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Learning-by-Doing, Learning-by-Exporting, and Productivity: Evidence from Colombia*

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Abstract: The empirical evidence on whether participation in export markets increases plant-level productivity has been inconclusive so far. We explain this inconclusiveness by drawing on Arrow's (1962) characterization of learning-by-doing, which suggests focusing on young plants and using measures of export experience rather than export participation. We find strong evidence of learning-by-exporting for young Colombian manufacturing plants between 1981 and 1991: total factor productivity increases 4%-5% for each additional year a plant has exported, after controlling for the effect of current exports on total factor productivity. Learning-by-exporting is more important for young than for old plants and in industries that deliver a larger percentage of their exports to high-income countries.

Key Words: learning, trade, total factor productivity, exports, export-led growth

JEL Classification: D21, F10, L60

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1. Introduction

Trade and development policies have often been supported by arguments stressing improvements in productivity at the microeconomic level. The traditional infant industry argument, for instance, suggests that new firms operate at such high costs that they would be unable to compete with well-established foreign firms without protection. While such protection would be detrimental to the country's welfare initially, by allowing domestic firms to start operations it would give them the opportunity to grow and learn by doing, decreasing production costs over time. When the infant firms mature, the argument concludes, protection would become unnecessary as they would be able to compete in international markets.

More recently, policies of export-led growth have also been supported on the grounds that they improve the productivity of exporting firms. One often-cited reason for such improvement is that foreign buyers transfer technology to firms that introduce new export products. Additionally, as case study evidence from Taiwan suggests, the possibility of exploiting profitable opportunities by selling in export markets may stimulate firms to improve their own technological capabilities (Westphal (2002)). Improvements in productivity associated with the access to export markets have been referred to by Clerides et al. (1998) and others as learning-by-exporting.

While the notion that firms learn by exporting is intuitively appealing, the empirical evidence has been inconclusive. Exporters have been found to be significantly more productive, larger, more capital-intensive, and to pay higher wages than nonexporters, but these desirable characteristics might be the cause and not the consequence of their participation in export markets. If entry into export markets is characterized by economically significant sunk costs, only firms that are productive enough would have the capability of exporting. It is possible, then, that the strong positive association between productivity and participation in export markets reflects the self-selection of the better firms into export markets and not the effect of exporting on productivity. In fact, many empirical studies using plant-level data have found support for this alternative causal interpretation.[1] Yet, self-selection and learning-by-exporting are not mutually exclusive possibilities, as high-productivity firms that can afford the sunk cost of entry to export markets may, in principle, continue to improve their productivity as a result of their exposure to exporting. Several studies have found support for learning-by-exporting, even after controlling for self-selection effects.[2]

Despite the large and growing literature on this subject, we believe that the lack of conclusive evidence on learning-by-exporting warrants further investigation. In this paper, we revisit a basic question: how to define learning-by-exporting? To answer this question we consider the parallels between learning-by-exporting and learning-by-doing. In his classical work on learning-by-doing, Arrow (1962) suggests two main characteristics of learning. First, "learning is the product of experience. Learning can only take place through the attempt to solve a problem and therefore only takes place during activity" (p. 155). Second, "learning associated with repetition of essentially the same problem is subject to sharply diminishing returns… To have steadily increasing performance, then, implies that the stimulus situations must themselves be steadily evolving rather than merely repeating" (pp. 155-6).

We believe that Arrow's general characterization of learning applies to domestic firms

[1] Bernard and Wagner (1997), Clerides et al. (1998), Bernard and Jensen (1999), Aw et al. (2000), Isgut (2001), Fafchamps et al. (2002), Delgado et al. (2002), Arnold and Hussinger (2004), Alvarez and Lopez (2004).

breaking into export markets. Those firms need to solve new problems such as adopting stringent technical standards to satisfy more sophisticated consumers. The production of export goods may require the introduction of new, more efficient equipment to which workers need to adjust. Export markets are likely to be more competitive than the domestic market, putting pressure on firms to meet orders in a timely fashion and ensure quality standards for their products. Meeting all these challenges may help firms improve their productivity. However, once—and provided that—firms succeed in meeting these challenges, the scope for further learning may be significantly diminished.

This characterization suggests reasons why many previous studies have not found evidence of learning-by-exporting. One common method to capture learning-by-exporting effects is to compare the performance of mutually exclusive groups, such as exporters and nonexporters. The problem is that not all exporters have the same level of engagement in export markets: while some firms devote considerable resources to their export activities, others are only marginally involved in exporting, with little scope for learning. The presence of firms marginally engaged in export markets in the group of exporters is likely to generate a downward bias in the estimated effect of learning-by-exporting. Another common method is to regress a performance variable, such as total factor productivity (TFP) or average variable costs, on a lagged indicator variable measuring export participation. This method is also subject to the criticism that export participation does not capture the level of engagement in exporting. A further disadvantage is that it does not take into account how long firms have participated in the export market. If, as Arrow suggested, learning is subject to sharply diminishing returns, successfully established exporters are unlikely to learn from exporting.

[2] Kraay (1999), Castellani (2002), Baldwin and Gu (2003), Van Biesebroeck (2004), Girma et al. (2004), Bigsten et al. (2004), Hahn (2004), Blalock and Gertler (2004), De Loecker (2004).

Therefore, their presence in the group of exporters is also likely to generate a downward bias in the effect of learning-by-exporting.

The previous discussion suggests two ideas to truly capture learning-by-exporting effects in the data. A first idea is to focus on young plants. Young plants are much more likely than established plants to face new stimulus situations, which require managers and workers to find solutions to new technical and organizational problems. This is the reasoning underlying the strong evidence of learning-by-exporting found by Delgado et al. (2002) and Baldwin and Gu (2003) for young Spanish and Canadian manufacturing plants, respectively. In our paper, we seek to confirm this evidence for young Colombian manufacturing plants. A second idea is to focus on measures of export experience, rather than on export participation, to capture learning-by-exporting effects. Our export experience measures, the number of years a firm has exported and an index of cumulative exports, require that we observe plants' complete production and export histories. This provides us with a second rationale for focusing on young plants born in 1981 or later as 1981 is the first year when plant-level export data is available in the annual Colombian manufacturing surveys.

Our results show robust evidence of learning-by-exporting effects for young plants, using both traditional export participation measures and our export experience measures. The average annual rate of TFP growth for young entrants into export markets is around 3% to 4% higher than that for young nonexporters. Each additional year of export experience increases plant TFP between 4% and 5%, even controlling for a dummy indicating whether the plant is currently exporting. In extensions to our main results we show that learning-by-exporting is significantly more important for young plants than for old plants. Also, we find that the relationship between export experience and productivity varies across industries. The volume of industry exports and the proportion of industry exports going to high-income countries contribute to this cross-industry variation.

The paper is organized as follows. In Section 2, we review the learning-by-exporting literature. Our empirical strategy and data are described in Sections 3 and 4. Our results are presented in Sections 5 and 6. Section 7 concludes.

2. The Measurement of Learning-by-Exporting Effects

Following the influential papers of Bernard and Jensen (1999) and Clerides et al. (1998), the literature has used two main methods to measure learning-by-exporting effects. The first method consists of separating the sample into mutually exclusive groups, such as exporters and nonexporters, to assess differences in plant performance between these groups. Consider the following equation explaining a measure of performance for firm *i* at year *t*:[3]

$$\ln Y_{it} = \alpha_0 + \alpha_1 D_{i0} + \alpha_2 ' Z_{io} + \beta_0 t + \beta_1 D_{i0} t + \beta_2 ' Z_{i0} t + \omega_i + \eta_{it} \, ,$$

where D_{i0} is a dummy variable equal to one if the plant belongs to the "treatment" group and equal to zero if the plant belongs to the "control" group during the baseline year $t = 0$; Z_{i0} is a vector of observable plant characteristics, such as size or industry affiliation in the baseline year; t is a time trend; ω_i is an unobservable, time-invariant plant effect; and η_{it} is an i.i.d. disturbance. Taking average annual differences between $t = 0$ and T, we obtain:

[3] We use the terms firms and plants interchangeably in the paper, but our empirical analysis relies on plant-level data.

$$\Delta \ln Y_{iT} \equiv \frac{1}{T}\left(\ln Y_{iT} - \ln Y_{i0}\right) = \beta_0 + \beta_1 D_{i0} + \beta_2 ' Z_{i0} + \varepsilon_{it} \, , \qquad (1)$$

where $\varepsilon_{iT} \equiv \eta_{iT} - \eta_{i0}$. The difference-in-difference estimator $\hat{\beta}_1$ measures the average differential in performance between plants in the treatment group and plants in the control group, after accounting for general trends influencing the performance of all plants equally, trends in performance related to observable plant characteristics, and unobserved time-invariant plant effects.

Several variants of Equation (1) have been estimated in the literature, using data from both industrial and developing countries, considering diverse treatment and control groups and time horizons (T). For example, Bernard and Jensen (1999) define their treatment group as U.S. manufacturing plants that export in the initial year of the sample, and estimate Equation (1) using different time periods - 1984-1988, 1989-1992, and 1984-1992 - and different time horizons - short run (T=1), medium run (T=3, 4), and long run (T=8).

One extension of Equation (1) developed in the literature has been the inclusion of more than one dummy identifying different, mutually exclusive treatment groups. Bernard and Jensen (1999), for example, consider three groups: (1) plants that do not export in t=0 but export in t=T (entrants), (2) plants that export in both years (continuous exporters), and (3) plants that export in t=0 but do not export in t=T (quitters). The control group consists of plants that do not export in either year. Another extension developed in the literature has been to select the treatment and control groups from a subset of the plants in the sample. For example, Aw et al. (2000) use three nonconsecutive years of plant-level data for Korea and Taiwan and consider (i) regressions where only entrants to export markets are the treatment group and nonexporters are the control group, excluding quitters and continuous exporters from the estimating sample; and (ii) regressions where quitters are the treatment group and continuous exporters are the control group, excluding both entrants and nonexporters from the estimating sample.

While most researchers have estimated some variant of Equation (1) using OLS, Delgado et al. (2002) use a nonparametric method to compare the distributions of productivity growth of Spanish manufacturing exporters and nonexporters during 1991-1996. Estimation is performed separately for subsamples of small and large firms. Interestingly, the authors cannot reject the null hypothesis that productivity growth is greater for exporters than for nonexporters when the sample includes only young firms (those that started operations between 1986 and 1991). This result is valid for small and large young firms.

The most recent innovation in the measurement of learning-by-exporting effects through group comparisons has been the use of matching methods to control more precisely for differences between firms in treatment and control groups. As the literature on evaluation methods for nonexperimental data suggests, the appropriate comparison to evaluate the effects of entry into export markets involves a counterfactual. Letting ΔY_{iT}^{1} denote the performance between *t*=0 and *T* of a firm that entered export markets at $\mathrm{t}=\tau \quad (0 \leq \tau < \mathrm{T})$ and ΔY_{iT}^{0} denote the hypothetical performance of the same firm had it not started to export, the causal effect of entry is captured by $\Delta Y_{iT}^{1} - \Delta Y_{iT}^{0}$. The average treatment effect on the treated is defined as the expectation of this counterfactual difference for the subpopulation of firms that actually entered the export market at time τ: $E[\Delta Y_{iT}^{1} \mid D_{i\tau}=1] - E[\Delta Y_{iT}^{0} \mid D_{i\tau}=1]$. Unfortunately, the second term is unobservable. What we observe is the difference in performance between entrants and nonexporters,

$E[\Delta Y_{iT}^{1} \mid D_{i\tau}=1]-E[\Delta Y_{iT}^{0} \mid D_{i\tau}=0]$. However, this difference provides a poor estimate of the causal effect of entering into export markets on performance if, as both theory and empirical evidence suggest, exporters have very different characteristics from nonexporters. Matching methods identify a subpopulation of nonexporters that are similar to the population of entrants into export markets before entry, where similarity is based on set of observable firm characteristics. Girma et al. (2004), Arnold and Hussinger (2004), and De Loecker (2004) use propensity score matching to select appropriate subpopulations of nonexporters. This method requires the estimation of probit regressions to explain the probability of entry into export markets. Once the subpopulation of nonexporters is identified, differences in performance can be estimated nonparametrically or through a parametrical form similar to Equation (1) above.

The second method of measurement of learning-by-exporting effects consists of adding one or more dummies for lagged export participation to a regression explaining a measure of firm performance. For example, Clerides et al. (1998) regress average variable costs on lagged export participation controlling for the real exchange rate, lagged capital stock and lagged average variable costs. Kraay (1999) regresses three alternative measures of performance (labor productivity, TFP, and unit costs) on lagged export participation, lagged performance and firm fixed effects. Bigsten et al. (2004) and Van Biesebroeck (2004) estimate production functions with a lagged export participation dummy added as a shifter of total factor productivity. A representative regression of the second method is given by:

$$\ln Y_{it}=\beta_0+\beta_1 D_{it-1}+\beta_2 \ln Y_{it-1}+\beta_2{}' X_{it}+\omega_i+\varepsilon_{it}\,, \qquad (2)$$

where $D_{\text{it-1}}$ is a dummy variable equal to one if the plant exported at time *t-1*; the vector X_{it} includes both time-varying variables, such as the capital stock or the number of workers, and fixed plant characteristics, such as industry affiliation; ω_i is an unobservable, time-invariant firm effect; and ε_{it} is a time-varying performance shock.

A major econometric problem with Equation (2) is that the export participation decision is endogenous because exporting is positively associated with performance; therefore, if ε_{it} is persistent, $\hat{\beta}_1$ may pick up the effects of past favorable performance shocks. One way to deal with this endogeneity problem is to estimate Equation (2) using instrumental variables or GMM. Kraay (1999) estimates a variant of this equation in first differences under the identifying restrictions that ε_{it} is i.i.d. and that the export participation decision is predetermined: $\mathrm{E}[\mathrm{D}_{\mathrm{it}} * \varepsilon_{\mathrm{is}}] = 0$ for all $s > t$. Notice that the latter restriction allows export participation to be positively correlated with current and past performance shocks, as the self-selection hypothesis suggests. Van Biesebroeck (2004) also estimates a variant of Equation (2) using Blundell and Bond (1998) System-GMM estimator.

A more involved method of dealing with the endogeneity of export participation is to estimate Equation (2) simultaneously with another equation explaining the decision to participate in export markets. This is the approach taken by Clerides et al. (1998), where the two equations are estimated using full information maximum likelihood. An important finding of Bigsten et al. (2004) is that this type of estimation result is not robust to the distributional assumption on the error terms. In Clerides et al. (1998) the four error terms of the model (i.e., one plant effect and one i.i.d. disturbance in each equation, with the two plant effects and the two i.i.d. errors allowed to be correlated across equations) are normally distributed. Bigsten et al. (2004) approximate the bivariate distribution of the two plant effects nonparametrically by a discrete multinomial distribution and find that this modification has dramatic effects on the estimation results: the coefficient on lagged export participation in their performance equation becomes positive and significant.[4]

Table 1 presents a selective overview of the methodology and results of learning-by-exporting studies. The table focuses only on segments of the cited studies that apply the methods examined in this section to the study of learning-by-exporting. The numbers (1) and (2) in the second column correspond, respectively, to studies based on variants of Equations (1) and (2). In some cases, more than one method is used in the same paper. While the majority of studies use dummy variables to define the treatment group of exporters or to indicate whether the firm has exported in an earlier period, there are a few exceptions. Kraay (1999) and Castellani (2002) use export intensity, defined as the ratio of exports to sales. Interestingly, Castellani (2002) finds evidence of learning-by-exporting for Italian manufacturing firms when the dummy D_{i0} is replaced by export intensity in the initial year. Fafchamps et al. (2002) use the number of years since the firm began exporting to identify learning-by-exporting for a cross-section of Moroccan exporters.[5]

As mentioned in Section 1, we believe that the phenomenon of learning-by-exporting is related, like learning-by-doing, to the intensity of exposure to new challenging tasks. Therefore, an important aspect of our methodology is to capture learning-by-exporting using measures of export experience that convey not only whether or not the firm has participated in export markets in the

[4] Van Biesebroeck (2004) proposes a third method of estimation of Equation (2) based on Olley and Pakes (1996).
[5] Blalock and Gertler (2004) introduce export intensity and the number of years a plant has exported as robustness checks to their main regression. Unfortunately, the main variable in those regressions is a dummy for contemporaneous exports, whose interpretation as learning-by-exporting is problematic due to the endogeneity of the export participation decision.

past but also the intensity and persistence over time of the firm's exposure to export markets. In the next section we explain in detail our approach to measuring learning-by-exporting effects.

3. Empirical Specification

The measure of plant performance used in this paper to assess the presence of learning-by-exporting effects is total factor productivity (TFP). In the literature reviewed in Section 2, researchers often rely on a two-step approach, first regressing output on inputs to obtain plant-level time series of TFP and then estimating a variant of Equations (1) or (2) above with TFP as the dependent variable. An alternative method is to test directly for learning-by-exporting effects in the estimation of the production function, the so-called one-step approach (Van Biesebroeck, 2004; Bigsten et al., 2004). In this paper, we show results using both approaches, though we emphasize the two-step approach due to its greater flexibility.

In our measurement of TFP, we take into account two elements: (i) factors of production differ in their quality, and (ii) the choice of variable inputs may be correlated with productivity shocks unobserved by the econometrician. Accounting for differences in factor quality is important in light of the criticism by Katayama et al. (2003) to plant-level TFP estimates that they consider to be unreliable since physical volumes of output and inputs are not observed but rather estimated by deflating nominal sales revenues and input expenditures using sector-wide price indexes. If there is a positive association between factor quality and sales revenue (resulting from either a higher volume or a better quality of output), omitting factor quality measures in the production function will make plants using better inputs look as if they are more productive. Similarly, if plant managers choose variable inputs based on knowledge of their plant's current productivity, the estimated coefficients on variable inputs in the production function will be upwardly biased. This bias will make plants that use relatively more variable inputs appear less productive.

In this paper, we consider the following production function:

$$Y_{it} = A_{it} L_{it}^{\beta_l} M_{it}^{\beta_m} K_{it}^{\beta_k} \exp\left(\beta_q ' Q_{it}\right), \tag{3}$$

where A_{it} is total factor productivity; L_{it}, M_{it}, and K_{it} are, respectively, labor, intermediate inputs, and capital; and Q_{it} is a vector of factor quality measures. The vector Q_{it} includes two measures of labor quality, skill intensity S_{it} and wage premium W_{it}, and one measure of capital quality, capital vintage V_{it}. Finally, we model total factor productivity as

$$A_{it} = \exp\left(\beta_{YE} YE_{it} + \beta_{EE} EE_{it} + \omega_{it} + \varepsilon_{it}\right), \tag{4}$$

where YE_{it} is a measure of output experience, EE_{it} is a measure of export experience, ω_{it} a plant-specific productivity shock known to the plant manager, and ε_{it} a zero-mean productivity shock realized after variable inputs are chosen. In our estimation, YE_{it} is a vector including two measures of output experience.

In the two-step approach, we estimate the production function without taking into account the potential dependence of TFP on output and export experience:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_S S_{it} + \beta_W W_{it} + \beta_V V_{it} + \omega_{it} + \varepsilon_{it}\,. \tag{5}$$

As mentioned above, a major econometric problem with Equation (5) is the possibility of an upward bias in the estimated coefficients on variable inputs (labor, intermediate inputs, skill ratio, and wage premium) and a corresponding downward bias in the estimated coefficients on quasi-fixed inputs (capital and vintage). To obtain consistent estimates of the production function parameters, we use a modified version of the combination of parametric and nonparametric techniques proposed by Levinsohn and Petrin (2003) [henceforth LP].

The LP estimation procedure makes use of plant-level intermediate inputs' choices to correct for the simultaneity between variable inputs and productivity. Estimation proceeds in two stages. First, the coefficients on labor, skill intensity, and wage premium are obtained by semi-parametric techniques. Following LP, we assume that a plant's demand for intermediate inputs increases monotonically with its productivity, conditional on its capital and vintage. Then, the inverse of the intermediate inputs demand function depends only on observable intermediate inputs, capital and vintage and its nonparametric estimate can be used to control for unobservable productivity, removing the simultaneity bias. Second, intermediate inputs, capital and vintage coefficients are obtained by generalized method of moments (GMM) techniques. The identification assumption is that capital and vintage adjust with a lag to productivity.[6] Further estimation details and results for a set of industries are provided in Appendix A.

Equation (5) is estimated separately for each of twenty four 3-digit ISIC Colombian manufacturing industries. We construct our measures of plant TFP as $\hat{a}_{it} \equiv \left(\omega_{it} \hat{+} \varepsilon_{it}\right) = y_{it} - \left(\hat{\beta}_0 + \hat{\beta}_l l_{it} + \hat{\beta}_m m_{it} + \hat{\beta}_k k_{it} + \hat{\beta}_S S_{it} + \hat{\beta}_W W_{it} + \hat{\beta}_V V_{it}\right)$ after obtaining consistent production function parameters. In the second step, we estimate

$$\hat{a}_{it} = \beta_0 + \beta_{YE} YE_{it} + \beta_{EE} EE_{it} + u_{it} \tag{6}$$

[6] More specifically, we assume that productivity follows a Markov process: $\omega_{it} = E[\omega_{it} / \omega_{it-1}] + \xi_{it}$ where

by different methods, such as OLS, fixed effects, and Blundell and Bond (1998) system-GMM.

In the one-step approach, we include output and export experience directly in the production function:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_S S_{it} + \beta_W W_{it} + \beta_V V_{it} + \beta_{YE} YE_{it} + \beta_{EE} EE_{it} + \omega_{it} + \varepsilon_{it} . \qquad (7)$$

As above, we use intermediate inputs to correct for the endogeneity of input choices with respect to productivity. We assume that the plant manager observes its current productivity ω_{it} before making profit-maximizing choices of labor, labor quality, and intermediates to be combined with the quasi-fixed input capital and its quality and produce output. To obtain the coefficients on production and export experience variables, we modify the LP estimation procedure. The main identifying assumption is that production and export experience are taken by plant managers as state variables like capital; hence their coefficients are obtained in the same stage of the estimation as that of capital. All details on the estimation procedure are provided in Appendix A.

4. Data

The dataset used in this study is constructed from the 1981-1991 annual census of Colombian manufacturing plants conducted by Departamento Administrativo Nacional de Estadística (DANE). The census covers all manufacturing plants with ten or more employees.[7] The variables provided by the census are in current pesos, except for the number of workers and the

ξ_{it} represents the unexpected part of current productivity to which capital and vintage do not adjust.

[7] More specifically, DANE requires a plant to have more than ten employees to enter the census for the first time, but then continues to cover the plant regardless of its employment levels. As a result, plants with less than ten employees are included in the sample in almost all years.

consumption of electric energy. Therefore, we use a series of price indexes to convert all the nominal variables into 1986 constant pesos. We obtain implicit price indexes for different types of capital goods and producer price indexes (PPI) at 3-digit ISIC (revision 2) from DANE, and construct our own indexes for domestic and imported raw materials and for exports. Details on the construction of price indexes and other data issues are provided in Appendix B.

The main variables for our analysis are output, labor, intermediate inputs, skill intensity, wage premium, capital, vintage, production experience, and export experience. Output Y_{it} is obtained as the sum of the value of domestic sales plus net inventory accumulation deflated by PPI and the value of exports deflated by the exports price index. Labor L_{it} is the total number of workers. Intermediate inputs M_{it} is the sum of raw materials consumption and energy consumption in constant pesos. Raw materials consumption in constant pesos is the sum of the values of domestic and imported raw materials consumed during the year deflated by the price indexes of, respectively, domestic and imported raw materials. Energy in constant pesos is the sum of electric energy consumed during the year valued at 1986 prices plus consumption of fuels and lubricants deflated by the PPI of the petroleum refineries sector.

Our measures of labor quality are skill intensity S_{it}, defined as the ratio of the number of white collar workers, managers, and technicians to the total number of workers, and the wage premium W_{it}, defined as the ratio of the plant's average wage in a given year to the average wage paid that year in the region where the plant is located.[8] Bahk and Gort (1993) use the plant's average wage as a measure of labor quality on the grounds that variations in wages "mainly

[8] We consider thirteen regions: eight major metropolitan areas (Bogotá, Medellín, Cali, etc.), four regions in the interior, and the rest of the country.

measure differences in skills rather than differences in the prices of identical classes of labor" (p. 565). Given the greater degree of geographical segmentation in Colombian labor markets, we normalize average plant wages by the regional average wage.

Following Bahk and Gort (1993), our measure of capital is gross capital. Gross capital at time *t*, K_{it}, is defined as cumulative purchases minus cumulative sales of capital goods up to *t-1*. To obtain this measure we aggregate purchases and sales of four types of capital goods (buildings and structures, machinery and equipment, transportation equipment, and office equipment) in constant pesos. The omission of depreciation rates in the measurement of the capital stock is justified under the assumption that maintenance outlays offset the adverse output effects of physical decay. Of course, capital equipments of different vintages are affected by different degrees of obsolescence. Given the observed continuous technological improvements in the international capital goods industry, newer plants and plants that invest more frequently will most likely be more productive.[9] For that purpose, our production function includes a measure of capital vintage V_{it}, whose construction is explained in Appendix B.

We consider two measures of production experience in our analysis. Our first measure is the number of years a plant has been in operation (age). A problem with this measure is that it assumes that the plant accrues a similar level of experience each year, which is unrealistic since production levels, which give rise to experience, are likely to vary from year to year. Our second measure is a plant-specific index of cumulative production up to *t-1*. The index is scaled by the level of

[9] The effect of embedded technological change on productivity is quantitatively significant. Jensen et al. (2001) find that the 1992 cohort of new entrants into the U.S. manufacturing industry were, on average, more than 50% more productive than the 1967 entrants in their year of entry, even after accounting for industry-wide factors and input differences.

production in the first year of operations of the plant.[10] This measure takes into account Arrow's assumption that learning will vary according to the degree of exposure to production experience. A similar measure, cumulative production without scaling by production in the first year, has been commonly used in the empirical learning-by-doing literature (Bahk and Gort (1993)). The absence of scaling, however, is problematic in panel data regressions since differences in the scale of production across plants are likely to confound the effect of experience on productivity for individual plants. Thus, we believe that our plant-specific cumulative production index is a better measure.

When accounting for learning-by-doing effects, the functional form is as important as the specific measures of output experience used. As Young (1991) pointed out, empirical studies of learning-by-doing have mostly ignored Arrow's (1962) assumption that learning-by-doing is subject to sharply diminishing returns. The problem is that output experience measures have been most often included as logarithmic terms, implying an unbounded effect of experience on productivity. Taking this criticism into account, we enter our output experience measures in the production function in reciprocal form. This functional form implies that the effect of experience on productivity converges to zero, and we expect to find a negative and significant β_{YE} in our regressions for evidence of learning-by-doing effects.

By analogy to the output experience variables, we define export experience alternatively as the number of years in which the plant has exported up to *t-1* or as an index of cumulative exports up to *t–1*. Similarly to the cumulative output index, the plant's cumulative exports are scaled by the

[10] This means that the index takes a value of one in the second year of operations of the plant.

level of exports in the first year the plant has exported. Unfortunately, we cannot use a reciprocal functional form in our regressions because both indexes of plant export experience are zero for the majority of observations in the sample.

Given our definitions of output and export experience, we need to restrict our main estimating sample to plants born in 1981 or later, the first year when information on exports is included in the census.[11] Besides limiting our sample to plants born in or after 1981, we require plants to have a minimum of three years of data and have positive values for the key variables output, labor, intermediate inputs, capital, and wage premium. We exclude plants that do not report data in some year between their first and last year in the survey and plants belonging to industries with less than 100 plant-year observations. In addition, given that our output and export experience measures depend on cumulative output and exports up to *t-1*, we exclude from the estimating sample the first observation of each plant. Applying these criteria, we obtain a sample of 3,324 young plants and 16,706 plant-year observations. Finally, since our estimation procedures are sensitive to outliers, we reduce further our sample to 3,091 plants and 15,457 plant-year observations. The criteria for the elimination of outliers are described in Appendix B. To compare the effect of export experience on productivity in young and old plants, Section 6 uses a larger sample including both young and old plants. The latter plants appear continuously in the Colombian manufacturing census since 1974. This sample includes 6,171 plants and 46,574 plant-year observations.

[11] A limitation of this procedure is that some of the "new" plants in 1981 could have actually been born before 1981, but were smaller than the cutoff level of ten employees required to fill out the census form. Similarly, if a new owner acquires a previously operating plant and registers it under a different name, it might be coded in the census as a new plant. Since we do not have information to sort out these potential sources of error, we consider plants that appear for the first time in the census as new plants.

We find that young plants are much smaller, since on average they employ one third of the labor and produce one fifth of the output of old plants. While the use of skilled labor by young and old plants is similar, the wages in the former are about one fourth lower than those in old plants. Young plants invest substantially more than old plants, with an investment/output ratio about 70% higher. Consequently, their capital is of a much newer vintage. This is perhaps the reason why young plants' TFP is only about 7% lower than that of old plants, although their labor productivity is 35% lower. Finally, while young plants are half as likely to participate in export markets, when they do so, their average exports are only 20% less than those of old plants.

5. Main Results

Some initial insights on the relationship between productivity and exporting can be gained from Figure 1 that shows levels and growth rates of plant TFP before, during, and after the year of entry into export markets. More specifically, the figure plots in bold lines the estimated coefficients of the dummy variables D_{it}^{τ} in regressions of the form $Y_{it} = \alpha + \beta' Z_{it} + \sum_{\tau} \delta_{\tau} D_{it}^{\tau} + \varepsilon_{it}$, where $D_{it}^{0} = 1$ if plant *i* enters the export market at time *t*; $D_{it}^{a} = 1$ (*a*<0) if plant *i* will enter the export market *a* years after time *t*; and $D_{it}^{b} = 1$ (*b*>0) if plant *i* has entered the export market *b* years before time *t*. Z_{it} contains year, industry, and region dummy variables, and Y_{it} is alternatively the level (in logs) and the average annual growth rates of plant *i*'s TFP at time *t* over horizons of one, three, and five years. The thinner lines show 95% confidence intervals around the parameter estimates.

Panel A of Figure 1 shows that the levels of TFP jump up at the time of entry into export markets and remain higher after entry. Although the figure shows some support for the self-selection hypothesis, i.e. that entrants are already more productive before entry, the estimates are not significantly different from zero. Panel B shows that TFP grows about 6% in the year of entry. Productivity growth continues to be positive and significantly different from zero up to four years after entry. Panels C and D show clear trends of increased productivity growth over longer time horizons, ranging from 3% to 4.5% between 3 and 8 years after entry.

While the results in Figure 1 are suggestive of learning-by-exporting, they should be taken with caution as they are not based on a clear-cut comparison between a treatment and a control group of plants. A better approach is based on the estimation of Equation (1) whose results are shown in Table 2 for unmatched (Panel A) and matched samples (Panel B). In both cases the treatment group consists of entrants into export markets, and the control group consists of plants that do not enter export markets during the sample period. To avoid spurious comparisons, all regressions include only one observation for each treated plant, and exclude plants that start exporting in their first year of life. However, the unmatched and matched samples differ dramatically in the number of observations in the control group. While the unmatched sample includes all the observations for all the nonexporters, the matched sample includes a single observation for each nonexporter that is matched to an entrant into export markets in the same industry and year. To obtain the matched sample, we use propensity score matching based on a probit regression explaining entry into export markets at time *t*.[12] The probit includes as regressors

[12] We thank Jens Arnold for sharing his STATA code for matching plants in the same year and industry. In our matching, we ensure that two technical conditions are verified: (i) plants in the matched sample belong to the common support defined by the lowest propensity score of a treated plant and the highest propensity score of a control plant, and (ii) the balancing condition is verified. See Becker and Ichino (2002) and Leuven and Sianesi (2003).

one period lagged values of plant size (labor), wage, capital vintage, productivity, the real exchange rate, the volume of exports in the industry and the region, and the number of exporters in the industry and the region. The number of exporters in the industry, plant size, the real exchange rate, and capital vintage are positively and significantly associated with entry into export markets.

Column (1) of Table 2 (Panel A) shows estimates of the coefficient β_1 in Equation (1) with average annual growth rates of plant TFP over one to five years horizons as dependent variables. The regressions using the unmatched samples include initial wage, skill, size (labor), capital intensity, and year, industry, and region dummies as controls. The regressions using the matched samples are estimated without additional controls. Due to the small sample size, it is not possible to include a full set of dummy variables as controls. Also, in regressions using only initial wage, skill, size capital intensity as controls, these variables turned out to be statistically insignificant and their inclusion did not change the estimates of the parameter of interest.[13] Interestingly, the estimation results are similar, regardless of the sample used. The average annual rate of growth of TFP of entrants into export markets is around 3% higher than that of nonexporters in the unmatched sample and around 4% higher in the matched sample. The regression results presented in column (2) of Table 2 (Panels A and B) provide a different perspective as they are based on differences in the plant's percentile in the TFP distribution for its industry and year. They suggest that between four and five years after entry, entrants into export markets advance 12 to 14 percentiles in their industry's TFP distribution.[14]

[13] Incidentally, the lack of significance of the controls suggests that the matching method is accurate in identifying nonexporters with very similar characteristics to those of the entrants into export markets.
[14] Note that although the sample size is substantially smaller, the standard errors in the regressions with the matched samples are only about 50% higher than those in the regressions with the unmatched samples.

The results in Table 2 are also suggestive of the presence of learning-by-exporting effects. However, as argued in Section 1, a dummy to identify entrants into export markets does not accurately capture their exposure to export activities. In Table 3, we present estimates of Equation (6) using both OLS with industry dummies and fixed plant effects. The fixed effects or within estimates are obtained by subtracting from each variable x_{it} its plant-specific mean over time $x_{i.}$ before estimation by OLS.[15] All regressions include year dummies. Since conventional F-tests reject the null hypothesis of no fixed effects, we focus on the results with fixed effects, although we also present OLS results for comparison. Interestingly, in all cases age has an unexpected sign, indicating that productivity decreases as plants get older. In contrast, the cumulative output index has always the expected positive sign. These results suggest that it is the intensity of exposure to production activities, and not the mere passage of time, that contributes to learning-by-doing.[16] Our measures of export experience are positive and significant in all regressions in Table 3. In the fixed effects regressions, plant TFP increases 4.8% for each additional year of export experience and 2.1% for an increase of one standard deviation (about 10) in the cumulative exports index.

Two counterarguments can be made to the proposition that export experience increases productivity. A first counterargument is that although plants typically experience a boost in measured TFP during the years when they export, this boost may not reflect a true productivity increase but merely a higher utilization of existing factors in response to the increased demand

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[15] We also estimated random effects specifications but found that often the Hausman test rejected the exogeneity of the regressors with respect to the random plant effects, making the fixed effects specification more appropriate.

[16] Olley and Pakes (1996) also find that age is inversely associated with plant productivity. Levhari and Sheshinski (1973) find that average workers' age is insignificant when average workers' experience is included in the production function.

facing the plant. To examine this possibility, we include in columns (3), (4), (8) and (9) of Table 3 a current exports dummy. As expected, we find that while plants increase substantially their TFP in the years when they export (about 7% in the fixed effects regressions), the effect of export experience remains positive and statistically significant. Moreover, in the fixed effects regressions, the estimated coefficients of export experience are essentially unchanged, with or without the current exports dummy.

A second counterargument is that exporters are better and more productive regardless of how much export experience they have. One way to investigate this possibility is to include an exporter dummy variable (equal to 1 for plants that export in at least one year) in the regressions. The results in columns (5) and (10) of Table 3 show that the export experience variables remain positive and statistically significant after accounting for the fact that exporters are on average more productive than nonexporters. Another way to address this point is by reestimating the regressions in columns (1)-(4) and (6)-(9) of Table 3 for the subsample of plants that export at least once during the sample period (2,576 observations). The results, available from the authors upon request, are very similar to those in Table 3. The coefficients on the numbers of years exported decrease slightly (to 4.3% and 3.5%, respectively, in the fixed effects regressions with or without the current exports dummy), but remain highly significant.

A potential concern with the results in Table 3 is that our TFP measures may be serially correlated. In fact, the main identifying assumption in the LP methodology used for the estimation of the production function is that productivity follows a Markov process, which plant managers can forecast before choosing their variable inputs. One way to address this possibility is by allowing the error term in Equation (6) to be autoregressive. Given the significance of plant effects found in Table 3, we include a fixed effect f_i to account for unobserved plant heterogeneity in TFP:

$$\hat{a}_{it} = \beta_0 + \beta_{YE} YE_{it} + \beta_{EE} EE_{it} + f_i + u_{it}$$

$$u_{it} = \rho u_{it-1} + \nu_{it}, \quad |\rho| \leq 1, \quad \nu_{it} \sim i.i.d.(0, \sigma_\nu). \tag{6'}$$

This specification leads to the following estimating equation:

$$\hat{a}_{it} = \rho \hat{a}_{it-1} + (1-\rho)\beta_0 + \beta_{YE} YE_{it} - \rho\beta_{YE} YE_{it-1} + \beta_{EE} EE_{it} - \rho\beta_{EE} EE_{it-1} + (1-\rho) f_i + \nu_{it}. \tag{8}$$

As is well known in the econometric literature (Nickell, 1981), fixed effects estimates of this model are biased when $|\rho| < 1$ and $\rho \neq 0$. Therefore, we estimate Equation (8) using the system-GMM method proposed by Blundell and Bond (1998). Note, however, that Equation (8) can be estimated consistently in first differences by OLS if ρ =1:

$$\Delta\hat{a}_{it} = \beta_{YE} \Delta YE_{it} + \beta_{EE} \Delta EE_{it} + \nu_{it} \tag{9}$$

In Table 4, we show the results from estimating Equation (8). As in Blundell and Bond (1998), we estimate the equation imposing no restrictions on the coefficients on the lagged explanatory variables. We assume that output and export experience are predetermined variables, implying that lagged values of those variables and of the dependent variable dated *t-2* and earlier are valid instruments to estimate Equation (8) in first differences. We find, however, that including instruments dated *t-2* leads to a rejection of the Sargan test of overidentifying restrictions. Thus, in our final specification we include as instruments lags of output and export experience variables and of the endogenous variable dated *t–3* or earlier. We find evidence of second order serial correlation in the first differenced residuals of Equation (8) in estimations for the full sample.[17] After extensive experimentation with alternative instruments sets and subsamples, we find evidence of no second order serial correlation only when we estimate Equation (8) for a subsample of young plants with 8 or 9 annual observations. The results presented in Table 4 are based on that subsample. The output experience coefficients change their sign, though age becomes statistically insignificant. Export experience continues to be positively associated with TFP, with each additional year of export experience increasing TFP by about 9% while the coefficient on the cumulative exports index is positive but not statistically significant.[18] The most noticeable result in Table 4, however, is that the estimate of ρ is very close to 1. Using a conventional *t* test of H_0: $\rho=1$ against H_1: $\rho<1$, we fail to reject the null hypothesis in both regressions with p-values of 0.25 and 0.47.

To obtain more information on the time series properties of the variables used in this model, we test for the null hypothesis of unit roots by estimating simple AR(1) specifications by OLS.[19] Our tests cannot reject the null hypothesis of a unit root in our TFP series, with p-values of 0.13 (with year dummies) and 0.46 (without year dummies). The tests overwhelmingly reject the null hypothesis of unit roots in the output and export experience variables. Although unit root tests have low power to distinguish between a random walk and a highly persistent AR(1) process, the evidence suggests that assuming that $\rho=1$ is a reasonable approximation. While estimating

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[17] By construction, the first differenced residuals of Equation (8) follow an MA(1) process; therefore, if v_t is i.i.d. we should find evidence of first order but not of second or higher order correlation in these residuals. The m1 and m2 statistics reported in Table 4 test, respectively, for first and second order serial correlation in the residuals.

[18] For comparison purposes we also estimate for this subpanel the regressions corresponding to Table 3 and find an effect of export experience on TFP that is larger than for the full sample: e.g., the coefficient on the number of years exported in the fixed effects specifications is 5.7%.

[19] Bond et al. (2002) show that the *t*-test on the OLS coefficient of the lagged value of the series has high power when the variance of unobserved heterogeneity is relatively small.

Equation (9) by OLS is perfectly feasible under this assumption, we prefer to estimate the model using a cross-section of long-differences, defined as the difference between the first and last observation of each plant in the sample.[20] This model allow us to focus on the cross-sectional differences in experience and productivity, exploiting the additional variability due to differences in the number of years that plants are in the sample.[21] The results are presented in Table 5 for the full sample and for a subsample of plants that export since their first year in the sample. The results for the full sample, shown in columns (1)-(4), are very similar to those from the fixed effects regressions in Table 3. This is reassuring because under the assumption that $\rho=1$, estimates obtained using the within transformation are consistent. The results suggest that an additional year of export experience increases productivity by 4.2% after accounting for current exports.

In columns (5)-(8) of Table 5 we show the results for the subsample of born exporters. It is important to focus on this group for two reasons. First, as Hallward-Driemeier et al. (2003) point out, focusing on plants that start exporting from their first year eliminates the problem of self-selection of more productive plants into export markets, allowing us to identify a truly causal effect of export experience on plant productivity. Second, when the estimating sample includes observations for which the export experience variables are zero, it is unclear whether the coefficients on those variables are just capturing a one-time boost in productivity when export experience increases from zero to one.[22] By including in the regression only plants with strictly

[20] Recall that since our output and export experience measures depend on cumulative output and exports up to *t-1*, we exclude from the estimating sample the first observation of each plant.

[21] Note that the error term of the long differences between the first (2) and last (T_i) time the plant is in the sample is $\sum_{\tau=3}^{T_i} v_{i\tau}$, which is, by construction, heteroskedastic.

[22] We thank Eduardo Engel for pointing out this possibility.

positive export experience, we ensure that the estimated coefficient captures the effect of the accumulation of additional export experience after entry into export markets on plant productivity. The results for born exporters show that plant TFP increases 7.7% for each additional year of export experience, after accounting for current exports. Since in this subsample the cumulative exports index is always strictly positive, we estimate the regressions with the cumulative exports index expressed in logs, which allows for an easier interpretation. The results suggest that a doubling of the index increases TFP by 7% after accounting for current exports.

6. Extensions

In order to better understand why export experience is conducive to plant learning, we consider in this section several extensions to our main results. A first question is whether only young plants learn from the exposure to export markets. As mentioned above, we focus in this paper on young plants because we observe their full history and measure export experience most accurately. The inclusion of old plants in the analysis requires some assumptions. We assume that old plants showing at least three years with zero exports before exporting for the first time during the 1981-1991 period (for which information on exports is available) are new entrants into export markets. Of course, it is possible that some of these plants have actually exported before 1981, but this criterion eliminates at least the group of established exporters that are likely to export every year.

Table 6 shows estimation results for a variant of Equation (1) using a matched sample. The regressions include two dummy variables identifying young and old entrants into export markets.

These specifications allow us to determine if young plants experience better performance after entering into export markets than old plants. As for Table 2, we find that control variables are insignificant and do not alter the estimated coefficients of interest; thus Table 6 shows results from regressions that do not include controls. Columns (1) and (2) show the estimated coefficients on the dummies for young and old entrants into export markets in regressions with the average annual growth rate of TFP as dependent variable. Note that young plants entering into export markets experience average annual rates of TFP growth around 3.5% faster than nonexporters over horizons of two to five years after entry, while old entrants' grow over the same horizons around 1.8% faster than nonexporters. Columns (3) and (4) also show differences in the changes of the plants' relative position in their industry-year TFP distribution. Young plants entering into export markets move up 10 percentile points five years after entry compared to nonexporters, twice as much as old plants.

Table 7 shows the results from estimating Equations (6) and (9) with an interaction term to capture differences in the impact of export experience on TFP for young and old plants. As in Table 5, we estimate Equation (6) with fixed effects and Equation (9) as a cross section of long differences. We present results for the full sample in columns (1)-(4) and for the subsample of exporters in columns (5)-(8). We include the current exports dummy in all regressions. The results indicate that young plants learn significantly more from exporting than old plants. On average the effect of an additional year of export experience on TFP is 6.3% for young plants and 1.9% for old plants, and the coefficient on the cumulative exports index is 7 times higher for young plants compared to old plants.

Another important question to investigate is whether results change when output experience and export experience are included directly in the production function as in Equation (7), the so-called one-step approach. Table 8 presents results for the five Colombian manufacturing industries with the largest number of young plants.[23] For simplicity, we show only the estimated coefficients on output and export experience variables. Export experience is measured either as the number of years the plant has exported or as the plant's cumulative exports index. We study whether the inclusion of a current exports dummy or an exporter dummy affects the estimated export experience effect. The results confirm the findings from our two-step regressions. Plant productivity decreases with age but increases with cumulative output experience and the coefficients on age and the cumulative output index tend to be statistically significant. As in Section 5, it appears as if the intensity of exposure to production activities, which is a better measure of experience than the number of years a plant has produced, leads to learning-by-doing.

The number of years the plant exported has a positive effect on TFP that is statistically significant in all but one of the LP regressions. The sign and significance of this effect is robust to the inclusion of either the current exports dummy or the exporter dummy in the production function equation. On average, an additional year of exports increases plant TFP by 5.4% without controls, by 4.7% when controlling for the exporter dummy, and by 3.4% when controlling for the current exports dummy. These estimates are on average consistent with those obtained using the two-step approach, but there are differences across industries: the effect is larger in the food processing and clothing industries and smaller in the plastics and metal products industries. The cumulative exports index is positive and statistically significant in most of the LP regressions, and three of the five

[23] These industries are the same as those shown in Table A1 of Appendix A.

cases in which it is not significant occur for the metal products industry. Including the current exports dummy does not alter the positive sign or the significance of the coefficient on the cumulative exports index. This coefficient is less robust, though, to the inclusion of the exporter dummy: in the food products and plastics industries, it remains positive but not statistically significant. These industry-specific results suggest that the relationship between export experience and productivity might vary across industries. Our last question is whether we can explain this variation.

We explore two hypotheses to explain differences in learning-by-exporting across industries. The first hypothesis is that plants have more scope for learning-by-exporting when they export to high-income countries. This hypothesis is motivated by the presumption that consumers in high-income countries are more discriminating about the quality of the goods they import. Therefore, their markets are likely to be more competitive than the markets of low-income countries. As a result, Colombian manufacturers exporting to those countries will face higher demands on such aspects as product quality, delivery time, and post-sale services, which in turn give managers and workers more opportunities for learning and productivity enhancement.

To investigate this possibility, we construct an additional variable using data from the *World Trade Flows, 1980-1997* database (WTDB) compiled by R. Feenstra: the share of industry exports going to high-income countries.[24] The list of high-income countries is obtained from the World Bank.[25] To match these additional data to our main dataset, we convert the industry classification codes of the WTDB files from the U.S. Department of Commerce Bureau of

[24] The data can be downloaded from http://data.econ.ucdavis.edu/international/.

Economic Analysis's industry classification into the ISIC rev. 2 by aggregating the twenty four industries in our sample into twenty industries before conducting the regression analysis. It should be noted that during the sample period a rather large share of Colombian manufacturing exports went to Panama and the Netherlands Antilles. Since these are important ports for transshipments, we assume that the share of Colombian exports to these countries that are transshipped to high-income countries in each industry can be approximated by the share of exports of Panama and the Netherlands Antilles in that industry that go to high-income countries.

In Table 9 we show regression results from estimating a modified version of Equation (6) to which we add the interaction between an export experience variable the share of industry exports going to high-income countries. We estimate all the regressions in Table 9 by fixed plant effects, and include the current exports dummy. The results in columns (1) and (2) show that the interaction between any of the export experience variables and the share of industry exports going to high-income countries is always positive and significant. To gain a better perspective on the economic significance of these estimates, we compare the textile and clothing industries, which direct on average 70% of their exports to high-income countries during the sample period, with the metal products industry (ISIC 381), whose share of exports going to high-income countries is only 24%. A simple calculation based on the regression results shows that an additional year of export experience increases TFP by 5.6% in the textile and clothing industries compared to 2.7% in the metal products industry. Similarly, the coefficient on the cumulative exports index is 2.5 higher in the textile and clothing industry than in the metals products industry.

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[25] http://www.worldbank.org/data/countryclass/countryclass.html.

The second hypothesis is that learning-by-exporting is positively associated with the total value of exports of the industry. This hypothesis is motivated by the possibility that network externalities facilitate the access to export markets. A higher value of exports from a particular Colombian industry may suggest that such industry has more developed channels of distribution, making it easier for newcomers to export markets to start exporting. If correct, this perspective implies that in industries characterized by low value of exports the barriers of access to export markets are substantial. In those industries, we should not find much evidence of learning-by-exporting due to the difficulties faced by plants in trying to establish themselves as exporters.

In columns (3) and (4) of Table 9 we show regression results from estimating a modified version of Equation (6) to which we add the interaction between an export experience variable and the log of the value of industry exports.[26] The results provide support to this hypothesis as well. In all cases the coefficients on the interaction between one of the export experience variables and the value of industry exports are positive and significant, while the coefficients on the experience variables per se are negative. To interpret the results, consider again the differences between the textile and clothing industries, with average annual exports of $327 millions during the sample period, with the metal products industry, which exports only $29 millions per year. Using the estimates in columns (3) and (4), we find that an additional year of export experience increases TFP by 6.3% in the textile and clothing industries compared to 2.5% in the metal products industry. Similarly, the coefficient on the cumulative exports index is 3.4 times higher in the textile and clothing industry than in the metals products industry.

[26] Industry exports are measured in thousands of current U.S. dollars.

7. Conclusion

While the hypothesis that firms improve their productivity when exposed to competitive export markets—learning-by-exporting—is intuitively appealing, the corresponding empirical evidence has been inconclusive. Researchers have often favored the alternative hypothesis that firms that improve their productivity self-select into export markets. In this paper we consider the parallels between learning-by-exporting and learning-by-doing. From Arrow's (1962) classical study of learning-by-doing, we know that learning occurs when workers and managers gain experience in solving new technical and organizational problems, and that learning associated with repetitive tasks is subject to sharply diminishing returns. Arrow's characterization of learning-by-doing applies to learning-by-exporting because firms breaking into export markets need to solve new problems, such as adopting new technical standards, introducing more efficient equipment, and ensuring product quality to satisfy sophisticated consumers. Drawing on this characterization, we focus our empirical investigation of learning-by-exporting on young plants, which are much more likely than old, established plants to face new technical and organizational challenges. We also favor using measures of export experience to study whether productivity improvements are associated with the extent of exposure to export markets.

We find strong evidence of learning-by-exporting for our sample of young Colombian manufacturing plants. First, we find that young plants that enter export markets experience annual average rates of TFP growth between 3% and 4% higher than those of young plants that never export. This gap is robust to the use of matching methods and to the use of the plant percentile in the industry-year distribution of TFP as an alternative measure of performance. Second, we find that TFP increases between 4% and 5% for each additional year a plant has exported, after accounting for the effect of current exports on TFP. A particularly important issue in our empirical specification is to take into account the persistence of TFP. In our data we cannot reject the hypothesis that TFP has a unit root. Therefore, using differences or the within transformation produces consistent estimates of the effect of export experience on plant TFP. Third, our results on export experience are robust to the use of different subsamples of our main dataset, such as the subsample of plants that export in at least one year (exporters) and the subsample of plants that start exporting from their first year (born exporters).

Fourth, using a larger dataset that includes also old, established plants, we compare the effect of entry into export markets and export experience on TFP for young and old plants. We find that the gap in annual average rates of TFP growth between entrants to the export markets and nonexporters is 3.5% for young plants compared to 1.8% for old plants. We also find that each additional year of export experience increases TFP by 6.3% in young plants, compared to 2% in old plants. Fifth, we include export experience directly in the estimation of the production functions of the five largest Colombian manufacturing industries, the so-called one-step approach. The results confirm that export experience variables have a positive and generally significant effect on young plants' TFP. The estimates of the effect of an additional year of export experience on TFP range between 3.4% and 5.4% on average, which are consistent with those obtained using the two-step approach. These regressions uncover important differences in the magnitude of the learning-by-exporting effect across industries. To explain these differences, we augment the dataset with Colombian export data by industry and country of destination. Our results, using the two-step approach, suggest that young Colombian manufacturing plants learn the most from exporting if they produce in industries that (i) deliver a larger percentage of their exports to high-income countries and (ii) are characterized by a larger volume of exports.

As mentioned in Section 1, evidence of improvements in productivity at the microeconomic level has supported various trade and development policies. Our robust evidence of TFP improvements for young plants as a result of learning-by-exporting points to two general policy recommendations. The first is to avoid policies that discourage access of domestic plants to export markets. Since plant productivity increases with cumulated export experience, policy makers should try to avoid policies that lead to marked drops or instability in the profitability of exporting. The second recommendation is to foster a competitive business environment that facilitates the reallocation of factors of production toward their most efficient uses. As young plants clearly benefit from exporting, an institutional framework that facilitates the process of creative-destruction by which failing plants give rise to new plants will allow the expedient redeployment of resources and entrepreneurial talent to productivity-enhancing exporting activities.

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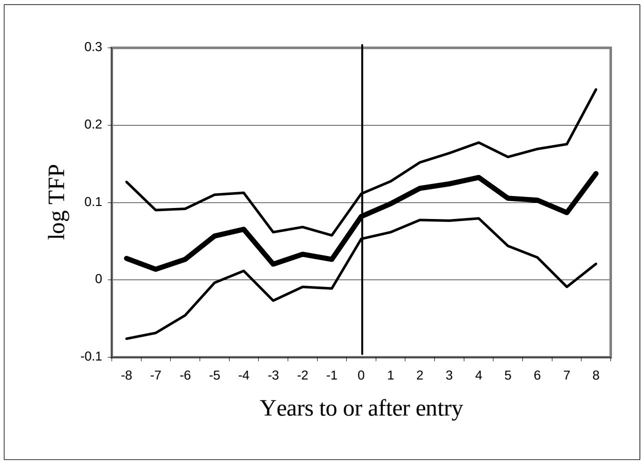
Table 1: Selective Review of Learning-by-Exporting (LBE) Studies using Plant-level Data [a]

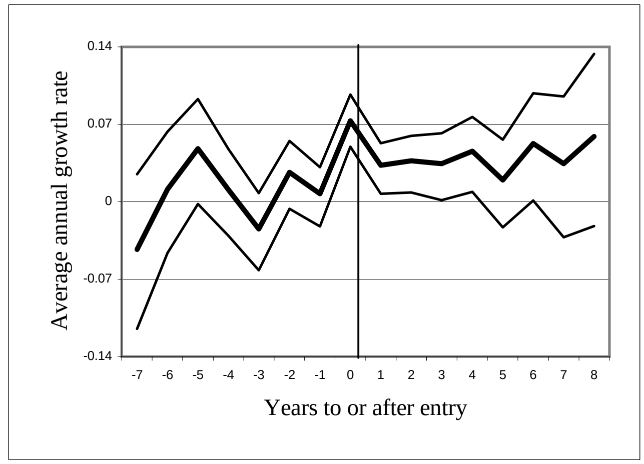
Study, Country, and Sample Period	Measurement Method and Estimation Technique [b]	Evidence of LBE?
Bernard & Wagner (1997): Germany 1978-1992	(1) OLS	No
Clerides et al. (1998): Colombia 1981-1991, Morocco 1984-1991	(2) FIML including an equation for export participation (2) GMM	No Some (Morocco)
Bernard and Jensen (1999): USA 1984-1992	(1) OLS	No
Kraay (1999): China 1988-1992	(2) Instrumental variables (lagged export intensity)	Yes
Aw et al. (2000): Taiwan 1981, 1986, and 1986; Korea 1983, 1988, and 1993	(1) OLS	Some (Taiwan)
Isgut (2001): Colombia 1981-1991	(1) OLS	No
Delgado et al. (2002): Spain 1991-1996	(1) Nonparametric estimation	Some (young plants)
Castellani (2002): Italy 1989-1994	(1) OLS (1) OLS (export intensity in t=0)	No Yes
Hallward-Driemeier et al. (2002): Indonesia, Korea, Malaysia, Phillipines, Thailand 1999	(1) OLS, cross section (dummy for born exporters)	Yes (except Korea)
Fafchamps (2002): Morocco 1999	(1) Instrumental variables, cross-section (years since first export)	No
Baldwin & Gu (2003): Canada 1974, 1979, 1984, 1990, and 1996	(1) OLS (2) SYS-GMM	Yes Yes
Van Biesebroeck (2004): Cameroon, Kenya, Tanzania, Zambia, Zimbabwe 1992-1994; Ghana 1991-1993; Cote d'Ivoire 1994-1995	(2) SYS-GMM (2) FIML as in Clerides et al. (2) OP	Yes Yes Yes
Girma et al. (2004): UK 1988-1999	(1) Matched samples	Yes
Bigsten et al. (2004): Cameroon, Kenya, Ghana, and Zimbabwe 1992-1995	(2) FIML as in Clerides et al. (2) FIML nonparametric errors	No Yes
Hahn (2004): Korea 1990-1998	(1) OLS	Yes
Blalock and Gertler (2004): Indonesia 1990-1996	(2) Various (contemporaneous exports)	Yes
Arnold and Hussinger (2004): Germany 1992-2000	(1) Matched samples	No
De Loecker (2004): Slovenia 1994-2000	(1) Matched samples	Yes
Alvarez and Lopez (2004): Chile 1990-1996	(1) OLS	No

Notes: (a) The information included in this table is based on what we consider to be the main regression(s) used to measure learning-by-exporting effects in each of the papers cited. (b) Most studies use dummy variables to define the treatment group of exporters or to indicate whether the firm has exported in a previous period; other types of export variables are noted in parentheses. When a study uses more than one method, we enter them in separate rows in the same cell.

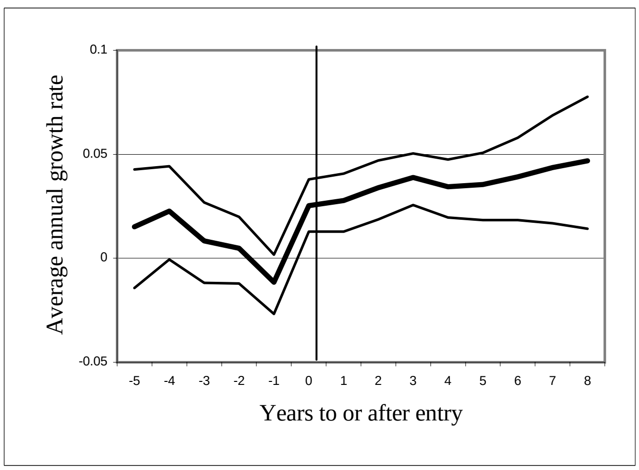
Figure 1: Plant TFP and TFP Growth Before and After Entry into Export Markets



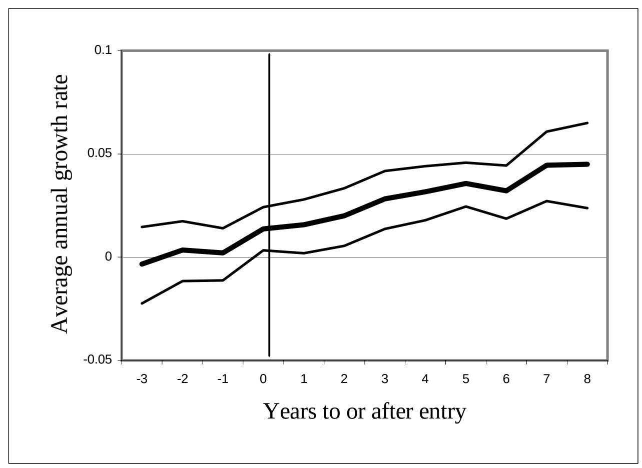
A. TFP Levels



B. TFP Growth over One-year Horizons



C. TFP Growth over Three-year Horizons



D. TFP Growth over Five-year Horizons

Table 2: Average Annual Growth Rate of Plant TFP and Plant TFP Percentile Changes after Entry into Export Markets

A. Unmatched Sample

Time Horizon	Number of Entrants	Number of Nonexporters	TFP Growth (1)	TFP Percentile (2)
1 Year	231	12881	0.015	1.3
			(0.014)	(1.5)
2 Years	154	10255	0.030 ***	5.5 ***
			(0.010)	(2.0)
3 Years	106	7629	0.026 ***	5.1 **
			(0.008)	(2.6)
4 Years	76	5604	0.037 ***	14.0 ***
			(0.008)	(3.2)
5 Years	56	3953	0.030 ***	12.8 ***
			(0.007)	(3.8)

B. Matched Sample

Time Horizon	Number of Entrants	Number of Nonexporters	TFP Growth (1)	TFP Percentile (2)
1 Year	228	187	0.036 *	1.8
			(0.021)	(2.2)
2 Years	151	126	0.058 ***	10.0 ***
			(0.016)	(3.3)
3 Years	103	94	0.041 ***	9.2 **
			(0.014)	(4.0)
4 Years	73	66	0.043 ***	14.3 ***
			(0.011)	(4.7)
5 Years	53	48	0.033 ***	11.8 **
			(0.010)	(4.6)

Notes: Standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence levels, respectively. TFP percentile indicates the percentile in the TFP distribution for the plant's industry in a given year. In Panel B, the sample used in the regressions is a matched sample where each entrant into export markets is matched to a control plant in the same industry and year.

Table 3. The Effect of Learning-by-Doing and Learning-by-Exporting on Plant Productivity

	OLS (1)	Fixed Effects (2)	OLS (3)	Fixed Effects (4)	OLS (5)	OLS (6)	Fixed Effects (7)	OLS (8)	Fixed Effects (9)	OLS (10)
Number of Years Plant Exported	0.039***	0.048***	0.022***	0.047***	0.028***					
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)					
Cumulative Exports Index						0.0029***	0.0020***	0.0024***	0.0020***	0.0026***
						(0.0007)	(0.0004)	(0.0007)	(0.0004)	(0.0007)
Current Exports Dummy			0.085***	0.066***				0.104***	0.070***	
			(0.015)	(0.011)				(0.012)	(0.011)	
Exporter Dummy					0.045***					0.066***
					(0.010)					(0.008)
Inverse of Plant Age	0.351***	0.123***	0.330***	0.116***	0.335***	0.350***	0.140***	0.320***	0.132***	0.324***
	(0.035)	(0.045)	(0.035)	(0.045)	(0.035)	(0.035)	(0.044)	(0.035)	(0.044)	(0.035)
Inverse of Cumulative Output Index	-0.282***	-0.097**	-0.265***	-0.091**	-0.268***	-0.288***	-0.115***	-0.259***	-0.108***	-0.260***
	(0.032)	(0.040)	(0.032)	(0.040)	(0.032)	(0.032)	(0.040)	(0.032)	(0.040)	(0.032)
Industry Effects (3-digit)	Yes		Yes		Yes	Yes		Yes		Yes
N. Observations	15457	15457	15457	15457	15457	15457	15457	15457	15457	15457
R-squared	0.95	0.99	0.95	0.99	0.95	0.95	0.99	0.95	0.99	0.95

Notes: Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence levels, respectively. All regressions include year dummies. The Current Exports Dummy equals 1 for plant *i* in year *t* if plant *i* engages in exports in year *t*. The Exporter Dummy equals 1 for plant *i* in all years if plant *i* engages in exports in at least one sample year.

Table 4. Accounting for Plant Productivity Dynamics

	System-GMM (1)	System-GMM (2)
Lagged Productivity *(t-1)*	0.995 ***	0.999 ***
	(0.008)	(0.006)
Number of Years Plant Exported *(t)*	0.092 **	
	(0.037)	
Lagged Number of Years Plant Exported *(t-1)*	-0.097 **	
	(0.043)	
Cumulative Export Index (*t*)		0.0013
		(0.0018)
Lagged Cumulative Export Index (*t*-1)		-0.0010
		(0.0024)
Inverse of Plant Age *(t)*	-1.213	-1.528
	(1.893)	(1.852)
Lagged Inverse of Plant Age *(t-1)*	1.185	1.474
	(1.292)	(1.265)
Inverse of Cum. Output Index *(t)*	1.578 *	1.925 **
	(0.912)	(0.878)
Lagged Inverse of Cum. Output Index *(t-1)*	-1.287 *	-1.588 **
	(0.776)	(0.751)
N. Observations	3038	3038
Tests of GMM Consistency (P-values)		
Sargan	0.270	0.262
m1	0	0
m2	0.215	0.208

Notes: The dependent variable is current productivity. All regressions include year dummies. Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence levels, respectively. The sample consists of plants remaining in the sample for 8 years or longer. The Current Exports Dummy equals 1 for plant *i* in year *t* if plant *i* engages in exports in year *t*. Lags dated *t-3* and earlier of the output experience variables, the export experience variable and the dependent variable are used as instruments in the first difference equation. The first difference dated *t-2* of the output experience variables, the export experience variable and the dependent variable are used as instruments in the levels equation. m1 is a test for first order serial correlation in the residuals of the first-differenced equation and m2 is a test for second order serial correlation in the residuals of the first-differenced equation.

Table 5. The Effect of Learning-by-Doing and Learning-by-Exporting on Plant Productivity Using Cross-Sections of Long Differences

	Full Sample				Subsample of Born Exporters			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Number of Years Plant Exported	0.046***	0.042***			0.078***	0.077***		
	(0.005)	(0.005)			(0.018)	(0.018)		
Δ Cumulative Exports Index			0.0017***	0.0017***			0.071**	0.070**
			(0.0003)	(0.0003)			(0.035)	(0.035)
Δ Current Exports Dummy		0.093***		0.111***		0.104**		0.108**
		(0.019)		(0.019)		(0.049)		(0.050)
Δ Inverse of Plant Age	0.319***	0.308***	0.336***	0.321***	0.714*	0.531	0.076	-0.103
	(0.071)	(0.071)	(0.072)	(0.071)	(0.388)	(0.385)	(0.392)	(0.398)
Δ Inverse of Cum. Output Index	-0.167***	-0.148**	-0.206***	-0.179***	-0.311	-0.171	-0.212	-0.072
	(0.065)	(0.065)	(0.065)	(0.065)	(0.375)	(0.370)	(0.426)	(0.433)
N.Observations	3091	3091	3091	3091	130	130	130	130
Adjusted R-squared	0.04	0.04	0.02	0.03	0.36	0.37	0.26	0.28

Notes: The dependent variable is the change in productivity between the last and the first year of the plant in the sample. The symbol Δ represents, for any regressor, the change in that regressor between the last and the first year of the plant in the sample. All regressions include year dummies. Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence levels respectively. The Current Exports Dummy equals 1 for plant i in year t if plant i exports in year t. In columns (5)-(8) the cumulative exports index is expressed in logs.

Table 6. Average Annual Growth Rate of Plant TFP and Plant TFP Percentile Changes after Entry into Export Markets for Young and Old Plants

Time Horizon	Number of Young Entrants	Number of Old Entrants	Number of Nonexporters	TFP Growth		TFP Percentile	
				Young Plants (1)	Old Plants (2)	Young Plants (3)	Old Plants (4)
1 Year	216	301	405	0.028	0.025	3.0	1.4
				(0.017)	(0.015)	(1.9)	(1.4)
2 Years	151	244	310	0.037 ***	0.010	10.6 ***	1.5
				(0.012)	(0.010)	(2.6)	(1.7)
3 Years	104	202	244	0.031 ***	0.018 **	13.4 ***	2.9
				(0.010)	(0.008)	(3.6)	(2.1)
4 Years	73	169	195	0.038 ***	0.019 **	17.4 ***	2.7
				(0.010)	(0.008)	(4.7)	(2.4)
5 Years	54	135	148	0.033 ***	0.021 **	16.0 ***	4.3
				(0.009)	(0.007)	(6.1)	(3.0)

Notes: Standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence levels, respectively. The sample used in the regressions is a matched sample where each entrant into export markets is matched to a control plant in the same industry and year. Columns (1) and (2) show coefficients obtained from a single regression for each time horizon having TFP growth as dependent variable. Columns (3) and (4) show coefficients obtained from a single regression for each time horizon having TFP percentile as dependent variable.

Table 7. The Effect of Learning-by-Doing and Learning-by-Exporting on Plant Productivity for Young and Old Plants

	Full Sample				Subsample of Exporters			
	Fixed Effects		Long Differences		Fixed Effects		Long Differences	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of Years Plant Exported * Young	0.067***		0.057***		0.065***		0.061***	
	(0.004)		(0.007)		(0.005)		(0.010)	
Number of Years Plant Exported * Old	0.022***		0.018**		0.017***		0.020**	
	(0.003)		(0.007)		(0.004)		(0.009)	
Cumulative Exports Index * Young		0.0027***		0.0024***		0.0024***		0.0019***
		(0.0004)		(0.0007)		(0.0004)		(0.0007)
Cumulative Exports Index * Old		0.0004***		0.0003		0.0003**		0.0004
		(0.0001)		(0.0003)		(0.0001)		(0.0003)
Current Exporter Dummy	0.076***	0.087***	0.115***	0.142***	0.069***	0.055***	0.127***	0.092***
	(0.006)	(0.006)	(0.166)	(0.015)	(0.007)	(0.007)	(0.022)	(0.021)
Inverse of Plant Age	0.223***	0.225***	0.416***	0.438***	0.354***	0.279***	0.801***	0.783***
	(0.040)	(0.040)	(0.082)	(0.082)	(0.107)	(0.104)	(0.252)	(0.252)
Inverse of Cumulative Output Index	-0.194***	-0.209***	-0.405***	-0.441***	-0.311***	-0.313***	-0.755***	-0.817***
	(0.037)	(0.037)	(0.077)	(0.077)	(0.097)	(0.095)	(0.231)	(0.230)
N. Observations	40208	40208	5455	5455	6351	6351	806	806
R-squared	0.99	0.99	0.06	0.05	0.99	0.99	0.21	0.18

Notes: The dependent variable is plant productivity in columns (1), (2), (5) and (6) and the change in productivity between the last and the first year of the plant in the sample in columns (3), (4), (7) and (8). All regressions include year dummies. Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence levels, respectively. The Current Exporter Dummy equals 1 for plant i in year t if plant i engages in exports in year t.

Table 8. Results from One-Step Estimation of the Effect of Learning-by-Doing and Learning-by-Exporting on Plant Productivity

	Number of Years Exported			Cumulative Exports Index		
	(1)	(2)	(3)	(4)	(5)	(6)
311 Food Products (1937 Obs.)						
Inverse of Plant Age	0.072	0.026	0.116	0.175 *	0.144 *	0.057
	(0.090)	(0.085)	(0.095)	(0.105)	(0.086)	(0.103)
Inverse of Cum. Output Index	-0.070	-0.020	-0.097	-0.151 *	-0.124 *	-0.054
	(0.079)	(0.074)	(0.082)	(0.085)	(0.071)	(0.081)
Export Experience	0.060 **	0.048 *	0.046 **	0.017 *	0.020 *	0.005
	(0.028)	(0.026)	(0.023)	(0.009)	(0.010)	(0.007)
Current Exports Dummy		0.038			0.166 ***	
		(0.045)			(0.047)	
Exporter Dummy			0.103			0.035
			(0.089)			(0.100)
321 Textiles (997 Obs.)						
Inverse of Plant Age	0.087	0.095	0.362 *	0.230	0.345 **	0.193
	(0.174)	(0.165)	(0.219)	(0.165)	(0.169)	(0.174)
Inverse of Cum. Output Index	-0.204 *	-0.213 *	-0.360 **	-0.195	-0.319 ***	-0.183
	(0.122)	(0.124)	(0.171)	(0.130)	(0.106)	(0.125)
Export Experience	0.036 *	0.028 *	0.059 **	0.009 **	0.009 ***	0.009 ***
	(0.020)	(0.016)	(0.026)	(0.004)	(0.002)	(0.003)
Current Exports Dummy		0.133 ***			0.040 *	
		(0.023)			(0.021)	
Exporter Dummy			-0.013			-0.009
			(0.082)			(0.111)
322 Apparel (3045 Obs.)						
Inverse of Plant Age	0.268 ***	0.200 *	0.250 **	0.283 **	0.252 **	0.250 **
	(0.101)	(0.107)	(0.100)	(0.119)	(0.108)	(0.105)
Inverse of Cum. Output Index	-0.216 ***	-0.161 *	-0.206 **	-0.231 **	-0.219 **	-0.210 **
	(0.083)	(0.089)	(0.087)	(0.104)	(0.089)	(0.083)
Export Experience	0.092 ***	0.041 *	0.065 **	0.018 ***	0.013 **	0.015 **
	(0.023)	(0.021)	(0.026)	(0.007)	(0.006)	(0.007)
Current Exports Dummy		0.157 ***			0.159 ***	
		(0.027)			(0.027)	
Exporter Dummy			0.095			0.156 ***
			(0.063)			(0.056)
356 Plastics (914 Obs.)						
Inverse of Plant Age	0.320 *	0.362 *	0.280 *	0.268 *	0.288 *	0.223
	(0.181)	(0.187)	(0.160)	(0.142)	(0.149)	(0.164)
Inverse of Cum. Output Index	-0.262 *	-0.279 **	-0.247 **	-0.240 **	-0.257 **	-0.233 **
	(0.136)	(0.131)	(0.115)	(0.094)	(0.108)	(0.110)
Export Experience	0.038 **	0.026 *	0.034 **	0.003 **	0.002 *	0.002
	(0.016)	(0.015)	(0.014)	(0.002)	(0.001)	(0.0017)
Current Exports Dummy		0.077 *			0.068 *	
		(0.041)			(0.037)	
Exporter Dummy			0.044			0.106
			(0.075)			(0.089)
381 Metal Products (1218 Obs.)						
Inverse of Plant Age	0.187 *	0.222 *	0.188	0.226 *	0.266 **	0.238 *
	(0.108)	(0.117)	(0.118)	(0.118)	(0.125)	(0.127)
Inverse of Cum. Output Index	-0.168 **	-0.195 **	-0.171 *	-0.205 **	-0.232 **	-0.199 *
	(0.082)	(0.097)	(0.098)	(0.100)	(0.107)	(0.110)
Export Experience	0.045 **	0.024	0.030 *	0.001	0.001	0.001
	(0.023)	(0.017)	(0.018)	(0.006)	(0.004)	(0.004)
Current Exports Dummy		0.114 **			0.094 *	
		(0.057)			(0.049)	
Exporter Dummy			0.075			0.160 *
			(0.079)			(0.083)

Notes: All coefficients are obtained from regressions that include also additional inputs (labor, wage premium, skill intensity, materials, capital and vintage) estimated by a modified Levinsohn-Petrin procedure. Bootstrapped standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence levels, respectively.

Table 9. The Effect of Export Experience on Plant Productivity Differentiated by Export Destination and Value of Exports in the Industry

	(1)	(2)	(3)	(4)
Number of Years Plant Exported	0.012		-0.140***	
	(0.008)		(0.031)	
Cumulative Exports Index		0.0002		-0.0130**
		(0.0005)		(0.0056)
Number of Years Plant Exported * Share of Industry Exports to High Income Countries	0.063***			
	(0.014)			
Cumulative Exports Index * Share of Industry Exports to High Income Countries		0.0034***		
		(0.0010)		
Number of Years Plant Exported * Log of Value of Industry Exports			0.016***	
			(0.003)	
Cumulative Exports Index * Log of Value of Industry Exports				0.0014***
				(0.0005)
Current Exports Dummy	0.068***	0.070***	0.681***	0.070***
	(0.011)	(0.011)	(0.011)	(0.011)
Inverse of Plant Age	0.114***	0.135***	0.111**	0.131***
	(0.044)	(0.044)	(0.045)	(0.044)
Inverse of Cumulative Output Index	-0.089**	-0.111***	-0.089**	-0.108***
	(0.040)	(0.040)	(0.040)	(0.040)
N. Observations	15457	15457	15457	15457
Adjusted R-squared	0.98	0.98	0.98	0.98

Notes: The dependent variable is plant productivity. All the regressions include year dummies and are estimated by fixed (plant) effects. Robust standard errors in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% confidence levels, respectively. The Current Exporter Dummy equals 1 for plant i in year t if plant i engages in exports in year t.

APPENDIX A: ESTIMATION METHOD

A1. Estimation of Equation (5)

We assume that in any year t the manager observes the plant's current productivity ω_{it} before choosing labor l_{it}, labor quality S_{it} and W_{it}, and intermediates m_{it} to combine with the quasi-fixed inputs, capital k_{it} and its quality V_{it} for the production of output y_{it}. Since ω_{it} is known to the plant manager but unknown to the econometrician and may be positively correlated with l_{it}, S_{it}, W_{it} and m_{it}, it generates a potential simultaneity bias that is addressed by our estimation procedure. The plant's variable input demands, derived from profit maximization, depend on privately known productivity, capital, and capital vintage. The intermediate inputs demand function $m_{it} = m(\omega_{it}, k_{it}, V_{it})$ can be inverted to obtain a productivity function by imposing the following monotonicity assumption: conditional on capital and its vintage, the demand for intermediates increases with productivity. Note that the productivity function $\omega_{it} = \omega(m_{it}, k_{it}, V_{it})$ depends on observable variables only. The first stage of the estimation proceeds by rewriting Equation (5) in a partially linear form:

$$y_{it} = \beta_l l_{it} + \beta_S S_{it} + \beta_W W_{it} + \phi(m_{it}, k_{it}, V_{it}) + \varepsilon_{it}, \tag{A1}$$

where

$$\phi(m_{it}, k_{it}, V_{it}) = \beta_o + \beta_m m_{it} + \beta_k k_{it} + \beta_V V_{it} + \omega(m_{it}, k_{it}, V_{it}). \tag{A2}$$

We allow the functions $m(.)$, $\omega(.)$, and $\phi(.)$ to differ across a period of recession (1982-1985) and a period of expansion (1986-1991) in Colombia. Since $E[\varepsilon_{it} \mid m_{it}, k_{it}, V_{it}] = 0$, taking the difference between Equation (A1) and its expectation conditional on intermediate inputs, capital, and vintage generates the following expression:

$$y_{it} - E[y_{it} \mid m_{it}, k_{it}, V_{it}] = \beta_l (l_{it} - E[l_{it} \mid m_{it}, k_{it}, V_{it}]) +$$

$$\beta_S (S_{it} - E[S_{it} \mid m_{it}, k_{it}, V_{it}]) + \beta_W (W_{it} - E[W_{it} \mid m_{it}, k_{it}, V_{it}]) + \varepsilon_{it} \quad \text{(A3)}$$

Equation (A3) is estimated by OLS (with no constant) to obtain consistent parameter estimates for labor, skill intensity, and wage premium. The conditional expectations in Equation (A3) are the intercepts of locally weighted least squares (LWLS) regressions of output, labor, skill intensity, and wage premium on (m_{it}, k_{it}, V_{it}) (see Fernandes (2003) for further details). After obtaining estimates for $(\beta_l, \beta_S, \beta_W)$, we estimate the function $\phi(.)$ as a LWLS regression of $y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_S S_{it} - \widehat{\beta}_W W_{it}$ on (m_{it}, k_{it}, V_{it}).

The second stage of the estimation obtains consistent estimates for $(\beta_m, \beta_k, \beta_V)$, assuming that productivity follows a first order Markov process as in Olley and Pakes (1996): $\omega_{it} = E[\omega_{it} \mid \omega_{it-1}] + \xi_{it}$ where ξ_{it} is the unexpected productivity shock and is independent and identically distributed (i.i.d.). The estimation strategy is based on the identification assumption that capital and capital vintage may be correlated with expected productivity but are uncorrelated with the unexpected productivity shock. The following three moment conditions are obtained by taking the expectation of Equation (5) conditional on, respectively, lagged intermediates, capital, and vintage, taking into account the fact that ω_{it} follows a first order Markov process:

$$E\left[y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_S S_{it} - \hat{\beta}_W W_{it} - \beta_m m_{it} - \beta_k k_{it} - \beta_V V_{it} - E[\omega_{it} \mid \omega_{it-1}] \mid m_{it-1}\right]$$

$$= E[\varepsilon_{it} + \xi_{it} \mid m_{it-1}] = 0 \quad \text{(A4)}$$

$$E\left[y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_S S_{it} - \hat{\beta}_W W_{it} - \beta_m m_{it} - \beta_k k_{it} - \beta_V V_{it} - E[\omega_{it} \mid \omega_{it-1}] \mid k_{it}\right]$$

$$= E[\varepsilon_{it} + \xi_{it} \mid k_{it}] = 0 \quad \text{(A5)}$$

$$E\left[y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_S S_{it} - \hat{\beta}_W W_{it} - \beta_m m_{it} - \beta_k k_{it} - \beta_V V_{it} - E[\omega_{it} \mid \omega_{it-1}] \mid V_{it}\right]$$

$$= E[\varepsilon_{it} + \xi_{it} \mid V_{it}] = 0 \qquad \text{(A6)}$$

Equations (A4)-(A6) indicate that intermediates in year *t-1*, and capital and vintage in year *t* are uncorrelated with the unexpected productivity shock in year *t*. The residuals $\varepsilon_{it} + \xi_{it}$ are calculated using the estimated coefficients $(\hat{\beta}_l, \hat{\beta}_S, \hat{\beta}_W)$, candidate parameter values $(\beta_m^*, \beta_k^*, \beta_V^*)$, and a nonparametric estimate for $E[\omega_{it} \mid \omega_{it-1}]$ obtained as a LWLS regression of $(\omega_{it} + \varepsilon_{it})^* = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_S S_{it} - \hat{\beta}_W W_{it} - \beta_m^* m_{it} - \beta_k^* k_{it} - \beta_k^* k_{it} - \beta_V^* V_{it}$ (from Equation (5)) on $(\omega_{it})^* = \hat{\phi}(m_{it}, k_{it}, V_{it}) - \beta_m^* m_{it} - \beta_k^* k_{it} - \beta_V^* V_{it}$ (from Equation (A2)). We construct a generalized method of moments (GMM) criterion function which weights the plant-year moment conditions, Equations (A4)-(A6), by their variance-covariance matrix. Our estimation algorithm uses OLS estimates of intermediates, capital, and vintage coefficients as initial parameter values and iterates on the sample moment conditions to match them to their theoretical value of zero and reach final parameter estimates. We use a derivative optimization routine complemented by a grid search. When the parameters that minimize the criterion function are obtained from grid search, these parameters are used as initial values for the derivative optimization routine to reach more precise final $(\beta_m, \beta_k, \beta_V)$ values. The standard errors for the parameter estimates are obtained by bootstrap. The bootstrap procedure consists of sampling randomly with replacement plants from the industry's original sample, matching or exceeding in any year the number of plant-year observations in that sample. If randomly selected, a plant is taken as a block (i.e. all of its observations are included in the bootstrap sample). We obtain estimates of

$(\beta_l, \beta_S, \beta_W, \beta_m, \beta_k, \beta_V)$ for 100 bootstrap samples. The standard deviation of a parameter across bootstrap samples constitutes its bootstrapped standard error.

We estimate Equation (5) separately for twenty-four 3-digit ISIC Colombian manufacturing industries. Table A1 shows regression results for the five Colombian industries with the largest number of young plants: food products (ISIC 311), textiles (ISIC 321), apparel (ISIC 322), plastics (ISIC 356), and metal products (ISIC 381). Columns (1) and (2) show results for production functions without factor quality variables, and columns (3) and (4) add wage premium, skill intensity, and vintage. OLS results are shown for comparison. Under the assumption that variable inputs' coefficients are upward biased and quasi-fixed inputs' coefficients are downward biased, the results suggest that the LP procedure corrects these biases for about two-thirds of the estimated parameters. It should be noted that bootstrapped standard errors are larger than OLS standard errors, especially for the coefficients obtained in the second stage of the LP procedure.

A2. Estimation of Equation (7)

The first stage of the estimation is very close to that described above for Equation (5). The main difference is that the productivity function resulting from the inversion of the intermediate inputs demand function depends on additional state variables, the output experience and export experience variables: $\omega_{it} = \omega(m_{it}, k_{it}, V_{it}, YE_{it}, EE_{it})$. Thus, the first stage requires the estimation of LWLS regressions of output, labor, skill intensity, wage premium, and $y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_S S_{it} - \hat{\beta}_W W_{it}$ on $(m_{it}, k_{it}, V_{it}, YE_{it}, EE_{it})$. Note that in some of the variants of Equation (7) presented in the paper we use, instead of LWLS, a third degree polynomial in $\omega_{it} = \omega(m_{it}, k_{it}, V_{it}, YE_{it}, EE_{it})$ to approximate the function $\phi(.)$ and obtain consistent parameter estimates for labor, skill intensity, and wage premium, as well as to obtain an estimate of $\phi(.)$. This choice is made for computational ease, as the two types of approximation give very similar results. In the second stage of the estimation, the GMM criterion function includes two additional moment conditions for the output and export experience variables. The residuals used in the moment conditions subtract from output the contribution of inputs and input quality (as in Equations (A4)-(A6)) but also the contribution of the output and export experience variables.

To check the robustness of our results we also estimate Equation (7) including (i) a dummy variable representing current exports (equal to 1 in any year when the plant is exporting) and (ii) a dummy variable representing exporter status (equal to 1 in all years for a plant if that plant exports in at least one sample year). The coefficient on the current exports dummy is estimated in the first stage of our modified LP procedure because a plant's decision to export, alike the usage of variable inputs, may be affected by productivity shocks not observed by the econometrician. In contrast, the exporter dummy is treated as a state variable thus its coefficient is estimated in the second stage of our modified LP procedure.

APPENDIX B

B1. Price indexes

To obtain price indexes for domestic raw materials, we construct a matrix A with typical element $\{a_{ij}\}$ equal to the share of raw materials originating in industry i in the total value of raw materials used by industry j aggregating data from Colombian input-output matrices for 1992 through 1998. This allows us to obtain a more robust measure of raw materials shares than that obtained using data for a single year. Although the input-output matrices used do not cover our sample period, 1981-1991, we believe that input-output relationships are relatively stable over these two decades. Matrix *A* has 22 rows and 17 columns corresponding to the Colombian national accounts classification of industries. The number of rows exceeds the number of columns because some raw materials used in manufacturing originate in the primary sector. Note that by construction $\sum_{i=1}^{22} a_{ij} = 1$. Hence, our domestic raw materials price indexes are weighted averages of producer price indexes: for each manufacturing industry $j = 1, \ldots, 17$ and time t, the domestic raw materials price index is defined as $p_{jt}^{RM} = \sum_{i=1}^{22} a_{ij} p_{it}$. To perform this calculation we aggregate 29 manufacturing producer price indexes at the 3-digit ISIC revision 2 into 17 producer price indexes at the broader Colombian national accounts classification. We use production weights for the period 1975-1989 to aggregate these price indexes. For the primary sectors included in the calculations we use wholesale price indexes.

The construction of exports price indexes is more involved because the series available from Banco de la República (Colombia's central bank) starts only in 1990. For the period 1975-1990, we construct export price indexes using detailed trade data from the Dirección de Impuestos y Aduanas Nacionales (DIAN). Export transactions in 1975-1990 are recorded at an 8-digit Colombian trade classification (NABANDINA) based on the Brussels Tariff Nomenclature. For each NABANDINA and year, we compute export prices in pesos per unit of weight by dividing the value of exports of each NABANDINA by its weight. This is an imprecise proxy for unit export prices but is the best available because only 5% of the observations have data on units other than weight. Note that even with better information on units, the calculation can be subject to errors due to variation in the mix of products included within each NABANDINA. To minimize potential spurious variation due these measurement problems we follow two procedures. First, we remove from the computations outliers defined as unit export prices whose average annual rate of growth exceeds the 90th percentile or is less than the 10th percentile for the whole sample. Second, we regress the log of the unit export price on a fixed NABANDINA effect, a set of time-industry dummies, and a variable representing the deviation of each export price from the law of one price. This variable is defined as $\log(EXPPES_{it}/EXPDOL_{it}) - \log(E_t)$, where $EXPPES_{it}$ is the value of exports in pesos of NABANDINA i at time t, $EXPDOL_{it}$ is the same value in dollars, and E_t is the average exchange rate at time t. Since NABANDINA positions with very small values of exports are more likely to be affected by measurement problems, we estimate our regression using weighted least squares, with weights proportional to the square root of the constant dollar value of exports. These regressions generate predicted log unit export values for every NABANDINA and year with export data (including positions excluded from the calculations due to outliers). We use these smoothed unit export prices to compute Tornqvist price indexes for each ISIC industry j: $\log p_{jt}^X - \log p_{jt-1}^X = \sum_{i=1}^{I_j} 0.5\left(w_{it}^j + w_{it-1}^j\right)\left(\log p_{it}^j - \log p_{it-1}^j\right)$, where $\log p_{it}^j$ is the estimated log unit export price of NABANDINA i belonging to industry j at time t. The weights w_{it}^j are the share of the value of exports in pesos of NABANDINA i in industry j at time t.

To obtain price indexes for imported raw materials, we first construct import price indexes from the DIAN trade data, following the same procedure as for the export price indexes. Then we follow a similar procedure to that used to construct domestic raw materials price indexes, but instead of using general input-output matrices we use the 1994 Colombian input-output matrix for imported inputs.

B2. Capital stock and capital vintage

Our measure of gross capital is defined as $K_{it} = FIRSTK_i + \sum_{\tau=F_i}^{t-1}(I_{i\tau} - S_{i\tau})$, where $FIRSTK_i$ is capital the plant had before its first year in the sample, F_i is the first year when plant i is in the sample, I_{it} are purchases and S_{it} are sales of capital. I_{it} and S_{it} are obtained by summing, respectively, purchases and sales of four different types of capital goods (buildings and structures, machinery and equipment, transportation equipment, and office equipment) expressed in constant pesos. We use the implicit price index for machinery and equipment to deflate purchases and sales of office equipment since a separate price index for the latter type of capital good is not available.

Our measure of capital vintage is the ratio of net capital to gross capital: $V_{it} = NK_{it}/K_{it}$, where net capital is the conventional measure of capital obtained through the permanent inventory method. More precisely, $NK_{it} = \sum_{j=1}^{4} K_{it}^{j}$, where j is a type of capital good, and K_{it}^{j} is defined recursively as $K_{it}^{j} = FIRSTK_{i}^{j}$ for $t = F_i$, and $K_{it}^{j} = (1-d^{j})K_{it-1}^{j} + I_{it}^{j} - S_{it}^{j}$ for $t > F_i$. The depreciation rates used are taken from Pombo (1999): 3.0% for buildings and structures, 7.7% for machinery and equipment, 11.9% for transportation equipment, and 9.9% for office equipment. Our measure of vintage provides a good summary of the temporal distribution of capital accumulation of a plant. While new plants or plants that invest frequently will have higher values of V_{it}, plants that have not invested for several years will have a low value of V_{it}, due to the effect of cumulative depreciation in the plant's net capital stock.

3. Outliers

DANE conducts checks of the accuracy of the information provided by manufacturing plants in the annual censuses, but there may still be some reporting errors. While it is impossible for us to assess whether or not an outlier observation is due to a reporting error, including outliers in the regressions can greatly distort the estimation of the production function parameters and our measures of productivity. To avoid this risk, we eliminate outliers from our dataset. To define outliers, we compute log differences between four inputs (capital, labor, wage premium, and intermediate inputs) and output. For each industry, we compute the first and third quartiles and the inter-quartile range (IQR) of each of these log differences. We define an outlier as a plant for which in at least one year one of the four log differences (a) exceeds the third quartile by x times the IQR or more, or (b) is less than the first quartile by x times the IQR or more. The threshold x is conventionally defined as 1.5, which corresponds to a 0.7% probability of finding an outlier if the variable was normally distributed. To minimize the loss of data, in nineteen out of twenty four industries we use a looser threshold of $x = 2.5$, which corresponds to a 0.005% probability of finding an outlier under the assumption of normality. In the remaining five industries, we apply a somewhat stricter threshold of $x = 2.0$ (corresponding to a 0.07% probability of finding an outlier under normality) since we find that the presence of outliers in the capital stock variable leads to negative coefficients for that variable under the looser 2.5 threshold.

Table A1: Production Function Coefficients - Selected Colombian Industries

Input	OLS (1)	Levinsohn Petrin (2)	OLS (3)	Levinsohn Petrin (4)
311 Food Products (1937 Obs.)				
Labor	0.137 ***	0.134 ***	0.149 ***	0.148 ***
	(0.007)	(0.017)	(0.007)	(0.021)
Wage Premium			0.255 ***	0.289 ***
			(0.026)	(0.051)
Skill Intensity			0.233 ***	0.228 ***
			(0.023)	(0.042)
Intermediate Inputs	0.829 ***	0.601 ***	0.813 ***	0.785 ***
	(0.005)	(0.087)	(0.005)	(0.054)
Capital	0.048 ***	0.221 ***	0.045 ***	0.051 *
	(0.005)	(0.055)	(0.004)	(0.029)
Vintage			0.202 ***	-0.060
			(0.04)	(0.138)
321 Textiles (997 Obs.)				
Labor	0.164 ***	0.165 ***	0.241 ***	0.234 ***
	(0.013)	(0.025)	(0.014)	(0.022)
Wage Premium			0.352 ***	0.393 ***
			(0.046)	(0.059)
Skill Intensity			0.477 ***	0.428 ***
			(0.046)	(0.070)
Intermediate Inputs	0.712 ***	0.540 ***	0.677 ***	0.482 ***
	(0.009)	(0.068)	(0.009)	(0.087)
Capital	0.095 ***	0.180 ***	0.075 ***	0.015
	(0.007)	(0.058)	(0.007)	(0.024)
Vintage			0.485 ***	0.268 **
			(0.071)	(0.135)
322 Apparel (3045 Obs.)				
Labor	0.335 ***	0.289 ***	0.384 ***	0.351 ***
	(0.008)	(0.017)	(0.008)	(0.015)
Wage Premium			0.437 ***	0.410 ***
			(0.035)	(0.05)
Skill Intensity			0.479 ***	0.489 ***
			(0.03)	(0.05)
Intermediate Inputs	0.639 ***	0.811 ***	0.605 ***	0.596 ***
	(0.005)	(0.044)	(0.005)	(0.055)
Capital	0.034 ***	0.041 **	0.025 ***	0.029
	(0.005)	(0.019)	(0.005)	(0.025)
Vintage			0.089 **	0.106
			(0.037)	(0.142)

Input	OLS (1)	Levinsohn Petrin (2)	OLS (3)	Levinsohn Petrin (4)
356 Plastics (914 Obs.)				
Labor	0.268 ***	0.263 ***	0.293 ***	0.295 ***
	(0.015)	-0.024	(0.014)	(0.022)
Wage Premium			0.501 ***	0.424 ***
			(0.046)	(0.067)
Skill Intensity			0.227 ***	0.146 **
			(0.047)	(0.070)
Intermediate Inputs	0.705 ***	0.846 ***	0.681 ***	0.749 ***
	(0.009)	(0.058)	(0.009)	(0.060)
Capital	0.067 ***	0.024	0.055 ***	0.032 *
	(0.007)	(0.015)	(0.006)	(0.018)
Vintage			0.608 ***	0.284
			(0.068)	(0.190)
381 Metal Products (1218 Obs.)				
Labor	0.277 ***	0.235 ***	0.334 ***	0.305 ***
	(0.016)	(0.028)	(0.016)	(0.034)
Wage Premium			0.453 ***	0.521 ***
			(0.043)	(0.080)
Skill Intensity			0.519 ***	0.472 ***
			(0.046)	(0.107)
Intermediate Inputs	0.698 ***	0.616 ***	0.657 ***	0.613 ***
	(0.009)	(0.063)	(0.009)	(0.086)
Capital	0.053 ***	0.004	0.040 ***	-0.056
	(0.007)	(0.04)	(0.006)	(0.095)
Vintage			0.391 ***	0.167 *
			(0.066)	(0.101)

Notes: Bootstrapped standard errors in parentheses in columns (2) and (4). ***, ** and * indicate significance at the 1%, 5% and 10% confidence levels, respectively.