Learning-by-Exporting Effects: Are They for Real?

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Abstract: We investigate whether exposure to export markets improves plant productivity. Our estimation framework adds export experience as an additional state variable and a fixed cost of entry into export markets to Olley and Pakes's (1996) behavioral model. We find robust evidence of a positive effect of export experience on productivity, controlling for the bias caused by self-selection of the most productive plants into exporting. The effect is stronger for plants with the most exposure to exporting, and statistically insignificant for exporters that stop exporting. Our analysis also suggests that matching methods may produce upwardly biased estimates of learning-by-exporting effects.

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I. Introduction

A burgeoning empirical literature over the last decade has tried to determine the direction of causality between the participation in export markets and productivity at the firm level. Exporters have been found to be significantly more productive, larger, more capital-intensive, and to pay higher wages than nonexporters, but these desirable characteristics may be the cause and not the consequence of their participation in export markets. If entry into export markets is characterized by large sunk costs, the strong positive association between productivity and participation in export markets may reflect the self-selection of the better firms into export markets.[1] However, self-selection and learning-by-exporting are not mutually exclusive possibilities, as high productivity firms that can afford the sunk costs of entry into export markets may continue to improve their productivity after entry as a result of their exposure to exporting.[2] Therefore, the question of whether learning-by-exporting actually takes place, and if so how important it is, is far from settled and 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

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[1] See e.g. Bernard and Wagner (1997), Clerides et al. (1998), Bernard and Jensen (1999), Isgut (2001), Delgado et al. (2002), Alvarez and Lopez (2005), and Arnold and Hussinger (2005).

[2] Several studies find support for learning-by-exporting while controlling for the self-selection effect. See e.g. Kraay (1999), Castellani (2002), Baldwin and Gu (2003), Bigsten et al. (2004), Girma et al. (2004), Van Biesebroeck (2005), and De Loecker (2006). See Greenaway and Kneller (2005) and Wagner (2007) for extensive reviews of this literature.

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 breaking into export markets. Export markets provide these firms with great opportunities to increase their revenues, but may also pressure them to improve their performance. Foreign customers are likely to be more sophisticated and discriminating than their domestic counterparts regarding the value and quality of their purchases. To satisfy these customers, new exporters may need to improve their production processes and technical standards, perhaps upgrading their capital equipment, which would require retraining their workers. Export markets are also more competitive than the domestic market due to the much larger number of suppliers. Consequently, firms must guarantee product quality and timely delivery of their orders to retain their foreign customers. As workers and managers attempt to meet all these challenges, they are likely to learn new skills, resulting in an improvement of the firm's productivity.

In this paper we empirically investigate whether the exposure to export markets leads to improvements in firm productivity. Our estimating framework is based on Olley and Pakes (1996) and Clerides et al. (1998). In Olley and Pakes (1996) the firm manager observes the firm-specific productivity index before deciding whether to exit or continue producing; in case of continuing, the manager then decides how much labor to hire and how much investment to undertake. We add to this framework a fixed cost of entry or re-entry into the export market and an additional state variable, export experience, which depends on past exports. With this addition, after observing the firm's productivity index the manager also needs to decide whether and how much to export. Exporting is beneficial not only because it provides an additional source of revenue for the firm but also because it allows the firm to accumulate export experience, which we hypothesize has a favorable effect on productivity. Of course, given the fixed costs of entry into exporting, only firms with high levels of productivity will be able to export.

The main hypothesis we test in this paper is whether the accumulation of export experience generates productivity gains. Our estimation method, based on Levinsohn and Petrin (2003), allows us to control for the potential upward bias caused by the self-selection of the most productive firms into exporting. In our estimations we use two alternative measures of export experience that capture the extent of the firm's involvement in export activities: the number of years the firm exported up to the previous year and the sum of export intensities of the firm up to the previous year. These measures extend the two most commonly used variables to capture exposure to exporting in the learning-by-exporting literature: lagged export status and lagged export intensity (the ratio of exports to output).

Our data comes from Colombia's Annual Manufacturing Surveys (AMS) for the years 1981 to 1991 and our unit of analysis is the plant. The proper measurement of export experience requires us to focus on plants for which we can observe the full export history. Thus our first sample is based on 'young' plants born in 1981 or later. However, we show that it is possible to include the "old" plants (born before 1981) in the sample for two reasons. First, we find evidence that export experience depreciates completely for exporters that do not export for three consecutive years, which allows us to include all the old plants that do not export over 1981-1983. Second, we find that it is reasonable to proxy for the unobserved pre-1981 export experience of old continuing exporters using their cumulated export experience over 1981-1983.

We find robust evidence of a positive effect of export experience on productivity across all the samples. Consistent with Arrow's (1962) view on learning, we find that the quantitative importance of the learning-by-exporting effect varies substantially with the degree of exposure to export activities. In our preferred specifications, export experience adds a minuscule 0.01-0.03 percent per year to productivity for plants in the 10th percentile of export intensity, compared to an economically significant 1.8-3.3 percent per year for plants in the 90th percentile. Also consistent with Arrow's (1962) view, we find no effect of export experience on productivity for plants that exit the export market.

A final contribution of our analysis is the observation that the use of matched samples based on a common characteristic of new exporters and nonexporters such as the propensity score of entering the export market may produce upwardly bias estimates of the learning-by-exporting effect. The reason is clear from our model, where the decision to enter the export market depends on the plant's productivity index. Plants may be able to start exporting as a result of favorable productivity shocks, and nothing prevents them from receiving additional favorable productivity shocks after entry. In contrast, nonexporters are, by definition, plants that do not enter the export market during the sample period, and our model suggests that a reason for not entering is that these plants do not receive favorable productivity shocks. As a result, the expected outcomes of the matched new exporters and nonexporters are unlikely to be conditionally independent from the decision to enter the export market, violating the main assumption of the method of matching (Heckman and Navarro-Lozano, 2004). Empirically, we find evidence of a positive bias in the estimates of the learning-by-exporting effect when using both the propensity score of entry into exporting and a simpler criterion to match new exporters and nonexporters.

The rest of the paper is organized as follows. Section II describes the model, Sections III and IV describe our econometric strategy and the samples to be used in the estimation, Section V presents the results, and Section VI concludes.

II. The Model

Plants use labor (L_{it}), intermediate inputs (M_{it}), and capital (K_{it}) to produce output with a Cobb-Douglas technology. Two variables are used to capture differences in labor quality across plants and over time: the ratio of skilled workers to the total number of workers or skill ratio (S_{it}) and the average wage paid by the plant (W_{it}). Following Olley and Pakes (1996) [henceforth OP] we include the plant's age (A_{it}) as an additional state variable. Capital and age accumulate according to:

$$K_{it} = (1-\delta)K_{it-1} + I_{it-1} \text{ and } A_{it} = A_{it-1} + 1, \tag{1}$$

where I_{it-1} is gross investment at t-1 and δ is the rate of depreciation. In order to account for the possibility of learning-by-exporting, we include a third state variable in the model: the plant's export experience, EE_{it}. We define export experience as a function of past values of exports Y_{it}^{F} :

$$EE_{it} = h\left(Y_{it-1}^{F}, Y_{it-2}^{F}, \ldots, Y_{FE_i}^{F}\right), \tag{2}$$

where FE_i represents the first year plant i exported. In the empirical part of the paper we use two alternative measures of export experience, the number of years the plant exported and the plant's cumulative export intensity:

$$EE^1_{it} = \sum_{\tau=FE_i}^{t-1} D_{i\tau} \tag{2a}$$

$$EE^2_{it} = \sum_{\tau=FE_i}^{t-1} \frac{Y^F_{i\tau}}{Y_{i\tau}} \ , \tag{2b}$$

where $D_{i\tau} \equiv 1\left(Y^F_{i\tau} > 0\right)$ is a dummy value equal one if the plant exported in year τ and Y_{it} is output. Notice that if we limit the sums above to a single term corresponding to τ = t - 1, then EE^1_{it} and EE^2_{it} simplify to the two most common variables used in the literature to capture learning-by-exporting effects: lagged export status and lagged export intensity.[3]

The production function is given by:

$$Y_{it} = L^{\beta_l}_{it} M^{\beta_m}_{it} K^{\beta_k}_{it} A^{\beta_A}_{it} \exp\left(\beta_0 + \beta_S S_{it} + \beta_W W_{it} + \beta_{EE} EE_{it} + \omega_{it}\right), \tag{3}$$

where ω_{it} is an index of productivity known to the plant manager at the beginning of period t but unknown to the econometrician. We assume that it follows an exogenous first-order Markov process:

$$p\left(\omega_{it} \mid \omega_{it-1}, \omega_{it-2}, ..., \omega_{i,FY_i}; J_{it-1}\right) = p\left(\omega_{it} \mid \omega_{it-1}\right), \tag{4}$$

where $J_{\text{it-1}}$ is plant i's information set at time t-1 and FY_{i} is the year when plant i started operations. The plant manager maximizes the expected discounted value of future net cash flows; her decision problem is captured by the following Bellman equation:

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[3] Van Biesebroeck (2005) also investigates the effect of exporting on productivity in a model similar to OP. Our paper differs from his in that instead of lagged export status we include as a state variable export experience, which captures more accurately the extent of the plant's exposure to exporting.

$$V(Z_{it}, D_{it-1}) = \max\left\{\Phi, \max_{Y_{it}, Y_{it}^F, I_{it}} \left\{\begin{array}{l} Y_{it}^H . p^H(Y_{it}^H) + Y_{it}^F . p^F(Y_{it}^F, r_t) - C_Y(Y_{it}, Z_{it}, w_t) - C_I(I_{it}) \\ -(1 - D_{it-1})F + \beta E_\omega[V(Z_{it+1}, D_{it}) \mid Z_{it}, Y_{it}, E_{it}, I_{it}] \end{array}\right\}\right\} \tag{5}$$

where $Z_{it} = (K_{it}, A_{it}, EE_{it}, \omega_{it})$, $Y_{it}^H \equiv Y_{it} - Y_{it}^F$ are home sales, $p^H(.)$ and $p^F(.)$ are inverse demand functions at home and abroad, $C_Y(.)$ and $C_I(.)$ are, respectively, the cost of production and the cost of adjustment of the capital stock, and *F* is a fixed cost of entry or re-entry into the export market. Following Clerides et al. (1998), we assume that plants are price takers in factor markets but operate in monopolistically competitive goods markets at home and abroad. Thus, plants face downward demand functions although they see themselves as too small to influence the behavior of other producers. We include the real exchange rate r_t as a shifter in the foreign demand function, and w_t in the cost function is a vector of variable input prices.

The timing of events is as follows. At the beginning of each period, the manager knows the plant's age and capital stock available for production (equation (1)), its export experience (equation (2)), the value of the productivity index, ω_{it}, and ω_{it}'s probability distribution for the following period (equation (3)). Based on this information, the manager decides whether the plant will continue in operation or exit. If the plant continues in operation, then the manager chooses how much to produce during the period (Y_{it}), how much to export (Y_{it}^F), and how much to invest (I_{it}). Since labor and intermediates are assumed to be fully flexible inputs, their choice is based on a static cost minimization problem conditional on the optimal level of output chosen for the period. The choices of investment and exports determine the plant's capital stock and export experience available for the next production period. Notice that the cost of entry into exporting depends on whether the plant exported the year before; therefore, lagged exports is an additional state variable in the value function.[4]

In this model, exports increase the plant's value in three ways: (i) by providing an additional source of revenue on top of sales to the domestic market, (ii) by allowing the plant to save on entry costs if it exported the year before, and (iii) by increasing productivity through learning effects. These advantages need to be weighted against the sunk cost of entry (or re-entry), which will be unaffordable for many plants. In order to facilitate the intuition, consider a simplified version of the model where the production function depends only on labor, export experience, and productivity, thus the parameters β_m, β_k, β_A, β_S, β_W are all equal to zero. In this simplified model the cost function is:

$$C\left(Y_{it}, EE_{it}, \omega_{it}, w_t^l\right) = w_t^l Y_{it}^{\frac{1}{\beta_l}} e^{-\left(\frac{\beta_0 + \beta_{EE} EE_{it} + \omega_{it}}{\beta_l}\right)},$$

where Y_{it} is the level of output that solves the inter-temporal optimization problem in equation (5) and w_t^l represents wages.[5] Production costs are increasing in output and decreasing in both productivity and export experience. Therefore, isocost lines in the $\left(\omega_{it}, EE_{it}\right)$ state space are downward-sloping. Figure 1 illustrates three isocost lines of particular interest that define thresholds for plants' entry and exit decisions. First, at a sufficiently low level of productivity the plant will be indifferent between exiting and receiving the termination payoff Φ or continuing in operation. Second, at a high enough

[4] Clerides et al. (1998) assume that cost of re-entry into export markets varies according to the number of years since the plant exported for the last time. We simplify the setup without much loss of generality by assuming that this cost is the same for both new entrants and re-entrants.

[5] This expression is obtained from the static cost minimization to choose the optimal amount of labor.

level of productivity, the plant will be indifferent between producing only for the domestic market or producing for both the domestic market and for exports. At this second threshold the sum of the current payoff from exporting and the contribution of exporting to the plant's expected value of exporting the following period will be just enough to compensate the sunk cost of entry. Finally, at an intermediate level of productivity an exporter will be indifferent between exiting the export market and producing only for the domestic market or continuing exporting for another period. The difference between the threshold for exit from export markets and the threshold for entry into export markets is due to the assumption of a fixed re-entry cost into exporting. Consider for example an exporter that receives a bad productivity shock that puts it below the export entry threshold. This plant would need to evaluate the immediate benefit of dropping from exporting against the need to pay the fixed re-entry cost the next year in case its productivity increases. If the plant's expected value in the case of continuing to export exceeds the negative current payoff caused by the adverse productivity shock, the plant will continue exporting.[6]

In Figure 1, the state space for plants that have never exported is the segment of the horizontal axis between the exit threshold and the export entry threshold marked in bold. The position of specific plants in the (ω_{it}, EE_{it}) state space is represented by N^1-N^4 and X^1-X^3, where N and X represent the plant's current export status. The N plants are not currently exporting, so they would need to pay the fixed entry cost if they decide to export in the next

[6] See Dixit and Pindyck (1994) for detailed analyses of entry and exit decisions under uncertainty with sunk entry costs. A recent paper by Irarrazabal and Opromolla (2006) applies these ideas to the case of entry into export markets. Our Figure 1 extends their Figure 5 to the case where export experience is an additional state variable.

period, while X plants are currently exporting and face no further cost if they decide to continue doing so. Plants N^1 and N^2 are examples of plants that have never exported. Once plants enter the export market, they start moving up in the state space as they accumulate export experience. The curvature of the thresholds reflects the assumption that plants learn from exporting, but such learning is subject to diminishing returns. Plants X^1-X^3 are examples of exporters. Plant X^1 has entered the export market in the current period; therefore, it still has not accumulated export experience [see equation (2)]. Plant X^3 has a negative current payoff from exporting but nevertheless finds it convenient to continue exporting (given the sunk cost of re-entry into exporting), hoping that its productivity will increase the following period. Notice finally that the region between the export entry threshold and the export exit threshold may include plants like N^3 that exported in the past but are not currently exporting. Such plants do not accumulate export experience; therefore they move only horizontally in the state space, similarly to plants that never exported before but at a positive level of export experience. In the empirical part of the paper we will test whether export experience depreciates as a former exporter continues not exporting for a few years. More specifically, we will test whether a plant like N^4 will "drop" to where N^1 is after three years without exporting.

III. Econometric strategy

Taking logs in equation (3) and adding a quadratic age term, a set of industry dummies γ^j and time dummies τ_t, and an i.i.d. error ε_{it}, we obtain our estimating equation:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_S S_{it} + \beta_W W_{it} + \beta_k k_{it} + \beta_a a_{it} + \beta_{a^2} a_{it}^2 + \gamma^j + \tau_t + \beta_{EE} EE_{it} + \omega_{it} + \varepsilon_{it},$$

(6)

where lower case variables are in logs. We include industry dummies to capture time-invariant differences across industries in production function parameters and input prices, and time dummies to capture variation over time in input prices and the exchange rate that affect all industries simultaneously. We follow Levinsohn and Petrin (2003) [henceforth LP] in assuming that the demand for intermediate inputs is a monotonically increasing function of the productivity index, conditional on the other state variables: capital, age, and export experience.[7] Therefore, it is possible to invert this function and express the unobservable productivity index as a function of intermediate inputs and the observable state variables: $\omega_{it} = \omega_{it}\left(m_{it}, k_{it}, a_{it}, EE_{it}\right)$.[8]

In the first stage of the estimation, we rewrite equation (6) in a semi-parametric form:

$$y_{it} = \beta_l l_{it} + \beta_S S_{it} + \beta_W W_{it} + \gamma^j + \tau_t + \phi\left(m_{it}, k_{it}, a_{it}, EE_{it}\right) + \varepsilon_{it}, \tag{7}$$

where

$$\phi\left(m_{it}, k_{it}, a_{it}, EE_{it}\right) \equiv \beta_o + \beta_m m_{it} + \beta_k k_{it} + \beta_a a_{it} + \beta_{a^2} a_{it}^2 + \beta_{EE} EE_{it} + \omega\left(m_{it}, k_{it}, a_{it}, EE_{it}\right).$$

We obtain consistent estimates for the coefficients on $\left(l_{it}, S_{it}, W_{it}, \gamma_j, \tau_t\right)$ from equation (7) using OLS with no constant, and replacing the unknown function $\phi(.)$ by a third-degree polynomial in $\left(m_{it}, k_{it}, a_{it}, EE_{it}\right)$.

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[7] We prefer to use the LP methodology rather than that proposed by OP because the latter requires dropping observations with zero investment – over 25 percent of our sample of young plants – leading to efficiency losses. However, for comparison purposes we show OP estimation results in the Appendix.

[8] LP and Van Biesebroeck (2005) provide details on the necessary conditions for the invertibility of the function proxying for ω_{it}.

In the second stage of the estimation, we obtain consistent estimates for the coefficients on $\left(m_{it}, k_{it}, a_{it}, a_{it}^2, EE_{it}\right)$ accounting for the possibility of selection bias due to plant exit decisions. Following OP we express the exit decision rule as:

$$\chi_{it} = \begin{cases} 1 \text{ (continue)} & \text{if } \omega_{it} > \overline{\omega}_t\left(k_{it}, a_{it}, EE_{it}\right) \\ 0 \text{ (exit)} & \text{otherwise,} \end{cases} \tag{8}$$

where $\overline{\omega}(.)$ is the plant's exit threshold. Defining $\tilde{y}_{it} \equiv y_{it} - \beta_l l_{it} - \beta_S S_{it} - \beta_W W_{it} - \gamma^j - \tau_t$, substituting into equation (6) and taking expectations conditional on information at $t - 1$, J_{it-1}, and survival we obtain:[9]

$$E\left[\tilde{y}_{it} \mid J_{it-1}, \chi_{it} = 1\right] = \beta_k k_{it} + \beta_a a_{it} + \beta_{a^2} a_{it}^2 + \beta_{EE} EE_{it} + \beta_m E\left[m_{it} \mid J_{it-1}, \chi_{it} = 1\right] + E\left[\omega_{it} \mid J_{it-1}, \chi_{it} = 1\right]. \tag{9}$$

As shown by OP, it is possible to approximate the last term by a function of lagged productivity and the survival probability p_{it}: $g(\omega_{it-1}, p_{it})$. Moreover, the Markov process assumption allows us to express the unobserved productivity index as $\omega_{it} = E[\omega_{it} / \omega_{it-1}, \chi_{it} = 1] + \xi_{it}$, where ξ_{it} is an i.i.d. innovation in productivity. Using these two facts and the definition of $\tilde{y}_{it}$, we can rewrite our estimating equation (6) as:

$$\tilde{y}_{it} = \beta_k k_{it} + \beta_a a_{it} + \beta_{a^2} a_{it}^2 + \beta_{EE} EE_{it} + \beta_m m_{it} + g\left(\omega_{it-1}, p_{it}\right) + \xi_{it} + \varepsilon_{it}. \tag{10}$$

Notice that ξ_{it} is orthogonal to k_{it} and EE_{it}, as the level of these state variables at time t depends on investment and export decisions taken at $t - 1$. Also, ξ_{it} is orthogonal to age, as this state variable increases deterministically. Finally, ξ_{it} is positively correlated with m_{it} but is orthogonal to m_{it-1}; therefore, we follow LP in using m_{it-1} as an instrument for m_{it} in the estimation of β_m in equation (10). In sum, the orthogonality of ξ_{it} with respect to

[9] Notice that a_{it-1}, k_{it-1}, and EE_{it-1} are known with certainty at $t - 1$, though this is not the case for m_{it}.

$\left(m_{it-1}, k_{it}, a_{it}, a_{it}^2, EE_{it}\right)$ allows us to identify the remaining coefficients of the model $\left(\beta_m, \beta_k, \beta_a, \beta_{a^2}, \beta_{EE}\right)$ through the following moment conditions (expressed in vector form):

$$E\left[\varepsilon_{it} + \xi_{it} \mid x\right] = 0, \tag{11}$$

where $x \equiv \left(m_{it-1}, k_{it}, a_{it}, a_{it}^2, EE_{it}\right)$. The estimation of equation (11) by GMM involves replacing the unknown function $g(.)$ by a third-degree polynomial in $\left(\omega_{it-1}, p_{it}\right)$, where p_{it} is replaced by a nonparametric estimate and ω_{it-1} is expressed as a function of observables using the definition of $\phi(.)$ in equation (7) as detailed in Appendix I (see also Ackerberg et al. (2006)). Standard errors for the coefficients $\left(\beta_l, \beta_S, \beta_W, \{\tau_t\}, \{\gamma_j\}, \beta_m, \beta_k, \beta_a, \beta_{a^2}, \beta_{EE}\right)$ are obtained by bootstrap.

If our model were estimated by OLS, β_{EE} could be downward biased due to exit decisions or upward biased due to self-selection into export markets. To understand the first possibility, consider the position of plants N^1 and N^4 in Figure 1. Both have about the same level of the productivity index; however, as a result of its positive export experience, plant N^4 is farther away from the exit threshold than plant N^1. If both plants suffer identical adverse shocks in their productivity index, plant N^1 is more likely to exit than plant N^4. Consequently, the sample may include a higher share of plants with positive export experience at low levels of ω than if plants did not exit as a result of adverse productivity shocks, exerting a negative bias on β_{EE}. This argument is analogous to that of OP regarding the possible negative selection bias on the estimated coefficient on capital due to plant exit decisions.

However, it is unlikely that many plants with positive export experience will be close to the exit threshold. We conjecture that most plants with positive export experience will be around or above the export entry threshold. Hence, if the model were estimated by OLS, the upward bias due to self-selection into exporting would likely dominate the downward bias due to exit. To understand the latter bias, consider first a plant that enters the export market for the first time at time *t*, such as plant X^1 in Figure 1. This plant may have experienced a favorable shock to its productivity index at *t*, allowing it to afford the fixed entry cost into exporting. However, as a new entrant, this plant has zero export experience at *t*, as export experience is defined as a function of lagged exports [see equation (2)]. Therefore, favorable productivity shocks that push a plant above the export entry threshold are *not* the reason why β_{EE} may be upward bias under OLS.

In contrast, consider a plant that already has positive export experience. It is likely that this plant continues to receive favorable productivity shocks, as a result of which it will continue exporting. If exporters tend to receive favorable productivity shocks, then there will be a positive correlation in the sample between unobserved innovations in the productivity index and export experience, biasing OLS estimates of β_{EE} upwards. Fortunately, the LP estimator used in this paper controls for this potential bias by imposing the condition that innovations in productivity are orthogonal to export experience [see equation (11)]. Therefore, while it is possible that exporters are very successful plants and likely to receive positive productivity shocks before and after entry into export markets, our econometric strategy allows us to correctly identify the effect of past export experience on plant productivity.

IV. Data description

The data used in this study come from 1981-1991 Annual Manufacturing Surveys

(AMS) conducted by Colombia's Departamento Administrativo Nacional de Estadística (DANE). Our analysis makes use of the following variables. Labor L_{it} is the total number of workers employed by the plant. Skill intensity S_{it} is the ratio of the number of white collar workers, managers, and technicians to the total number of workers. The wage premium W_{it} is the ratio of the plant's labor cost per worker to the average labor cost per worker in the region where the plant is located.[10] Capital K_{it} is the sum of the stocks of buildings and structures, machinery and equipment, transportation equipment, and office equipment in constant pesos, each of them obtained through the perpetual inventory method.[11] Intermediate inputs M_{it} are the sum of materials, outsourcing expenses, and energy in constant pesos. Output Y_{it} and exports Y_{it}^{F} are expressed in constant pesos.[12] Our two alternative measures of export experience, EE_{it}^{1} and EE_{it}^{2}, are constructed using equations (2a) and (2b).

In our estimating samples we exclude plants with less than three consecutive years

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[10] The rationale for using the plant's average wage as a measure of labor quality is based on the assumption that variations in wages capture differences in skills rather than differences in the prices of identical classes of labor (see e.g. Bahk and Gort, 1993). Given the high degree of geographical segmentation in Colombian labor markets, we scale average plant wages by the regional average wage, considering thirteen regions.

[11] 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. Investment flows in each of the capital classes are deflated by a corresponding price index from Banco de la República.

[12] We deflate output sold in the domestic market, exports, materials bought in the domestic market, and imported materials using different industry-specific price indexes. Details on the construction of the price indexes, which follows Clerides et al. (1998), are available from the authors upon request.

of data, plants with missing years of data, and plants with outlier observations.[13] In a first sample we include only 'young' plants, those that reported information to the AMS for the first time in 1981. Since the AMS included a question on exports only from 1981 onwards, we observe the full export history only for those plants. In order to include the 'old' plants, we first hypothesize that the export experience of exporters that do not export for three consecutive years depreciates completely. As shown in Section V, we find strong evidence supporting this hypothesis. The following alternative measures of export experience impose the restriction that export experience resets to zero after three years of export inactivity:

$$EER_{it}^{1} = \begin{cases} \sum_{R}^{t-1} D_{i\tau} & \text{if } \prod_{R=2}^{R} D_{i\tau} = 0, \quad R \leq t-1 \\ EE_{it}^{1} & \text{otherwise} \end{cases} \tag{12a}$$

$$EER_{it}^{2} = \begin{cases} \sum_{R}^{t-1} \frac{Y_{i\tau}^{F}}{Y_{i\tau}} & \text{if } \prod_{R=2}^{R} D_{i\tau} = 0, \quad R \leq t-1 \\ EE_{it}^{2} & \text{otherwise,} \end{cases} \tag{12b}$$

where R is the third year in a spell of three years during which the plant does not export. Notice that if the plant does not re-enter the export market, both EER_{it}^{1} and EER_{it}^{2} will be zero. If the plant re-enters the export market, it will start to accumulate export experience from then on; the past experience before the spell without exporting will be lost.

In a second sample we include young plants and old plants that do not export in any year between 1981 and 1983, using the measures of export experience EER_{it}^{1} and EER_{it}^{2} for all plants. We exclude observations for the years 1981-1983 for the old plants because we

[13] We define an outlier observation as a plant-year in which the log difference between output and one of the main production inputs (capital, labor, intermediate inputs, and the wage premium) is more than 2.5 inter-quartile ranges away from the industry median.

need at least three years of data to measure EER_{it}^{1} and EER_{it}^{2} properly. We also exclude 'old continuing exporters' defined as plants that export in any of the years 1981-1983, because we are unable to observe their pre-1981 export history.

In a third sample, we include all the plants, including the old continuing exporters. We conjecture that truncating export experience from 1981 onwards causes an upward bias in the estimates of β_{EE}. The reason is that the unobserved pre-1981 export experience of old continuing exporters, which may be positively correlated with the observed post-1981 export experience, will be part of the error term of the regression. In order to verify this conjecture, we generate a proxy for the unobserved pre-1981 export experience of old continuing exporters to use in the estimation. However, Section V shows that the results with or without the proxy are very similar, leading us to conclude that it is acceptable to use truncated measures of export experience for old continuing exporters. As in the second sample, the EER_{it}^{1} and EER_{it}^{2} measures of export experience are used and we exclude observations during 1981-1983 for all the old plants.

In the first three samples, the proportion of exporters, defined as plants that export in at least one year in the sample period, is relatively small. Moreover, the comparison groups for the exporters consist of *all* the nonexporters, including many low productivity plants that are unlikely to be close to the export entry threshold. In our last two samples we reduce the number of nonexporters by matching a smaller number of them to exporters according to some common characteristic. In the fourth sample, the characteristic is the propensity score of entering into the export market, following Girma et al. (2004) and De Loecker (2006). We estimate the propensity score through a probit regression using the second sample and restricting the matches to occur in the same industry and year.[14] More details on the probit are provided in the Appendix.

Matching on the propensity score of entering the export market is expected to reduce or eliminate the potential positive bias on the estimate of the learning-by-exporting effect caused by the self-selection of the most productive plants into exporting. However, the effectiveness of this method in reducing the self-selection bias depends critically on the assumption that, conditional on the propensity score, the outcomes of exporters and nonexporters are independent of the former's decision to enter the export market.[15] Our model suggests that this assumption is unlikely to hold. To understand why, refer to Figure 1. What the propensity score does is to select plants in the vicinity of plant N^2, among which some – the exporters – will start exporting, while others – the nonexporters – will not. It is clear from the figure that while exporters may be able to move further to the right after starting to export, for example to the position of plant X^2, the nonexporters will be confined to the region to the left of the export entry threshold. As a result, we conjecture that matching on the propensity score of entering the export market will increase rather than reduce the bias of the estimated learning-by-exporting effect.

Finally, in a fifth sample we use a different characteristic to match exporters to nonexporters: the rate of growth of labor productivity before entry into exporting. For that purpose, we compute the log difference of labor productivity of exporters between $t - 3$ and $t - 1$, where t is their year of entry into exporting.[16] To be able to compute pre-exporting

[14] Old continuing exporters are not included in the matched sample since we do not observe their entry into export markets.

[15] See Heckman and Navarro-Lozano (2004) for a critical discussion of matching methods.

[16] We exclude old continuing exporters because we cannot observe their year of entry into exporting.

rates of productivity growth, we exclude from the sample exporters that start exporting in one of their first three years. We match each of the chosen exporters with the two nonexporters that have the most similar labor productivity growth over a period of two years restricting the matches to occur in the same industry and year. We drop matches where the differences in labor productivity growth are at the top two percentiles. With this second matching criterion, it is less likely that the matched nonexporters will be close to plant N^2 in Figure 1. Nevertheless, the problem mentioned above that nonexporters will be confined to the region to the left of the entry into exporting threshold remains, possibly violating the assumption of conditional independence of outcomes on the decision to export.

Table 1 describes the data for each of the samples. The first two rows show the number of exporters and nonexporters. In the full sample, exporters represent 23 percent of plants. The following two rows show the size of exporters and nonexporters, measured by their average employment. As repeatedly shown in the literature, exporters are significantly larger than nonexporters, pay higher wages, are more capital- and skill-intensive, and have significantly higher labor productivity. Table 1 shows that this is particularly true when old continuing exporters are included in the sample. It also shows that exporters exhibit a premium in the use of intermediate inputs. The matched sample based on the propensity score of entry into exporting is characterized, as expected, by significantly smaller, sometimes negative, exporter premia, as the exporters and nonexporters included are more similar. Table 1 also shows the averages of EER_{it}^{1} and EER_{it}^{2} for exporters and the incidence of observations in which export experience is positive.[17] Old continuing

[17] The averages of EER_{it}^{1} and EER_{it}^{2} are taken over all the observations for exporters, including observations where export experience is zero, such as those before exporters start to export or after they do

exporters have significantly more export experience than either young exporters or old exporters that do not export during 1981-1983. However, as shown in the last line of the table young exporters tend to sell a larger share of their output abroad in the years when they export.

To complete the description of the data, we show in Figure 2 the distribution of the log of labor productivity across three groups of plants in the full sample: nonexporters, exporters that are not exporting in the current period, and exporters that are exporting in the current period. Each observation in these distributions is a plant-year, and the log of labor productivity is expressed as a deviation from the industry-year mean. As expected, the most productive plants on average are the exporters that are currently exporting, and the least productive are the nonexporters. The difference is substantial: evaluated at their means, the former are 75 percent more productive, and the latter are 14 percent less productive than their industry-year mean. Notice that the exporters that are not currently exporting occupy an intermediate position, with a 26 percent productivity advantage over their industry-year mean. The lower productivity of this group is consistent with the model shown in Figure 1. Some of these plants are exporters before entering the export market and others are exporters that stopped exporting. In the first case, they are located to the left of the export entry threshold and in the second to the left of the export exit threshold. Therefore, both should be less productive than the active exporters.

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not export for three consecutive years. Notice that in the estimations shown in Table 2, we use the EE_{it}^{1} and EE_{it}^{2} measures of export experience, whose averages are, respectively, 1.18 and 0.29.

V. Results

Table 2 shows estimation results for the sample of young plants. Columns (1) and (2) show OLS estimates and columns (3) and (4) show LP estimates. The estimates confirm the expectation of a positive OLS bias on the variable inputs – labor, skill ratio, wage premium, and intermediates – and a negative OLS bias on capital. We find, like OP, that age has a negative coefficient in the production function. As a result, we verify that the OLS bias on the age coefficient is positive (see Olley and Pakes (1996), pp. 1274). The coefficient on age is statistically significant for the sample of young plants, but it is usually insignificant in the other samples, as shown in Tables 3-5.

Columns (1) and (3) report estimates based on EE_{it}^{1} while columns (2) and (4) are based on EE_{it}^{2}. In all cases, the coefficients on export experience are positive and statistically significant. As discussed in Section III, two possible biases can affect the coefficients on export experience when using OLS: a negative bias due to exit decisions and a positive bias due to self-selection of the best plants into exporting. The results suggest that the positive bias dominates. This seems to be particularly true when using EE_{it}^{2}, whose estimated coefficient drops almost by half, from 0.5 in OLS to 0.28 in LP.

Regarding the quantitative importance of the learning-by-exporting effects, the estimates in column (3) suggest that an additional year of export experience is associated with an increase in output of 2.3 percentage points. However, this effect is not homogeneous across exporters, as their degree of participation in export markets varies substantially. Our second measure of export participation, cumulative export intensity or EE_{it}^{2}, allows us to capture these differences. The learning-by-exporting effect varies proportionally to the first differences in this measure, ΔEE_{it}^{2}. For example, evaluating the coefficient on EE_{it}^{2} in column (4) at the 10th percentile of ΔEE_{it}^{2} (0.008) gives a learning-by-exporting effect of only 0.2 percentage points; evaluating it at the 90th percentile of ΔEE_{it}^{2} (0.85) gives a much higher effect of 2.4 percentage points.

We should also note that the finding of learning-by-exporting effects on plant productivity is not driven by the choice of estimation technique. In Appendix Table A.2 we show results corresponding to columns (3) and (4) in Table 2 but using OP estimation techniques (where investment is used as a proxy for unobserved productivity) instead of LP. Although based on a smaller sample, the results show significant learning-by-exporting effects using both EE_{it}^{1} and EE_{it}^{2}.

While the results in Table 2 provide evidence of learning-by-exporting, they refer to young plants only, and it is unclear whether they can be generalized to the entire Colombian manufacturing sector. In order to incorporate into the sample some of the old plants we conjecture that the beneficial effect of export experience on productivity 'resets' to zero if a plant ceases to export for some time. Possibly, part of the learning associated with exporting is given by commercial contacts with foreign customers. If a plant stops exporting for some time, those contacts will be gone, forcing the plant to start from scratch if it wishes to re-enter the export market.

The hypothesis we want to test is whether the export experience of a plant that has not exported for three consecutive years resets to zero. For this purpose, we express the original export experience measures as:

$$EE_{it}^{j} \equiv EER_{it}^{j} + \left(EE_{it}^{j} - EER_{it}^{j}\right),\ j \in (1,2),$$

where EER_{it}^{j}'s are defined in equation (12). To conduct the tests, we estimate regressions of the form:

$$y_{it} = \beta x_{it} + \beta_{EER} EER_{it} + \beta_{EE-EER}\left(EE_{it} - EER_{it}\right) + \omega_{it} + \varepsilon_{it},$$

where x_{it} is a vector containing all the remaining explanatory variables in equation (6). The hypothesis of interest is $H_0 : \beta_{EE-EER} = 0$ and it is tested using the sample of young plants. As shown in columns (1) and (2) of Table 3, we cannot reject H_0 for the two measures of export experience. Consequently, we assume that the resetting of export experience is valid for both young and old plants. This allows us to include in the sample the old plants that do not export during 1981-1983. This group of plants consists of old plants that will start exporting after 1983 and of old plants that will never export. Columns (3) and (4) of Table 3 show regression results for the sample of young and old plants using the *EER* measures of export experience. Notice that the addition of old plants – excluding old continuing exporters – more than doubles the sample size. However, the estimated coefficients on export experience are still positive and statistically significant, and only slightly smaller in magnitude than those obtained using the sample of young plants.

Our next step is to add to the sample old plants that export during 1981-1983. For these plants, we cannot reset their export experience, since we do not observe it entirely. We can, of course, use in the regressions measures of export experience truncated at 1981, the first year when export data is available in the Colombian AMSs. In that case, the effect of the pre-1981 export experience for those plants will be included in the error term. If plants with positive pre-1981 export experience tend to continue exporting after 1981 and if export experience has a positive effect on productivity, omitting the unobserved pre-1981 export experience may create an upward bias in the estimates of β_{EE}.

In columns (5) and (6) of Table 3, we show estimation results for the full sample, truncating the export experience of old continuing exporters at 1981 and using the *EER* measures of export experience. The coefficients on export experience continue to be positive and significant, although substantially smaller when using the number of years of exports, EER_{it}^{1}.

To investigate whether the estimated coefficients on export experience are upward biased due to the use of truncated measures for the old continuing exporters, we re-estimate these regressions using a proxy for the unobserved pre-1981 export experience of those plants. To compute the proxy, we regress, using the sample of young plants, export experience in 1989 on age and cumulated export experience during 1989-1991.[18] We then use the estimated coefficients from those regressions to construct a proxy for the export experience of old continuing exporters in 1981 based on their age as of 1981 and their cumulated export experience during 1981-1983. In the regressions shown in columns (1) and (2) of Table 4 we have added the proxy for the pre-1981 export experience to the observed export experience of old continuing exporters since 1981. Interestingly, the results are very similar to those in columns (5) and (6) or Table 3. While the coefficient on EER_{it}^{1} decreases when using the proxy for unobserved

[18] Specifically, we regress $EE_{i,1989}^{1}$ on $a_{i,1989}$ and $\sum_{\tau=1989}^{\tau=1991} D_{i\tau}$ and we regress $EE_{i,1989}^{2}$ on $a_{i,1989}$ and $\sum_{\tau=1989}^{\tau=1991} Y_{i\tau}^{F} / Y_{i\tau}$. In both regressions, the explanatory variables are highly significant and the R-squared's are 0.29 and 0.46, respectively.

experience, the one on EER_{it}^2 increases, so overall there is little evidence of an upward bias when the measures of export experience of the old continuing exporters are truncated. The cumulated export experience of these plants during 1981-1983 is likely to be a good proxy for their unobserved pre-1981 export experience, therefore excluding the first three years of data, as we do, appears to be sufficient to deal with the problem.

Columns (3)-(6) of Table 4 show the results for the two matched samples described in Section IV. As we mentioned in Section IV, it is likely that samples in which exporters are matched with nonexporters according to some characteristic will generate upwardly biased estimates of learning-by-exporting effects. The reason is that exporters, after moving past the export entry threshold, are likely to continue increasing their productivity. In contrast, nonexporters are unlikely to do so because, by definition, these plants do not reach during the sample period a high enough level of productivity that will allow them to pay the sunk costs of entry to the export market.

In both matched samples the estimated coefficients on EER_{it}^2 increase by a factor of three relative to the estimates obtained with unmatched samples. Remarkably, the results are very similar in the two samples, although very different criteria are used to match exporters to nonexporters. As described in Section IV, the first matched sample is obtained, following other researchers, using the propensity score of entering into exporting. The second sample is obtained using a much simpler criterion of matching exporters to nonexporters according to their labor productivity growth. That these two very different matching criteria lead to similar estimation results suggests that the problem is not the specific matching criterion used, but the fact that the two groups from which plants are matched are to be expected a priori to have very different productivity trajectories. As a result, the assumption that the outcomes of exporters and nonexporters are conditionally independent of the decision to enter the export market is unlikely to be satisfied, making the method of matching invalid (see Heckman and Navarro-Lozano (2004)).

A final issue to be investigated is whether the learning-by-exporting effect differs according to whether or not a plant is participating in the export market. As Arrow (1962) pointed out, learning takes place while performing activities. An exporter that is currently not exporting is obviously not performing export activities and is therefore unable to learn from them. Our finding that the beneficial effect of export experience on productivity 'resets' to zero if a plant ceases to export for three years in Table 3 can be interpreted as validating Arrow's view. Moreover, Figure 1 suggests that exporters that exit the export market must have received an adverse productivity shock that pushes them to the left of the export exit threshold in the (ω_{it}, EE_{it}) state space. As a result, their productivity should be lower than that of active exporters and even of nonexporters such as plant N^2, that are close to the export entry threshold. For these reasons, it seems like exporters that are not currently exporting should be treated differently in the regressions than exporters that continue exporting.

We estimate the following model to test the hypothesis that learning-by-exporting occurs when a plant is actually exporting and not when it has temporarily stopped exporting:

$$y_{it} = \beta x_{it} + \beta_{D*EER} D_{it-1} * EER_{it} + \beta_{EER} EER_{it} + \omega_{it} + \varepsilon_{it},$$

where x_{it} is a vector containing all the remaining explanatory variables in equation (6), and D_{it-1} is the plant's lagged export status (=1 if the plant exported during the previous year). The hypothesis of interest is $H_0 : \beta_{EER} = 0$, which indicates that only active exporters have a positive effect of export experience on productivity. Notice that the interaction term includes the lagged rather than the current export status. The reason is that the current export status is positively correlated with ω_{it}, which would cause an upward bias in the estimate of β_{D*EER}.

We show the results for this test in Table 5 for the three main samples using EER_{it}^2 as our measure of export experience. We are unable to reject H_0 in either of the three regressions. Moreover, the estimated coefficients on the interaction term β_{D*EER} are between 45 percent and 75 percent larger than the corresponding coefficients on β_{EER} in Table 3. We believe that the estimates of β_{D*EER} capture more accurately learning-by-exporting effects on plant productivity. How important is this learning-by-exporting effect? As mentioned earlier, when using cumulative export intensity to measure export experience, the effect varies proportionally to the first differences in this measure. For the young sample, the estimated learning-by-exporting effect based on the coefficient in column (1) of Table 5 now ranges from 0.03 percent at the 10th percentile of ΔEER_{it}^2 (0.008) to 3.3 percent at the 90th percentile of ΔEER_{it}^2 (0.85). Repeating this calculation for the full sample, the learning-by-exporting effect is smaller, ranging from 0.01 percent at the 10th percentile (0.003) to 1.8 percent at the 90th percentile (0.52). The fact that the effect is higher for plants that increase more their exposure to export activities, provides support to Arrow's (1962) view that learning is a function of the time and effort involved in performing new activities.

VI. Conclusion

In this paper we find robust evidence of a positive effect of export experience on productivity. Consistent with Arrow's (1962) view on learning, we find this effect to vary substantially with the degree of plants' exposure to exporting activities. The effect is almost negligible for plants that participate marginally in export markets but economically important for the plants most involved in exporting. In our preferred specifications, learning-by-exporting adds between 1.8 and 3.3 percent per year to productivity for plants in the 90th percentile of export intensity. Also consistent with Arrow's (1962) view, we find no significant effect of export experience on productivity for plants that exit the export market. Finally, both our analysis and estimation results cautions that the commonly used method of matching new exporters to similar nonexporters according to the propensity score of entering the export market may generate a positive bias on the estimates of the learning-by-exporting effect.

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Appendix A: Estimation details

To estimate $\left(\beta_m, \beta_k, \beta_a, \beta_{a^2}, \beta_{EE}\right)$ from equation (11), we first estimate the survival probability $\hat{p}_{it}$ non-parametrically by a probit model of plant survival on a third degree polynomial in $\left(m_{it-1}, k_{it-1}, a_{it-1}, EE_{it-1}\right)$. Second, we replace the unknown ω_{it-1} in $g\left(\omega_{it-1}, p_{it}\right)$ with $\hat{\omega}_{it-1} = \hat{\phi}_{it-1} - \beta_m m_{it-1} - \beta_k k_{it-1} - \beta_a a_{it-1} - \beta_{a^2} a_{it-1}^2 - \beta_{EE} EE_{it-1}$, where $\hat{\phi}_{it-1}$ is the polynomial estimated in the first stage. Third, recall from equation (9) that the unknown function $g\left(\omega_{it-1}, p_{it}\right)$ approximates $E\left[\omega_{it} \mid J_{it-1}, \chi_{it} = 1\right]$. For candidate coefficients $\left(\beta_m^*, \beta_k^*, \beta_a^*, \beta_{a^2}^*, \beta_{EE}^*\right)$, we estimate this function as the predicted value from an OLS regression of: $\left(\hat{\omega}_{it} + \hat{\varepsilon}_{it}\right)(\beta)^* = \tilde{y}_{it} - \beta_m^* m_{it} - \beta_k^* k_{it} - \beta_a^* a_{it} - \beta_{a^2}^* a_{it}^2 - \beta_{EE}^* EE_{it}$ on a third degree polynomial in the estimated probability of survival $\hat{p}_{it}$ and in $\hat{\omega}_{it-1}(\beta^*) = \hat{\phi}\left(m_{it-1}, k_{it-1}, a_{it-1}, a_{it-1}^2, EE_{it-1}\right) - \beta_m^* m_{it-1} - \beta_k^* k_{it-1} - \beta_a^* a_{it-1} - \beta_{a^2}^* a_{it-1}^2 - \beta_{EE}^* EE_{it-1}$. Our generalized method of moments (GMM) criterion function weights the plant-year moment conditions in equation (11) by their variance-covariance matrix. Our estimation algorithm uses OLS estimates of $\left(\beta_m, \beta_k, \beta_a, \beta_{a^2}, \beta_{EE}\right)$ as candidate parameter values and iterates on the sample moment conditions to match them to their theoretical value of zero and reach final parameter estimates (see also Fernandes, 2007). 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 $\left(\beta_m, \beta_k, \beta_a, \beta_{a^2}, \beta_{EE}\right)$ values. The standard errors for the parameter estimates are obtained by a bootstrap procedure which consists of sampling randomly with replacement plants from the 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 $\left(\beta_l, \beta_S, \beta_W, \{\tau_t\}, \{\gamma_j\}, \beta_m, \beta_k, \beta_a, \beta_{a^2}, \beta_{EE}\right)$ for 100 bootstrap samples. The standard deviation of a parameter across bootstrap samples constitutes its bootstrapped standard error.

Appendix B: Matching Sample 1

Appendix Table A1 shows the results from a probit regression for entry into export markets that generates the propensity score used to match each exporter to its nearest neighbour nonexporter. The covariates are capital and age (known to the manager when the export market entry decision is made), lagged labor productivity to proxy for the plant's unobserved productivity, and additional covariates known to the manager when the export market entry decision is made and used in previous studies of export participation: lagged skill ratio, lagged wage premium, a real exchange rate index, and a corporation dummy (see e.g., Clerides et al., 1998; Bernard and Jensen, 2004). In order to match each exporter to a similar nonexporter, we exclude from the probit estimating sample the observations of exporters in which they have positive export experience. Similarly, we exclude exporters that start to export since their first year in the sample since the lagged variables used as covariates in the probit regression are unobservable for these plants.[19]

[19] We thank Jens Arnold for sharing his STATA code for matching plants in the same year and industry.

Figure 1: Exit, Export Entry, and Export Exit Thresholds

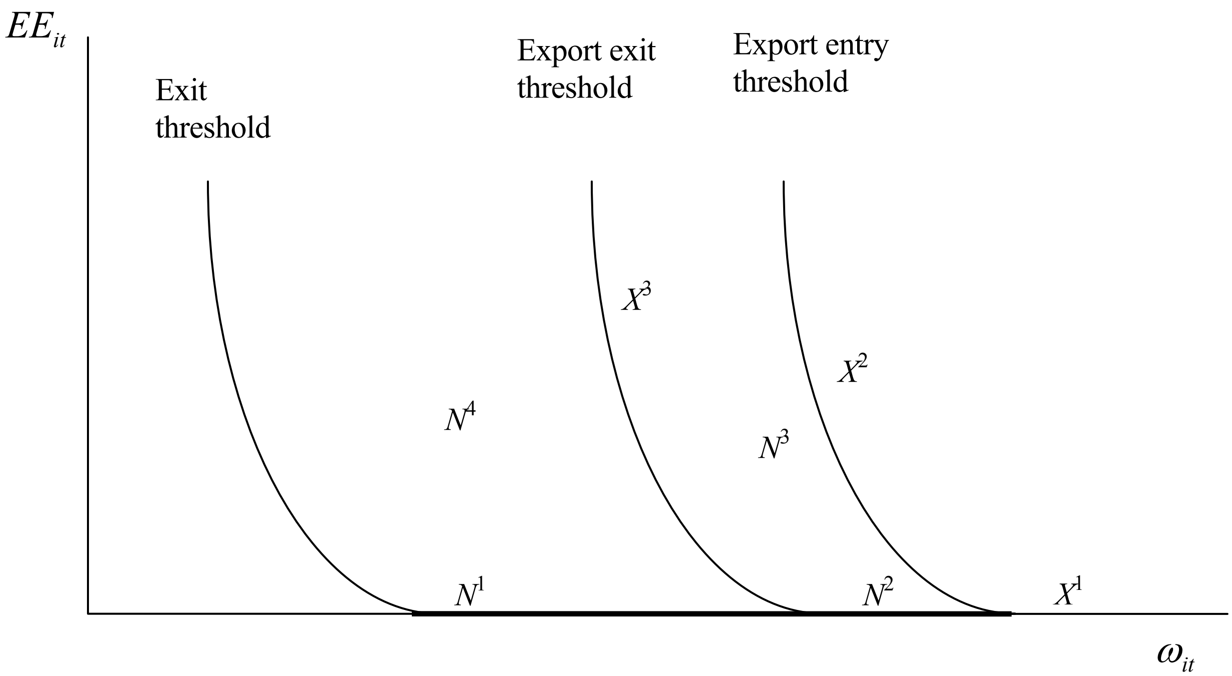
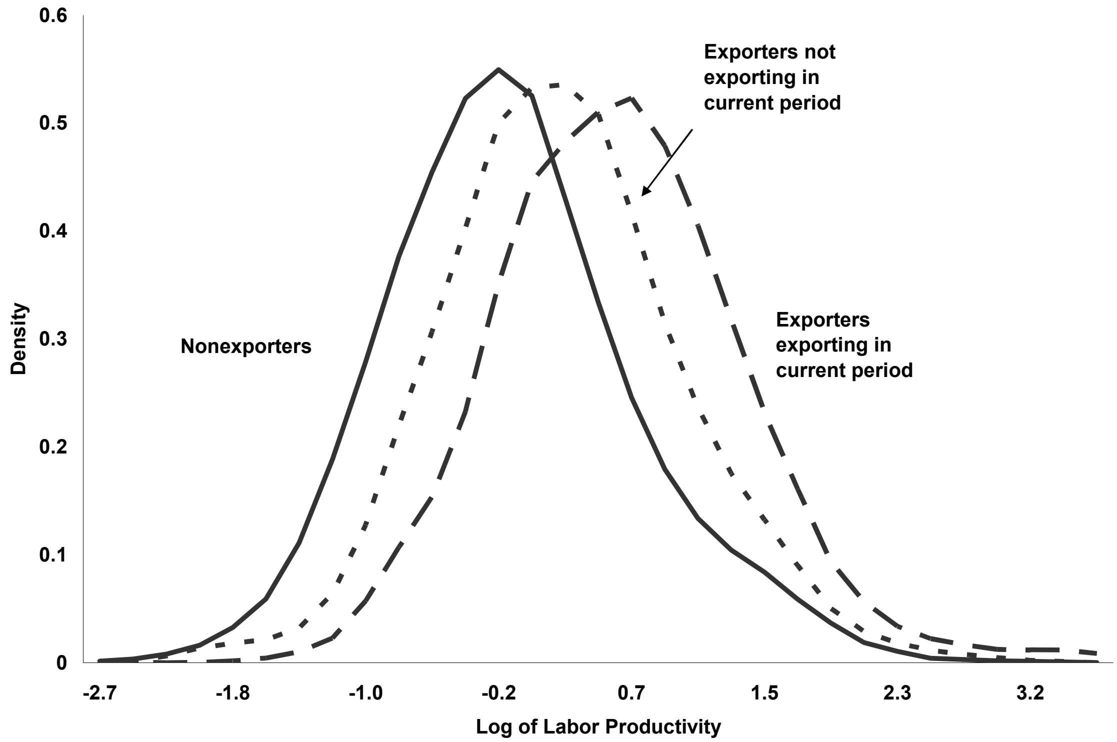


Figure 2: Distributions of Plant-Year Labor Productivity for Full Sample



Notes: Density estimates shown are based on Epanechnikov kernel functions using the same support points for the three distributions and optimal widths. The variable represented is the deviation of plant labor productivity from its industry-year mean.

Table 1. Summary Statistics

	Sample of Young Plants	Sample of Young and Old Plants (Without Continuing Exporters)	Full Sample	Matched Sample 1	Matched Sample 2
Number of Plants					
Exporters	476	871	1,563	694	423
Nonexporters	2,627	5,111	5,111	571	736
Average Number of Workers					
Exporters	56	110	165	92	139
Nonexporters	30	46	46	67	46
Average Exporter Premia					
Labor Productivity	0.53	0.45	0.69	0.08	0.58
Capital-Labor Ratio	0.64	0.48	1.07	-0.17	0.63
Intermediate Inputs-Labor Ratio	0.56	0.49	0.67	0.08	0.59
Skill Intensity	0.11	0.05	0.08	-0.01	0.08
Wage Premium	0.23	0.24	0.46	0.04	0.26
Average Export Experience					
Number of Years the Plant Exported	1.10	0.92	2.57	0.70	0.87
Cumulative Export Intensity	0.28	0.16	0.45	0.07	0.07
Incidence of Positive Export Experience	0.46	0.40	0.61	0.33	0.41
Average Export Intensity when Exporting	0.25	0.18	0.18	0.13	0.11

Notes: The exporter premia are all significant at the 1 percent confidence level, with the exception of that for wage premium in matched sample 1. Labor productivity is defined as the ratio of output minus intermediate inputs to the total number of workers. The last four rows show data for exporters only. The averages of the export experience measures are taken over all the observations for exporters.

Table 2. Main Results for Sample of Young Plants

	OLS Estimation		Modified Levinsohn and Petrin (2003) Estimation	
	Sample of Young Plants			
	(1)	(2)	(3)	(4)
Labor (l_{it})	0.267	0.27	0.247	0.248
	(0.005)***	(0.005)***	(0.008)***	(0.008)***
Skill Intensity (S_{it})	0.299	0.306	0.244	0.249
	(0.014)***	(0.014)***	(0.019)***	(0.020)***
Wage Premium (W_{it})	0.365	0.369	0.328	0.325
	(0.012)***	(0.012)***	(0.019)***	(0.019)
Intermediate Inputs (m_{it})	0.688	0.688	0.612	0.564
	(0.003)***	(0.003)***	(0.026)***	(0.019)***
Capital (k_{it})	0.061	0.061	0.103	0.131
	(0.002)***	(0.002)***	(0.017)***	(0.015)***
Age (a_{it})	-0.046	-0.047	-0.071	-0.098
	(0.024)**	(0.024)**	(0.028)***	(0.034)***
Age Squared (a_{it}^2)	-0.003	-0.002	-0.129	-0.067
	(0.008)	(0.008)	(0.061)**	(0.064)
Export Experience (EE_{it}^1)	0.026		0.023	
	(0.002)***		(0.010)***	
Export Experience (EE_{it}^2)		0.05		0.028
		(0.006)***		(0.010)***
Number of Observations	15537	15537	15537	15537

Notes: The dependent variable is the logarithm of plant output (y_{it}). *** and ** indicate significance at the 1 and 5 percent confidence levels, respectively. In columns (1)-(2), robust standard errors are in parentheses. In columns (3)-(4) bootstrapped standard errors are in parentheses. Labor, intermediate inputs, capital, and age are in logarithms. Age squared is the square of the logarithm of age. The export experience variables are defined in the text. Years included are 1982-1991.

Table 3. Tests for Resetting of Export Experience to 0 and Results for Samples of Young and Old Plants

	Modified Levinsohn and Petrin (2003) Estimation					
	Sample of Young Plants		Sample of Young and Old Plants (Without Continuing Exporters)		Full Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Labor (l_{it})	0.248	0.248	0.245	0.246	0.240	0.243
	(0.008)***	(0.008)***	(0.005)***	(0.005)***	(0.004)***	(0.004)***
Skill Intensity (S_{it})	0.246	0.249	0.242	0.246	0.248	0.255
	(0.018)***	(0.020)***	(0.016)***	(0.015)***	(0.015)***	(0.015)***
Wage Premium (W_{it})	0.332	0.326	0.271	0.272	0.254	0.258
	(0.020)***	(0.022)***	(0.012)***	(0.012)***	(0.011)***	(0.011)***
Intermediate Inputs (m_{it})	0.457	0.468	0.549	0.580	0.549	0.551
	(0.014)***	(0.016)***	(0.010)***	(0.007)***	(0.010)***	(0.007)***
Capital (k_{it})	0.164	0.168	0.120	0.089	0.119	0.125
	(0.012)***	(0.012)***	(0.013)***	(0.018)***	(0.013)***	(0.010)***
Age (a_{it})	-0.030	-0.037	-0.012	0.035	-0.009	-0.029
	(0.028)	(0.024)	(0.021)	(0.020)	(0.016)	(0.013)***
Age Squared (a_{it}^2)	-0.004	-0.047	-0.005	-0.052	-0.009	0.030
	(0.038)	(0.043)	(0.032)	(0.043)	(0.027)	(0.036)
Export Experience (EER_{it}^1)	0.029		0.020		0.013	
	(0.007)***		(0.005)***		(0.004)***	
Difference Term (EE_{it}^1-EER_{it}^1)	0.000					
	(0.026)					
Export Experience (EER_{it}^2)		0.027		0.022		0.022
		(0.010)***		(0.010)***		(0.010)***
Difference Term (EE_{it}^2-EER_{it}^2)		-0.004				
		(0.122)				
Number of Observations	15537	15537	35637	35637	40774	40774

Notes: The dependent variable is the logarithm of plant output (y_{it}). *** indicates significance at the 1 percent confidence level. Bootstrapped standard errors are in parentheses. Labor, intermediate inputs, capital, and age are in logarithms. Age squared is the square of the logarithm of age. The export experience variables are defined in the text. Years included are 1982-1991 for the young plants and 1984-1991 for the old plants.

Table 4. Results for Full Sample and for Matched Samples

	Modified Levinsohn and Petrin (2003) Estimation					
	Full Sample		Matched Sample 1		Matched Sample 2	
	(1)	(2)	(3)	(4)	(5)	(6)
Labor (l_{it})	0.240	0.242	0.239	0.243	0.251	0.253
	(0.004)***	(0.005)***	(0.010)***	(0.010)***	(0.009)***	(0.009)***
Skill Intensity (S_{it})	0.248	0.253	0.360***	0.367***	0.363	0.366
	(0.015)***	(0.015)***	(0.032)***	(0.032)***	(0.031)***	(0.031)***
Wage Premium (W_{it})	0.253	0.255	0.256***	0.257***	0.263	0.263
	(0.011)***	(0.011)***	(0.021)***	(0.021)***	(0.030)***	(0.031)***
Intermediate Inputs (m_{it})	0.549	0.553	0.522	0.516	0.530	0.541
	(0.006)***	(0.010)***	(0.064)***	(0.034)***	(0.037)***	(0.030)***
Capital (k_{it})	0.118	0.122	0.113	0.120	0.065	0.065
	(0.013)***	(0.012)***	(0.030)***	(0.032)***	(0.023)***	(0.028)***
Age (a_{it})	-0.009	-0.026	0.040	0.073	0.047	0.074
	(0.018)	(0.014)*	(0.059)	(0.076)	(0.049)	(0.049)
Age Squared (a_{it}^2)	-0.003	0.020	-0.021	-0.046	-0.014	-0.045
	(0.031)	(0.032)	(0.096)	(0.165)	(0.065)	(0.110)
Export Experience (EER_{it}^1)	0.010		0.024		0.020	
	(0.003)***		(0.006)***		(0.007)***	
Export Experience (EER_{it}^2)		0.025		0.074		0.067
		(0.010)***		(0.027)***		(0.033)**
Number of Observations	40774	40774	8554	8554	8665	8665

Notes: The dependent variable is the logarithm of plant output (y_{it}). *** indicates significance at the 1 percent confidence level. Bootstrapped standard errors are in parentheses. Labor, intermediate inputs, capital, and age are in logarithms. Age squared is the square of the logarithm of age. The measures of export experience are described in the text. In columns (1)-(2) the measures of export experience for old continuing exporters include a proxy for their pre-1981 export experience. Years included are 1982-1991 for the young plants and 1984-1991 for the old plants.

Table 5. Learning-By-Exporting and Current Export Participation

	Modified Levinsohn and Petrin (2003) Estimation		
	Sample of Young Plants	Sample of Young and Old Plants (Without Continuing Exporters)	Full Sample
	(1)	(2)	(3)
Labor (l_{it})	0.249	0.246	0.243
	(0.008)***	(0.008)***	(0.008)***
Skill Intensity (S_{it})	0.251	0.245	0.254
	(0.020)***	(0.016)***	(0.016)***
Wage Premium (W_{it})	0.328	0.272	0.258
	(0.023)***	(0.013)***	(0.012)***
Intermediate Inputs (m_{it})	0.459	0.540	0.451
	(0.016)***	(0.018)***	(0.005)***
Capital (k_{it})	0.157	0.131	0.173
	(0.012)***	(0.009)***	(0.005)***
Age (a_{it})	-0.008	-0.066	-0.011
	(0.028)	(0.014)***	(0.012)
Age Squared (a_{it}^2)	-0.002	0.018	-0.002
	(0.048)	(0.015)***	(0.010)
Export Experience (EER_{it}^2) * Lagged Export Dummy (D_{it-1})	0.039	0.039	0.035
	(0.015)***	(0.016)***	(0.016)***
Export Experience (EER_{it}^2)	0.012	0.026	0.015
	(0.023)	(0.018)	(0.020)
Number of Observations	15537	35637	40774

Notes: The dependent variable is the logarithm of plant output (y_{it}). *** indicates significance at the 1 percent confidence level. Bootstrapped standard errors are in parentheses. Labor, intermediate inputs, capital, and age are in logarithms. Age squared is the square of the logarithm of age. The measures of export experience are described in the text. Years included are 1982-1991 for the young plants and 1984-1991 for the old plants.

Appendix Table A1. Propensity Score for Entry into Export Markets

	Probit Estimation
	Sample of Young and Old Plants (Without Continuing Exporters)
Lagged Labor Productivity	0.13
	(0.030)***
Capital (k_{it})	0.217
	(0.015)***
Age (a_{it})	-0.500
	(0.089)***
Age Squared (a_{it}^2)	0.079
	(0.019)***
Lagged Skill Intensity (S_{it-1})	0.118
	(0.109)
Lagged Wage Premium (W_{it-1})	-0.146
	(0.063)**
Real Exchange Rate	1.732
	(0.120)***
Corporation Dummy	0.185
	(0.063)***
Number of Observations	40030

Notes: The dependent variable is a dummy variable indicating the year when a plant first enters export markets. *** and ** indicate significance at the 1 and 5 percent confidence levels, respectively. Robust standard errors are in parentheses. Year and industry dummies are included in the regression. Labor productivity is defined as the ratio of output minus intermediate inputs to the total number of workers. Labor productivity, capital, and age are in logarithms. Age squared is the square of the logarithm of age. Years included are 1982-1991 for the young plants and 1984-1991 for the old plants.

Appendix Table A2. Results using Modified Olley and Pakes (1996) Estimation

	OLS Estimation		Modified Olley and Pakes (1996) Estimation	
	Sample of Young Plants			
	(1)	(2)	(3)	(4)
Labor (l_{it})	0.249	0.252	0.237	0.239
	(0.005)***	(0.005)***	(0.009)***	(0.008)***
Skill Intensity (S_{it})	0.298	0.305	0.279	0.284
	(0.015)***	(0.015)***	(0.020)***	(0.020)***
Wage Premium (W_{it})	0.349	0.353	0.327	0.330
	(0.013)***	(0.013)***	(0.022)***	(0.021)***
Intermediate Inputs (m_{it})	0.688	0.688	0.681	0.680
	(0.004)***	(0.004)***	(0.006)***	(0.006)***
Capital (k_{it})	0.068	0.068	0.114	0.113
	(0.003)***	(0.003)***	(0.014)***	(0.015)***
Age (a_{it})	-0.054	-0.055	-0.103	-0.130
	(0.027)**	(0.027)**	(0.027)***	(0.026)***
Age Squared (a_{it}^2)	0.000	0.001	0.102	0.150
	(0.009)	(0.009)	(0.033)***	(0.029)***
Export Experience (EE_{it}^1)	0.026		0.026	
	(0.003)***		(0.012)**	
Export Experience (EE_{it}^2)		0.051		0.045
		(0.007)***		(0.022)***
Number of Observations	11578	11578	11578	11578

Notes: The dependent variable is the logarithm of plant output (y_{it}). *** and ** indicate significance at the 1 and 5 percent confidence levels, respectively. Robust standard errors are in parentheses. Labor, intermediate inputs, capital, and age are in logarithms. Age squared is the square of the logarithm of age. In all columns, observations with investment equal to zero are excluded from the estimation. Years included are 1982-1991