OXFORD JOURNALS
OXFORD UNIVERSITY PRESS

Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco

Author(s): Sofronis K. Clerides, Saul Lach and James R. Tybout

Source: *The Quarterly Journal of Economics*, Aug., 1998, Vol. 113, No. 3 (Aug., 1998), pp. 903-947

Published by: Oxford University Press

Stable URL: https://www.jstor.org/stable/2586877

JSTOR is a not-for-profit service that helps scholars, researchers, and students discover, use, and build upon a wide range of content in a trusted digital archive. We use information technology and tools to increase productivity and facilitate new forms of scholarship. For more information about JSTOR, please contact support@jstor.org.

Your use of the JSTOR archive indicates your acceptance of the Terms & Conditions of Use, available at https://about.jstor.org/terms

Oxford University Press is collaborating with JSTOR to digitize, preserve and extend access to *The Quarterly Journal of Economics*

JSTOR

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

IS LEARNING BY EXPORTING IMPORTANT? MICRO-DYNAMIC EVIDENCE FROM COLOMBIA, MEXICO, AND MOROCCO*

SOFRONIS K. CLERIDES
SAUL LACH
JAMES R. TYBOUT

Do firms become more efficient after becoming exporters? Do exporters generate positive externalities for domestically oriented producers? In this paper we tackle these questions by analyzing the causal links between exporting and productivity using plant-level data. We look for evidence that firms' cost processes change after they break into foreign markets. We find that relatively efficient firms become exporters; however, in most industries, firms' costs are not affected by previous exporting activities. So the well-documented positive association between exporting and efficiency is explained by the self-selection of the more efficient firms into the export market. We also find some evidence of positive regional externalities.

I. INTRODUCTION

Many analysts believe that export-led development strategies improve technical efficiency. And one oft-cited reason is that exporters may benefit from the technical expertise of their buyers:[1]

> Participating in export markets brings firms into contact with international best practice and fosters learning and productivity growth [World Bank 1997].
>
> . . . 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

* We thank Eli Berman, Andrew Bernard, Donald Keesing, Lawrence Katz, Wolfgang Keller, Yair Mundlak, Dani Rodrik, and an anonymous referee for their comments, as well as seminar participants at Johns Hopkins University, the University of California at Los Angeles, the University of Maryland, the World Bank, Michigan State University, and the NBER Summer Institute (International Trade and Investment session). We are also grateful to Manuel Arellano and Steven Bond for the use of their Dynamic Panel Data program. This paper was funded by the World Bank research project "Micro-Foundations of Successful Export Promotion," RPO 679-20 and the World Bank's International Trade Division, International Economics Department. This paper was written while Clerides was a Summer Intern at the World Bank, Lach was visiting the Industrial Output Section of the Federal Reserve Board, and Tybout was visiting the International Trade Division in the International Economics Department of the World Bank. The views expressed herein are those of the authors, and do not necessarily reflect those of the World Bank or the Federal Reserve System.

1. For a recent catalog of additional reasons, see World Bank [1993, pp. 316–324].

© 1998 by the President and Fellows of Harvard College and the Massachusetts Institute of Technology.

The Quarterly Journal of Economics, August 1998

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

> their sourcing activities. Some part of the efficiency of export-led development must therefore be attributed to externalities derived from exporting [Evenson and Westphal 1995].
>
> Buyers want low-cost, better-quality products from major suppliers. To obtain this, they transmit tacit and occasionally proprietary knowledge from their other, often OECD-economy, suppliers [World Bank 1993, p. 320].
>
> 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, Ross-Larson, and Pursell 1984, p. 41].
>
> When local goods are exported the foreign purchasing agents may suggest ways to improve the manufacturing process [Grossman and Helpman 1991, p. 166].

In support of this view, empirical studies often find that exporting plants are more efficient than their domestically oriented counterparts [Aw and Hwang 1995; Bernard and Jensen 1995; Chen and Tang 1987; Haddad 1993; Handoussa, Nishimizu, and Page 1986; Tybout and Westbrook 1995; Roberts, Sullivan, and Tybout 1995]. But, with the exception of Bernard and Jensen, none of these studies has asked the question of whether exporting *causes* efficiency gains. Plausible arguments can be made for causality to flow in the opposite direction: relatively more efficient plants self-select into export markets because the returns to doing so are relatively high for them.

In this paper we attempt to sort out the direction of causality, and in so doing, determine whether there is any evidence that firms learn to be more efficient by becoming exporters. Further, to assess the case for active export promotion, we test whether exporters generate external benefits to other firms, either by acting as a conduit for knowledge that they acquire through trade, or by causing improvements in international transport and export support services.[2]

Our methodology for detecting learning effects is based on a simple idea. If exporting indeed generates efficiency gains, then firms that begin to export should thereafter exhibit a change in

2. Many believe that these spillover effects are significant in developing countries. For example, Aitken, Hanson, and Harrison [1997] write that ". . . the development of garment exporters in Bangladesh, suggests that informational externalities are likely to be extremely important. The entry of one Korean garment exporter in Bangladesh led to the establishment of hundreds of exporting enterprises, all owned by local entrepreneurs. . . . Spillovers may take a variety of forms. The geographic concentration of exporters may make it feasible to construct specialized transportation infrastructure, such as storage facilities or rail lines, or may improve access to information about which goods are popular among foreign consumers."

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

the stochastic process that governs their productivity growth. Hence their productivity trajectories must improve in some sense after they enter foreign markets. Similarly, if the presence of exporters generates positive externalities, nonexporters in the affected industry or region should exhibit changes in their cost process when the number of exporters changes. Increases in the number of exporters may also make it easier for others to break into foreign markets.

To keep track of causal linkages, we begin by specifying the general optimization problem that we envision firms as solving (Section II). Each manager faces stochastic cost and foreign demand processes, and chooses which periods to participate in foreign markets. Their decisions are complicated by the presence of sunk start-up costs when they first sell abroad, since managers must research foreign demand and competition, establish marketing channels, and adjust their product characteristics and packaging to meet foreign tastes. The basic features of this model are taken directly from the hysteresis literature developed by Baldwin [1989], Dixit [1989], and Krugman [1989]. Our twist is to add the possibility of learning-by-doing or, more precisely, learning-by-exporting, and examine how this affects the productivity trajectories of exporters and plants that switch markets, relative to those of nonexporters.

Because the framework we develop does not lend itself to closed-form solutions, we discuss its implications heuristically and using simulations. Under certain assumptions on the exogenous shocks to productivity and demand, the simulations suggest that (a) nonexporters experiencing positive productivity shocks self-select into foreign markets, (b) exporters experiencing negative productivity shocks quit foreign markets, and (c) the presence of learning-by-exporting effects implies that firms improve their relative productivity after they begin exporting.

With these results in hand, we examine the actual performance of Colombian, Mexican, and Moroccan producers (Section III). To familiarize ourselves with the data, we begin by comparing the productivity trajectories of producers that enter export markets with those of nonexporters, ongoing exporters, and firms that exit foreign markets (productivity is proxied by average variable cost and by labor productivity). This exercise reveals patterns that our simulations suggest we should find in the *absence* of learning-by-exporting effects. That is, the plants that become exporters typically have high productivity before they enter foreign mar-

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

kets, and their relative efficiency does not systematically increase after foreign sales are initiated. In some instances the relatively strong performance of exporters traces to high labor productivity; in other instances it is due to relatively heavier reliance on skilled labor.

This first look at the actual trajectories casts doubt on the importance of learning-by-exporting. But it does not constitute a formal test of whether becoming an exporter changes a firm's productivity trajectory. Accordingly, in Section IV we estimate econometrically a reduced-form version of the theoretical model that takes explicit account of the two alternative, but not incompatible, explanations for the positive association between export-participation status and productivity: self-selection of the relatively more efficient plants, and learning-by-exporting. For the countries with sufficient data to support inference—Colombia and Morocco—we find that export market participation generally depends upon past participation and (weakly) upon past average variable cost (*AVC*), as implied by the model. However, conditioning on capital stock and past *AVC* realizations, current *AVC* does *not* typically depend negatively upon previous export market participation, as implied by the learning-by-exporting hypothesis. Thus, with a few possible exceptions, the conclusion suggested by our descriptive analysis is borne out by formal Granger causality tests.[3] Finally, extending our model in order to look for externalities, we find some support for the hypothesis that a firm is more likely to export if it belongs to an export-intensive industry or region, and that Colombian firms in export-oriented regions enjoy relatively lower production costs, regardless of their own market orientation.

3. These conclusions are also consistent with Bernard and Jensen's [1995] findings using data on U. S. manufacturing plants and firms during 1984–1992. Both papers address the same basic question: does exporting cause increases in productivity, or do increases in productivity increase the probability of export participation? Besides differences in the data, and in that Bernard and Jensen's paper also looks at other measures of performance, the two papers differ in the methodology of the analysis. In our paper we build an econometric model that is tightly linked to a theoretical model. The econometric model both is dynamic and accounts for unobserved (and observed) sources of heterogeneity across firms. This approach has the advantage that regression results can be interpreted within the context of the model, and that it enables us to deal with the endogeneity of the key variables in the analysis, i.e., export participation and the measure of productivity, in order to obtain consistent estimates of their effects. The disadvantage is the computational complexity of the estimation procedure. Despite these differences, it is comforting that the empirical findings in both papers are virtually the same.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

II. A Model of Export Participation with Learning Effects

Our first task is to present a model that specifies endogenous and exogenous sources of variation in the two producer characteristics we are interested in: exporting status and production costs. This model, which will guide us in our empirical analysis, is a simple modification of existing models to accommodate potential learning effects from export participation [Baldwin 1989; Dixit 1989; Krugman 1989].

We begin by assuming monopolistic competition, so that each firm faces a downward sloping demand curve in the foreign market, yet views itself as too small to strategically influence the behavior of other producers. Specifically, we write foreign demand q^f for the firm's product at price p' as $q^f = z^f \cdot (p^f)^{-\sigma^f}$, where the random variable z^f captures the usual demand shifters (foreign income level, exchange rates, and other goods' prices) and $\sigma^f > 1$.[4] Firms face similar demand conditions in the domestic market, $q^h = z^h \cdot (p^h)^{-\sigma^h}$, and can price discriminate between foreign and domestic buyers.

Assuming that marginal costs (c) do not depend upon output, the current period gross operating profits can be expressed as a function of marginal costs and demand conditions in both markets:

$$
\begin{aligned}
(1) \qquad \pi(c,\boldsymbol{z}) &= c^{1-\sigma^f} z^f (\sigma^f - 1)^{\sigma^f - 1} (\sigma^f)^{-\sigma^f} \\
&\quad + c^{1-\sigma^h} z^h (\sigma^h - 1)^{\alpha^h - 1} (\sigma^h)^{-\alpha^h} \\
&= \pi^f(c,z^f) + \pi^h(c,z^h),
\end{aligned}
$$

where $\boldsymbol{z} = (z^f, z^h)$. The profits from exporting are the shaded area depicted in Figure I, where $(1 - (1/\sigma^f)) \cdot p^f$ and $(1 - (1/\sigma^h)) \cdot p^h$ are foreign and home market marginal revenue, respectively.[5] We represent the home demand curve as approaching the vertical axis above the foreign demand curve because transport costs and trade barriers eat up a fraction of each unit of revenue generated in foreign markets.

Let the per-period, fixed costs of being an exporter (e.g., dealing with customs and intermediaries) be M. Then, the plant will earn positive *net* operating profits from exporting whenever

4. This particular functional form for the demand function is generated by the Dixit-Stiglitz utility function over varieties.

5. We have linearized the demand and marginal revenue curves to simplify this figure.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

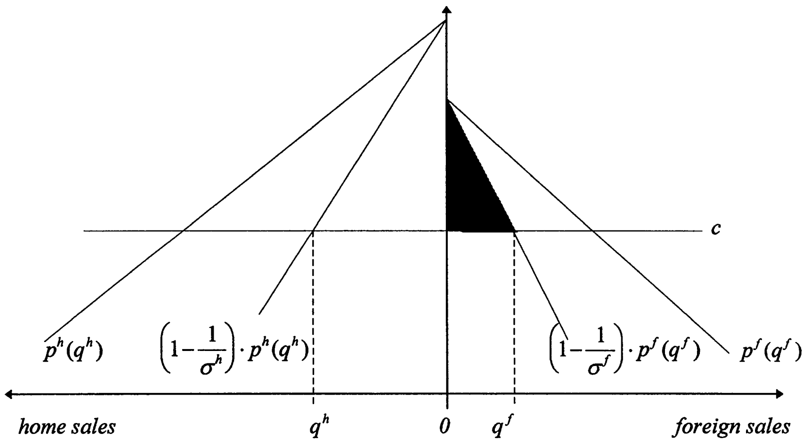

FIGURE I
Gross Operating Profits from Exporting

$\pi^f(c,z^f) > M$. Accordingly, if there were no start-up costs associated with becoming an exporter and no learning effects, producers would simply participate in foreign markets—choosing the profit-maximizing level of exports—whenever this condition was satisfied. As Figure I demonstrates, given demand conditions, all firms with marginal costs below some threshold would self-select into export activities.

But as Baldwin [1989], Dixit [1989], and Krugman [1989] have stressed, sunk start-up costs modify the problem in a nontrivial way. Suppose that an entry cost of F dollars is incurred every time the plant decides to enter or reenter foreign markets. Then, once exporting, it may be optimal to keep exporting even if $\pi^f(c,z^f)$ is currently less than M since, by remaining in the export market, the plant avoids future reentry costs. So, if sunk costs are important—and microevidence suggests that they are (e.g., Roberts and Tybout [1997])—producers face a dynamic optimization problem where, in each period, they must choose whether or not to export on the basis of currently available information. This makes decision-making forward-looking and opens the possibility that firms export today in anticipation of cost reductions, or foreign demand increases, later on.

Because expectations are important in this context, we must be specific about the processes that generate the state variables c and z. On the demand side, we assume that z is exogenous to the

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

plant and follows some serially correlated, plant-specific process (for simplicity, the plant-subscript is omitted until Section IV):

$$z_t^f = f(\boldsymbol{x}_t, \boldsymbol{z}_{t-1}^f). \tag{2}$$

Here x_t is a vector of exogenous variables that shift the demand processes, e.g., the exchange rate and plant-specific noise, and $\boldsymbol{z}_{t-1}^f = (z_{t-1}^f, z_{t-2}^f, z_{t-3}^f, \ldots)$ denotes the vector of previous realizations of z up to and including period $t-1$.

Marginal cost also follows a plant-specific serially correlated process. In addition, it is potentially affected by the firm's exporting decisions if there are learning effects:

$$c_t = g(\boldsymbol{w}_t, \boldsymbol{c}_{t-1}, \boldsymbol{y}_{t-1}), \tag{3}$$

where $\boldsymbol{w}_t$ is a vector of exogenous cost shifters, e.g., factor prices and plant-specific noise, $\boldsymbol{c}_{t-1}$ denotes the vector of previous realizations of c up to and including period $t-1$, and $\boldsymbol{y}_{t-1}$ denotes the history of the binary variable y_t which, in turn, indicates whether the plant was exporting j periods ago ($y_{t-j} = 1$) or was not ($y_{t-j} = 0$).

Note that equation (3) implies learning-by-exporting depends only on a firm's previous *participation* in foreign markets, and not on the cumulative volume of its exports. This keeps the simulations in this section tractable. However, in Section IV we will econometrically test alternative specifications in which the history of exporting *volumes* enters the cost function. In addition, we will add variables that measure the amount of exporting activity in firms' industry or geographic region in order to test for spillover effects.

A test for learning-by-exporting effects using equation (3) must recognize that $\boldsymbol{y}_{t-1}$ is a vector of endogenous variables depending upon the same observed and unobserved factors that affect the cost and the demand processes. Thus, we need to model the process by which firms self-select into export markets if we are to sort out the relationship between c and y. Following the hysteresis literature, we assume that managers take equations (1) through (3) into consideration, and plan their export market participation to satisfy

$$V_t = \max_{\{y_{t+r}\}_{r=0}^{\infty}} E_t \sum_{\tau=0}^{\infty} \delta^\tau [y_{t+\tau}(\pi^f(c_{t+\tau}, z_{t+\tau}^f) - M - (1 - y_{t+\tau-1})F) + \pi^h(c_{t+\tau}, z_{t+\tau}^h)], \tag{5}$$

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

where E_t is an expectations operator conditioned on the set of information available at time t, and δ is the one-period discount rate.[6] Domestic profits enter this expression only because, with learning, participation affects the future cost trajectory. We assume that firms never wish to liquidate.

Equivalently, managers can be viewed as choosing the current y_t value that satisfies Bellman's equation:

$$V_t = \max_{y_t} [y_t(\pi^f(c_t,z_t^f) - M - (1 - y_{t-1})F) + \pi^h(c_t,z_t^h) + \delta E_t(V_{t+1}|y_t)].$$

This characterization of behavior implies that producers participate in export markets whenever

$$\text{(6)} \quad \pi^f(c_t,z_t^f) - M + \delta[E_t(V_{t+1}|y_t = 1) - E_t(V_{t+1}|y_t = 0)] \geq F(1 - y_{t-1}).$$

That is, incumbent exporters continue exporting whenever current net operating profits from exports plus the expected discounted future payoff from remaining an exporter is positive, and nonexporters begin exporting whenever this sum, net of start-up costs, is positive. Expected future payoffs include the value of avoiding start-up costs next period *and* any positive learning effects that accrue from foreign market experience. Without learning effects, expression (6) has appeared in various forms in the hysteresis literature; it will prove useful in Section IV.

If we allow for much generality in the cost process (3), or we allow start-up costs to depend upon exporting experience more than one period ago, it is very difficult to characterize optimal behavior in this framework. However, some insights can be gained by assuming that c follows a discrete, first-order Markov process that depends only on y_{t-1}.[7] Learning-by-exporting can then be captured by changes in the transition matrix governing the evolution of c over time. Specifically, let $\boldsymbol{P}_0$ be the transition matrix for c when the firm is not exporting, and let some stochastically better matrix, say $\boldsymbol{P}_1$, be the transition matrix when

6. This formulation implies that producers who exit the export market and reenter face the same start-up costs as producers who never exported. In our econometric rendering of the decision to export in Section IV, we will allow start-up costs to depend upon previous exporting experience.

7. Demand shifters can be held constant since their effect on profits is qualitatively the same as that of c.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

the firm is exporting. That is, when $\boldsymbol{P}_1$ governs c realizations, the probability of a decrease in c is greater than when $\boldsymbol{P}_0$ governs c. In the no-learning case $\boldsymbol{P}_0$ is assigned to all firms.

In this type of problem, the optimal participation policy usually involves two threshold levels defined, for our purposes, in terms of marginal cost levels $c_L < c_U$ such that a nonexporting firm will start exporting when its costs fall to c_L and an exporting firm will cease exporting when its costs rise to c_U. We will assume that this is indeed the type of policy followed by the firm. Thus, if learning effects are present, the transition matrix governing the Markov process c changes at c_L from $\boldsymbol{P}_0$ to $\boldsymbol{P}_1$, and returns to $\boldsymbol{P}_0$ when c reaches c_U.

Simulations of cost trajectories based on this relatively restrictive framework and arbitrary parameter values are presented in Figure II (details are provided in Appendix 1 of the working paper version; see Clerides, Lach, and Tybout [1996]). The trajectories are averages over repeated simulations for four subgroups of firms, labeled "*nonexporters*" (those that never export), "*exporters*" (those that always export), "*entrants*" (those that begin exporting), and "*quitters*" (those that cease exporting). For all firms that begin or cease exporting, we measure time relative to the transition year (period 0). For example, period -2 is two years prior to entry for the *entrant* group, and two years prior to exit for the *quitter* group. Firms that export may or may not be subject to learning effects.

Several patterns merit note. First, and most obviously, regardless of whether learning effects are present, costs among the *exporter* firms are lower than costs among the nonexporters. This reflects the self-selection of efficient firms into export markets, as we discussed earlier in connection with Figure I.

Second, firms that become exporters exhibit cost declines before they enter the market. This occurs with and without learning effects. These firms self-select into exporting only when their unit costs fall below the entry threshold, c_L, so they must experience a period of falling costs prior to entry. Selection effects may thus create the illusion that becoming an exporter actually *retards* productivity growth. More generally, self-selection means that cross-sectional differences in the productivity growth rates of exporters versus nonexporters should not be used to quantify learning effects.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

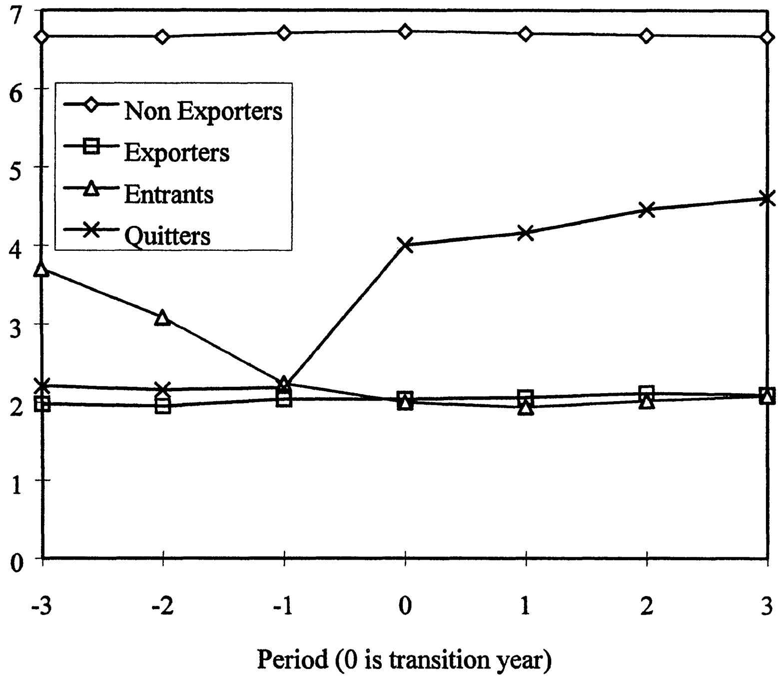

FIGURE IIa
Simulated Average Cost Trajectories without Learning

Third, regardless of whether learning effects are present, firms that eventually cease exporting exhibit cost increases before they quit the export market. This is also a reflection of the two-threshold policy followed by the firm in the presence of sunk start-up costs.

Fourth, one distinguishing feature of the learning trajectories is that exporting firms exhibit ongoing cost reductions after initiating foreign sales as a result of the switch to a better transition matrix. Only when learning effects are present, do firms continue to pull away from nonexporters after entering the foreign market.

Finally, relative to the *no-learning* case, learning allows firms to enter (and stay in) export markets with higher production costs. This occurs because the incentives to export are larger when learning occurs. Productivity dispersion may thus be *higher* among exporters when learning effects are present, and the

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

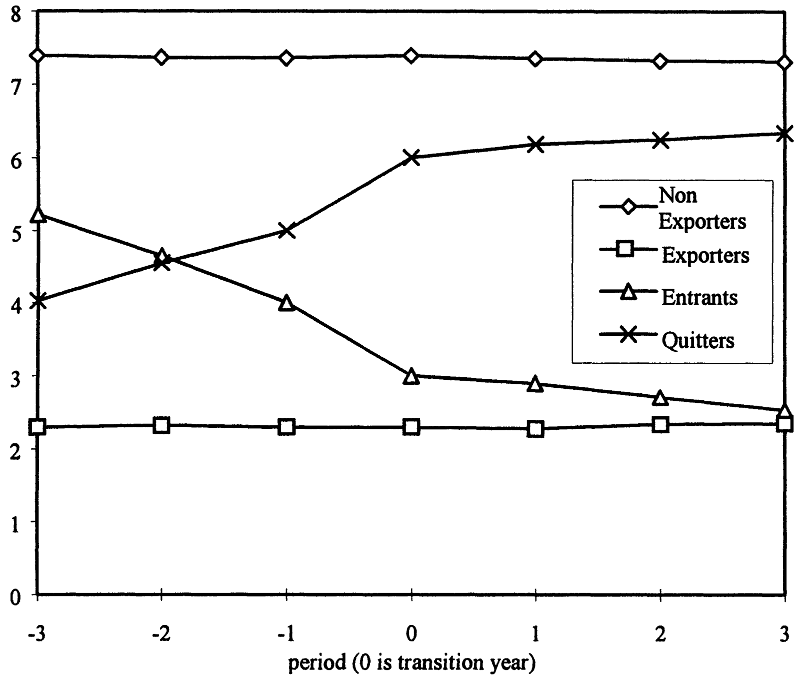

FIGURE IIb
Simulated Average Cost Trajectories with Learning

productivity gap between exporters and nonexporters may be smaller. More generally, this result suggests caution interpreting studies that use productivity dispersion as a performance measure (as in the "efficiency frontier" literature), and that relate these measures to trade orientation.[8]

Of course, these results are only suggestive, and more complicated cost processes might reverse some of the patterns. For example, if costs were to follow a second- or higher-order autoregressive process, they might continue to trend downward after export market entry even without learning effects. Or, if for $c < c_L$ expected cost increases were relatively large, then learning effects

8. For example, Caves and Barton [1991] regress dispersion-based productivity measures on measures of export intensity and find that "[p]articipation in exporting activities . . . is negatively related to technical efficiency" [p. 93]. They go on to hypothesize that "any procompetitive effects of exporting activity may be swamped by the uneven distribution of quasi-rents and apparent technical inefficiency that exporting is likely to produce" [p. 94].

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

would not necessarily imply cost reductions after entry. Learning effects imply only a change for the better in the stochastic process followed by the cost variable after the firm enters the export market. Accordingly, in order to look for learning effects and externalities, we rely on econometric estimates of a *general* form of the cost function (3), recognizing that export market participation is governed by the behavioral rule (6).

III. Learning Effects: A Look at Actual Data

Before we report the results of this exercise, however, it is instructive to visually examine cost data on actual producers from three semi-industrialized countries. Though merely suggestive, this will familiarize the reader with the basic patterns we are trying to explain, and provide an informal check for the distinguishing patterns that our simulations suggest we should find when learning effects are present.

A. The Data

Our data allow us to follow individual producers through time in Colombia, Mexico, and Morocco. In the case of Colombia they describe virtually all plants with at least ten workers over the period 1981–1991; in Mexico they describe 2800 of the larger firms over the period 1986–1990, and in Morocco they cover nearly all firms with at least ten workers over the period 1984–1991.[9] Standard information on inputs, outputs, and costs is provided in each of these databases, as well as information on export levels. To simplify estimation, we eliminate firms that do not report information for the entire sample period, creating a balanced panel.[10] The Appendix provides details on our data cleaning and deflation procedures.

9. Although some countries report plant-level data and some report firm-level data, we will hereafter use the term "plant" to describe the unit of observation. In semi-industrialized countries where the calculation is possible, we have found that 95 percent of the plants are owned by single-plant firms.

10. Excepting the Moroccan apparel and textiles industries, firms that do not report information for the entire sample period are mostly very small nonexporters. Because these firms are either new or failing, they probably have below-average performance, so their elimination from the sample probably improves the performance of nonexporters (again, Moroccan apparel and textiles are an exception). This may have biased the estimated effect of past participation on the level of costs against the finding of learning effects, but given their small market share we do not think this bias is likely to be quantitatively large.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE I
ENTRY, EXIT, NUMBER OF PLANTS, AND EXPORT INTENSITY BY COUNTRY
(EXPORT-ORIENTED INDUSTRIES)

	Average annual entry rate	Average annual exit rate	Average number of plants	Average export intensity
Colombia 1981–1991	.027	.017	1354	.095
Morocco 1984–1991	.049	.037	938	.360
Mexico 1986–1990	.048	.015	1327	.230

Finally, to sharpen the analysis, we focus only on the export-oriented industries in each country. These industries exported at least 10 percent of their output, and had at least twenty exporting plants.[11] Table I provides descriptive information on each country. Note that there are substantial transitions in the data even though most plants tend to stay in or out of the export market.

B. Comparing Productivity Trajectories

We wish to familiarize ourselves with the marginal cost trajectories of plants with different export market participation patterns, controlling for industrywide time effects, and observable plant-specific productivity determinants like capital stocks and age. We use two marginal cost proxies: average variable cost (*AVC*) and labor productivity (*LAB*). The former is defined as the sum of real labor and real intermediate input costs divided by real output, and the latter is real output divided by number of workers. Real labor and intermediate costs are reported nominal values of these variables deflated by the manufacturing-wide wholesale price index. Real output is the sum of nominal output for the domestic market and nominal output for export, each deflated by its own product-specific deflator.

To purge these productivity measures of industrywide time effects and observable plant-specific characteristics, each is expressed in logarithms and regressed on time dummies, D_{jt} (specific to year t and the jth three-digit ISIC industry), age of the plant (A), age of the plant squared, capital stock of the plant (K),

11. In a few cases, industries that exported less than 10 percent of their output were included because they had many exporting plants or accounted for a substantial share of total manufactured exports.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE II
TYPES OF FIRMS

Nonexporters:	firms that never exported during the sample period.
Exporters:	firms that always exported during the sample period.
Entrants:	firms that began the period as nonexporters, but began exporting during the sample period and never stopped.
Quitters:	firms that began the period as exporters, but ceased during the sample period and never resumed exporting.
Switchers:	firms that switched exporting status more than once during the sample period.

and capital stock of the plant squared. Both age and capital stocks are measured in logarithms:

$$\ln (AVC_{it}) = \sum_{j=1}^{J} \sum_{t=1}^{T} \gamma_{jt} D_{jt} + \beta_1 \ln (A_{it}) + \beta_2 \ln (A_{it})^2 + \beta_3 \ln (K_{it}) + \beta_4 (\ln K_{it})^2 + \epsilon_{it}^{c}$$

$$\ln (LAB_{it}) = \sum_{j=1}^{J} \sum_{t=1}^{T} \gamma_{jt}^{L} D_{jt} + \beta_1^{L} \ln (A_{it}) + \beta_2^{L} \ln (A_{it})^2 + \beta_3^{L} \ln (K_{it}) + \beta_4^{L} (\ln K_{it})^2 + \epsilon_{it}^{L}.$$

The residuals from these two regressions—denoted $\hat{\epsilon}^c$ and $\hat{\epsilon}^L$, respectively—are then used as our indices of deviation from time- and industry-specific productivity norms. Note that industry-specific time dummies control for industrywide variation in relative prices (inter alia). Also, because logarithmic variable costs are purged of correlation with capital, the residuals can be viewed as the measure of variable factor productivity that obtains from a short-run total cost function of the form, $TC_{it} = \lambda_0(K_{it}, \boldsymbol{W}_{it}) + \lambda_1(K_{it}, \boldsymbol{W}_{it})Q_{it}$, where parentheses denote functions, K_{it} is capital, and $\boldsymbol{W}_{it}$ is the vector of factor prices.

To isolate the relation between export market participation and productivity performance, we distinguish the five varieties of plants defined in Table II, and for each plant we redefine period 0 to be the year in which a change in export status takes place. Then we isolate five-year blocks of time, running from two years prior to the status change ($t = -2$) to two years after ($t = 2$).[12] For

12. The Colombian panel is long enough to allow us to go from three years prior to three years after the switch.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

nonexporters and exporters there is no change in status, so we take five years in the middle of the sample period (for Colombia we take seven years). Finally, after reindexing time in this way, we aggregate our productivity indices by plant type and compare them. Because switching firms strongly resemble exporters, we omit them from our graphs to reduce clutter.[13]

C. Basic Trajectory Patterns

Average Variable Costs: Average trajectories for average variable costs are presented by plant type in Figures IIIa through IIIc. We begin by considering Colombia and Mexico, since these countries show similar patterns. Most strikingly, plants that cease exporting get steadily worse before they drop out of foreign markets, and are substantially less efficient than the other plant types. Also, entering plants and exporting plants have the lowest variable costs, and nonexporters consistently exhibit costs slightly above average, but less than quitters. These patterns are similar to the simulations in Figure II for both the learning and nonlearning models, except in that the performance of quitting plants is somewhat worse in the actual data.

One might argue about whether the entrants show evidence of reducing their costs after beginning to export, but the effect is certainly not dramatic. The F-statistic for the null hypothesis that the mean average cost level among entrants shows *no* variation relative to the industry norms and has a p-value of 0.08 in Colombia and a p-value of 0.25 in Mexico.[14] Further, in Mexico, entrants' average costs after two years of exporting are slightly higher relative to industry norms than they were two years before.

The Moroccan graph is more complex. Most obviously, there is much less variation in trajectories here than in Colombia and Mexico. Further, what little variation there is does not conform to the patterns described above. Two years after exiting, the plants that abandon foreign markets emerge as the worst plants, but their average variable costs are highly volatile, and no higher

13. A possible explanation for the resemblance is that switching plants are always relatively efficient, but they experience relatively dramatic foreign demand shocks that drive them in and out of the export market.

14. These tests are based on generalizations of the regression model to include annual dummies by plant type. We also allow the coefficients on age, age squared, capital, and capital squared to vary across industry, and we treat the disturbance as composed of a fixed plant effect plus random noise.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

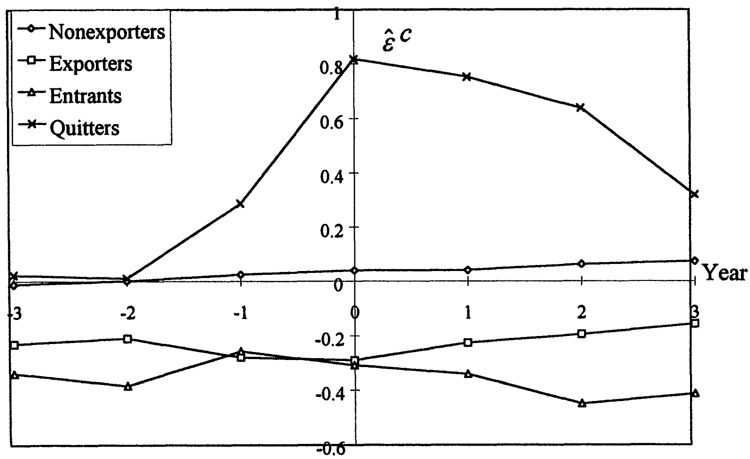

FIGURE IIIa
COLOMBIA—Path of Average Variable Cost (purged of time, age, and size effects)

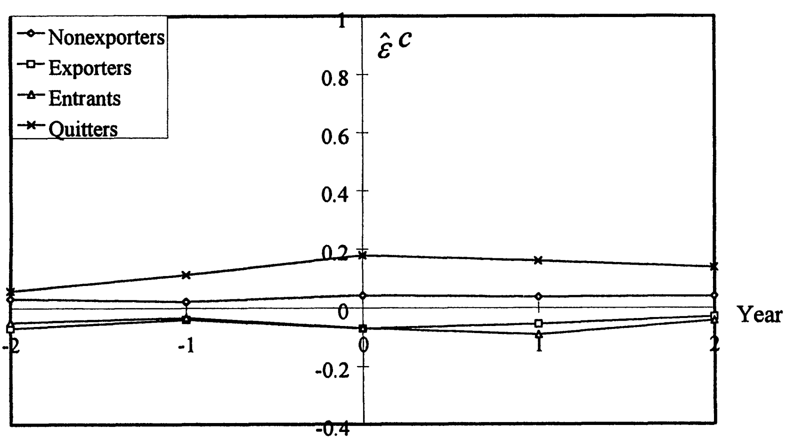

FIGURE IIIb
MEXICO—Path of Average Variable Cost (purged of time and size effects)

than the industry norm *one* year after exiting. Exporters usually do better than nonexporters, but even this is not guaranteed.

These patterns may well reflect the fact that, unlike in Mexico and Colombia, most of the impetus to become an exporter in Morocco came from firm-specific *demand* side shocks. Many

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

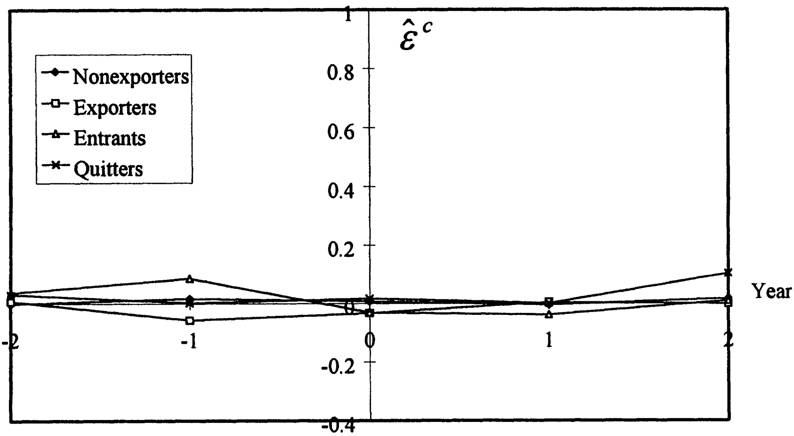

FIGURE IIIc
MOROCCO—Path of Average Variable Cost (purged of time, size, and age effects)

Moroccan exporters are young plants that were founded with the exclusive purpose of selling particular apparel and textile products abroad [Sullivan 1995; World Bank 1994; Roberts, Sullivan and Tybout 1995]. Moroccan policies during the sample period also provided various subsidies to exporters, and these may have allowed less efficient plants to compete. Once again, there is little statistical evidence that average costs among plants that begin exporting are anything but flat relative to industry norms (the p-value is 0.24).

Labor productivity: For several reasons (discussed in Section IV below), average variable costs may pick up spurious correlation between exporting status and efficiency. Hence we also examine output per worker. Like average variable costs, labor productivity is not a true measure of total factor productivity, but after it has been purged of correlation with capital stocks, it is conceptually closer.

Figure IVa presents average values of this productivity measure by plant type for Colombia. The entrants once again perform the best, and in contrast to their average cost patterns, they *do* seem to improve when they initiate foreign sales.[15] Ongoing exporters continue to show the next best performance,

15. The F-statistic for the null hypothesis that average labor productivity among these plants does not change relative to industry norms has a p-value of 0.01. Also see footnote 13.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

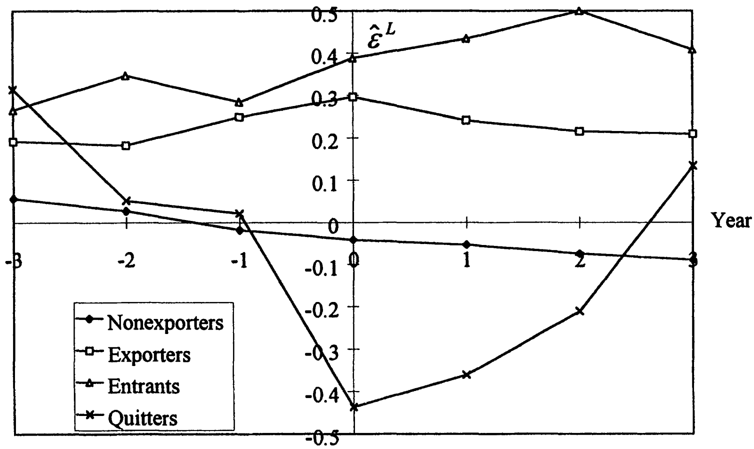

FIGURE IVa
COLOMBIA—Path of Average Labor Productivity (purged of time, age, and size effects)

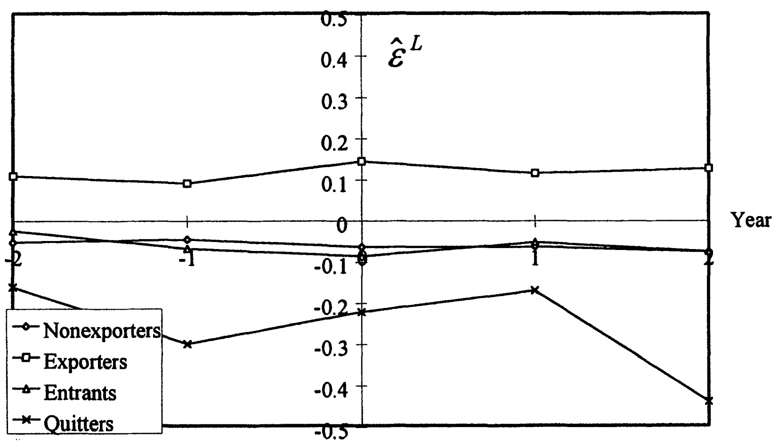

FIGURE IVb
MEXICO—Path of Average Labor Productivity (purged of time and size effects)

and quitters continue to show the worst performance, particularly around the time of their exit. So, in Colombia it appears that output per worker is one important source of variation in average variable costs, and we have the first bit of evidence that exporting might improve performance.

Quitters and ongoing exporters in Mexico follow the Colombian pattern. But Mexican entrants do not. Their average labor

This content downloaded from 59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

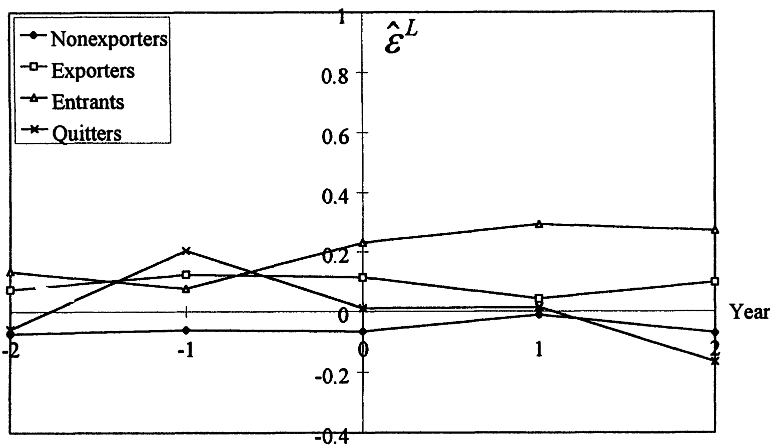

FIGURE IVc
MOROCCO—Path of Average Labor Productivity (purged of time, size, and age effects)

productivity is very stable relative to industry norms (p-value = 0.61), and a bit below average (Figure IVb). So there is no suggestion of a learning effect from exporting in this country, nor, for that matter, does it appear that cross-plant exporting patterns can be traced to differences in labor productivity.

Finally, in terms of labor productivity, Moroccan patterns appear to resemble Colombia's (Figure IVc). Entrants' productivity jumps in the year that they begin exporting (although the p-value is 0.41), and ongoing exporters exhibit higher labor productivity than either nonexporters or quitters.[16] Interestingly, there is much more variation across plant types in our Moroccan labor productivity series than we found in our average cost series, suggesting that labor costs covary negatively with intermediate goods costs in this country.

One fundamental source of variation in labor productivity is the associated variation in the skill mix of employees. To see whether differences in skill mixes are behind the labor productivity differences, we analyzed the ratio of skilled to total labor in Colombia and Mexico.[17] The results for Colombia indicate that

16. The one exception is that labor productivity is high for exiting plants during their last year in foreign markets.
17. Graphs of this variable are not reported to conserve space. See Clerides, Lach, and Tybout [1996] for the figures tracing the path of labor quality for the different varieties of plants. No results are presented for Morocco because of lack of appropriate data.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

entrants have high labor productivity partly because they use skilled labor relatively intensively, and quitters have low productivity because they use little skilled labor. There is also some evidence that relative skill-intensity increases over time for the Colombian entrants (the p-value is 0.09). The high labor productivity of *ongoing* exporters does not, however, appear to come from unusually high skill intensity. One interpretation is that breaking into foreign markets requires new product design and other forms of technical assistance, but established export production can be routinized.

In Mexico, skill intensity trajectories match labor productivity trajectories for ongoing exporting plants (which are skill-intensive) and exiting plants (which are not). However, although Mexican entrants resemble Colombian entrants in terms of skill intensity, this is not sufficient to get them high labor productivity.

In sum, our performance measures indicate that entrants generally do better than nonexporters and exiting plants. They have higher labor productivity, and this appears to be partly due to their heavier reliance on skilled labor. Also, despite their high quality workers, new exporters have relatively low average variable costs. On the other hand, we find little to suggest that productivity gains follow entry into foreign markets. Labor productivity and skill intensity appear to improve for Colombian plants that begin exporting, but this phenomenon did not show up in the other countries.[18]

IV. An Econometric Test of Learning Effects

The figures we report in the previous section are revealing, but they do not constitute a direct test for whether past export market participation influences current costs; the F-statistics we calculated merely indicate whether cost trajectories for entering

18. The results discussed thus far are based on unweighted averages of our variable cost measures. But small plants are much more common than large plants so the figures do not necessarily describe sectorwide performance. To determine whether aggregate performances looked similar, we redid the calculations, weighting each plant's average cost by its share in the total output among those of its type. We also redid the plant-specific average cost measures themselves, leaving capital stocks and age out of the regression, because we did not want them to be purged of correlation with size for this exercise. Overall, the pattern looks very similar to the unweighted ones, although with some exceptions. It remains true, however, that entrants exhibit relatively low average costs, both before and after the transition year, and that there is no obvious tendency for costs to fall after exporting operations are initiated. Complete results, including figures, are reported in the working paper version [Clerides, Lach, and Tybout, 1996].

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

firms deviate significantly from industry norms. Hence in this section we develop an alternative approach to test for the presence of learning-by-exporting effects in the data. Specifically, we estimate equation (3) and test whether exporting history, $\boldsymbol{y}_{it-1}$, enters significantly in the cost equation. In other words, we perform a type of Granger causality test.

We obtain estimates of (3) in two alternative ways. First, we fit (3) jointly with a reduced-form version of (6) using full information maximum likelihood (*FIML*). This approach allows us to characterize the self-selection process, and to explore the relation between the error terms in the two equations. However, the participation equation (6) is nonlinear, dynamic, and has serially correlated errors, so *FIML* estimation is relatively complex, and the cost function (3) must be kept fairly simple. Thus, as a robustness check, we also fit generalized versions of equation (3) using a generalized method of moments (*GMM*) estimator to deal with endogeneity and serial correlation.[19]

A. The Econometric Model

For *FIML* estimation we must develop an estimable version of the participation equation (6). Our approach follows Roberts and Tybout [1997]. First, we generalize (6) so that firms that exit and reenter the export market pay different start-up costs than firms that never exported. Specifically, define F^0 as the start-up cost for a nonexporter with no previous experience, and F^j as the start-up cost faced by a firm that last exported $j-1$ years ago (note that $F^1 = 0$). Then this generalization of equation (6) implies that the ith firm will export in year t (i.e., will choose $y_{it} = 1$) whenever

$$(7)\quad \pi^f(c_{it}, z_{it}^f) - M + \delta[E_t(V_{it+1}|y_{it} = 1) - E_t(V_{it+1}|y_{it} = 0)] \geq F^0 - \sum_{j=1}^{J} (F^0 - F^j)\tilde{y}_{it-j},$$

where $\tilde{y}_{it-j}$ is one if the firm last exported in year $t-j$ and zero otherwise.[20] Next, we define the latent variable y_{it}^* as current net

19. If we allow for much generality in the average variable cost process, it becomes very difficult to estimate all of the structural parameters of the model. Yet imposing restrictions on these processes may lead us to incorrectly conclude that past participation influences current costs. For example, misspecifying the cost function to be a first-order process may force any dependence of current costs on additional lags (e.g., c_{t-2} or c_{t-3}) to induce correlation with y_{t-1}, given that export market participation decisions are based partly on lagged costs.

20. Note that $\tilde{y}_{it-1} = y_{it-1}$, and for $j > 1$, $\tilde{y}_{it-j} = y_{it-j}\,\Pi_{k=1}^{j-1}(1 - y_{it-k})$.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

operating profits plus the expected future return from being an exporter in year t:

$$y_{it}^{*} = \pi^{f}(c_{it}, z_{it}^{f}) - M + \delta[E_t(V_{it+1} | y_{it} = 1) - E_t(V_{it+1} | y_{it} = 0)].$$

Equation (7) then implies that y_{it} obeys the following dynamic discrete process:

$$(8) \qquad y_{it} = \begin{cases} 1 & \text{if } y_{it}^{*} \geq F^{0} - \sum_{j=1}^{J} (F^{0} - F^{j})\tilde{y}_{it-j} \\ 0 & \text{otherwise.} \end{cases}$$

Finally, we express the latent variable $y_{it}^{*} - F^{0}$ as a reduced form in demand shifters, marginal costs, and the variables that help predict future marginal costs and demand in each market.[21] Operationally, this means including exogenous plant characteristics ($\boldsymbol{X}_{it}$), the exchange rate (e_t), a distributed lag in our marginal cost proxy, AVC_{it}, and a serially correlated disturbance:

$$(9) \qquad y_{it}^{*} - F^{0} = \boldsymbol{\beta}^{x}\boldsymbol{X}_{it} + \beta^{e}e_{t} + \sum_{j=1}^{J} \beta_{j}^{c} \ln(AVC_{it-j}) + \eta_{it}.$$

Then substituting (9) into (8), we obtain a representation of export market participation decisions that can be estimated:

$$(10) \qquad y_{it} = \begin{cases} 1 & \text{if } 0 \leq \boldsymbol{\beta}^{x}\boldsymbol{X}_{it} + \beta^{e}e_{t} + \sum_{j=1}^{J} \beta_{j}^{c} \ln(AVC_{it-j}) \\ & \qquad + \sum_{j=1}^{J} (F^{0} - F^{j})\tilde{y}_{it-j} + \eta_{it} \\ 0 & \text{otherwise.} \end{cases}$$

Notice that the estimated coefficients on our lagged participation variables measure the discount on entry costs that plants with exporting experience in previous years enjoy, relative to plants with no exporting experience. Further discussion may be found in Roberts and Tybout [1997].

As noted in Section II, if firms learn by exporting, the stochastic process that generates costs also depends upon the history of y_{it} values. Accordingly, a general log-linearized specification of the marginal cost function (3) includes not only capital

21. This reduced-form approach is also used in Sullivan [1995] and Roberts, Sullivan, and Tybout [1995].

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

stocks and lagged average variable costs, but lagged y_{it} values as well:

$$(11) \quad \ln (AVC_{it}) = \gamma_0 + \sum_{j=1}^{J_K} \gamma_j^k \ln (K_{it-j}) + \gamma^e \ln (e_t) + \sum_{j=1}^{J_C} \gamma_j^c \ln (AVC_{it-j}) + \sum_{j=1}^{J_Y} \gamma_j^y y_{it-j} + v_{it}.$$

Here the real exchange rate (e) controls for changes in relative prices that are common to all plants, the distributed lags in K, AVC and y_{it} capture systematic plant-specific deviations from these industrywide patterns, and v_{it} represents unobserved idiosyncratic shocks.

Together, equations (10) and (11) describe export market participation patterns and marginal cost realizations (learning externalities will be added to these equations later). Estimated as a system, industry by industry, they should reveal whether marginal costs influence the export participation decision as the model implies, and whether firms typically experience cost reductions once they have begun to service foreign markets, as posited by the learning-by-exporting hypothesis. Tests on the cost coefficients in the participation equation indicate whether firms respond to cost reductions by becoming more likely to export, and tests on the y_{it-j} coefficients in the cost function indicate whether exporting experience leads to lower costs. It is, of course, the latter direction of casuality that is of primary interest to us.

Serial correlation is likely in both equations because persistent unobserved plant characteristics and demand conditions make some firms consistently low cost or consistently prone to exporting, conditioning on observable variables. Hence, we model the disturbances as composed of unobserved (random) plant effects, α_1 and α_2, plus transitory noise: $\eta_{it} = \alpha_{1i} + \epsilon_{1it}$ and $v_{it} = \alpha_{2i} + \epsilon_{2it}$. We allow the plant effects and the transitory noise to be correlated across equations. Also, without loss of generality, we impose the normalization var $(\eta_{it}) = 1$ so that all coefficients in equation (10) are measured relative to total unexplained variation.

Unfortunately, the combination of lagged dependent variables with serial correlation creates special problems in panel data. Equation (10) and equation (11) represent the processes that generates y_{it} and $\ln (AVC)_{it}$ only for the years $J + 1$ through T. But realizations on y_{i1} through y_{iJ} and on $\ln (AVC)_{i1}$ through $\ln (AVC)_{iJ}$

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

are themselves endogenous, since they are functions of the unobserved plant effects, α_1 and α_2. Treating them as orthogonal to the disturbances η_{it} and v_{it} for $t > J$ would yield inconsistent estimates.

We adopt Heckman's [1981a, 1981b] solution to this "initial conditions problem." This amounts to adding J equations to the system that represent the probability of becoming an exporter in years 1 through J as functions of α_{1i} and the other variables in equation (10) *except* the lagged participation variables. Similarly, we also add J equations representing AVC_{i1} through AVC_{iJ} as functions of α_{2i} and the other variables in equation (11) *except* the lagged cost and participation variables. The result is a variant of Keane, Moffitt, and Runkle's [1988] and Sullivan's [1997] estimator.[22] The system is estimated using full information maximum likelihood (*FIML*), integrating out the two random effects with Gaussian quadrature. Details of the likelihood function may be found in Appendix II of Clerides, Lach, and Tybout [1996].

The *FIML* approach yields estimates of the cost function (11) jointly with the participation equation (10). But the cost function—unlike the participation equation—is linear, so it can also be estimated by itself using the *GMM* estimator described by Holtz-Eakin, Newey, and Rosen [1988] and Arellano and Bond [1991]. This single-equation approach provides a robustness check in several senses. First, once we abandon our *FIML* estimator, it is feasible to let average variable costs depend upon output levels.[23] Second, we can test whether learning is related to firms' cumulative export volumes rather than simply to export participation in the recent past. Finally, if we are not trying to simultaneously identify the parameters of the participation equation (10), our cost function estimator demands less of the data in terms of length of time period and number of transitions in exporting status. So we can fit the cost equation by itself to more industries than we are able to treat with our system approach, and we can use more general specifications without overparameterizing the model.

22. Sullivan's [1995] estimator does not deal with initial conditions problems in the equation that has a continuous dependent variable; and Keane, Moffit, and Runkle's [1988] estimator does not deal with dynamics at all. Otherwise, the structure of our estimator is the same.

23. To do so in the context of maximum likelihood, we would have needed to add an additional equation representing output choices, with a disturbance that was potentially correlated with those of the cost equation and the participation equation. The resulting system would have involved trivariate integration, and it would have been highly parameterized. For these reasons, we considered it an unattractive option.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

Our generalized cost function is

$$(11') \quad \ln(AVC_{it}) = \gamma_0 + \sum_{j=1}^{J'_K} \gamma_j^k \ln(K_{it-j}) + \sum_{\tau=1}^{T} \gamma_\tau^d D_t^\tau$$
$$+ \sum_{\tau=1}^{J_Q} \gamma_\tau^q \ln(q_{t-\tau+1}^h + q_{t-\tau+1}^f) + \sum_{m=1}^{M} \gamma_m^B B_i^m$$
$$+ \gamma_1^A \ln(A_{it}) + \gamma_2^A \ln(A_{it})^2 + \sum_{j=1}^{J'_C} \gamma_j^c \ln(AVC_{it-j})$$
$$+ \sum_{j=1}^{J_Y} \gamma_j^y y_{it-j} + v'_{it}.$$

This equation is distinguished from (11) in that (a) the distributed lags on both capital stocks (K) and average variable costs are longer ($J'_K > J_K, J'_C > J_C$); (b) it controls for relative prices using annual time dummies rather than the real exchange rate; and (c) it allows average variable costs to depend upon output levels, business type (B) and age (A). We will also estimate a variant of equation (11′) in which the distributed lag in foreign market participation dummies, y_{it}, is replaced with a distributed lag in logs of export volumes, $\ln(q_{it}^f + 1)$.

B. The Evidence on Learning

Because we expect the cost function, the profit function, entry costs, and the potential for active learning to differ across industries, we fit our system of equations separately to each industry in which we have sufficient observations to support inference. We include industries that are relatively intensive in human capital (e.g., Chemicals) as well as those that are not (e.g., Apparel) in order to look for corresponding variation in active learning effects. Although the model can be fit to our Mexican panel, the time period spanned by that data set proved too short to isolate random effects from the lagged endogenous variables.[24] We

24. In Mexico we observe only five years of data, and three of these years are lost to lags on participation and average costs, leaving two in-sample years. Estimates of the model (available upon request) attribute too much explanatory power to lagged cost and export participation, and imply that var (α_1) = var $(\alpha_2) = 0$. Nonetheless, the results concerning the effect of lagged participation on cost realizations are consistent with those obtained in the other countries. The convergence of random effect Probit estimators to simple Probit estimators when T is small is discussed in Guilkey and Murphy [1993].

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE IIIa
FIML ESTIMATES OF EQUATIONS (10) AND (11)
COLOMBIA 1983–1991

	Chemicals	Textiles	Apparel
	Participation equation		
Intercept	−15.06 (5.87)*	−4.34 (1.33)*	−5.20 (1.58)*
$\ln(e_t)$	.462 (2.27)	3.93 (1.14)*	3.60 (0.94)*
$\ln(K_{it-1})$	3.73 (0.72)*	1.71 (0.34)*	2.03 (0.37)*
$\ln(A_{it})$	5.94 (3.87)	−0.12 (0.85)	0.64 (1.07)
$\ln(A_{it})^2$	−0.88 (0.58)	0.09 (0.14)	−0.01 (0.18)
B_{it}	−0.00 (0.28)	0.23 (0.15)	0.28 (0.14)*
$\ln(AVC_{it-1})$	−0.14 (0.28)	−0.18 (0.18)	−0.05 (0.11)
$\ln(AVC_{it-2})$	0.06 (0.29)	−0.16 (0.18)	−0.10 (0.13)
$\tilde{y}_{it-1}$	1.86 (0.41)*	2.04 (0.27)*	1.03 (0.25)*
$\tilde{y}_{it-2}$	0.18 (0.40)	0.25 (0.29)	−0.10 (0.25)
$\tilde{y}_{it-3}$	0.26 (0.40)	−0.57 (0.46)	−0.20 (0.25)
	Cost function		
Intercept	−0.16 (0.13)	−0.33 (0.06)*	−0.36 (0.06)*
$\ln(K_{it})$	−0.17 (0.11)	0.05 (0.04)	0.09 (0.06)
$\ln(AVC_{it-1})$	0.36 (0.05)*	0.65 (0.02)*	0.74 (0.02)*
$\ln(AVC_{it-1})$	0.45 (0.05)*	0.16 (0.03)*	0.12 (0.03)*
y_{it-1}	0.09 (0.05)	0.01 (0.03)	0.08 (0.03)*
y_{it-2}	0.22 (0.09)*	0.04 (0.06)	0.01 (0.08)
y_{it-3}	0.11 (0.10)	0.06 (0.07)	0.01 (0.08)
	Variance-covariance matrix for disturbances		
var (α_1)	0.298	0.167	0.574
var (α_2)	0.005	0.0001	0.001
corr (α_1,α_2)	−0.106	−0.147	−0.082
var (ϵ_1)	0.702	0.823	0.426
var (ϵ_2)	0.995	0.106	0.163
corr (ϵ_1,ϵ_2)	0.180	−0.110	−0.026
No. observations	567	1,854	2,547
Log-likelihood	−309.61	−938.45	−1,679.24

Standard errors are in parentheses. An asterisk indicates that the estimate is significant at a 95 percent significance level.

therefore focus our attention on the Colombian and Moroccan results reported in Tables IIIa and IIIb.

Our *FIML* estimates of the participation equation yields results similar to those reported elsewhere [Roberts and Tybout 1997; Roberts, Sullivan, and Tybout 1995]. In all countries, and in all industries, plants with large capital stocks are more likely to

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE IIIb
FIML ESTIMATES OF EQUATIONS (10) AND (11)
MOROCCO 1984–1990

	Chemicals	Food	Textiles
	Participation equation		
Intercept	17.66 (18.18)	16.35 (15.04)	16.49 (10.05)
ln (e_t)	5.69 (3.90)	3.58 (3.22)	3.50 (2.13)
ln (K_{it-1})	2.64 (0.67)*	1.03 (0.46)*	2.45 (0.43)*
ln (A_{it})	2.45 (3.23)	−1.56 (1.73)	−2.09 (1.47)
ln $(A_{it})^2$	−0.39 (0.48)	0.28 (0.26)	0.35 (0.24)
B_{it}	0.81 (0.70)	0.26 (0.15)	0.07 (0.16)
ln (AVC_{it-1})	−1.16 (0.60)	−0.18 (0.42)	0.06 (0.18)
ln (AVC_{it-2})	−1.05 (0.89)	0.92 (0.47)	−0.24 (0.30)
$\tilde{y}_{it-1}$	1.14 (0.45)*	1.25 (0.54)*	0.91 (0.36)*
$\tilde{y}_{it-2}$	0.09 (0.05)	1.25 (0.51)*	0.50 (0.28)
$\tilde{y}_{it-3}$	0.28 (0.35)	0.67 (0.47)	0.02 (0.28)
	Cost function		
Intercept	0.05 (0.03)	−0.07 (0.03)*	−0.12 (0.03)*
ln (K_{it})	−0.06 (0.04)	−0.16 (0.04)*	−0.07 (0.04)
ln (AVC_{it-1})	0.39 (0.05)*	0.20 (0.05)*	0.15 (0.04)*
ln (AVC_{it-1})	0.40 (0.07)*	0.25 (0.05)*	0.07 (0.05)
y_{it-1}	−0.02 (0.03)	0.12 (0.02)*	−0.02 (0.02)
y_{it-2}	0.03 (0.05)	0.02 (0.04)	0.00 (0.05)
y_{it-3}	0.02 (0.04)	0.01 (0.10)	−0.12 (0.06)
var (α_1)	0.546	0.724	0.677
var (α_2)	0.0001	0.003	0.001
corr (α_1,α_2)	0.046	−0.559	−0.590
var (ϵ_1)	0.454	0.276	0.323
var (ϵ_2)	0.024	0.022	0.057
corr (ϵ_1,ϵ_2)	−0.019	−0.040	−0.057
No. observations	637	1,169	1,722
Log-likelihood	69.13	117.79	−517.87

Standard errors are in parentheses. An asterisk indicates that the estimate is significant at a 95 percent significance level.

be exporters. One likely interpretation is that there are fixed costs associated with export shipments, and producers who can produce large batches are better able to spread these costs. Consistent with our conceptual framework, plants that have lower marginal costs are more likely to be exporters, other things being equal. Although some of the distributed lag coefficients are positive, their sum is negative for all industries and countries. Nonetheless, individual lags of this variable are never statistically signifi-

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

cant, partly because of the high collinearity between them.[25] The fact that standard errors for cost coefficients are relatively large for Morocco is consistent with the lack of cost variation across types of firms observed in the graphs discussed earlier in Section III.

The effect of previous export experience is substantial in all industries, and most dramatic for plants that exported the previous year. In Morocco the effect is smaller in textiles than in chemicals. This result jibes with our priors that breaking into the foreign textiles market involves less sunk cost than breaking into the foreign chemicals markets. Although exporting experience acquired more than one year ago proved marginally significant in earlier work on participation [Roberts and Tybout 1997], it appears to be unimportant for most industries in the present application. This finding is probably due to the relatively small samples we use here, since the coefficients on lagged participation variables themselves are not systematically smaller.

In theory, devaluations should increase the probability of becoming an exporter, but we only find significant effects of the exchange rate in Colombian textiles and apparel industries. These are the goods that Colombia sends north, so it is not surprising that the real exchange rate vis-à-vis the dollar is a strong predictor for both industries. Chemicals, on the other hand, are mainly sold in Latin America, and producers in that industry do not show as much responsiveness to real exchange rates. Point estimates of the response to devaluation in Morocco resemble those for Colombia, but have larger standard errors.

Now consider our *FIML* estimates of the cost equation. As expected, plants with larger capital stocks tend to have lower marginal costs, although there are some insignificant coefficients. Also, conditioning on capital stocks and unobserved plant effects, marginal costs appear to follow a second-order, or higher, autoregressive process.[26] But, critically, exporting history contributes little to the explanation of marginal costs once we have conditioned on these variables. Indeed, in the few instances where

25. One reason these results are less dramatic than our graphs is that here we condition on lagged participation, which is collinear with *AVCAVC*. Put differently, firms with low unit costs tended to be exporters in the past, so recent innovations in *AVC* have limited explanatory power.

26. Because of the increased complexity of the estimation, we used the more parsimonious specification for our *FIML* estimates. The same reasoning led us to use only one lag on the capital stock, and to use the exchange rate instead of time dummies. All of these restrictions were relaxed in our *GMM* estimates (to be discussed below).

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

lagged experience is statistically significant, the coefficient suggests that exporting *increases* costs. So these results provide even less support for the learning-by-exporting hypothesis than our descriptive analysis in Section III.

Finally, note that positive unexplained cost shocks (coming through α_{2i} and ϵ_{2i}) are associated with negative unexplained shocks to exporting probabilities shocks (coming through α_{1i} and ϵ_{1i}), as one would expect. But the variance of α_2 is quite small, presumably because most of the serial correlation in costs is controlled for by our distributed lags.[27] Hence the bias associated with cost function estimators that treat lagged participation as exogenous may be negligible.

Are the cost function results robust? To address this issue, we fit the more general average variable cost function (11′) using *GMM* estimators.[28] Coefficients on our export market participation variables are reported along with several specification tests in Tables IVa (Colombia) and IVb (Morocco). Coefficients on business type, age, time dummies, and lagged values of ln $(q_{it}^h + q_{it}^f)$ and ln (K_{it}) were estimated but are too voluminous to report.

Note first that the model appears to be well specified. Arellano and Bond's [1991] tests reveal no evidence of serial correlation in v'_{it}, even though this disturbance term should be contaminated by α_2. This is consistent with our earlier *FIML* finding that var (α_{2i}) is nearly zero (Table III), and it implies that there is no reason to sweep out plant effects by differencing the data.[29] Further, the instrument set easily passes Sargan's test of overidentifying restrictions in all cases. Finally, our (unreported) distributed lag coefficients on ln $(q_{it}^h + q_{it}^f)$ indicate that output levels matter in some cases, so leaving these variables out of equation (11) may have led to some misleading results in Tables IIIa and IIIb.[30]

Nonetheless, Tables IVa and IVb are consistent with these earlier tables in terms of their basic message on learning: whether

27. Estimation of the cost function as a simple random effects model confirms that the variance in the plant effect is very small.

28. These estimates were obtained using Arellano and Bond's Dynamic Panel Data program.

29. Estimates of equation (11′) based on first differences or orthogonal deviations frequently failed tests for serial correlation, so we do not report them to conserve space. It is nonetheless worth mentioning that they are consistent with the level-form results reported here in terms of their implications for learning-by-exporting.

30. In Colombia coefficients on current output are always significantly negative, and the sum of the current and lagged coefficients is always close to zero. In Morocco output levels did not typically play a significant role in the regression.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE IVa
GMM ESTIMATES OF COST FUNCTION (11′), COLOMBIA, 1986–1991

	Apparel	Other chemicals	Textiles	Paper	Industrial chemicals	Nonbeverage food processing	Beverages
Exporting experience measured with $y_{it-1}, y_{it-2}, y_{it-3}$							
Coefficient on:							
y_{it-1}	0.021 (0.041)	−0.015 (0.027)	0.018 (0.027)	−0.041 (0.035)	0.012 (0.027)	−0.030 (0.030)	−0.083 (0.053)
y_{it-2}	−0.010 (0.049)	−0.013 (0.026)	0.004 (0.025)	−0.005 (0.020)	0.002 (0.016)	0.040 (0.025)	0.101 (0.044)
y_{it-3}	0.081 (0.043)	0.048 (0.033)	0.005 (0.025)	0.050 (0.030)	0.029 (0.021)	0.017 (0.025)	0.014 (0.016)
Wald test, joint signif., $\chi^2(3)$	9.03*	2.24	2.39	2.80	4.46	7.25	7.77
Sargan test, instr., $\chi^2(26)$	24.11	24.18	30.62	27.02	31.04	26.55	29.33
1st order autocorr., $N(0,1)$	−0.737	0.950	−1.737	−0.89	−0.100	−0.487	−0.168
2nd order autocorr., $N(0,1)$	−0.830	0.882	−0.926	−1.44	1.002	−1.077	−1.751
Exporting experience measured with $\ln(q^f_{it-1}+1), \ln(q^f_{it-2}+1), \ln(q^f_{it-3}+1)$							
Coefficients on:							
$\ln(q^f_{it-1}+1)$	0.002 (0.005)	−0.003 (0.002)	0.003 (0.003)	−0.006 (0.004)	0.002 (0.003)	−0.004 (0.003)	−0.006 (0.005)
$\ln(q^f_{it-2}+1)$	−0.004 (0.006)	−0.001 (0.003)	0.002 (0.003)	−0.001 (0.002)	−0.001 (0.002)	0.004 (0.003)	0.006 (0.005)
$\ln(q^f_{it-3}+1)$	0.010 (0.006)	0.006 (0.004)	−0.002 (0.003)	0.008 (0.004)	0.002 (0.002)	0.002 (0.003)	0.003 (0.002)*
Wald test, joint signif., $\chi^2(3)$	10.41*	3.31	3.59	4.32	3.40	7.96*	6.61
Sargan test, instr., $\chi^2(26)$	23.94	24.33	30.87	26.33	30.51	26.58	29.442
1st order autocorr., $N(0,1)$	−0.711	0.984	−1.749	−0.994	−0.100	−0.490	−0.161
2nd order autocorr., $N(0,1)$	−0.809	0.931	−0.948	−1.437	1.007	−1.058	−1.744
No. plants	283	169	206	69	63	301	93
No. observations	1698	1014	1236	414	378	1806	558

Standard errors are in parentheses; an asterisk indicates that the estimate is significant at a 95 percent significance level.

In addition to measures of exporting experience, the regressions include the following variables: three lags of cost, three lags of capital stock, three lags of output, current output, business type, age, age squared, and annual time dummies. All are included in the instrument set except current output.

The Wald test is for the joint null hypothesis that the three variables measuring previous exporting experience have zero coefficients.

The Sargan test, which is based on overidentifying restrictions, is for the null hypothesis that the instrument set is orthogonal to the disturbance.

The autocorrelation tests are for first- and second-order serial correlation in the (undifferenced) residuals.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE IVb

GMM Estimates of Cost Function (11′), Morocco, 1988–1990

	Food	Textiles	Apparel	Leather	Metalworking	Chemicals
	Exporting experience measured with $y_{it-1}, y_{it-2}, y_{it-3}$					
Coefficient on:						
y_{it-1}	0.108 (0.068)	−0.020 (0.023)	0.033 (0.033)	−0.031 (0.049)	−0.008 (0.046)	−0.010 (0.018)
y_{it-2}	0.017 (0.041)	0.037 (0.022)	−0.018 (0.029)	−0.080 (0.030)*	−0.022 (0.841)	−0.009 (0.016)
y_{it-3}	−0.051 (0.051)	−0.042 (0.022)	−0.049 (0.024)*	0.042 (0.035)	−0.027 (0.066)	−0.007 (0.018)
Wald test, joint signif., $\chi^2(3)$	29.92*	4.92	6.66	9.89*	4.51	0.92
Sargan test, instr., $\chi^2(5)$	7.40	10.84	7.50	6.93	4.27	5.65
1st order autocorr., $N(0,1)$	−0.584	−0.754	−0.600	−0.022	−1.711	−0.662
2nd order autocorr., $N(0,1)$	0.040	0.453	0.771	0.450	−1.132	0.395
	Exporting experience measured with $\ln(q^f_{it-1}+1), \ln(q^f_{it-2}+1), \ln(q^f_{it-3}+1)$					
Coefficients on:						
$\ln(q^f_{it-1}+1)$	0.013 (0.009)	−0.003 (0.007)	0.010 (0.008)	0.007 (0.010)	−0.001 (0.008)	−0.002 (0.003)
$\ln(q^f_{it-2}+1)$	0.002 (0.004)	0.001 (0.004)	−0.008 (0.005)	−0.020* (0.005)	−0.002 (0.015)	−0.002 (0.003)
$\ln(q^f_{it-3}+1)$	−0.007 (0.007)	−0.002 (0.003)	−0.008 (0.004)	0.005 (0.006)	−0.004 (0.011)	−0.000 (0.003)
Wald test, joint signif., $\chi^2(3)$	27.55*	1.99	9.11*	16.41*	4.05	0.90
Sargan test, instr., $\chi^2(5)$	7.69	10.47	7.74	6.09	4.28	5.44
1st order autocorr., $N(0,1)$	−0.681	−0.840	−0.705	0.032	−1.568	−0.582
2nd order autocorr., $N(0,1)$	−0.049	0.599	0.780	0.696	−1.194	0.352
No. plants	167	246	157	105	116	91
No. observations	501	738	471	315	348	273

Standard errors are in parentheses; an asterisk indicates that the estimate is significant at a 95 percent significance level.

In addition to measures of exporting experience, the regressions include the following variables: three lags of cost, three lags of capital stock, three lags of output, current output, business type, age, age squared, and annual time dummies. All are included in the instrument set except current output.

The Wald test is for the joint null hypothesis that the three variables measuring previous exporting experience have zero coefficients.

The Sargan test, which is based on overidentifying restrictions, is for the null hypothesis that the instrument set is orthogonal to the disturbance.

The autocorrelation tests are for first- and second-order serial correlation in the (undifferenced) residuals.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

measured by the history of y_{it} or by the history of ln $(q_{it}^f + 1)$, participating in export markets does not typically improve firms' average variable cost trajectories. In Colombia (Table IVa), exporting history is rarely significant. When it is, the coefficients tend to be positive rather than negative. In Morocco (Table IVb), exporting experience does not tend to significantly reduce costs in the food, textiles, or chemicals industry, and prior exporting experience is associated with *higher* variable costs among food producers.

The only qualification pertains to the additional Moroccan industries treated in Table IVb but not in Table IIIb: apparel, leather, and metalworking. In these sectors the coefficients on our export experience variables tend to be negative, and in apparel and leather they are jointly significant in at least one of the specifications. One interpretation is that learning-by-exporting has indeed occurred in these sectors. But export-oriented multinationals are unusually common in these sectors, so their relative efficiency may also reflect technology transfers from parent companies [Haddad and Harrison 1993; Haddad de Melo, and Horton, 1996]. Further, given that apparel exporters relied especially heavily on imported fabrics, we may be picking up the effects of Morocco's duty drawback scheme, which exempted firms from paying tariffs on imported inputs that they used to produce exports [World Bank 1994].[31]

In short, the data are consistent with learning by exporting only in the Moroccan apparel and leather products industries; otherwise, we find that exporting experience either has no effect on costs or tends to *increase* cost. Could this lack of support for the learning-by-exporting hypothesis be a statistical artifact? One source of bias derives from the fact that we are not measuring total costs. If the production technology for exports is more labor-intensive (or skilled-labor intensive) than the technology for domestic goods produced by the same firm, we might miss offsetting reductions in capital costs by focusing exclusively on labor and materials. We might also miss learning effects if workers capture efficiency gains as higher wages, leaving average variable costs unaffected. Finally, we may well be picking up some

31. Our measure of input costs is pretariff, but duty drawbacks should still affect our tests relating exporting status to unit costs if (1) decisions on input sourcing are related to the decision to export, and (2) the price of domestically produced inputs is higher than the pretariff price of imported substitutes. The first condition is likely to be met by Moroccan apparel firms that entered into outsourcing agreements with European firms, and the second condition is likely to be met whenever tariffs protect domestic producers of intermediate inputs.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

of the sunk entry costs associated with becoming an exporter in our variable cost measure. But in Colombia, the (*FIML* and most *GMM*) estimates of the coefficients on all three lags of export market participation are positive, so that for at least three years, these entry costs are not offset by productivity gains due to learning-by-exporting effects. Overall, then, although we cannot rule out alternative interpretations, none of them seems compelling.

C. The Evidence on Externalities

In order to test for regional and industry spillover effects, we expanded equations (10) and (11) to include regional and industry export intensity variables. For the ith firm, belonging to region R_i and industry I_i, these were $\Sigma_{j \in R_i} y_{jt-1}/n_{R_i}$ and $\Sigma_{j \in I_i} y_{jt-1}/n_{I_i}$, respectively, where n_{R_i} and n_{I_i} are the total number of firms in the region and industry. Coefficients on these variables in the participation equation indicate whether sunk entry costs (F^0) are correlated with previous exporting activity by other firms. In the cost function they indicate whether all firms have lower or higher costs when some firms have been exporting. To control for permanent, unobserved regional effects like access to ports, regional dummies were also included.

Adding our measure of industry-specific export activity to the model increased the collinearity of the explanatory variable set because, like the exchange rate, it is common to all firms in the industry. The (absolute) correlation between these two variables lies between 0.66 and 0.76 in Colombia, and between 0.62 and 0.91 in Morocco, depending upon the industry. These correlations, while high, do not prohibit estimation. However, the condition number of the moment matrix of the regressors—the square root of the ratio of the largest to the smallest characteristic root—lies between 648 and 1018 in Morocco, but only between 47 and 56 in Colombia.[32] In addition, the estimated coefficients of the exchange rate and the spillover variables in Morocco were absurdly high and imprecisely estimated. For these reasons, we decided to focus our *FIML* analysis of spillovers on Colombia only.

Suppressing the nonexternality coefficients, which are simi-

32. For the purposes of these calculations the regressors include only a constant, the exchange rate, the proportion of exporters in the industry, the proportion of exporters in the region, and the regional dummies. A condition number above 30 suggests potential multicollinearity problems [Belsley, Kuh, and Welsch 1980].

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE V
FIML ESTIMATES OF SPILLOVER VARIABLES
COLOMBIA 1983–1991

	Chemicals	Textiles	Apparel
	Participation equation (10)		
% Firms exporting, industry	−2.03 (3.07)	0.04 (6.07)	1.63 (1.30)
% Firms exporting, region	2.74 (5.00)	6.14 (10.37)	5.01 (0.82)*
	Cost function (11)		
% Firms exporting, industry	2.72 (0.65)*	0.24 (0.85)	−0.43 (0.62)
% Firms exporting, region	−3.31 (0.94)*	1.02 (1.30)	1.76 (1.30)
No. observations	567	1854	2547
Log-likelihood	−289.28	−924.65	−1,603.87

Standard errors are in parentheses; an asterisk indicates that the estimate is significant at a 95 percent significance level.

lar to those in Tables III and IV, we report *FIML* coefficients for the Colombian externality variables in Table V. All but one of the externality coefficients in the participation equation are positive; however, only one is significant. Nonetheless, this seems to provide some evidence that the presence of many exporters increases a firm's chances of being an exporter itself. These results are consistent with Aitken, Hanson, and Harrison's [1997] conclusions based on cross-sectional analysis of Mexican data, and in principle, they suggest that export promotion may be welfare improving. But caution is warranted, as such policies have often missed their mark [Keesing and Lall 1992].

The case for *AVC*-reducing spillovers is weaker. Four out of six *FIML* coefficients are positive, suggesting that high export intensity actually raises costs. The chemical industry is particularly noteworthy because the two coefficients are both significant and they have opposing effects. Unit production costs are reduced by export intensity in the region, perhaps because of demonstration effects, and the development of better transport services for exporters. On the other hand, the presence of other *chemical* exporters appears to increase unit costs, perhaps because they bid up the prices of specialized inputs in response to rising export demand. An alternative interpretation is that correlation between our industrywide externality measures and average variable costs simply reflects trends in both variables (recall that we could not include annual time dummies in this model).

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

As in subsection C above, we can adopt a more general specification of the cost function and test for robustness using *GMM* estimators. Table VI summarizes the results of this exercise for eight different versions of equation (11′) augmented by spillover variables. The first four specifications, denoted (*i*) through (*iv*), control for own exporting experience with our foreign market participation dummies, y_{it-1}, y_{it-2}, and y_{it-3}, while the other four specifications, denoted (*v*) through (*viii*), control for own exporting experience using the logs of export volumes: $\ln(q^f_{it-1} + 1)$, $\ln(q^f_{it-2} + 1)$, and $\ln(q^f_{it-3} + 1)$.

Specifications (*i*) and (*v*) use the same spillover variables that appear in our *FIML* specification (Table V), while (*ii*) and (*vi*) use the share of output exported last period by firms in the region, $\Sigma_{j \in R_i} q^f_{jt-1} / \Sigma_{j \in R_i} (q^f_{jt-1} + q^h_{jt-1})$ or industry, $\Sigma_{j \in I_i} q^f_{jt-1} / \Sigma_{j \in I_i} (q^f_{jt-1} + q^h_{it-1})$. One would expect the number of exporters to affect the prevalence of knowledge about foreign technologies and markets, while the *volume* sold abroad might affect the size and efficiency of upstream industries that supply transport and other services to exporters.

Versions that include industry spillover variables—specifications (*i*), (*ii*), (*v*), and (*vi*)—control for relative price variation using the real exchange rate, since time dummies would be perfectly collinear with our industrywide spillover variables. But in the remaining specifications we replace the industrywide spillover variables with time dummies and focus only on regional spillovers. This approach better controls for relative prices, although it does not yield estimates of industrywide spillover effects. As indicated in the tables, specifications (*iii*), (*iv*), (*vii*), and (*viii*) are distinguished only by the regional spillover variable and by the set of variables that control for exporting experience.

The Colombian results are presented in Table VIa. Specification (*i*) is closest to the cost function used for our *FIML* estimates in Table V. It yields results consistent with Table V in that the textiles and apparel industries show no significant spillovers, while the spillover effects for industrial chemicals producers are significantly cost decreasing for regionwide exporting and significantly cost *increasing* for industrywide exporting. Like textiles and apparel, most of the other industries show little evidence of spillover effects. But in the paper industry, average variable costs are significantly lower when the number of paper exporters increases, while average variable costs are significantly higher

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE VIa
GMM ESTIMATES OF SPILLOVER COEFFICIENTS, GENERALIZED COST FUNCTION (11′)
COLOMBIA, 1986–1991

	Apparel	Other chemicals	Textiles	Paper	Industrial chemicals	Nonbeverage food processing	Beverages
	Own exporting experience measured with $y_{it-1}, y_{it-2}, y_{it-3}$						
Coefficient on:							
(i) *% firms exporting, industry*	−0.407 (0.653)	−0.029 (0.584)	−0.118 (0.527)	−0.818 (0.267)*	1.096 (0.531)*	−1.400 (1.495)	2.156 (1.263)
% firms exporting, region	1.027 (1.207)	0.297 (0.716)	−0.370 (0.976)	1.132 (0.411)*	−3.082 (0.603)*	1.110 (0.515)*	0.289 (0.657)
(ii) *% output exported, industry*	2.372 (1.330)	0.188 (2.002)	5.782 (1.530)*	−0.754 (0.522)	0.665 (1.062)	2.627 (1.867)	3.567 (1.544)*
% output exported, region	−1.679 (0.831)*	0.298 (0.511)	−2.515 (0.670)*	0.394 (0.482)	−1.815 (0.745)*	0.205 (0.498)	−1.163 (0.584)*
(iii) *% firms exporting, region*	0.604 (0.987)	−0.668 (1.269)	−0.104 (1.021)	0.877 (0.900)	−3.149 (2.215)	0.290 (0.713)	2.089 (0.848)*
(iv) *% output exported, region*	−1.747 (1.364)	−0.576 (0.938)	−1.709 (0.831)*	−0.082 (0.888)	−0.660 (1.640)	0.295 (0.617)	−0.925 (1.072)
	Own exporting experience measured with $\ln(q^f_{it-1}+1), \ln(q^f_{it-2}+1), \ln(q^f_{it-3}+1)$						
(v) *% firms exporting, industry*	−0.409 (0.642)	0.011 (0.579)	−0.107 (0.533)	−0.789 (0.271)*	1.214 (0.543)*	−1.417 (1.495)	2.108 (1.255)
% firms exporting, region	0.972 (1.179)	0.273 (0.712)	−0.432 (0.985)	1.226 (0.425)*	−3.057 (0.622)*	1.108 (0.515)*	0.332 (0.656)
(vi) *% output exported, industry*	2.310 (1.340)	0.301 (1.998)	5.702 (1.544)*	−0.713 (0.525)	0.734 (1.070)	2.585 (1.863)	3.608 (1.527)*
% output exported, region	−1.681 (0.833)	0.292 (0.509)	−2.544 (0.679)*	0.466 (0.493)	−1.852 (0.778)*	0.196 (0.497)	−1.132 (0.546)*
(vii) *% firms exporting, region*	0.627 (1.075)	0.234 (1.008)	−0.206 (1.048)	1.149 (0.797)	−4.406 (2.005)*	0.354 (0.518)	2.333 (0.866)*
(viii) *% output exported, region*	−2.168 (1.438)	0.034 (0.878)	−1.781 (0.831)*	−0.522 (0.781)	−1.310 (1.965)	−0.166 (0.606)	0.288 (0.998)
No. plants	283	169	206	69	63	301	93
No. observations	1698	1014	1236	414	378	1806	558

Standard errors are in parentheses; an asterisk indicates that the estimate is significant at a 95 percent significance level.
The regressions include, in addition to the spillover variables listed in the first column, all the variables used in Table IVa.
The instrument set includes lagged values of capital stocks, output, exports, age, regional dummies, and time dummies or the exchange rate.
Specifications (i) through (iv) use $y_{it-1}, y_{it-2}, y_{it-3}$ to measure own exporting experience, while specifications (v) through (viii) use $\ln(q^f_{it-1}+1), \ln(q^f_{it-2}+1), \ln(q^f_{it-3}+1)$. In addition, in specifications (i), (ii), (v), and (vi), the real exchange rate was included, while in specifications (iii), (iv), (vii), and (viii), time dummies were used.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE VIb
GMM ESTIMATES OF SPILLOVER COEFFICIENTS, GENERALIZED COST FUNCTION (11′)
MOROCCO, 1988–1990

	Food	Textiles	Apparel	Leather	Metalworking	Chemicals
Own exporting experience measured with $y_{it-1}, y_{it-2}, y_{it-3}$						
Coefficient on:						
(i) *% firms exporting, industry*	−11.46* (3.882)	2.208* (0.780)	−5.880 (5.270)	−4.408* (1.095)	1.270 (3.517)	4.396* (1.408)
% firms exporting, region	0.137 (0.729)	−0.038 (0.589)	−2.547* (0.987)	0.273 (1.059)	0.481 (0.941)	0.632 (1.060)
(ii) *% output exported, industry*	−18.53* (6.168)	3.015* (1.077)	−2.587 (1.348)	−0.956* (0.237)	2.852 (3.871)	−9.232* (2.981)
% output exported, region	0.352 (0.261)	−0.312 (0.572)	4.895* (1.695)	0.381 (0.682)	−0.277 (0.233)	0.107 (0.223)
Own exporting experience measured with $\ln(q^f_{it-1}+1), \ln(q^f_{it-2}+1), \ln(q^f_{it-3}+1)$						
(v) *% firms exporting, industry*	−10.42* (3.812)	2.213* (0.645)	−6.373 (5.139)	−4.476* (1.019)	0.474 (2.280)	4.634* (1.409)
% firms exporting, region	0.064 (0.727)	0.046 (0.593)	−2.503* (0.977)	0.519 (1.007)	−0.140 (1.074)	0.692 (1.072)
(vi) *% output exported, industry*	−18.65* (6.318)	3.111* (0.891)	−2.701* (1.316)	−0.982* (0.223)	2.794 (3.946)	−9.467* (2.952)
% output exported, region	0.317 (0.260)	−0.391 (0.595)	4.955* (1.673)	0.300 (0.675)	−1.108 (0.944)	0.113 (0.221)
No. plants	167	246	157	105	116	91
No. observations	501	738	471	315	348	273

Standard errors are in parentheses; an asterisk indicates that the estimate is significant at a 95 percent significance level.
The regressions include, in addition to the spillover variables listed in the first column, all the variables used in Table IVa.
The instrument set includes lagged values of capital stocks, output, exports, age, regional dummies, and time dummies or the exchange rate.

Specifications (i) through (iv) use $y_{it-1}, y_{it-2}, y_{it-3}$ to measure own exporting experience, while specifications (v) through (viii) use $\ln(q^f_{it-1}+1), \ln(q^f_{it-2}+1), \ln(q^f_{it-3}+1)$. In addition, in specifications (i), (ii), (v), and (vi), the real exchange rate was included, while in specifications (iii), (iv), (vii), and (viii), time dummies were used.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

when the number of manufacturing exporters in the region increases.

Controlling for own exporting experience with export volumes rather than export market participation (specification (*v*)) has no effect on these patterns. However, it does matter how spillovers are measured. If we focus on export volumes rather than on the number of exporters (specifications (*ii*) and (*vi*) rather than (*i*) and (*v*)), we find that significantly negative (cost-reducing) effects of regionwide exporting activity are more common, as are significantly positive (cost-increasing) effects of industrywide exporting activity. In fact, all of the significant coefficients fit this pattern, which we first mentioned in connection with the industrial chemicals sector.

Finally, by including time dummies, we can do a better job of controlling for industrywide shocks, but we must drop our industrywide spillover variables and focus only on regional effects. (We are able to retain regional dummies in all eight specifications because no industry produces exclusively in one region.) This exercise is pursued in specifications (*iii*), (*iv*), (*vii*), and (*viii*). Once again, the regional spillover variables tend to be associated with cost reductions, particularly when we measure exporting activity with volumes rather than number of exporters. The only significant exception to this pattern is found in the beverage industry when spillovers are measured with the number of firms exporting.

One interpretation of this fairly robust pattern is that Colombian firms *do* become more efficient by exporting, but they cannot exclude domestically oriented producers from sharing in their cost reductions. This would occur, for example, if exporters tended to improve upstream input suppliers through scale effects or technical advice, making them cheaper or better. On the other hand, we cannot rule out the possibility that regions experiencing factor cost reductions—say falling real wages—do an increasing amount of exporting because of selection effects, and even the nonexporters enjoy lower average variable costs.

We report *GMM* cost function estimates for Morocco in Table VIb, which follows the format of Table VIa. However, models (*iii*), (*iv*), (*vii*), and (*viii*) are not reported because they yield identical coefficients for the regional spillover variables as models (*i*), (*ii*), (*v*), and (*vi*), respectively.[33] Compared with Colombia, the results

33. This is because of the shorter time period available in Morocco. The two time dummies span the same space as the exchange rate and the industrywide spillover variables, so replacing the former with the latter has no effect on the remaining coefficients (except for the intercept).

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

are rather mixed. Except for metalworking and apparel, each industry shows significant industrywide spillovers. Yet the effect of industrywide exporting activity is cost-increasing for some sectors and cost-reducing for others. This mixed pattern holds for regional spillovers as well, although most coefficients are statistically insignificant. The exceptions are apparel producers, which appear to have lower variable costs when others are exporting in their region, and food producers, which have *higher* variable costs when large volumes of exports are coming from their region. The lack of a clear message for Morocco probably reflects the relatively short time span of the Moroccan panel. Our spillover coefficients are identified with industrywide or regionwide temporal variation in the data, but given our lag specifications, there are only three in-sample years.

V. Summary and Conclusions

Micro data in developing countries often show that exporting firms are more efficient than nonexporting firms. This study confirms that pattern, and adds the finding that plants that cease exporting are typically less efficient, sometimes dramatically so. But more importantly, this study addresses the question of whether the association between exporting and efficiency reflects causation flowing from exporting experience to improvements in performance. Despite many anecdotes in the literature to the contrary, we find that data from most export-oriented industries in Colombia and Morocco are inconsistent with this causality pattern.

If learning by exporting is important, then the stochastic processes that generate cost and productivity trajectories should improve with changes in exporting status. To get some sense of the nature of the response, we began by plotting cost and exporting trajectories from actual plant-level panel data from Colombia, Morocco, and Mexico. We found that plants that begin exporting tend to have relatively low average variable cost, and plants that cease exporting are becoming increasingly high cost, as implied by the model. Similar patterns emerged when we used labor productivity as our performance measure. However, cost and productivity trajectories generally did not continue to change after entering foreign markets. That is, the patterns we found in the actual data resembled our no-learning-by-exporting scenario, under which the positive association between export status and productivity is

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

due solely to the self-selection of relatively more efficient plants into foreign markets.

To formally test whether the association between exporting and efficiency reflects more than self-selection, we simultaneously estimated an autoregressive cost function and a dynamic discrete choice equation that characterized export market participation decisions. Exporting history did not significantly shift the cost function, and to the extent that it did, the shift was usually in the "wrong" direction. Robustness tests confirmed our cost function results under a variety of specifications and an expanded set of industries, although they also suggested that learning by exporting may have occurred among Moroccan apparel and leather producers. Thus, with some possible exceptions, the association between exporting and efficiency is most plausibly explained as low-cost producers choosing to become exporters.

Finally, looking for evidence of externalities, we found that the presence of other exporters might make it easier for domestically oriented firms to break into foreign markets. We also found evidence that, other things being equal, production costs become lower in those regions of Colombia where export activity increases, even though the exporters themselves do not enjoy a special advantage. One interpretation is that exporters become more efficient by participating in foreign markets, but domestically oriented producers are able to share in the cost reductions. Another possibility is that regions that experience factor cost declines become relatively export-oriented (because of selection effects), but the factor cost reductions benefit nonexporters too.

Appendix: Data Preparation

A. The Panel Data Sets

The Colombian data were obtained from the Departamento Administrativo Nacional de Estadistica (DANE) for the period 1981–1991. They provide annual information on the inputs, outputs, exports, and characteristics of all plants with at least ten workers. Similar annual survey data were obtained from Morocco's Ministry of Commerce and Industry for the period 1984–1990 and from Mexico's Instituto Nacional de Estadistica Geografia e Informacion (INEGI) for the period 1984–1990, although the Mexican data cover only 3200 of the larger firms and do not include exporting information for the first two years. The data were cleaned and deflated in connection with a previous World Bank project, which is summarized in Roberts and Tybout [1996].

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE VII
INDUSTRIES AND NUMBERS OF PLANTS IN THE DATABASE, BY COUNTRY

Colombia	Morocco	Mexico
Coffee processing (127)	Food processing (937)	Food processing (376)
Other food processing (965)	Textiles (564)	Textiles (185)
Textiles (457)	Apparel (671)	Chemicals (395)
Apparel (962)	Leather products (292)	Glass (21)
Leather products (94)	Transport equipment (103)	Metal products (166)
Paper (353)	Metalworking (354)	Nonelectrical machinery (151)
Industrial chemicals (113)	Chemicals, nonphosphate (285)	Electric machinery (142)
Other chemicals (284)	Phosphate products (324)	Transport equipment (149)
		Electronic components

The analysis in this paper is based solely on firms in export-oriented industries that reported all the variables of interest over the entire sample period. These industries exported at least 10 percent of their output, and had at least twenty exporting plants. In a few cases, industries that exported less than 10 percent of their output were included because they had many exporting plants or they accounted for a substantial share of total manufactured exports. Table VII lists the export-oriented industries and average number of plants by country.

Comparing the average numbers of plants in each industry with the numbers of plants present during every sample year (reported in Tables IV and VI) reveals that many producers are not included in the analysis. The discrepancy is particularly large in high turnover industries like food processing, textiles, leather, and apparel, where more than half of the firms turned over at some point during the sample periods. However, the selectivity problem is mitigated by two factors. First, plants that turn over tend to be much smaller than those that continue. For example, in a typical year during the period 1984–1989, 16 percent of the plants in Morocco's export-oriented industries were new entrants and 6 percent were in their final year, yet these plants accounted for only 3.3 percent of output and 0.9 percent of output, respectively [Haddad, de Melo, and Horton 1996]. In Colombia the average entry rate for all manufacturing industries was around 12.5 percent during the mid-1980s, and the average exit rate was 11.4 percent; yet these two groups accounted for only 3.5 percent of output and 3.1 percent of output, respectively [Roberts and Tybout 1996]. Second, with the exception of Morocco's apparel

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

TABLE VIII
COMPONENTS OF TOTAL VARIABLE COST, BY COUNTRY

Colombia	Morocco	Mexico
Employee compensation: • salaries • benefits	Cost of personnel	Total labor remuneration: • salaries • fringe benefits • social security contributions
Cost of intermediate inputs: • value of raw materials consumed • goods purchased for sale without transformation • purchases of replacement parts of less than one year duration • energy consumed • other fuels and lubricants	Materials and other noncapital expenditures	Cost of materials: • primary/raw materials consumed • packaging materials • fuels • electricity • spare parts
Cost of services and transport: • payments for industrial work by other establishments • payments to third parties for repairs and maintenance		Cost of services and transport: • cost of subcontracted assembly work • cost of shipping • sales commissions

and leather/footwear sectors, most new and dying plants were nonexporters.

B. Variables Costs

Total variable costs (*TVC*) were constructed as the sum of labor costs, intermediate input costs, and subcontracted production costs. The variables in the original data sets differed somewhat across countries, so it was not possible to use identical *TVC* concepts in each case. Table VIII summarizes the components of *TVC* by country. The Mexican and Colombian surveys were similar, but the Moroccan survey provided considerably less detail. Total personnel costs were not broken down there, and intermediate costs were not directly reported, so it was necessary to infer these as the value of output less value-added. Haddad, de Melo, and Horton [1996] provide further details. Average variable

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

costs (*AVC*) were constructed as *TVC* divided by nominal output, so they really measure costs per unit revenue.

C. Capital Stocks, Domestic Sales, and Exports

Several other variables appear in the estimated equations. Capital stocks were constructed in each country using the perpetual inventory method and capital stock price indices. Details on variable construction are provided in the country study chapters of Roberts and Tybout [1996]. Real output $(q^d + q^f)$ was constructed as domestic and foreign sales plus the change in inventories after each component of this expression was converted to constant prices using the price deflators described below. (Final product inventories were considered to be destined for the domestic market.)

D. Price Indices[34]

To deflate the domestic component of output (defined as domestic sales plus change in final product inventory), industry-specific domestic output price indices were obtained from each country at roughly the three-digit ISIC level. For Colombia these deflators were implied by real and nominal output figures in the original data set obtained from DANE. For Morocco the industry-specific domestic output price indices were taken from various years of the *Moroccan Statistical Bulletin*. For Mexico INEGI supplied the output price deflators.

No export price deflators were readily available, so converting exports to constant prices proved to be an involved process. First, product-specific data on the values and quantities of manufactured imports and exports were obtained from the United Nations Trade Database for each of the three countries. These data implied unit values of trade flows at a very detailed level. However, they were expressed in nominal U. S. dollars and were much more disaggregated than the product classifications reported in our plant-level panel data, so a number of steps were necessary before they could be used as export price deflators.

First, each country's industrial classification system had to be concatenated with the U. N.'s Standard International Trade Classification (SITC) system. Inspection of the product descriptions for each system yielded, for each three-digit ISIC industry, a list of

34. This section is adapted from Roberts, Sullivan, and Tybout [1995], which is based on the same data.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

SITC products that were potentially exported and their shares in total exports of the industry.

Second, for each product included in these lists, it was necessary to purge the associated SITC unit value series of spurious variation due to changes in the mix of individual items being traded. For example, if T-shirts cease to be exported and dress shirts begin to be exported, unit export values for shirts will jump. This problem was dealt with by instrumenting each SITC unit export value series with *import* unit values in the same product category and a time trend. (The imports of all three countries were included in the instrument set.)

Third, the unit values were aggregated up to roughly the three-digit ISIC level (depending upon the country) weighting each by its average export shares of the products within each four-digit industry over the sample period.

Fourth, using the annual average nominal exchange rate between each country's domestic currency and the U. S. dollar (taken from various issues of *International Financial Statistics*), the export unit values were converted to domestic currency units.

Finally, the nominal export price series for each industry in each country were normalized to the same base year as the domestic output price indices, so that both exports and domestic sales could be expressed in terms of the same real domestic currency units.

YALE UNIVERSITY
THE HEBREW UNIVERSITY AND NATIONAL BUREAU OF ECONOMIC RESEARCH
GEORGETOWN UNIVERSITY

REFERENCES

Aitken, Brian, Gordon H. Hanson, and Ann Harrison, "Spillovers, Foreign Investment, and Export Behavior," *Journal of International Economics,* XLIII (1997), 103–132.
Arellano, Manuel, and Steven Bond, "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies,* LVIII (1991), 277–297.
Aw, Bee-Yan, and Amy R. Hwang, "Productivity and the Export Market: A Firm-Level Analysis," *Journal of Development Economics,* XLVII (1995), 313–332.
Baldwin, Richard, "Sunk Cost Hysteresis," NBER Working Paper No. 2911, 1989.
Belsley, David A., Edwin Kuh, and Roy E. Welsch, *Regression Diagnostics: Identifying Data and Sources of Collinearity* (New York: Wiley, 1980).
Bernard, Andrew B., and J. Bradford Jensen, "Exceptional Exporter Performance: Cause, Effects, or Both?" mimeo, 1995.
Caves, Richard, and David Barton, *Efficiency in U. S. Manufacturing Industries* (Cambridge, MA: MIT Press, 1990).
Chen, Tain-jy, and De-piao Tang, "Comparing Technical Efficiency between Import-Substitution and Export Oriented Firms in a Developing Country," *Journal of Development Economics,* XXVI (1987), 277–289.

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms

Clerides, Sofronis, Saul Lach, and James Tybout, "Is 'Learning-By-Exporting' Important? Micro-Dynamic Evidence from Colombia, Mexico and Morocco," NBER Working Paper No. 5715, 1996.
Dixit, Avinash, "Exit and Entry Decisions under Uncertainty," *Journal of Political Economy,* XCVII (1989), 620–638.
Evenson, Robert, and Larry Westphal, "Technological Change and Technology Strategy," in T. N. Srinivasan and Jere Behrman, eds., *Handbook of Development Economics, Volume 3* (Amsterdam: North-Holland, 1995).
Grossman, Gene, and Elhanan Helpman, *Innovation and Growth in the World Economy* (Cambridge, MA: MIT Press, 1991).
Guilkey, David, and James L. Murphy, "Estimation and Testing in the Random Effects Probit Model," *Journal of Econometrics,* LIX (1993), 301–317.
Haddad, Mona, "How Trade Liberalization Affected Productivity in Morocco," World Bank, Policy Research Working Paper No. 1096, 1993.
Haddad, Mona, Jaime de Melo, and Brendan Horton, "Morocco, 1984–89: Trade Liberalization, Exports and Industrial Performance," in M. Roberts and J. Tybout, eds., *Industrial Evolution in Developing Countries* (New York, Oxford University Press, 1996).
Haddad, Mona, and Ann Harrison, "Are There Positive Spillovers from Foreign Direct Investment? Evidence from Panel Data for Morocco," *Journal of Development Economics,* XLII (1993), 51–74.
Handoussa, Heba, Mieko Nishimizu, and John Page, "Productivity Change in Egyptian Public Sector Industries after the 'Opening,' " *Journal of Development Economics,* XX (1986), 53–74.
Heckman, James, "Statistical Models for Discrete Panel Data," in C. Manski and D. McFadden, eds., *Structural Analysis of Discrete Data with Econometric Applications* (Cambridge, MA: MIT Press, 1981a).
——, "The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process," in C. Manski and D. McFadden, eds., *Structural Analysis of Discrete Data with Econometric Applications* (Cambridge, MA: MIT Press, 1981b).
Holtz-Eakin, Douglas, Whitney Newey, and Harvey Rosen, "Estimating Vector Autoregressions with Panel Data," *Econometrica,* XLVI (1988), 1251–1272.
Keane, Michael, Robert Moffit, and David Runkle, "Real Wages over the Business Cycle: Estimating the Impact of Heterogeneity with Micro Data," *Journal of Political Economy,* XCVI (1988), 1232–66.
Keesing, Donald, and Sanjay Lall, "Marketing Manufactured Exports from Developing Countries: Learning Sequences and Public Support." in Gerald Helleiner, ed., *Trade Policy, Industrialization and Development* (Oxford: Oxford University Press, 1992).
Krugman, Paul, *Exchange Rate Instability* (Cambridge, MA: MIT Press, 1989).
Rhee Yung, Bruce Ross-Larson, and Garry Pursell, *Korea's Competitive Edge: Managing the Entry into World Markets* (Baltimore: Johns Hopkins University Press, 1984).
Roberts, Mark, Theresa Sullivan, and James Tybout, "Micro-Foundations of Export Booms," World Bank, mimeo, 1995.
Roberts, Mark, and James Tybout, eds. *Industrial Evolution in Developing Countries: Micro Patterns of Turnover, Productivity and Market Structure* (New York: Oxford University Press, 1996).
Roberts, Mark, and James Tybout, "The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs," *American Economic Review,* LXXXVII (September 1997) 545–564.
Sullivan, Theresa, "Micro-Foundations of Export Supply in Morocco," Ph.D. thesis, Georgetown University, 1997.
Tybout, James, and M. Daniel Westbrook, "Trade Liberalization and Dimensions of Efficiency Change in Mexican Manufacturing Industries," *Journal of International Economics,* XXXI (1995), 53–78.
World Bank, *The East Asian Miracle* (New York: Oxford University Press, 1993).
——, *Kingdom of Morocco-Republic of Tunisia, Export Growth: Determinants and Prospects,* Report No. 12947-MNA, 1994.
——, *World Development Report 1997: The State in a Changing World* (New York, Oxford University Press, 1997).

This content downloaded from
59.129.101.251 on Sun, 09 May 2021 13:05:17 UTC
All use subject to https://about.jstor.org/terms