*** (0.0692)	0.762*** (0.0693)	0.783*** (0.0692)
Large			1.033*** (0.0735)	1.130*** (0.0767)	1.028*** (0.0776)	1.029*** (0.0777)	1.061*** (0.0783)
Very Large			1.342*** (0.0896)	1.539*** (0.0947)	1.358*** (0.0978)	1.347*** (0.0992)	1.404*** (0.101)
Age					0.0114*** (0.00159)	0.0111*** (0.00159)	0.00931*** (0.00163)
HQ						0.271*** (0.0833)	0.250*** (0.0847)
Affiliate						-0.00272 (0.0812)	0.0175 (0.0816)
Conglomerate						-0.0474 (0.0814)	-0.0240 (0.0817)
Year		x	x	x	x	x	x
Size			x	x	x	x	x
Sector				x	x	x	x
Age					x	x	x
Legal						x	x
Department							x
Observations	19,738	19,738	19,706	19,706	19,706	19,706	19,623

Notes: Standard errors (in parenthesis) clustered by firm. ***, **, and * refer to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Productivity and Exporter Status: Arellano Bond

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EXP _(t-1)	0.229*** (0.0311)	0.213*** (0.0267)	0.211*** (0.0267)	0.210*** (0.0268)	0.210*** (0.0268)	0.210*** (0.0268)	0.209*** (0.0269)
Productivity _t	0.0257** (0.0101)	0.0245** (0.0101)	0.0239** (0.0101)	0.0238** (0.0102)	0.0238** (0.0102)	0.0237** (0.0102)	0.0231** (0.0102)
Small			0.0231 (0.0164)	0.0218 (0.0165)	0.0218 (0.0165)	0.0219 (0.0165)	0.0238 (0.0166)
Medium			0.0316 (0.0220)	0.0306 (0.0221)	0.0306 (0.0221)	0.0307 (0.0221)	0.0347 (0.0221)
Large			0.0192 (0.0257)	0.0194 (0.0257)	0.0194 (0.0257)	0.0191 (0.0257)	0.0231 (0.0258)
Very Large			0.0260 (0.0297)	0.0258 (0.0296)	0.0258 (0.0296)	0.0250 (0.0296)	0.0292 (0.0298)
Age					0.00867*** (0.00259)	0.00860*** (0.00259)	0.00989*** (0.00322)
HQ						0.0110 (0.0153)	0.0113 (0.0155)
Affiliate						0.00572 (0.0153)	0.00686 (0.0154)
Conglomerate						0.0149 (0.0174)	0.0145 (0.0177)
Year		x	x	x	x	x	x
Size			x	x	x	x	x
Sector				x	x	x	x
Age					x	x	x
Legal						x	x
Department							x
Observations	14,919	14,919	14,919	14,919	14,919	14,919	14,813

Notes: Robust standard errors in parenthesis. ***, **, and * refer to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Continuous vs. Occasional Exporters: Marginal Effects

Continuous Exporters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Productivity	0.217*** (0.00789)	0.217*** (0.00793)	0.0778*** (0.0108)	0.0893*** (0.0109)	0.0933*** (0.0110)	0.0926*** (0.0110)	0.0870*** (0.0109)
Year		x	x	x	x	x	x
Size			x	x	x	x	x
Sector				x	x	x	x
Age					x	x	x
Legal						x	x
Department							x
Observations	26,165	26,165	26,165	26,165	26,165	26,165	26,087

Occasional Exporters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Productivity	-0.0209** (0.00838)	-0.0199** (0.00842)	-0.0293** (0.0114)	-0.0283** (0.0114)	-0.0289** (0.0115)	-0.0278** (0.0114)	-0.0245** (0.0114)
Year		x	x	x	x	x	x
Size			x	x	x	x	x
Sector				x	x	x	x
Age					x	x	x
Legal						x	x
Department							x
Observations	26,165	26,165	26,165	26,165	26,165	26,165	26,087

Notes: Standard errors (in parenthesis) clustered by firm. ***, **, and * refer to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Ex-ante Productivity Advantage

Baseline Sample					
	(1)	(2)	(3)	(4)	(5)
Productivity	0.113* (0.0606)	0.0687 (0.0996)	0.0752 (0.101)	0.0636 (0.0882)	0.0656 (0.0891)
Size		x	x	x	x
Sector			x	x	x
Age				x	x
Legal					x
Observations	3,245	3,245	3,013	3,013	3,013

Alternative Sample					
	(1)	(2)	(3)	(4)	(5)
Productivity	0.154** (0.0630)	0.157 (0.119)	0.179 (0.119)	0.181* (0.105)	0.188* (0.105)
Size		x	x	x	x
Sector			x	x	x
Age				x	x
Legal					x
Observations	2,280	2,280	2,128	2,128	2,128

Notes: Robust standard errors in parenthesis. ‘***’, ‘**’ and ‘*’ refer to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Ex-Post Productivity Advantage

Baseline Sample					
	(1)	(2)	(3)	(4)	(5)
Productivity	0.487*** (0.0617)	-0.0645 (0.101)	-0.0690 (0.103)	-0.0202 (0.0912)	-0.0562 (0.0920)
Size		x	x	x	x
Sector			x	x	x
Age				x	x
Legal					x
Observations	1,273	1,273	1,273	1,273	1,273

Alternative Sample					
	(1)	(2)	(3)	(4)	(5)
Productivity	0.498*** (0.0744)	-0.0676 (0.121)	-0.0483 (0.123)	0.0288 (0.109)	-0.0148 (0.110)
Size		x	x	x	x
Sector			x	x	x
Age				x	x
Legal					x
Observations	888	888	883	883	883

Notes: Robust standard errors in parenthesis. ‘***’, ‘**’ and ‘*’ refer to statistical significance at the 1%, 5%, and 10% levels, respectively.