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Learning by Exporting: Does It Matter Where One Learns?

Evidence from Colombian Manufacturing Plants

by

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Learning by Exporting: Does It Matter Where One Learns? Evidence from Colombian Manufacturing Plants*

Abstract:

Learning-by-exporting proponents argue that exporting increases productivity by exposing producers to new technologies or through product quality upgrading. This study is based on the observation that the technological superiority and severity of product quality requirements are not the same in all export markets. If learning occurs through the acquisition of new knowledge, exporting to less developed markets should not generate as much productivity growth as exporting to advanced countries. Using plant-level data from Colombia, I demonstrate that exporting to advanced countries generates the highest productivity premium and that the ability to benefit from exporting in general and exporting to advanced markets in particular increases monotonically as one moves along the conditional productivity distribution.

Keywords: learning by exporting, total factor productivity, export destination, quantile regression, instrumental variables

JEL–classification: F10, D24

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I. Introduction

Start exporting to boost your productivity! Want to see improvements in your productivity? – Look abroad! Expand into export markets for tips on efficiency! Improve your productivity through export!

(<www.NewBusiness.com.uk>, <www.ProfitGuide.com>)

The business press is very optimistic in its interpretation of the main finding of the "learning-by-exporting" literature: in virtually all countries exporters are more productive than firms who sell only to domestic markets. The rationale behind this finding seems very intuitive. There is a wealth of anecdotal evidence suggesting that exchange of knowledge is a big part of the exporting experience.[1] Exporters acquire from their foreign customers information on how

[1] "The important thing about foreign buyers, many of which have offices in Seoul, is that they do much more than buy and specify… They come in, too, with models and patterns for Korean engineers to follow, and they even go out to the production line to teach workers how to do things." (Rhee et al 1984).
"… a good deal of the information needed to augment basic capabilities has come from the buyers of exports who freely provided product designs and offered technical assistance to improve process technology in the context of their sourcing activities. Some part of the efficiency of export-led development must therefore be attributed to externalities derived from exporting." (Evanson and Westphal 1995)
"… a Japanese firm's desire for extremely consistent cloth color renditions prompted us [Indonesian manufacturing firm] to invest in new machinery imported from Switzerland." (Blalock and Gertler 2004)
Korean firms "benefit from their foreign buyers through the provision of blueprints and technical specifications of competing products, visits to the production plants by engineers from the importing countries, and constant feedback on the design, quality and technical performance of products." (Rhee, Ross-Larson and Pursell 1984)
In Indonesia "some firms have Japanese customers annually review their production methods to suggest improvements that would minimize costs, while others have their German customers advise on how to expand their production capacity." (Blalock and Gertler 2004).

to improve the manufacturing process, decrease production costs, improve product design, and upgrade product quality.

This information, it is argued, gives exporters a performance edge. However appealing these arguments may be, skeptics reject them. When Clerides et al. (1998) linked exporting to productivity, they broached a debate between those who believe that exporting is truly good for firms because it increases their efficiency and those who attribute most of the positive correlation between exporting and productivity to self-selection.[2] According to the latter, only firms that are more productive to start with are able to pay the high entry costs associated with exporting (such as networking, collection of information, adopting product to new standards, quality upgrading, etc.) and it is unclear whether there are any additional efficiency gains from exporting per se.

Few studies of learning by exporting address the issue of the quality of the environment in which learning takes place.[3] Omitting this factor, however, hinders our understanding of how learning occurs. If learning by exporting

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[2] Evidence in favor of learning by exporting, i.e. additional productivity gains from exporting, has been found by Aw et al. (2000) in Korea, Girma et al. (2003) in UK, Yasar et al. (2004b) in Turkey, De Loecker (2005) in Slovenia, and Van Biesbroeck (2005) in Cote-d'Ivoire. No evidence of learning has been found in Clerides et al. (1998), Bernard and Jensen (1999), Wagner (2002), Arnold and Hussinger (2004).

[3] In an unpublished manuscript, Fernandes and Isgut (2005) examine the effect of exporting on productivity and, as an extension of their work, they interact exporting experience with a share of 3-digit industry's trade going to high income countries. Similarly, De Loecker (2005) extends his study of learning-by-exporting in Slovenia and, as a robustness check, estimates the learning parameter separately for firms exporting to high income (North America, Western and Southern Europe) and poor countries.

occurs through knowledge exchange, are all markets equally valuable for learning? Wouldn't experience in a more advanced country be of superior quality? If learning occurs through the acquisition of knowledge of new production methods, inputs, and product designs abroad, an advanced country surely offers greater "learning potential" – there are simply more things to learn. An advanced country also sets higher standards with respect to product quality, timing of shipments, etc., and will challenge the exporter to meet these expectations. Hence, a market in an advanced country offers a much more rigorous "teach and discipline" experience than that in a less advanced country.

In this paper I explore empirically how the return to exporting is influenced by the development level of a trading partner. First, I expand the model of the decision to export in the presence of sunk entry costs and learning effects (Bernard and Jensen 1999, Clerides et al. 1998, Roberts and Tybout 1997) to accommodate heterogeneous destination markets and allow entry costs and rate of learning to vary by the development level of the destination market. I then test the theoretical prediction that there is a premium in the form of additional productivity gains to the firms who export to more developed markets.

My analysis focuses on the impact of exporting to advanced markets in the context of Colombian manufacturing plants in the 1980s. Colombia is a developing country and, due to its geographic location, trades heavily with countries of similar development level, regional leaders (Chile, Argentina) and the world's most advanced economies (US, Canada). This variation in the development level of Colombian export markets allows me to identify the influence of market sophistication on exporter productivity growth.

I use an unbalanced panel of 5,938 plants (1,057 exporters) from 1981 to 1991 to estimate the effect of the development level of a trading partner on an exporter's productivity. I measure productivity using the Levinsohn-Petrin method which controls for the endogeneity of input choices. I measure destination market's development level using the industry- and time-varying share of exports going to poor, lower middle income, upper middle income, rich non-OECD and OECD countries.

Two selection problems complicate the analysis. High entry costs associated with exporting create a barrier that only the most successful firms can overcome, so only the more productive firms self-select into exporting. Furthermore, the theoretical model employed here allows these entry costs to vary by the development level of a trading partner. Assuming that advanced markets are harder to penetrate, more productive exporters self-select into more advanced markets. As shown in section 4, both types of selection are clearly present in the data: exporters are more productive than non-exporters before they enter the foreign market and a higher productivity is required of those exporters who intend to target rich countries. Thus, any methodology that does not take into account selection will lead to exaggeratedly large estimates of the benefits of exporting in general and exporting to advanced countries in particular.

I use the following strategy to address possible selection bias. Given the focus of the paper on the differential return to exporting across various markets, I restrict the sample to those plants who have exported during at least one period between 1981–1991 and estimate the exporting premium as the productivity differential between exporting plants and plants who are selling only into the domestic market, but either have exported in the past or plan to export in the future or are between exporting spells. Since all three types of plants in the latter category are consistently more productive than plants who never export (see Tables 2A and 2B), the bias associated with self-selection of more productive plants into exporting is greatly reduced, if not eliminated. To control for selection of more productive exporters into advanced markets, I use a gravity equation to create instruments for the endogenous shares of exports going to advanced countries.

Finally, I explore the hypothesis that the ability to benefit from exporting hinges upon the plant's performance. This hypothesis has already received some empirical support from Yasar et al. (2004a) who find that the exporting premium increases monotonically, as one moves along the conditional productivity distribution: it appears that relatively less productive plants have difficulty converting their exporting experience into higher productivity. This may be particularly true of the premium of exporting to advanced countries. Low-productivity plants may be unprepared to adopt the state-of-the-art technologies available in advanced markets. I use standard quantile and instrumental variables quantile regression techniques to explore this possibility.

I find that the ability to benefit from exporting increases with the relative efficiency of the plant and this is particularly true of exporting to advanced countries: statistically significant incremental returns to exporting to OECD countries are found only for the more productive plants (50^{th} quantile and higher in OLS specification and 75^{th} quantile and higher in instrumental variables specification). Conversely, less productive exporters appear to be particularly good at generating productivity gains from exporting to similar and less developed markets. This last finding, however, does not withstand controls for unobserved plant heterogeneity. The overall pattern of monotonically increasing returns to exporting in general and exporting to advanced markets in particular is preserved.

This paper makes several primary contributions to the literature on learning by exporting. First, it reveals the direct effects of the development level of a trading partner on the return to exporting. Second, it confirms the earlier findings that relatively more productive plants benefit more from exporting. Third, it corrects these earlier findings for unobserved plant heterogeneity and finds that the estimates without such correction overestimate the return to exporting by approximately 5 percent. Finally, this paper raises the issue of self-selection of more productive exporters into advanced countries.

II. A Model of Export Participation with Sunk Costs, Learning Effects and Heterogeneous Destination Markets

To see how exporting to more developed markets can generate higher productivity than exporting to less developed markets, I start with the model of export participation in the presence of sunk costs and learning effects presented in Clerides et al. (1998). According to this model, a profit-maximizing plant operates in an environment characterized by monopolistic competition and faces a downward sloping demand curve. Assuming that marginal costs, c, do not depend on output, gross operating profits of such plant, $\pi(c,z,x)$, can be expressed as a function of exogenous determinants of profitability (e.g., exchange rate, foreign demand conditions, foreign income level, etc.) and plant-specific factors (e.g., capital stocks, size, labor composition, ownership structure, etc.).

To allow for self-selection of more productive plants into exporting, the authors introduce per-period fixed costs of being an exporter, M. These costs may consist of expenses associated with keeping a representative in a foreign country, dealing with customs, or intermediaries. A firm will choose to export whenever its gross operating profits are higher than the per-period fixed costs: $\pi(c,z,x) > M$. Hence, there exists some threshold on marginal costs below which plants have positive operating profits and choose to export. Plants with marginal costs above this threshold will choose to serve the domestic market. Since lower marginal costs translate into higher productivity, exporters will have higher productivity than non-exporters due to self-selection of more productive plants into exporting.

Along with fixed per-period costs of exporting there may be significant costs which are sunk in nature: the cost of information gathering about demand conditions abroad, search costs of identifying local bankers, networking, adopting the product to new standards, cost of product quality upgrading, etc. These costs, F, recur every time a plant exits the export market.[4] The plant does not have to pay these costs if it exported in the previous period. Existence of sunk costs implies that it may be optimal for a plant to continue exporting even when marginal costs are temporarily high and net operating profits are negative, $\pi(c,z,x) < M$, since the plant avoids paying reentry costs in the future.

Learning by exporting is modeled similarly to learning by doing where marginal costs are a decreasing function of plant's age (or other measures of production experience, such as cumulative output). Assuming that marginal costs are a decreasing function of plant's exporting experience, one can say that

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[4] Whether they recur in full or only partially is an empirical question. Roberts and Tybout (1997), for example, show that these costs recur partially if a plant does not stay out of the foreign market for more than 2 years.

exporting lowers plant's marginal costs, which translates into higher productivity.

Because of the sunk costs and learning by exporting, the decision of whether to participate in exporting becomes a forward-looking problem in which a plant makes its decision based on the current net operating profits and the expected future payoffs from exporting (which consist of the value of avoiding future reentry costs as well as expected productivity gains from exporting). A plant will export when the sum of its current net operating profits, $\pi(c,z,x) - M$, and expected future discounted payoff from exporting is greater than sunk costs.

I introduce market heterogeneity along two dimensions. Following Helpman et al. (2003) who distinguish between exporting and FDI by assuming different costs for each of these activities, I allow sunk entry costs, M, to depend on the development level of the destination market. A priori it is difficult to say which markets will have higher entry barriers. Entry costs consist of many elements, among which are information gathering costs and costs of upgrading product quality. The latter will most likely be substantial in advanced countries while the former will be higher in less developed markets due to the absence of developed trade infrastructure in the form of trading companies and distribution agents.

For Colombia's case, there is evidence that entry costs into advanced markets are higher than entry costs into developing markets. When surveyed by the World Bank, Colombian exporters claimed to have been specifically asked to upgrade the quality of their products if they were to access advanced markets during the 1980s (Roberts and Tybout 1997).[5] Higher entry costs in advanced markets imply that only the most productive exporters will choose to operate in those markets, i.e. selection effects will be higher for plants exporting to more developed markets. An important empirical implication of this is that exporters to advanced markets will be more productive prior to exporting.

Secondly, I allow the rate of learning (i.e. the rate of productivity growth) to vary by the development level of a destination market. In particular, I assume that the increase in productivity generated by operations in advanced markets is bigger than the increase in productivity generated by operations in developing markets. This differential means that in the presence of learning effects, the difference in productivity between exporting plants and non-exporting plants will be largest within industries targeting OECD countries and smallest within industries targeting similar countries.

The final point worth noting is that the model described above moves away from a representative firm framework. Melitz (2002), Yeaple (2002), Bernard et

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5 This finding is very similar to the case of Hungarian producers who were frequently required to make substantial investments in machinery, equipment and marketing channels and to upgrade the quality of their products in order to enter West European markets (Szalavetz and Lücke 1997).

al. (2005) among others emphasize productivity differences among firms and suggest differential outcomes for low and high productivity firms. For example, the impact of decreasing trade costs on productivity exists primarily at the upper end of the productivity distribution, due to the disproportionately high entry rate into exporting and increased market share among more efficient firms. This pattern received some empirical support by Yasar et al. (2004a) who find that exporting has significantly larger effects at higher quantiles of the productivity distribution. This finding suggests that under-performing plants have difficulties converting their exporting experience into higher productivity and it may be particularly true for exporting to advanced countries: less productive exporters may be unprepared to adopt the stat-of-the-art technologies available in advanced markets and to benefit from trade with those markets. A testable implication of this is that exporting to advanced markets will generate productivity gains only at the upper end of the productivity distribution.

Based on the model described in this section I anticipate the following patterns in the data:

(1) Future exporters are more productive than plants who never export;

(2) In the presence of learning by exporting, the marginal effect of exporting on productivity is positive and significant even after controlling for self-selection of more productive plants into exporting;

(3) Assuming higher entry costs in advanced markets, future exporters to those markets are more productive than future exporters to less developed markets;

(4) In the presence of the “quality of the learning environment” effects, the marginal effect of exporting to advanced markets is positive and significant;

(5) Exporters at the upper tail of the conditional productivity distribution have higher returns to exporting and a greater share of those returns is attributed to exporting to advanced countries.

III. Econometric Framework

A common measure of return to exporting is the average differential in performance between exporters and non-exporters. Some measure of plant performance (usually labor or total factor productivity) is regressed on the lagged export status dummy Y_{ijt} (which is equal to 1 if the plant exports in year t and zero otherwise) and a vector of control variables Z_{ijt} that usually includes plant’s age, size, as well as region, industry and year dummies:

$$\ln TFP_{ijt} = \alpha + \beta Y_{ijt-1} + \gamma Z_{ijt-1} + \varepsilon_{ijt-1} \qquad (1)$$

where subscripts i, j and t denote plant, industry and year.

Transforming the parameter β by $100(e^{\beta}-1)$ gives the average differential in productivity between exporters and non-exporters. This differential has been estimated as low as 2.5–7.5 percent in Korea (Chin Hee Hahn 2004) and as high as 17.4–18.6 percent in African countries (Taye and Pattillo 2004). In Colombia, estimates of this differential are around 8 percent when measured in terms of total factor productivity for young plants (Fernandes and Isgut 2005) and around 20 percent when measured in terms of labor productivity (Isgut 2001).

Fernandes and Isgut (2005) examine the effect of exporting on productivity and, as an extension of their main focus, they test the hypothesis that plants have more scope for learning when they export to high-income countries. They interact a measure of exporting experience (cumulative exports index and number of years the plant has exported, depending on specification) with the share of each 3-digit industry's exports going to rich countries. I build on their specification, however, unlike them I (1) introduce a gradation in the sophistication level of the trading partner and differentiate between similar or less developed, more developed and most developed (OECD) countries; (2) consider the possibility of self-selection of more productive exporters into advanced markets; (3) consider the possibility of different benefits from exporting for under-performing and over-performing plants. Also, the variation used in this study is at the four, rather than three digit, industry level.

I begin by estimating the following equation:

$$\begin{aligned} \ln TFP_{ijt} = {} & \alpha + \delta_R RICHER_{jt-1} + \delta_{OECD} OECD_{jt-1} \\ & + \beta Y_{ijt-1} + \beta_R Y_{ijt-1} RICHER_{jt-1} + \beta_{OECD} Y_{ijt-1} OECD_{jt-1} + \gamma Z_{ijt-1} + \varepsilon_{ijt-1} \end{aligned} \quad (2)$$

The dependent variable is the logarithm of total factor productivity. Total factor productivity is measured as the difference between actual and predicted output, as recovered from an estimated production function. I construct the TFP measure following Levinsohn and Petrin (2003) and take into account endogeneity engendered the fact that productivity is known to the firm and affects the firm's input choices (see Appendix C for details).

The term $RICHER_{jt}$ is the share of the industry's exports going to upper middle income or rich non-OECD countries. The term $OECD_{jt}$ is the share of the industry's exports going to OECD countries. The reference group is countries with the development level less or similar to that of Colombia (lower middle income). By construction, the share of exports to similar, richer and OECD countries add to 1. Appendix A offers the complete list of country groupings. The terms $Y_{ijt}RICHER_{jt}$ and $Y_{ijt}OECD_{jt}$ are the interactions of current exporting status with the shares of the industry's exports going to upper middle income or rich non-OECD and OECD countries.

The vector of control variables Z_{ijt} contains additional variables that can help explain total factor productivity. Those include industry dummies to control for sectoral differences in productivity and time dummies to capture time-specific economic policy shocks common to all plants. I include plant's age to account for the possibility that starting plants may need time to adjust to the market before they are able to function at their best. Since older plants may be using outdated technology, I also include a quadratic age term. In order to control for the potential effect of agglomeration economies on productivity, as well as any region-specific factors, I use dummy variables for plant location. Other controls include plant size (based on the total employment) and ownership structure. To account for serial correlation of outcomes within a plant over time, I correct the standard errors by clustering at the plant level.[6]

The marginal return to exporting, i.e. exporting premium, is given by $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean}$. I expect it to be positive and, given previous literature, highly significant. The contribution of advanced countries to this premium is given by $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean}$. Parameter β is the return to exporting in general, irrespective of the development level of the destination market.[7] Parameter β_R is the additional increment to the returns to exporting associated with exporting to more developed, but not advanced (OECD) countries. Similarly, parameter β_{OECD} is the additional increment to the returns to exporting associated with exporting to the most advanced countries. In the presence of the differentiated return to exporting in advanced markets, the estimates of β_R and β_{OECD} would be positive and significant. If β_R and β_{OECD} are

6 I also experiment with clustering at the industry level.

7 More precisely, this is the return to exporting for a plant within an industry exporting to similar or less developed markets. One can think of it as the minimum productivity edge that any exporter gets simply from operating in a foreign market. It reflects the part of learning-by-exporting which is not associated with acquisition of new technologies since similar or less developed markets are unlikely to possess the technologies that are not available in the domestic market.

found to be jointly zero, the development level of the destination market has no bearing on the return to exporting.

A problem with interpreting estimates β_R and β_{OECD} as the productivity effects of exporting to more advanced countries is two-fold. First of all, the coefficients are biased due to self-selection. This possibility follows directly from the discussion in Section 2: high costs associated with entry into foreign markets create a barrier that only plants with a productivity above some predetermined threshold level can overcome. The situation is further complicated by potentially different entry costs in advanced and developing markets. If higher costs are associated with entry into advanced markets, then only the most productive exporters will be able to penetrate those markets.

Secondly, the OLS specification in equation (2) fails to account for the heterogeneity in the effect of exporting in general, and in the effect of exporting to the advanced markets in particular, on productivity. Given the significant inter-plant variation in productivity levels, especially in developing countries like Colombia, the marginal effect of exporting at the lower end of the productivity distribution may be quite different from the marginal effect of exporting at the upper end.

To simultaneously address the aforementioned issues, I use a quantile regression framework on the sub-sample of exporters.[8] Under such framework, the θ^{th} quantile of the conditional distribution of ln*TFP*, given the vector of covariates, is specified as:

$$Q_\theta(\ln TFP_{ijt} \mid X) = \alpha(\theta) + X'_{ijt-1}\lambda(\theta), \qquad \theta \in (0,1) \tag{3}$$

where $Q_\theta(\ln TFP_{ijt}|X)$ denotes the quantile θ of the logarithm of the total factor productivity conditional on the vector of covariates X (current exporting status, shares of exports going to richer and OECD countries, interactions of the exporting status with the shares of exports going to richer and OECD countries, as well as the additional controls described earlier).[9] The coefficients obtained from the quantile regression have the same interpretation as those obtained from the equation (2), but at the relevant quantile rather than at the conditional mean of the dependent variable. Intuitively, the specification in equation (3) allows comparison of the return to exporting for those plants whose productivity is lower than expected based on plant characteristics (i.e. under-performing plants) and those whose productivity is higher than expected (i.e. over-performing plants).

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8 See Yasar et al. (2004a) for an application of the quantile regression to the analysis of the return to exporting.

9 Note that in the regression conducted on the sub-sample of exporters, Y_{ijt} indicates the plant's exporting status and is equal to zero if the plant is a future exporter, an exporter who is temporarily out of the foreign market or a quitter, i.e. a plant who has stopped exporting permanently.

Restricting the sample to exporters greatly reduces, if not eliminates, the bias associated with the selection of more productive plants into exporting. To account for any remaining endogeneity in the current exporting status and the selection of more productive exporters into advanced markets, I employ a two-stage quantile regression in which I use instrumental variables in place of endogenous variables *Y*, *RICHER*, *OECD* and their interactions:[10]

$$Q_{\theta}(\ln TFP_{ijt} \mid X) = \alpha(\theta) + X^{IV}_{ijt-1}\lambda(\theta), \qquad \theta \in (0,1) \tag{4}$$

In the first stage I estimate five equations (one for each endogenous variable) in which I regress the corresponding endogenous variable on the assumed instruments, as well as the remaining exogenous variables of the model. I test several candidates for their validity as instruments for exporting status, including roads per square kilometer in the region in which a plant is located, distance to port cities, density of phone lines, number of domestic and international airports, region's remoteness measured as distance between plant's location and other cities, weighted by their population, and the plant's export subsidies. The use of these variables as instruments for the exporting status is based on the supposition that a region's infrastructure and export subsidies are closely related to the opportunities for exports and do not affect the plant's productivity directly. I find roads per square kilometer, region's remoteness and

[10] The variance-covariance matrices of the estimates are obtained using bootstrapping.

subsidies to be the best instruments in terms of their correlation with exporting status. They have also been found uncorrelated with the residuals of the model.

To construct instruments for the shares of exports destined for similar, richer, and OECD countries, I use a modified gravity equation. The use of the gravity equation to construct instruments was first proposed by Frankel and Romer (1999) in their study of the effect of trade on growth. The key insight of the gravity equation is that a country's geographic and geopolitical attributes, such as distance from its trading partners, shared borders, presence of military conflicts, shared language, etc. produce a very good estimate of the expected volume of trade between any pair of countries. These geographic and geopolitical attributes are highly correlated with trade flows, yet they are not affected by plant productivity and do not determine plant performance other than through facilitating trade and, hence, transfer of knowledge. Therefore, I can use these attributes to construct exogenous instruments for the share of Colombia's exports to similar, richer and OECD countries.

I start by adopting the standard gravity equation with minor modifications to obtain a prediction of Colombia's "natural" level of trade:

$$\frac{\text{PartnerExports}}{\text{TotalIndustryExports}}_{cjt} = \text{GDP}_{ct} + \text{PerCapitaGDP}_{ct} + \text{EconomicRemoteness}_{ct} + \text{Distance}_{c} + \text{PhoneRates}_{c} + \text{Expatriates}_{c} + \%\text{Catholic}_{c} + \text{Roads}_{c} + g_{t} + \varepsilon_{cjt} \quad (5),$$

where subscripts *c*, *j* and *t* denote trading partner, industry and year.

The variables on the right hand side are sources of friction between Colombia and its trading partners and they approximate costs of doing business in country *c* for Colombian producers. For example, distance (measured as the logarithm of the great-circle distance between countries' capital cities) is a proxy for transportation costs. Per capita GDP reflects similarity of tastes in Colombia and its trading partner and is, therefore, at least in part a proxy for the costs of adopting product to the tastes of foreign customers. The number of Colombian expatriates residing in various countries reflects the possible network ties between Colombia and its trading partners. This variable is a proxy for the informal trade barriers (such as inadequate information about trading opportunities, weak international legal institutions, etc.) that ethnic networks have been shown to help overcome (Rauch and Trindade 2002, Head and Ries 1998, Blanes 2004). Tariffs on long-distance calls from Colombia also reflect costs of doing business in a given country. Not only are they direct communication costs, but they are also closely related to other factors that make a country more or less open for Colombian producers. Finally, variable "Roads" is what I use in place of "Shared Borders" dummy from the standard gravity equation. This variable reflects the costs of penetrating a foreign market even when the distance between the countries is minimal. I opt for using the indicator for road connections in place of border dummies, because Colombia's major roads connect to Ecuador and Venezuela, but not to Panama, Brazil or Peru. I believe that trade flows between Colombia and the latter would be greater than trade flows with countries that do not border Colombia, but less than with the countries with which Colombia shares borders and roads.

I construct the instruments by aggregating predicted shares of trade obtained from equation (5) over three groups of countries: poor or lower middle income (similar), upper middle income or rich non-OECD (richer), and OECD countries. Having constructed the instruments, I estimate equation (2) via standard 2SLS regression to find the mean return to exporting to advanced markets and equation (4) via two stage quantile regression to find the return to exporting along the points of the conditional productivity distribution.

Finally, I investigate the effect of unobserved plant heterogeneity on the coefficients from equation (3). Following new developments in the literature on quantile regression in panel setting (Arias et al. 2001), I employ an approach similar to the correlated random effects model and use observables (the share of skilled workers in total labor force, capital per worker, and share of imported raw materials) as proxies for the unobserved plant effect.[11] To obtain standard errors, I supplement Arias et al.'s approach by a modified bootstrap procedure from Abrevaya and Dahl (2005) that accounts for the dependence of observations within a plant.

[11] See Abrevaya and Dahl (2005) or Arias et al. (2001) for the discussion of problems related to the use of fixed effects or differencing in a quantile regression.

IV. Data Source and Descriptive Statistics

I assemble the data from two primary sources. The plant level data come from the annual surveys of Colombian manufacturing and cover the period 1981–1991. The data on destination markets are constructed from Feenstra's World Trade Flows database.

The annual surveys of Colombian manufacturing (see Roberts and Tybout 1996 for institutional details on data collection) exhibit several strengths. First of all, these surveys encompass virtually all plants with ten or more employees across 93 manufacturing industries at the 4-digit ISIC. Secondly, they offer detailed longitudinal information on a variety of plant characteristics: year of start up, ownership structure, geographic location, employment and labor costs by gender and skill, expenditures on materials, consumption of domestic and imported raw materials, expenditures, inventories, taxes and subsidies, foreign and domestic sales, and value added, to name a few. Finally, the data on raw materials offer information not only on the purchase of materials (which may reflect storage), but also on their use, which will prove useful for the construction of the measure of plant productivity.

The records from the manufacturing surveys produce most of the variables required for the analysis (see Appendix B for the definitions and details on the construction of variables). However, these data have one serious limitation – they do not provide destination markets for plant's exports. I turn to Feenstra's bilateral trade flows data and obtain the share of industry's exports (at 4-digit level) going to any given country.

To group Colombian export markets according to their development level, I argue that the development level is highly correlated with income and use the World Bank classification of countries into low income, lower middle income, upper middle income, rich non-OECD and rich-OECD groups. According to this classification, Colombia is a lower middle income country. Hence, from the point of view of a Colombian exporter, other lower middle income countries (for example, Peru and Brazil) are perceived as similar and all markets from upper middle income and above are perceived as advanced. One point worth highlighting: there are too few observations to be able to include 'low income' and 'rich non-OECD' as separate categories. To ensure a sufficient number of observations, I consolidate countries into three groups: similar (low-income and lower middle income), more developed (upper middle income and rich non-OECD) and advanced (OECD). Once I get the shares of Colombia's exports going to each of the aforementioned country groups, I append those to the plant-level data.

Bilateral trade flows data and plant-level data use different industry classifications and there is no one-to-one concordance between all 4-digit level industries. I construct a concordance between SITC (the World Trade Flows database) and ISIC (Colombian manufacturing surveys) classifications and take care to ensure that the data contain only those observations for which an exact, unambiguous match between the 4-digit industry classifications is found. The sample is further restricted to include only plants with a minimum of three consecutive years of data and belonging to 19 major exporting industries.[12] I also exclude observations with incomplete data on output and factor inputs.

The restrictions yield 5,938 plants, of which 1,057 are exporters. Their average characteristics are tabulated in Table 1 by the industry's primary destination market. On average, exporters are much larger than non-exporters; they pay higher wages than the region's average; they employ more skilled labor; they are more capital-intensive; and they use a larger share of imported (and potentially better quality) raw materials. The breakdown by the industry's primary destination market reveals that both exporters and non-exporters in the industries who send over 50 percent of their exports to poor or similar countries are much more skill-intensive and use more imported materials: exporters import over 30 percent of their raw materials (compared to 21 percent for the firms within industries trading primarily with richer countries and 11 percent for the firms within industries trading primarily with OECD); non-exporters import

[12] The 19 industries and their respective ISIC codes are: 311 (food products), 312 (other food products), 321 (textiles), 322 (clothing and apparel), 323 (leather products, excluding clothing and shoes), 324 (leather shoes), 241 (paper), 342 (printing and publishing), 351 (industrial chemicals), 352 (other chemicals), 356 (plastic products), 362 (glass products), 369 (other products of non-metallic minerals), 371 (iron and steel), 381 (metal products), 382 (machinery), 383 (electronic machinery and equipment), 384 (transportation equipment), 390 (miscellaneous manufacturing, such as jewelry, musical instruments, sporting goods, etc.). These industries account for over 96 percent of Colombia's manufacturing-sector exports.

13 percent of their raw materials (compared to 7 percent for the firms within industries trading primarily with richer countries and 4 percent for the firms within industries trading primarily with OECD). This evidence appears to be consistent with the finding that trade among developing countries tends to be comprised of manufactures that are skill- and learning- intensive (Amsden 1986). Finally, the first row of the table suggests that the development level of a trading partner may account for the differences in productivity. The firms in the industries that export primarily to more advanced countries are, on average, more productive than the firms who export to poor and similar countries.

Dynamic patterns in the data are reported in Table 2A, which tabulates plants' average characteristics by the industry's primary destination market and by the current exporting status (non-exporter; not exporting now, but eventually does; not exporting now, but has in the past and will in the future; currently exporting; has exported in the past, but not now and does not return to exporting before the end of the observation period). This table supports the hypothesis that "better" plants become exporters: irrespective of the development level of the destination market, exporters are more productive and exhibit other characteristics associated with better efficiency before they start exporting (compare columns "not yet" and "exporting now" and/or "between spells" within the same destination market). This underlines the importance of accounting for self-selection of more productive plants into exporting.

Moreover, patterns in Table 2A give grounds for concern with selection of more productive exporters into advanced markets: higher productivity is necessary to start exporting within industries trading primarily with OECD countries (compare columns "not yet" across different destination markets).

V. Results

Tables 3A-3C consolidate the findings from estimating equations (2) and (4) from Section 3. In Table 3A, I illustrate the importance of omitting the development level of the destination market from the analysis of the return to exporting and show how the self-selection of more productive plants into exporting biases the estimates of the return to exporting. In Table 3B, I illustrate the extent to which exporting in general, and exporting to advanced countries in particular, varies across the productivity distribution. In Table 3C, I illustrate the importance of taking into account not only the selection of more productive plants into exporting, but also the selection of more productive exporters into advanced markets.

Comparisons of columns (1) and (2) of Table 3A shows the importance of taking into account the development level of the trading partner. When this factor is omitted, the productivity differential between exporters and non-exporters is approximately 36 percent. Evaluated at the mean, the exporting premium increases by merely one percent when I take into account the development level of the destination market (from 35.9 to 36.6 percent).

However, omitting this factor masks some interesting patterns. In particular, the productivity differential may be as small as 14 percent (within industries trading solely with richer countries) or as large as 60 percent (within industries trading solely with OECD countries).[13]

Columns (3) and (4) report the effect of exporting on productivity, purged of the selection of more productive plants into exporting. Having restricted the sample to exporters only, allows us to compare exporting plants to a group of plants which is comprised of (1) plants about to enter foreign markets, (2) sporadic exporters (i.e. plants who are currently not exporting, but have in the past and will in the future) and (3) quitters (i.e. plants who exported in the past and do not return to exporting by 1991, the end of the observation period). Since those three groups of plants are consistently more productive than plants who never export (see Tables 2A and 2B), the bias associated with the selection of more productive plants into exporting is greatly reduced and this is reflected in much lower estimated exporting premium (16-17 percent in columns (3) and (4) compared to 36-37 percent in columns (1) and (2)). The additional premium of exporting to advanced markets is 5 percent and is significant at 12 percent level. It is driven entirely by exporting to OECD countries.

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[13] The difference between exporters and non-exporters within an industry trading entirely with richer countries is given by $\beta+\beta_R$. Similarly, the difference between exporters and non-exporters within an industry trading entirely with OECD countries is given by $\beta+\beta_{OECD}$. The difference between exporters within an industry trading entirely with similar countries and exporters within and industry trading entirely with OECD countries is given by $\delta_{OECD}+\beta_{OECD}$.

The OLS regression assumes that the return to exporting is homogeneous for all exporters, where in fact the return is likely to be different for under-performing (in terms of low productivity level relative to the conditional mean) and over-performing (high productivity level relative to the conditional mean) exporters. In Table 3B, along with the results from the OLS regression on the sub-sample of exporters, I report the findings of the quantile regression analysis at the 10th, 25th, 50th, 75th and 90th quantiles. The difference in the estimates reported in column (1) and the rest of the table indicates that the OLS conceals important heterogeneity in the return to exporting. The significance of the differences between the quantiles can be evaluated from the plots in Figure 1, which presents the quantile regression estimates for the returns to exporting by destination market and the corresponding 95 percent confidence bounds. Homogeneity in returns would result in plots so flat that one would be able to draw a horizontal line within the confidence interval band and this is not the case in this study.

The marginal return to exporting (i.e. exporting premium), evaluated at the mean values of the shares of exports going to richer and OECD countries, is positive and significant for all plants and goes from 10.5 percent for the least productive plants to 18.3 percent for the most productive plants. The additional premium of exporting to advanced countries becomes positive and significant only at the 50th quantile where it is estimated at 4.7 percent and increases to 11 percent at the 75th quantile and to 17.6 percent at the 90th quantile. The incremental return to exporting to OECD is positive and significant for all but the least productive plants. The incremental return to exporting to richer countries is significant only for the most productive plants. In other words, the plants that are relatively less productive appear to have difficulty in converting the experience of trading with advanced countries into higher productivity. The positive 11 percent marginal return to exporting for the less productive plants (see column (2)) seems to be driven entirely by trade with similar and poor countries – there are no additional gains from trading with advanced countries.

The findings reported in Table 3B can be summarized as follows: (1) the ability to benefit from exporting, especially exporting to advanced countries, increases with the productivity level of the plant; (2) exporting to advanced countries is the driving force behind the higher than average productivity; and (3) it is exporting to the most advanced markets (i.e. OECD countries) that generates the highest productivity gains. The first result is identical to the one reported by Yasar et al. (2004a) in the context of the Turkish manufacturing plants. The last result is qualitatively the same as the one reported by Fernandes and Isgut (2005) who find that the interaction between any measure of export experience and the share of industry exports going to high income countries is always positive (roughly 6 percent) and significant.

In Table 3C I examine the empirical implications of allowing for the selection of more productive exporters into advanced markets. In column (1) I report the results from the standard 2SLS regression, in which I instrument for endogenous variables (exporting status, share of exports to richer countries, share of exports to OECD countries and their interactions with the exporting status) with export subsidies, roads per square kilometer, region's remoteness and the shares obtained from the gravity equation. In columns (2) through (6) I report the results from the Instrumental Variables Quantile Regression.

Table 3C confirms the existence of positive and significant productivity gains associated with exporting. Table 3C also confirms the pattern found earlier that the gains from exporting increase as one moves from the lower to the upper tail of the productivity distribution (the exporting premium ranges from 14 percent for the under-performing to 25 percent for the over-performing plants). The pattern of increasing returns to exporting to advanced countries has been lost, however: although the incremental return to exporting to OECD countries, β_{OECD}, follows the pattern established in Table 3B, the marginal return varies sporadically across quantiles and its significance has been lost due to the larger standard errors (the tests cannot reject the hypothesis of equality of returns between extreme quantiles).

Comparison of the estimated coefficients with Table 3B shows that for all quantiles the marginal return to exporting is higher in the IV estimation. The incremental return to exporting to OECD countries, β_{OECD}, is smaller for the high-productivity plants and larger, although insignificant, for low-productivity plants. Specifically, for the 90th quantile the return to exporting to OECD countries goes down by 2.4 percentage points when estimated via the instrumental variables quantile regression. Conversely, for the 10th quantile the return to exporting to OECD countries increases from 2 percent in the non-IV estimation to 9 percent in the IV estimation.

The reliability of the IV estimates depends entirely on the quality of the assumed instruments. In particular, the large standard errors observed in Table 3C are usually associated with weak instruments. However, the instruments in this study pass all standard diagnostic tests (Table 4). The reported Hansen J statistic (equal to the number of observations times the value of the objective function at the optimal coefficient estimates) from the test on over-identifying restrictions and associated p-value show that the chosen variables are valid instruments to the extent that they are uncorrelated with the error term and are correctly excluded from the estimated equation (Baum et al. 2005).[14] This finding is very encouraging because even a weak correlation between the instrument and the error in the original equation may lead to large inconsistencies in the IV estimates. This is particularly true when the

[14] The test statistic is based on the R-squared from the regression of the second stage residuals on all exogenous variables, including the assumed instruments. For the instruments to be valid, the R-squared (and the estimated coefficients on the assumed instruments) should be close to zero.

instruments are only weakly correlated with the endogenous variables. In this case, the IV estimates will be biased in the same direction as the OLS estimates and the magnitude of the bias will approach that of the OLS estimates as the correlation between the instruments and the endogenous variables approaches zero. The partial F statistics from the tests of excluded instruments in this study are well over 100 and indicate that the selected instruments are relevant.[15]

To briefly summarize the first-stage results, the regression of the decision to export on the logarithms of export subsidies, roads per square kilometer and region's remoteness shows that these variables are strongly correlated with the decision to export (R-squared of 81 percent). Export subsidies and the roads per square kilometer increase propensity to engage in exporting (both effects are significant at 1 percent level). The coefficient on the logarithm of the region's remoteness has an anticipated negative sign and is –0.024 (also significant at 1 percent level). The coefficients on all variables in the gravity equation have anticipated signs and, with the exception of the partner's economic remoteness and the percentage of catholics, are estimated precisely (significant at 2 percent level). High tariffs on long-distance calls from Colombia reduce trade (estimated coefficient of –0.142). Everything else equal, Colombia trades most with the countries with which it shares roads in addition to borders (15 percent

[15] The null hypothesis of this test is that the instruments are irrelevant and should be excluded from the first stage regression. Failing to reject this hypothesis indicates that the potentially endogenous variable and the assumed instruments do not have sufficiently high correlation for the 2SLS estimates to be reliable: they are biased in the direction of the OLS estimates.

more when compared to the partners without common borders). The effect of common borders without shared road systems is estimated at 3 percent. I also find that a ten percent increase in the number of Colombian expatriates is associated with a three percent increase in the share of Colombian exports to the host country. This effect is almost identical to the effect of immigrants on Canadian trade with the immigrant's home country found by Head and Ries (1998) and supports the idea that ethnic networks expand trade, probably because of their superior knowledge of the market opportunities and/or the rigmarole for conducting business. The predicted export shares generated by the gravity equation are strongly correlated with the actual export shares: the R-squared from the regression of the predicted share on the actual share is 0.64 for similar, 0.60 for richer and 0.69 for OECD countries.

While the findings of the diagnostic tests are encouraging, the standard errors in the instrumental variables regression prompt me to conclude that the estimated coefficients are not significantly different from the ones produced by the OLS.[16] The most likely explanation to this finding is that the absence of

[16] The first stage equations in both the standard 2SLS regression and the two stage quantile regression are estimated using the linear probability model. This model, however, has fallen into disfavor among many economists because it can yield predicted probabilities outside 0–1 interval, i.e. the range of my endogenous variables. I repeat the analysis using a binomial probit model to produce predicted values for the endogenous decision to export in the first stage. This exercise does not affect any of the conclusions reported in Table 3C. Using a probit model in the first stage also fails to reduce standard errors sufficiently to generate statistically significant differences between the OLS and the two-stage regression estimates.

firm-level data on market destinations does not allow for an adequate solution to the problem via instrumental variables.

Unfortunately, the use of fixed effects or differencing, the most common solutions to the self-selection problem in the literature on learning by exporting, is problematic in the quantile regression setting. In Table 5 I use the share of skilled workers in total labor force, capital per worker, and share of imported raw materials as proxies for the unobserved plant effect and find that the positive effects of exporting on productivity are approximately 5 percentage points lower in magnitude across all quantiles as compared to the benchmark analysis in Table 3B. Moreover, the large and significant return to exporting within industries exporting to similar countries has been reduced to 2–5 percent and has lost its statistical significance. The overall pattern of the findings, however, remains remarkably similar to the specification in Table 3B: the marginal returns are increasing for higher quantiles of the conditional distribution of productivity; while overall exporting premium is positive and significant along the entire productivity distribution, the premium of exporting to advanced markets becomes significant only for relatively more productive plants. To put these findings in prospective, the overall return to exporting of 11.2 percent and the advanced market premium of 6.8 percent in column (1) are in sync with the fixed effects estimates of approximately 8 and 6 percent reported by Fernandes and Isgut (2005).

Levinshohn and Petrin (2003) approach to estimate total factor productivity has been criticized for failing to control for endogenous exit of plants from the sample (Amiti and Konings 2005). In Table 6, I add an indicator variable for the plants that will exit the sample in the following period to the list of control variables. Negative and highly significant, this factor, however, does not change the coefficients on other variables in the model.[17] Adding a control for failing exporters (Table 7) also fails to generate any important difference in the estimated returns to exporting.

Levinsohn and Petrin, as well as Olley and Pakes, estimates of productivity have also been shown to capture to a large extent pricing power or higher mark ups (Bartelsman and Doms 2000; De Loecker 2005). To address this problem, in Table 8 I report the findings from a regression with a Herfindahl index of market concentration as an additional control variable. The coefficient on this variable is extremely small in magnitude and does not affect any of the previous findings. In Table 9, I report the findings from a regression with the plant's market share, defined as the ratio of plant's sales in total industry sales, as an additional control variable. This variable is highly significant, especially at the upper end of the conditional productivity distribution, and decreases the

[17] Amiti and Konings (2005) also experiment with different measures of total factor productivity that explicitly account for plant exit and find that their findings are robust to the use of alternative approaches.

incremental return to exporting to OECD countries by approximately 3 percentage points at the 75th and 90th quantiles.[18]

One may argue that exposure to new technologies may be more important in high-tech industries and this is where one would expect to find higher returns to exporting. Comparison of Panels A and B of Table 10 indicates very distinct patterns of learning in high-tech (with the median skill intensity greater than 0.25) vs. low-tech industries. Although the marginal effect of exporting is very similar in both types of industries, in high-tech industries productivity gains along all points of the conditional productivity distribution are driven entirely by trade with OECD countries. Moreover, there is no evidence of heterogeneous returns between less productive and more productive plants. In low-tech industries, it is trade with similar countries that generates positive productivity gains for the less productive exporters, it is trade with richer but not richest countries that generates positive returns for the median exporter and it is trade with OECD, in addition to richer, countries that generates positive productivity gains for the most productive exporters. The fact that only plants with higher

[18] Of course, adding a Herfindahl index and the plant's market share cannot capture all the pricing effects in the estimates. In particular, the fact that exporting within industries trading with similar countries remains insignificant may be an indicator that exporters get higher prices in developed markets. However, this is not necessarily a drawback in this study. The anecdotal evidence cited earlier suggests that exporters were required to improve the quality of their products if they wanted to export to developed markets. Since higher quality will be reflected in higher prices, even pricing effects will contain information on learning. Moreover, studies that attempt to disentangle efficiency gains, quality control and pricing in productivity estimates (De Loecker 2005; Foster et al. 2005) find much smaller learning effects than reported by other authors, but the sign or significance level have never been reversed.

than average productivity can benefit from exporting to OECD markets is in sync with the supposition that better plants are better prepared to adopt the state-of-the-art technologies available in those markets. Less productive plants learn by being exposed to less advanced, but nevertheless new to them, technologies available in similar markets.

Finally, I recognize that the analysis in Tables 3–10 blurs potentially different effects from the first entry into exporting (instantaneous impact) and additional years of exporting experience. Table 11 reports the findings from the analysis in which I distinguish between exporters in the year(s) prior to exporting, first entry into exporting, continuing exporters, exporters temporarily selling only in domestic markets and quitters. Contrary to Indonesian firms (Blalock and Gertler 2002), Colombian exporters do not experience a one time jump in productivity upon the entry into foreign markets – the highest productivity gains are appropriated by continuing exporters (Table 12). The difference in productivity between continuing and future exporters is much higher and increases monotonically as one moves from the lower to the upper tail of the conditional productivity distribution: from 9.1 percent for the least productive (Column (2)) to 13.4 percent for the most productive (Column (6)) plants.[19] This productivity gain wears off fairly quickly once the plant exits the foreign market. The plants who stop exporting entirely (quitters) lose whatever

[19] This finding is virtually identical to the results reported in Table 3B.

productivity gains they may have accumulated – quitters are less productive than future exporters at all points of the conditional productivity distribution (bottom row of Table 12). Comparing quitters with the plants who never export, however, indicates that quitters remain approximately 7 percent more productive than non-exporters.[20] This is an important finding because it implies that even if learning-by-exporting effects were driven only by preparatory efficiency improvements prior to the entry into foreign markets, their beneficial effects do not dissipate completely.

Going back to Table 11 and looking at the dynamics of exporting experience across different destination markets reveals some very interesting patterns. First, the instantaneous impact of exporting within industries exporting to similar markets is negative and significant: it ranges from negative 16.6 percent for the 10^{th} quantile to smaller but still negative 7.3 percent for the 90^{th} quantile (first row of Table 11). My reading of the evidence in the first four rows of Table 11 suggests that the plants within the industries trading mostly with similar countries invest into efficiency improvements prior to the entry into foreign markets and do not experience any additional productivity gains from exporting per se.

The instantaneous impact of exporting within the industries exporting to advanced markets is dramatically different – it is positive and highly significant,

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[20] This finding is qualitatively identical to the one by Blalock and Gertler (2004) in the context of Indonesian firms. Regression results are available upon request.

as indicated by rows (7) and (11).[21] Gains from exporting appear to be a one-time productivity jump for the plants within the industries exporting to upper-middle income and rich non-OECD countries. Positive and significant 27.9 percent (10th quantile) to 24.4 percent (75th quantile) productivity differentials for first-time exporters in row (7) drop in size for continuing exporters for all but the most productive plants. As shown in rows (12) and (13), continuing exporters to OECD countries (even those with gaps in exporting experience) are more productive than future exporters and the productivity differential is bigger than within industries exporting to other developed markets.

To summarize the findings reported in Tables 11 and 12, a finer breakdown by the exporting status supports the earlier finding that the marginal effect of exporting is positive and significant for all plants, that it is driven by exporting to advanced markets and that the ability to benefit from exporting in general, and exporting to advanced markets in particular, depends on the plant's relative efficiency. Table 11 also provides detail on how learning by exporting takes place. Within the industries exporting mostly to similar countries, plants become more productive prior to exporting, experience a strong negative shock when they start exporting and rarely recover to the level they achieved prior to exporting. Apart from the preparatory efficiency improvements, there are no additional productivity gains from exporting. Within the industries exporting

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[21] This pattern has already found some support in the literature using aggregated data – Chao and Buongiorno (2002) find that the strongest relationship between exports and productivity is instantaneous.

mostly to upper-middle income and rich non-OECD countries, plants experience a very strong instantaneous productivity boost from exporting that dissipates with time, especially for less efficient plants (10^{th} and 25^{th} quantiles). Within the industries exporting mostly to OECD countries, there is a strong instantaneous productivity boost from exporting and the positive effects accumulate over time.

VI. Conclusions

In this study I examine how development level of a trading partner affects returns to exporting in the context of Colombian manufacturing plants during 1981–1991. I demonstrate that failure to control for the development level conceals interesting composition patterns in the marginal effect of exporting, patterns that may be useful in pinpointing the mechanism driving the high productivity of exporters. I confirm the importance of controlling for self-selection of more productive plants into exporting and examine the consequences of ignoring self-selection of more productive exporters into advanced markets. I confirm the finding that the plants at the upper tail of the conditional productivity distribution have higher returns to exporting in general and to exporting to advanced markets in particular and show that failure to account for unobserved plant heterogeneity in quantile regression setting overestimates the return to exporting by approximately 5 percent. I show that the return to exporting to advanced markets is especially large in high-tech industries. In low-tech industries the impact of exporting to advanced markets is significant only for the most productive plants. Finally, I demonstrate very distinct learning patterns across similar, richer and OECD markets.

Important policy implications from this study are that (1) exporting is not a panacea for development since plants must have high productivity before they gain the exporting boost and (2) export markets should be chosen wisely in order to benefit from exporting activity. Hence, raising productivity of domestic firms through other means and facilitating access to developed markets remains important to additional growth.

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Table 1A: Plant Characteristics by Exporting Status and Primary Destination of Exports – mean values

			> 50% Similar		> 50% Richer		> 50% OECD	
	Exporter	Non-Exporter	Exporter	Non-Exporter	Exporter	Non-Exporter	Exporter	Non-Exporter
log(TFP)	4.643	4.382	4.215	4.073	4.810	4.475	4.927	4.677
Capital Per Worker	847.361	487.820	1038.360	616.175	815.535	479.907	770.694	457.351
log(Employment)	4.343	3.228	4.501	3.227	4.297	3.290	4.292	3.197
Skilled Workers / Total Employment	0.290	0.251	0.352	0.318	0.285	0.239	0.256	0.231
Wage Premium (over regional average)	1.226	0.907	1.526	0.993	1.207	0.914	1.095	0.872
Share of Imported Raw Materials	0.192	0.065	0.317	0.126	0.209	0.065	0.105	0.043
Export Subsidies	5980.090	0.000	4919.650	0.000	4826.910	0.000	7552.300	0.000
Exports / Total Sales	0.117	0.000	0.121	0.000	0.099	0.000	0.136	0.000
N	8,933	32,573	1,554	4,341	2,472	9,389	3,520	13,786

Table 1B: Plant Characteristics by Exporting Status and Primary Destination of Exports – median values

			> 50% Similar		> 50% Richer		> 50% OECD	
	Exporter	Non-Exporter	Exporter	Non-Exporter	Exporter	Non-Exporter	Exporter	Non-Exporter
log(TFP)	4.817	4.388	4.295	4.260	4.828	4.638	5.149	4.618
Capital Per Worker	398.771	228.019	514.744	310.874	408.739	238.619	318.600	189.471
log(Employment)	4.304	3.091	4.554	3.068	4.263	3.135	4.248	3.091
Skilled Workers / Total Employment	0.252	0.211	0.318	0.286	0.250	0.200	0.220	0.183
Wage Premium (over regional average)	1.062	0.828	1.313	0.910	1.065	0.836	0.950	0.798
Share of Imported Raw Materials	0.001	0.000	0.223	0.000	0.024	0.000	0.000	0.000
Export Subsidies	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Exports / Total Sales	0.005	0.000	0.007	0.000	0.004	0.000	0.002	0.000
N	8,933	32,573	1,554	4,341	2,472	9,389	3,520	13,786

Table 2A: Plant Characteristics by Current Exporting Status and Primary Destination of Exports (mean values)

	Industries direct over 50% to similar countries				
	never export	not yet	between spells	exporting now	quitter
log(TFP)	4.073	4.391	4.592	4.049	4.528
Capital Per Worker	616.175	1031.070	791.209	1108.800	861.898
log(Employment)	3.227	4.220	4.506	4.703	3.870
Skilled Workers / Total Employment	0.318	0.308	0.305	0.371	0.359
Wage Premium (over regional average)	0.993	1.284	1.346	1.673	1.273
Share of Imported Raw Materials	0.126	0.252	0.287	0.357	0.233
Export Subsidies	0.000	0.000	0.000	8048.000	0.000
Exports / Total Sales	0.000	0.000	0.000	0.198	0.000
	Industries direct over 50% to richer countries				
	never export	not yet	between spells	exporting now	quitter
log(TFP)	4.475	4.646	5.096	4.879	4.804
Capital Per Worker	479.907	820.283	558.558	807.869	984.588
log(Employment)	3.290	4.020	4.398	4.453	4.266
Skilled Workers / Total Employment	0.239	0.246	0.312	0.300	0.314
Wage Premium (over regional average)	0.914	1.067	1.208	1.274	1.282
Share of Imported Raw Materials	0.065	0.161	0.203	0.246	0.157
Export Subsidies	0.000	0.000	0.000	8917.880	0.000
Exports / Total Sales	0.000	0.000	0.000	0.184	0.000
	Industries direct over 50% to OECD countries				
	never export	not yet	between spells	exporting now	quitter
log(TFP)	4.677	4.991	5.153	4.857	4.942
Capital Per Worker	457.351	609.770	706.454	914.611	555.985
log(Employment)	3.197	3.838	4.360	4.595	4.056
Skilled Workers / Total Employment	0.231	0.216	0.298	0.270	0.278
Wage Premium (over regional average)	0.872	0.953	1.107	1.199	0.976
Share of Imported Raw Materials	0.043	0.076	0.103	0.126	0.088
Export Subsidies	0.000	0.000	0.000	14436.300	0.000
Exports / Total Sales	0.000	0.000	0.000	0.260	0.000

Table 2B: Productivity Differential Between Exporters and Non-Exporters

Dependent Variable: $\log(TFP)_{ijt}$	
Prior To Exporting	0.202***
	(0.015)
First Time Exporter	0.273***
	(0.015)
Continuing Exporter	0.411***
	(0.019)
Continuing Exporter Temporarily Out of Market	0.360***
	(0.035)
Quitter	0.184***
	(0.033)
N	41,512

Standard errors are clustered by plant. Additional controls include year and industry dummies. Omitted category is plants that never export.

Table 3A: Market-Specific Exporting Premium and Selection of More Productive Plants into Exporting

Dependent Variable: $\log(TFP)_{ijt+1}$	OLS full sample (1)	OLS full sample (2)	OLS exporters (3)	OLS exporters (4)
Exporting Status $_{ijt}$ (β)	0.359***	0.262***	0.169***	0.119**
	(0.017)	(0.046)	(0.016)	(0.048)
Share Richer $_{ij}$ (δ_R)		-0.099***		-0.061
		(0.017)		(0.059)
Share OECD $_{ij}$ (δ_{OECD})		-0.221***		-0.097
		(0.021)		(0.059)
Exporting Status * Share Richer $_{ijt}$ (β_R)		-0.119***		-0.034
		(0.069)		(0.072)
Exporting Status * Share OECD $_{ijt}$ (β_{OECD})		0.352***		0.159**
		(0.069)		(0.063)
Sample Size	35,574	7,882	35,574	7,882
Exporting Premium	0.359	0.366	0.169	0.173
H_0: $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.000]	[0.000]	[0.000]	[0.000]
Exporting to Advanced Market Premium		0.104		0.054
H_0: $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$		[0.009]		[0.122]

Standard errors are clustered by plant (5,938 plants, 1057 exporters are used in the regressions). All dependent variables are lagged one period. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region. Omitted categories are plants who are not currently exporting and countries of similar development level. Values in square brackets are p-values.

Table 3B: Market-Specific Exporting Premium Across Conditional Productivity Distribution

	OLS	Quantile Regression on Exporters				
	exporters	10th	25th	50th	75th	90th
Dependent Variable: $\log(TFP)_{ijt+1}$	(1)	(2)	(3)	(4)	(5)	(6)
Exporting Status $_{ijt}$ (β)	0.119**	0.133**	0.103**	0.079**	0.043	0.007
	(0.048)	(0.061)	(0.046)	(0.053)	(0.058)	(0.061)
Share Richer $_{ij}$ (δ_R)	-0.061	0.061	-0.014	-0.019	-0.167***	-0.212***
	(0.059)	(0.067)	(0.061)	(0.071)	(0.072)	(0.080)
Share OECD $_{ij}$ (δ_{OECD})	-0.097	0.003	-0.056	-0.073	-0.164***	-0.196***
	(0.059)	(0.077)	(0.064)	(0.066)	(0.069)	(0.068)
Exporting Status * Share Richer $_{ijt}$ (β_R)	-0.034	-0.092	-0.058	-0.039	0.041	0.148*
	(0.072)	(0.086)	(0.075)	(0.079)	(0.089)	(0.091)
Exporting Status * Share OECD $_{ijt}$ (β_{OECD})	0.159**	0.015	0.081**	0.146***	0.226***	0.288***
	(0.063)	(0.073)	(0.062)	(0.065)	(0.078)	(0.076)
Sample Size	7,882	7,882	7,882	7,882	7,882	7,882
Exporting Premium	0.173	0.105	0.116	0.126	0.153	0.183
H_0: $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exporting to Advanced Market Premium	0.054	-0.028	0.013	0.047	0.110	0.176
H_0: $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.122]	[0.234]	[0.336]	[0.093]	[0.001]	[0.000]

Standard errors are clustered by plant (1057 exporters are used in the regressions). Standard errors in quantile regression are bootstrapped. All dependent variables are lagged one period. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region. Omitted categories are plants who are not currently exporting and countries of similar development level. Values in square brackets are p-values.

Table 3C: Market-Specific Exporting Premium and Selection of More Productive Exporters into Advanced Markets

	OLS	Quantile Regression on Exporters				
	exporters	10th	25th	50th	75th	90th
Dependent Variable: $\log(TFP)_{ijt+1}$	(1)	(2)	(3)	(4)	(5)	(6)
Exporting Status $_{ijt}$ (β)	0.051	0.096	0.089	0.157	0.147	0.139
	(0.137)	(0.146)	(0.098)	(0.106)	(0.122)	(0.168)
Share Richer $_{ij}$ (δ_R)	-0.293*	0.014	-0.113	-0.064	-0.308**	-0.323*
	(0.170)	(0.182)	(0.123)	(0.135)	(0.143)	(0.178)
Share OECD $_{ij}$ (δ_{OECD})	-0.224*	-0.052	-0.095	-0.047	-0.202**	-0.213*
	(0.122)	(0.134)	(0.082)	(0.088)	(0.092)	(0.118)
Exporting Status * Share Richer $_{ijt}$ (β_R)	0.108	0.013	-0.005	-0.135	-0.106	0.001
	(0.213)	(0.213)	(0.161)	(0.164)	(0.187)	(0.253)
Exporting Status * Share OECD $_{ijt}$ (β_{OECD})	0.295**	0.092	0.155	0.151	0.203*	0.262*
	(0.142)	(0.161)	(0.097)	(0.110)	(0.123)	(0.157)
Sample Size	7,882	7,882	7,882	7,882	7,882	7,882
Exporting Premium	0.215	0.139	0.152	0.170	0.193	0.249
H_0: $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exporting to Advanced Market Premium	0.164	0.043	0.063	0.013	0.046	0.110
H_0: $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.119]	[0.382]	[0.244]	[0.442]	[0.368]	[0.326]

Standard errors are clustered by plant (1057 exporters are used in the regressions). Standard errors in the quantile regression are bootstrapped. All dependent variables are lagged one period. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region. Omitted categories are the plants who are not currently exporting and countries of similar development level. Values in square brackets are p-values.

Table 4: First Stage Diagnostics

Endogenous Variable and Assumed Instruments	F-Statistic of the Test of Excluded Instruments	Partial R^2 of Excluded Instruments	Coefficients on Assumed Instruments[a]
Exporting Status	976.77	0.67	
Log(Export Subsidies)			0.064 (0.000)
Log(Roads per Square Kilometer)			0.151 (0.024)
Log(Region's Remoteness)			-0.024 (0.003)
Share Richer	348.19	0.45	
Predicted Share Richer			0.525 (0.015)
Share OECD	503.54	0.53	
Predicted Share OECD			0.579 (0.013)
Exporting Status * Share Richer	794.80	0.60	
Log(Export Subsidies) * Predicted Share Richer			0.064 (0.003)
Exporting Status * Share OECD	509.22	0.55	
Log(Export Subsidies * Predicted Share OECD)			0.064 (0.004)

Hansen J-Statistic: 0.662
p-value: [0.416]

[a]Following the convention, a first stage equation for every endogenous variable includes all assumed instruments and other exogenous variables of the model.

Clustered standard errors in parentheses. P-values in square brackets.

Table 5: Quantile Regression Alternative to Fixed Effects

	OLS	Quantile Regression on Exporters				
	exporters	10th	25th	50th	75th	90th
Dependent Variable: $\log(TFP)_{ijt+1}$	(1)	(2)	(3)	(4)	(5)	(6)
Exporting Status $_{ijt}$ (β)	0.057	0.020	0.051	0.035	0.015	0.020
	(0.045)	(0.033)	(0.040)	(0.033)	(0.043)	(0.059)
Share Richer $_{ij}$ (δ_R)	-0.033	0.010	0.019	-0.022	-0.115 **	-0.161 ***
	(0.064)	(0.038)	(0.053)	(0.042)	(0.051)	(0.061)
Share OECD $_{ij}$ (δ_{OECD})	-0.114 **	-0.049	-0.061	-0.072 *	-0.097 **	-0.176 ***
	(0.055)	(0.040)	(0.041)	(0.039)	(0.047)	(0.052)
Exporting Status * Share Richer $_{ijt}$ (β_R)	0.001	0.012	-0.030	0.009	0.069	0.084
	(0.069)	(0.046)	(0.059)	(0.050)	(0.065)	(0.089)
Exporting Status * Share OECD $_{ijt}$ (β_{OECD})	0.161 ***	0.102 **	0.076 *	0.144 ***	0.200 ***	0.220 ***
	(0.056)	(0.044)	(0.049)	(0.042)	(0.050)	(0.066)
Exporting Premium	0.125	0.067	0.072	0.099	0.124	0.144
H_0: $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exporting to Advanced Market Premium	0.068	0.047	0.021	0.064	0.109	0.123
H_0: $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.122]	[0.135]	[0.588]	[0.051]	[0.009]	[0.022]

Standard errors are clustered by plant (1057 exporters are used in the regressions). Standard errors in the quantile regression are bootstrapped. All dependent variables are lagged one period. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region, skill intensity, capital per worker, share of imported raw materials. Omitted categories are the plants who are not currently exporting and countries of similar development level. Values in square brackets are p-values.

Table 6: Added Controls for Exiting Plants

	OLS	Quantile Regression on Exporters				
	exporters	10th	25th	50th	75th	90th
Dependent Variable: $\log(TFP)_{ijt+1}$	(1)	(2)	(3)	(4)	(5)	(6)
Exporting Status $_{ijt}$ (β)	0.055	0.013	0.047	0.038	0.015	0.026
	(0.045)	(0.032)	(0.031)	(0.032)	(0.039)	(0.051)
Share Richer $_{ij}$ (δ_R)	-0.036	-0.001	-0.001	-0.018	-0.115 **	-0.156 ***
	(0.064)	(0.040)	(0.049)	(0.040)	(0.046)	(0.060)
Share OECD $_{ij}$ (δ_{OECD})	-0.117 **	-0.071 *	-0.073 *	-0.072 **	-0.097 **	-0.165 ***
	(0.054)	(0.038)	(0.038)	(0.030)	(0.042)	(0.050)
Exporting Status * Share Richer $_{ijt}$ (β_R)	0.006	0.026	-0.013	0.009	0.069	0.079
	(0.069)	(0.051)	(0.048)	(0.047)	(0.061)	(0.076)
Exporting Status * Share OECD $_{ijt}$ (β_{OECD})	0.164 ***	0.129 ***	0.085 *	0.146 ***	0.200 ***	0.218 ***
	(0.056)	(0.044)	(0.045)	(0.041)	(0.047)	(0.061)
Exporting Premium	0.126	0.077	0.078	0.103	0.124	0.147
H_0: $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exporting to Advanced Market Premium	0.071	0.064	0.031	0.064	0.109	0.121
H_0: $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.103]	[0.048]	[0.335]	[0.043]	[0.003]	[0.011]

Standard errors are clustered by plant (1057 exporters are used in the regressions). Standard errors in the quantile regression are bootstrapped. All dependent variables are lagged one period. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region, skill intensity, capital per worker, share of imported raw materials, a dummy variable for exiting plants. Omitted categories are the plants who are not currently exporting and countries of similar development level. Values in square brackets are p-values.

Table 7: Added Control for Exiting Exporters

	OLS	Quantile Regression on Exporters				
	exporters	10th	25th	50th	75th	90th
Dependent Variable: $\log(TFP)_{ijt+1}$	(1)	(2)	(3)	(4)	(5)	(6)
Exporting Status $_{ijt}$ (β)	0.032	0.004	0.043	0.013	-0.008	0.002
	(0.045)	(0.030)	(0.034)	(0.032)	(0.035)	(0.052)
Share Richer $_{ij}$ (δ_R)	-0.045	0.003	0.018	-0.030	-0.122 **	-0.155 **
	(0.064)	(0.041)	(0.046)	(0.045)	(0.053)	(0.063)
Share OECD $_{ij}$ (δ_{OECD})	-0.117 **	-0.047	-0.062 *	-0.087 **	-0.099 **	-0.176 ***
	(0.054)	(0.039)	(0.034)	(0.038)	(0.042)	(0.059)
Exporting Status * Share Richer $_{ijt}$ (β_R)	0.031	0.035	-0.015	0.028	0.095 *	0.104 *
	(0.069)	(0.048)	(0.051)	(0.052)	(0.049)	(0.074)
Exporting Status * Share OECD $_{ijt}$ (β_{OECD})	0.170 ***	0.106 ***	0.090 *	0.160 ***	0.208 ***	0.227 ***
	(0.056)	(0.039)	(0.048)	(0.040)	(0.049)	(0.060)
Exporting Premium	0.115	0.061	0.076	0.090	0.114	0.136
H_0: $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exporting to Advanced Market Premium	0.083	0.057	0.032	0.078	0.122	0.134
H_0: $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.058]	[0.053]	[0.341]	[0.014]	[0.000]	[0.006]

Standard errors are clustered by plant (1057 exporters are used in the regressions). Standard errors in the quantile regression are bootstrapped. All dependent variables are lagged one period. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region, skill intensity, capital per worker, share of imported raw materials, a dummy variable for exiting plants and exiting exporters. Omitted categories are the plants who are not currently exporting and countries of similar development level. Values in square brackets are p-values.

Table 8: Added Control for Market Structure

	OLS	Quantile Regression on Exporters				
	exporters	10th	25th	50th	75th	90th
Dependent Variable: $\log(TFP)_{ijt+1}$	(1)	(2)	(3)	(4)	(5)	(6)
Exporting Status $_{ijt}$ (β)	0.032	0.006	0.040	0.010	-0.009	0.001
	(0.045)	(0.033)	(0.036)	(0.036)	(0.045)	(0.056)
Share Richer $_{ij}$ (δ_R)	-0.044	0.009	0.018	-0.031	-0.123 **	-0.157 **
	(0.064)	(0.043)	(0.052)	(0.043)	(0.054)	(0.069)
Share OECD $_{ij}$ (δ_{OECD})	-0.117 **	-0.040	-0.064 *	-0.084 **	-0.107 **	-0.170 ***
	(0.054)	(0.044)	(0.035)	(0.038)	(0.047)	(0.056)
Exporting Status * Share Richer $_{ijt}$ (β_R)	0.031	0.030	-0.008	0.038	0.093	0.108
	(0.069)	(0.046)	(0.057)	(0.056)	(0.065)	(0.087)
Exporting Status * Share OECD $_{ijt}$ (β_{OECD})	0.170 ***	0.101 **	0.087 **	0.159 ***	0.213 ***	0.227 ***
	(0.056)	(0.044)	(0.041)	(0.044)	(0.058)	(0.064)
Exporting Premium	0.115	0.060	0.074	0.091	0.115	0.136
H_0: $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exporting to Advanced Market Premium	0.083	0.054	0.034	0.081	0.124	0.135
H_0: $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.059]	[0.091]	[0.326]	[0.023]	[0.006]	[0.013]

Standard errors are clustered by plant (1057 exporters are used in the regressions). Standard errors in the quantile regression are bootstrapped. All dependent variables are lagged one period. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region, skill intensity, capital per worker, share of imported raw materials, a dummy variable for exiting plants, a dummy variable for exiting exporters and a Herfindahl index of market concentration. Omitted categories are the plants who are not currently exporting and countries of similar development level. Values in square brackets are p-values.

Table 9: Added Control for Market Share

	OLS	Quantile Regression on Exporters				
	exporters	10th	25th	50th	75th	90th
Dependent Variable: $\log(TFP)_{ijt+1}$	(1)	(2)	(3)	(4)	(5)	(6)
Exporting Status $_{ijt}$ (β)	0.028	0.004	0.043	0.018	0.005	0.017
	(0.045)	(0.032)	(0.033)	(0.033)	(0.036)	(0.051)
Share Richer $_{ij}$ (δ_R)	-0.047	0.008	0.023	-0.019	-0.100 *	-0.172 ***
	(0.064)	(0.045)	(0.050)	(0.045)	(0.052)	(0.067)
Share OECD $_{ij}$ (δ_{OECD})	-0.113 **	-0.040	-0.064 *	-0.077 **	-0.089 **	-0.165 ***
	(0.054)	(0.043)	(0.038)	(0.036)	(0.043)	(0.050)
Exporting Status * Share Richer $_{ijt}$ (β_R)	0.038	0.031	-0.016	0.021	0.056	0.105 *
	(0.069)	(0.052)	(0.053)	(0.050)	(0.050)	(0.076)
Exporting Status * Share OECD $_{ijt}$ (β_{OECD})	0.167 ***	0.105 ***	0.087 **	0.151 ***	0.184 ***	0.196 ***
	(0.056)	(0.044)	(0.042)	(0.042)	(0.047)	(0.062)
Exporting Premium	0.112	0.059	0.073	0.090	0.103	0.139
H_0: $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exporting to Advanced Market Premium	0.084	0.055	0.031	0.071	0.098	0.121
H_0: $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.054]	[0.074]	[0.342]	[0.027]	[0.004]	[0.012]

Standard errors are clustered by plant (1057 exporters are used in the regressions). Standard errors in the quantile regression are bootstrapped. All dependent variables are lagged one period. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region, skill intensity, capital per worker, share of imported raw materials, a dummy variable for exiting plants, a dummy variable for exiting exporters, a Herfindahl index of market concentration and plant's market share. Omitted categories are the plants who are not currently exporting and countries of similar development level. Values in square brackets are p-values.

Table 10A: High Tech vs. Low Tech Industries – Return to Exporting in High Tech Industries

	OLS	Quantile Regression on Exporters				
	exporters	10th	25th	50th	75th	90th
Dependent Variable: $\log(TFP)_{ijt+1}$	(1)	(2)	(3)	(4)	(5)	(6)
Exporting Status $_{ijt}$ (β)	0.042	-0.044	0.020	0.026	0.020	0.039
	(0.063)	(0.043)	(0.040)	(0.039)	(0.052)	(0.063)
Share Richer $_{ij}$ (δ_R)	-0.034	-0.090 *	-0.034	-0.037	-0.125 *	-0.164 *
	(0.090)	(0.055)	(0.055)	(0.051)	(0.067)	(0.084)
Share OECD $_{ij}$ (δ_{OECD})	-0.206 ***	-0.167 ***	-0.123 ***	-0.202 ***	-0.201 ***	-0.217 ***
	(0.079)	(0.057)	(0.044)	(0.043)	(0.057)	(0.059)
Exporting Status * Share Richer $_{ijt}$ (β_R)	-0.003	0.065	0.018	-0.022	0.012	-0.028
	(0.100)	(0.067)	(0.055)	(0.063)	(0.079)	(0.105)
Exporting Status * Share OECD $_{ijt}$ (β_{OECD})	0.250 ***	0.274 ***	0.180 ***	0.306 ***	0.252 ***	0.175 **
	(0.088)	(0.068)	(0.059)	(0.065)	(0.076)	(0.078)
Exporting Premium	0.146	0.095	0.103	0.146	0.130	0.102
H_0: $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exporting to Advanced Market Premium	0.104	0.139	0.083	0.120	0.110	0.063
H_0: $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.114]	[0.003]	[0.033]	[0.005]	[0.042]	[0.165]

Standard errors are clustered by plant. Standard errors in the quantile regression are bootstrapped. All dependent variables are lagged one period. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region, skill intensity, capital per worker, share of imported raw materials, a dummy variable for exiting plants, a dummy variable for exiting exporters, a Herfindahl index of market concentration and plant's market share. Omitted categories are the plants who are not currently exporting and countries of similar development level. Values in square brackets are p-values.

Table 10B: High Tech vs. Low Tech Industries – Return to Exporting in Low Tech Industries

	OLS	Quantile Regression on Exporters				
	exporters	10th	25th	50th	75th	90th
Dependent Variable: $\log(TFP)_{ijt+1}$	(1)	(2)	(3)	(4)	(5)	(6)
Exporting Status $_{ijt}$ (β)	0.013	0.105 *	0.091 **	0.014	-0.041	-0.035
	(0.057)	(0.063)	(0.047)	(0.044)	(0.048)	(0.076)
Share Richer $_{ij}$ (δ_R)	-0.026	0.124	0.040	-0.060	-0.113 *	-0.084
	(0.075)	(0.080)	(0.056)	(0.064)	(0.067)	(0.097)
Share OECD $_{ij}$ (δ_{OECD})	-0.013	0.033	-0.016	-0.040	-0.031	-0.003
	(0.065)	(0.078)	(0.050)	(0.058)	(0.062)	(0.072)
Exporting Status * Share Richer $_{ijt}$ (β_R)	0.107	-0.084	-0.024	0.107 *	0.196 ***	0.182 *
	(0.088)	(0.096)	(0.070)	(0.068)	(0.079)	(0.102)
Exporting Status * Share OECD $_{ijt}$ (β_{OECD})	0.104	-0.036	-0.045	0.053	0.165 ***	0.166 **
	(0.069)	(0.069)	(0.059)	(0.051)	(0.057)	(0.084)
Exporting Premium	0.097	0.058	0.063	0.076	0.100	0.102
H_0: $\beta+\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exporting to Advanced Market Premium	0.083	-0.046	-0.028	0.062	0.142	0.137
H_0: $\beta_R*RICHER_{mean}+\beta_{OECD}*OECD_{mean} = 0$	[0.130]	[0.433]	[0.542]	[0.116]	[0.003]	[0.054]

Standard errors are clustered by plant. Standard errors in the quantile regression are bootstrapped. All dependent variables are lagged one period. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region, skill intensity, capital per worker, share of imported raw materials, a dummy variable for exiting plants, a dummy variable for exiting exporters, a Herfindahl index of market concentration and plant's market share. Omitted categories are the plants who are not currently exporting and countries of similar development level. Values in square brackets are p-values.

Table 11: Market-Specific Exporting Premium at Various Stages of Exporting

	OLS	Quantile Regression				
		10th	25th	50th	75th	90th
Dependent Variable: log(TFP)$_{ijt+1}$	(1)	(2)	(3)	(4)	(5)	(6)
(1) First Year Exporter$_{ijt}$	-0.137 ***	-0.166 **	-0.116 *	-0.163 ***	-0.160 ***	-0.073
	(0.058)	(0.070)	(0.060)	(0.051)	(0.062)	(0.073)
(2) Continuing Exporter$_{ijt}$	-0.040	-0.001	-0.027	-0.052	-0.100 **	-0.119 **
	(0.057)	(0.036)	(0.049)	(0.037)	(0.044)	(0.051)
(3) Sporadic Exporter$_{ijt}$	-0.021	0.017	-0.028	-0.023	-0.133 **	-0.203 ***
	(0.083)	(0.096)	(0.083)	(0.070)	(0.063)	(0.080)
(4) Quitter$_{ijt}$	-0.104	0.020	0.020	-0.210 **	-0.198 *	-0.055
	(0.112)	(0.092)	(0.080)	(0.085)	(0.119)	(0.139)
(5) Share Richer$_{jt}$	-0.135 *	-0.055	-0.133 **	-0.134 ***	-0.190 ***	-0.143 ***
	(0.075)	(0.050)	(0.070)	(0.049)	(0.053)	(0.054)
(6) Share OECD$_{jt}$	-0.183 ***	-0.073 *	-0.157 ***	-0.166 ***	-0.188 ***	-0.227 ***
	(0.062)	(0.046)	(0.052)	(0.040)	(0.051)	(0.048)
(7) Share Richer * First Year Exporter$_{ijt}$	0.251 ***	0.279 **	0.272 ***	0.291 ***	0.244 ***	0.091
	(0.086)	(0.118)	(0.087)	(0.077)	(0.094)	(0.101)
(8) Share Richer * Continuing Exporter$_{ijt}$	0.163 **	0.098	0.130 *	0.161 ***	0.199 ***	0.223 ***
	(0.085)	(0.057)	(0.073)	(0.059)	(0.065)	(0.084)
(9) Share Richer * Sporadic Exporter $_{ijt}$	0.080	0.142	0.133	0.082	0.112	0.224
	(0.127)	(0.169)	(0.134)	(0.104)	(0.118)	(0.159)
(10) Share Richer * Quitter$_{ijt}$	0.218	0.008	0.058	0.375 ***	0.272	0.024
	(0.187)	(0.121)	(0.129)	(0.149)	(0.181)	(0.207)
(11) Share OECD * First Year Exporter$_{ijt}$	0.174 ***	0.156 **	0.136 **	0.177 ***	0.187 ***	0.164 *
	(0.066)	(0.075)	(0.067)	(0.060)	(0.070)	(0.091)
(12) Share OECD * Continuing Exporter$_{ijt}$	0.293 ***	0.135 ***	0.207 ***	0.251 ***	0.348 ***	0.406 ***
	(0.072)	(0.041)	(0.058)	(0.043)	(0.053)	(0.062)
(13) Share OECD * Sporadic Exporter$_{ijt}$	0.144	0.081	0.188 *	0.202 **	0.266 ***	0.323 ***
	(0.109)	(0.126)	(0.104)	(0.089)	(0.085)	(0.102)
(14) Share OECD * Quitter$_{ijt}$	-0.100	-0.258 **	-0.239 *	0.023	0.001	-0.009
	(0.129)	(0.109)	(0.128)	(0.096)	(0.156)	(0.184)
Sample Size	7,882	7,882	7,882	7,882	7,882	7,882

Standard errors are clustered by plant. Standard errors in the quantile regression are bootstrapped. Additional controls include industry and time dummies, linear and quadratic plant age terms, dummies for plant size and region, skill intensity, capital per worker, share of imported raw materials, a dummy variable for exiting plants, a Herfindahl index of market concentration and plant's market share. Omitted category is exporters prior to exporting. Sporadic Exporter is a continuing exporter who is temporarily not exporting.

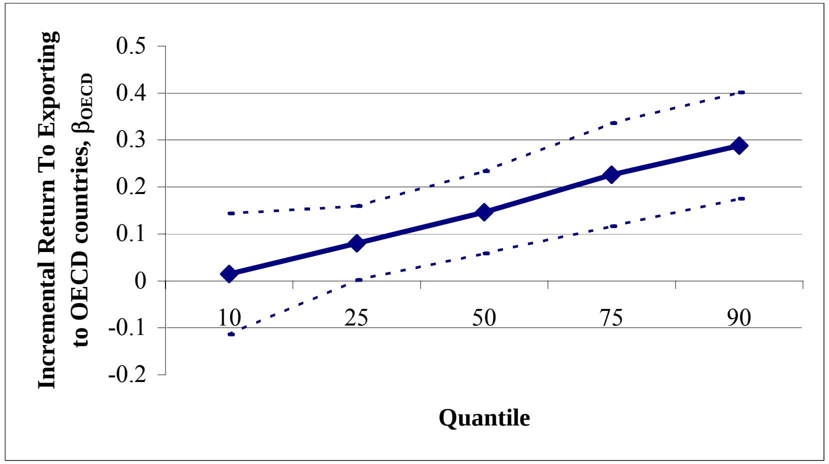
Table 11: Exporting Premium at Various Stages of Exporting
(testing H0: b+bR*RICHERmean+bOECD*OECDmean = 0)

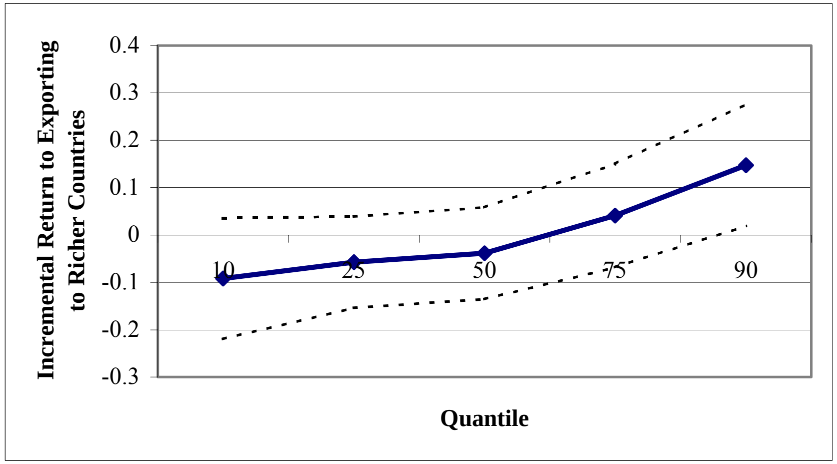
	OLS	Quantile Regression				
		10th	25th	50th	75th	90th
	(1)	(2)	(3)	(4)	(5)	(6)
	Relative to Exporters in the Year(s) Prior to Exporting					
First Time Exporter	0.029	0.003	0.042	0.019	0.008	0.030
	[0.093]	[0.850]	[0.008]	[0.140]	[0.516]	[0.116]
Continuing Exporter	0.143	0.091	0.108	0.113	0.120	0.134
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Continuing Exporter Temporarily Out of Market	0.070	0.103	0.100	0.093	0.020	0.016
	[0.016]	[0.002]	[0.000]	[0.000]	[0.422]	[0.515]
Quitter	-0.065	-0.086	-0.059	-0.061	-0.097	-0.050
	[0.084]	[0.003]	[0.038]	[0.017]	[0.001]	[0.181]

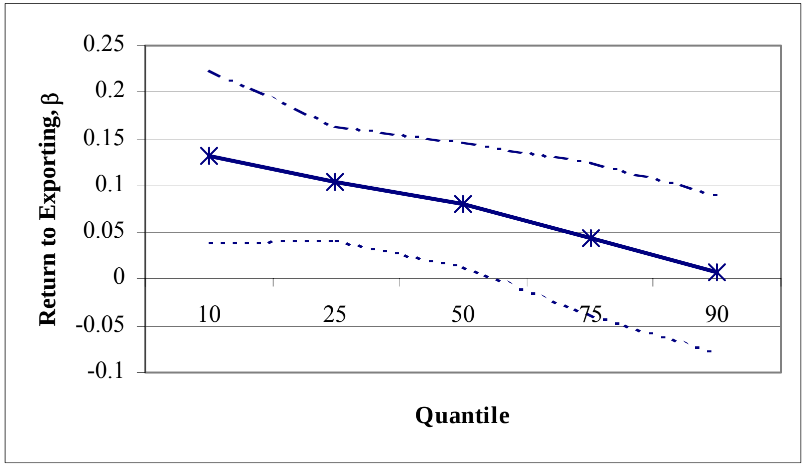
Exporting premium is computed based on the regression results reported in Table 11. Values in square brackets are p-values for the two-tail test.

Figure 1: The pattern of return to exporting across the quantiles of the conditional productivity distribution

The figures are based on the estimates in Table 3B. Solid line indicates the pattern of the return. Dashed lines are the error bands for the 95% confidence interval.







APPENDIX A

World Bank Country Classification (in alphabetical order)

Economy	Income group
Afghanistan	Low income
Albania	Lower middle income
Algeria	Lower middle income
American Samoa	Upper middle income
Andorra	High income: nonOECD
Angola	Low income
Antigua and Barbuda	High income: nonOECD
Argentina	Upper middle income
Armenia	Lower middle income
Aruba	High income: nonOECD
Australia	High income: OECD
Austria	High income: OECD
Azerbaijan	Low income
Bahamas, The	High income: nonOECD
Bahrain	High income: nonOECD
Bangladesh	Low income
Barbados	High income: nonOECD
Belarus	Lower middle income
Belgium	High income: OECD
Belize	Upper middle income
Benin	Low income
Bermuda	High income: nonOECD
Bhutan	Low income
Bolivia	Lower middle income
Bosnia and Herzegovina	Lower middle income
Botswana	Upper middle income
Brazil	Lower middle income
Brunei	High income: nonOECD
Bulgaria	Lower middle income
Burkina Faso	Low income
Burundi	Low income
Cambodia	Low income
Cameroon	Low income
Canada	High income: OECD
Cape Verde	Lower middle income
Cayman Islands	High income: nonOECD
Central African Republic	Low income
Chad	Low income
Channel Islands	High income: nonOECD
Chile	Upper middle income
China	Lower middle income
Colombia	Lower middle income
Comoros	Low income
Congo, Dem. Rep.	Low income
Congo, Rep.	Low income
Costa Rica	Upper middle income
Côte d'Ivoire	Low income
Croatia	Upper middle income
Cuba	Lower middle income

Economy	Income group
Cyprus	High income: nonOECD
Czech Republic	Upper middle income
Denmark	High income: OECD
Djibouti	Lower middle income
Dominica	Upper middle income
Dominican Republic	Lower middle income
Ecuador	Lower middle income
Egypt, Arab Rep.	Lower middle income
El Salvador	Lower middle income
Equatorial Guinea	Low income
Eritrea	Low income
Estonia	Upper middle income
Ethiopia	Low income
Faeroe Islands	High income: nonOECD
Fiji	Lower middle income
Finland	High income: OECD
France	High income: OECD
French Polynesia	High income: nonOECD
Gabon	Upper middle income
Gambia, The	Low income
Georgia	Low income
Germany	High income: OECD
Ghana	Low income
Greece	High income: OECD
Greenland	High income: nonOECD
Grenada	Upper middle income
Guam	High income: nonOECD
Guatemala	Lower middle income
Guinea	Low income
Guinea-Bissau	Low income
Guyana	Lower middle income
Haiti	Low income
Honduras	Lower middle income
Hong Kong, China	High income: nonOECD
Hungary	Upper middle income
Iceland	High income: OECD
India	Low income
Indonesia	Low income
Iran, Islamic Rep.	Lower middle income
Iraq	Lower middle income
Ireland	High income: OECD
Isle of Man	High income: nonOECD
Israel	High income: nonOECD
Italy	High income: OECD
Jamaica	Lower middle income
Japan	High income: OECD
Jordan	Lower middle income
Kenya	Low income
Kiribati	Lower middle income

Economy	Income group
Korea, Dem. Rep.	Low income
Korea, Rep.	High income: OECD
Kuwait	High income: nonOECD
Lao PDR	Low income
Latvia	Upper middle income
Lebanon	Upper middle income
Lesotho	Low income
Liberia	Low income
Libya	Upper middle income
Liechtenstein	High income: nonOECD
Lithuania	Upper middle income
Luxembourg	High income: OECD
Macao, China	High income: nonOECD
Macedonia, FYR	Lower middle income
Madagascar	Low income
Malawi	Low income
Malaysia	Upper middle income
Maldives	Lower middle income
Mali	Low income
Malta	High income: nonOECD
Marshall Islands	Lower middle income
Mauritania	Low income
Mauritius	Upper middle income
Mayotte	Upper middle income
Mexico	Upper middle income
Micronesia, Fed. Sts.	Lower middle income
Moldova	Low income
Monaco	High income: nonOECD
Mongolia	Low income
Morocco	Lower middle income
Mozambique	Low income
Myanmar	Low income
Namibia	Lower middle income
Nepal	Low income
Netherlands	High income: OECD
Netherlands Antilles	High income: nonOECD
New Caledonia	High income: nonOECD
New Zealand	High income: OECD
Nicaragua	Low income
Niger	Low income
Nigeria	Low income
Northern Mariana Islands	Upper middle income
Norway	High income: OECD
Oman	Upper middle income
Pakistan	Low income
Palau	Upper middle income
Panama	Upper middle income
Papua New Guinea	Low income
Paraguay	Lower middle income
Peru	Lower middle income
Philippines	Lower middle income
Poland	Upper middle income
Portugal	High income: OECD
Puerto Rico	High income: nonOECD

Economy	Income group
Qatar	High income: nonOECD
Romania	Lower middle income
Russian Federation	Lower middle income
Rwanda	Low income
Samoa	Lower middle income
San Marino	High income: nonOECD
São Tomé and Principe	Low income
Saudi Arabia	Upper middle income
Senegal	Low income
Serbia and Montenegro	Lower middle income
Seychelles	Upper middle income
Sierra Leone	Low income
Singapore	High income: nonOECD
Slovak Republic	Upper middle income
Slovenia	High income: nonOECD
Solomon Islands	Low income
Somalia	Low income
South Africa	Lower middle income
Spain	High income: OECD
Sri Lanka	Lower middle income
St. Kitts and Nevis	Upper middle income
St. Lucia	Upper middle income
St. Vincent&the Grenadines	Lower middle income
Sudan	Low income
Suriname	Lower middle income
Swaziland	Lower middle income
Sweden	High income: OECD
Switzerland	High income: OECD
Syrian Arab Republic	Lower middle income
Tajikistan	Low income
Tanzania	Low income
Thailand	Lower middle income
Timor-Leste	Low income
Togo	Low income
Tonga	Lower middle income
Trinidad and Tobago	Upper middle income
Tunisia	Lower middle income
Turkey	Lower middle income
Turkmenistan	Lower middle income
Uganda	Low income
Ukraine	Lower middle income
United Arab Emirates	High income: nonOECD
United Kingdom	High income: OECD
United States	High income: OECD
Uruguay	Upper middle income
Uzbekistan	Low income
Vanuatu	Lower middle income
Venezuela, RB	Upper middle income
Vietnam	Low income
Virgin Islands (U.S.)	High income: nonOECD
West Bank and Gaza	Lower middle income
Yemen, Rep.	Low income
Zambia	Low income
Zimbabwe	Low income

APPENDIX B: Data

Variables, Definitions and Sources

A. Total Factor Productivity Estimates

Output. Output is the sum of the value of domestic sales, exports and net inventory accumulation, deflated by PPI.

Labor. Labor is the total number of workers. Skilled labor is the number of non-production workers. Unskilled labor is the number of production workers, including apprentices.

Capital. I construct the measure of capital stock according to the perpetual inventory method for each reported type of capital: buildings and structures, machinery and equipment, transportation equipment, and office equipment. Following other authors, I assume the following depreciation rates: 3.0% for buildings and structures, 7.7% for machinery and equipment, 11.9% for transportation equipment, and 9.9% for office equipment.

Intermediate Inputs. Raw materials, electric energy, fuels and lubricants consumed during the year in constant 1986 prices.

B. Gravity Equation

GDP. From Penn World Tables and Andrew Rose's website.

Per Capital GDP. From Penn World Tables and Andrew Rose's website.

Economic Remoteness. Time- and country-varying indicator of partner's remoteness. Measured as percent of the world GDP within 10,000 km or as a distance to the Rest of the World GDP. Estimates provided by Ewing and Battersby 2003.

Distance. Geographic distance between Bogota (Colombia) and the capital city of a trading partner.

Phone Rates. Long distance tariff for a phone call from Colombia to a land-line in the capital city of a trading partner. From Internet sources on Colombian calling cards.

Expatriates. Number of Colombian expatriates residing in a country. Only includes those expatriates who are registered in online forums. From Investor's Information Gateway (links for expatriate families).

Percent of Catholics. Percent of catholic population in a country. From CIA World Fact Books.

Roads. An indicator variable equal to 1 if a country shares roads with Colombia.

C. Instruments for Exporting Status

Roads per square kilometer. Time- and region-varying measure provided by Maria Teresa Ramirez.

Distance to port cities. Computed based on geographic coordinates provided by TravelJournals.Net

Density of Phone Lines. Time- and region- varying measure of the phone lines in active use weighted by the region's population. Provided by *la Comisión de Regulación de Telecomunicaciones* and *el Ministerio de Comunicaciones*.

Number of airports. Number of domestic and international airports (excluding military) within a 50 miles radius. Computed based on the airports' geographic coordinates obtained from the World's Airport Directory.

Region's remoteness. Distance between the capital of the department in which a plant is located and other department capitals weighted by their population. Author's calculation.

Construction of Price Deflators

Except for the consumption of electric energy, the variables provided by the census of Colombian manufacturing plants are given in current person. I convert all nominal variables into 1986 constant pesos.

I obtain implicit three digit sector output price index by dividing the reported values of nominal and real production. To deflate the consumption of fuels and lubricants, I create a deflator by averaging the plant-level price indices across the petroleum refineries sector. For the deflators of different types of capital goods, I average the plant-level PPI over corresponding industry (machinery and equipment, electronic machinery and equipment, transportation equipment) or over the entire sample (for buildings and structures).

Data Cleaning and Correction for Outliers

First I identified and eliminated the plants that switched industries during the sample period. Secondly, I identified the earliest and the latest year of observation for each plant and used interpolation to fill in gaps of one year. If more than one year of data were missing, I dropped the plant from the sample.

To identify outliers, I computed log differences between inputs into production (skilled and unskilled labor, intermediate inputs, and capital) and output. For each of the log differences, I computed quartiles and inter-quartile range by industry and year. I replaced the observations for which one of the log differences exceeded the third quartile by 2.5 times the inter-quartile range or was smaller than the first quartile by 2.5 times the inter-quartile range with missing values. I used interpolation to fill in gaps of one year, if they were not at the beginning or at the end of the reporting period.

APPENDIX C: Total Factor Productivity Estimates

Total factor productivity is measured as the difference between actual and predicted output and can be recovered from an estimated production function as follows. I start with a Cobb-Douglas production function of the following form:

$$Y_{it} = A_{it} L_{it}^{\beta_L} K_{it}^{\beta_K} \tag{1}$$

Above, A_{it} is total factor productivity and L_{it} and K_{it} are labor and capital. In the logarithmic form, this production function becomes

$$y_{it} = a_{it} + \beta_L l_{it} + \beta_K k_{it} \tag{2}$$

Equation (2) has been traditionally estimated by OLS:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \varepsilon_{it} \tag{3}$$

Productivity can then be derived as

$$A_{it} = \exp(y_{it} - b_L l_{it} - b_K k_{it}) \tag{4}$$

However, lately researchers question the validity of this approach as it results in biased coefficients on the inputs of production. This problem arises because productivity, although unobserved by the researcher, is known to the plant manager and affects the input decisions that he makes. For example, when faced with a positive productivity shock, a profit-maximizing plant will respond by expanding output, which requires additional inputs. In other words, productivity ε_{it} consists of two components: a truly random component ν_{it} and a known (or anticipated) by the plant manager component ω_{it}:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \omega_{it} + \nu_{it} \quad (5)$$

While component ω_{it} is unobservable for the econometrician, it can be approximated. I follow Levinsohn and Petrin (2003) who propose to use intermediate inputs (in particular, energy, as it cannot be stored from period to period) to derive a proxy for ω_{it}.

Demand for energy is a function of the anticipated productivity shock ω_{it} and of capital k_{it}, which is treated as a state variable and does not respond to contemporaneous noise: $e_{it}=e(\omega_{it}, k_{it})$. Imposing the assumption that conditional on capital, the demand for energy increases with productivity, I can invert $e(\omega_{it}, k_{it})$ and represent ω_{it} as a function of e_{it} and k_{it}: $\omega_{it}=\omega(e_{it}, k_{it})$. Substituting this expression for ω_{it} in equation (4), I get

$$y_{it} = \beta_L l_{it} + \beta_E e_{it} + \beta_K k_{it} + \omega(e_{it}, k_{it}) + \nu_{it} \quad (6)$$

The inverse of the energy demand function, $\omega(e_{it}, k_{it})$, depends only on observable variables, however its functional form is not known. So, nonparametric methods are used to estimate it (see Petrin et al. 2004 for details).

In this paper I use the version of the Levinsohn-Petrin procedure in which labor is separated into skilled and unskilled:

$$y_{it} = \beta_S s_{it} + \beta_U u_{it} + \beta_E e_{it} + \beta_K k_{it} + \omega(e_{it}, k_{it}) + \nu_{it} \tag{7}$$

I also slightly modify the definition of intermediate inputs. I supplement electricity and fuels, the intermediate inputs suggested by Levinsohn and Petrin, by raw materials. This adjustment is strictly data driven: not all plants report use of energy. However, data on raw materials are available for almost all plants and, fortunately, offer information not only on the purchase of materials, but also on their use. Therefore, I am not very concerned that raw materials may reflect storage and may not be very responsive to productivity shocks.

Having obtained consistent coefficients on the production inputs, I construct the measure of total factor productivity as

$$A_{it} = \exp(y_{it} - b_S s_{it} - b_U u - b_E e_{it} - b_K k_{it}).$$