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

Ana M. Fernandes
The World Bank

Alberto E. Isgut
UNESCAP

Abstract: This paper thoroughly examines the learning-by-exporting (LBE) hypothesis for Colombian manufacturing plants during 1981-1991 and finds significant evidence in its favor. The results are robust to the use of different samples of the dataset, different econometric methods, and different modeling approaches. We find that export experience acquired by plants in years before the previous year has an important effect on plant productivity and that the effect of export experience on productivity is non-significant for exporters that stopped exporting in the previous year. We also find evidence of diminishing returns to export experience in that LBE effects are quantitatively lower for the experienced exporters in our sample.

Keywords: Learning by Exporting, Learning by Doing, Total Factor Productivity, Exports, Export-Led Growth, Simultaneity and Production Functions.

JEL Classification: C14, D21, D24, F10, L60

Address correspondence to Ana M. Fernandes, Trade and International Integration Unit, Development Research Group, The World Bank, 1818 H Street, N.W., Washington, DC 20433, USA. E-mail: afernandes@worldbank.org

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] Specifically, LBE has been shown mostly for firms in developing countries in Africa (Van Biesebroeck, 2005) or in emerging countries such as Slovenia (De Loecker, 2007), 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, 2010).

The lack of conclusive evidence about learning-by-exporting (LBE) should not be surprising. According to Arrow (1962, pp. 155), learning is "the product of experience", which can only take place through the attempt to solve a problem and thus only "takes place during activity". This suggests that only firms for which exporting is challenging would be able to learn from it. This would certainly be the case for new exporting firms in developing countries, but could also apply to new and smaller firms in developed countries, as those firms find foreign customers to be more

[1] See, e.g. Bernard and Wagner (1997) and Arnold and Hussinger (2005) for Germany and ISGEP (2008) for 14 countries across the globe. Wagner (2007, 2012) provides a survey of empirical studies on exporting and productivity.

[2] See e.g., Alvarez and Lopez (2005) for Chile, Andersson and Lööf (2009) for Sweden, Baldwin and Gu (2003) for Canada, Bigsten et al. (2004), Bigsten and Gebreeyesus (2009), for African countries, Blalock and Gertler (2004) for Indonesia, Castellani (2002) for Italy, Girma et al. (2004) for the U. K., Kraay (1999) and Park et al. (2010) for China, Mánez-Castillejo et al. (2010) and Manjón et al. (2013) for Spain. Focusing on Colombia, Isgut (2001) does not find evidence of increases in productivity after entry into exporting but finds that entrants into export markets significantly increase investments in physical capital before entry and in human capital after entry.

sophisticated and discriminating than their domestic counterparts. By accessing a significantly larger and more competitive market those firms are likely to face major technical and managerial challenges, whose resolution may require upgrading production processes, equipment and technical standards, retraining workers, and improving quality control and inventory management techniques. As workers and managers engage in new activities to meet these challenges, they are likely to learn new skills, resulting in improvements of the firm's productivity.[3] In contrast, we would expect to find less evidence of LBE for firms in countries such as the U.S. or Germany, where firms do not need to access the export market to operate in a large and highly competitive market. For those firms entering the export market is likely to be just as challenging as it is to enter the domestic market.[4]

Arrow (1962, p. 155-6) argues that "learning associated with repetition of essentially the same problem is subject to sharply diminishing returns" and that only when "stimulus situations" are "steadily evolving rather than merely repeating" will learning-by-doing (LBD) result in a "steadily increasing performance". This suggests that LBE is a temporary phenomenon, as firms get "up to speed" operating in a more challenging market environment. It also suggests that LBE is more likely to be observed in developing countries where a large number of domestic firms are entering the export market for the first time. In this paper we test the LBE hypothesis using manufacturing plant-level data from Colombia for the period 1981-1991. The focus on this period is particularly relevant because the Colombian peso depreciated significantly in the mid-1980s leading many plants with no prior exporting experience to venture into the export market. Since large real depreciations have often preceded major export surges in developing countries as shown by Freund and Pierola (2012), Colombia in the 1980s is a good case to explore the relevance of the LBE hypothesis.

[3] This rationale can explain the evidence of LBE found by Delgado et al. (2002) for young Spanish firms and Lileeva and Trefler (2007) for lower-productivity Canadian firms. Similarly to developing countries' new exporters, these Spanish and Canadian firms may have profited from accessing a much larger and more competitive market than their respective domestic markets.

[4] The absence of LBE effects found for higher-productivity Canadian firms by Lileeva and Trefler (2010) is consistent with this view.

The main contribution of this paper is to test a series of hypotheses on LBE in Colombia based on Arrow's (1962) conceptual framework for LBD. For that purpose, we include in our regressions measures of export experience based on the plant's history of participation in export markets. These measures encompass as special cases the two most common export experience measures used in the LBE literature: a lagged export status dummy and the lagged export-output ratio. In addition, we use different subsamples of the data, ranging from a subsample of young plants, for which we can observe their whole export history, to the full sample that includes also old continuing exporters. By using measures of export experience based on multiple lags of export status and the export-output ratio and various subsamples of the data we are able to test for example whether further lags of exports affect productivity, whether LBE effects disappear for plants that stopped exporting the previous year, or whether LBE effects are more pronounced for younger than for older plants.

Our results provide evidence of significant LBE effects for Colombian manufacturing plants during the period 1981-1991. We find that export experience acquired by plants in years before the previous year has an important effect on plant productivity. We also show that the effect of export experience on productivity exhibits a high rate of depreciation – i.e., it is non-significant for exporters that stopped exporting in the previous year – and that there are diminishing returns to export experience in that LBE effects are quantitatively lower for the experienced exporters in our sample. The results are robust to the use of different econometric methods, including modified versions of the semi-parametric methods of Levinsohn and Petrin (2003), Olley and Pakes (1996), and Ackerberg et al. (2006), allowing for a second-order Markov process in productivity, a full information maximum likelihood (FIML) method which models explicitly the decision to export as in Clerides et al. (1998) and Van Biesebroeck (2005), and allowing export experience to influence the Markov process for productivity as in De Loecker (2007, 2010) and Manjón et al. (2013).

The rest of the paper is organized as follows. Section II describes a model of LBE to motivate our empirical approach. Section III discusses our econometric strategy and Section IV describes the data. Section V presents the main results, Section VI presents extensions and robustness checks and Section VII concludes.

II. A Model of Learning-by-Exporting

To motivate our empirical approach, this section describes a stylized model of LBE where plants use labor in efficiency units (H_{it}), intermediates (M_{it}), and capital (K_{it}) to produce output with a Cobb-Douglas technology. The first two variables are modeled as fully flexible variable inputs. Following Olley and Pakes (1996) [henceforth OP], plant age (A_{it}) is included as a state variable. Capital and age accumulate according to the laws of motion $K_{it} = (1-\delta)K_{it-1} + I_{it-1}$ and $A_{it} = A_{it-1} + 1$, where $I_{it\text{-}1}$ is gross investment in t-1 and δ is the depreciation rate. To account for the possibility of LBE, plant export experience (EE_{it}) is included also as a state variable. Export experience is a function of past values of exports Y_{it}^F with FE_i being the first year plant i exported:

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

The production function is given by:

$$Y_{it} = H_{it}^{\beta_h} M_{it}^{\beta_m} K_{it}^{\beta_k} A_{it}^{\beta_A} \exp\left(\beta_0 + \beta_{EE} EE_{it} + \omega_{it}\right) \tag{2}$$

where ω_{it} is a productivity index known to the plant manager at the beginning of period t but unknown to the econometrician. As in OP we assume it follows an exogenous first-order Markov process $p\left(\omega_{it} \mid \omega_{it-1}, \omega_{it-2}, \ldots, \omega_{i,FY_i}; J_{it-1}\right) = p\left(\omega_{it} \mid \omega_{it-1}\right)$, where $J_{\text{it-1}}$ is plant i's information set in t-1 and FY_{i} is the year when plant i started operations. Export experience is modeled as a predetermined variable which, like capital, shifts the mean of the production function but does not affect ω_{it}.

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

$$V\left(Z_{it}, D_{it-1}\right) = \max\left\{\Phi, \max_{Y_{it}, Y_{it}^{F}, I_{it}} \left\{ \begin{array}{l} Y_{it}^{H}.p^{H} + Y_{it}^{F}.p^{F} - C_{Y}\left(Y_{it}, Z_{it}, w_{t}\right) - C_{I}\left(I_{it}\right) \\ -\left(1 - D_{it-1}\right)F + \beta E_{\omega}\left[V\left(Z_{it+1}, D_{it}\right) \mid Z_{it}, Y_{it}, Y_{it}^{F}, I_{it}\right] \end{array} \right\}\right\} \tag{3}$$

where $Z_{it} \equiv (K_{it}, A_{it}, EE_{it}, \omega_{it})$, $D_{it-1} \equiv 1\left(Y_{it-1}^{F} > 0\right)$ is a dummy variable equal to one if the plant exported in t-1, $Y_{it}^{H} \equiv Y_{it} - Y_{it}^{F}$ 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 capital, w_t is a vector of variable input prices, F is a fixed cost of entry or re-entry into the export market, and Φ is the scrap value obtained if the plant shuts down. The existence of fixed costs of entry or re-entry implies that the export market is segmented from the domestic market, implying that the prices in the two markets p^{H} and p^{F} could differ.

The timing of events is as follows. At the beginning of each period t, the manager knows the plant's age and capital stock available for production, its export experience (equation 1), the value of the productivity index ω_{it}, and its probability distribution for the following period. 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 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. Investment and export choices determine the plant's capital stock and export experience available in the next production period. The cost of entry into exporting depends on whether the plant exported the period before; thus, the lagged export dummy is a state variable in the value function.[5] This setup can accommodate new plants that produce for the first time at period *t*. We assume that those plants need to invest in capital the year before entry, so at the beginning of period *t* their state variables are K_{it}>0, A_{it}=1, EE_{it}=0, and D_{it}=0. For those plants, ω_{it} also follows a first-order Markov process whose first realization is observed at the beginning of period *t*. Depending on that realization, in period *t* those plants face a choice between three possibilities: (i) not to enter the market that period, (ii) to enter only the domestic market, or (iii) to enter the export market right away.

In this stylized model, exports increase the plant's value in three ways: (i) by providing an additional source of revenue on top of domestic market sales, (ii) by allowing the plant to save on entry costs if it exported in the previous period, and (iii) by increasing productivity through learning effects. These advantages need to be weighed against the sunk cost of entry (or re-entry), which is unaffordable for many plants. To facilitate the intuition, consider a simplified version of the model where the production function depends only on labor, export experience, and productivity: β_m, β_k, and β_A are equal to zero. The cost function is $C(Y_{it}, EE_{it}, \omega_{it}, w_t^h) = w_t^h Y_{it}^{1/\beta_h} \exp[-(\beta_0 + \beta_{EE} EE_{it} + \omega_{it})/\beta_h]$, where Y_{it} is the level of output that solves the inter-temporal optimization problem in equation 3 and w_t^h are wages.[6] Production costs increase in output and decrease in productivity and in export experience. Hence, isocost lines in the (ω_{it}, EE_{it}) state space are downward-sloping.

Figure 1 illustrates three isocost lines of interest that define thresholds for plants' entry and exit decisions. First, at a sufficiently low productivity level the plant will be indifferent between exiting and receiving the termination payoff Φ or continuing in operation. Second, at a high enough

[5] Clerides et al. (1998) assume that the 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 loss of generality, by assuming that this cost is similar for new entrants and re-entrants. Our assumption is consistent with evidence by Bernard and Jensen (2004) that investments required to export depreciate rapidly.
[6] This expression is obtained from the static cost minimization to choose the optimal amount of labor.

productivity level, the plant is indifferent between producing just for the domestic market or producing also for the export market.[7] 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 entry cost. Finally, at an intermediate productivity level an exporter will be indifferent between stopping to export or continuing to export 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 stopping to export against the need to pay the fixed re-entry cost the next period in case its productivity increases. If the plant's expected value from continuing to export exceeds the negative current payoff caused by the bad productivity shock, then the plant will continue exporting.[8]

In Figure 1, the state space for plants that have never exported (EE_{it}=0) 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}) space is represented by $N^1 - N^4$ and $X^1 - X^3$, where N plants are currently not exporting that would need to pay the fixed entry cost if they decided to export in the next period, while X plants are currently exporting and face no cost if they decide to continue doing so. Plants N^1 and N^2 have never exported. When a plant enters the export market for the first time, it moves up in the state space from EE_{it}=0 to EE_{it}=1 and keeps moving up to EE_{it}=2, EE_{it}=3, etc. with each additional year of export experience. The curvature of the thresholds reflects the assumption that plants learn from exporting, but learning is subject to diminishing returns. Plants $X^1 - X^3$ are

[7] These thresholds correspond to the φ^* and φ_x^* productivity thresholds in Melitz (2003).

[8] See Impullitti, Irarrazabal, and Opromolla (2013) for an application of the concepts of Dixit and Pindyck (1994) to export market entry and exit decisions under uncertainty with sunk entry costs. Our Figure 1 extends their Figure 5 to the case where export experience is an additional state variable. Máñez et al. (2013) show the importance of sunk costs in explaining hysteresis in exports by Spanish firms.

exporters. Plant X^1 entered the export market in the current period thus it still has not accumulated export experience (see equation 1). Plant X^3 has a negative current payoff from exporting but finds it convenient to continue exporting (given the sunk re-entry cost into exporting), hoping that its productivity will increase the following period. The region between the export entry and export exit thresholds may include plants like N^3 that exported in the past but are not exporting currently. Such plants do not accumulate export experience; they move horizontally in the state space as do plants that never exported before but at a positive export experience level. In Section IV we will test whether export experience depreciates as a former exporter stops exporting for a few years. 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. This stylized model is close to that estimated by Van Biesebroeck (2005), the main difference being that his export experience measure is the plant's lagged export status (D_{it-1}) which is the last term of our export experience measure EE_{it}^1 defined below. Whether the remaining terms of EE_{it}^1 are relevant for productivity is an empirical question tackled in Section IV.

III. Econometric Strategy

Taking logs in equation 2, adding age squared as in Clerides et al. (1998), industry and year fixed effects (γ^j, τ_t) and an i.i.d. error (ε_{it}), we obtain our baseline estimating equation:

$$y_{it} = \beta_0 + \beta_h h_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_a a_{it} + \beta_{a^2} a_{it}^2 + \gamma^j + \tau_t + \beta_{EE} EE_{it} + \omega_{it} + \varepsilon_{it} \tag{4}$$

where lower case variables are in logs. Industry fixed effects capture time-invariant differences across industries in the production function intercept and in input prices, and year fixed effects capture variation over time in input prices and the exchange rate affecting all industries simultaneously. The problems associated with the estimation of equation 4 are well-known. On the one hand, since plant managers decide the use of variable inputs on the basis of ω_{it} realizations, which are unobservable to the econometrician, OLS estimates of their coefficients are upward biased (Marschak and Andrews, 1944). On the other hand, as OP point out, if the capital stock and the ω_{it} realization affect positively the probability of plant survival, OLS estimates of the coefficient on capital are downward biased.

OLS estimates of our parameter of interest β_{EE} have two potential biases of opposite sign: a negative selection bias due to exit decisions, as that on the capital coefficient, and a positive bias due to self-selection into exporting. To understand the negative bias, consider plants N^1 and N^4 in Figure 1. Although they have similar productivity levels, N^4 is farther away from the exit threshold than N^1 due to its positive export experience. If both plants suffer similar bad productivity shocks, N^1 is more likely than N^4 to exit. Hence, the sample may include a higher share of plants with positive export experience at low levels of ω, exerting a negative bias on the β_{EE} estimate. A positive bias in the OLS estimate of β_{EE} is possible because EE_{it} is a predetermined endogenous variable. While EE_{it} is uncorrelated with contemporaneous productivity innovations, it could be positively correlated with past positive productivity innovations that allowed the plant to enter into exporting, increasing the value of EE_{it} from zero to a positive value. After entry, however, exporters may receive either good or bad productivity shocks. Thus, the actual endogeneity bias in β_{EE} is an empirical question. We employ semi-parametric methods to correct for this bias.

Two popular semi-parametric estimation methods to control for the endogeneity and selection biases of the OLS estimator are those proposed by OP and Levinsohn and Petrin (2003) [henceforth LP]. They are based on the assumption that the unobservable ω_{it} can be proxied by a nonparametric function of observable variables, such as investment (in OP) or intermediates (in LP). While the LP method is our main estimation method, in Section IV we consider alternative semi-parametric methods: OP and the method of Ackerberg et al. (2006) [henceforth ACF].[9]

A potential concern with the LP, OP, and ACF methods is that all are based on the assumption that unobserved productivity follows a first-order Markov process. To understand the implications of that assumption, let us assume that productivity follows an AR(1) process, $\omega_{it} = \rho\omega_{it-1} + \xi_{it}$, with ρ > 0. As seen in Section II, plants self-select into exporting if an increase in productivity pushes them to the right of the export entry threshold (a move from N^2 to X^1 in Figure 1). Thus, plants that enter the market in *t-1* have $\omega_{it-1} > \omega_{it-2}$ and $EE_{it} > EE_{it-1} = 0$ implying a positive correlation between EE_{it} and ω_{it-1} and an upward bias in the OLS estimate of β_{EE}. The three methods control for this endogeneity bias by using a function of observables to proxy for the unobservable ω_{it-1}. But if productivity follows a longer-term memory process, additional lags of ω_{it} would be part of the error term. To address this potential problem we estimate in Section IV a variant of the LP method suggested by Ackerberg et al. (2007) where unobserved productivity follows a second-order Markov process. Moreover, the three methods assume exogenous Markov processes for productivity whereas such processes may actually be affected by the plant's export experience. We address this possibility in Section IV following the method proposed by De Loecker (2007, 2010) and Manjón et al. (2013).[10]

IV. Data Description

The data used in this study come from the 1981-1991 Annual Manufacturing Surveys (AMS) conducted by Colombia's Departamento Administrativo Nacional de Estadística. The variables used in our analysis are briefly defined as follows.[11] Labor in efficiency units H_{it} is a weighted average of

[9] A disadvantage of the OP method is that the estimation includes only observations with positive investment, entailing a 25% sample size reduction and a bias towards plants that are larger or have better productivity shocks.

[10] The LP estimation follows Fernandes (2007). See the Technical Appendix available online for details on all the semi-parametric methods used in the paper.

[11] The detailed definitions of output and input variables are provided in the Technical Appendix available online.

seven types of workers - apprentices, blue collar workers, white collar workers, local technicians, foreign technicians, managers, and owners - with weights given by the relative average wages of each type of worker. Capital K_{it} is the sum of the stocks of buildings and structures, machinery and equipment, transportation equipment, and office equipment in constant pesos, measured at the beginning of the period and obtained through the perpetual inventory method. Intermediates M_{it} are the sum of raw materials consumed, outsourcing expenses, and energy in constant pesos while output Y_{it} and exports Y_{it}^{F} are also expressed in constant pesos all based on industry-specific price indexes.

We consider alternative export experience measures corresponding to different specifications for the function $f(.)$ in equation 1 using the number of years the plant exported, the plant's cumulative export-output ratio, and cumulative exports scaled by the average number of workers in the plant:

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

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

$$EE_{it}^{3} = \ln\left(\sum_{\tau=FE_i}^{t-1} \frac{Y_{i\tau}^{F}}{\overline{L}_i} + 1 \right) \tag{5c}$$

where $D_{i\tau} \equiv 1\left(Y_{i\tau}^{F} > 0\right)$ is an export status dummy variable equal to one if the plant exports in year τ, Y_{it} is total plant output, and $\overline{L}_i$ is the plant's average number of workers. These measures follow the empirical LBD literature, where plant experience is measured as cumulative output from the year production started.[12] If the sums in EE_{it}^{1} and EE_{it}^{2} are limited to a single term corresponding to $\tau = t\text{-}1$ they simplify to the two traditional measures used in the literature to capture LBE effects: lagged export status and lagged export intensity.

[12] The average $\overline{L}_i$ is taken over the last three years of data available for each plant as in Bahk and Gort (1993) thus our measure EE_{it}^{3} is identical to their S_1 measure using exports instead of gross output.

In 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.[13] Our first sample includes only 'young' plants that reported information to the AMS for the first time in 1981or later. Since information on exports is included in the AMS only from 1981 onwards, we observe the full export history only for those young plants. In order to include also '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 Section IV will show, we find strong evidence supporting this hypothesis. The following alternative export experience measures impose to our baseline measures (equations 5a-5c) the restriction that export experience resets to zero after three years of export inactivity:

$$EER_{it}^{j} = \begin{cases} 0 & \text{if } \prod_{\tau=t-3}^{\tau=t-1} D_{i\tau} = 0 \\ \sum_{\tau=T_i}^{t-1} X_{i\tau}^{j} & \text{otherwise} \end{cases} \qquad j\text{=1,2} \tag{6a, 6b}$$

$$EER_{it}^{3} = \begin{cases} 0 & \text{if } \prod_{\tau=t-3}^{\tau=t-1} D_{i\tau} = 0 \\ \ln\left(\sum_{\tau=T_i}^{t-1} \frac{Y_{i\tau}^{F}}{\overline{L}_i} + 1 \right) & \text{otherwise} \end{cases} \tag{6c}$$

where $X_{i\tau}^{1} \equiv D_{i\tau}$ and $X_{i\tau}^{2} \equiv Y_{i\tau}^{F} / Y_{i\tau}$. For young plants, for which we observe the entire export history, T_i is 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 the entire export history, T_i is the first year they export after three years or more without exporting. The EER measures allow us to treat plants re-entering the export market after a spell of three or more years without exporting as new entrants. We use these EER measures in our second sample which

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

includes young plants and old plants that do not export in any year during 1981-1983.[14] Using EER measures allows us to double the number of plants from about 3,000 in the 'young' sample to almost 6,000 in the 'young and old without continuing exporters' sample as shown in Table 1.

These two samples still leave out the bulk of Colombia's exporters, old plants that export at least one year during 1981-1983. i.e., 'old continuing exporters'. In order to include them and rely on the full sample, we impose an alternative restriction to our baseline export experience measures (equations 5a-5c): we assume that only the export experience of the last n years counts.[15] The resulting alternative measures are n-year moving sums where $X_{i\tau}^1 \equiv D_{i\tau}$ and $X_{i\tau}^2 \equiv Y_{i\tau}^F / Y_{i\tau}$:[16]

$$EEM_{it}^{j} = \sum_{\tau=t-n}^{t-1} X_{i\tau}^{j} \qquad j=1,2 \tag{7a, 7b}$$

$$EEM_{it}^{3} = \ln\left(\sum_{\tau=t-n}^{t-1} \frac{Y_{i\tau}^{F}}{\overline{L}_{i}}{}^{j}_{i\tau} + 1 \right) \tag{7c}$$

Table 1 presents summary statistics for the various export experience measures described above.[17]

Preliminary evidence of LBE for Colombian plants is obtained for the full sample based on relative TFP Tornqvist indexes and the EEM_{it}^1 measure.[18] Significant TFP increases are found as plants increase their export experience, not only for plants entering the export market but also for plants already exporting that accumulate additional export experience.

IV. Main Results

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[14] This sample excludes observations for old plants in years 1981-1983 since their EER measures cannot be computed for those years.
[15] This restriction is imposed on all plants: young, old, and old continuing exporters and n is either 4 or 5 in the empirical specifications.
[16] This sample excludes the first n years for each plant since they are used to construct the moving sums. The moving sum and the "reset" export experience measures may decrease as well as increase, in contrast to the original measures, which cannot decrease.
[17] The smaller number of plants/observations in the full sample relative to the 'young and old without continuing exporters' sample is due to the use of the EEM measures for the full sample which require the elimination of the first five years of data for each plant thus resulting in the elimination of plants with less than five years of presence in the sample.
[18] This evidence is provided in the Technical Appendix available online.

Table 2 shows our LP estimation results for equation 4 using the sample of young plants and the EE_{it}^{1} - EE_{it}^{3} measures. OLS coefficients on export experience are shown at the bottom of the table for comparison. The LP coefficients on export experience are all positive and significant. As discussed in Section III, OLS coefficients on export experience may suffer from a downward bias due to exit decisions or an upward bias due to self-selection of the best plants into exporting. Table 2 shows a likely upward bias: OLS coefficients are 18 to 37 percent higher than LP coefficients.

The LP input coefficients in Table 2 are all significant and their magnitudes are aligned with those in previous studies..[19] Note that in column 3 domestic experience, defined as cumulative domestic market sales up to the previous year scaled by the plant's average number of workers, is included instead of age and its coefficients are often non-significant.[20] This lack of significance of domestic experience contrasted with the positive and significant coefficient on EE_{it}^{3} suggests that learning is driven only by exporting.

The use of the EE measures in Table 2 restricts the sample to plants for which we can observe the full export history which is unsatisfactory since young plants are a minority of Colombia's manufacturing sector, are smaller, pay lower wages, and are less likely to export than more established plants. Hence, Table 2's results cannot be generalized to the entire manufacturing sector. In order to add some of the old plants to the sample we conjecture that the beneficial effect of export experience on productivity 'resets' to zero if a plant ceases to export for some time, a hypothesis that is consistent with Arrow's (1962) LBD characterization. If a plant's workers and managers stop performing specific tasks required to export, their skills erode over time. For

[19] We find, as OP, that age has a negative coefficient in the production function. A potential rationale for this finding is that the capital stock may be under-measured when plants start producing, but its measurement becomes more accurate as more observations for the plant are available. 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 which case the capital stock will be too small initially, though its measurement becomes more accurate as plants accumulate more capital over time. Thus, 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. However, it should be noted that in most specifications in the rest of the paper the coefficients on age and age squared are non-significant.

[20] This variable is defined in the same way as EE_{it}^{3} but using output sold in the domestic market instead of exports.

concreteness, we assume that export-related skills are totally forgotten after three years without exporting.[21] 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 decompose the original export experience measures as $EE_{it}^{j} \equiv EER_{it}^{j} + \left(EE_{it}^{j} - EER_{it}^{j}\right)$ for $j \in (1,2)$, where EER_{it}^{j}'s are defined in equations 6a-6b, and we estimate a variant of equation 4 including both right-hand side terms in the decomposition as separate regressors.[22] We test whether the coefficient on $\left(EE_{it}^{j} - EER_{it}^{j}\right)$ is equal to 0 using the sample of young plants and show the results in columns 1-2 of Table 3. The coefficients on $\left(EE_{it}^{j} - EER_{it}^{j}\right)$ are non-significant which enables us to assume that the resetting of export experience is valid for both young and old plants. Thus we are able to include in the sample the old plants that do not export during 1981-1983 (those that start exporting after 1983 and those that never export). Columns 3-5 of Table 3 show estimates based on the sample of young and old plants and the *EER* measures. Adding old plants more than doubles the sample size, but the effects of export experience on productivity are still positive and significant.

Research by Eaton et al. (2007) for Colombia over a more recent period shows that most new entrants to the export market last only one year suggesting that not all of them are characterized by persistent favorable productivity shocks. We conjecture that the presence of 'transient' exporters in the sample is likely to bias downward our export experience effect. Figure 1 suggests that exporters exiting the export market must have received a bad productivity shock pushing them to the left of the export exit threshold in the (ω_{it}, EE_{it}) space. As a result, their productivity should be lower than that of active exporters and even of non-exporters close to the export entry threshold. The inclusion in the sample of plants that exported in the past but are currently not exporting bring us

[21] Alternatively, exporting may require specialized personnel, which is dismissed after the plant exits the export market.
[22] This decomposition cannot be used for the EER_{it}^{3} measure which is not linear in past values of exports.

back to Arrow (1962). Since they are not performing the tasks required to export, they should not be learning. Thus, pooling them with plants currently exporting may underestimate LBE effects.

To test the hypothesis that LBE occurs when a plant is actually exporting and not when it temporarily stops exporting, we estimate a variant of equation 4 where the EER measures enter separately and interacted with the plant's lagged export status (D_{it-1}).[23] The D_{it-1} variable enters also by itself to distinguish its effect on the regression intercept from that on the slope. We present the results in Table 3 in columns 7-9 for the young sample and in columns 10-12 for the young and old sample. In all cases the coefficient on the interaction between export experience and the lagged export status is positive and significant, while that on the export experience measure itself is non-significant, suggesting that 'transient' exporters do not learn from exporting. However, we do not find clear evidence that the LBE effect is underestimated due to transient exporters. The coefficient on the interaction term is higher than that on the export experience measure in the corresponding baseline specification in Table 3 for EER_{it}^{2}, while the opposite is true for EER_{it}^{1} and EER_{it}^{3}.

This result is important from a policy standpoint. It suggests that promoting entry into the export market for the sake of it is unlikely to be beneficial. In that respect, it is important to note that the second part of our sample period was characterized by a very attractive real exchange rate that stimulated more and more Colombian plants to start exporting. While supporting a large real devaluation was successful in increasing export volumes, the fact that many entrants stopped exporting after one or two years and did not experience any productivity gain afterwards suggests that the selection may have shifted towards plants that were less productive and less likely to learn from exporting.[24] This suggests that the twin explanations of the higher productivity of exporters -

[23] Current status cannot be used since it is positively correlated with ω_{it} which would bias upward the effect of the interaction term.

[24] The heterogeneity of learning by new entrants to the export market was also suggested by Abegaz and Basu (2011) as an explanation for their findings of no effects of trade liberalization on productivity using data on the twenty-eight three-digit

self-selection and LBE - should be considered complements rather than substitutes.

One of the contributions of our study is the use of novel export experience measures to identify LBE effects. Hence, it is important to examine whether they convey additional information relative to the two traditional measures used in the literature: lagged export status and lagged export intensity. In Section IV we mention that those two traditional measures are the last terms of the sums in equations 6a and 6b. We are interested in knowing whether, after including lagged export status or lagged export intensity in the regression, the remaining terms of EER_{it}^{1} or EER_{it}^{2} have a positive and significant effect. Thus, we estimate the following variants of equation 4 and test $H_0 : \beta_2 = 0$:

$$y_{it} = \beta_x x_{it} + \beta_1 D_{it-1} + \beta_2 \left(EER_{it}^{1} - D_{it-1} \right) + \omega_{it} + \varepsilon_{it} \tag{8a}$$

$$y_{it} = \beta_x x_{it} + \beta_1 \left(\frac{Y_{it-1}^{F}}{Y_{it-1}} \right) + \beta_2 \left(EER_{it}^{2} - \frac{Y_{it-1}^{F}}{Y_{it-1}} \right) + \omega_{it} + \varepsilon_{it} \tag{8b}$$

where x_{it} is a vector with all other explanatory variables in equation 4. The results for these tests using the sample of young and old plants (excluding old continuing exporters) shown in columns 1-2 of Table 4 reject the null hypothesis at the 5% level. Hence, export experience acquired in years before the previous year has an important effect on plant productivity.

The 'reset' tests shown in Table 3 allowed us to include in the sample 'old' plants (born before 1981) that did not export during 1981-1983, but our analysis still excludes old established exporters which account for the bulk of Colombian manufacturing exports. The common use of lagged export status or lagged export intensity as export experience measures is one way to incorporate these plants, but the tests just discussed suggest that export experience acquired in the years before the previous year has a positive effect on productivity. An alternative way to add 'old continuing exporters' to the sample is to redefine export experience as moving sums of functions

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industries from six countries.

of past exports as in equations 7a-7c. In columns 3-4 of Table 4 we repeat the tests for equations 8a-8b using the full sample and the EEM^{1}_{it} - EEM^{2}_{it} measures. The coefficients on the terms from the moving sums that represent export experience acquired in years before the previous year are positive and significant, as are those on lagged export status and lagged export intensity.

IV. Extensions and Robustness

Two of our export experience measures, the number of years the plant exported up to the previous year EER^{1}_{it} and the cumulative export-output ratio EER^{2}_{it} are related. The former is the maximum value the latter could take if the plant exported all its output every year, and can be decomposed as $EER^{1}_{it} \equiv EER^{2}_{it} + \left(EER^{1}_{it} - EER^{2}_{it}\right)$.[25] This decomposition allows us to test whether EER^{1}_{it} conveys additional information to that contained in EER^{2}_{it} by estimating a variant of equation 4 where both the right-hand side terms enter as separate regressors. Using the sample of young plants, column 6 of Table 3 shows that the coefficient on $\left(EER^{1}_{it} - EER^{2}_{it}\right)$ is positive and significant suggesting that LBE effects are not proportional to the export-output ratio but rather that indivisibilities in tasks related to exporting exist. These tasks are likely to be beneficial for the plants adopting them regardless of the share of exports in their output. For instance, if exporting requires a better management of the plant's inventories, then the efficiency gains associated with this improvement are unrelated to the share of exports in the plant's output.

An important question that we are able to tackle in this paper is whether there is evidence of diminishing returns to export experience. As mentioned in Section I, this element of Arrow's (1962) characterization of learning may help explain the differences in the LBE effects estimated across different datasets. To answer this question, we estimate a variant of equation 4 where the

[25] Note that both right-hand-side terms in this decomposition are non-negative.

EEM measures enter separately as well as interacted with a dummy variable identifying the 'old continuing exporters', i.e., the plants that export since 1981, the first year when information about exports is available in the dataset (OCE_i). These are the oldest and most established exporters in Colombian manufacturing, for which LBE would be less likely in the presence of diminishing returns to export experience. The OCE_i variable is also included on its own to distinguish its effect on the intercept of the regression from that on the slope. The results reported in columns 5-7 of Table 4 show a significantly negative coefficient on the interaction variable, suggesting that the LBE effect is less important for the more established exporters. In fact, with the exception of EEM_{it}^{2}, the coefficient on export experience is smaller in absolute value than the coefficient on the interaction variable, suggesting that 'old continuing exporters' do not learn from exporting. This is consistent with Arrow's (1962) characterization of learning as occurring only through exposure to new activities. This result is of importance to explain the differences in findings of LBE in the literature. It suggests that sample composition matters - with LBE being less likely to be found in samples that include a large share of experienced exporters.

Next, we investigate the robustness of the results when using alternative estimation methods and when accounting for differences in the production functions across exporters and non-exporters and across industries. A first robustness check concerns the estimation method. Table 6 shows in columns 1-2 the results from estimating equations 8a-8b using a simpler estimation method, first differences, that control for the effects of time-invariant unobserved plant differences in productivity. The results from estimating equations 8a-8b using the other semi-parametric methods mentioned in Section III are also shown in Table 6: OP in columns 3-4, ACF in columns 5-6, and LP allowing unobserved productivity to follow a second-order Markov process in columns 7-8. The estimated effects of export experience are always positive and significant. While there is some variation in the magnitude of the estimates in Table 6, their averages are close to the corresponding LP estimates in Table 4.[26] Note that while the coefficient on lagged export intensity is non-significant in column 2 of Table 6, the coefficient on export experience acquired in the years before the previous year - which is the 'value added' of our export experience measure - is positive and significant. The robustness of our results to the assumption of a second-order Markov process in productivity is particularly relevant since it shows that the coefficients on our export experience measures are not capturing the effects of more persistent productivity shocks.

A second robustness check allows the input coefficients to differ across exporters and non-exporters to account for the fact that the former tend to be more capital- and skill-intensive than the latter (Bernard and Jensen, 1999). Not accounting for these differences could bias the estimated coefficient on export experience. However, the sign of the bias is not clear a priori because export experience is positively correlated with capital in the sample, which would bias the estimate of β_{EE} upward, but export experience is also positively correlated with labor in the sample, which would bias the estimate of β_{EE} downward. Columns 1-4 of Table 7 show the results from estimating variants of equations 8a-8b where inputs, age, and age squared enter the equation separately and interacted with a dummy for exporters, defined to be plants that export at least one year during their presence in the sample. The effects of export experience do not show systematic evidence of a bias and remain positive and significant at the 5% level. In an additional attempt to control for a potential bias arising from differences in the production functions of exporters and non-exporters, columns 5-6 of Table 7 show estimation results for a smaller sample that includes only exporters. The effects of export experience are positive, significant, and quantitatively similar to those obtained using the full sample.

A third robustness check allows for differences in production function coefficients across

[26] For example, the coefficients on $EER_{it}^{1} - D_{it-1}$ average 0.026 in Table 5 compared to their average of 0.028 in Table 3.

industries which can be even more accentuated than the differences across exporters and non-exporters. Table 8 presents the results from estimating equations 8a-8b separately for selected 3-digit industries.[27] LBE effects are not uniform across industries: they are stronger in the food, apparel, and plastic industries, but weak or non-existent in the chemicals and electrical machinery industries. In the non-electrical machinery industry, though the coefficient on lagged export participation is non-significant, the coefficient on export experience acquired in the years before the previous year is positive and significant at the 5% level. Two hypotheses have been suggested to explain the differences across industries. First, LBE effects may be stronger in industries that export relatively more to high-income countries where the demands for product quality, delivery time, and post-sale services are more stringent and the ensuing potential opportunities for learning and productivity enhancement are larger. Second, LBE effects may be stronger in industries with a higher value of exports if such industries have better developed channels of distribution and thus their plants face lower barriers to enter into export markets. Fernandes and Isgut (2005) and Trofimenko (2008) provide evidence in support of these hypotheses using the Colombia dataset.[28]

A fourth robustness check considers a different estimation methodology and specification, a system of equations with a production function equation (as equation 8a) and a probit model of the decision to participate in the export markets based on Van Biesebroeck (2005):

$$D_{it} = \begin{cases} 1 \quad if \quad \alpha_0 + \alpha_{RER} RER_t + \alpha_k k_{it} + \alpha_a a_{it} + + \alpha_{a^2} a_t^2 + \alpha_B B_{it} \\ \qquad\qquad + \alpha_{o1} o_{it-1} + \alpha_{D1} D_{it-1} + \alpha_{\tilde{D}2} \tilde{D}_{it-2} + \alpha_{\tilde{D}3} \tilde{D}_{it-3} + \varpi_{1i} + \varepsilon_{1it} \geq 0 \\ 0 \qquad otherwise, \end{cases} \tag{9}$$

$$y_{it} = \beta_x x_{it} + \beta_D D_{it-1} + \beta_{EE} \left(EEM_{it}^1 - D_{it-1} \right) + \rho_1 o_{it-1} + \varpi_{2i} + \varepsilon_{2it}, \tag{10}$$

[27] The industries selected were the six largest by number of observations among the group of industries with the highest average percentage of exporters and/or the highest average export intensity over the sample period.
[28] Other studies using richer information on firms' export destinations also support the first hypothesis: e.g., De Loecker (2007) shows a larger productivity increase for Slovenian firms entering high-income destinations than low-income destinations and Mánez-Castillejo et al. (2010) show stronger productivity growth following entry to highly competitive (thus more difficult) EU markets by Spanish firms.

where x_{it} is a vector including the same inputs as in equation 4. The system of equations is estimated by FIML as in Clerides et al. (1998). Besides capital and age, the export participation equation includes an index of Colombia's peso real effective exchange rate (RER_t), a dummy variable identifying corporations (B_{it}), dummy variables that equal 1 if the plant last exported in year *t–j* and 0 otherwise ($\tilde{D}_{it-j}$ for 2≤*j*≤*3* as in Clerides et al. (1998), fn. 20, p. 923), and a proxy for lagged productivity ($o_{it-1} \equiv y_{it-1} - \beta_x x_{it-1} - \beta_D D_{it-2} - \beta_{EE}\left(EEM^1_{it-1} - D_{it-2}\right)$ where β_x, β_D and β_{EE} are production function (equation 10) parameters estimated simultaneously with equation 9). The plant random effects (ϖ_{1i}, ϖ_{2i}) are normally distributed and the noise terms (ε_{1it} , ε_{it2}) are normally distributed.[29]

The FIML estimates for the system of equations 9-10 for various samples are provided in Appendix Table 2 in the Technical Appendix available online.[30] The results for the export participation equation are qualitatively similar to those in Clerides et al. (1998) (their Table III.A) in that there is no evidence of self-selection of the most productive plants into exporting, and the probability of exporting is very high for plants that exported the year before but less high for plants that exported two or three years ago, suggesting a high cost of re-entry into exporting. In addition, depreciations of the real effective exchange rate (measured as dollars per peso) play an important role in attracting plants to the export market. However, in contrast with CLT, our estimates provide clear support to the LBE hypothesis. For the full sample and for the sample that pools all industries included in the CLT dataset the estimated coefficients on both D_{it-1} and $EEM^1_{it} - D_{it-1}$ are positive and significant. In addition, for five of the six industries included in the CLT dataset there is evidence of LBE either through D_{it-1} (apparel, industrial chemicals and other chemicals) or

[29] The Technical Appendix available online provides further details on these results.
[30] Sofronis Clerides generously shared the original CLT dataset which included the six individual industries shown in their paper as well as a few additional industries not used in their paper but which we use in the sample that pools all industries in the CLT dataset.

$EEM_{it}^{1} - D_{it-1}$ (food and paper).

A detailed assessment of why our results differ from those of Clerides et al. (1998) who use the same data and estimating technique, although with a different specification, is beyond the purpose of the present paper. One possible explanation is that the dependent variable is rather different, with our paper using an estimate of real output and Clerides et al. (1998) using the ratio of two nominal variables (variable costs to nominal output). If upon entry into export markets variable costs increased because plants hired more qualified workers or used higher quality materials, which are more expensive, then it is possible that the variable cost to nominal output ratio would not decrease after entry into exporting. This possibility could occur even if real output increased.[31]

Overall, our findings show robust evidence of LBE for Colombian plants during 1981-1991 across a variety of export experience measures, estimation methodologies, and samples, including smaller industry samples. The magnitudes of the estimated coefficients are rather consistent across the various specifications estimated in the paper. For instance of 27 estimates for the EE_{it}^{1} measure and its variants, the mean value is 2.6%, while the 10th and 90th percentiles are, respectively, 1% and 4.2%. A comparison with other papers in the literature is difficult due to the differences in the measures of export experience used. In our paper, the estimated coefficient of EE_{it}^{1} and its variants represents the average increase in real output, controlling for all production inputs, when export experience increases by one year. Most papers in the literature measure the increase in output or in estimated productivity when a firm changes its status from being a non-exporter to being an exporter. Nevertheless, a representative paper using the latter measure, Blalock and Gertler (2004) finds the impact of entry into exporting on output (controlling for inputs) for Indonesian manufacturing firms to be between 2% and 5%, which is comparable to our estimates.

[31] See Isgut (2013) for a further investigation on the lack of LBE evidence for Colombian plants in the CLT paper.

A final robustness check addresses the criticism to previous LBE tests made by De Loecker (2007) that the Markov process for productivity assumed by LP, OP, and ACF could be endogenous in that a plant's export status could impact its future productivity trajectory and the argument by De Loecker and Warzynski (2012) that materials demand functions should be allowed to differ according to export status (whether export status is a state variable or not). In Tables 2-6 export experience is modeled as a state variable shifting the production function mean and its coefficient provided us with the LBE estimate. Following Manjón et al. (2013) we take a totally different approach by estimating two variants of equation 4 where export experience is dropped. A first variant allows productivity to follow an exogenous Markov process and has a unique materials demand function for all plants (as in Section II) whereas a second variant allows productivity to follow an endogenous Markov process where export experience (EER_{it}^{1}) is allowed to influence the dynamics of productivity and has a materials demand differing for plants with and without export experience. After estimating these two variants of equation 4 by LP using the young and old sample we obtain the corresponding measures of plant exogenous Markov productivity and plant endogenous Markov productivity. We estimate the additional productivity growth of export starters relative to non-exporters for the two measures relying on propensity score matching techniques.[32]

The estimates of plant productivity growth across time periods ranging from 1 year after starting to export to 4 years after starting to export are provided in Appendix Table 3 in the Technical Appendix available online. The estimated additional productivity growth for export starters relative to non-exporters is significant across all time periods for both the plant exogenous Markov productivity and the plant endogenous Markov productivity. Our estimates of additional productivity growth of 0.9%, 2.1%, and 4%, respectively 2, 3, and 4 years after starting to export

[32] The Technical Appendix available online provides further details on these results.

are smaller in magnitude than those obtained for Spanish firms by Manjón et al. (2013) and for Slovenian firms by De Loecker (2007). While in Manjón et al. (2013) LBE effects for Spanish firms are present only when the firm endogenous Markov productivity measure is used, for Colombian plants over the 1984-1991 period the consideration of an exogenous or an endogenous Markov process for productivity does not affect the evidence of strong LBE effects.

VII. Conclusion and Caveats

This paper examines thoroughly the LBE hypothesis for Colombian manufacturing plants during 1981-1991 and finds substantial evidence in its favor. The results are robust to the use of different samples, econometric methods, and modeling approaches. Among other results we show that export experience acquired by plants in years before the previous year has an important effect on productivity. Interestingly, we also find that the effect of export experience on productivity is non-significant for exporters that stop exporting in the previous year and that there are diminishing returns to export experience in that LBE effects are lower for the most experienced exporters.

Our evidence of a lack of LBE effects for exporters that drop from export markets, which was also found by Eaton et al. (2007) using Colombian data, has important methodological implications. Bernard and Jensen (1999) and ISGEP (2008) assess LBE effects by regressing differences in productivity between year 0 and year $T > 0$ on a dummy variable equal to 1 for plants that enter the export market for the first time in year 0 and equal to 0 for non-exporters. But in light of our findings, the difference in productivity is likely to be negative for plants that drop from the export market after year 0, exerting a negative bias on the coefficient on the export dummy, as well as increasing its standard error.

The interpretation of our results as providing evidence of LBE depends however crucially on the assumption that our measures of output sold in domestic and export markets, capital, and domestic and imported raw materials provide good approximations to the underlying unobservable quantities. According to Katayama et al. (2009), measures of TFP obtained through such approximations, which are in reality indices of revenue per unit input expenditure, can be misleading, especially when applied to differentiated product industries. In that case the results of this paper could be interpreted as capturing increases in markups for plants with export experience. The LBE literature has only recently started to address this issue, with papers such as De Loecker (2011) and De Loecker and Warzynski (2012) providing useful insights. Hence, concerns about whether our results are picking up increases in productivity or in markups are legitimate and worthy of being addressed in future research.

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References

Abegaz, B., Basu, A., 2011. The elusive productivity effect of trade liberalization in the manufacturing industries of emerging economies. Emerging Markets Finance & Trade 47(1), 5–27.

Ackerberg D., Benkard L., Berry S., Pakes A., 2007. Econometric tools for analyzing market outcomes. In: Heckman J. (Ed.), Handbook of Econometrics, 6(partA), 4171-4276.

Ackerberg D., Caves K,. Frazer G., 2006. Structural identification of production functions. Mimeo, UCLA.

Alvarez R., López R., 2005. Exporting and firm performance: Evidence from Chilean plants. Canadian Journal of Economics 38(4), 1384-1499.

Andersson M., Lööf H., 2009. Learning-by-exporting revisited: The role of intensity and persistence. Scandinavian Journal of Economics 111(4), 893-916.

Arnold J., Hussinger K., 2005. Export behavior and firm productivity in German manufacturing: A firm-level analysis. Review of World Economics, 141(2), 219-243.

Arrow K., 1962. The economic implications of learning-by-doing. Review of Economic Studies 29(3), 155-173.

Bahk B., Gort M., 1993. Decomposing learning-by-doing in new plants. Journal of Political Economy 101(4), 561-583.

Baldwin J., Gu W., 2003. Export-market participation and productivity performance in Canadian manufacturing. Canadian Journal of Economics 36(3), 634-657.

Bernard A., Jensen J., 1999. Exceptional export performance: Cause, effect, or both? Journal of International Economics 47(1), 1-25.

Bernard A., Jensen J., 2004. Why some firms export. Review of Economics and Statistics 86(2), 561-569.

Bernard A., Wagner J., 1997. Exports and success in German manufacturing. Review of World Economics 133(1), 134-157.

Blalock G., Gertler P., 2004. Learning from exporting revisited in a less developed setting. Journal of Development Economics 75(2), 397-416.

Bigsten A., Collier P., Dercon S., Fafchamps M., Gauthier B., Gunning J., Oduro A., Oostendorp R., Pattillo C., Söderbom M., Teal F., Zeufack A., 2004. Do African manufacturing firms learn from exporting? Journal of Development Studies 40(3), 115-141.

Bigsten A., Gebreeyesus M., 2009. Firm productivity and exports: evidence from Ethiopian manufacturing. Journal of Development Studies 45(10), 1594-1614.

Castellani D., 2002. Export behavior and productivity growth: Evidence from Italian manufacturing firms. Review of World Economics 138(4), 605-628.

Clerides S., Lach S., Tybout J., 1998. Is learning-by-exporting important? Micro-dynamic evidence from Colombia, Mexico, and Morocco. Quarterly Journal of Economics 113(3), 903-47.

De Loecker J., 2007. Do exports generate higher productivity? Evidence from Slovenia. Journal of International Economics 73(1), 69-98.

De Loecker, J., 2010. A Note on Detecting Learning by Exporting, NBER Working Papers 16548.

De Loecker J., 2011. Product differentiation, multi-product firms and estimating the impact of trade liberalization on productivity. Econometrica 79(5), 1407-1451.

De Loecker, J., Warzynski, F., 2012. Markups and firm-level export status. American Economic Review 102(6), 2437-2471.

Delgado M., Fariňas J., Ruano S., 2002. Firm productivity and export markets: A non-parametric approach. Journal of International Economics 57(2), 397-422.

Dixit A., Pyndick P., 1994. Investment under Uncertainty. Princeton University Press: Princeton, NJ.

Eaton J., Eslava M., Kugler M., Tybout J., 2007. Export dynamics in Colombia: Firm-level evidence. NBER Working Paper No. 13531.

Fernandes, A., Isgut, A., 2005. Learning-by-doing, learning-by-exporting, and productivity : evidence from Colombia. Policy Research Working Paper Series 3544, The World Bank.

Fernandes A., 2007. Trade policy, trade volumes and plant-level productivity in Colombian manufacturing industries. Journal of International Economics 71(1), 52-71.

Freund, C., Pierola, M. 2012. Export surges. Journal of Development Economics 97(2), 387-395.

Girma S., Greenaway D., Kneller R., 2004. Does exporting increase productivity? A microeconometric analysis of matched firms. Review of International Economics 12(5), 855-866.

Isgut A., 2001. What's different about exporters? Evidence from Colombian manufacturing. Journal of Development Studies 37(5), 57-82.

Isgut, A., 2013. Learning-by-exporting re-examined: A note on Clerides, Lach and Tybout (1998), mimeo.

Impullitti, G., Irarrazabal A., Opromolla L., 2013. A theory of entry into and exit from export markets. Journal of International Economics 90(1), 75-90.

International Study Group on Exports and Productivity (ISGEP), 2008. Exports and productivity: comparable evidence for 14 Countries. Review of World Economics 144(4), 596-635.

Katayama H., Lu S., Tybout J., 2009. Firm-level productivity studies: Illusions and a solution. International Journal of Industrial Organization 27(3), 403-413.

Kraay A., 1999. Exportations et performances economiques: Etude d'un panel d'entreprises

Chinoises. Revue d'Economie du Developpement 1-2 183-207.

Levinsohn J., Petrin A., 2003. Estimating production functions using inputs to control for unobservables. Review of Economic Studies 70(2), 317-341.

Lileeva A., Trefler D., 2010. Improved access to foreign markets raises plant-level productivity… for some plants. Quarterly Journal of Economics 125(3), 1051-1099.

Manjón M., Máñez, J., Rochina-Barrachina, M., Sanchis-Llopis, J., 2013. Reconsidering learning by exporting. Review of World Economics 149(1), 5-22.

Máñez, J., Rochina-Barrachina M., Sanchis, J., 2008. Sunk costs hysteresis in Spanish manufacturing exports. Review of World Economics, 144(2), 271-294.

Mánez-Castillejo, J., Rochina-Barrachina, J. Sanchis-Llopis, J., 2010. Does firm size affect self-selection and learning-by-exporting? The World Economy, 33(3), 315-346.

Marschak, J., Andrews, W., 1944, Random simultaneous equations and the theory of production. Econometrica 12(3/4), 143–205.

Melitz M., 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica 71(6), 1695-1725.

Olley G., Pakes A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64(6), 1263-1297.

Park A., Yang D., Shi X., Jiang Y., 2010. Exporting and firm performance: Chinese exporters and the Asian financial crisis. Review of Economics and Statistics 92(4), 822-842.

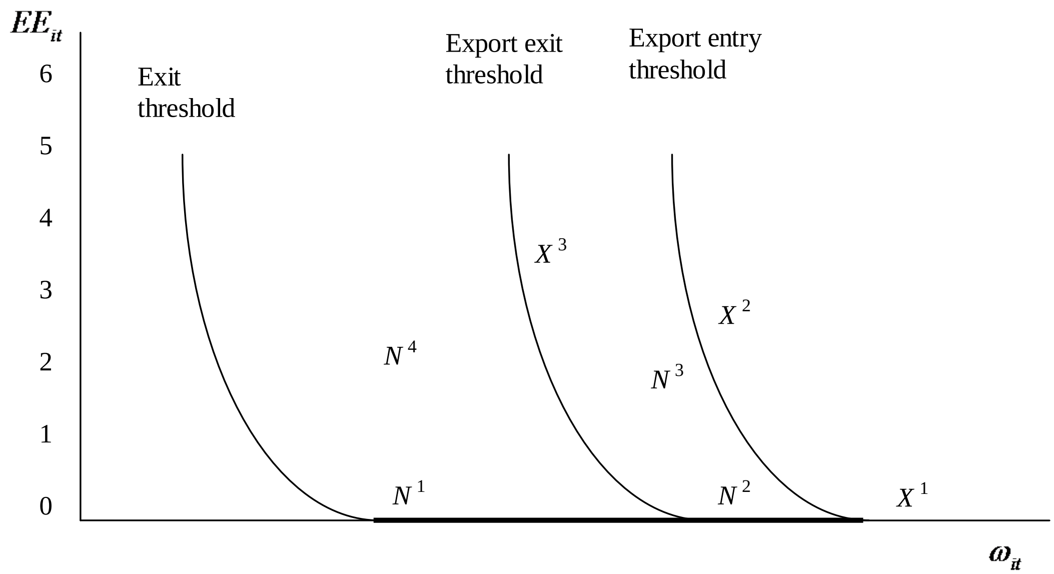
Trofimenko, N., 2008. Learning by exporting: does it matter where one learns? Economic Development and Cultural Change 56(4), 871-894.

Van Biesebroeck J., 2005. Exporting raises productivity in Sub-Saharan African manufacturing plants. Journal of International Economics 67(2), 373-391.

Wagner, J. 2007. Exports and productivity: a survey of the evidence from firm-level data. World Economy 30(1), 60-82.

Wagner, J. 2012. International trade and firm performance: a survey of empirical studies since 2006. Review of World Economics 148(2), 235-267.

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



Note: the y-axis represents the export experience measure EE1 defined in equation 5a, that is the number of years in which the plant exported since it started operations., and the x-axis represents the productivity index ω_{it} . N^1-N^4 represent examples of combinations of export experience and the productivity index for plants that are exporting in the current period, and X^1-X^3 represent examples of combinations of export experience and the productivity index for plants that are not exporting in the current period.

Table 1. Summary Statistics

	Sample of Young Plants	Sample of Young and Old Plants (Excluding Continuing Exporters)	Full Sample
Number of Plants			
Exporters	476	871	1,196
Nonexporters	2,627	5,111	3,696
Number of Observations			
Exporters (Covering Years with Positive Exports or Not)	2,608	5,708	5,581
Nonexporters	12,929	29,929	17,571
Average Number of Workers			
Exporters	56	110	194
Nonexporters	30	46	56
Average Export Experience			
EE^1	1.18		
EE^2	0.29		
EE^3	3.03		
EER^1		0.92	
EER^2		0.16	
EER^3		2.14	
EEM^1			2.78
EEM^2			0.45
EEM^3			5.1
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. The measures of export experience EE1-EE3, EER1-EER3, and EEM1-EEM3 are defined in equations 5a-5c, 6a-6c, and 7a-7c, respectively. Exporters are defined as plants that export at least in one sample year. The averages of the export experience measures are taken over all the observations for exporters, including those observations for which the measures are zero (i.e., those in years when those exporters are not exporting). The incidence of positive export experience is the share of exporters' observations for which export experience is positive.

Table 2. Baseline Estimation Results - Young Plants

	Sample of Young Plants		
	LP Estimation		
	(1)	(2)	(3)
Labor (h_{it})	0.239	0.240	0.257
	(0.009)***	(0.009)***	(0.010)***
Intermediates (m_{it})	0.633	0.632	0.749
	(0.032)***	(0.025)***	(0.027)***
Capital (k_{it})	0.115	0.129	0.058
	(0.017)***	(0.014)***	(0.020)***
Age (a_{it})	-0.047	-0.082	
	(0.023)**	(0.028)***	
Age Squared (a_{it}^2)	-0.171	-0.027	
	(0.052)***	(0.038)	
Domestic Experience (DE_{it})			-0.009
			(0.017)
Export Experience (EE_{it}^1)	0.022		
	(0.009)***		
Export Experience (EE_{it}^2)		0.031	
		(0.013)***	
Export Experience (EE_{it}^3)			0.010
			(0.004)***
Number of Observations	15537	15537	15537
Memo Item: OLS Estimates			
Export Experience (EE_{it}^1)	0.026		
	(0.003)***		
Export Experience (EE_{it}^2)		0.043	
		(0.007)***	
Export Experience (EE_{it}^3)			0.013
			(0.001)***

Notes: LP is 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 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 EE measures are defined in equations 5a-5c and domestic experience is defined in the text. Years included are 1982-1991. The LP estimation controls for year fixed effects and 3-digit industry fixed effects. The memo item includes OLS estimates for the coefficients on export experience variables, with robust standard errors clustered by plant shown in parentheses.

Table 3. Tests of Reset Hypothesis for Inactive Exporters, Proportionality, and Learning-By-Exporting for Transient Exporters

	Sample of Young Plants		Sample of Young and Old Plants (Excluding Continuing Exporters)			Sample of Young Plants	Sample of Young Plants			Sample of Young and Old Plants (Excluding Continuing Exporters)		
	Testing Reset Hypothesis					Testing Proportionality to Export-Output Ratio	Testing Learning-By-Exporting for Transient Exporters					
	LP Estimation						LP Estimation					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Export Experience (EER_{it}^{1})	0.024		0.025				0.019			-0.021		
	(0.008)***		(0.006)***				(0.012)			(0.021)		
(EE_{it}^{1}-EER_{it}^{1})	0.008											
	(0.033)											
Export Experience (EER_{it}^{2})		0.024		0.019		0.026		0.008			-0.033	
		(0.010)**		(0.008)**		(0.012)**		(0.029)			(0.074)	
(EE_{it}^{2}-EER_{it}^{2})		-0.004										
		(0.116)										
Export Experience (EER_{it}^{3})					0.022				0.008			-0.013
					(0.003)***				(0.005)			(0.011)
(EE_{it}^{3}-EER_{it}^{3})												
EER_{it}^{1} - EER_{it}^{2}						0.018						
						(0.007)***						
Lagged Export Status (D_{it-1})							0.001	0.006	-0.006	0.000	0.035	-0.014
							(0.018)	(0.016)	(0.032)	(0.035)	(0.052)	(0.031)
EER_{it}^{1} * D_{it-1}							0.018			0.042		
							(0.009)**			(0.020)***		
EER_{it}^{2} * D_{it-1}								0.079			0.063	
								(0.018)***			(0.031)**	
EER_{it}^{3} * D_{it-1}									0.01			0.031
									(0.004)***			(0.012)***
Number of Observations	15537	15537	35637	35637	35637	15537	15537	15537	15537	35637	35637	35637

Notes: LP is 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 levels, respectively. Bootstrapped standard errors are in parentheses. The EE measures are defined in equations 5a-5c and the EER measures are defined in equations 6a-6c. All regressions include the logs of labor, intermediates, and capital. The regressions in columns 1-4, 6-8, and 10-11 include also the log of age and its square, and the regressions in columns 5, 9, and 12 include also domestic experience. Years included are 1982-1991 for young plants and 1984-1991 for old plants. The LP estimation controls for year fixed effects and 3-digit industry fixed effects.

Table 4. Effects of Export Experience Prior to Previous Year on Productivity and Diminishing Returns to Export Experience

	Sample of Young and Old Plants (Excluding Continuing Exporters)		Full Sample		Full Sample		
	Effects of Export Experience Prior to Previous Year				Diminishing Returns to Experience		
	LP Estimation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged Export Status (D_{it-1})	0.044		0.045				
	(0.017)***		(0.019)***				
Export Experience (EER_{it}^{1}) - D_{it-1}	0.022						
	(0.010)**						
Lagged Export Intensity (Y_{it}^{F} / Y_{it})		0.101		0.074			
		(0.039)***		(0.031)***			
Export Experience (EER_{it}^{2}) - Y_{it}^{F} / Y_{it}		0.032					
		(0.016)**					
Export Experience (EEM_{it}^{1}) - D_{it-1}			0.028				
			(0.012)**				
Export Experience (EEM_{it}^{2}) - Y_{it}^{F} / Y_{it}				0.047			
				(0.013)***			
Export Experience (EEM_{it}^{1})					0.041		
					(0.021)**		
Export Experience (EEM_{it}^{2})						0.099	
						(0.042)***	
Export Experience (EEM_{it}^{3})							0.044
							(0.014)***
Old Cont. Exporters Dummy (OCE_{i})					0.073	0.027	0.040
					(0.037)**	(0.063)	(0.039)
EEM_{it}^{1} * OCE_{i}					-0.059		
					(0.028)**		
EEM_{it}^{2} * OCE_{i}						-0.052	
						(0.023)**	
EEM_{it}^{3} * OCE_{i}							-0.098
							(0.037)***
Number of Observations	35637	35637	23152	23152	23152	23152	23152

Notes: LP is 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 levels, respectively. Bootstrapped standard errors are in parentheses. The EER measures are defined in equations 6a-6b and the EEM measures are defined in equations 7a-7c using *n* =5. All regressions include the logs of labor, intermediates, and capital. The regressions in columns 1-6 include also the log of age and its square while the regression in column 7 includes also domestic experience. 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. Years included in the full sample are 1986-1991. The LP estimation controls for year fixed effects and 3-digit industry fixed effects.

Table 5. Alternative Semi-Parametric Estimation Methods

	Full Sample							
	First Differences Estimation		OP Estimation		ACF Estimation		LP - Second Order Markov Estimation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Export Status (D_{it-1})	0.011		0.064		0.040		0.037	
	(0.005)**		(0.013)***		(0.014)***		(0.017)***	
Export Experience (EEM_{it}^{1}) - D_{it-1}	0.011		0.016		0.033		0.042	
	(0.004)***		(0.008)**		(0.010)***		(0.017)***	
Lagged Export Intensity (Y_{it}^{F} / Y_{it})		0.042		0.047		0.054		0.063
		(0.028)		(0.014)***		(0.025)**		(0.032)**
Export Experience (EEM_{it}^{2}) - Y_{it}^{F} / Y_{it}		0.069		0.021		0.038		0.090
		(0.015)***		(0.010)**		(0.015)***		(0.034)***
Number of Observations	23152	23152	15369	15369	23152	23152	16571	16571

Notes: First differences are estimated by OLS. OP is Olley and Pakes (1996) estimation, ACF is Ackerberg, Caves and Frazer (2007) estimation, and LP-Second Oder Markov is based on Ackerberg, Benkard, Berry and Pakes (2007). 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 1-2 robust standard errors clustered by plant are in parentheses. In columns 3-8 bootstrapped standard errors are in parentheses. The EEM measures are defined in equations 7a-7b using *n* =5. All regressions include the logs of labor, intermediates, capital, and age, and the log of age squared. Years included are 1986-1991. The OP estimation and the ACF estimation controls for year fixed effects and 3-digit industry fixed effects.

Table 6. Production Function Differences across Exporters and Non-Exporters and Across Industries

Panel A. Across Exporters and Non-Exporters

	Sample of Young and Old Plants (Excluding Continuing Exporters)		Full Sample		Full Sample - Only Exporters	
	LP Estimation					
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Export Status (D_{it-1})	0.050		0.042		0.024	
	(0.018)***		(0.015)***		(0.012)***	
Lagged Export Intensity (Y_{it}^F / Y_{it})		0.069		0.100		0.043
		(0.016)***		(0.037)***		(0.021)**
Export Experience (EER_{it}^1) - D_{it-1}	0.025					
	(0.012)**					
Export Experience (EER_{it}^2) - Y_{it}^F / Y_{it}		0.046				
		(0.019)***				
Export Experience (EEM_{it}^1) - D_{it-1}			0.027		0.037	
			(0.012)**		(0.007)**	
Export Experience (EEM_{it}^2) - Y_{it}^F / Y_{it}				0.034		0.047
				(0.015)**		(0.022)**
Number of Observations	35637	35637	23152	23152	6299	6299

Panel B. Across Industries

	Full Sample by 3-digit ISIC Industry					
	311 Food	322 Apparel	352 Chemicals	356 Plastics	382 Electrical Machinery	383 Nonelectrical Machinery
	LP Estimation					
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Export Status (D_{it-1})	0.082	0.037	0.048	0.113	-0.015	0.031
	(0.032)***	(0.017)**	(0.031)*	(0.023)***	(0.036)	(0.046)
Export Experience (EEM_{it}^1) - D_{it-1}	0.050	0.034	0.039	0.031	0.021	0.065
	(0.016)***	(0.015)**	(0.033)	(0.014)**	(0.013)*	(0.035)**
Number of Observations	3577	2720	1262	1065	1108	749

Notes: LP is 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 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 EER measures are defined in equations 6a-6b and the EEM measures are defined in equation 7a-7b using *n* =5. The sample used in columns 5-6 of Panel A includes only plants with $Exporter_i$ equal to one (where $Exporter_i$ is a dummy variable identifying plants that export in at least one sample year). All regressions include the logs of labor, intermediates, capital, age, and age squared. Years included in the sample of young and old plants (excluding continuing exporters) in Panel A are 1982-1991 for young plants and 1984-1991 for old plants. Years included in the full sample in Panels A and B are 1986-1991. The LP estimation controls for year fixed effects and 3-digit industry fixed effects.