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

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Abstract: We investigate whether export experience improves plant productivity in Colombia. Based on Arrow's (1962) characterization of learning, we make use of novel measures of plant export experience based on sums of past values of exports. We find evidence of positive learning-by-exporting effects controlling for the bias caused by self-selection of the most productive plants into exporting. However, these effects are not present for plants with a discontinued participation in the export market. Learning-by-exporting effects are more than proportional to the export-output ratio, suggesting the existence of spillovers of efficiency gains from export-related tasks to domestic market production. Finally, we find evidence of diminishing returns to export experience, as learning-by-exporting effects are smaller for the most experienced exporters in our sample.

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I. Introduction

Exporting firms have been found everywhere to be significantly more productive, larger, more capital-intensive, and to pay higher wages than non-exporting firms. A development strategy that promotes exporting should, therefore, provide opportunities for the creation and expansion of more firms with these desirable characteristics. While this idea is mostly uncontroversial, recent economic research has focused on the narrower question of whether individual firms improve their productivity *as a consequence* of their participation in export markets—i.e., whether they experience learning-by-exporting (LBE). Several papers, starting with the seminal contributions of Clerides et al. (1998) and Bernard and Jensen (1999), found that the answer to that question was 'no'.[1] Other papers, however, found positive evidence of LBE.[2]

In all, evidence of LBE effects have been found for some countries, mostly developing countries, and for some firms in industrial countries, such as young Spanish firms (Delgado et al., 2002) and lower-productivity Canadian firms that were induced to start exporting in response to the Canada-US Free Trade Agreement (FTA) (Lileeva and Trefler, 2007). But why do some firms seem to learn from exporting while others don't? To answer this question it is worthwhile to relate learning-by-exporting with the

[1] Bernard and Wagner (1997); Isgut (2001); Alvarez and Lopez (2005); Arnold and Hussinger (2005); and International Study Group on Exports and Productivity (2007) provide corroborating evidence.

[2] See e.g., Kraay (1999); Castellani (2002); Baldwin and Gu (2003); Bigsten et al. (2004); Girma et al. (2004); Blalock and Gertler (2004); Van Biesebroeck (2005); De Loecker (2007); and Park et al.(2007). Greenaway and Kneller (2007) and Wagner (2007) provide extensive reviews of this literature.

traditional concept of learning-by-doing (LBD). While the empirical literature on LBD has a long tradition in economics, a seminal theoretical paper by Arrow (1962) provides the clearest characterization of LBD.[3] First, he suggests that "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).

The first element of Arrow's characterization of LBD suggests that only firms for which exporting constitute a challenge will be able to learn from it. This is certainly the case for developing countries' firms. These firms are likely to find foreign customers that are more sophisticated and discriminating than their domestic counterparts. To satisfy them, new exporters from developing countries may need to improve their production processes and technical standards, upgrade their capital equipment, and retrain their workers. They may also need to learn new techniques of quality control and inventory management to guarantee product quality and the timely delivery of their orders. 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.

This rationale can explain the evidence of LBE found by Delgado et al. (2002) and Lileeva and Trefler (2007), respectively, for young Spanish firms and lower-productivity

[3] Starting with the work of Wright (1936) on airframe production, this literature has documented an association between experience, usually measured by past cumulative output, and measures of performance, such as labor productivity and unit costs.

Canadian firms that found it attractive to start exporting to the United States as a consequence of the FTA. Similarly to developing countries' new exporters, these Spanish and Canadian firms may have profited from accessing a market that is much larger and more competitive than their respective domestic markets. Conversely, the lack of evidence of LBE in Germany and the United States may be explained by the large size and highly competitive character of their domestic markets. For German or American firms, it is possible that entering the export market is just as challenging as entering the domestic market. Consequently, we would not expect to find evidence of LBE for those firms. The finding by Lileeva and Trefler (2007) of no LBE effects for higher-productivity Canadian firms is consistent with this view.

The second element of Arrow's characterization of LBD, their sharply diminishing returns, also contributes to explaining the uneven evidence of LBE across countries and types of firms. It suggests that LBE is a temporary phenomenon, as firms get "up to speed" operating in a new and more challenging market environment. Its main implication is that we should expect to find much less evidence of LBE in countries where most exporters are experienced exporters. This is likely the case of countries like Germany or the United States. In contrast, in countries where exports are growing fast, domestic firms may find many opportunities to start exporting for the first time. Slovenia, with its increased access to the European Union, and China, with its long-standing export-led growth policies, are two countries where the share of new exporters in the total number of exporters should be relatively large, making LBE effects more likely to be found.[4] The same is true for the

[4] Indeed, evidence of LBD is found for these two countries by De Loecker (2007) (Slovenia), and Kraay (2002) and Park et al. (2007) (China).

country studied in this paper, Colombia, during the second half of the 1980s, when manufacturing exports boomed as a result of a substantial real depreciation of the exchange rate.

In sum, Arrow's characterization of LBD has two main implications for the empirical study of LBE. First, we should not expect to find evidence of LBE for successful firms that operate in large and competitive domestic markets, as these firms do not need to acquire additional skills to succeed also in the export market. In contrast, we might find evidence of LBE for firms whose domestic market is substantially less competitive than the export market, or located in countries where goods for domestic consumption differ in quality to those traded in the export market. Second, we should not expect to find strong evidence of LBE for established exporters, even in developing countries.

The parallel between the concepts of LBE and LBD suggests the possibility of potentially fruitful parallels in empirical strategies. In particular, the hypothesis that LBE is a transient phenomenon, experienced only by new exporters, requires us to identify which exporters are new and which are experienced. For that purpose, in this paper we suggest using novel measures of export experience based on the firms' past exports, similarly to the use of cumulative output as a measure of experience in LBD studies. Our two measures are the number of years of exports until the previous year and the firm's cumulative export-output ratio until the previous year. These measures add further lags to the two measures of export experience most commonly used in the literature: a lagged export participation dummy or the lagged export-output ratio. In the empirical analysis we show that the additional lags contribute to productivity. Moreover, our measures allow us to test various hypotheses about the differential LBE effect for firms that have followed different temporal patterns of past participation in the export market.

Our results suggest that Colombian manufacturing plants do learn-by-exporting, even when controlling for the bias caused by self-selection of the most productive plants into the export market. However, not all the exporters learn to the same extent, and some of them forget what they have learned. Among the novel results of this paper we can mention the following: (i) the effect of past export experience on productivity is shown to be statistically insignificant for plants that stop exporting for at least three years; (ii) LBE effects are statistically insignificant for 'transient' exporters, defined as plants that have prior export experience but did not export in the previous year; (iii) LBE effects are more than proportional to the export-output ratio, suggesting the existence of spillovers of efficiency gains from export-related tasks to domestic market production; and (iv) LBE effects are smaller for the experienced exporters in our sample, providing evidence of diminishing returns to export experience.

The rest of the paper is organized as follows. Section II describes the model, Section III describes our econometric strategy and the samples to be used in the estimation, Section IV presents the results, and Section V 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 ratio of the average wage paid by the plant to the regional average wage or the wage premium (W_{it}).[5] These variables, along with labor and intermediates, are modeled as fully flexible variable inputs.[6] Following Olley and Pakes (1996), 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 $I_{it\text{-}1}$ 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 alternative measures of export experience, which can be thought of as different specifications for the function $h(.)$. In our baseline specifications, we consider the number of years the plant exported and the plant's cumulative export-output ratio:

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

$$EE_{it}^{2} = \sum_{\tau=FE_i}^{t-1} \frac{Y_{i\tau}^{F}}{Y_{i\tau}}, \tag{2b}$$

[5] We assume that labor markets are perfectly competitive and that there are different markets for different types of labor, such as for mechanical engineers, machinists, or bookkeepers. In this setting, plants differ in their wage premia because of the mix of different types of labor that they employ.

[6] In the empirical part of the paper, we will also relax this assumption by allowing labor to be 'less variable' than intermediates and making use of Ackerberg et al. (2007b) estimation techniques.

where $D_{i\tau} \equiv 1(Y_{i\tau}^F > 0)$ is a dummy value equal one if the plant exported in year τ and Y_{it} is total plant output. Notice that if we limit the sums above to a single term corresponding to $\tau = t - 1$, then EE_{it}^1 and EE_{it}^2 simplify to the two most common variables used in the literature to capture learning-by-exporting effects: lagged export status and lagged export intensity. In additional specifications, we consider alternative measures of export experience based on restricting the terms that enter EE_{it}^1 and EE_{it}^2 .

The production function is given by:

$$Y_{it} = L_{it}^{\beta_l} M_{it}^{\beta_m} K_{it}^{\beta_k} A_{it}^{\beta_A} \exp(\beta_0 + \beta_S S_{it} + \beta_W W_{it} + \beta_{EE} EE_{it} + \omega_{it}), \qquad (3)$$

where ω_{it} is an index of productivity known to the plant manager at the beginning of period t but unknown to the econometrician. Following Olley and Pakes (1996) we assume that it follows an exogenous first-order Markov process:

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

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. Notice that in our framework export experience is modeled as a predetermined variable which, like the capital stock, shifts the mean of the production function but does not affect ω_{it} . Assuming that productivity follows an exogenous first-order Markov process is conventional in production function estimation, and is the approach adopted by Van Biesebroeck (2005) in his study of LBE in Africa.[7]

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[7] An emerging econometric literature is starting to estimate production functions where ω_{it} is endogenous; see e.g. Doraszerlski and Jaumandreu (2008). In the LBE literature, De Loecker (2007) estimates as a robustness check a production function where ω_{it} depends on lagged export intensity and EE_{it}^1 . His results are qualitatively similar to those from his main production function estimation.

The plant manager maximizes the expected discounted value of future net cash flows; her decision problem is captured by the following Bellman equation:

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

where $Z_{it} \equiv (K_{it}, A_{it}, EE_{it}, \omega_{it})$, $Y_{it}^H \equiv Y_{it} - Y_{it}^F$ are home sales, p^H and p^F are, respectively, domestic and foreign prices, $C_Y(.)$ 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. We assume that plants are price takers in factor markets and goods markets at home and abroad. The cost function includes a vector of variable input prices w_t.

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, intermediates, the skill ratio, and the wage premium are assumed to be fully flexible variable 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.[8]

In this model, exports increase the plant's value in three ways: (i) by providing an additional source of revenue on top of sales in 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.[9] 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 level of productivity, the plant will be indifferent

[8] 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.

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

between producing only for the domestic market or producing for both the domestic market and for exports.[10] 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, then the plant will continue exporting.[11]

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

[10] These thresholds correspond to the φ^* and φ_x^* thresholds in the model by Melitz (2003).

[11] See Dixit and Pindyck (1994) for detailed analyses of entry and exit decisions under uncertainty with sunk entry costs. Irarrazabal and Opromolla (2006) apply 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.

the next 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 exporting currently. 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 after three years without exporting a plant like N^4 will "drop" to the position of N^1 in the figure.

The model we have just described is very similar to that estimated by Van Biesebroeck (2005). The main difference is that in that study the export experience variable is the plant's lagged export status, D_{it-1}, which is the last term of our export experience variable EE_{it}^1 (equation (2a). Whether the remaining terms of EE_{it}^1 are relevant is an empirical question, which we tackle in Section IV.

III. Econometric strategy and data description

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:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_S S_{it} + \beta_W W_{it} + \beta_k k_{it} + \beta_a a_{it} + \beta_{a^2} a_{it}^2 + \gamma^j + \tau_t + \beta_{EE} EE_{it} + \omega_{it} + \varepsilon_{it}, \tag{6}$$

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.

The problems associated with the estimation of equation (6) when ω_{it} follows a first-order Markov process (equation (3)) are well-known and arise from the fact that plant managers decide the use of variable inputs partly on the basis of realizations of ω_{it}, which is unobservable to the econometrician. Most researchers have employed the methods proposed by Olley and Pakes (1996) [henceforth OP] and Levinsohn and Petrin (2003) [henceforth LP] to address these problems. Their methods are based on the assumption that the unknown ω_{it} can be proxied by a nonparametric function of observable variables. The main difference between the two methods is that OP includes investment in the proxy function, while LP includes intermediate inputs. In a recent paper, Ackerberg et al. (2007b) [henceforth ACF] have critically examined these methods, arguing that they suffer from collinearity problems. Their proposed alternative estimation technique is based on estimating the coefficients on all the inputs, including those on the labor inputs, in the second stage of the procedure of OP or LP.[12]

In this paper we rely mostly on the LP method. We prefer it to OP because the latter requires using only observations with non-zero investment, entailing a 25 percent reduction in the sample size used for estimation. However, we show that our results are robust to the use of alternative estimation methods: OLS, LP, OP, and two variants of ACF. The two variants of ACF, which we label ACF-LP and ACF-OP differ in the proxy for the unobserved ω_{it}. In ACF-OP we use, as in OP, investment, while in ACF-LP we use, as in LP, intermediate inputs. As we shall see, estimates of the export experience coefficient using these alternative methods are all positive, statistically significant, and quantitatively similar. Details about our estimation strategy are provided in the Appendix.

Our estimation method controls for two potential biases in the estimate of β_{EE} under OLS: a negative selection bias due to exit decisions and a possibly positive bias due to self-selection into exporting. 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 the estimate of β_{EE}. This argument is analogous to that of OP regarding the possible negative selection bias on the estimated coefficient on

[12] This allows the labor inputs to be 'less variable' than the intermediate inputs, thus correcting the potential multicollinearity problems preventing the identification of the coefficients on the labor inputs.

capital due to plant exit decisions. However, we believe that this bias is more likely to affect β_k than β_{EE}, because most plants with positive export experience are likely to be around or above the export entry threshold, and thus farther to the right of the exit threshold compared to plants that do not export.

Regarding the possible upward bias in the OLS estimate of β_{EE} due to self-selection into exporting, it should be pointed out that the bias is not caused by favorable productivity shocks that push plants above the export entry threshold. If a plant receives a favorable productivity shock at time *t*, as a result of which it starts exporting for the first time that year, then its export experience in year *t* will be zero (recall equation (2)). Thus, that year the correlation between export experience and the unobserved productivity index will be zero. But if plants that enter the export market continue receiving favorable productivity shocks after entry, then there will be a positive correlation between export experience and unobserved productivity, biasing OLS estimates of β_{EE} upwards. The LP estimator used in this paper controls for this potential bias by imposing the identifying restriction that innovations in productivity are orthogonal to export experience [see equation (A5) in the Appendix].[13] 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 current plant productivity.

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[13] The critical assumption common to the LP, OP, and ACF methods is that unobserved productivity follows a first-order Markov process. Ackerberg et al. (2007a) discuss how to extend the OP method to the case where unobserved productivity follows a second-order Markov process.

The data used in this study come from 1981-1991 Annual Manufacturing Surveys (AMS) conducted by Colombia's Departamento Administrativo Nacional de Estadística (DANE). The variables used in our analysis are defined as follows. Labor L_{it} is the total number of workers employed by the plant. The skill ratio 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.[14] 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.[15] 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.[16] Our two measures of export experience, EE_{it}^1 and EE_{it}^2, are constructed using equations (2a) and (2b).

Accounting for differences in labor quality through S_{it} and W_{it} in the production function estimation is important because we do not observe physical volumes of outputs

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[14] Bahk and Gort (1993) use this variable to control for differences in labor quality in a study of LBD with U.S. data. We scale average plant wages by the regional average wage to control for systematic differences in wages across thirteen Colombian regions.

[15] 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.

[16] 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.

and of most inputs. As Katayama et al. (2003) pointed out, plant-level TFP estimates based on nominal sales revenues and input expenditures deflated with sector-wide price indexes are can be unreliable. One problem is that factor quality is likely to be positively associated with sales revenue (resulting from either a higher volume or a better quality of output), making plants using better inputs look as if they are more productive than they really are. Adding our measures of labor quality helps ameliorate this problem, which can be particularly serious for entrants into the export market.[17]

In all our estimating samples we exclude plants with less than three consecutive years of data, plants with missing years of data, and plants with outlier observations.[18] In the 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 proceed in two steps. First, we hypothesize that the export experience of exporters that do not export for three consecutive years depreciates completely. As we will show in Section IV, 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:

[17] Isgut (2001) finds that in Colombia new entrants into the export market during 1981-1991 increased both their sales revenue and their hiring of white collar workers, technicians and managers after entry. Not accounting for labor quality would thus exaggerate the effect of entry into exporting on productivity.

[18] 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.

$$EER_{it}^{1} = \begin{cases} 0 & \text{if } \prod_{\tau=t-3}^{\tau=t-1} D_{i\tau} = 0 \\ \sum_{\tau=T_i}^{t-1} D_{i\tau} & \text{otherwise} \end{cases} \tag{7a}$$

$$EER_{it}^{1} = \begin{cases} 0 & \text{if } \prod_{\tau=t-3}^{\tau=t-1} D_{i\tau} = 0 \\ \sum_{\tau=T_i}^{t-1} \frac{Y_{i\tau}^{F}}{Y_{i\tau}} & \text{otherwise} \end{cases} . \tag{7b}$$

For young plants, for which we observe their entire export history, T_i represents either their first year of exports (FE_i) or the year the plant re-enters the export market after three or more years without exporting. For old plants, for which we do not observe their entire export history, T_i represents the first year they export, after three or more years without exporting.

EER_{it}^{1} and EER_{it}^{2} allow us to treat plants that re-enter the export market after a spell of three or more years without exporting as new entrants. We use these measures of export experience in our second sample, which includes young plants and old plants that do not export in any year between 1981 and 1983. We exclude observations for the years 1981-1983 for the old plants because we need to observe that they did not export for at least three years in order to be able to measure their EER_{it}^{1} and EER_{it}^{2}. Notice also that we cannot measure EER_{it}^{1} and EER_{it}^{2} for old plants that exported in at least one year between 1981 and 1983. We refer to these plants as the 'old continuing exporters'.

Using EER_{it}^{1} and EER_{it}^{2} as measures of export experience allows us to double the number of plants, from about 3,000 in the 'young' sample to close to 6,000 in the 'young and old without continuing exporters' sample as shown in Table 1. However, these two samples leave out the bulk of Colombia's manufacturing exporters, the 'old continuing exporters'. In order to include those plants and thus use the full sample, we impose an alternative restriction to our baseline measures of export experience (equations (2a) and (2b)), by assuming that only the export experience of the last 5 years counts.[19] The resulting alternative measures are simply five-year moving sums of lagged export participation or lagged export intensity:

$$EEM_{it}^{1} = \sum_{\tau=t-5}^{t-1} D_{i\tau} \tag{8a}$$

$$EEM_{it}^{2} = \sum_{\tau=t-5}^{t-1} \frac{Y_{i\tau}^{F}}{Y_{i\tau}} \ . \tag{8b}$$

In this sample we exclude the first four years for each plant, because we use them to construct the moving sums.

Table 1 describes the data for each of the samples. The first two rows show the number of exporters and nonexporters. The share of exporters increases from 17-18 percent of the plants in the 'young' and 'young and old without continuing exporters' samples to 24 percent of plants in the full sample. 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. Table 1 also shows the averages of export experience for exporters and the incidence of observations in which export experience is positive. Old continuing exporters have significantly more export experience than either young exporters or old exporters that do not export during 1981-

[19] Note that this restriction is imposed on all plants young, old, and old continuing exporters.

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.

IV. Results

Table 2 shows estimation results for the sample of young plants using the export experience measure EE_{it}^{1}, the number of years the plant exported up to the previous year. Columns (1) and (2) compare OLS and LP estimates, while columns (3) and (4) compare

OLS and OP estimates for a smaller sample that includes only plants with positive investment. The estimates confirm the expectation of a positive OLS bias for the coefficients on the variable inputs – labor, skill ratio, wage premium, and intermediates – and a negative OLS bias for the coefficient on capital. We find that age has a negative coefficient in the production function. As Olley and Pakes (1996, p. 1274) argue, if older plants are less profitable conditional on their capital, productivity, and other state variables, then OLS estimates of the age coefficient will be upward biased, which is what we find. It is not entirely clear why older plants should be less profitable conditional on their state variables. One potential explanation could be that the capital stock may be under-measured when plants start producing, though its measurement becomes more accurate as more observations for the plant are available.[20] In that case, plants that are starting production may appear to be very productive given their measured capital stock, and this effect is picked up by the variable age. It should be pointed out, however, that in most specifications shown later in this paper, the coefficient on age turns statistically insignificant, as is also the case for the coefficient on age squared. Table 3 shows estimation results for the sample of young plants using the export experience measure EE_{it}^{2}, the plant's cumulative export intensity up to the previous year. The OLS biases for the variable input coefficients, capital, and age described above are also observed in these estimates.

In Tables 2 and 3, the estimates for the coefficient on export experience are all

[20] This problem is common when the capital stock is measured using the perpetual inventory method and the initial level of capital is either not reported or under-reported. In that case, the capital stock will be too small initially, though its measurement becomes more accurate as plants accumulate more capital over time.

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 show some evidence of a positive bias. For instance, in Table 2 the estimate for EE_{it}^{1} drops from 0.026 when using OLS to 0.023 when using LP. In Table 3 the estimate for EE_{it}^{2} drops more substantially, from 0.050 when using OLS to 0.028 when using LP. However, the evidence of a positive bias on the export experience coefficient estimates is not conclusive because the OP estimate of the EE_{it}^{1} coefficient is identical to the OLS estimate, and the ACF estimates of the EE_{it}^{2} coefficient exceed the OLS estimates. A possible reason why the data does not provide stronger evidence of a positive OLS bias on the export experience estimates is that not all new exporters are plants characterized by persistent favorable productivity shocks. As a matter of fact, recent research by Eaton et al. (2007) for Colombia covering a more recent period finds that the majority of new entrants to the export market do not last more than one year. We investigate this issue in more detail below.

The use of the export experience measures EE_{it}^{1} and EE_{it}^{2} in Tables 2 and 3 forces us to restrict the sample to those plants for which we can observe their full export history.[21] But this restriction is somewhat unsatisfactory, because the new plants constitute a minority of Colombia's manufacturing sector and are different in many respects from the more established plants. In particular, young plants are much smaller,

[21] We follow the empirical literature on LBD, which typically measures plant experience as cumulative output since the year production started (see e.g. Bahk and Gort, 1993).

pay lower wages, and are less likely to participate in export markets, a point that can be inferred from Table 1. It is unclear, then, whether the results shown in Tables 2 and 3 can be generalized to the entire Colombian manufacturing sector. In order to incorporate into the sample some of the old plants we start by conjecturing that the beneficial effect of export experience on productivity 'resets' to zero if a plant ceases to export for some time. This hypothesis is consistent with Arrow's (1962) characterization of learning-by-doing. If a plant's workers and managers stop performing specific tasks required to export but not to sell in the domestic market, then over time their skills in performing those tasks will erode. For concreteness, we assume that export-related skills are completely forgotten after a period of three years without exporting.[22]

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:

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

where EER_{it}^{j}'s are defined in equations (7a) and (7b). To conduct the tests, we estimate regressions of the form:

$$y_{it} = \beta x_{it} + \beta_{EER} EER_{it}^{j} + \beta_{EE-EER}\left(EE_{it}^{j} - EER_{it}^{j}\right) + \omega_{it} + \varepsilon_{it}, \quad j \in (1,2), \tag{9}$$

where x_{it} is a vector containing all the remaining explanatory variables in equation (6).[23] The hypothesis of interest is $H_0 : \beta_{EE-EER} = 0$. We test it using the sample of young plants. In column (1) of Table 4 and Table 5, we show the results for this test,

[22] Another possibility is that exporting requires hiring specialized personnel, which is dismissed after the plant drops out of the export market.

[23] This definition of x_{it} will be maintained in all equations hereafter.

respectively, for the number of years the plant exported until the previous year and for cumulative export intensity. In both cases we cannot reject H_0. 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 start exporting after 1983, as well as old plants that never export. Column (2) of Tables 4 and 5 shows 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: 0.020 for EE_{it}^1 and 0.022 for EE_{it}^2.

As mentioned above, the lack of strong evidence of a positive bias in OLS estimates of the export experience coefficients suggests that not all entrants into the export market are characterized by persistent favorable productivity shocks, a fact recently confirmed by Eaton et al. (2007). We conjecture that the presence of these 'transient' exporters in the sample is likely to bias downward our LP estimates of the coefficient on export experience. To understand this point, refer to Figure 1. It 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, which are close to the export entry threshold.

The presence in the sample of a group of exporters that are currently not exporting bring us back to Arrow (1962). Since these plants are not performing specific tasks required to export, they should not be learning. Thus, pooling those plants with plants actively engaged in the export market may underestimate the LBE effect. In order to test the hypothesis that learning-by-exporting occurs when a plant is actually exporting and not when it has temporarily stopped exporting, we estimate the following specification:

$$y_{it} = \beta x_{it} + \beta_{D*EER} D_{it-1} * EER_{it}^{j} + \beta_{EER} EER_{it}^{j} + \omega_{it} + \varepsilon_{it} \qquad j \in (1,2), \tag{10}$$

where D_{it-1} is the plant's lagged export status (=1 if the plant exported during the previous year). The hypotheses of interest are $H_0 : \beta_{D*EER} > 0$ and $H_0 : \beta_{EER} = 0$. Together, they indicate that only for active exporters does export experience have a positive effect 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 using EER_{it}^{1} as our measure of export experience in Table 4 and using EER_{it}^{2} in Table 5. The results for the young sample are presented in column (3) of both tables, and for the young and old (without continuing exporters) sample in column (4) of both tables. In all cases β_{D*EER} is positive and statistically significant, and β_{EER} is not statistically different from zero, suggesting that 'transient' exporters do not learn from exporting. However, we do not find clear evidence that the LBE effect is underestimated if transient exporters are included in the regression. When using EER_{it}^{2} (Table 5) the estimate of the interaction term β_{D*EER} is higher than the estimate of β_{EER} in the baseline specification, the opposite is true when using EER_{it}^{1} (Table 4).

Up to this point we measured export experience using two alternative variables:

the number of years the plant exported up to the previous year, EER_{it}^{1}, and the cumulative export-output ratio, EER_{it}^{2}. It is therefore natural to ask whether one of the two variables is better than the other, in the sense of conveying more information. A priori, it is conceivable to believe that cumulative export intensity conveys more information, as the learning effect of exporting should not be the same for a plant that exports 1 percent of its output versus a plant that exports 90 percent of its output. On the other hand, it is possible that some of the tasks required for exporting affect also production for the domestic market. For instance, if exporting requires a better management of the plant's inventories, then the gains in efficiency associated with this improvement will be unrelated to the share of exports in the plant's output.

In order to test whether EER_{it}^{1} conveys additional information to that included in EER_{it}^{2}, consider the identity $EER_{it}^{1} \equiv EER_{it}^{2} + \left(EER_{it}^{1} - EER_{it}^{2}\right)$. The term in parenthesis is non-negative because EER_{it}^{1} is based on the sum of past values of the lagged export participation dummy, which equals one when the plant exports, while EER_{it}^{2} is based on the sum of past values of export intensity, which takes values in the (0 1] interval when the plant exports. We thus estimate the following specification:

$$y_{it} = \beta x_{it} + \beta_{EER^2} EER_{it}^{2} + \beta_{EER^1 - EER^2}\left(EER_{it}^{1} - EER_{it}^{2}\right) + \omega_{it} + \varepsilon_{it} \,. \tag{11}$$

The hypothesis of interest is $H_0 : \beta_{EER^1 - EER^2} = 0$. It indicates that EER_{it}^{1} does not convey additional information to that included in EER_{it}^{2}. We test it using the sample of young plants. In column (5) of Table 5 we show results for this test for the sample of young plants. The null hypothesis is strongly rejected suggesting therefore the existence of indivisibilities in tasks related to exporting. These tasks are likely to be beneficial to the plants adopting them regardless of the share of exports in their output.

Having shown that EER_{it}^{1} conveys additional information to that included in EER_{it}^{2}, our next task is to investigate whether these measures of export experience convey additional information to that included in the two measures of export experience commonly used in the literature: lagged export participation dummy and lagged export intensity. For that purpose, notice that these two common measures are the last terms of the sums that define EER_{it}^{1} and EER_{it}^{2} (equations (7a) and (7b)). We are interested in knowing whether, after including lagged export participation or lagged export intensity in the regression, the remaining terms of EER_{it}^{1} and EER_{it}^{2} are positive and statistically significant. More precisely, we want to test $H_0 : \beta_2 = 0$ in the following regressions:

$$y_{it} = \beta x_{it} + \beta_1 DX_{it-1} + \beta_2 \left(EER_{it}^{1} - DX_{it-1} \right) + \omega_{it} + \varepsilon_{it}, \tag{12a}$$

$$y_{it} = \beta x_{it} + \beta_1 \left(\frac{Y_{it-1}^{F}}{Y_{it-1}} \right) + \beta_2 \left(EER_{it}^{2} - \frac{Y_{it-1}^{F}}{Y_{it-1}} \right) + \omega_{it} + \varepsilon_{it}. \tag{12b}$$

The results for these tests, using the sample of young and old plants (excluding old continuing exporters), are shown in columns (1) and (2) of Table 6. In both cases, we reject the null hypothesis at the 5 percent level.

As mentioned above, it is somewhat unsatisfactory to base our analysis on samples that do not include the established exporters, as they account for the bulk of Colombian manufacturing exporters. While the 'reset' tests shown in Tables 3 and 4 allowed us to include in the analysis 'old' plants (born before 1981) that did not export during 1981-1983, this addition to the sample still leaves out the major exporters. The common use of lagged export participation or lagged export intensity as measures of export experience is one way to incorporate these plants, but the tests just discussed suggests that exports realized in the years before the previous year convey information about export experience. An alternative way to incorporate the 'old continuing exporters' into the sample is to redefine export experience as moving sums of functions of past exports, as we do with our EEM_{it}^{1} and EEM_{it}^{2} measures (equations (8a) and (8b)).

In columns (3) and (4) of Table 6 we repeat the tests for regressions (12a) and (12b), but using the full sample and substituting EEM_{it}^{1} and EEM_{it}^{2} for EER_{it}^{1} and EER_{it}^{2}, respectively. The results show that terms from the moving sums EEM_{it}^{1} and EEM_{it}^{2} in addition to lagged export participation and lagged export intensity convey information about export experience. In this case, the null hypothesis is rejected at the 1 percent level.

Notice that in the four regressions shown in Table 6 the estimated coefficients on lagged export participation and on lagged export intensity exceed those on the additional export experience variables. The difference in the magnitude of the coefficients is particularly large for the 'young and old (without continuing exporters)' sample. A possible rationale for this difference could be given by the presence in the sample of exporters with only one year of export experience. In fact, the proportion of observations with one year of export experience over the total number of observations with positive export experience is 45 percent in the 'young and old (without continuing exporters)' sample, compared to 20 percent in the full sample. A large share of observations with a value of zero for the additional experience variables contributes to bringing down their estimated coefficient.[24]

[24] As a robustness check, we replicated the regressions in columns (3) and (4) of Table 6 restricting the full

A final important question that we tackle in this paper is whether there is evidence of diminishing returns to export experience. As mentioned in Section 1, this element of Arrow's (1962) characterization of learning may help explain the differences in estimates of LBE effects found by researchers across different datasets. To answer this question, we estimate the following specification:

$$y_{it} = \beta x_{it} + \beta_{EEM} EEM_{it}^{j} + \beta_{OCE*EEM} OCE_i * EEM_{it}^{j} + \omega_{it} + \varepsilon_{it} \quad j \in (1,2), \qquad (13)$$

OCE_i is a dummy variable identifying the 'old continuing exporters'. The results are shown in Table 7. They indicate that the interaction variable is significantly negative, suggesting that the LBE effect is less important for the more established exporters.

It should be pointed out, though, that the negative coefficients on the interaction variables are smaller in absolute value than the positive coefficients on the export experience variables, particularly when using moving sums of lagged export intensity (column 2). This suggests that the 'old continuing exporters' do experience LBE effects, though smaller than those experienced by new entrants into the export market. A possible explanation for this phenomenon could be that the period covered by the full sample, 1986-1991, was characterized by a very attractive real exchange rate that stimulated Colombian manufacturers not only to enter exporting buy also to increase their exports. In that context, it is possible that established exporters expanded their sales abroad significantly, giving rise to opportunities for further learning-by-exporting.

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sample to observations of plants with a maximum of 2 or more years of export experience. In that case, the magnitude of the estimated coefficient on $\left(EER_{it}^{1} - DX_{it-1}\right)$ exceeded that on DX_{it-1}.

V. Conclusion

The controversy about whether there is a causal effect from exporting to productivity is alive, despite the fact that a growing empirical literature has obtained evidence of learning-by-exporting. In this paper we argue that Arrow's (1962) conceptual characterization of learning-by-doing applies to learning-by-exporting, and we construct novel measures of export experience based on past export participation and past export-output ratios, inspired by the empirical literature on learning-by-doing. Our findings of learning-by-exporting effects for Colombian manufacturing plants are robust to differences in estimation methods, export experience measures, and samples.

Our results can be summarized as follows. First, we find some evidence of an upward bias in OLS estimates of the LBE effect, which is likely to be caused by the self-selection of plants with persistent favorable productivity shocks into exporting. Second, the effect of past export experience on productivity is insignificant for plants that stop exporting for at least three years. Third, we find no LBE effects for 'transient' exporters, defined as plant with prior export experience that did not export in the previous year. Fourth, we find evidence that LBE effects are not proportional to the plant's export-output ratios, suggesting the existence of indivisibilities in export-related tasks, which may bring efficiency gains to domestic market production as well. Fifth, we find that our measures of export experience, which are based on sums of lagged values of export participation or export-output ratios convey additional information to that included in one-year lags of those variables, which are the measures of export experience most commonly used in the literature. Finally, we find evidence of diminishing returns to export experience in that LBE effects are quantitatively lower for the experienced exporters in our sample.

Overall, our results are consistent with Arrow's (1962) view of learning in the sense that (i) only plants consistently exposed to the export market learn from it and (ii) new entrants to the export market learn more than experienced exporters. Of particular significance is the finding of no learning effects for plants that stop exporting or plants that export irregularly. It is consistent both with recent plant-level evidence for Colombia found by Eaton et al. (2007) and with disaggregated bilateral manufacturing export data analyzed by Besedeš and Prusa (2007). It suggests that export promotion policies are not necessarily a lever of riches because, by reducing the cost of entry into exporting, they may facilitate the entry of less productive plants that are more likely to fail and less likely to learn from the experience. Further research should address the connection between export promotion and other policies that encourage entry into exporting and their resulting learning effects.

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Appendix: Estimation details

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. 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: $\omega_{it} = \omega_{it}(m_{it}, k_{it}, a_{it}, EE_{it})$.[25] In the first stage of the estimation, we rewrite equation (6) in a semi-parametric form:

$$y_{it} = \beta_l l_{it} + \beta_S S_{it} + \beta_W W_{it} + \gamma^j + \tau_t + \phi(m_{it}, k_{it}, a_{it}, EE_{it}) + \varepsilon_{it}, \tag{A1}$$

where

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

We obtain consistent estimates for the coefficients on $(l_{it}, S_{it}, W_{it}, \gamma_j, \tau_t)$ from equation (A1) using OLS with no constant, and replacing the unknown function $\phi(.)$ by a third-degree polynomial in $(m_{it}, k_{it}, a_{it}, EE_{it})$.

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

$$\chi_{it} = \begin{cases} 1 \text{ (continue)} & \text{if } \omega_{it} > \overline{\omega}_t(k_{it}, a_{it}, EE_{it}) \\ 0 \text{ (exit)} & \text{otherwise,} \end{cases} \tag{A2}$$

where $\overline{\omega}(.)$ is the plant's exit threshold. Defining $\tilde{y}_{it} \equiv y_{it} - \beta_l l_{it} - \beta_S S_{it} - \beta_W W_{it} - \gamma^j - \tau_t$,

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

substituting into equation (6) and taking expectations conditional on information at $t-1$, J_{it-1}, and survival we obtain:[26]

$$E[\tilde{y}_{it} \mid J_{it-1}, \chi_{it}=1] = \beta_k k_{it} + \beta_a a_{it} + \beta_{a^2} a_{it}^2 + \beta_{EE} EE_{it} + \beta_m E[m_{it} \mid J_{it-1}, \chi_{it}=1] + E[\omega_{it} \mid J_{it-1}, \chi_{it}=1]. \tag{A3}$$

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 $\omega_{it} = E[\omega_{it} \mid \omega_{it-1}, \chi_{it}=1] + \xi_{it}$, 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:

$$\tilde{y}_{it} = \beta_k k_{it} + \beta_a a_{it} + \beta_{a^2} a_{it}^2 + \beta_{EE} EE_{it} + \beta_m m_{it} + g(\omega_{it-1}, p_{it}) + \xi_{it} + \varepsilon_{it}. \tag{A4}$$

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 (A4). In sum, the orthogonality of ξ_{it} with respect to $(m_{it-1}, k_{it}, a_{it}, a_{it}^2, EE_{it})$ allows us to identify the remaining coefficients of the model $(\beta_m, \beta_k, \beta_a, \beta_{a^2}, \beta_{EE})$ through the following moment conditions (expressed in vector form):

$$E[\varepsilon_{it} + \xi_{it} \mid x] = 0, \tag{A5}$$

where $x \equiv (m_{it-1}, k_{it}, a_{it}, a_{it}^2, EE_{it})$.

To estimate $(\beta_m, \beta_k, \beta_a, \beta_{a^2}, \beta_{EE})$ from equation (A5), we first estimate the survival

[26] 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}.

probability $\hat{p}_{it}$ non-parametrically by a probit model of plant survival on a third degree polynomial in $(m_{it-1}, k_{it-1}, a_{it-1}, EE_{it-1})$. Second, we replace the unknown ω_{it-1} in $g(\omega_{it-1}, p_{it})$ 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 (A3) that the unknown function $g(\omega_{it-1}, p_{it})$ approximates $E[\omega_{it} \mid J_{it-1}, \chi_{it} = 1]$. For candidate coefficients $(\beta_m^*, \beta_k^*, \beta_a^*, \beta_{a^2}^*, \beta_{EE}^*)$, we estimate this function as the predicted value from an OLS regression of: $(\hat{\omega}_{it} + \hat{\varepsilon}_{it})(\beta)^* = \tilde{y}_{it} - \beta_m^* m_{it} - \beta_k^* k_{it} - \beta_a^* a_{it} - \beta_{a^2}^* a_{it}^2 - \beta_{EE}^* EE_{it}$ on a third degree polynomial in the estimated probability of survival $\hat{p}_{it}$ and in $\hat{\omega}_{it-1}(\beta^*) = \hat{\phi}(m_{it-1}, k_{it-1}, a_{it-1}, a_{it-1}^2, EE_{it-1}) - \beta_m^* m_{it-1} - \beta_k^* k_{it-1} - \beta_a^* a_{it-1} - \beta_{a^2}^* a_{it-1}^2 - \beta_{EE}^* EE_{it-1}$. Our generalized method of moments (GMM) criterion function weights the plant-year moment conditions in equation (A5) by their variance-covariance matrix.

Our estimation algorithm uses OLS estimates of $(\beta_m, \beta_k, \beta_a, \beta_{a^2}, \beta_{EE})$ 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 $(\beta_m, \beta_k, \beta_a, \beta_{a^2}, \beta_{EE})$ 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.

To obtain Olley and Pakes (1996) estimates, we use investment as a proxy for the unobserved productivity, instead of intermediate inputs as in LP. The first stage of the estimation obtains coefficients on $\left(l_{it}, S_{it}, W_{it}, m_{it}, \gamma_j, \tau_t\right)$ using a semi-parametric equation similar to equation (A1) but where the unobservable productivity index is a function of investment and the observable state variables. In the second stage of the estimation, we use non-linear least squares to obtain consistent estimates for the coefficients on $\left(k_{it}, a_{it}, a_{it}^2, EE_{it}\right)$ accounting for the possibility of selection bias due to plant exit decisions.

To obtain Ackerberg, Caves, and Frazer (2007b) estimates, we use intermediate inputs for ACF-LP or investment for ACF-OP as the proxy for unobserved productivity. The crucial difference relative to the LP or OP estimation techniques is that the coefficients on labor variables are no longer estimated in the first stage but rather in the second stage along with the coefficients on the state variables. The second stage of the estimation uses a GMM criterion function based on moment conditions for $\left(l_{it-1}, S_{it-1}, W_{it-1}, k_{it}, a_{it}, a_{it}^2, EE_{it}\right)$.

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

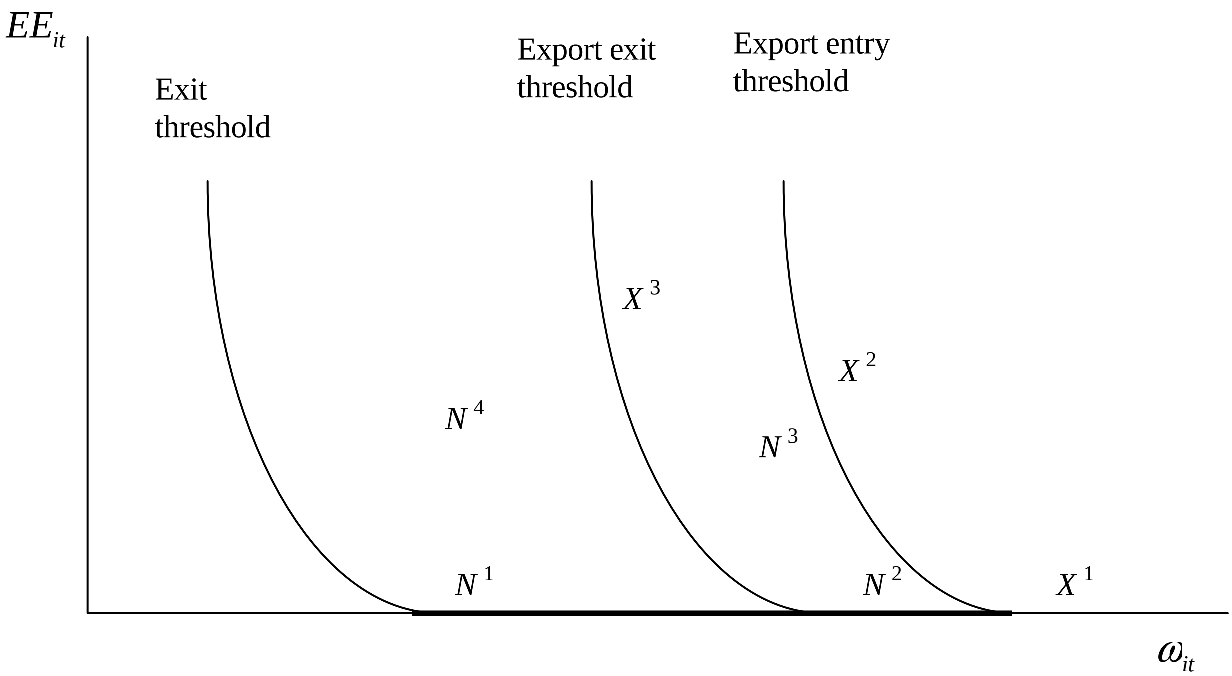
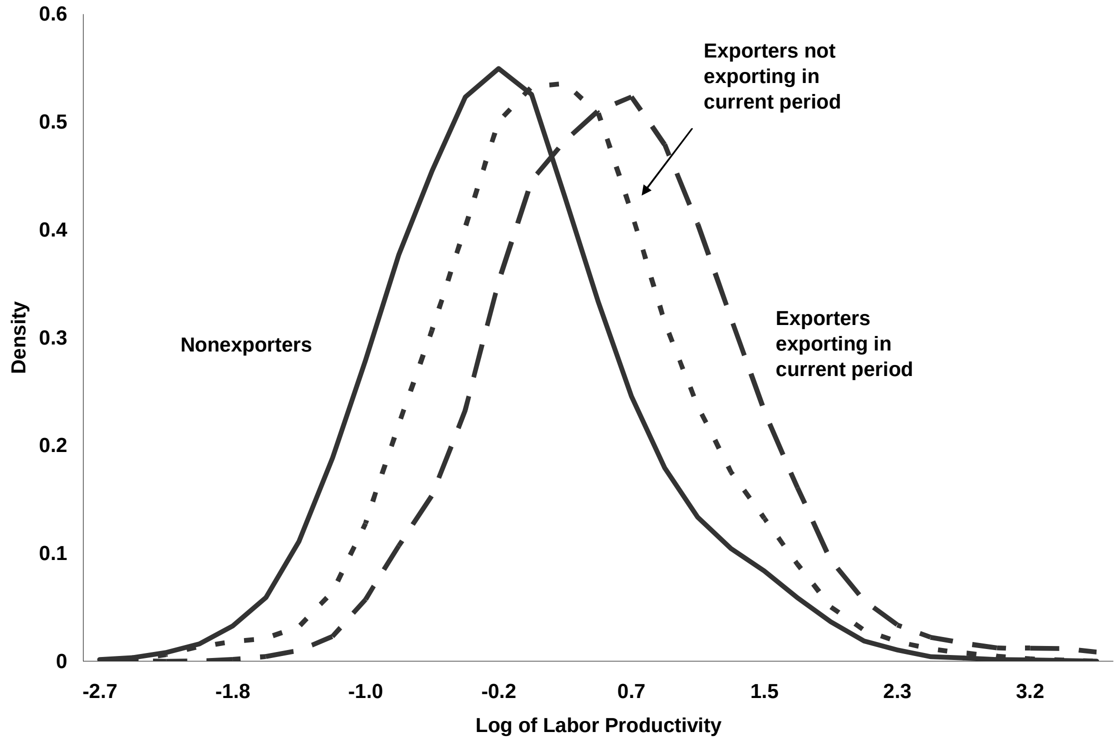


Figure 2: Distributions of Plant-Year Labor Productivity for Full Sample



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
Number of Plants			
Exporters	476	871	1,196
Nonexporters	2,627	5,111	3,696
Average Number of Workers			
Exporters	56	110	194
Nonexporters	30	46	56
Average Exporter Premia			
Labor Productivity	0.53	0.45	1.05
Capital-Labor Ratio	0.64	0.48	1.17
Intermediates-Labor Ratio	0.56	0.49	0.00
Skill Intensity	0.11	0.05	0.09
Wage Premium	0.23	0.24	0.48
Average Export Experience			
EE^1	1.18		
EE^2	0.29		
EER^1		0.92	
EER^2		0.16	
EEM^1			2.78
EEM^2			0.45
Incidence of Positive Export Experience	0.46	0.40	0.81
Average Export Intensity when Exporting	0.25	0.18	0.17

Notes: The exporter premia are all significant at the 1 percent confidence level. Labor productivity is defined as the ratio of output minus intermediates to the total number of workers. The measures of export experience EE^1, EE^2, EER^1, EER^2, EEM^1, and EEM^2 are defined in the text. The averages of the export experience measures are taken over all the observations for exporters, including those when the measures are zero. Exporters are defined as plants that export at least in one year. The incidence of positive export experience is the share of exporters' observations for which export experience is positive.

Table 2. Baseline Results for the Sample of Young Plants - Export Experience Measure EE^1

	OLS	LP	OLS	OP	ACF-LP	ACF-OP
	(1)	(2)	(3)	(4)	(5)	(6)
Labor (l_{it})	0.267	0.247	0.249	0.237	0.271	0.247
	(0.005)***	(0.008)***	(0.005)***	(0.009)***	(0.008)***	(0.009)***
Skill Intensity (S_{it})	0.299	0.244	0.298	0.279	0.298	0.296
	(0.014)***	(0.019)***	(0.015)***	(0.020)***	(0.022)***	(0.023)***
Wage Premium (W_{it})	0.365	0.328	0.349	0.327	0.367	0.349
	(0.012)***	(0.019)***	(0.013)***	(0.022)***	(0.019)***	(0.020)***
Intermediates (m_{it})	0.688	0.612	0.688	0.681	0.690	0.672
	(0.003)***	(0.026)***	(0.004)***	(0.006)***	(0.005)***	(0.006)***
Capital (k_{it})	0.061	0.103	0.068	0.114	0.062	0.073
	(0.002)***	(0.017)***	(0.003)***	(0.014)***	(0.006)***	(0.005)***
Age (a_{it})	-0.046	-0.071	-0.054	-0.103	-0.041	-0.062
	(0.024)**	(0.028)***	(0.027)**	(0.027)***	(0.023)*	(0.025)***
Age Squared (a_{it}^2)	-0.003	-0.129	0.000	0.102	0.046	0.065
	(0.008)	(0.061)**	(0.009)	(0.033)***	(0.018)***	(0.011)***
Export Experience (EE_{it}^1)	0.026	0.023	0.026	0.026	0.023	0.024
	(0.002)***	(0.010)***	(0.003)***	(0.012)**	(0.008)***	(0.005)***
Number of Observations	15537	15537	11578	11578	15537	11578

Notes: The dependent variable is the logarithm of plant output (y_{it}). *** , **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. In columns (1) and (3) robust standard errors are in parentheses. In columns (2), (4), (5), and (6) bootstrapped standard errors are in parentheses. Labor, intermediates, capital, and age are in logarithms. Age squared is the square of the logarithm of age. The export experience variable EE^1 is defined in the text. Years included are 1982-1991.

Table 3. Baseline Results for the Sample of Young Plants - Export Experience Measure EE^2

	OLS	LP	OLS	OP	ACF-LP	ACF-OP
	(1)	(2)	(3)	(4)	(5)	(6)
Labor (l_{it})	0.27	0.248	0.252	0.239	0.269	0.248
	(0.005)***	(0.008)***	(0.005)***	(0.008)***	(0.008)***	(0.009)***
Skill Intensity (S_{it})	0.306	0.249	0.305	0.284	0.305	0.304
	(0.014)***	(0.020)***	(0.015)***	(0.020)***	(0.022)***	(0.022)***
Wage Premium (W_{it})	0.369	0.325	0.353	0.330	0.370	0.352
	(0.012)***	(0.019)	(0.013)***	(0.021)***	(0.019)***	(0.020)***
Intermediates (m_{it})	0.688	0.564	0.688	0.680	0.689	0.673
	(0.003)***	(0.019)***	(0.004)***	(0.006)***	(0.005)***	(0.005)***
Capital (k_{it})	0.061	0.131	0.068	0.113	0.064	0.049
	(0.002)***	(0.015)***	(0.003)***	(0.015)***	(0.006)***	(0.005)***
Age (a_{it})	-0.047	-0.098	-0.055	-0.130	-0.047	-0.052
	(0.024)**	(0.034)***	(0.027)**	(0.026)***	(0.023)**	(0.025)**
Age Squared (a_{it}^2)	-0.002	-0.067	0.001	0.150	-0.02	-0.094
	(0.008)	(0.064)	(0.009)	(0.029)***	(0.019)	(0.019)***
Export Experience (EE_{it}^2)	0.050	0.028	0.051	0.045	0.051	0.058
	(0.006)***	(0.010)***	(0.007)***	(0.022)***	(0.012)***	(0.013)***
Number of Observations	15537	15537	11578	11578	15537	11578

Notes: The dependent variable is the logarithm of plant output (yit). *** , **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. In columns (1) and (3) robust standard errors are in parentheses. In columns (2), (4), (5), and (6) bootstrapped standard errors are in parentheses. Labor, intermediates, capital, and age are in logarithms. Age squared is the square of the logarithm of age. The export experience variable EE^2 is defined in the text. Years included are 1982-1991.

Table 4. Specification Tests for Export Experience Measure EE^1

	Sample of Young Plants	Sample of Young and Old Plants (Without Continuing Exporters)	Sample of Young Plants	Sample of Young and Old Plants (Without Continuing Exporters)
	(1)	(2)	(3)	(4)
Labor (l_{it})	0.248	0.245	0.249	0.245
	(0.008)***	(0.005)***	(0.008)***	(0.005)***
Skill Intensity (S_{it})	0.246	0.242	0.248	0.241
	(0.018)***	(0.016)***	(0.020)***	(0.018)***
Wage Premium (W_{it})	0.332	0.271	0.333	0.271
	(0.020)***	(0.012)***	(0.017)***	(0.012)***
Intermediates (m_{it})	0.457	0.549	0.446	0.452
	(0.014)***	(0.010)***	(0.021)***	(0.013)***
Capital (k_{it})	0.164	0.120	0.161	0.170
	(0.012)***	(0.013)***	(0.011)***	(0.006)***
Age (a_{it})	-0.030	-0.012	-0.006	0.002
	(0.028)	(0.021)	(0.025)	(0.014)
Age Squared (a_{it}^2)	-0.004	-0.005	-0.060	-0.008
	(0.038)	(0.032)	(0.032)	(0.006)
Export Experience (EER_{it}^1)	0.029	0.020	0.003	0.008
	(0.007)***	(0.005)***	(0.007)	(0.007)
Difference Term (EE_{it}^1-EER_{it}^1)	0.000			
	(0.026)			
Export Experience (EER_{it}^1) * Lagged Export Dummy (D_{it-1})			0.026	0.012
			(0.008)***	(0.005)***
Number of Observations	15537	35637	15537	35637

Notes: Modified Levinsohn and Petrin (2003) estimation. The dependent variable is the logarithm of plant output (y_{it}). *** indicates significance at the 1 percent level. Bootstrapped standard errors are in parentheses. Labor, intermediates, capital, and age are in logarithms. Age squared is the square of the logarithm of age. The export experience variables EE^1 and EER^1 are defined in the text. Years included are 1982-1991 for young plants and 1984-1991 for old plants.

Table 5. Specification tests for Export Experience Measure EE^2

	Sample of Young Plants	Sample of Young and Old Plants (Without Continuing Exporters)	Sample of Young Plants	Sample of Young and Old Plants (Without Continuing Exporters)	Sample of Young Plants
	(1)	(2)	(3)	(4)	(5)
Labor (l_{it})	0.248	0.246	0.249	0.246	0.248
	(0.008)***	(0.005)***	(0.008)***	(0.008)***	(0.008)***
Skill Intensity (S_{it})	0.249	0.246	0.251	0.245	0.246
	(0.020)***	(0.015)***	(0.020)***	(0.016)***	(0.020)***
Wage Premium (W_{it})	0.326	0.272	0.328	0.272	0.330
	(0.022)***	(0.012)***	(0.023)***	(0.013)***	(0.020)***
Intermediates (m_{it})	0.468	0.580	0.459	0.540	0.521
	(0.016)***	(0.007)***	(0.016)***	(0.018)***	(0.005)***
Capital (k_{it})	0.168	0.089	0.157	0.131	0.130
	(0.012)***	(0.018)***	(0.012)***	(0.009)***	(0.008)***
Age (a_{it})	-0.037	0.035	-0.008	-0.066	-0.034
	(0.024)	(0.020)	(0.028)	(0.014)***	(0.024)*
Age Squared (a_{it}^2)	-0.047	-0.052	-0.002	0.018	-0.039
	(0.043)	(0.043)	(0.048)	(0.015)***	(0.028)*
Export Experience (EER_{it}^2)	0.027	0.022	0.012	0.026	0.028
	(0.010)***	(0.010)***	(0.023)	(0.018)	(0.013)**
Difference Term (EE_{it}^2-EER_{it}^2)	-0.004				
	(0.122)				
Export Experience (EER_{it}^2) * Lagged Export Dummy (D_{it-1})			0.039	0.039	
			(0.015)***	(0.016)***	
Export Experience (EER_{it}^1) - Export Experience (EER_{it}^2)					0.019
					(0.008)***
Number of Observations	15537	35637	15537	35637	15537

Notes: Modified Levinsohn and Petrin (2003) estimation. The dependent variable is the logarithm of plant output (y_{it}). *** , **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. Bootstrapped standard errors are in parentheses. Labor, intermediates, capital, and age are in logarithms. Age squared is the square of the logarithm of age. The export experience variables EE^2, EER^2, and EER^1 are defined in the text. Years included are 1982-1991 for young plants and 1984-1991 for old plants.

Table 6. Export Experience vs. Lagged Export Participation or Lagged Export Intensity

	Sample of Young and Old Plants (Without Continuing Exporters)		Full Sample	
	(1)	(2)	(3)	(4)
Labor (l_{it})	0.245	0.246	0.230	0.233
	(0.005)***	(0.005)***	(0.005)***	(0.005)***
Skill Intensity (S_{it})	0.242	0.245	0.258	0.264
	(0.017)***	(0.016)***	(0.014)***	(0.014)***
Wage Premium (W_{it})	0.271	0.272	0.245	0.246
	(0.011)***	(0.011)***	(0.010)***	(0.009)***
Intermediates (m_{it})	0.547	0.549	0.649	0.643
	(0.008)***	(0.005)***	(0.006)***	(0.004)***
Capital (k_{it})	0.114	0.118	0.019	0.010
	(0.008)***	(0.010)***	(0.006)***	(0.005)**
Age (a_{it})	-0.010	-0.012	-0.006	-0.021
	(0.017)	(0.020)	(0.016)	(0.012)
Age Squared (a_{it}^2)	0.015	0.003	-0.003	0.011
	(0.065)	(0.104)	(0.050)	(0.045)
Lagged Export Participation (DX_{it-1})	0.046		0.040	
	(0.016)***		(0.019)***	
Lagged Export Intensity (Y_{it}^F / Y_{it})		0.101		0.106
		(0.017)***		(0.022)***
Export Experience (EER_{it}^1) minus DX_{it-1}	0.013			
	(0.006)**			
Export Experience (EER_{it}^2) minus XQ_{it-1}		0.024		
		(0.011)**		
Sum of $DX_{i\tau}$ from $\tau = t - 5$ to $\tau = t - 2$			0.029	
			(0.011)***	
Sum of $Y_{i\tau}^F / Y_{i\tau}$ from $\tau = t - 5$ to $\tau = t - 2$				0.042
				(0.012)***
Number of Observations	35637	35637	23152	23152

Notes: Modified Levinsohn and Petrin (2003) estimation. The dependent variable is the logarithm of plant output (y_{it}). *** and ** indicate significance at the 1 and 5 percent level, respectively. Bootstrapped standard errors are in parentheses. Labor, intermediates, capital, and age are in logarithms. Age squared is the square of the logarithm of age. The export experience variables EER^1 and EER^2 are defined in the text. The years included in the sample of young and old plants (excluding continuing exporters) are 1982-1991 for young plants and 1984-1991 for old plants. The full sample includes the years 1986-1991.

Table 7. Evidence of Diminishing Returns to Export Experience

	Full Sample	
	(1)	(2)
Labor (l_{it})	0.231	0.234
	(0.006)***	(0.005)***
Skill Intensity (S_{it})	0.257	0.267
	(0.019)***	(0.020)***
Wage Premium (W_{it})	0.244	0.247
	(0.012)***	(0.010)***
Intermediates (m_{it})	0.628	0.605
	(0.012)***	(0.010)***
Capital (k_{it})	0.012	0.047
	(0.006)**	(0.007)***
Age (a_{it})	0.020	-0.036
	(0.041)	(0.041)
Age Squared (a_{it}^2)	-0.002	0.001
	(0.017)	(0.025)
Export Experience (EER_{it}^1)	0.043	
	(0.009)***	
Export Experience (EER_{it}^2)		0.125
		(0.016)***
Export Experience (EEM_{it}^1) * OCE_i	-0.027	
	(0.012)***	
Export Experience (EEM_{it}^2) * OCE_i		-0.040
		(0.019)**
Number of Observations	23152	23152

Notes: Modified Levinsohn and Petrin (2003) estimation. The dependent variable is the logarithm of plant output (y_{it} *** and ** indicate significance at the 1 and 5 percent level, respectively. Bootstrapped standard errors are in parentheses. Labor, intermediates, capital, and age are in logarithms. Age squared is the square of the logarithm of age. The export experience variables EEM^1 and EEM^2 are defined in the text. OCE_i is a dummy variable equal to 1 for the subsample of old continuing exporters, and 0 otherwise. Years included are 1986-1991.